UNIVERSITY
OF TECHNOLOGY
SYDNEY

Examining resource recovery pathways for low carbon waste management in New South Wales, Australia

by Benjamin Madden

Thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy

under the supervision of:

Associate Professor Nick Florin
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March, 2023

Certificate of original authorship

I, Benjamin Madden declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor Philosophy, at the Institute for Sustainable Futures at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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"While none of the work we do is very important, it is important that we do a great deal of it."
General Peckem, *Catch-22*

Acknowledgements

I wish to sincerely thank my supervisor Nick Florin. His support and mentorship over the years has helped me to become a better scholar and writer. I thank him also for his dedication and the countless hours spent discussing my research, and having faith in me pursuing this PhD. I could not have asked for a better supervisor.

Thank you also to Steve Mohr and Damien Giurco for their supervision. Without Steve's guidance in particular, much of this work could not have been accomplished. His own thesis was a huge inspiration in me undertaking quantitative research. Damien, I thank for all of his fantastic advice and enthusiasm, and for helping to open the door to the wonderful world of ISF.

At the Institute for Sustainable Futures, I thank colleagues Melita Jazbec and Andrea Turner, for discussions on the problems and solutions of organic waste management. Melita in particular, I am grateful for our friendship. Thank you also to Suzanne Cronan for administrative help, and to RAO Prof. Jason Prior.

Thank you to my Mum and brother Matt, who have always encouraged me through my long education. Significant thanks is owed to Mary-Anne Williams for her support, and for her advice in navigating the world of academia. Special thanks also to Brailey Sims for his encouragement, and advice especially related to the transport modelling in Chapter 5. Thank you to Henry, Ida, Lodi and Olive: for their understanding and patience, happy distractions, and for motivating me to do good work and to finish this PhD.

Finally, to you Anthea: this was not possible without your love and support. Thank you for taking care of me over this odyssey, and thank you for always being there to hear my thought-bubbles and offer advice: no one's opinion do I value more than yours. You always inspire me, and I hope that this impresses you.

Dedicated to John Peter Madden, 1942-2009

Publication authorship declarations

Publication 1: Madden, B., Florin, N., Mohr, S., Giurco, D. (2019). Using the waste Kuznet's curve to explore regional variation in the decoupling of waste generation and socioeconomic indicators. *Resources, Conservation and Recycling*, 149, 674-686, https://doi.org/10.1016/j.resconrec.2019.06.025

The candidate conceptualised and carried out the research, and wrote the entirety of the original draft. Nick Florin provided detailed review and editing for the final draft submission, and supervision. Steve Mohr provided guidance on the mathematics in the paper, and provided review for the final draft submission. Damien Giurco provided detailed review and editing for the final draft submission.

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I, as a co-author, endorse that this level of contribution by the candidate indicated above is appropriate

Co-author 1: Associate Professor Nick Florin

Signature of co-author: Date: 9/11/2022

Production Note:
Signature removed
prior to publication.

Co-author 2: Dr. Steve Mohr

Signature of co-author: Date: 9/11/2022

Production Note:
Signature removed
prior to publication.

Co-author 3: Professor Damien Giurco

Signature of co-author: Date: 20/10/2022

Production Note:
Signature removed
prior to publication.

Publication 2: Madden, B., Florin, N., Mohr, S., Giurco, D. (2021). Spatial modelling of municipal waste generation: Deriving property lot estimates with limited data. *Resources, Conservation and Recycling*, 168, 105442, https://doi.org/10.1016/j.resconrec.2021.105442

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Production Note:
Signature removed
prior to publication.

Co-author 3: Professor Damien Giurco

Signature of co-author: Date: 20/10/2022

Production Note:
Signature removed
prior to publication.

Publication 3: Madden, B., Florin, N., Mohr, S., Giurco, D. (2022). Estimating emissions from household organic waste collection and transportation: The case study of Sydney and surrounding areas, Australia. *Cleaner Waste Systems*, 2, 100013, https://doi.org/10.1016/j.clwas.2022.100013

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Signature of co-author: Date: 8/11/2022

Production Note:
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prior to publication.

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Signature of co-author: Date: 20/10/2022

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Abstract

The household organic waste stream is problematic, with high rates of waste generation and large quantities of waste disposed to landfill each year. Through better management of the household organic waste stream, waste may be diverted from landfill to resource recovery processes, leading to emissions reductions and the realisation of circular resource flows. These resource recovery processes however carry an emissions burden, and limited data on emissions associated with waste management systems as in Australia, make assessing resource recovery pathways from a low carbon perspective difficult. The aim of this study was to better characterise the emissions associated with household organic waste management in New South Wales, in order to examine the emissions reduction and resource recovery potential of the waste stream. It is hoped that the work contained in this thesis will help inform future household organic waste management strategies, aligned with greenhouse gas reduction and landfill diversion objectives in the state and other Australian jurisdictions.

This study developed a hybrid modelling approach, consisting of several different methodologies addressing limitations in the data. Firstly, the spatial distribution of waste generation was analysed, to estimate household waste generation at a fine spatial scale where ground truth data does not exist. A probabilistic spatial disaggregation model was developed, used to estimate waste generation at the property lot level with accuracy, for households in the Greater Sydney and surrounding areas.

Secondly, property lot waste estimates were combined with road network and waste infrastructure data in a route optimisation model, to estimate emissions from waste collection and transport. For the household organic waste stream, these emissions were estimated as approximately 43,700 tonnes CO_2-e—representing 2% of total NSW road transportation emissions in the study time frame. The between bin travel and bin lifting components were the most emissions intensive part of overall transport emissions from the components analysed. Findings indicated that increasing the intensity of bin lifts per stop; and improvements to collection vehicle efficiency and electrification, would have the greatest impact on reducing transport emissions.

Next, transport emissions estimates were combined with council organic waste recovery data to characterise emissions over the entire household organic waste management chain. Material

flow modelling was utilised to estimate emissions from compost recovery as well as from alternate waste treatment of household organics in the mixed waste stream. Lifetime emissions from organic waste disposed to landfill, as well as emissions avoided through landfill diversion, were also estimated, following approaches used in the Australian National Greenhouse Gas Accounts. Analysis found that emissions associated with household organic waste management were approximately 245,000 tonnes CO_2-e in the study timeframe. Lifetime landfill emissions from household organics disposed, accounted for approximately 56% of these emissions. Management of the mixed waste stream, accounting for the majority of waste disposed to landfill, had the largest impact on overall emissions; and thus, presents the most important opportunity for achieving low carbon resource recovery.

Finally, potential household organic waste management pathways were evaluated from a low carbon resource recovery perspective, where greenhouse gas emissions are minimised while maximising resource recovery. This evaluation was performed through scenario simulations, and multi-criteria analysis. Increased diversion of food waste from the mixed stream to dedicated organic waste collection was identified as a key characteristic of optimal organic waste management pathways. Significant potential emissions reductions were also found, via fossil fuel avoidance through the deployment of anaerobic digestion. Potential electricity generation from biogas utilisation from household organic waste was between 84,000 MWh and 171,000 MWh for standalone digestion facilities and digesters located at alternate waste facilities. Findings from this analysis highlights the potential for a food waste only kerbside collection system, which could encourage further diversion of food waste out of the mixed stream and landfill, while also providing a cleaner and more appropriate feedstock stream for municipal scale digestion.

The work in this thesis fills an important gap in the assessment of household organic waste management from a low carbon resource recovery perspective. Modelling approaches developed in this work can also be used to assess the emissions potential for a wider variety of waste management systems and pathways in NSW and elsewhere. The findings from this study suggest that the collection of combined food and garden organic waste favoured by councils in NSW, may not be the best approach when considering emissions and higher value resource recovery outcomes. Considering also emissions intensive electricity supply reliant on fossil fuels, organic recovery can be geared towards offsetting fossil fuels with biogas from digestion. This would support a broader system evolution powered by renewable energy, and net zero emission objectives in the state.

Commonly used acronyms and terms

AD	Anaerobic digestion
ASGS	Australian Statistical Geography Standard
AWT	Alternate/alternative waste treatment
CH_4	Methane
CO_2-e	Carbon dioxide equivalent
(C)VRP	(Capacitated) vehicle routing problem
EKC	Environmental Kuznet's curve
EU	European Union
GHG	Greenhouse gas
GIS	Geographical information system
G(T)WR	Geographically (and temporally) weighted regression
GWP	Global warming potential
IPCC	Intergovernmental Panel on Climate Change
LCA	Life cycle assessment
LGA	Local government area
MBT	Mechanical biological treatment
MCA	Multi-criteria analysis
MCDM	Multi-criteria decision making
MFA	Material flow analysis
MRF	Material recycling facility
MSW	Municipal solid waste
N_2O	Nitrous oxide
NGA	National Greenhouse Accounts
OFMSW	Organic fraction of municipal solid waste
OLS	Ordinary least squares
SA1	Statistical area 1
SAM	Simple additive model
TSP	Travelling salesman problem
WARR	Waste avoidance and resource recovery
WKC	Waste Kuznet's curve

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Chapter 1.
Introduction

1.1. Background

The impacts of anthropogenic greenhouse gas (GHG) emissions must be curtailed across all sectors of the economy to limit the impacts of climate change (IPCC, 2021). Although small compared to the fossil fuel electricity sector, waste management is an important contributor to overall emissions with landfilling alone contributing approximately 3% to global emissions annually (IPCC, 2021). Due to a reliance on fossil fuels, significant emissions also occur from the consumption of fuel and electricity over the entire waste management chain from collection to recovery. Waste management systems can also deliver emission reductions, including through offsetting emissions intensive primary material consumption via recycled material utilisation; generating energy from waste materials to replace fossil-fuel derived energy sources; and diverting waste from landfill thus avoiding future landfill emissions.

Historically in Australia, jurisdictions have been guided by the 'waste hierarchy' in establishing priorities for waste management planning and measuring waste system performance. The waste hierarchy is a decision-making framework, evolved from the concept of 'Lansink's Ladder', which establishes an order of preference for waste management (Figure 1-1). Under this hierarchy, prevention of waste is top priority, with the recovery of material resources prioritised above energy recovery, other forms of waste treatment, and landfill disposal. Under guidance from the waste hierarchy, there is no direct prioritisation of environmental performance including emissions reduction. Equally, local jurisdictions have typically set weight based waste recovery rate targets as a key measure of the performance of waste systems, which also overlooks environmental performance. Indeed, recovery rates are simple for jurisdictions to quantify, and demonstrate progress up (or down) the hierarchy (Pires & Martinho, 2019). However, there are limitations with measuring performance of waste systems using recovery rate metrics alone. These include a lack of consistency on where in the system (e.g., before or after collection for recycling) recovery is calculated (van Eygen et al., 2018); lack of distinction between high quality and low-quality recovery (Dieterle et al., 2018; Haupt et al., 2017); and other indicators being needed to assess management performance of the system holistically (Pires & Martinho, 2019), especially where environmental impacts including GHG emissions are concerned. Moreover, materials recycling may not be the most resource or environmentally efficient approach for waste recovery when the energy intensity of recovery for some waste streams, such as mixed household wastes, is high (Arena, 2015). As such, recovery rate metrics alone are not sufficient in measuring the overall quality, resource efficiency, and sustainability of waste systems (Iacovidou et al., 2017a).

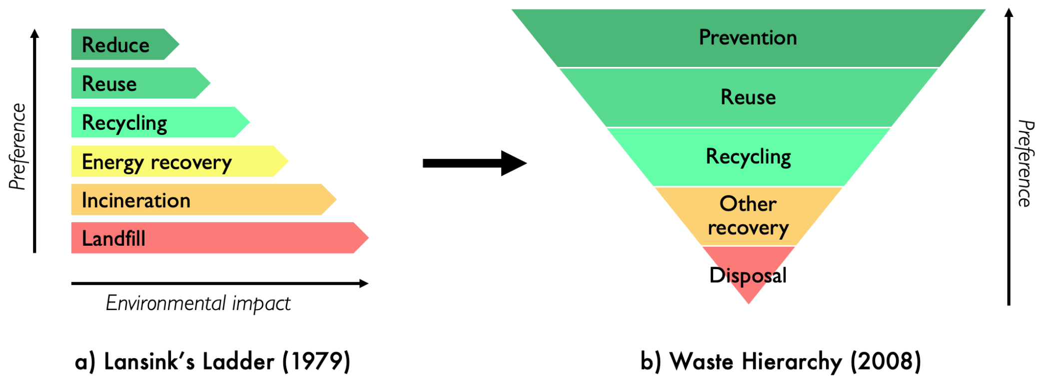


Figure 1-1: Evolution of the waste hierarchy, adapted from (Zhang et al., 2022)

Given the urgent need to reduce economy wide GHG emissions, there is an opportunity to better align GHG reduction priorities with waste system performance priorities in how waste is managed. This PhD examines the potential role that recovering resources from the household organic waste stream may have towards meeting sustainable waste management, and GHG emission reduction objectives in New South Wales, Australia.

1.1.1. Waste as a resource

When materials are no longer considered useful at the end of their functional, economic, and/or physical lives, they become wastes to be managed. The generation of waste is inevitable in the linear 'make-use-dispose' model of production and consumption, for which the waste hierarchy was developed to address. While modern waste management systems evolved to process this waste from society in an effort to protect human health, the definitions and objectives of waste management have also changed over time (Brunner & Rechberger, 2016). Now, the concept of the 'circular economy' is guiding sustainable best-practice in waste management worldwide, including in Australia. Recent adoption of a circular economy framework (NSW EPA, 2019b); and the development of strategies for plastic waste (DPIE, 2020) and long-term waste management (NSW EPA, 2020a) aim to move future decision making in NSW more towards a circular economic framework. A circular economy is in contrast to the linear make-use-dispose model (Figure 1-2) and encourages the prevention of wastes and harmful emissions wherever possible, through rethinking product design and consumption models, and the reuse of products and resources (Rood & Hanemaaijer, 2017). The circular flow of materials has implications for waste management, with a greater emphasis placed on extracting the maximum value of resources whilst in use, and at their end of life via resource recovery (e.g., materials, energy, and nutrients). This has led to a reframing of waste as a resource in contemporary sustainable waste management.

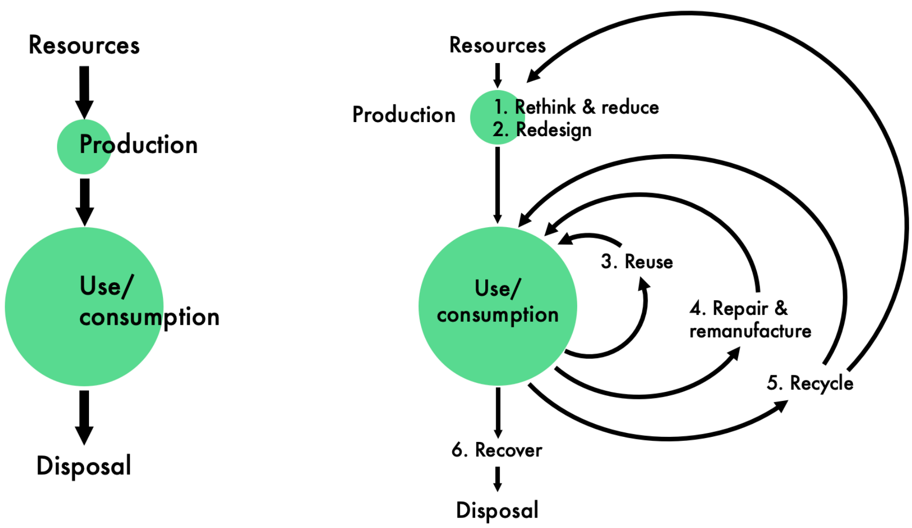


Figure 1-2: Comparison of linear and circular product use systems, adapted from Rood and Hanemaaijer (2017)

1.1.2. Resource recovery from waste streams

Recognising the importance of circular resource flows is not only a priority from an environmental perspective, but also can be an economic opportunity. Resource recovery enables these circular resource flows, and includes materials recovery processes, and also those processes that recover energy, nutrients and/or chemicals from waste streams—ready to be used as alternatives to primary resource consumption (Figure 1-3). Non-material recovery, namely energy and chemical recovery processes, have typically been held at lower levels of prioritisation following the waste hierarchy. Besides composting, non-material resource recovery processes are not deployed at large scales in Australia for municipal waste, despite the positive contribution such processes can make towards waste recovery targets and GHG reductions.

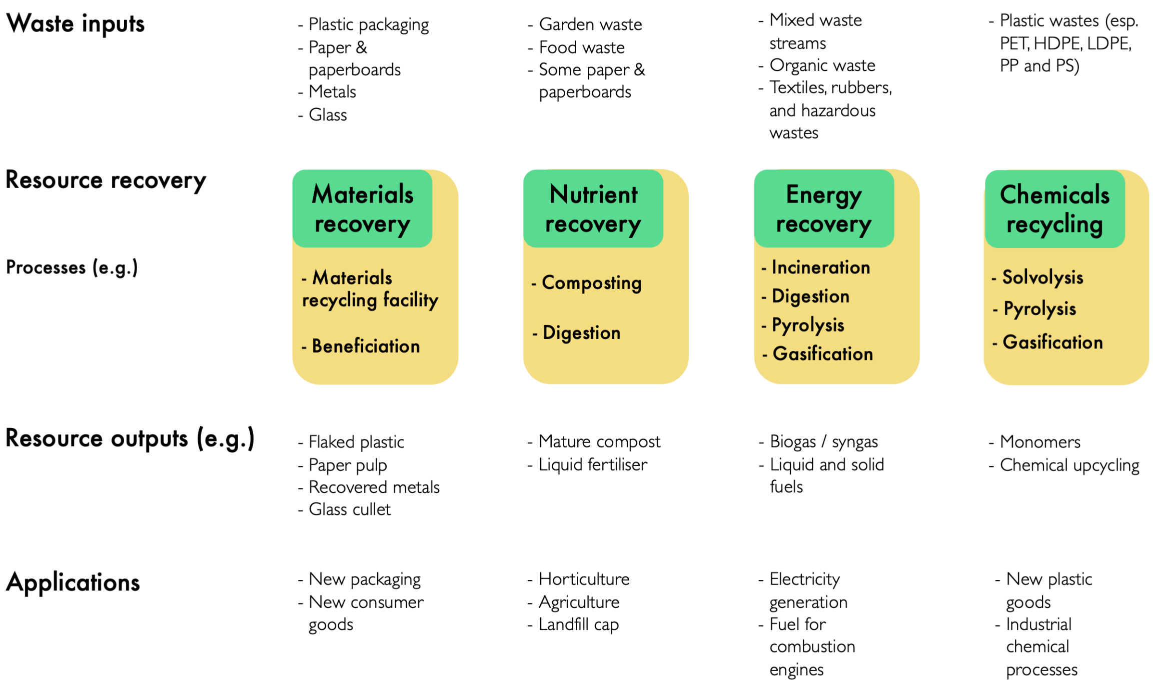


Figure 1-3: Overview of resource recovery from waste sources, adapted from insights in Babu et al. (2021); Meys et al. (2021); Pressley et al. (2015); Stunzenas and Kliopova (2018); Vanotti et al. (2019)

Resource recovery processes do have trade-offs. For example, materials cannot be infinitely recovered from waste streams nor at sufficient quality to be used in the same products, and some materials also require excessive amounts of energy to recover from waste streams (Arena, 2015). With energy recovery, processes such as direct incineration can have significant impacts on increasing recovery rates for municipal waste streams, as has been the case in The Netherlands (van Leeuwen et al., 2017). The positive benefits in landfill diversion and in offsetting the need for fossil-fuel resources however are balanced by significant direct emissions including GHGs and harmful toxins that may also occur depending on the waste stream and technology utilised (Demetrious & Crossin, 2019). The case of energy recovery as a resource recovery pathway for waste streams illustrates that looking at recovery rates alone is limiting when assessing waste system performance. Selecting optimal recovery pathways aligned with waste and environmental performance objectives is complex.

1.1.3. Household organic waste as a case study

Food waste is a global issue. More than 930 million tonnes of food sold worldwide was disposed to landfills in 2019 (UNEP, 2021), representing somewhere between 30% and 50% of all food produced (Khalil et al., 2022). Food waste is generated across multiple sectors, including in retail and food service industries. Households however are responsible for approximately 61% of the 930 million tonnes of food waste disposed (UNEP, 2021). Compared to other countries, Australia is a poor performer when it comes to household food waste generation, with approximately 102 kg generated per person, per year (Figure 1-4).

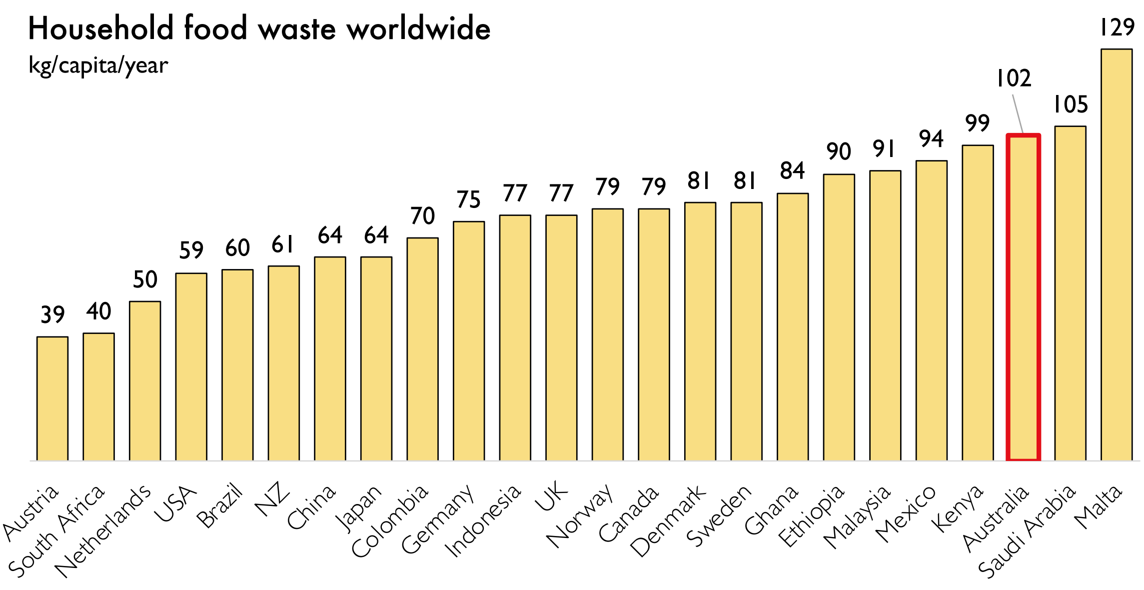


Figure 1-4: Estimates for household food waste generation for selected countries, from UNEP (2021)

In NSW, food waste makes up approximately 19% of all household waste collected (NSW EPA, 2021; Rawtec, 2020b), and is primarily collected via mixed waste collections and destined for landfill. The organic fraction of municipal waste (OFMSW) also consists of garden organics

(GO) including grass clippings and branches; however, this material stream is typically collected separately, with approximately 4,000 tonnes (or 1% of total generated) disposed to landfill in 2019-20 (NSW EPA, 2021). The separate collection of food waste alongside garden waste is a growing collection pathway in NSW, expanding from 22 councils in 2014-15 to 38 councils in 2019-20. While quantities of separate food and garden (FOGO) collections are low (Figure 1-5), the recent *NSW Waste and Sustainable Material Strategy 2041* anticipates mandatory FOGO collection for households in NSW, along with expansion in necessary infrastructure to manage this stream (DPIE, 2021).

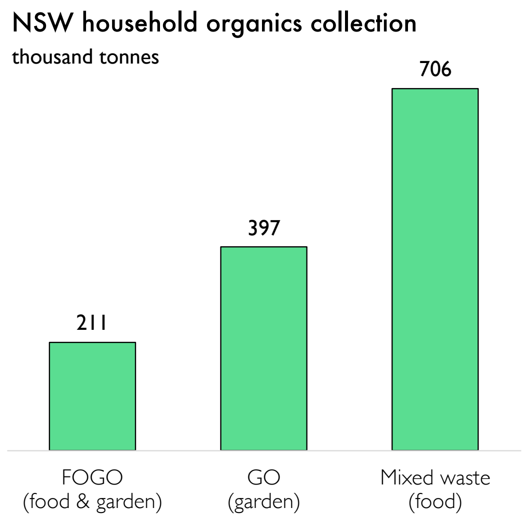


Figure 1-5: Breakdown of NSW household organic waste collection in 2019-20, from NSW EPA (2021) and Rawtec (2020b)

With baseline levels of emissions from waste management in NSW unclear outside of estimated landfill emissions (DISER, 2021c), the impact of emissions associated with expansion to kerbside collection systems is uncertain. Moreover, the lack of data characterising emissions from kerbside collection, as well as emissions and abatement potential from OFMSW, makes measuring progress aligned with sustainable waste strategies in NSW, and prioritising appropriate management pathways and technologies, difficult.

1.1.4. Emissions from the management of organic waste

Organic wastes disposed to landfill undergoes anaerobic decomposition, eventually generating methane gas emissions which have a significant global warming potential—approximately 28 times greater than CO_2 (DISER, 2021b). Up to 30% of these methane emissions occur within

2 years of landfill disposal (Liu et al., 2017), and approximately 48% of the organic waste stream will decompose to CO_2 and methane in landfills (Babu et al., 2021). As such, avoiding landfill emissions from organic wastes is a priority for low carbon waste management in many jurisdictions around the world, including in Australia and NSW.

Recovered resources from organic streams, including nutrients in the form of fertilisers and composts; and energy in the form of biogas, can lead to whole-of-system emissions reductions by avoiding landfill disposal, and mitigating consumption of fossil-derived products. Such emission reductions are also balanced by the direct and indirect emissions via the management system, for example, from the consumption of fuel and fossil-fuel derived electricity during the recovery processes themselves (Figure 1-6). Therefore, to align waste management with GHG emissions reduction planning and policy objectives for household waste, it is important then to consider the net emissions of waste management pathways over the whole waste management chain.

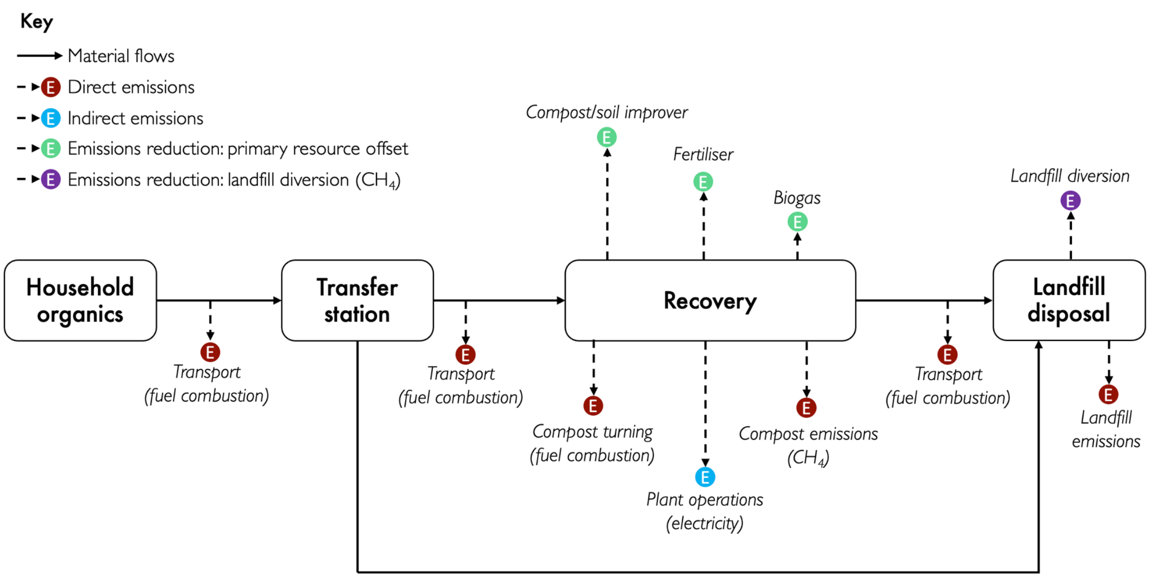


Figure 1-6: Illustrative example of sources of emissions over the household organic waste management chain

1.1.5. Measuring waste management emissions in Australia

The National Greenhouse Accounts (NGA) trace Australia's greenhouse gas emission estimates to fulfil GHG inventory reporting commitments under the *National Greenhouse and Energy Reporting Act 2007*, as well as provide a basis for tracking progress towards GHG reductions (DISER, 2022b). Emissions are estimated across all Australian states for a number of economic sectors following Intergovernmental Panel on Climate Change (IPCC) guidelines (DISER, 2021d). Waste-related emissions are included in the NGA, however only complete estimates for solid waste disposal and wastewater treatment and discharge are available (DISER, 2022a). From the NGA for 2019, NSW generated approximately 4,790,000 tonnes of CO_2-equivalent, primarily from landfill disposal.

The contribution of other components of waste management towards GHG emissions is less clear. For example, emissions from waste collection and transportation are not known and assumed to be small (NSW EPA, 2022), however could in fact be significant given the large distances between urban centres in NSW, and the dispersed nature of Australian housing. These emissions would likely be accounted for in road transport emissions (approximately 24,300,000 tonnes CO_2-e in NSW for 2019), however there is no resolution on waste vehicle types. The emissions from the recovery processes in Australia, are also unclear.

Waste recovery rates are typically traced to measure progress against targets, for example the NSW *Waste avoidance and resource recovery (WARR)* target of 70% recovery of municipal waste by 2021-22 (NSW EPA, 2014b). Targets focusing on improving waste related emissions or abatement however do not exist in NSW. Better accounting of waste related emissions and potential abatement is the primary aim of this thesis. Greater resolution of emissions associated with waste management could help decision makers in identifying optimal organic waste recovery pathways that maximise waste recovery, while minimising net emissions.

1.2. Research aims and approach

Household organic waste can be managed in such a way that limits the overall emissions impact of waste management, while maximising the recovery of resources from the waste stream. Data on waste related emissions and emissions factors specific to the local municipal organic waste context are at best uncertain, and at worse not available. This hampers the evaluation of waste recovery from a technical and environmental perspective, which has implications on the selection of optimal pathways maximising waste recovery and environmental performance.

Overcoming data gaps to determine more precisely the environmental performance of the management of household organic waste is a primary aim of this PhD. Without understanding more accurately the emissions associated with organic waste management, identifying the most optimal pathways that meet waste recovery and emissions objectives will be difficult. The key motivating question guiding this work is therefore:

Key motivating question: What are the most optimal pathways for low carbon resource recovery of the household organics waste stream?

This is a complex question, which requires many different assumptions, data sets, approaches, and types of analysis: i) There are some key data limitations including the high-resolution spatial distribution of the municipal waste supply, and a lack of data on waste transportation and infrastructure flows. Without this data, understanding more clearly transport emissions, and the impact on overall emissions intensity will be difficult. Spatial modelling can help to address this data gap, through for example spatial network analysis to model the waste collection and transport system. Moreover, local governments are varied, with councils having different waste collection systems in place, and different drivers impacting on how much waste is generated. A spatially nuanced approach in evaluating low carbon resource recovery performance may be beneficial, in identifying what areas may be best suited to a particular management pathway, or whereabouts should be targeted. ii) Emissions are generated, directly and indirectly, across the entire waste management chain. Understanding the quantities of waste that are managed by processes within a waste management system is required to properly account for these emissions. This can be achieved with mass balance modelling, LCA, and environmental accounting techniques. iii) Scenario analysis is also helpful in evaluating outcomes from planned and potential resource recovery pathways, to help determine recovery pathways best suited to low carbon waste management. Multi-criteria analysis could also inform the assessment of pathways with respect to waste recovery performance and GHG reductions to identify optimal pathways from a low carbon resource recovery perspective.

Given these considerations, the key motivating question is quite broad. It can be broken down into five, more detailed research questions, which are described below. Each question addresses important data gaps, or brings to light interesting analysis or observations that can help address the overall motivating question. Further background including literature review related to these research questions is provided in the relevant thesis chapters.

Research question 1: What is the spatial distribution of waste generation in NSW, and is regional variability significant?

Rates of waste generation can vary significantly over space, which can be a result of varying socioeconomics, demographics, and other factors that drive waste generation behaviours (Kontokosta et al., 2018). Assessing how significant regional variation in waste generation might be, is an important consideration when analysing waste systems over such a broad area as is the geographical scope of this thesis (geographical scope is explained in detail in Section 1.2.1). Moreover, data on the spatial distribution of waste is important for decision making, including for facility planning, and provisioning collection services to communities. This research question is addressed in Chapters 3 and 4.

Research question 2: How can waste generation data be modelled at high resolutions, where data is limited?

Detailed data of the NSW municipal waste supply (for example, at the scale of the property lot or household) is unavailable, however is useful in identifying optimal waste treatment or recovery facility locations (Kontokosta et al., 2018; Lin et al., 2020; Yadav et al., 2017); analysing waste collection routing efficiency (Hannan et al., 2018; Sarmah et al., 2019; Vu et al., 2019); and in planning for targeted dwelling specific systems, such as insinkerators and district/building scale anaerobic digestion and composting (Edwards et al., 2016; Jouhara et al., 2017; Lou et al., 2013). Methods for estimating high resolution waste generation data are addressed through research question 2, and described in detail in Chapter 4.

Research question 3: What are the emissions associated with kerbside organic waste collection and transportation?

Considering factors such as suburban sprawl, and large transport distances between NSW towns, cities and regional centres, it is hypothesised in this thesis that waste collection and transport emissions are a significant component of the overall emissions associated with organic waste management. Data on waste related emissions is non-existent for NSW, therefore addressing research question 3 will fill an important gap in knowledge. This research question is addressed in detail in Chapter 5.

Research question 4: What are the emissions associated with the recovery of household organic waste in NSW?

Along with emissions related to waste collection and transportation, there is a critical gap in knowledge on the emissions associated with current waste management practices for household organic waste. This makes decision making around identifying waste recovery pathways that have reduced impacts on emissions difficult. Addressing research question 4 will help fill this critical gap in knowledge, and is described in detail in Chapter 6.

Research question 5: What are the optimal low carbon resource recovery pathways for household organic waste in NSW, and how may they be identified?

This final research question draws together analysis performed to address research questions 1 to 4, which enables detailed analysis and estimation of emissions related to household organic waste management. Once performance can be quantified, potential organic management pathways can be evaluated from a low carbon resource recovery perspective—that is, maximum waste recovery with minimal GHG emissions. This will contribute to the evidence base for informing the future deployment of optimal resource recovery processes in NSW and Australia, including in what segments of the waste management chain prioritisation should occur, and what actors should be targeted, for example, households, local governments, and industry. This final research question is addressed in Chapter 7:

The work presented in this thesis is a compilation of published and to-be-published work that addresses these research questions as part of an analytical framework. Figure 1-7 gives an overview of this analytical framework, and elements of the framework that each research question addresses.

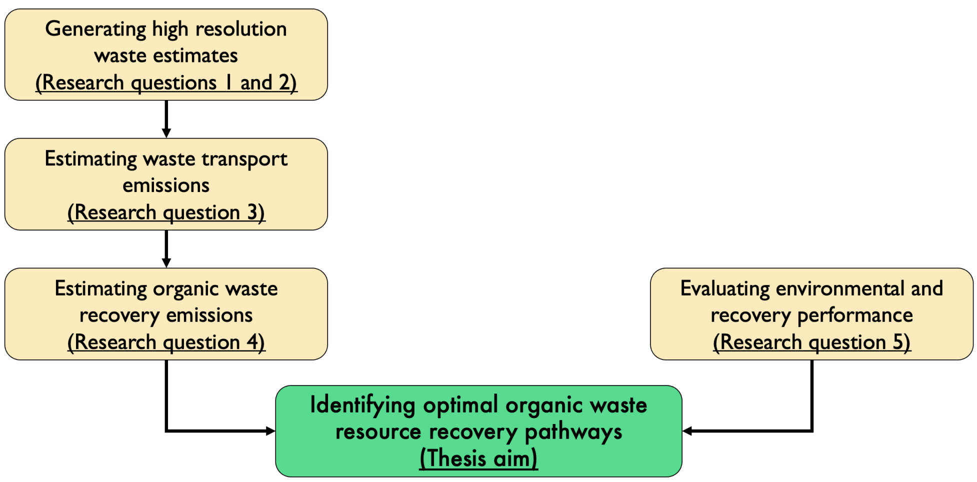


Figure 1-7: Analytical framework guiding this work, and relation to thesis research questions

1.2.1. Scope of work

OFMSW is the waste material scope for this PhD, chosen due to the significant quantities of organic waste generated and disposed to landfill in NSW each year. Methods explored and insights gained through this PhD however have implications for other waste streams not in scope, including organics from commercial and industrial waste streams, packaging waste, and other recyclable waste streams generated from households. These implications are discussed with respect to future research directions in Chapter 8 of this thesis.

The geographical scope is NSW, which is the Australian state responsible for the greatest quantities of waste generated annually across all sources. Some aspects of this research are appropriate to evaluate at smaller scales, such as the Sydney metropolitan and surrounding areas, which accounts for 77% of the state population (ABS, 2021), and 60% of waste generated (NSW EPA, 2021) in an area approximately 3% of the state's total area. Implications of research findings from this PhD for other geographical scales and jurisdictions is also further discussed in Chapter 8.

The timeframe of analysis varies; however, timeframes are relevant to the WARR target for 2021-22 (NSW EPA, 2014b); and 2030 in the *NSW Waste and Sustainable Material Strategy* (DPIE, 2021). Work presented here however can be applied for projecting organic waste recovery performance to timescales beyond what is presented in this thesis.

Technological pathways for resource recovery evaluated are bound by what is currently employed in NSW, what is planned for deployment, and what might be feasible for deployment in the future. For organic waste processing at the municipal scale, this includes industrial composting, and recovery via alternate waste treatment (AWT)—a form of mechanical biological treatment (MBT) employed in NSW. Other process types explored are limited to energy and nutrient recovery via AD, which is identified as a key technology for achieving objectives in the *NSW Waste and Sustainable Materials Strategy* (DPIE, 2021). Resource recovery technologies and processes for organic waste are explored in more detail in the literature review in Chapter 6.

Evaluating resource recovery systems and performance is complex—made more complicated by consideration of multiple, and sometimes competing, value domains. Many frameworks that exist for evaluating resource recovery, and waste streams more generally, do so in a single domain, for example environmental accounting, and material flow analysis. Iacovidou et al. (2017a) presents a holistic framework for complex value optimisation for resource recovery across four value domains—environmental, social, economic, and technical (see Figure 1-8). Holistic evaluation of resource recovery should consider multiple value domains. Trade-offs exist between one value domain and another, for example, establishing energy recovery facilities may increase economic and technical value, but impact on environmental and social value. Evaluating resource recovery then where there are competing domains is complex. For this thesis and its focus on low carbon resource recovery, the domains of environmental and technical values are considered in scope. While organic resource recovery will have impacts on other domains, there are not considered in scope of this thesis, but may be considered in future research (see Chapter 8).

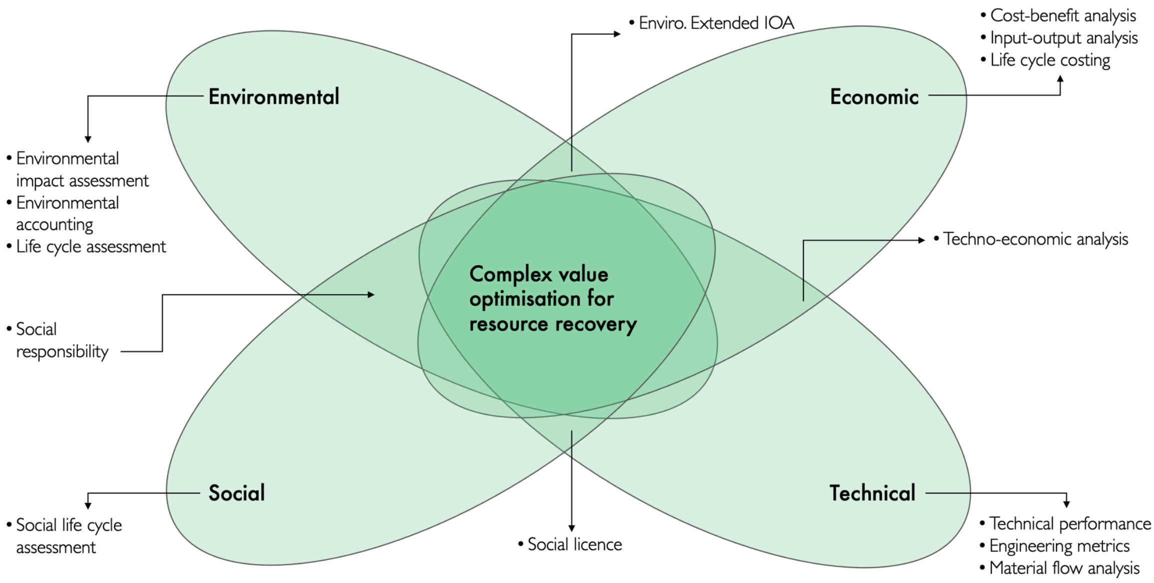


Figure 1-8: Frameworks, methods and tools used for appraisal of resource recovery value, adapted from Iacovidou et al. (2017a). The value domains considered in scope of this thesis are highlighted with bold outline

1.2.2. Overview of published and to-be-published materials in this thesis

This thesis includes published and yet-to-be published papers following the *thesis by compilation* style. Each paper already published has been reproduced within the thesis, and full bibliographical information is provided in each relevant chapter. Table 1-1 gives an overview of the papers published, and yet to be submitted, included in the thesis.

Table 1-1: Overview of publications included in this thesis

Paper	Title	Status
1 (Chapter 3)	Madden, B., Florin, N., Mohr, S., Giurco, D. (2019). Using the waste Kuznet's curve to explore regional variation in the decoupling of waste generation and socioeconomic indicators	Published *Resources, Conservation and Recycling* 149, pp. 674-686
2 (Chapter 4)	Madden, B., Florin, N., Mohr, S., Giurco, D. (2021). Spatial modelling of municipal waste generation: deriving property lot estimates with limited data	Published *Resources, Conservation and Recycling* 168, article 105442
3 (Chapter 5)	Madden, B., Florin, N., Mohr, S., Giurco, D. (2022). Estimating emissions from household organic waste collection and transportation: the case of Sydney and surrounding areas, Australia	Published *Cleaner Waste Systems* 2, article 100013
4 (Chapter 6)	Emissions from the management of household organic waste: estimates over the entire waste management chain	Submitted January 2023 to *Cleaner Waste Systems*
4/5 (Chapter 7)	Optimal low carbon resource recovery pathways for household organic waste management: scenario analysis	Not yet submitted

1.3. Thesis structure

Chapter 2 of the thesis contains a high level review of literature related to the evaluation of waste systems from a resource recovery and emissions reduction perspective, where key concepts are defined, and common approaches described.

In Chapter 3, the first published paper from this research is presented, where regional variation in waste generation in NSW is explored, with a case study in the context of decoupling of waste generation from socioeconomic metrics. This chapter tests a method for evaluating variation in waste generation spatially, and justifies the use of a spatial modelling approach when evaluating waste in NSW.

Chapter 4 builds on some of the findings from Chapter 3, and presents a novel approach to derive high-resolution, spatially resolved data for waste generation, enabling detailed evaluation of waste management systems. This chapter presents the second published paper from this research, where a spatial model is developed, and applied to estimate waste generation at the property lot for 1.2 million households in the Sydney Metropolitan Area.

Chapter 5 is concerned with filling a crucial knowledge gap in the evaluation of low carbon resource recovery, which is the emissions associated with waste collection and transportation. The chapter presents the third paper from this research, which hypothesises that emissions from waste collection and transportation are significant, and tests this using a network route optimisation model using high-resolution data derived from the model presented in Chapter 4.

Chapter 6 presents an analysis of the net emissions associated with the recovery of OFMSW in the Greater Sydney and surrounding areas. The model presented in this chapter utilises waste transport emission estimates from Chapter 5, along with a material flow analysis and emissions accounting, to estimate the direct and indirect emissions, as well as potential emissions reductions, for OFMSW recovery.

Chapter 7 is a synthesis chapter, which draws together findings and data from the preceding chapters to evaluate optimal organic waste management pathways for low carbon resource recovery. The chapter presents a scenario analysis, developed based on the *NSW Waste and Sustainable Materials Strategy*, and also presents a multi-criteria evaluation to assess potential organic waste pathways.

Chapter 8 will conclude the thesis, providing recommendations, as well as potential future research directions based on the work presented in this thesis.

Chapter 2.
Optimal pathways for low carbon resource recovery from waste

This chapter summarises some key concepts and related research on low carbon resource recovery from waste streams. This review of the literature helps locate the thesis within the broad field of waste management; provides background and establishes some key definitions and broad trends related to waste related emissions; and identifies some knowledge gaps justifying the broad thesis aims and research questions introduced in Chapter 1.

The following sections cover some key literature related to the above, and seeks to clarify and define the following aspects related to the research problem of the thesis:

Low carbon waste management: including key definitions of concepts and current trends in the literature, and considerations for evaluating emissions from waste management (Section 2.1)

Low carbon resource recovery: including definitions and trends related to resource recovery from waste in a circular economy context; how the concepts of low carbon waste management and resource recovery converge; and potential complexities between low carbon and resource recovery objectives (Section 2.2)

Optimal pathways for low carbon resource recovery: including approaches for evaluating pathways for maximised resource recovery and low carbon performance; and how optimal recovery pathways may be identified (Section 2.3)

The chapter concludes with a summary of considerations relating to the thesis research problem, as well as critical gaps in the literature identified.

Further review of more specific literature, for example related to specific modelling and evaluation approaches, are covered later in this thesis, in the context of work published and to-be-published (Chapters 3 to 7), and have not been included here to avoid repetition.

2.1. Low carbon waste management

Emissions need to be reduced from all sectors of the economy to address the threats of anthropogenic climate change. With the global energy sector responsible for approximately 75% of emissions worldwide (IEA, 2022), transitioning to low carbon energy systems is a priority agenda for governments around the world (Drożdż et al., 2022). Utilising less emissions intensive energy sources, and improving the efficiency of energy systems, all effectively work towards achieving a transition to low carbon energy (Chapman et al., 2021). Although less significant than the energy sector, the waste sector is also considered one of 4 significant societal sources of global emissions (Eurostat, 2020). Therefore, addressing emissions from the waste sector is also important, and many recent waste management policies and initiatives, especially in Europe, have been connected with strategies addressing the threats of climate change (Gavrilescu, 2022).

Consistent with the low carbon energy concept, 'low carbon waste management' implies the reduction of emissions intensity of waste systems, and reducing this intensity can be achieved via a number of means. As noted in Figure 1-6, emissions occur at several points along the waste management chain from a number of sources, including direct emissions from fuel consumption and decomposition of material via composting or in landfill; and indirect emissions via the consumption of electricity for waste treatment processes. Opportunities also exist across the waste management chain for reductions of emissions intensity, including moving to less emissions intensive energy sources for waste management processes, and recirculating recovered materials to offset more emissions intensive primary resource consumption.

Several studies have evaluated the management of wastes from a low carbon waste management perspective. While these do not often refer specifically to 'low carbon waste management', they nonetheless conform with the concept of lowering emissions intensity either via reduced direct/indirect emissions, or through emissions avoidance.

Most related studies to focus on emissions reductions via energy recovery, to be used as an alternative energy source to fossil fuel-derived energy. At municipal waste scales, energy recovery via direct combustion or incineration is mature in many countries, and is often part of sustainable waste management, for example in the Netherlands (van Leeuwen et al., 2017), and Italy (Lombardi et al., 2015). From an economics perspective, Papargyropoulou et al. (2015) reviewed 16 low carbon waste management measures for a large city in Indonesia, ranging from waste prevention and recycling, to municipal scale energy recovery from waste and landfill gas capture. The authors found that recovery of energy from waste via combined heat and power systems, led to by far the largest 'savings' in emissions compared to the base case of landfilling, mitigating up to 3,000,000 tonnes of CO_2-equivalent each year.

Other authors have noted the benefits of energy recovery as part of sustainable waste systems (Chen & Liu, 2021; Drożdż et al., 2022; Gohlke, 2009; Yaman, 2020), with some arguing a contested view, that energy recovery has a critical role in the circular economy as a resource recovery pathway for waste (Arena, 2015; Lombardi et al., 2015). Apart from offsetting fossil fuel-derived energy, municipal scale energy recovery can also lead to significant reductions in quantities of waste disposed to landfill. For waste streams with a large proportion of biodegradable material, such as household waste streams, this can be a significant source of emissions savings (Assamoi & Lawryshyn, 2012; Kumar et al., 2020; Kumar & Samadder, 2020; Papargyropoulou et al., 2015). This also points to the potential that zero-waste to landfill pledges targeting organic waste may have in transitioning to low carbon waste management, such as NSW's commitment to reducing food waste to landfill (DPIE, 2021).

Recent studies have also examined the potential of other recovery pathways and their impact on emissions intensity, including materials and nutrient recovery, and energy recovery via other processes such as anaerobic digestion. As noted by Iacovidou et al. (2017a) in their review of circular economy performance metrics, and in Gavrilescu (2022) in their review of footprint analysis in waste management, 'carbon footprint' metrics are commonly used for evaluating the emissions intensity of waste processes and systems. The carbon footprint of a system or process characterises its emissions intensity, usually in terms of carbon-equivalent emissions per quantity of waste treated, managed or generated.

Some recent studies evaluating the carbon footprint of OFMSW and related waste streams include: Obersteiner et al. (2021) for example, who reviewed strategies for reducing the carbon footprint of waste management associated with tourism via a life cycle assessment (LCA) approach. They found that various measures including on-site composting and food donations, can lead to significant reductions in the carbon footprint of tourist locations between approximately 5 and 190 kg CO_2-e per 1000 tourists. In a similar study,

In other city-level studies, Thanh et al. (2015) evaluated the potential for decarbonisation of OFMSW management through the introduction of composting as a recovery pathway in Hanoi City, Vietnam. The authors used a bottom-up approach to estimate the carbon footprints of a range of different interventions for improving organic waste recovery, finding that the implementation of composting for OFMSW in the city could lead to emissions reductions of up to 98% compared to baseline levels, where incineration is widely practice. Finally, Yoshida et al. (2012) is another example, where the authors evaluated the existing carbon footprint of OFMSW management in Wisconsin, USA; and in comparison with management alternatives. The authors found the existing carbon footprint of OFMSW was 224 kg CO_2-e per tonne of waste. Implementing measures including advanced windrow composting, anaerobic digestion, and anaerobic co-digestion (with sewage sludge) found reductions in the carbon footprint of OFMSW management between 60% and 180%. The carbon footprint of waste systems and process can vary considerably as indicated in the literature—dependent on waste stream composition, and waste collection and recovery pathways.

In other national-level studies, Marrucci et al. (2020) examined the carbon footprints of a number of waste treatment pathways for supermarket wastes in Italy. They found that implementation of improved packaging recycling, and technology targeting the organic waste fraction of supermarket waste (i.e., anaerobic digestion) led to both improved organic waste recovery and decarbonisation through a reduction in carbon footprint of approximately 9 kg CO_2-e per kg of supermarket waste generated. In Paes et al. (2020), the authors examined the transition towards eco-efficient management of municipal waste across regions in Brazil, by estimating the emissions and potential for emissions reductions, for several organic and dry recyclable waste management pathways via an LCA approach. The authors found a mix of 70% composting and 30% landfill with methane capture was the most eco-efficient pathway for municipal organics, leading to significant reduction in carbon footprint compared to baseline conditions, by up to 850 tonnes CO_2-e per tonne of OFMSW managed. In Lou et al. (2017), the authors used available emissions inventories to estimate the carbon footprint of the waste sector in China between 1949 and 2013. The authors found that landfilling was responsible for the majority of the carbon footprint of the waste sector (responsible for up to 82% of all waste-related emissions), and identified sanitary landfill improvements and methane gas flaring as priority pathways for decarbonisation.

Approaches in the literature for evaluating carbon footprints also vary widely, and include methods such as lifecycle analysis, material flow analysis, input output analysis, and environmental impact assessment (Iacovidou et al., 2017a). LCA is perhaps the most common approach for estimating emissions, however is limited insofar that most studies rely on average intensity factors where region-specific data is limited (Gavrilescu, 2022). This is something raised also in Edwards et al. (2016), who developed an approach to overcome unreliable LCA factors for waste collection and transport in their study of fuel requirements for waste collection in Melbourne. The Edwards et al. (2016) study is discussed in further detail in Chapter 5.

Regardless of the approach taken when assessing emissions intensity, a detailed understanding of the waste management system under investigation is required. From the review of literature, this understanding should include at a minimum: the quantities of waste managed and its composition; what management pathways exist, including technologies and collection systems employed; and quantities and composition of waste disposed landfill. Some further considerations are also necessary. As noted previously, emissions intensity of a waste system or process can be affected at multiple points along the waste management chain. Therefore, careful consideration of the boundaries of the waste management system investigated is critical when evaluating emissions intensity. Some studies for example do account for emissions from waste collection and transport to some degree (Demichelis et al., 2022; Friedrich & Trois, 2013), however others exploring waste management system treatment processes do not consider transport (Dastjerdi et al., 2019; Liu et al., 2017; Lou et al., 2013; Thanh et al., 2015). Transport emissions in particular can be significant for municipal waste collection, especially when the density of households is low, for example in suburban or rural areas (Friedrich &

Trois, 2013). This is an important point particularly for Australian jurisdictions, where suburban sprawl is prevalent, and as indicated in Section 1.2, transport emissions are rarely considered in studies focused on Australian cities and regions.

Downstream impacts on emissions are also an important consideration. As noted in Iacovidou et al. (2017a), emissions intensity is commonly estimated in the literature for waste recovery processes, however landfill emissions are sometimes not considered. Studies including Boldrin et al. (2009) and Friedrich and Trois (2013) for example, which investigate the emission savings from OFMSW recovery, do not include the lifetime emissions saved from diversion of waste to landfill. Not including the potential for landfill gas mitigation could significantly underestimate the potential contribution of a waste system or process towards transitioning to low carbon waste management. While selection of boundaries of an investigation is reliant on its aims, impacts of upstream and downstream waste management, such as collection and transport, on overall emissions intensity should not be ignored when comparing different waste management pathways.

The exclusion of landfill diversion in Boldrin et al. (2009) and Friedrich and Trois (2013) noted above highlights another important consideration for emissions intensity accounting, especially with respect to evaluating organic waste management. That is, the handling of biogenic emissions: those resulting from the production, harvest, combustion, digestion, fermentation, decomposition and processing of biologically based materials by humans (US EPA, 2022). Biogenic carbon emissions, for example, from carbon dioxide generated from aerobic composting or from landfill, is typically not accounted for directly when assessing the carbon footprint of a waste system or process. The reason for these emissions to be excluded, is that they occur as part of the natural degradation of biodegradable material. Other emissions from landfill however are accounted for, namely N_2O (nitrous oxide) and CH_4 (methane), and are included in official emissions accounting methodologies employed for assessment of waste systems internationally (DISER, 2022a; US EPA, 2010). Both methane and nitrous oxide emissions from landfill are typically converted to CO_2-equivalent for carbon footprint analysis using global warming potential (GWP) factors that relate to the severity of these gases as contributors to the greenhouse effect. Notably for methane and nitrous dioxide, both gases are considerably more impactful as greenhouse gases compared to carbon dioxide. In fact, methane and nitrous dioxide are 28 times and 265 times more potent as greenhouse gases than carbon dioxide respectively (DISER, 2022a). Australian greenhouse gas accounting and even the *Entreprises pour l'Environnement* (EpE) protocol (EpE, 2013), developed specifically for waste managers in accounting for emissions from the waste sector, give guidance for accounting for these non-biogenic emissions from landfill. In the case of methane, while the carbon contained in methane is of biogenic origin, its generation under anaerobic conditions in compost piles and landfills is not considered in scope of carbon accounting. Therefore methane generation from landfills is an important consideration in evaluating carbon footprints, given that methane typically makes up between 40-60% of landfill gas emitted (DISER, 2022a; Scheutz et al., 2009; Zhang et al., 2019). Emissions from landfills emissions as well as emissions from composting and other organic waste management sources are discussed in further detail in Chapter 6.

In summary, the concept of low carbon waste management is concerned with minimising the GHG emissions intensity, or carbon footprint, of waste systems and processes. This intensity is typically measured by quantity of GHG emissions per tonne of waste managed, or even per tonne of waste recovered when evaluating recovery systems specifically, and should consider emissions over the entire waste management chain, including transportation and landfill disposal. Progress towards low carbon waste management can be made at several points along the waste management chain, and therefore can involve collaboration among many stakeholders and decision makers. These might include local and state governments for strategic level decision making, waste minimisation initiatives and infrastructure investment, as well as waste management system actors, such as government agencies, facility operators and waste logistics services.

2.2. Low carbon resource recovery from waste

The circular economy framework is becoming more widespread as a decision making framework for waste management, promoting a more nuanced view of waste management in many developed countries. This is true in Australia and more specifically NSW, with the recent NSW Government's Circular Economy Policy Statement (NSW EPA, 2019b) and Waste and Sustainable Material Strategy (DPIE, 2021). Given much decision making in waste management in the near future will be guided by circular economy principles, the aim of this section of the literature review is to consider if there is convergence between the circular economy, and low carbon waste management.

While the circular economy has relevance across entire material, product and logistic chains, recycling and recovery of wastes is currently where most global circular economy development is concentrated (Ghisellini et al., 2016; Sharma et al., 2021). Zhang et al. (2022) in their review of circular economy implementation in the waste sector, differentiate pre-use, use, and post-use phases for materials and products, with most circular economy progress being aimed at the post-use phase. This is expected given that waste management deals with materials and products no longer in use. Reviews of worldwide circular economy implementations, for example in Allwood (2011), Ghisellini et al. (2016), Kirchherr et al. (2017), Iacovidou et al. (2017a), and Kalmykova et al. (2018), note that much circular economy progress in contemporary waste management is focused on promoting resource recovery. Indeed, with one aim of the circular economy being to preserve value of materials, components and products for as long as possible (Ellen MacArthur Foundation, 2013), resource recovery plays a critical role in converting waste in the post-use phase into secondary resources for inputs into new products.

In the review by Iacovidou et al. (2017a) on performance metrics for a circular economy, the authors argued that initiatives promoting circular economy do so from the perspective of resource efficiency. From the recent reviews of circular economy concepts and implementations, there is not one singular definition of the circular economy, however common across all practical definitions is the concept of efficiency—both from a resource perspective (i.e., resource efficiency); and from an environmental perspective (i.e., eco-efficiency). The concepts of resource efficiency and eco-efficiency are closely related—they both imply the creation of more goods and services with fewer resources, which has the effect of creating less waste, pollution, and environmental impacts (Čuček et al., 2015; Glavič et al., 2012). Some definitions of the circular economy from the literature convey this: for example, the Ellen Macarthur Foundation defined the circular economy as an industrial economy that: is restorative by intention; that aims to rely on renewable energy; tracks and eliminates the use of toxic chemicals; and eradicates waste through careful design (Ellen MacArthur Foundation, 2013). The European Commission define the circular economy as a system where the value of products, materials and resources is maintained in the economy for as long as possible, and the generation of waste is minimised (European Commission, 2015). Yu et al. (2022) define the circular economy in their study as a model to stimulate the promotion of sustainable practices to achieve resource efficiency and environmental protection.

Compared to resource efficiency, eco-efficiency places a greater emphasis on minimising environmental impacts when reducing the resource intensity of goods and services. With respect to environmental impacts, Iacovidou et al. (2017a) in their assessment, found that GHG emissions were the most considered environmental impact when assessing resource recovery processes. This corresponds to the point raised previously by Gavrilescu (2022) noted in Section 2.1, in that many recent waste management policies and initiatives have been connected with strategies addressing the threats of climate change.

Compared to low carbon waste management which prioritises low emissions, resource recovery from a circular economy perspective prioritises waste recovery with as little environmental impact as possible. While resource recovery can lead to avoided emissions, low carbon waste management does not necessarily imply circular economy or recovery of resources from waste. Electrification of waste collection vehicles for example, would have an impact on reducing the emissions intensity of waste treatment (if transport emissions are significant), but would have negligible impact on waste recovery. The literature is unclear here on what should be prioritised when comparing different initiatives from a low carbon and resource recovery perspective.

Recovery rates are generally used when comparing waste initiatives from a resource recovery perspective (Iacovidou et al., 2017a), expressed as a proportion of waste generated or treated that is effectively recovered for resources. Recovery rates do give an indication of the efficiency of a system or process in converting waste to new resources (Di Foggia & Beccarello, 2021), but do not give any indication of the environmental impacts, whether positive or negative, of resource recovery activities. Similarly, the carbon footprint of a waste management system also does not give an indication of the performance of the system in recovering materials. This is true even if the carbon footprint is calculated on an emissions per tonne recovered (or diverted) basis, which is a common footprint metric for evaluating the impacts of recovery (Gavrilescu, 2022; Iacovidou et al., 2017a). This complexity around prioritisation of waste management alternatives is illustrated in Table 2-1, which gives some performance metrics for three example waste system interventions. While based loosely on real world examples, the data in Table 2-1 is illustrative only, and does not reflect any real world waste management system. Example Option A sees the highest waste recovery rates, however also the greatest emissions due to the utilisation of emissions intensive advanced mechanical recycling. Option B sees only a small amount of waste recovered, however at much lower emissions intensity due to electrification of waste collection vehicles. Option C sees high recovery rates, and improved emissions intensity compared to Option A via increasing rates of composting. It is difficult to see how these options might be prioritised under low carbon and resource recovery agendas. Under a resource recovery priority, Option A would clearly be favoured, however Option A would be the less preferred option under an emissions prioritisation. Option B is similar, with most-preferred and least-preferred status under emissions and recovery prioritisation respectively. Option C appears to be the best alternative given amounts of waste recovered and relative net emissions compared to the other example pathways, however this is not clear based on the metrics chosen. This shows that further analysis beyond simple metrics is necessary to identify optimal pathways that meet both low carbon and resource recovery prioritisation.

Table 2-1: Performance metrics and ranking by resource recovery and emissions minimisation priorities for 3 illustrative waste management pathways

	Option A: Advanced mechanical recycling	**Option B: Electrification of waste collection vehicles**	**Option C: Increased rates of composting**
Waste generated [tonnes]	1,000	1,000	1,000
Waste recovered [tonnes]	900	100	750
Net emissions [tCO_2-e]	1,000	50	500
Recovery rate [-]	90%	10%	75%
Emissions intensity [kg CO_2-e/t-recovered]	1,111	500	666
Rank (recovery priority)	1	3	2
Rank (emissions priority)	3	1	2

Simple performance metrics, like recovery rates and carbon footprints, are valuable. They are transparent and easy to understand, making them useful for evaluating and comparing waste management options at a high-level, and certainly play a role in decision making and policymaking in waste management (Iacovidou et al., 2017a; Singh et al., 2012). As pointed out above, more complicated analysis is necessary to better identify optimal low carbon resource recovery pathways. Multi-criteria analysis is a broad suite of tools and approaches often used for such problems as illustrated, and aids in evaluating decision alternatives on the basis of sometimes conflicting criteria (Malczewski, 2018; Nautiyal & Goel, 2021). Some of these approaches are discussed in the following section.

In summary, low carbon resource recovery can be regarded as an extension to low carbon waste management, whereby recovery of resources and minimisation of GHG emissions are both prioritised. This has convergence with the principles of the circular economy where environmental impacts from waste systems should be minimised. However, under a circular economy framework, the prioritisation of lowering waste related emissions is unclear.

Evaluating pathways for low carbon resource recovery does however require more complicated analysis that what is typically performed when assessing resource recovery from a circular economy perspective.

2.3. Evaluating optimal low carbon resource recovery pathways

Evaluating and identifying optimal low carbon resource recovery pathways is complex, due to the multiple, and sometimes competing, priorities of both maximising waste recovery and minimising GHG emissions. Iacovidou et al. (2017a) discusses the complexities of optimal waste management in regards to 4 key value domains related to the management of wastes, namely environmental, technical, social and economic value domains—introduced previously in Section 1.2, and shown in Figure 1-8. Achieving high performance in one value domain does not necessarily imply high performance in another, and different domains of value may be placed at higher prioritisation than others. Energy recovery from waste again serves as a good example of this, whereby technical (large quantities diverted from landfill) and economic (reduced landfill disposal costs; increased revenue from sale of electricity) value is largely prioritised above social and environmental value.

The problem of finding some optimal set of preferences or pathways, given competing value dimensions, is well-defined. Multi-criteria analysis (MCA), also commonly referred to as multi-criteria decision making (MCDM), is a sub-discipline of operations research, and refers to a framework for evaluating criteria in a decision making context. It is especially useful for supporting decision makers where no single ideal solution simultaneously satisfies the decision maker across all decision criteria (Nautiyal & Goel, 2021). There is a large range of quantitative MCDM approaches used in the waste management literature, although qualitative approaches also do exist. Historically, MCDM in a waste context has typically focused on minimising system costs (Inghels et al., 2019), however more recently, complementary system modelling approaches including LCA, material flow analysis and environmental accounting have been incorporated with MCDM frameworks to optimise systems for reduced environmental impacts (Deshpande et al., 2020).

MCDM approaches have been classified into two categories by a range of authors, including in Coban et al. (2018) and Zavadskas et al. (2019), namely: multi-attribute decision making

(MADM), and multi-objective decision making (MODM). MADM approaches relate to problems that involve discrete decision spaces with a predetermined and limited number of alternatives (Chang & Pires, 2015; Zavadskas et al., 2019). In this approach, alternatives are ranked and selected based on the attributes of a given set of alternatives, and are applied often to more strategic level decision making problems, such as selection of optimal locations of waste treatment facilities (Coban et al., 2018). On the other hand, MODM approaches relate to problems without a predetermined set of alternatives, and where several often competing objectives are required to be optimised simultaneously (Zavadskas et al., 2019). MODM are applied more so at an operational level, for example in identifying optimal feedstock composition for an energy recovery system, or for identifying optimal waste collection routes (Coban et al., 2018; Tirkolaee et al., 2020).

Most studies in MCDM fall into the first category, while studies in the second category are often simply referred to as optimisation (e.g., Münster et al. (2015); Movahed et al. (2020); Abdallah et al. (2021)). This is corroborated in Vlachokostas et al. (2021), who performs a comprehensive review of MCDM in waste management across 153 studies in the context of energy recovery from waste. Whilst the focus of that paper is energy recovery, it is relevant for assessing other technological recovery pathways for waste streams. The authors do not classify MCDM approaches as MADM or MODM, however all but one of the identified approaches reviewed fit within the MADM classification in Coban et al. (2018) and Zavadskas et al. (2019), with the remaining approach, multi-objective programming, aligning with MODM.

From the 153 studies reviewed in Vlachokostas et al. (2021), the authors found that the analytical hierarchy process (AHP) was the most widely utilised approach for solving waste-related MCDM problems. Put simply, AHP is an approach that ranks a set of alternatives by performing pairwise comparison between them against criteria to meet some overarching objective (Ramanathan, 2004). Criteria are weighted by importance, which is typically informed via stakeholder or expert guidance. Developed originally in the 1960s (Saaty, 1970), AHP has been used across multiple fields to aid in decision making. In waste management, the approach has been used in evaluating energy recovery as summarised in Zavadskas et al. (2019), but also in facility allocation problems (Islam et al., 2020; Wichapa & Khokhajaikiat, 2017), and in assessing strategic-level waste management options for plastic packaging waste (Balwada et al., 2021); rural waste (Yadav et al., 2022); e-waste (Lin et al., 2010), and system-wide initiatives (Antonopoulos et al., 2014; Contreras et al., 2008). Shahnazari et al. (2020) gives a comprehensive overview of the principles and mechanics of AHP as applied in the selection of optimal waste to energy technologies.

The second most common approach identified in Vlachokostas et al. (2021) is the simple additive model (SAM) approach. The term SAM itself is an umbrella term in Vlachokostas et al. (2021) and is treated as such hereafter, and can refer to a number of approaches that appear in the literature, including simple additive weighting, weighted aggregated sum, and weighted linear combination. While not as commonly utilised as AHP as indicated in Vlachokostas et al. (2021), SAM approaches are nonetheless common in the MCDM literature, with SAMs first defined in Churchman and Ackoff (1954). In fact, SAMs are the approach suggested by Infrastructure Australia for performing multi-criteria analysis for local infrastructure projects (Infrastructure Australia, 2021). Common across SAM approaches are criteria used to compare alternatives against some overall objective, an aggregation of criteria into some overall scoring value, and the use of weights that indicate the importance of each criteria in meeting the objective (Infrastructure Australia, 2021). Criteria can represent quantitative values for some attribute, for example, distance to nearest waste treatment facility or avoided emissions. More qualitative criteria can also be represented quantitatively, by scoring criteria on a numerical range. For example, criteria such as ease of implementation or social acceptance (Almanaseer et al., 2020) can be represented in this way, with higher scores indicating greater level of agreement with the criteria. Normalisation of criteria values is therefore a critical consideration when using SAM approaches. Vafaei et al. (2022) provides a comprehensive review of normalisation approaches for SAMs.

Practically, SAM approaches are similar to the AHP approach, however have less computational demands therefore suitable when pairwise comparison is impractical (Al-Garni & Awasthi, 2017); and they do not necessitate the sometimes intensive input from stakeholders, giving flexibility to how criteria weights are implemented. SAMs have been utilised for MCDM in a waste management context, for example in the assessment of energy recovery (Almanaseer et al., 2020; Joseph & Prasad, 2020; Khan & Kabir, 2020). SAMs are in particular well suited for spatial-based problems, where spatially represented attributes, for example distances to infrastructure or land attributes including slope, or precipitation, may be useful as criteria (Comber et al., 2015; Lozano-García et al., 2020; Ma et al., 2005).

Some approaches fall outside of the typical MCDM approaches covered in reviews such as in Vlachokostas et al. (2021) and Coban et al. (2018), which might be more broadly considered evaluation approaches. Pareto optimality (or efficiency) for example, is a concept that has received much attention in the literature as a decision support tool, especially in the fields of engineering, manufacturing, and economics. The concept implies that when selecting preferences based on competing value dimensions, there exists a set of optimal preferences whereby performance in one value dimension cannot improve without worsening performance in another (Inghels et al., 2019). In some optimisation studies, for example in multi-objective optimisation where it is not possible to identify the single most optimal alternative, the goal is instead to identify the Pareto optimal alternatives (Mavrotas et al., 2015). Figure 2-1 shows an illustrative example of Pareto optimality in the context of pathways for emissions reduction and resource recovery. The horizontal axis in the figure represents increasing waste recovery performance, for example measured as a waste recovery rate. The vertical axis represents GHG reduction performance, for example measured as total avoided emissions. The Pareto front in the figure represents the set of most optimal recovery pathways, where GHG reduction and/or waste recovery is maximised, and illustrates how the Pareto optimality concept might indicate pathways that are most optimal in terms of a low carbon resource recovery priority. The Pareto curve in Figure 2-1 is also closely related to the production possibility frontier—a concept used in production efficiency analysis and data envelopment analysis. From a production perspective, the curve characterises production whereby an increase in production of one good cannot occur without sacrificing production of another.

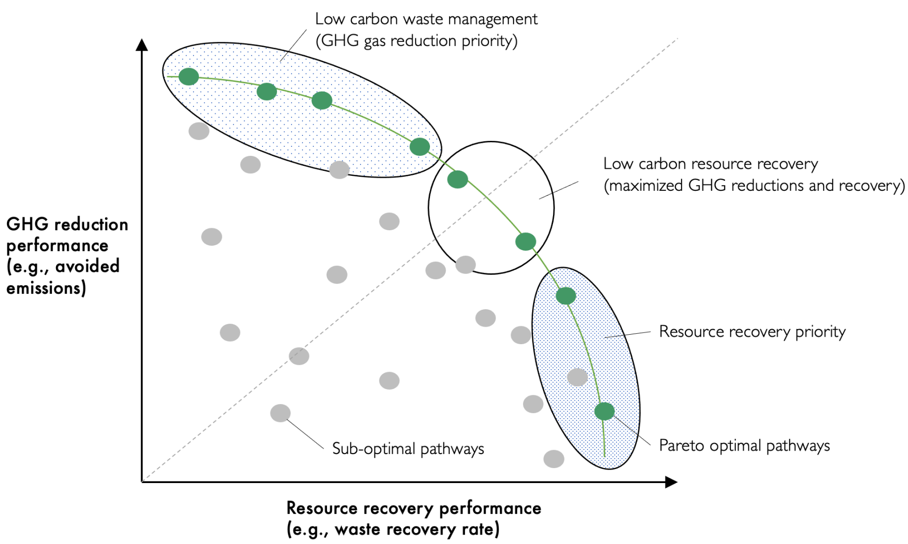


Figure 2-1: Illustrative example of a Pareto frontier. The green line and dots represent the Pareto optimal alternatives, which have been characterised according to prioritisation (low carbon waste management, resource recovery, and low carbon resource recovery priorities)

The concept of Pareto optimality has been used in the context of waste management. Inghels et al. (2019) for example evaluated the trade-offs between materials and energy recovery from an environmental impact perspective. This was achieved by identifying Pareto optimal waste system configurations by solving a multi-objective optimisation problem, with environmental impacts estimated based on LCA. The authors noted the importance of their study as a decision support tool that combines optimisation and environmental accounting approaches. Das et al. (2012) explored using Pareto frontier analysis as a decision support tool for optimising hazardous waste transport. In that study, the authors incorporated stakeholder preferences with route optimisation in a multi-objective optimisation, to determine Pareto optimal transportation linkages that are low-cost, and have minimum risk to human health. The authors noted the usefulness of Pareto frontier analysis as a tool for decision makers, and incorporated additional cost elasticity analysis, and analysis of the Pareto frontier curve, to further identify most optimal alternatives from the identified set of Pareto optimal alternatives. In Mavrotas et al. (2015), the authors solved a multi-objective optimisation to identify Pareto optimal solutions for waste to energy options for municipal waste management in Athens, Greece. The authors considered costs associated with capital equipment as well as environmental and social externality costs, and the potential for GHG reductions. They found that the incorporation of externalities results in a steeper trade off curve—that is, the slope of the Pareto frontier. For that study, the implications were that when externalities are considered, more environmentally favourable energy recovery technologies including anaerobic digestion become more optimal. The Mavrotas et al. (2015) study highlights the usefulness of Pareto frontier analysis as a decision support tool, and the aforementioned studies show how the Pareto optimality concept can be used to help solve MCDM problems and identify optimal solution sets.

In summary, where there are multiple competing criteria and value domains, identifying optimal system pathways and interventions is difficult and complex. This is certainly true with respect to low carbon resource recovery, where both GHG emission avoidance and waste recovery need to be prioritised. Fortunately, the field of operations research has considerable tools for evaluating systems through MCDM and optimisation approaches, which can be drawn on to help identify waste management pathways most aligned with low carbon resource recovery for OFMSW. The MCDM approaches reviewed in this section are in no way exhaustive, and MCDM is a very broad and open field. However, the approaches presented have precedent in waste management, and their application as evaluation tools are explored further in Chapter 7.

2.4. Literature review conclusions

Low carbon resource recovery is defined as an extension to low carbon waste management, where recovery of waste and the minimisation of GHG emissions are both prioritised. The concept is closely aligned with the circular economy, however greater emphasis on GHG emissions reductions is given in a low carbon resource recovery context.

The complexities between waste recovery and emissions reduction priorities make MCDM and other multi-criteria optimisation approaches appropriate for evaluating optimal potential pathways. From a low carbon resource recovery perspective, such approaches do require detailed knowledge of the systems under investigation, including quantities of waste generated and recovered, and emissions along the waste management chain. Information in this regard however is limited with respect to NSW household organic waste management, and certainly in regards to emissions from waste transportation and OFMSW recovery activities, although effort is being made to better characterise these emissions (NSW EPA, 2022). This need for comprehensive data on waste system emissions and material flows presents an important gap in knowledge which necessitates further analysis, which is presented in the following chapters of this thesis.

Some important considerations in the evaluation of optimal low carbon resource recovery pathways identified from the review of the literature are summarised here:

System boundaries: waste-related emissions occur at all points of the waste management chain, and careful considerations of the system boundaries; where important emissions are accounted for; and spatial scale, is required when evaluating waste systems from a low carbon perspective.

Biogenic emissions, and accounting of emissions from landfill: official emissions accounting frameworks and many studies assessing emissions do not consider biogenic carbon emissions from landfill. This is appropriate considering these emissions are part of the natural degradation of organic material. Other emissions from landfill however are not strictly considered biogenic in some accounting frameworks, for example the EpE framework (EpE, 2013), and the Australian National Greenhouse Accounts (DISER, 2021b). These emissions, namely methane and nitrous oxide, should be considered in any evaluation of landfill emissions including emissions avoidance.

Spatial considerations, and waste collection and transport: studies in the literature evaluating waste system emissions tend to rely on international LCA data or average transportation distances to estimate waste collection and transport emissions (e.g., Friedrich and Trois (2013)). Some studies ignore collection and transport all together, or consider only simplified collection and transportation assumptions (e.g., Boldrin et al. (2009), Edwards et al. (2016)). Given the sparse spatial distribution of Australian households consistent with suburban sprawl, and the large distances between Australian regions and cities, emissions from waste collection and transport may be a significant contributor to waste related emissions, and should be considered in any accounting of waste sector emissions. Analysis of waste collection and transport may necessitate the consideration of the spatial distribution of waste generation, and locations of important waste infrastructure.

Performance metrics for low carbon resource recovery: no performance metric exists that perfectly captures low carbon resource recovery performance. The waste recovery rate is ubiquitous, and gives a simplified indication of the efficiency of a waste system in converting waste into secondary resources. However, it does not indicate environmental performance, namely carbon emission performance. Similarly, carbon footprints give an indication of the emissions intensity of a waste system in terms of managed waste or recovered waste, however is not sufficient when evaluating optimal recovery pathways that maximise resource recovery while minimising emissions. Further analysis is required to evaluate low carbon resource recovery.

Evaluation approaches: key to low carbon resource recovery is a complexity between waste recovery and emissions minimisation priorities. The field of operations research has a large number of tools that can be utilised for evaluating waste recovery pathways from a low carbon resource recovery perspective, without which, it is difficult to properly evaluate pathways.

Chapter 3.

Exploring the spatial distribution of waste generation

New South Wales is a large state, and can be characterised by large distances between key regional centres, sprawling suburbs, and a varied population. Each of these characteristics and more can have implications on low carbon resource recovery performance. For instance, large distances and sprawl might mean that waste collection vehicles need to travel longer distances, consuming more fuel and generating more emissions. Differences in waste collection systems, not to mention in population sizes and socioeconomics also, mean that some council areas generate waste that differs in quantity and composition, compared to neighbouring councils.

Considering the above, this chapter explores the use of spatial modelling to investigate waste management systems. The requirement for spatial modelling approaches for addressing the key motivating question in this thesis was described in Sections 1.2 and 2.4. It is true that spatial techniques can help address some data gaps required to more accurately characterise emissions intensity, as is the case with transport emissions. This chapter however will instead focus on an exploration of the variation in waste management across NSW. This will help to further justify that spatial approaches are sensible, and sometimes necessary, for evaluating waste systems, and can yield unique insights to assist waste decision makers. This chapter helps to address the following:

Research question 1: What is the spatial distribution of waste generation in NSW, and is regional variability significant?

Specifically, this chapter is focused on the second part of this question, presenting work that explores the regional variability and spatial modelling of waste systems in general. The chapter presents an analysis performed examining the existence of the 'waste Kuznet's curve'—a curve representing a decoupling relationship between waste generation, and economic performance.

This analysis was performed for several reasons, and provides some important contributions for addressing the key motivating question, and to the literature as well. Firstly, it was an opportunity to explore what spatially varying factors contribute to waste generation in NSW—important for any in depth analysis of how household waste is managed. The analysis showed that council areas across NSW do have significant regional variability, in terms of factors impacting quantities of waste generated and recovered. Secondly, the analysis allowed for the testing and refining of approaches to modelling waste generation spatially, and identifying how further research questions that require a spatial modelling might be addressed. The analysis included an in-depth review of the modelling of waste generation—what approaches are utilised in the literature, and what factors best determine how much waste a jurisdiction or area might generate. A geographically weighted regression modelling approach was tested through this analysis, which has potential for analysing waste systems with consideration to drivers for waste generation and recycling that vary over space (e.g., between different local government areas). Insights from the spatial modelling conducted for this analysis ultimately helped inform further analysis performed for Chapters 4 to 7. Thirdly, the analysis has some broader significance in the literature, providing some insights into the study of the Kuznet's curve—a relationship under study by academics since first being hypothesised in 1959 (Kuznets, 1955).

The work presented in this chapter was published as a standalone paper in 2019, as follows:

Madden, B., Florin, N., Mohr, S., Giurco, D. (2019). Using the waste Kuznet's curve to explore regional variation in the decoupling of waste generation and socioeconomic indicators, *Resources, Conservation and Recycling*, 149, 674-686, DOI: 10.1016/j.resconrec.2019.06.025.

This chapter includes the above published paper in full, and includes some minor additions compared to the published version of the paper. The paper's primary aim was to investigate the waste Kuznet's curve relationship in NSW, and to contribute to the evidence base confirming or rejecting the Kuznet's curve hypothesis. Conclusions in this chapter are specific to these aims which appear in the standalone paper. Specific conclusions and insights drawn from this analysis in relation to the thesis research questions, are discussed in Chapter 8.

3.1. Introduction

Historically when populations and economies grow, the amount of waste generated as a result of consumption and economic activity generally also increases. This presents a significant future challenge for the sustainable management of wastes. The circular economy concept is one response to unsustainable levels of consumption, waste generation, and their associated environmental impacts that has received much attention in recent years (Kirchherr et al., 2017). In the context of sustainable waste management, the circular economy maintains the value of end-of-life materials and products in the economy for as long as possible by avoiding disposal. This is done through better product design and manufacturing, reuse, remanufacturing, and recycling, thereby minimising waste generation along the entire supply chain (Ellen MacArthur Foundation, 2015). This has important implications for waste management systems, which must provide the waste infrastructure and collection systems to enable the transition to the circular economy.

A recognised key step in the transition towards the circular economy is the decoupling of resource consumption from economic growth (Ellen MacArthur Foundation, 2015; Suárez-Eiroa et al., 2019). Decoupling can generally be defined as either 'relative' or 'absolute' decoupling, and can occur at different levels of the economy. Relative decoupling sees economic growth occur at a faster pace than resource consumption, implying a gain in efficiency rather than a total delinking of economic performance and environmental impact (Ward et al., 2016). On the other hand, absolute decoupling sees a decrease in resource use despite increasing economic performance. Absolute decoupling can be an indication that environmental pressure is stable or falling, and is therefore an essential concept for sustainable economic growth (Jackson, 2009; Montevecchi, 2016).

Global economy wide data on domestic material consumption has implied that a relative, and in some cases absolute, decoupling has been achieved in a number of countries (OECD, 2018). However, findings in Wiedmann et al. (2016) indicate that when non-domestic sources of resource consumption such as imported consumer goods are taken into account, no level of decoupling, relative or absolute, has been achieved globally. Whilst the viability of simultaneously pursuing economic growth and reduced environmental impacts remains contested (Fletcher & Rammelt, 2017; Ward et al., 2016), achieving an absolute decoupling of waste generation from economic growth is also an important objective to strive for, in light of increasing volumes and environmental impacts of waste generated annually that must be dealt with sustainably (Mazzanti et al., 2008).

Where a decoupling between waste and economic performance exists, waste generation might follow an inverted-U shape relationship against economic indicators (Ichinose et al., 2011; Montevecchi, 2016). Typically, economic indicators include gross domestic product (GDP), the more spatially resolved gross regional product (GRP), or population mean income. The economist Simon Kuznets first hypothesised this relationship between income levels and economic inequality which increases with income until reaching a `tipping point' from where it begins to decrease (Kuznets, 1955). This `Kuznets curve' relationship has since been applied in the form of the environmental Kuznets curve (EKC) to model decoupling behaviour between environmental impact and economic growth, and is shown in Figure 3-1. In this context, Mazzanti et al. (2008) and Ichinose et al. (2011) define absolute decoupling as the descending part of the inverted-U shape, and relative decoupling as the ascending part of the inverted-U shape. Ichinose et al. (2011) furthers these definitions by defining absolute decoupling to occur only when the tipping point from the estimated Kuznets curve is within the range of the economic indicator for the area under investigation, and relative decoupling where the estimated tipping point occurs outside this range. Such decoupling like behaviour may indicate an economy shifting away from manufacturing towards a more de-materialised, service based economy where environmental degradation might decrease (Ercolano et al., 2018), owing to reduced pressure on the environment.

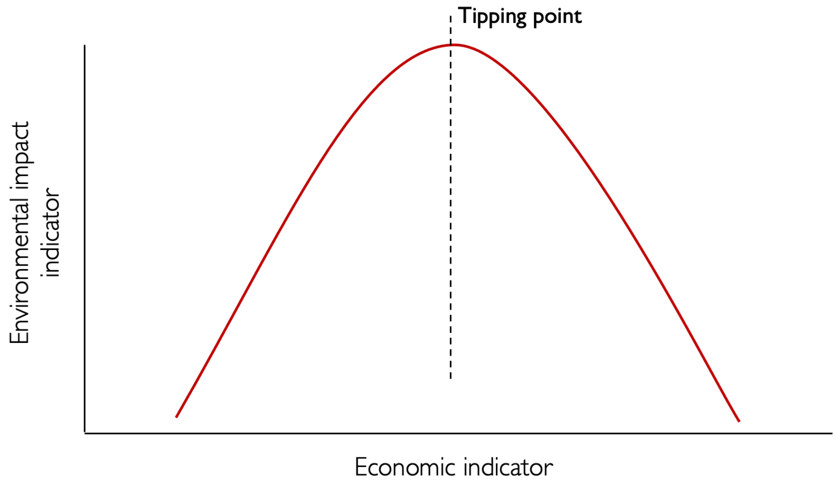


Figure 3-1: Illustrative example of the environmental Kuznet's curve (EKC) relationship

Recently, the EKC has been applied to examine solid waste generation (Ercolano et al., 2018; Jaligot & Chenal, 2018; Kim et al., 2018; Mazzanti et al., 2008). Despite the causal links between economic growth and waste generation, there is a lack of consensus on the existence of the `waste Kuznets curve' (WKC). This demonstrates a need for further research on the application of the WKC for identifying decoupling like behaviour. Ercolano et al. (2018) identifies that studies that do support the WKC hypothesis are primarily at sub-national scales, which compared to cross-country analyses, allow for consideration of within country/region heterogeneity in waste generation and other driving factors. Analyses performed at a spatially disaggregated level require spatially explicit data, such as waste generation data for local government areas. Such data however often shows robust patterns of spatial dependency where for example nearby locations share similar attributes and influence each other, requiring spatiality to be a feature of analysis (Goodchild, 1992; Montello & Sutton, 2012).

This paper explores regional variation in decoupling of municipal waste and mean income following the WKC hypothesis. A geographically and temporally weighted regression model (GTWR) is developed to explore this variation across municipalities in the Australian state of New South Wales (NSW), where a circular economy agenda has recently been put in place (NSW EPA, 2019b). This paper uses annual municipal per-capita waste generation data for LGAs in NSW for the years 2011 to 2015, in addition to relevant socioeconomic, demographic, and urban morphology variables derived from census data. The primary goal of this study is to identify local government areas (LGAs) within NSW that conform to the WKC hypothesis, and to examine locally varying determinants of per-capita waste generation in NSW. This study gives insights into the application of the WKC for assessing the status of decoupling between per-capita waste generation and mean income. We apply this approach to NSW for the first time, and the findings from this study may have important implications supporting regionally appropriate and targeted policy development towards more circular economy practices.

3.2. Background

3.2.1. The WKC hypothesis

There is a lack of consensus on the existence of the WKC in the literature. Mazzanti et al. (2008) reviews studies undertaken from 1995 to 2007 to examine the existence of the WKC. Of the 13 studies reviewed in Mazzanti et al. (2008), 5 studies found evidence supporting the existence of the WKC. Berrens et al. (1998) and Wang et al. (1998) found evidence of the WKC in studies undertaken across the United States, examining hazardous waste data across 3,141 counties. Concu (2000) found evidence of the WKC in their study in Sardinia, Italy for municipal waste generation. Fischer-Kowalski and Amann (2001) found evidence of the WKC across OECD countries, but for landfilled waste only, and not waste generation. Ercolano et al. (2018) identifies that the studies that do support the WKC hypothesis are primarily at the sub-national level, which better allows for the consideration of within country/region heterogeneity in waste generation and other factors due to the disaggregated nature of sub-national data (e.g., municipalities, counties, etc.). Sub-national level studies are much rarer in the literature compared to cross country analyses, where cross-country studies show little evidence supporting the WKC hypothesis (Ercolano et al., 2018). Recent research into the existence of the EKC and WKC has also examined regional effects at the sub-national level. Kim et al. (2018) employs a geographically weighted regression (GWR) approach to examine regional specific industrial pollutants (SO_2 emissions, wastewater discharge, and solid waste generation) across 29 provinces in China. The authors find significant spatial variation in the existence of the EKC, with spatial patterns identified through the GWR attributed to regional policy making. Jaligot and Chenal (2018) use a panel regression model on waste generation data across 10 districts in the Swiss canton of Vaud, using tax point value (income) as an economic development proxy. Findings from Jaligot and Chenal (2018) indicate the existence of the WKC, and the trend emerges more strongly when additional socioeconomic factors are incorporated into the authors' model. Mazzanti et al. (2008) perform a regression analysis on municipal waste generation data from municipalities in northern and southern Italy, using provincial value added per capita as an economic performance proxy, finding evidence of a WKC that varies across the regions investigated.

This study builds on the existing literature by applying GTWR in the context of decoupling waste generation from economic performance to a region where the WKC hypothesis has yet to be examined. Owing to the lack of consensus in previous studies to the existence of the WKC at the sub-national level, there is value in examining the relationship in a new region, and such analysis might provide further evidence for or against its existence. Moreover, the recent Chinese National Sword policy limiting waste imports into China (World Trade Organization, 2017) has led to focused attention for regions in transitioning towards circular economic practices. The NSW Circular Economy Statement (NSW EPA, 2019b) specifically references decoupling economic growth from resource consumption as a core principle in the state's circular economy transition for both municipal and commercial/industrial waste streams. In this context, this research provides new information to support policy development in the context of the municipal waste stream, by identifying areas of the state where material decoupling may be taking place, which may lead to more appropriately targeted policies in the transition to the circular economy, and could also be important for measuring progress in transitioning towards a circular economy.

3.2.2. Study area

The study area is the Australian state of New South Wales, consisting of 128 local government areas (see Figure 3-2). The local government areas of NSW all operate independent waste management systems, with kerbside collection being the main form of municipal waste collection across the state. For this study, the 'Unincorporated Far West Region' was excluded, as this area is not part of a local government area and is administered federally.

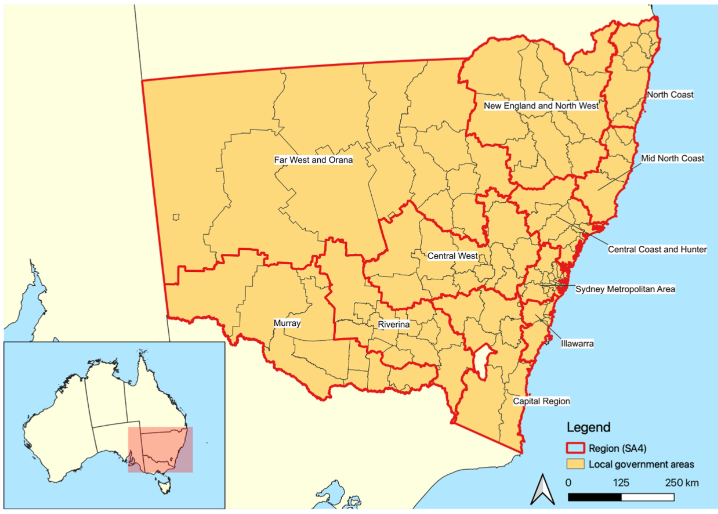


Figure 3-2: Map showing the New South Wales study area highlighted, and the local government area boundaries

The study area has a total population as of the 2016 census of 7,608,010. The vast majority of the population is located on the east coast around population centres such as the Sydney Metropolitan area, where approximately 60% of the total state's population resides in an area less than 1% of the total state's land area. Figure 3-3 shows the distribution of resident population over the study area for 2016.

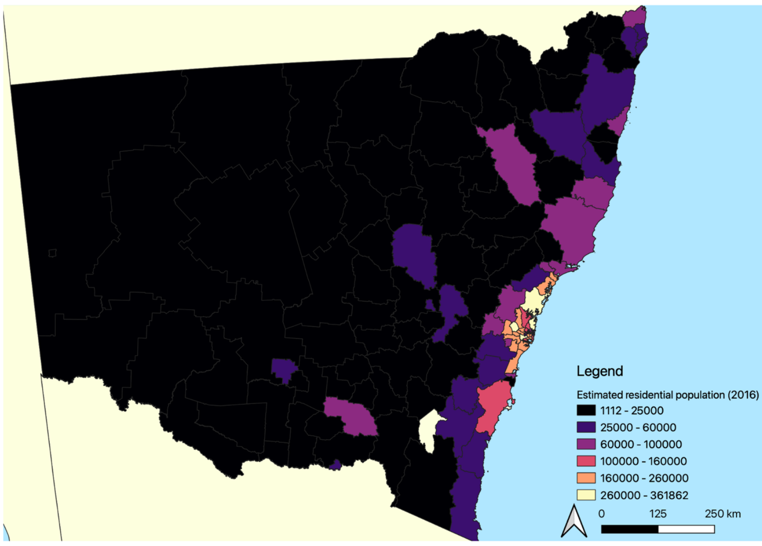


Figure 3-3: Estimated resident population for 2016, derived from population estimates in NSW EPA (2017)

3.2.3. Data

The dataset used includes data on 128 local government areas over the timeframe 2011 to 2015. Waste data were gathered from the NSW Environment Protection Authority annual

Waste Avoidance and Resource Recovery reports, describing each local government area's municipal waste generation for a given reporting year. At the time of this analysis (October 2018-February 2019), the most recent published waste data for NSW is the 2014/15 financial year (NSW EPA, 2017), however data is now available (as of February 2023) up to the 2021/22 financial year. Future studies further analysing the WKC for NSW should utilise this full dataset, and it should be noted that data quality and consistency (including for example, LGA boundaries) have changed over time.

Figure 3-4 shows the distribution of municipal waste generation across the dataset. While the scope of the analysis is the municipal/household waste stream, some LGAs may collect commercial waste via municipal collections, especially in regional areas where commercial collection services are limited. Resolution on this complexity is not available in the data, and is a limitation in the modelling. Average rates of per-capita municipal generation are relatively consistent across the study timeframe. The proportion of recycling collected (that is, waste material destined for downstream recycling) to total waste collected per LGA was calculated from data in NSW EPA (2017), and used as a proxy for the performance of an area's waste management system under the assumption that high rates of recycling collection infers a good-performing waste management system.

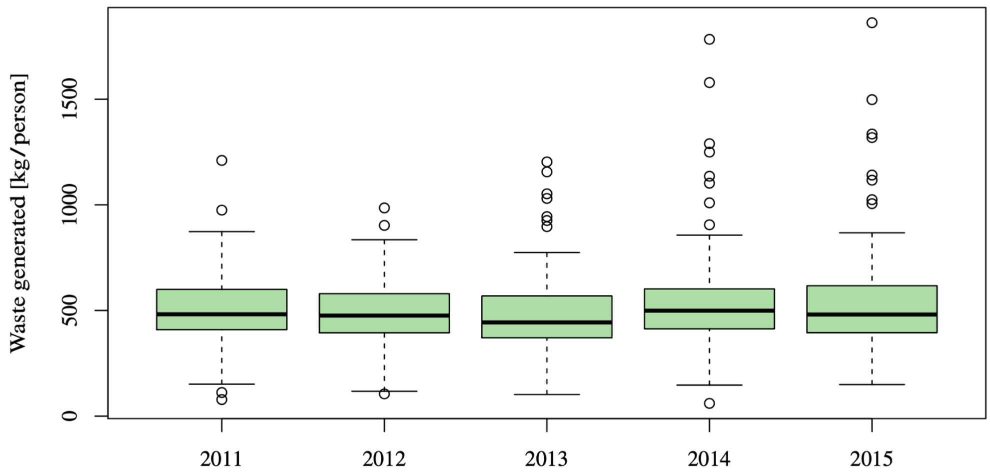


Figure 3-4: Distribution of MSW generated per capita, 2011-2015

Figure 3-5 shows the spatial distribution of average waste generated per capita across the study area and study timeframe, showing that there is some spatial heterogeneity in the average rates of MSW generated per capita. An example of this heterogeneity can be seen in the two adjacent LGAs along the Riverina and Murray region border (Carrathool LGA and Hay LGA), which exhibit significantly contrasting rates of per capita waste generation. Socioeconomic and demographic drivers of waste generation in the study area are discussed later on in this study.

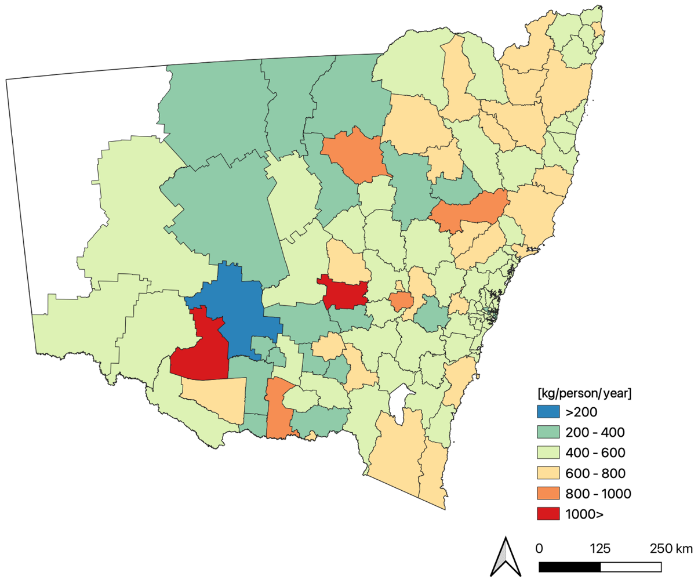


Figure 3-5: Spatial distribution of average per capita MSW generation for 2011-2015 over the study area

Spatial data was gathered from the Australian Bureau of Statistics, which provides local government area boundaries. It is important to note that from 2015 some NSW local government areas were merged to form new, larger local government areas. Socioeconomic and demographic data collected for the 2016 Australian census is aligned to these new government boundaries. In order to align the datasets, waste data were aggregated from pre-merged council areas to the new local government boundaries using GIS and published weighting factors (ABS, 2016a).

Demographic and socioeconomic data were collected from yearly data published by local government area across NSW (ABS, 2018). This data spans from the 2011 Australian census to 2017. Only the 2011 to 2015 demographic and socioeconomic data were used to align with available waste data. Initial variables selected for this study were subject to availability and model selection, as data is not available for all socioeconomic and demographic factors that appear in each census conducted in 5-yearly intervals. Variables for analysis in this study are those that are published by the Australian Bureau of Statistics based on yearly intervals only (ABS, 2018), and include population, number of households, household occupancy, income, and population density. Tourism, which is noted as being a driver for waste generation (Oribe-

Garcia et al., 2015), was not available over the timeframe or at a municipal level (as it is generally considered commercial waste) therefore was excluded from our analysis.

The WKC hypothesis relates to economic growth and development, and an appropriate proxy for economic development must be selected. The granular gross regional product (GRP) indicator is well suited for sub-national studies, however to the best of the authors' knowledge, there are no published data on GRP at the LGA level in the study timeframe, therefore other proxies for economic growth and development must be considered. Many studies in the literature have indicated the positive correlation between income and/or wealth with waste generation (Dyson & Chang, 2005; Kannangara et al., 2018; Keser et al., 2012; Khan et al., 2016; Oribe-Garcia et al., 2015; Sun & Chungpaibulpatana, 2017; Trang et al., 2017). Ercolano et al. (2018), Jaligot and Chenal (2018), and Mazzanti et al. (2008) use the average tax return per person, tax point value (income), and value added per person respectively for economic development proxies. Kim et al. (2018), testing both the EKC and WKC hypotheses, uses GRP per capita as a proxy. For this study, we use the mean annual household income measure.

Final variables to be used in the GTWR model were selected based on minimising multicollinearity between candidate independent variables, as GWR and GTWR models can be sensitive to multicollinearity. For this, the variance inflation factor (VIF) was calculated iteratively for each independent variable $k \in K$ (Belsley et al., 1980) (Equation 3.1):

$$\mathrm{VIF}_k = \frac{1}{1 - R_k^2} \qquad 3.1$$

The VIF is calculated by forming a regression model with the independent variable k acting as the dependent variable, regressed against the other potential independent variables. Variable screening is done by iteratively calculating the VIF for each independent variable, and removing potential variables from K whose VIF exceeds a cut-off threshold. For this study, the cut-off threshold was chosen as $1/(1 - R^2)$, where R^2 is the coefficient of determination of the full regression model with K independent variables. Descriptive statistics of the final selected variables are tabulated in Table 3-1.

Table 3-1: Descriptive statistics of the variables used in this study

Variable	Mean	Minimum	Maximum	Standard deviation
Per-capita waste generation [PCG] (kg/pers)	510.7	60.4	1,862.1	206.2
Mean income [INC] ($)	50,111.22	32,312	134,180	14,479.31
Pop. Density [POP.DENS] (pers/km^2)	731.5	0.04	8,055.3	1,582.8
Households [HHLDS] (num)	22,960.1	749	143,549	27,764
Household size [HHLD.SIZE] (pers/hhld)	2.3	1.4	3.7	0.4
Proportion recycling [PROP.REC] (dmnl)	0.38	0	0.73	0.2
Distance to urban [DIST.URBAN] (km)	44.77	0	396.59	66.71

3.3. Method

3.3.1. Overview of method

We examine the existence of the WKC in NSW by first establishing a functional relationship between waste generation and selected socioeconomic and urban morphological variables. A number of different functional relationships have been utilised in the literature for testing the Kuznets curve relationship, most often using a regression based approach (Ercolano et al., 2018; Jaligot & Chenal, 2018; Kim et al., 2018; Maddison, 2006; Mazzanti et al., 2008). The general functional relationship for testing this hypothesis is in Equation 3.2:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_1^2 + \beta_k X_k + \epsilon \qquad 3.2$$

Where Y is the waste generation variable, ϵ is the error term, β_i are regression coefficients to be estimated, X_1 is the economic development proxy variable, and X_k are other variables used to establish the relationship between waste generation and other socioeconomic drivers. Equation 3.2 is quadratic, which implies the dependent variable in Equation 3.2 tends to $\pm\infty$ as the independent variable(s) increases. Some studies such as Jaligot and Chenal (2018) use higher order polynomial functions in addition to the quadratic form to model more complex relationships (i.e., an N-shaped curve, where rebound occurs after decoupling) between the environmental variable and economic performance. For this study, we focus on the quadratic form of the WKC relationship as expressed in Equation 3.2 due to the short timeframe of this study, where more complex behaviour may have yet to emerge. The WKC hypothesis can thus be tested by comparing the β_1 and β_2 coefficients as per the relationships presented in Table 3-2.

Table 3-2: WKC hypothesis framework

β coefficient values	**Relationship between environmental and economic indicator**
$\beta_1 = \beta_2 = 0$	No relationship
$\beta_1 > 0$ & $\beta_2 = 0$	Linear increasing relationship between
$\beta_1 < 0$ & $\beta_2 = 0$	Linear decreasing relationship between
$\beta_1 < 0$ & $\beta_2 > 0$	Positive parabolic (U shaped) relationship
$\beta_1 > 0$ & $\beta_2 < 0$	Negative parabolic (inverted U shape—the WKC) relationship

The relationships in Table 3-2 can be confirmed in Equation 3.2 if the β_1 and β_2 coefficients are found to be statistically significant. Moreover, β_1 must be positive to ensure a positive tipping point can be estimated from the model.

We use municipal waste generation per-capita and mean income as the waste and economic indicators respectively for our study. Other variables used and their selection are discussed previously. The functional relationship is examined firstly by using pooled OLS regression across NSW by pooling all LGAs, with the WKC hypothesis being validated as per the framework presented in Table 3-2. This 'global' model (global in the sense that a single model relates to the entire study space) gives a baseline of state-wide WKC conformity, and estimates a tipping point in annual mean income terms for all of NSW, used to compare with results from further regional analysis using GTWR. The global model is also used to assess spatial autocorrelation of the pooled OLS residuals, to ascertain the level of spatial association in the data. Assessing spatial autocorrelation, and evaluating the fit of the pooled OLS model provides further justification for the use of a spatial model (i.e., the GTWR model) to determine regional WKC conformity across NSW. The results of the GTWR model are analysed to identify the LGAs that conform with the WKC hypothesis for each year of the study, and to estimate individual tipping points for WKC conforming LGAs.

3.3.2. Geographically weighted regression

To analyse regional variation in the existence of the WKC, GTWR is used. GTWR is an extension of geographically weighted regression, with the addition of temporal non-stationarity being taken into account. GWR/GTWR are examples of spatially varying coefficient models, which extend OLS regression such that regression parameters can vary over space and are estimated locally (Du et al., 2018; Huang et al., 2010; Keser et al., 2012; Ma et al., 2005). Before describing GTWR, GWR is first introduced. A GWR model can be expressed as follows in Equation 3.3:

$$Y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)X_{ik} + \epsilon_i \quad i = 1, \dots, N \qquad 3.3$$

Where N is the number of locations, (u_i, v_i) are the coordinates of a regression point i (for this study, the geometric centroid of an LGA, based on Huang et al. (2010) and Wu et al. (2014)) in space, $\beta_0(u_i, v_i)$ is the intercept at location i, and $\beta_k(u_i, v_i)$ is the estimated coefficient of the k^{th} variable X_k at location i. The geometric centroid was chosen, as it is an unbiased estimate of the centre point of an LGA. While this choice of centroid may fall on areas with no urban development (e.g., crop land, national parks, water bodies, etc.), development within LGA can be dispersed with multiple urban areas located within non-developed land, making selection of i that accurately represents the centre of urban areas difficult. Considering the scale of the analysis at the LGA level, the choice of centroid selected was not judged as a significant limitation.

A further limitation of GWR is that temporal (i.e., related to time) non-stationarity is not considered. GTWR extends the GWR framework by considering temporal, in addition to spatial, non-stationarity by constructing an appropriate spatiotemporal weighting matrix to measure the distance between regression locations in both space and time. The GTWR model is presented in Equation 3.4:

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_k \beta_k(u_i, v_i, t_i)X_{ik} + \epsilon_i \quad i = 1, \dots, N \qquad 3.4$$

For parameter estimation, it is assumed that observed data near the i^{th} point would have a greater influence in the estimation of the $\beta_k(u_i, v_i, t_i)$ parameters than data located further away in space and time from location i (Huang et al., 2010). Parameter estimation for $\beta_k(u_i, v_i, t_i)$ is given by Equation 3.5:

$$\beta(u_i, v_i, t_i) = \left[\mathbf{X}^T\mathbf{W}(u_i, v_i, t_i)\mathbf{X}\right]^{-1}\mathbf{X}^T\mathbf{W}(u_i, v_i, t_i)\mathbf{Y} \qquad 3.5$$

Where $\mathbf{W}(u_i, v_i, t_i)$ is an $n \times n$ matrix of spatiotemporal weights relative to the position of (u_i, v_i, t_i), $\mathbf{X}$ is the vector of independent variables, and $\mathbf{Y}$ is the vector of dependent variable values. The weight matrix $\mathbf{W}(u_i, v_i, t_i)$ has zeros in its off-diagonal elements, and the spatiotemporal weighting of observation data for observation i in its diagonal elements (Huang et al., 2010):

$$\mathbf{W}(u_i, v_i, t_i) = \text{diag}\{W_{i1}, W_{i2}, \dots, W_{in}\} \tag{3.6}$$

The weighting matrix refers to the relative importance of each individual observation across the data set based on Tobler's law, where nearer observations to i have greater influence on parameter estimation than observations further from i (Lewandowska-Gwarda, 2018). GTWR extends this by also considering that observations closer in time to i are also more influential than observations occurring further in the past.

Deriving the weighting matrix is through either a fixed or adaptive kernel based weight function. For the adaptive kernel, distance is constant but the number of nearest neighbours to location i varies (Huang et al., 2010). For fixed, this case is reversed where the number of nearest neighbours is fixed, but distance varies.

Typically, two potential kernels are used as weighting functions--Gaussian based functions, and the bi-square weighting function, although a wide range of other distance decay functions can be utilised (for example, the exponential function). For this study, the fixed bi-square kernel is used as it offered the greatest model fit, and is described as follows in Equation 3.7:

$$W_{ij} = \begin{cases} \left[1 - \left(\frac{d_{ij}^{ST}}{h}\right)^2\right] & \text{if } d_{ij}^{ST} < h \\ 0 & \text{otherwise} \end{cases} \tag{3.7}$$

Where h is the bandwidth or distance threshold, and d_{ij}^{ST} is the spacetime distance between observations i and j.

Estimating h regardless of the weighting regime chosen is done through optimisation against a goodness of fit statistic, such as cross-validation or the corrected Aikaike Information Criterion (AICc). Minimising the AICc provides greater accuracy for small sample sizes according to Kim et al. (2018), and is defined as follows in Equation 3.8:

$$\text{AIC}_c = 2n \ln\left(\hat{\sigma}^2\right) + n \ln(2\pi) + n \left(\frac{n + \text{tr}(S)}{n - 2 - \text{tr}(S)}\right) \tag{3.8}$$

Where $\hat{\sigma}^2$ is the estimated standard deviation of the error term, and $\text{tr}(S)$ is the trace of the hat matrix which maps the vector of dependent variable values to the vector of fitted values.

Estimating spatiotemporal distance d^{ST} is difficult due to distance and time being measured in different units (here, meters and years) and therefore have different scale effects (Huang et al., 2010). Given a spatial distance d^S and a temporal distance d^T, spatiotemporal distance d^{ST} can be calculated such that (Equation 3.9):

$$d^{ST} = d^S \otimes d^T \tag{3.9}$$

Where $\otimes$ represents some operator. Du et al. (2018), Ma et al. (2005) and Huang et al. (2010) define $\otimes$ as a simple linear combination of spatial and temporal distance, with scale parameters λ and μ to balance the different scale effects, for example, if d^S is much larger than d^T, then spatial distance will dominate d^{ST}, and vice-versa (Wu et al., 2014):

$$d^{ST} = \lambda d^S + \mu d^T \tag{3.10}$$

For this study, we use the *GWmodel* (Gollini et al., 2015) implementation of GTWR in the *R Statistical Computing* language to estimate the GTWR model, which implements an improved GTWR model based on Wu et al. (2014). Here, a more complex $\otimes$ operator is utilised to control the interaction of space and time effects, and to ensure that only previous 'time neighbours' (i.e., observations occurring in the past) are taken into consideration (Equation 3.11):

$$\begin{cases} d_{ij}^{ST} = d_{ij}^S \otimes d_{ij}^T = \lambda d_{ij}^S + \mu d_{ij}^T + 2\sqrt{\lambda \mu d_{ij}^S d_{ij}^T} \cos \xi & t_j < t_i \\ d_{ij}^{ST} = \infty & t_j > t_i \end{cases} \tag{3.11}$$

Where λ and μ are adjustment parameters between 0 and 1 to scale the different scale effects (with $\mu = 1 - \lambda$ as implemented by *GWmodel*). ξ is a parameter introduced by Wu et al. (2014) to control the interaction of space and time effects, and is between 0 and π. Selection of the λ and ξ parameters is done through optimisation of a goodness-of-fit statistic.

3.4. Results & discussion

The final functional relationship for this study is expressed as (Equation 3.12):

$$\widehat{PCG}_{it} = \beta_0 + \beta_1 \log INC_{it} + \beta_2 \log INC_{it}^2 + \beta_3 PCG_{i,t-1}$$
$$+\beta_4 \log POP.DENS_{it} + \beta_5 HHLDS_{it}$$
$$+\beta_6 PROP.REC_{it} + \beta_7 \log DIST.URBAN_i + \beta_8 HHLD.SIZE_{it} + \epsilon \quad 3.12$$

Where PCG is per-capita municipal waste generation. A lagged per-capita waste generation term (PCG_{t-1}) is included under the expectation that historical waste generation would influence waste management decision making, and thus be a determinant of future waste generation. INC is mean household income, $POP.DENS$ is population density, $HHLDS$ is the number of households, $HHLD.SIZE$ is the size (occupancy) of households, $PROP.REC$ is the proportion of municipal waste collected as recycling, and $DIST.URBAN$ is the minimum distance from the geometric centroid of an LGA to the nearest significant urban area (ABS, 2017). INC, $POP.DENS$ and $DIST.URBAN$ variables have been log transformed to account for skew in the data.

3.4.1. Global model results

The global model serves as a baseline to compare the results of the estimated GTWR model to be discussed in the following section, and expresses the relationship between the independent and dependent variables for the entire state of NSW without consideration for spatial effects. Table 3-3 presents the results of the global model across the pooled LGA data.

Table 3-3: Global regression model results

Variable	**β Estimate**	**SE**	***t* value**	***p* value**
Intercept	-43,440	13,040	-3.332	<0.001
log *INC*	8,024	2,379	3.373	<0.001
log INC^2	-365.3	108.3	-3.374	<0.001
PCG_{t-1}	0.6538	0.0509	12.852	<0.001
log *POP.DENS*	-6.78	6.656	-1.019	0.309
HHLDS	-0.0001	0.0004	-0.238	0.812
PROP.REC	171.7	53.75	3.194	0.001
log *DIST.URBAN*	1.239	3.893	0.318	0.750
HHLD.SIZE	-0.602	31.10	-1.936	0.053
R^2				0.2861
AIC				6789.946
p value				<0.001

Both mean income and its square are significant, with signs of each income term agreeing with the Kuznets curve hypothesis indicating that without consideration of LGA variation in the independent variables, there is a decoupling of waste generation and income over the state. In addition, PCG_{t-1} and $PROP.REC$ are also statistically significant. From these results, we can calculate the tipping point from the values of the β coefficients for the two income terms β_1 and β_2 (Equation 3.13):

$$\exp\left(-\frac{\beta_1}{[2\beta_2]}\right) \quad 3.13$$

From Equation 3.13, the global tipping point was estimated as a mean income of AUD$58,839 (AUD = Australian Dollar, where AUD$1 = USD$0.69, as of June 2019). It was found that 22 LGAs had mean incomes above the estimated tipping point over the study time period, with 17 of these LGAs located within the Sydney Metropolitan Area (SMA). This result is expected, considering that economic activity is much greater within the SMA and therefore higher mean incomes compared to regional LGAs is likely. Figure 3-6 the distribution of mean incomes and per-capita generation rates for LGAs, relative to the estimated tipping point.

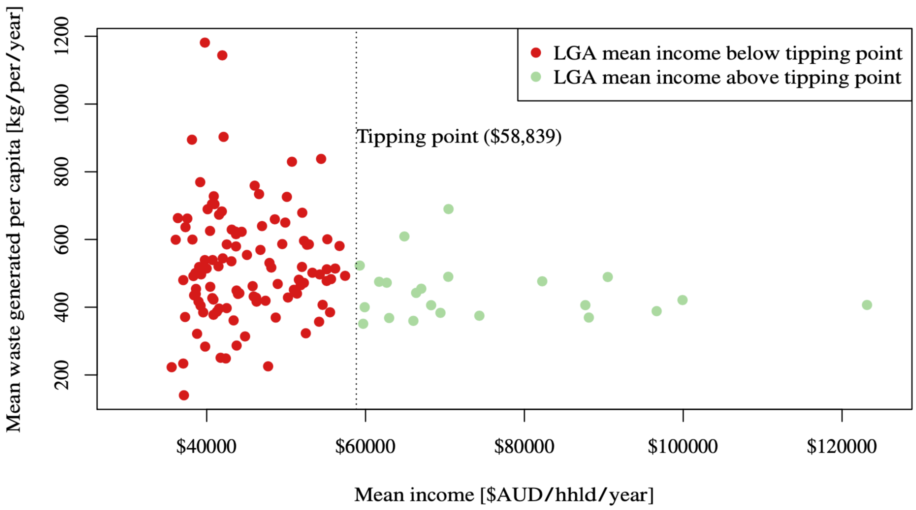


Figure 3-6: Average LGA mean incomes vs. average LGA per-capita waste generation, compared to global model tipping point estimate

Overall model fit of the global pooled OLS model is poor, demonstrated by an adjusted-R^2 value of 0.286, however such a fit is consistent with similar models in the waste management literature. Lebersorger and Beigl (2011) for example note that in their review that coefficients of determination (R^2) rarely exceed 0.5 for regression models estimating waste generation, however Oribe-Garcia et al. (2015) for example obtained R^2 values of between 0.279 and 0.980 for their regression models estimating waste generation in Biscay. Oribe-Garcia et al. (2015) cite several other similar studies (i.e., regression based models for estimating waste generation) in their paper, with R^2 values ranging from 0.51 to 0.88.

We test for spatial autocorrelation of model residuals from the global model by calculating Moran's I, which is a measure of spatial autocorrelation taking values [-1,1]. A Moran's I between 0 and 1 indicates a clustering of values, whereas a Moran's I between -1 and 0 indicates regular distribution of values. A Moran's I of approximately 0 indicates random distribution (i.e., no spatial association) of values being tested. Moran's I can be calculated from the following (Bivand et al., 2013):

$$I = \frac{n \sum_i \sum_{j \neq i} w_{ij} \left(Y_i - \bar{Y}\right)\left(Y_j - \bar{Y}\right)}{\left(\sum_i \sum_{j \neq i} w_{ij}\right) \sum_i \left(Y_i - \bar{Y}\right)^2} \tag{3.14}$$

Where Y_n is the model residual for observation n from the global model, $\bar{Y}$ is the mean model residual, and w_{ij} is the i, j^{th} element of the $n \times n$ spatial proximity matrix $\mathbf{W}$, which provides a distance weighting for each pair of observation points i and j. Proximity is determined by the number of nearest neighbours to observation points i, which describes the maximum number of adjacent neighbours to i from which distance is measured. Statistical significance of the Moran's I estimate is obtained by comparing the standard deviate of the Moran's I statistic with the normal distribution (Bivand et al., 2013).

The results from the Moran's I analysis are presented in Table 3-4, indicating that spatial autocorrelation of residuals exists for all levels of nearest neighbours tested (2 to 10 nearest neighbours), and that model residuals for the global OLS model are more clustered than random. The value of the Moran's I shows a decreasing trend as the number of nearest neighbours increase. This is expected as the distance between observation points increase as additional neighbours are considered (Goovaerts, 1997). This is consistent with findings from Keser et al. (2012) who identified a similar pattern of spatial autocorrelation of residuals in their GWR study modelling waste generation in Turkey. The importance of this finding is that there is a spatial association between the dependent and independent variables, indicating that explicitly controlling for spatiality (for example, through GWR/GTWR) is appropriate for this study.

Table 3-4: Results of Moran's I test for spatial autocorrelation of residuals from global OLS model

Num. nearest neighbours	Moran's I	p value
2	0.5339	<0.001
3	0.5880	<0.001
4	0.6627	<0.001
5	0.6627	<0.001
6	0.4887	<0.001
7	0.3754	<0.001
8	0.2875	<0.001
9	0.2198	<0.001
10	0.2198	<0.001

3.4.2. GTWR local model results

The GTWR model uses the same functional relationship as the pooled OLS global model expressed in Equation 3.12, with estimated regression coefficients varying across LGAs, as per Equation 3.4. λ and ξ parameters used to control the interaction of space and time effects (Equation 3.11) were selected using a Monte-Carlo simulation approach, with λ and ξ values sampled from a uniform distribution of candidate values ($\lambda \in [0,1]$; $\xi \in [0, \pi]$). The GTWR model with the highest adjusted coefficient of determination was selected as the final model from 10,000 iterations. Figure 3-7 shows the results of these simulations. From these results, model fit is highly sensitive to variations in λ above a certain threshold. Adjusted R^2 values increase monotonically with λ until $\lambda \approx 0.6$, from which point adjusted R^2 values are erratic. For $\lambda < 0.6$, values of ξ appear to not have a significant impact on the model fit, indicating that there is little interaction between spatial and temporal effects for $\lambda < 0.6$, and that coefficient estimates are more heavily weighted towards spatial effects than temporal for models with high R^2 values. Table 3-5 shows the selected parameter values for the final GTWR model. Appendix A.1 shows β coefficient estimates and t-values for the two mean income variables in the final GTWR model for different levels of λ.

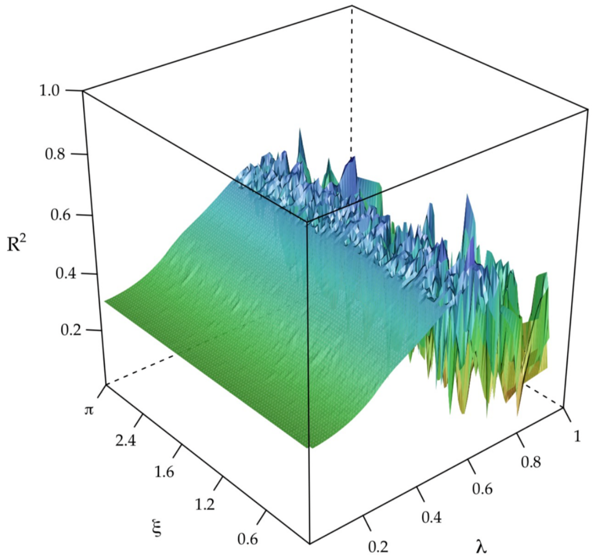


Figure 3-7: Results of Monte-Carlo simulation for selection of ξ and λ GTWR parameters

Table 3-5: Selected GTWR parameter values

Parameter	Value
λ	0.61
ξ	0.02

Table 3-6 summarises coefficient estimates for all LGAs and years from the GTWR model, exhibiting variation over the study space. Comparing with results from the global model in Table 3-3, GTWR estimates fluctuate around those given from the global model, however variation is large indicating that the global model lacks the complexity given by considering spatiality.

Table 3-6: Results of the GTWR local model

Variable	Mean	Minimum	First Quartile	Third Quartile	Maximum
Intercept	-45,620.04	-1.31e06	-32,232.80	14.78	1.73e06
log *INC*	8,142.39	-328,968.73	16.76	5,758.00	242,580.40
log INC^2	-361.06	-11,196.32	-260.32	3.19	15,518.12
PCG_{t-1}	0.60	-1.23	0.52	0.69	1.55
log *POP.DENS*	44.50	-7,656.40	-38.77	36.68	8,122.30
HHLDS	-0.01	-1.06	-0.01	0.01	1.83
PROP.REC	-18.67	-1,922.00	-125.81	135.71	1,509.06
log *DIST.URBAN*	52.81	-9,907.82	-5.52	8.48	10,347.85
HHLD.SIZE	-60.04	-2,828.03	-158.46	33.24	3,314.31

Confirming the spatial and temporal non-stationarity of GTWR coefficient estimates further justifies the use of GTWR over the global OLS model. Ma et al. (2005) confirm the spatiotemporal non-stationarity of GTWR coefficient estimates following Fotheringham et al. (2002) and Fotheringham et al. (2015) by comparing the interquartile range from the GTWR estimates for each variable with twice the standard error of the pooled OLS model estimates for each variable. For this paper, we also examine the spatiotemporal heterogeneity of the GTWR estimates by comparing with the global pooled OLS estimates under the null hypothesis that coefficient estimates from the GTWR model are not significantly different from the pooled OLS estimates (i.e., spatiotemporal non-stationarity does not exist), using the nonparametric Wilcoxon signed-rank test. Results for both of these analyses are presented in Table 3-7. These results show that the coefficient estimates from the GTWR exhibit spatiotemporal non-stationarity, indicating that locally weighted GTWR coefficients significantly differ from those produced from the global pooled OLS model.

Table 3-7: Summary of spatial non-stationarity of GTWR coefficient estimates

Variable	Interquartile (GTWR)	2 x SE (OLS)	Wilcoxon test statistics	*p*- value
Intercept	32,247.58	26,073.11	0.49	<0.001
log *INC*	5,742.17	4,757.62	0.50	<0.001
log INC^2	263.51	216.54	0.51	<0.001
PCG_{t-1}	0.18	0.10	0.81	<0.001
log *POP.DENS*	77.45	13.31	0.21	<0.001
HHLDS	0.00	0.00	0.22	<0.001
PROP.REC	261.52	107.50	0.87	<0.001
log *DIST.URBAN*	14.00	7.79	0.16	<0.001
HHLD.SIZE	191.70	62.19	0.63	<0.001

A benefit of GWR/GTWR as an exploratory tool is the possibility of mapping model coefficient estimates over space and time. Statistically significant GTWR model coefficients (with *p*-values <0.05) are presented as thematic maps in Figure 3-8. For Figure 3-8, the average coefficient values (β in the figure) over time are used for visualisation following Ma et al. (2005), who suggests that mapping the eigenvalues of the coefficients (e.g., the average values) is useful for visualising spatial variation (Ma et al., 2005). Of note from these results is that significant income coefficients occur for a set of clustered LGAs, west of the Sydney metropolitan area. Further discussion is provided below.

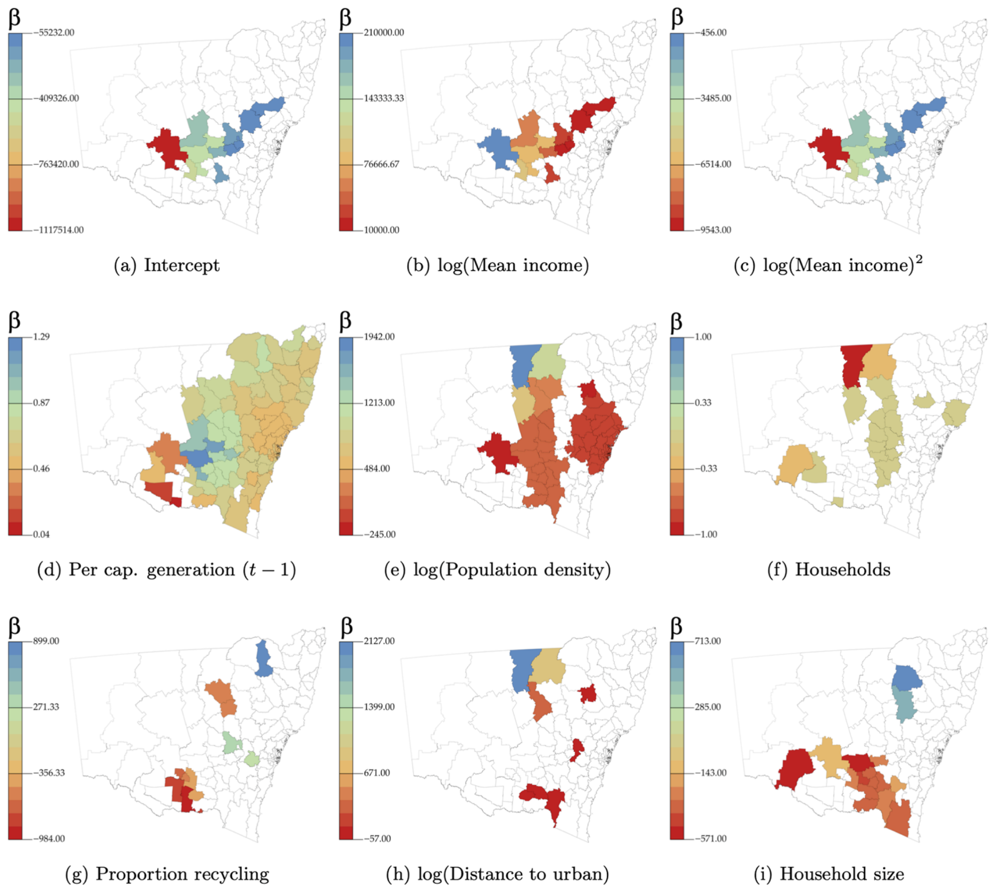


Figure 3-8: Average coefficient estimates from GTWR model

Other variables exhibit significant coefficients across a greater proportion of the state, most notably the lagged per-capita waste generation, number of households, household size, and population density variables. The analysis found that household size is a greater determinant of per-capita waste generation compared with the number of households, whose coefficient estimates across the study area are approximately 0. A significant negative relationship is identified between per-capita waste generation and household size. This effect is most strongly associated with LGAs within the Murray and Southern Inland regions along the Victoria-NSW state border. Kolekar et al. (2016) cites in a review of predictive models that household size is often a significant determinant of waste generation. Kumar and Samadder (2017) and Trang et al. (2017) find significant positive relationships between household size and waste generation. A negative relationship between these variables may indicate that as the number of household occupants increase, households become more efficient in using materials through for example sharing and re-use, resulting in a lower per-capita rate of waste generation.

Coefficient estimates for the proportion of waste collected as recycling was found to be quite clustered, with LGAs near more developed regions showing a positive relationship with per-capita waste generation. This relationship may be expected where improvements in waste management practices (e.g., increased separately collected recycling) are a response to increasing rates of waste generation, not as a measure to reduce waste generation through better waste disposal behaviour. Coefficient estimates for the lagged per-capita waste generation variable shows that across NSW, a mild increasing trend in per-capita waste generation is identified, indicated by coefficients <1.

Significant population density coefficients show a generally negative relationship with per-capita waste generation, which is mostly strongly associated with the Greater Sydney Metropolitan Area and its surrounds. A similar relationship between waste generation and population density was found in Oribe-Garcia et al. (2015). Such a relationship could indicate areas with a higher proportion of high-density residential development, where rates of per-capita generation are typically lower due to reduced green waste generated for example. Conversely, areas showing a positive relationship between population density and per-capita generation, may indicate LGAs with a lower level of urban development and waste infrastructure.

Model fit of the GTWR model is superior to that of the global OLS model, indicated by goodness-of-fit statistics reported in Table 3-8. The improvement of model fit by utilising GTWR is consistent with the literature, as Lewandowska-Gwarda (2018) report. GWR/GTWR will usually produce better fitting models over global OLS models given that the spatial model better controls for spatial (and temporal, in the case of GTWR) heterogeneity (Lewandowska-Gwarda, 2018).

Table 3-8: Goodness-of-fit statistics for local GTWR and global OLS models

Statistics	**Local GTWR model**	**Global OLS model**
R^2	0.699	0.297
Adjusted R^2	0.611	0.286
AIC	6,435.682	6,789.946

3.4.3. Empirical findings for the WKC hypothesis

The existence of the WKC can be identified following the framework presented in Section 3.2.1. Figure 3-9 shows the LGAs where the WKC hypothesis is met across the time period analysed, based on interpretation of regression coefficient estimates following Table 3-2. Figure 3-10 shows the ratio of tipping points to mean income for WKC conforming LGAs.

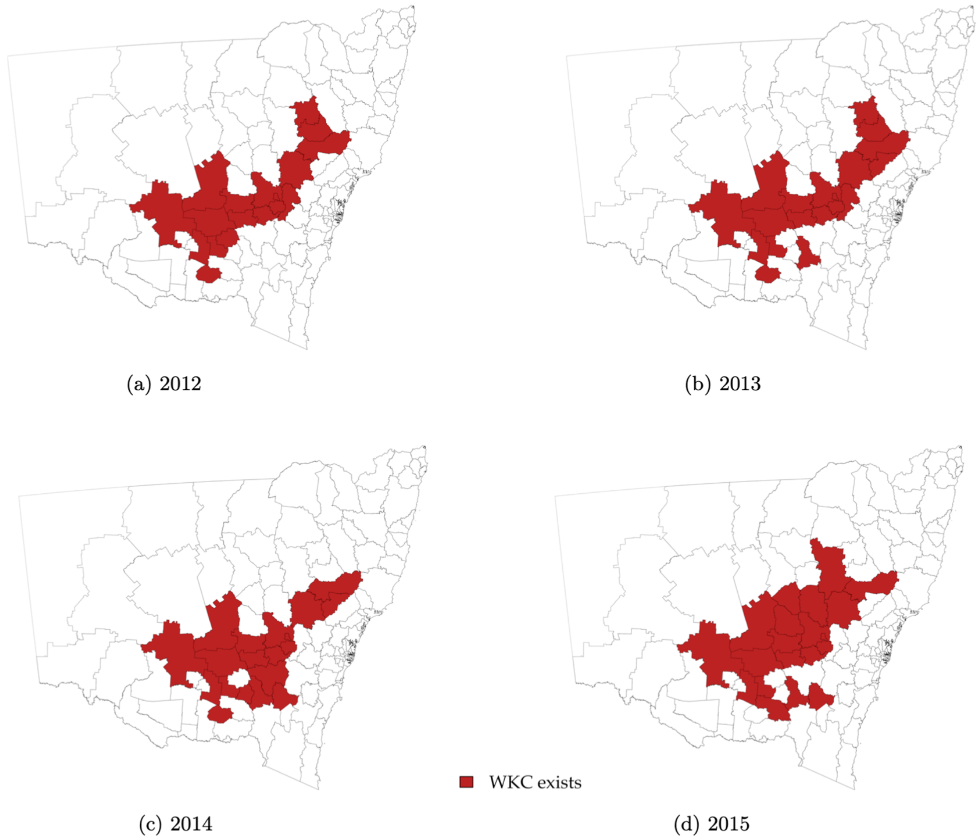
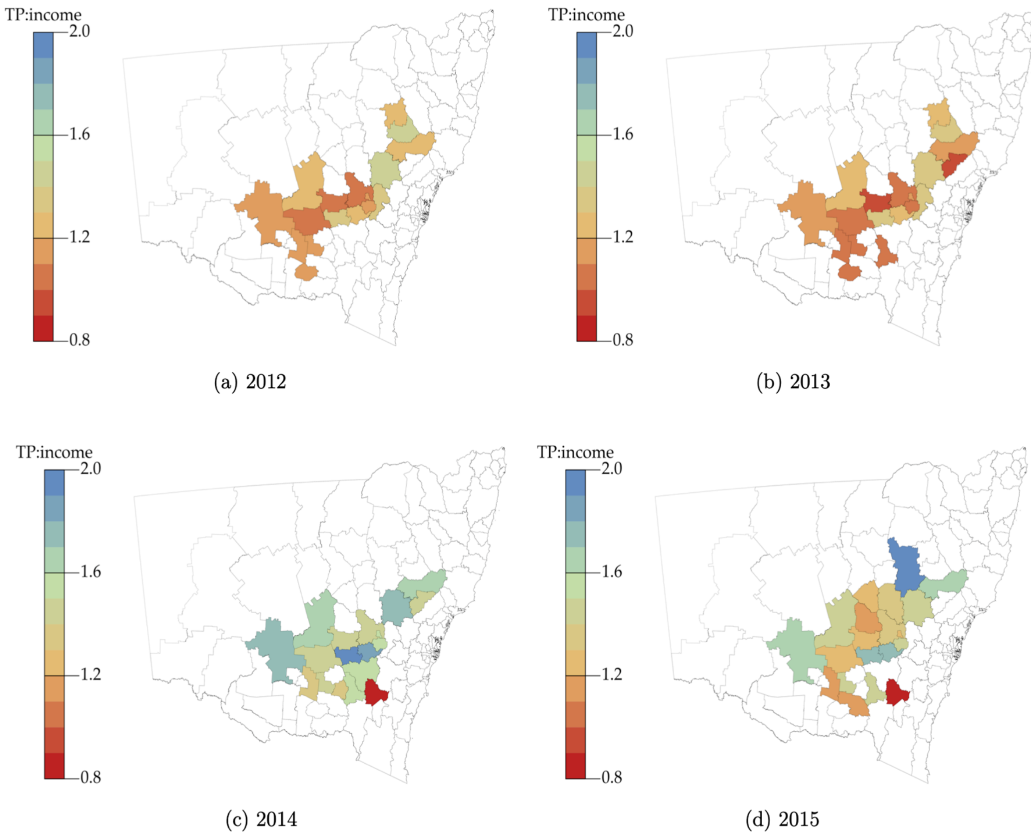


Figure 3-9: Local government areas conforming to the WKC hypothesis



(a) 2012 (b) 2013

(c) 2014 (d) 2015

Figure 3-10: Ratio between estimated tipping points and mean incomes for WKC conforming local government areas

LGAs within NSW that exhibit the WKC are located across the Orana, Hunter, Central West, Murray, and Riverina regions directly west of the Sydney metropolitan area. The total number of LGAs conforming to the WKC hypothesis vary over the time frame, showing an increasing trend. Table 3-9 shows the number of LGAs conforming to the WKC for each year, including the proportion of WKC conforming LGAs to total state LGAs, proportion of the NSW population residing in WKC conforming LGAs, and average estimated tipping points for these LGAs.

Table 3-9: Summary of WKC conforming LGAs

	Num. WKC LGAs	% of NSW LGAs	% NSW population	Avg. tipping point
2012	18	14.1%	3.0%	$58,875
2013	19	14.8%	3.3%	$59,345
2014	19	14.8%	3.0%	$57,700
2015	20	15.6%	4.3%	$56,260

Tipping point mean incomes have been estimated between approximately $48,000 per annum to $76,000 per annum. Average mean income across these LGAs in 2015 is approximately $47,400 per annum, compared to $54,400 for all other LGAs. The ratio of tipping point to mean income ranges from 0.8 to 2 times local mean income for these LGAs (Figure 3-10). These ratios are quite high for some LGAs, considering a lower level of economic development in regional NSW where the WKC conforming LGAs are located. High tipping point estimates also emerged in Mazzanti and Zoboli (2009), where value added per-capita was used as the economic indicator. Following from Ichinose et al. (2011) and Mazzanti and Zoboli (2009), such high tipping points occur outside the range of observable mean incomes for most WKC conforming LGAs, indicating a relative decoupling of waste generation and income in NSW generally rather than an absolute decoupling. This is also partly confirmed from the global model results, which indicate a global tipping point above the state-wide mean income.

Figure 3-11 shows the distribution of per-capita waste generation rates, proportion of waste collected as recycling, population density, and mean incomes for WKC and non-WKC conforming LGAs. LGAs conforming to the WKC hypothesis generally exhibit higher per-capita generation rates, and significantly lower proportion of waste collected as recycling. This might suggest that WKC conforming LGAs may in fact have poorer performing waste management systems than non-WKC conforming LGAs. It may be the case that the WKC conforming LGAs have taken steps to improve waste management practices in recent years, which has caused a WKC-type relationship to emerge. However the short time-series dataset used for this study makes confirming this difficult.

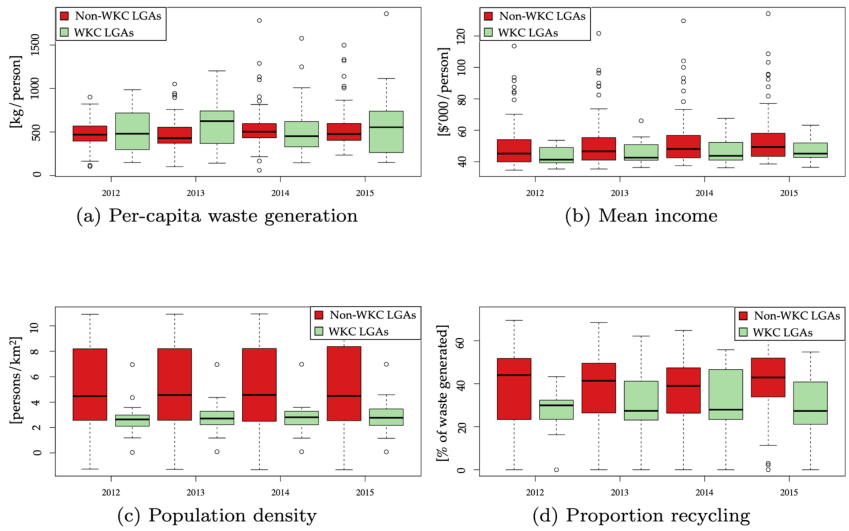


Figure 3-11: Comparison of WKC conforming and non-conforming LGAs

The distribution of mean incomes is expected, with non-WKC conforming LGAs including LGAs within the Sydney metropolitan area having a greater level of economic development, and thus higher mean income levels. Considering that mean income is higher, and per-capita generation rates are generally lower in non-WKC LGAs, it may be true that some currently non-WKC conforming LGAs have in fact already experienced a decoupling of waste generation from income. However a longer time-series dataset would be required to confirm this.

Differences in urbanisation, indicated by population density, are found between LGAs conforming to the WKC hypothesis, and those that do not. Mean population density for WKC conforming LGAs is approximately 10 persons/km^2, compared to 865 persons/km^2 for the non-conforming LGAs. This large difference in urbanisation is expected, given that LGAs within the Sydney metropolitan area, the most heavily populated area in Australia, do not exhibit the WKC relationship. The effect of population density on WKC-like behaviour however can only be speculated. Previous studies suggest that population density has a positive effect on per-capita generation rates (Mazzanti et al., 2008). Findings from our study show that population density has a mostly negative impact on per-capita generation, which is especially true for WKC conforming LGAs. Reasons for this may be that denser locales have better access to improved waste management and avoidance infrastructure. This finding is consistent with those presented in Jaligot and Chenal (2018), who found higher levels of population density led to decreased waste generation when testing a similar WKC.

The strength of the divergence between income and per-capita generation for WKC conforming LGAs is measured in Table 3-10. We compare the percentage difference in per-capita generation rates, and the income elasticity on per-capita generation over the study period for the two sets of LGAs. A Student's *t*-test found no significant difference between distributions for WKC conforming and non-conforming LGAs. This finding might suggest that per-capita rates of waste generation across the non-WKC conforming LGAs are relatively stable and in decline, whereas the WKC-conforming LGAs are in various stages of decoupling, therefore may only recently be experiencing the initial stages of relative decoupling.

Table 3-10: Income elasticity of per-capita generation for WKC conforming and non-conforming LGAs

LGA type	Mean %Δ PCG	Mean %Δ INC	Mean elasticity
Non-WKC conforming	-3.66%	3.35%	2.19
WKC conforming	-1.88%	3.49%	-1.56

Table 3-10 also compares the mean income elasticity of per-capita generation for each set of LGAs. Mean elasticity for WKC conforming LGAs shows a negative elasticity, providing further evidence of the relative decoupling status for these LGAs. Non-WKC conforming LGAs experience a greater, positive elasticity. Considering the findings from both the global and local models, this is consistent as a general trend in decreasing waste generation and increasing mean income exists across the entire state. In fact, LGAs identified not to be following a WKC trajectory within our study's time frame, may have already experienced a decoupling, and are in the final stages of decline with stabilisation. Further investigation on a more complete dataset (i.e., over a longer time period) would be needed to identify the stage of decoupling an LGA in the study might be at, as well to measure the strength of decoupling if it is taking place.

The results of our study show that there is progress towards the decoupling of per-capita waste generation from mean income across NSW following the WKC hypothesis. While NSW has an agenda for transitioning to the circular economy, with decoupling as a key focus area (NSW EPA, 2019b), there has been little action towards establishing benchmarks to measure progress towards circular economy objectives. The results of this study give a baseline of decoupling progress at the municipal level following the WKC, and may inform policy through the targeting of specific initiatives towards LGAs not exhibiting decoupling-like behaviour, or for establishing regionally specific decoupling related targets.

3.5. Conclusion

This study has estimated the existence of the WKC across the Australian state of NSW using a GTWR approach, accounting for spatial and temporal heterogeneity in socioeconomic, demographic and structural factors over the 2011 to 2015 period. The GTWR model allowed us to identify specific LGAs within the study area that conform to the WKC hypothesis over time. Our analysis showed that the region to the west of the Sydney metropolitan exhibit the WKC relationship when accounting for spatially varied socioeconomic and structural factors. The ratios of tipping point to mean income for WKC conforming LGAs are between 0.8 and 2, indicating that generally LGAs conforming to the WKC are in stages of relative decoupling rather than absolute.

Findings from the GTWR model show that LGAs conforming to the WKC hypothesis have higher rates of per-capita generation, and lower proportions of waste collected as recycling than non-WKC conforming LGAs in NSW. This suggests that WKC conforming LGAs may have poorer waste management systems, and poorer waste disposal practices than non-WKC conforming LGAs, however this was not able to be confirmed within the scope of this analysis. While it may follow that targeted investment in waste management infrastructure or waste avoidance programs in these regions may drive decoupling, it is unclear from these findings the impact of such strategies in supporting decoupling. The study does not analyse the degree to which LGAs may be decoupling waste generation from household income, however the lower rates of per-capita waste generation suggests that some non-WKC conforming LGAs (namely, those located within the Sydney metropolitan area) may have in-fact already experienced a decoupling before the study time period. Additionally, findings show that WKC-conforming LGAs also have lower mean household incomes compared to non-WKC conforming LGAs, however this finding is expected considering mean incomes in the Sydney metropolitan area and other major regional and urban centres tend to have higher mean incomes and greater levels of economic development than regional LGAs.

This analysis demonstrates a new methodology applied in NSW for exploring waste and income decoupling relationships—significant in transitioning to sustainable waste management and the circular economy more broadly. The methodology could also be applied to other Australian jurisdictions where studies on the WKC at the sub-national level are lacking. Findings from our study may be used in a strategic policy making context, for example benchmarking and measuring performance against state-wide circular economy objectives using the WKC framework might enable appraisal of the effectiveness of circular economy and sustainable waste management policy implementation in driving decoupling. Findings may also inform future policy and/or waste management programs such as waste prevention and initiatives that are tailored to not only current stages of decoupling, but also to locally specific drivers of waste generation.

Chapter 4.

High-resolution estimation of household waste generation

Chapter 3 explored spatial variability in waste generation across NSW, finding evidence to support the waste Kuznet's curve hypothesis. While not explicitly addressing the key motivating research question, Chapter 3 nevertheless helps inform the modelling of waste management systems, by offering evidence that supports the use of spatial modelling for NSW. In particular, findings from that study indicated that drivers for waste generation do vary over space in NSW, and should be a consideration for any future modelling of NSW waste streams.

This chapter is concerned with addressing research question 1 in full, as well as research question 2 as follows:

Research question 1: What is the spatial distribution of waste generation in NSW, and is regional variability significant?

Research question 2: How can waste generation data be modelled at high resolutions, where data is limited?

Where Chapter 3 addressed the second part of research question 1 (i.e., regional variability), this chapter focuses on modelling and estimating the spatial distribution of waste generation at a high resolution. Data on the distribution of waste generation is limited for NSW, with council area waste generation data the highest resolution data available. Therefore addressing this research question is significant in a number of instances, where higher resolution on the spatial distribution of waste might be beneficial. For example, understanding the spatial distribution of waste generation is important from a management and planning perspective. Knowing what kinds of waste are generated and where, can help inform where waste management resources, for example treatment facilities, might be needed.

In the case of this thesis however, high resolution waste generation data can help address some critical gaps in the data, namely, the estimation and impact of waste collection and transportation emissions. Data on this source of emissions is also limited, and overcoming this data gap is essential to addressing the overarching aims of this thesis. With no data available on the distances travelled by waste collection vehicles or their emissions, this data must also be modelled and estimated. For this, data characterising the quantities of waste generated at the property lot level can be utilised to model the movements of waste collection vehicles, thereby enabling the bottom-up estimation of waste collection emissions intensity. The focus of this chapter in addressing research question 1, is therefore developing a methodology for estimating the spatial distribution of waste generation at a high resolution—specifically, at the property lot level. The method developed is applied in the estimation of annual quantities of kerbside waste generation for more than 1.2 million property lots in the Sydney metropolitan area.

The work presented in this chapter was published as a standalone paper in 2021, as follows:

Madden, B., Florin, N., Mohr, S., Giurco, D. (2021). Spatial modelling of municipal waste generation: deriving property lot estimates with limited data, *Resources, Conservation and Recycling*, 168, 105442, DOI: 10.1016/j.resconrec.2021.105442.

This chapter includes the above published paper in full, and differs from the paper published in the above in formatting only. The paper's primary aim was to model and estimate property lot waste generation with limited data. Conclusions in this chapter are specific to these aims which appear in the standalone paper. Specific conclusions and insights drawn from this analysis in relation to the thesis research questions, are discussed in Chapter 8.

4.1. Introduction

The management of municipal solid waste presents multiple environmental, human health, logistical and economic challenges for cities and regions (Essin & Cosgun, 2007; Ferrão & Fernández, 2013). In Australia, waste management is in focus with industry and communities committed to reducing waste, avoiding landfilling, and eliminating the risk of material losses to the environment throughout the resource recovery system. Exporting waste for overseas processing is no longer an option for many waste types, especially plastic material not sorted into high quality single polymer streams (COAG, 2020), and new landfill diversion pathways for Australian waste must be prioritised to avoid increases in landfilling in the future. Recently, the government of the Australian state of New South Wales adopted a circular economy framework to guide future waste decision making in the state towards a `waste-as-a-resource' framework (NSW EPA, 2019b). Under this updated policy direction, there is a significant opportunity now for the promotion of waste management initiatives focused on improving resource recovery with greater circularity in resource flows.

High resolution data on quantities of waste generated, for example at the property lot or household level, can be very useful for informing decision making around targeted waste management initiatives. For example, such data is useful for: identifying optimal waste treatment or recovery facility locations (Lin et al., 2020; Yadav et al., 2017; Yadav et al., 2018); optimising waste collection routing (Hannan et al., 2018; Sarmah et al., 2019; Vu et al., 2019); and in planning for targeted dwelling specific systems, such as insinkerators and basement anaerobic digestion and composting (Edwards et al., 2016; Lou et al., 2013). Waste generation data is often limited at high resolution scales despite its usefulness (Kontokosta et al., 2018), typically due to individual household privacy concerns and the high cost associated with large-scale household bin audits and surveys. There is a need then for an approach to disaggregate available, low spatial-resolution waste generation data down to a finer spatial scale, when such data might be beneficial for informing waste management decisions.

There is a gap in the literature concerning the estimation of waste generation data at high spatial resolutions, where real data is not available. This data gap is the key motivation for this work. In a recent study, Kontokosta et al. (2018) presents a novel analytical approach for predicting daily and weekly waste generation at the building level in New York City, USA. In Kontokosta et al. (2018), the authors address the issue that understanding patterns of waste generation at building level is limited as data at this scale is generally lacking. For their approach, the authors develop a predictive model utilising detailed census, weather, and waste data to estimate household waste generation at the building level. The resulting model has high accuracy when compared to validation data, and has several important contributions and applications, including in designing more efficient waste collection routing, and for detecting areas of New York City that have higher (or lower) likelihood to recycle for more targeted waste behaviour initiatives.

Kontokosta et al. (2018) use statistical and computational approaches for disaggregating low spatial resolution (e.g., city, region etc.) data to the building level. While studies applying similar, small-area estimation methods are not common in a waste context, spatial disaggregation models are more widespread across other fields including public health (Albright et al., 2019; Eberth et al., 2018; Truong & Stein, 2019), socioeconomic research (Buil-Gil et al., 2019; Fabrizi & Trivisano, 2016), resource assessment (Goerndt et al., 2019), and the management of waste and debris due to natural disasters (Hayes et al., 2021; Tabata et al., 2019). These small-area estimation methods are widely used for producing estimates of attributes at spatially disaggregated scales where data is limited, by 'borrowing' from data at other scales (Buil-Gil et al., 2019; Chandra et al., 2012). However, small-area estimation models generally require microdata (data available at very fine scale) for calibration and validation. In the absence of such data, microsimulation and other spatial approaches are often used to generate required data for small areas, using appropriate deterministic, probabilistic and/or computational modelling approaches (NATSEM, 2008; Rich, 2018).

The aim of this research was to develop a spatial model for estimating quantities of household waste generated annually at the property lot level. The model described in this paper is motivated by limited availability of data at the property lot level, namely information on household characteristics and quantities and composition of waste generated itself. In this paper, we describe an approach that was used to estimate annual quantities of waste generated for more than 1.2-million property lots in the Sydney metropolitan area (SMA), Australia. The model described first estimates the distribution of dwelling types at the property lot level using council and neighbourhood level census data (ABS, 2016b, 2017). Average rates of annual waste generation by dwelling type were derived from council reported waste statistics (NSW EPA, 2017) and local kerbside audit data (APC, 2019), and combined with the estimated dwelling type distribution to estimate annual waste generated per property lot in our study area. The model presented in this paper has wide ranging local applications for informing waste management policy, including analyses requiring high spatial resolution waste generation data such as new infrastructure planning. More broadly, the approach developed has modest data requirements and could be readily applied to other jurisdictions.

4.2. Methodology

For our approach, we first developed a probabilistic model from area-level data to estimate the number of occupied dwellings by type for each property lot within the 31 local government areas (LGA) of the SMA. The estimated number of dwellings by type was then multiplied by estimated dwelling-type waste generation intensities (i.e., tonnes/hh/yr), derived from literature data (APC, 2019; NSW EPA 2017) to estimate annual quantities of household waste generated at property lots for each LGA in the SMA.

Our approach implicitly accounts for variation in waste generation behaviours between different dwelling type occupants amongst the LGAs investigated. We considered two high-level dwelling types in our study: detached dwellings (i.e., a single dwelling located on a property lot); and multi-unit dwellings, including apartments, townhouses, and other residential structures where multiple households are located on a single lot. Focus on these two dwelling types has been made for two key reasons; Firstly, kerbside audits of the municipal waste stream in Southern Sydney were conducted in 2008 and 2019 for detached and multi-unit dwellings only (APC, 2008, 2019), and found that dwelling type is a significant determinant of waste generation, with detached dwellings generating on average between 1.7 and 2.8 times more total household waste than multi-unit dwellings. This finding is somewhat expected, given that the number of occupants in detached dwellings is typically greater than multi-unit dwellings (ABS, 2016b), however the composition of waste generated between dwelling types also differs significantly. Secondly, waste generated by multi-unit dwellings presents unique challenges, with increased rates of bin contamination, and often complex bin collection systems making management of waste on site difficult (APC, 2019; Waste Management Review, 2020). As such, high resolution data on the spatial distribution of waste generated from multi-unit dwellings can help inform waste management planning that specifically targets these dwelling types.

Figure 4-1 provides a high-level overview of the methodological approach. Each component of our approach is described in further detail in the following subsections.

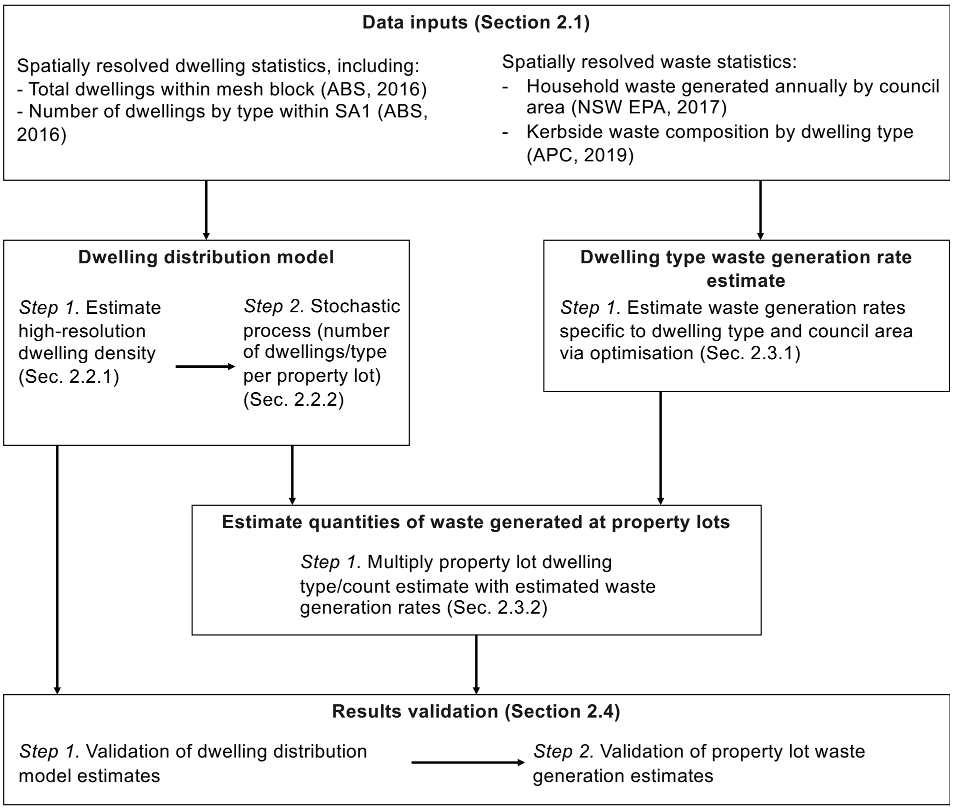


Figure 4-1: Overview of the methodological approach for this study

4.2.1. Study area and data

Figure 4-2 shows the study area located within the Australian state of New South Wales, and for context, quantities of total municipal household waste generated reported by local government areas (LGAs) in 2016 (NSW EPA, 2017). As we are interested in dwelling types, Figure 4-3 shows the distribution of dwelling types over the study area at the Statistical Area 1 resolution. This spatial scale is explained in detail further in this section.

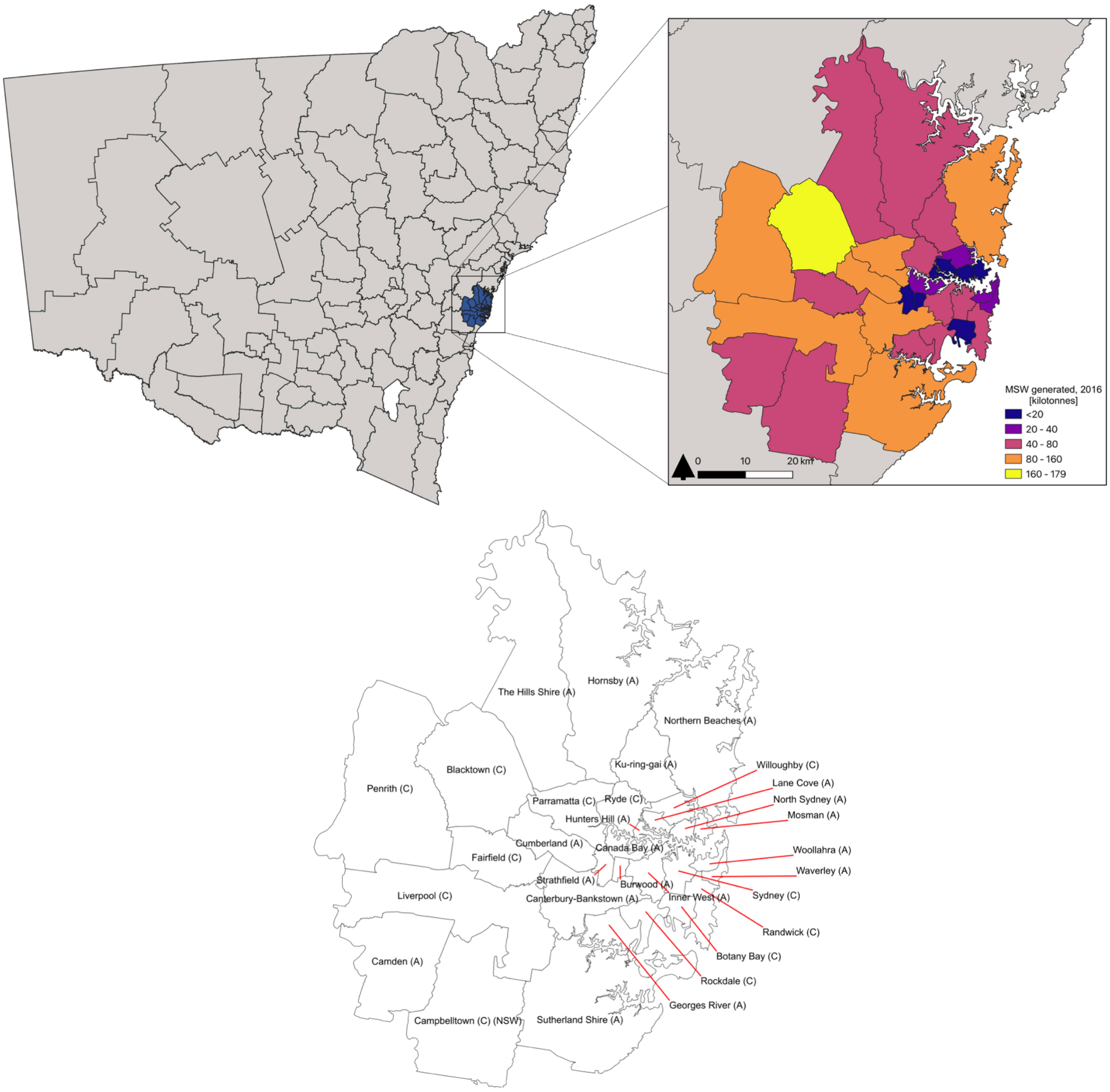


Figure 4-2: New South Wales and council boundaries. The Sydney Metropolitan Area study area is highlighted, and total municipal households waste generated in 2016 from NSW EPA (2017) is shown. LGA names are also included for context

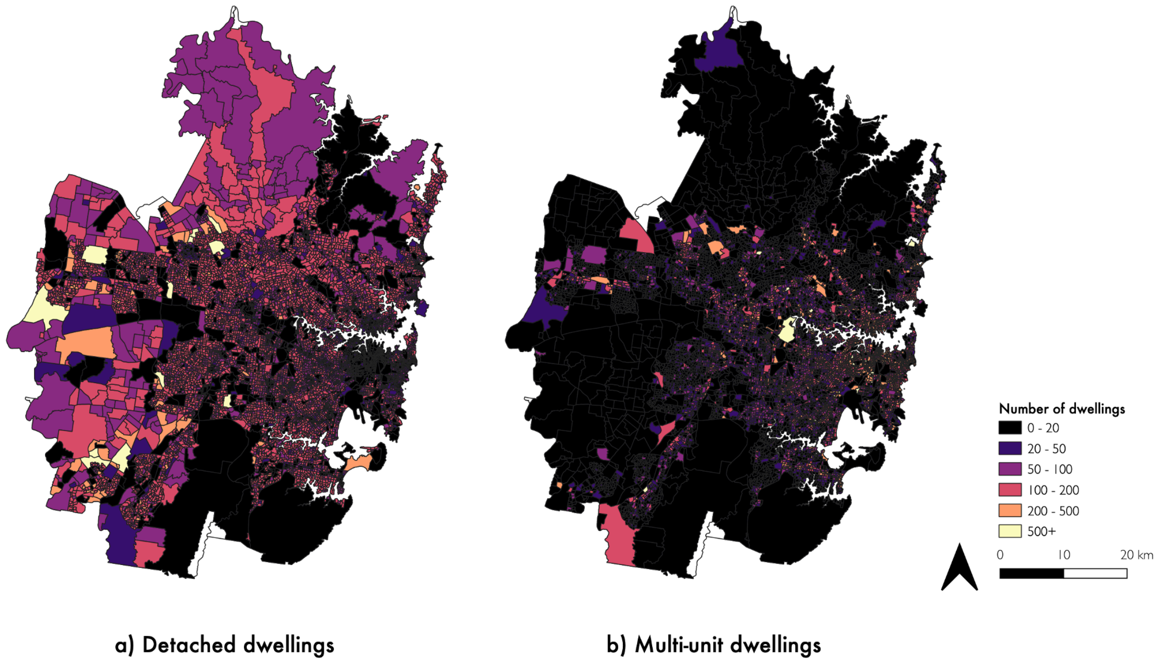


Figure 4-3: Distribution of dwelling types over the study area, at the Statistical Area 1 resolution (ABS, 2017)

For our study, we are interested in the annual quantity of municipal waste generated at the household level for three key waste streams that are collected by LGAs in the SMA, namely the residual (or non-recyclable) fraction, dry recyclables, and garden organics. The composition of these waste streams are summarised in Table 4-1. Annual quantities of household waste generated was the variable of interest for this study. Quantities of household waste collected is often used as a proxy for waste generated, given that littering, at home composting, hoarding etc. are not typically measured. Annual waste generation was also chosen, as statistics are typically reported at this interval locally (e.g., NSW EPA (2017), DoEE (2018)). As a result of this, seasonal variations affecting waste generation behaviours are not directly considered. Other methods of waste collection, namely bulk collection at the kerbside and household drop-offs of waste directly at landfill and transfer stations were not considered for this analysis. This was due to a lack of data on the composition of these collections, and dwelling type profiles for these collection streams.

Table 4-1: Composition of the residual, dry recyclable, and garden waste fractions of the municipal waste stream in the Sydney Metropolitan Area (NSW EPA, 2014a)

Material group	**Residual waste**	**Dry recyclables**	**Garden waste**	**Total waste**
Paper and paper products	20%	55%	<1%	21%
Organics	54%	2%	99%	58%
Glass	4%	30%	<1%	9%
Plastics	11%	8%	<1%	6%
Ferrous metal	2%	2%	<1%	1%
Non-ferrous metal	1%	1%	<1%	<1%
Other	10%	2%	<1%	5%

Table 4-2 lists the data used for this study. Waste data on the aforementioned waste streams were derived from LGA reported waste generation data for 2016, which includes total municipal household waste collected (NSW EPA, 2017). This data is available over the 2005 to 2018 period, and the 2016 year was chosen to align with census data. Census data at a number of spatial scales were utilised, which are illustrated in Figure 4-4. The mesh block scale is the finest spatial resolution for census data available in Australia. At this scale, data describing the total number of occupied dwellings and total residential population is available, however no further information on household characteristics including type is available. Land use characteristics are described at the mesh block level, however only by majority land use within the mesh block. Mesh blocks categories as commercial for example then, still are likely to have occupied residential dwellings in the form of mixed-use zoning. We therefore only consider mesh blocks that contain occupied residential dwellings, as of the 2016 census night. SA1s are built from whole mesh blocks boundaries in the national census data, with target populations of between 200 and 800 persons in urban locals (ABS, 2017). At the SA1 scale, the total number of dwellings by type is available, and is the highest level of spatial resolution available for this level of detail on dwelling types. Property lot boundaries are taken from the NSW Digital Cadastral Database (DFSI, 2012). This spatial data does not include characteristics of the property lot, including land use, number of dwellings etc, primarily due to privacy reasons. This spatial scale is the target spatial scale in our study for disaggregation of the area-level (i.e., SA1) dwelling type distribution data.

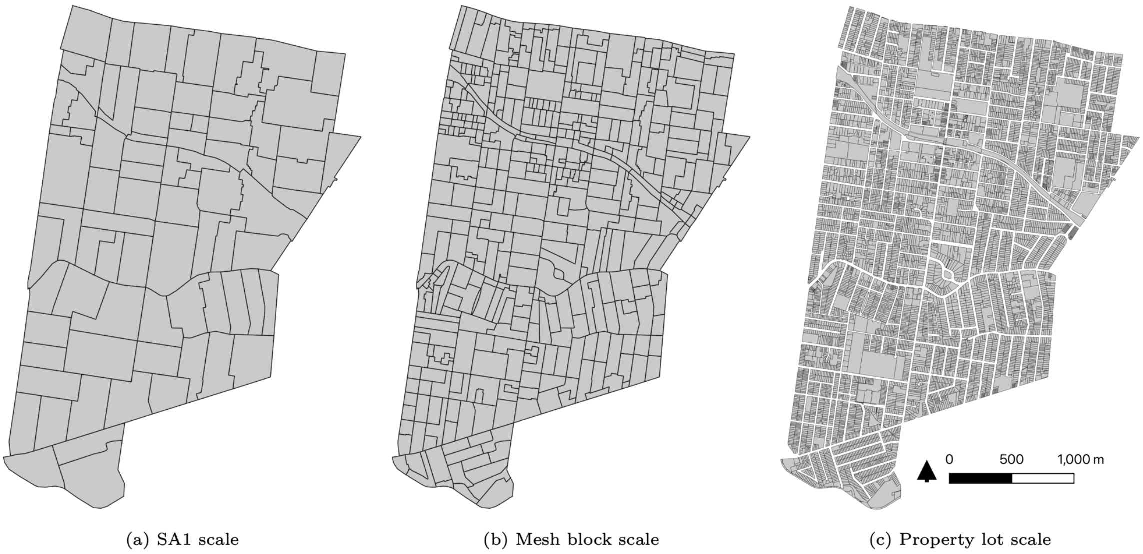


Figure 4-4: Different geographical scales of analysis, example Burwood local government area in New South Wales

Table 4-2: Summary of data sources utilised in this work

Data	Spatial scale	Remarks
2016 census data (ABS, 2016b)	SA1 (frame (a) in Figure 4-4)	Total number of dwellings by type in the SA1, used in model calibration
	Mesh blocks (frame (b) in Figure 4-4)	Total number of dwellings, used in model calibration
Cadastral data (DFSI, 2012)	Property lot (frame (c) in Figure 4-4)	Property lot boundaries, used for calibration of model and visualisation
Australian statistical geography standard boundaries (ABS, 2017)	LGA, SA1, mesh block	Spatial boundaries for LGA, SA1 and mesh block scales. Used for calibration and visualisation
Local council waste and resource recovery data (NSW EPA, 2017)	LGA	Annual waste generated by households, by waste fraction for the year 2016. Used for model calibration
Kerbside waste audit data (APC, 2019)	N/A (avg. per-household rates)	Weekly per-household waste generation rates, by dwelling type, from sample of kerbside audit data. Used for model calibration

A more detailed description of the approach outlined in Figure 4-1, including model validation, is provided in the following sections.

4.2.2. Dwelling distribution model

We developed a probabilistic model to estimate the number of occupied detached and multi-unit dwellings for property lots in our study area. We perform this model for property lots within each SA1, as this is the finest resolution of census data describing the breakdown of dwelling types. We model the number and distribution of dwelling types for a set of property lots within an SA1 as a discrete stochastic process--a family of discrete random variables, indexed over a countable set (Parzen, 2015). In our application, the index set is the set of property lots located within an SA1. Stochastic models can be advantageous, especially for our application where precise approximations of real data are required, despite limited data availability (Fortin et al., 2003; Fuqua & Doty, 2012). With no spatial covariates describing the determinants of dwelling type location at our resolution, we base our model on the observation that SA1s in the study area with higher dwelling densities (number of dwellings per km^2) have a greater number of multi-unit dwellings (Figure 4-5). This is expected given that multi-unit buildings feature a greater number of dwellings per floor area than detached dwellings, and is also consistent with local and state government urban planning strategies, preferencing high-density dwelling types in urban areas and around transportation corridors (Bunker, 2014; Roberts et al., 2019).

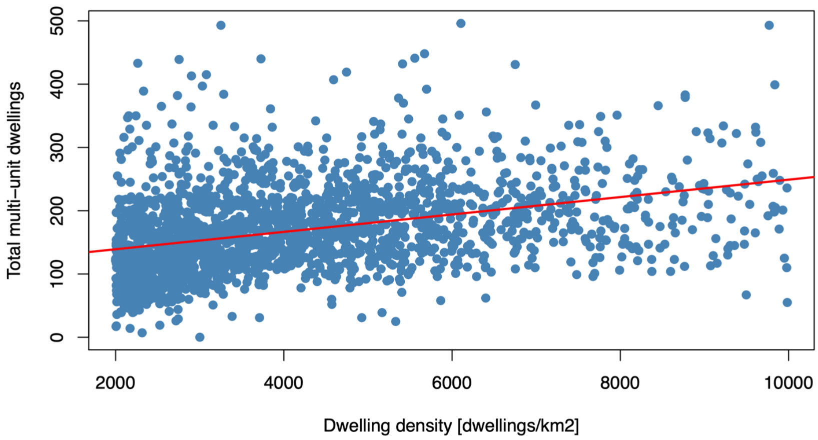


Figure 4-5: Relationship between dwelling density (number of dwellings/ km^2) and number of multi-unit dwellings in an SA1, n = 9,868. The red regression line represents a Pearson's r *correlation of 0.37*

In our approach, numbers of detached and multi-unit dwellings in an SA1 are modelled separately as the stochastic process $X_T = \{X_T(l) \ : \ l = 1, \cdots, n\}$; where T is the dwelling type, n is the number of property lots in an SA1, and $X_T(l)$ is a random variable describing the number of dwellings in the property lot l. The random variable $X_T(l)$ is drawn from a probability distribution, which is calibrated on the underlying estimated dwelling density of property lots in the SA1. The following subsections describe the elements of the dwelling distribution model in further detail.

4.2.2.1. Dwelling density surface

While data on dwelling density is available at the mesh block level, we require estimation of this data at the higher resolution property lot level to calibrate the stochastic process X_T. Considering the spatial hierarchy in Figure 4-4, data at the mesh block level can give a coarse indication of the within-SA1 variation in dwelling density. However, the within-mesh block variation in dwelling density is unknown. Without the within-mesh block variation characterised, in our approach property lots within a mesh block would have uniform probability of a particular number and type of dwelling. To estimate dwelling density at the property lot, we generated an interpolated surface of dwelling density values from the mesh block data over the SA1 of interest. This interpolated surface gives a smooth, non-uniform dwelling density estimate over the SA1, with mean dwelling density at areas along the boundary of mesh blocks influenced by dwelling density from adjacent mesh blocks. From this surface, mean dwelling density estimation for each property lot can be achieved through aggregation.

We generated a continuous 2-dimensional dwelling density surface confined to the boundary of the SA1 polygon to calibrate our dwelling density model. This was performed for each SA1 across the study area. We performed a spatial interpolation of calculated mesh block dwelling density using inverse distance weighted (IDW) interpolation. IDW is a deterministic and computationally efficient technique for generating an interpolated surface, which is especially advantageous in our study given the number of SA1s located within the study area (9,868 SA1s over an approximately 3,600km^2 area). Selection of interpolation approach can be subjective, with no one method necessarily superior than others for a given application (Wu & Hung, 2016). Other interpolation techniques including kriging and spline interpolation were considered for this work. IDW was ultimately chosen as the interpolation approach, as a lack of spatial covariate data at the mesh block scale and below excluded the use of kriging, and spline interpolation has been found to have greater computational demands with little if any improvement in performance over IDW (Kravchenko, 2003; Lu & Wong, 2008; Mueller et al., 2001).

The IDW interpolation approach estimates values at unknown points x on the Cartesian surface S, in our application, a grid of points at 1m^2 resolution, based on known values at N sample interpolation points (Shepard, 1968) (Equations 4.1 and 4.2). The 1m^2 resolution was chosen as property lots within each SA1 are of varying shape, including complex shapes such as 'battle-axe' blocks and others, and are generally at angles other than 90° from the centreline axes of the SA1. High resolution (i.e. 1m^2) ensures that the estimated dwelling density surface can be aggregated to these complex property lot shapes and arrangements. Moreover, modern computing power ensures that IDW with high resolution can be performed efficiently. Preliminary testing with lower resolutions (e.g., 10m^2 and 100m^2), using an Intel machine with 10-core 3.6 GHz processor and 32 GB of RAM, showed little difference in computation time and outputs compared to 1m^2. Further evaluation of choice of resolution was not performed for this study, but could be an avenue of further research.

For our model, sample observation points are the centroids (geometric centre) of the mesh blocks located within the SA1. Some mesh blocks within the study area are irregularly shaped, which can cause estimated centroid locations to fall outside mesh block bounds. In these cases, mesh block centroids are approximated using the *PointOnSurface* method from the *rgeos* library (Bivand & Rundel, 2020) in the *R* statistical computing language.

$$\mathcal{D}(x) = \begin{cases} \dfrac{\sum_{n=1}^{N} w_n(x)\mathcal{D}(m_n^*)}{\sum_{n=1}^{N} w_n(x)} & \text{if } d(x, m_n^*) \neq 0 \\ \mathcal{D}(m_n^*) & \text{if } d(x, m_n^*) = 0 \end{cases} \tag{4.1}$$

$$w_n(x) = \frac{1}{d(x, m_n^*)^\gamma} \tag{4.2}$$

Where $\mathcal{D}(x)$ is the estimated dwelling density at point $x \in S$, $d(x, m_n^*)$ is the Euclidean distance between points x and mesh block centroids m_n^*, and γ is the power parameter where higher values of γ give greater influence to points closer to sample observation points. $\mathcal{D}(m^*)$ is the estimated dwelling density at mesh block centroid m^* (Equation 4.3):

$$\mathcal{D}(m^*) = \frac{N_D(m)}{A(m)} \tag{4.3}$$

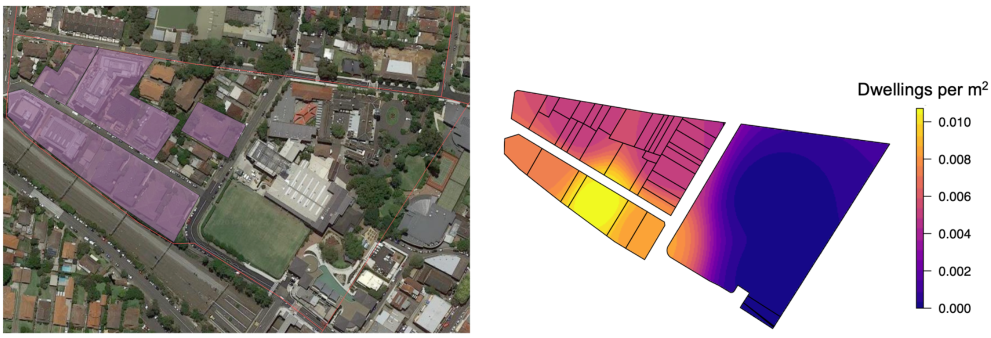
Where $N_D(m)$ is the known number of dwellings in mesh block m from (ABS, 2016b, 2017), and $A(m)$ is the area of mesh block m in m^2.

For the surface S, we seek a smooth surface of interpolated dwelling density values across the SA1. In Equation 3.2, we set $\gamma = 2$, which results in a smooth interpolated surface. As values of γ increase, the resulting IDW interpolation becomes tessellated, with interpolated values approaching that of nearest neighbour interpolation (Bivand et al., 2013). This type of interpolation would result in uniform values where the surface S overlaps with the mesh block, resulting in uniform property lot dwelling densities within, which would be insufficient for our application as previously described.

We finally estimate the mean dwelling density per property lot from S. Let S^* be the set of points in S that lie within the intersection of property lot l and the surface S (i.e., $S^* = \{x : x \in l \cap S\}$). We calculate mean dwelling density as follows (Equation 4.4):

$$\mathcal{D}(l) = \frac{\sum_{x \in S^*} \mathcal{D}(x)}{|S^*|} \tag{4.4}$$

Figure 4-6 illustrates the described methodology for estimating the dwelling density surface, and aggregated mean dwelling density per property lot for an example SA1 located in the Burwood LGA. The estimated dwelling surface is compared with an aerial image of the SA1, with multi-unit and detached dwellings confirmed visually from Google Streetview imagery (Google, n.d.) and highlighted.



(a) Aerial image (b) Example dwelling density surface estimate

Figure 4-6: Estimated dwelling density surface for an example SA1, located in the Burwood LGA in the SMA

4.2.2.2. Estimating dwelling counts for detached dwelling type

We estimated the number of detached dwellings for a property lot l in an SA1 as a random variable drawn from a Bernoulli distribution: $X_{det}(l) \sim \text{Ber}(p)$, where p is the mean probability that $X_{det}(l) = 1$. The Bernoulli distribution is a discrete probability distribution of a random variable taking a value of 0 or 1, with a value of 1 indicating in our application that a property lot contains a detached dwelling. This distribution was chosen, as our application meets the Bernoulli distribution's criteria, in that there are only two possible outcomes; each draw from the distribution is independent of other draws, and that outcomes have a fixed probability p of occurring. Values for p can be determined such that the sum of expected values for $X_{det}(l)$ over all property lots in an SA1 equals the known number of detached dwellings in the SA1.

We determine the value of p indirectly for each property lot from $\mathcal{D}(l)$ in Equation 4.4. Based on the distribution of estimated mean dwelling density for property lots, we determine a threshold range $\tau = [\tau_{min}, \tau_{max}]$ that characterises the likely range of dwelling densities where detached dwellings are most likely. Let L^a be the set of property lots in L that have mean density values within τ (e.g., $L^a = \{l : \mathcal{D}(l) \in \tau\}$). For this paper, we determine τ as the interquartile range of $\mathcal{D}(l)$ values in L^a, assuming that property lots more on the tails of the distribution of average dwelling density values would either contain no residential properties, or multi-unit dwellings. We then determine p as follows (Equation 4.5):

$$p = \frac{N_{det}(\mathcal{S})}{|L^a|} \tag{4.5}$$

Where $N_{det}(\mathcal{S})$ is the known number of detached dwellings in the SA1 $\mathcal{S}$.

We assumed that property lots with average dwelling density outside of τ to have either no residential properties, or have multi-unit dwellings. Therefore, the number of detached dwellings in a property lot l \$l\$ in an SA1 is then (Equation 4.6):

$$X_{det}(l) = \begin{cases} \sim \mathrm{Ber}(p) & \text{if } l \in L^a \\ 0 & \text{if } l \notin L^a \end{cases} \tag{4.6}$$

To implement the above, we use the *R* statistical computing language, using the base 'stat' package and spatial methods within the 'sp' (Bivand et al., 2013) and 'raster' (Hijmans, 2020) packages. We estimate $X_{det}(l)$ using the *rbinom* function in *R* which simulates a Binomial point process of the form $\mathbf{X} \sim \mathrm{Binom}(n, k, p)$ (when $k = 1$, the Binomial distribution is equivalent to the Bernoulli), where each $X \in \mathbf{X}$ are Bernoulli random variables. We set n as the number of property lots in L^a, with values for k and p described in the preceding paragraphs. As described in Equation 4.6, lots not within L^a are given values of 0.

As a final step, we take the sum of estimated detached dwellings across an SA1 as $\widehat{N}_{det}(\mathcal{S}) = \sum_l X_{det}(l)$, and repeat the described process iteratively until $\widehat{N}_{det}(\mathcal{S})$ equals the known number in the SA1 ($N_{det}(\mathcal{S})$), or until an exit condition is reached, in which case the realisation with $\widehat{N}_{det}(\mathcal{S})$ closest to $N_{det}(\mathcal{S})$ is chosen. The pseudo-code in Algorithm 1 found in Appendix B.1 describes this fitting process.

4.2.2.3. Estimating dwelling counts for multi-unit dwelling type

We estimated the number of multi-unit dwellings per property lot for an SA1 as a random variable from the Poisson distribution $X_{mul}(l) \sim \text{Pois}(\lambda(l))$, where $\lambda(l)$ is a non-uniform intensity function (hence a non-homogenous process), giving the average number of dwellings per lot l. The Poisson distribution is a discrete probability distribution, that models the number of occurrences as a discrete random variable taking values $\{0,1,2,\dots\}$ over some fixed interval (Haight, 1967). In our application, occurrences are the number of multi-unit dwellings located at a property lot. This distribution was chosen given that for multi-unit dwellings, there are >1 dwellings located at the property lot. In our application, the distribution is truncated at values less than 2. The truncated Poisson distribution is useful in situations where the Poisson distribution is a good model for the data, but the range of possible values is restricted due to some external factor (in our application, this is that multi-unit dwellings have at least 2 dwellings located at the property lot).

We focus on the set of property lots L^b that have mean dwelling density greater than τ_{max}, as these property lots are more likely to contain multi-unit dwellings. Note that L^a and L^b are disjoint sets, and $L^a \cap L^b = \emptyset$.

We estimate $\lambda(l)$ such that the expected (or mean) number of occurrences of multi-unit dwellings in L^b (i.e., $\mathbb{E}[N_{mul}(L^b)]$) equals the known number of multi-unit dwellings in an SA1 (Equation 4.7):

$$\lambda(l) = \mathcal{D}(l) \times \frac{N_{mul}(\mathcal{S})}{\sum_{l \in L^b} \mathcal{D}(L)} \qquad 4.7$$

Where $N_{mul}(\mathcal{S})$ is the number of multi-unit dwellings in an SA1 $\mathcal{S}$.

Similarly with detached dwellings, we let the number of dwellings in property lots not in L^b equal 0. The number of multi-unit dwellings for property lots in an SA1 is then given by (Equation 4.8):

$$X_{mul}(l) = \begin{cases} \sim \text{Pois}\big(\lambda(l)\big) & \text{if } l \in L^b \\ 0 & \text{if } \notin L^b \end{cases} \qquad 4.8$$

$X_{mul}(l)$ is estimated using the *rpois* function in R which can simulate a Poisson point process of length n, equal to the number of property lots within L^b. Estimates for $X_{mul}(l)$ go through a similar fitting procedure as detached dwelling estimates. This procedure is described in pseudo-code in Algorithm 2 found in B.2.

4.2.3. Estimating quantities of waste generated at the property lot

We estimated the annual quantities of household waste generated at property lots, by multiplying the dwelling count estimate $X_T(l)$ by an average rate of waste generation specific to dwelling type. Data on per-dwelling generation rates for each LGA in our study area can be calculated from the council-reported waste data described in Table 4-2. While this rate captures the between-LGA differences in rates of waste generation, it does not account for the differences in waste generation rates between detached and multi-unit dwellings, as reported in APC (2019), and presented in Table 4-3. Data in APC (2019) includes observed per-dwelling rates of waste generation for each waste fraction and dwelling type of interest for a sample of 13 non-identified LGAs in Southern Sydney. While this data includes direct measurements of waste generation rates, audits were conducted over a small window of time (approximately 3 months) therefore reported rates of waste generation may be influenced by unknown time-of-year effects, and the sample of households surveyed was small.

Table 4-3: Summary of surveyed per-dwelling generation rates by waste fraction and dwelling type from APC (2019)

Dwelling type	Residual fraction	Dry recyclables	Garden organics
Detached dwellings [kg/hh/wk]	10.6±4	4.6±1	4.1±3
Multi-unit dwellings [kg/hh/wk]	6.3±3	2.5±2	0.7±0.6
Detached:multi-unit ratio (*R*)	1.6	1.8	6.8

4.2.3.1. Estimating dwelling-type specific annual rates of waste generation

We used the ratio between the reported average detached and multi-unit dwelling generation rates from APC (2019), to calibrate adjusted per-dwelling generation rates by dwelling type from the overall council-reported annual waste generation data (NSW EPA, 2017). We did this for each council, such that variations in waste generation behaviours between councils as a result of varied socioeconomic, and other waste drivers, are implicitly accounted for. Impacts of within-LGA variation in socioeconomics on waste generation was not accounted for in our model. This was due to lack of waste generation data at scales finer than the LGA level. Improving the results of our model to account for variation in waste generation behaviours within LGAs could be achieved via sophisticated small-area estimation methods, however is beyond the scope of research.

We first define for each LGA an overall per-dwelling generation rate estimate for waste fraction f. This simple estimate is calculated over all dwellings, and does not take into account dwelling types (Equation 4.9):

$$P_f = \frac{Q_f}{N} \tag{4.9}$$

Where P_f is the simple per-dwelling waste generation rate, Q is the known quantity of waste generated from the LGA for waste fraction f in 2016 from the data (NSW EPA, 2017), and N is the total number of dwellings in the LGA, from 2016 census data (ABS, 2016b). Given the differences in detached and multi-unit generation in APC (2019), total waste generation in an LGA can be calculated by summing detached dwelling waste, and multi-unit dwelling waste generated annually (Equation 4.10):

$$\hat{Q}_f = \sum_T \left(P_{f,T} \times N_T\right) \tag{4.10}$$

Where $\hat{Q}_f$ is the estimated waste generated, and N_T are the number of dwellings of type T in the LGA. As $P_{f,T}$ is not known and must be estimated, we introduce a parameter β_T to Equation 4.10 such that $P_{f,T}$ can be found based on the overall dwelling generation rate estimate P_f estimate (Equation 4.11):

$$\hat{Q}_f = \sum_T \left(\beta_T P_f \times N_T\right) = \left(\beta_{det} P_f \times N_{det}\right) + \left(\beta_{mul} P_f \times N_{mul}\right) \tag{4.11}$$

Values for β_T in Equation 4.11 can be found via optimisation. We applied a non-linear constrained least squares approach (Schittkowski, 1988), by fitting β_T parameters that minimise the squared error between the simple per-dwelling rate P_f (Eq.: 4.9), and the recalculated simple per-dwelling rate $\hat{P}_f$. $\hat{P}_f$ is calculated based on the estimated value $\hat{Q}_f$ in Equation 4.10 with estimated β_T parameters: $\hat{P}_f = \hat{Q}_f / N$, where N is total number of dwellings in the LGA. We set the constraints, such that the ratio R of the estimated dwelling type generation rates are equal to that in APC (2019), and that β_T take only positive values greater than or equal to 0. We solved the optimisation problem (Equation 4.12) using the generalised reduced gradient method--a popular method to solve general nonlinear optimisation problems (Lasdon et al., 1978; Maia et al., 2017), implemented using the *Solver* tool in the Microsoft Excel software:

$$\min_{\beta_T} \left(P_f - f(\beta_T)\right)^2$$

$$\text{where } f(\beta_T) = \hat{P}_f = \sum_T \frac{\beta_T \left(P_f \times N_T\right)}{N}$$

$$\text{subject to } \frac{\beta_{det}}{\beta_{mul}} = R;\ \beta_T \geq 0 \tag{4.12}$$

Equation 4.12 was solved heuristically, with initial values for β_{det} and β_{mul} chosen as $\sqrt{R}$ and $1/\sqrt{R}$ respectively, such that the ratio of the estimated dwelling type generation rates equals R in the initial solution. Estimated per-dwelling generation rates estimated for each council from our method can be found in B.3.

4.2.3.2. Estimating quantities of waste generated at the property lot

With values for $\hat{P}_{f,T}$ determined from $\beta_T P_f$, we estimate the total annual household waste generated at a property lot for waste fraction f in LGA c (Equation 4.13):

$$\hat{Q}_{f,c}(l) = \sum_T \left[\hat{P}_{c,f,T} \times X_T(l)\right] \tag{4.13}$$

We performed sensitivity analysis on selection of initial values, by varying values of R. From data in APC (2019), we could determine the likely range of the ratio R, based on the sample of 13 LGAs. We estimated a minimum and a maximum value for R from the 95% confidence range in APC (2019). We then calculated a range of values for $\hat{Q}_{f,c}(l)$ in Equation 4.13, based on $[R_{min}, R_{max}]$. Model validation is further described in the following section.

4.2.4. Model validation

The method for this study was developed owing to a paucity of high spatial resolution data, and model validation is an inherent challenge. Kontokosta et al. (2018) approach this challenge by comparing their building level estimates of waste generation with available data aggregated to lower spatial resolutions where data is more available (in that instance, New York City sanitation sub-sections). Goerndt et al. (2019) take a similar approach in their study estimating biomass availability, and so to do Cockx and Canters (2015) in their paper on improved dasymetric population mapping. The approach of comparing aggregated estimates against source data, or data available at other aggregation levels, is typical for quantitatively comparing spatial disaggregation procedures (European Commission, 2019; Li et al., 2007; Monteiro et al., 2019).

Considering the absence of reliable validation data at the property lot level, we verified our model by comparing results aggregated to lower spatial resolutions where actual data is available. This is done under the assumption that accurate estimations of waste generation at aggregated spatial units would be associated with reliable estimations at the property lot level.

To verify the dwelling distribution estimates, we first conducted a Monte-Carlo simulation by performing 1,000 iterations of the model as described in the previous sections. Considering estimated dwellings per lot is a random variable, the Monte-Carlo simulation generates a probability distribution of estimated dwelling counts per lot, characterising the sensitivity of dwelling counts to randomness in our model. We aggregate these results to the SA1 level, to compare actual versus estimated dwelling counts by type. We also estimate the mean absolute percentage error (MAPE) of SA1 aggregated dwelling estimates, to give an indication of the variation in accuracy across SA1s in the study area. We also present dwelling count estimates as a range at the 95% confidence level, to compare the actual data with the range of possible estimates from our model.

To validate the estimates of waste generated for each property lot, we also aggregate our property lot estimates to the LGA scale, and compare with the LGA reported waste data (NSW EPA, 2017). We first test for sensitivity on the estimation of the dwelling-type waste generation rates, by estimating minimum and maximum (at the 95% confidence interval) estimates for $\hat{P}_{f,c,T}$. Further, we combine the minimum and maximum estimates of $\hat{P}_{f,c,T}$ with the distribution of X_T(l) estimates generated from the Monte-Carlo simulation, to derived a 95% confidence range of $\hat{Q}_{f,c}(l)$ estimates, which are aggregated to the LGA level and compared to actual data. Similar to the dwelling estimates, we calculate MAPE values to characterise the model accuracy when estimates are aggregated to the LGA level.

4.3. Results and discussion

4.3.1. Estimation of dwelling counts at the property lot

Figure 4-7 shows the distribution of errors when comparing mean dwelling counts with actual data at the SA1 level. This data is also summarised in Table 4-4. Errors in the dwelling counts at the SA1 level occur where the fitting procedures described (Appendices B.1 and B.2) fail to converge on the optimal solution (that is, estimated SA1 dwelling count is equal to actual data). Causes for this are generally due to inconsistencies in the data, for example where the number of property lots within an SA1 is less than the number of occupied dwellings. Approximately 98% of all SA1s had prediction errors of 10% or less compared to actual detached dwelling count data. For multi-unit dwelling estimates, 92% of SA1s had prediction errors of 10% or less, indicating that model accuracy is good, and acceptable for the aims of this study.

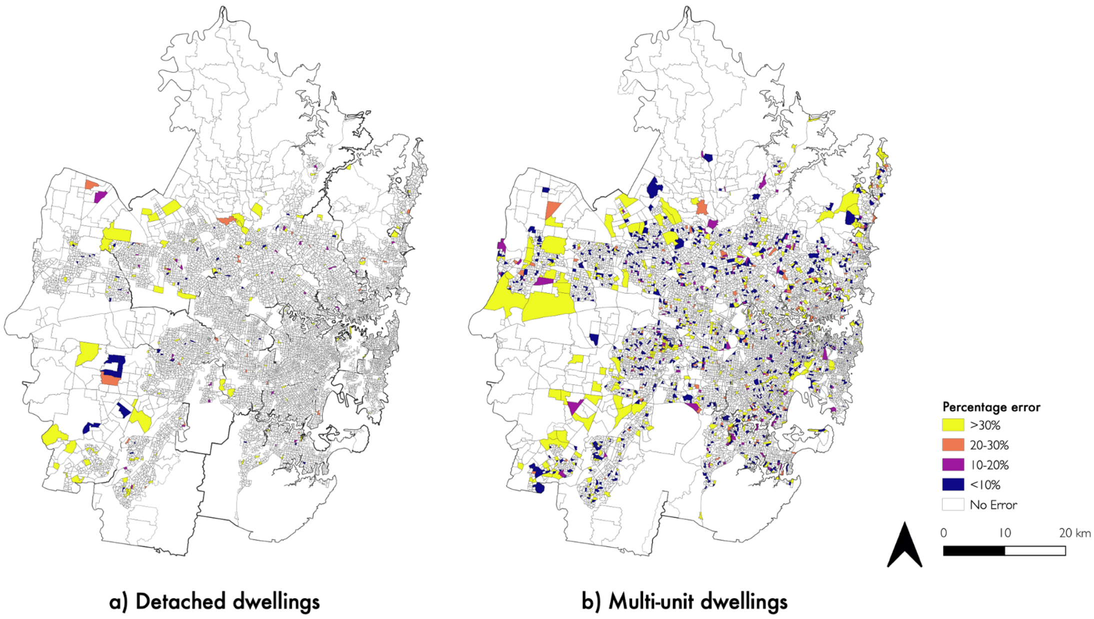


Figure 4-7: Spatial distribution of estimated dwelling count errors by dwelling type at the SA1 scale, from the dwelling distribution model

Table 4-4: Summary dwelling distribution estimation errors at the SA1 scale

	No error	<10%	10-20%	20-30%	30%+
Detached dwellings	97.70%	0.46%	0.30%	0.23%	1.31%
Multi-unit dwellings	84.51%	7.10%	1.25%	1.04%	6.10%

It was expected that the error for multi-unit dwellings would be greater than detached dwellings, due to the wider range of potential values for the random variable $X_{mul}(l)$. The Moran's I test for spatial autocorrelation (Bivand et al., 2013) was performed on the absolute percentage error values for each dwelling type, revealing that errors are randomly distributed, indicating there is no significant systematic spatial bias in model errors (Table 4-5).

Table 4-5: Summary of Moran's I *analysis of clustering of SA1 absolute percentage values. Values of* I *approaching 1 indicate clustering of observations, and values approaching -1 indicate perfect dispersion. Values around 0 indicate random dispersion*

	I-statistic	*p*-value	Interpretation
Detached dwellings	0.0045	0.002	Random dispersion
Multi-unit dwellings	0.1148	0.002	Random dispersion

Table 4-6 shows the total number of estimated dwellings in the study area using our model, compared with actual dwelling counts by type from the 2016 census (ABS, 2016b). The estimated mean dwelling counts and range in Table 4-6 are derived from the Monte Carlo analysis as described in Section 4.2.4. Errors are calculated by comparing mean dwelling count estimates with the actual data. The accuracy of the dwelling distribution model is good, with detached dwellings having a mean absolute percentage error (MAPE) value of 1.3%, and multi-unit dwellings a value of 5.2% when aggregated to the SA1 level. The error on multi-unit dwellings being greater compared to detached dwellings is expected, given the additional modelling complexity for estimating multi-unit dwellings. However, there is a consistent under-estimation of dwellings for both dwelling type estimations. This can be attributed to cases where the fitting procedure described in Section 4.2.2 did not converge on an estimated dwelling count equal to actual data at the SA1 level. Reasons for non-convergence included cases where the underlying data is inconsistent, for example where estimated dwelling density calculated from mesh block data is not consistent with the expected number of multi-unit dwellings from the SA1 level data.

Table 4-6: Summary dwelling distribution estimation results

	Detached dwellings	**Multi-unit dwellings**
Actual (ABS, 2017)	768,709	650,863
Estimated (mean value)	760,906	614,970
Estimated range	760,884 – 760,928	607,640 – 622,299
MAPE	1.32%	5.24%

To examine dwelling distribution model results at a greater level of spatial detail, Figure 4-8 shows dwelling count estimates for the sample local government area of Burwood. We selected this local government area due to its centralised location within the study area, and the fact that there is a mix of low-, medium- and high-density residential, and commercial land-use types. LGA-wide results presented on the left-hand side of Figure 4-8 are direct estimations of $\widehat{N}_D(l)$ from the first iteration of the model performed. Three test SA1s were selected at random within the council area boundaries to compare estimates with aerial imagery from Google Maps (Google, n.d.). Areas with multi-unit developments were confirmed from Google Streetview and highlighted for comparison with model estimates.

The task of manually validating estimates for SA1s is labour intensive, so a small number of test SA1s were selected for illustration purposes, however summary results in Figure 4-7 and Table 4-4indicate that results are generally consistent across the study area. Estimates of dwelling count standard deviation on the right side of Figure 4-8 are presented as heat maps derived from the 1,000 iterations of the model performed, with lighter colours indicating greater deviation from the mean. High standard deviation values indicate which property lots within each SA1 are more likely to contain multi-unit dwellings from our model. Property lots with high standard deviation align well with identified multi-unit dwellings from the aerial imagery. Notable exceptions can be seen in test SA1 3. Differences between the aerial imagery and our estimates for this test SA1 can be explained by differences in the time when the aerial imagery which was captured (2019) compared to census data collection (2016). This was confirmed for test case 3 where it was observed that the actual number of multi-unit dwellings within the SA1 does not align with the number of multi-unit dwellings counted from Google Maps and Streetview, likely owing to additional dwellings being constructed between 2016 and 2019.

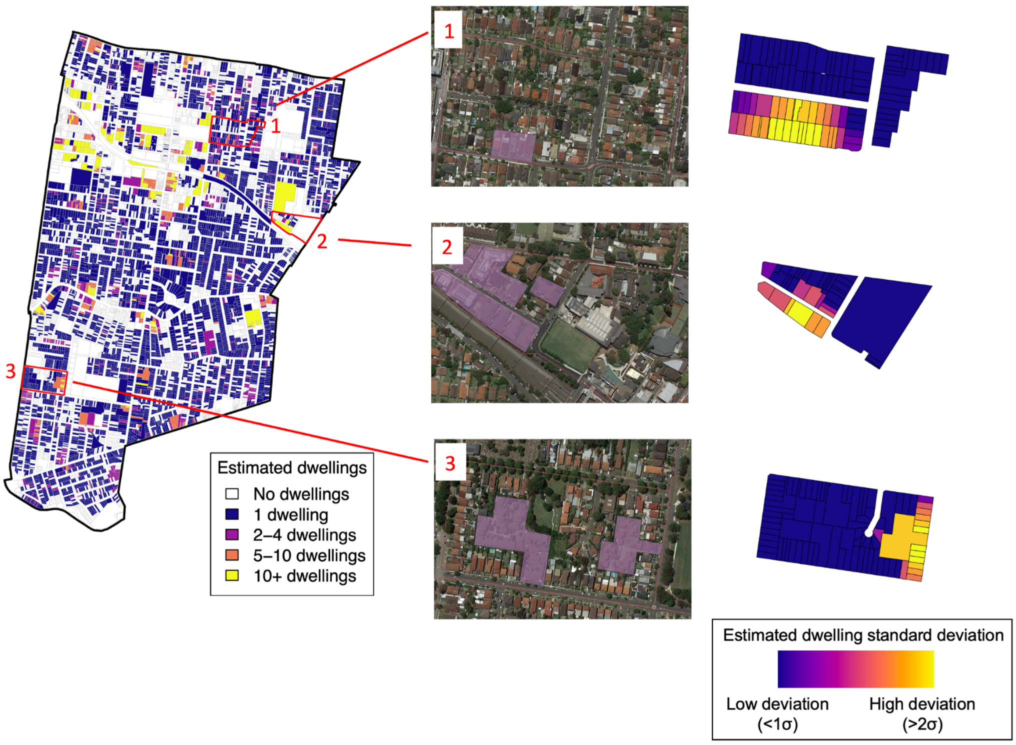


Figure 4-8: Illustration of property lot-scale results for the example local government area of Burwood. Aerial images correspond to the three sample SA1s in Burwood, with actual multi-unit dwellings highlighted. Estimates of standard deviation on property lot dwelling estimates are shown on the right, with light colours indicating higher standard deviation values

4.3.2. Estimation of waste generation at the property lot

Property lot waste generation is calculated by multiplying the estimated number of dwellings by type, by the estimated annual waste generation per-dwelling rates as per Equation 4.13. Table 4-7 shows a summary of estimated dwelling-specific annual waste generation rate for each fraction across all 31 LGAs, following the optimisation procedure described in Section 4.2.3. Full estimated per-dwelling generation rates for each LGA in the study area are located in Appendix B.3.

Table 4-7: Estimated annual per-dwelling waste generation rates by dwelling type for each waste fraction

Dwelling type	Residual fraction	Dry recyclables	Garden waste
Detached dwellings [t/hh/yr]	0.929±0.2	0.371±0.1	0.394±0.02
Multi-unit dwellings [t/hh/yr]	0.551±0.1	0.202±0.04	0.05±0.1
Detached:multi-unit dwelling ratio (*R*)	1.6	1.8	6.8

Table 4-8 shows the total quantity of waste generated by fraction in the SMA compared to actual data (NSW EPA, 2017). SMA aggregated estimates closely align with actual data, with the actual reported waste generated totals falling within the range of estimates from our model (at the 95% confidence interval). Mean absolute percentage error is small, and is consistent across the three waste fractions. There is a consistent under-estimation of total waste generated across all LGAs in the SMA from our model. This error can be traced back to errors in dwelling count estimates as shown in Table 4-6, where a consistent under-estimation was also identified. Improvements to the dwelling distribution model, namely calibration data, and more up-to-date spatial property lot boundary data may improve the estimates in Table 4-8.

Table 4-8: Summary of estimated waste generated compared to actual waste generation data

Dwelling type	Residual fraction	Dry recyclables	Garden waste
Actual [t/year]	1,108,845	388,040	324,738
Estimated (mean) [t/year]	1,077,900	377,679	319,721
Estimated range [t/year]	522,803 – 1,549,926	181,746 – 537,735	154,987 – 403,810
MAPE	2.98%	2.76%	2.00%

Property lot waste generation estimates for the SMA are shown in Figure 4-9. The majority of property lots in the SMA generated up to an estimated 2 tonnes of waste from all collected fractions in 2016. Areas with intense waste generation in Figure 4-9 are associated with property lots with high dwelling count numbers, such as those lots with high-density multi-unit dwelling types (i.e., apartments). These results can inform future waste management development and planning, for example: high resolution estimates as shown in Figure 4-9 can inform more efficient waste collection routing; quantities of waste at properties can also be combined with other property-level data such as wastewater to estimate and map total household organic flows (e.g., in Turner et al. (2017)); useful in the planning of precinct or district wide organic waste management pathways.

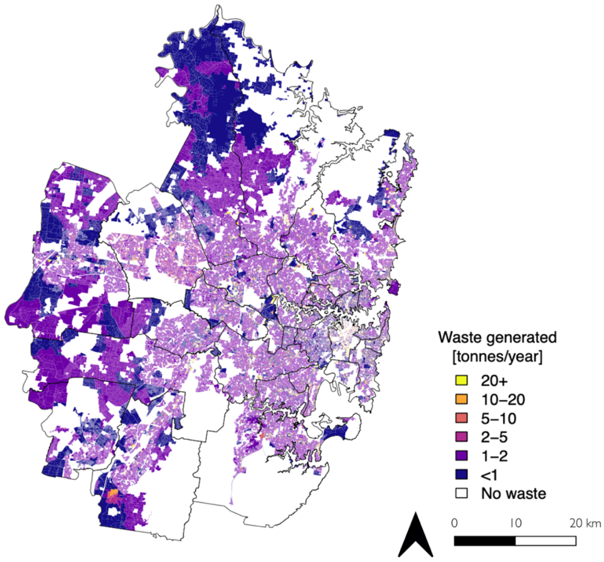


Figure 4-9: Estimated annual total waste generated at the property lot level for the Sydney Metropolitan Area

Data in Figure 4-9 is useful for identifying hot spots of waste generation. For identifying suitable areas for targeted waste interventions, or economically viable locations of recovery facilities, understanding the distribution and availability of supply over an area is important to determine the viability of a new facility (Comber et al., 2015; Lozano-García et al., 2020; Shi et al., 2008; Sliz-Szkliniarz & Vogt, 2012). This application of our results is illustrated in Figure 4-10, which shows the total garden waste available within an arbitrary 5km collection radius across the study area, without consideration for land use or existing waste management infrastructure (left panel). The transport distance was chosen to represent a small-scale, district-sized recovery process, such as a composting facility. A clear 'hot-spot' of resource availability can be identified in Figure 4-10, which is highlighted in green. This garden organics supply area is located within the northern Sydney Ku-ring-gai council area. Figure 4-10 also shows this supply area in greater detail (right panel).

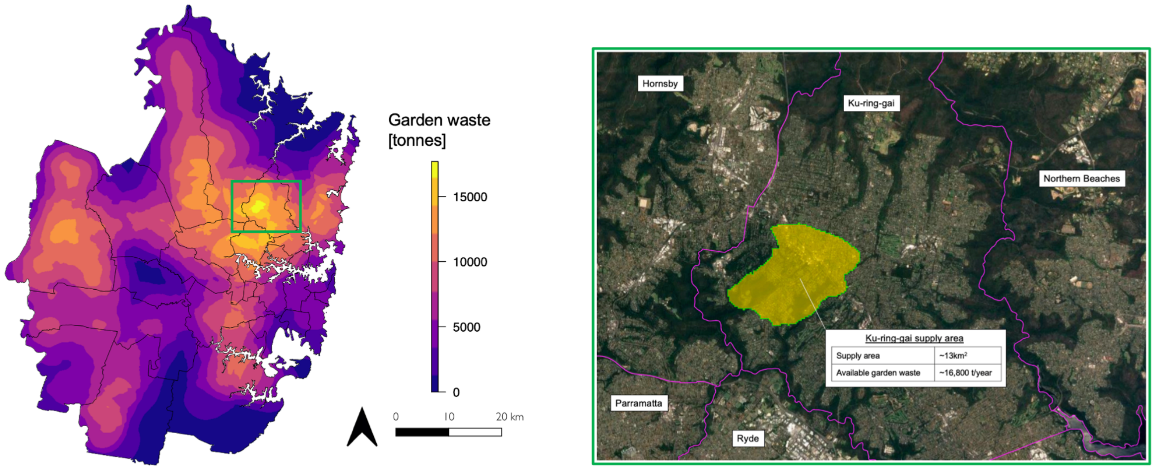


Figure 4-10: Availability of municipal garden waste within a 5km radius. An identified hot spot of garden waste is identified in the northern suburbs of Sydney (identified by green box), and detail of this identified hot spot is shown

Data in this figure can be used to identify areas with the greatest resource supply to inform decision making around optimal locations for facilities and realistic transportation distances. Locations in the northern areas of the SMA have the greatest available quantities of garden waste in general and are ideal locations for suitable organics recovery. This is expected, as suburbs in this area of the SMA are well vegetated, have large property lot sizes, and have a high proportion of detached dwellings. The identified garden organics supply area is located within the northern Sydney Ku-ring-gai council area. From this analysis, there is an approximate annual supply of garden waste of 16,800 tonnes of garden waste per year, within a supply area of approximately 13km^2. This feedstock availability would suit medium scale (approx. 20,000t/year throughput), municipal garden organics processing facility, potentially processing waste from adjacent council areas.

The data shown in Figure 4-10 is illustrative of potential further applications of the model presented in this paper, and a more robust study on the fine scale availability of the waste supply, and optimal locations for economically viable recovery processes is outside the scope of this work. The data in Figure 4-10 does serve as an example of the capabilities of high spatial resolution waste estimates for informing strategic waste policy and planning.

4.4. Conclusion

The aim of this research was to develop an approach to estimate high resolution waste generation data at the property lot level, that might be used to inform future waste management planning and infrastructure development. We developed a spatial model to disaggregate council level waste generation down to the property lot scale with a high degree of accuracy. The modelling approach requires modest data inputs, and enables a detailed appraisal of the distribution of household waste generation despite significant gaps in available data. The modelling framework developed in this work, and the resulting outputs, are useful for further studies that require high resolution waste generation data, including for example in waste collection planning, and optimal facility location identification. The data generated from the modelling presented is granular, and can be readily combined with other property-level data sets, for example household wastewater flows.

This study adds to the literature on spatial estimation methods for urban waste generation, and on data driven waste management policy. For the first time, the approach was applied to an important population centre in Australia and the approach could be applied to other jurisdictions. Data generated from our model is accurate, and model performance can be improved if more up-to-date validation data becomes available. Moreover, the approach presented may also have value in estimating commercial and industrial waste at a fine spatial scale, and is worthy of further research.

Chapter 5.

Waste collection and transportation emissions

With Chapter 3 confirming spatial variability in waste generation is significant, and Chapter 4 providing a methodology for estimating the spatial distribution of waste generation, attention can now be turned to estimating the emissions associated with waste management.

As first introduced in Chapter 1, waste related emissions are poorly characterised for NSW and Australia in general. Studies in the waste management literature tend to rely heavily on life cycle analysis and generic assumptions for estimating waste related emissions. This is especially true for waste collection and transport emissions, where assumptions, often derived from unrelated locales, are relied on due to a lack of data. Considering that large transport distances and sprawling suburbs characterise much of the populated areas of NSW, waste collection and transport may make a significant contribution to the overall emissions intensity of waste management locally. Moreover, an understanding of collection and transport emissions is required to accurately account for emissions intensity over the entire waste management chain. This chapter is therefore concerned with addressing the following thesis research question:

Research question 3: What are the emissions associated with kerbside organic waste collection and transportation?

The focus of this chapter is in developing a method for modelling waste collection and transport, from points of collection at the kerbside, to facilities along the waste management chain. The method developed is then applied to address research question 3, by estimating the collection and transportation-related emissions associated with household organic waste in the Greater Sydney area of NSW.

The work presented in this chapter was published as a standalone paper in 2022, as follows:

Madden, B., Florin, N., Mohr, S., Giurco, D. (2022). Estimating emissions from household organic waste collection and transportation: the case of Sydney and surrounding areas, Australia, *Cleaner Waste Systems*, 2, 100013, DOI: 10.1016/j.clwas.2022.100013.

This chapter includes the above published paper in full, and differs from the paper published in the above in formatting only. The paper's primary aim was to estimate waste collection and transportation emissions, and conclusions in this chapter are specific to these aims. Further insights drawn from this analysis in relation to the thesis research questions, are discussed in Chapter 8.

5.1. Introduction

Recent policy advancements in Australia have created an opportunity to align waste management and greenhouse gas (GHG) emission reduction objectives. Such policies include waste recovery targets (NSW EPA, 2014b, 2020a); a national target to halve food waste (DAWE, 2021); a circular economy decision making framework (NSW EPA, 2019b); and commitment to net-zero by 2050 (NSW Government, 2020). However, the contribution of waste management to overall emissions is poorly characterised in Australian greenhouse gas inventories, with only landfill emissions directly attributed (DISER, 2021b). Still, direct and indirect emissions occur at all points along the waste management chain, resulting from the consumption of energy and fuel during collection, transportation, and waste recovery. Without detailed understanding of these waste related emissions, it is difficult to evaluate the potential of waste management pathways for achieving resource recovery and emission reduction objectives.

Given the large transport distances between cities and regional centres in Australia, and also given the sprawling nature of Australian cities, emissions from road transport can be significant, contributing approximately 19% to overall national GHG emissions in 2020 (DISER, 2021b). The proportion of this owing to the collection and transportation of kerbside waste is however unknown.

Studies in the literature tend to utilise life cycle assessment (LCA) for examining waste transport emissions. For example, the Organic Waste Research model—*ORWARE* (Sonesson, 2000) is a life cycle-based model for estimating the fuel requirements associated with organic waste collection, intended to be applicable to different jurisdictions and waste management systems. *ORWARE* considers the energy consumption of collection vehicles during haulage and travel between bins, however it utilises default parameters relevant to Swedish municipalities for which the model was originally developed, limiting its applicability to other jurisdictions, despite it being a commonly used model (Edwards et al., 2016). Other more recent studies have developed region-specific emissions intensity factors for kerbside waste collection based on LCA, including for Taipei City, Taiwan (Chen & Lin, 2008); Aarhus, Denmark (Larsen et al., 2009); Ontario, Canada (Nguyen & Wilson, 2010); and South Africa (Friedrich & Trois, 2013). Such factors however have high variability owing to these models being dependent on widely varying local conditions, with emissions factors between 3 and 40 kg CO_2-e per tonne of waste reported in the literature (Friedrich & Trois, 2013). Moreover, variability in emissions intensity can also occur within a region, with emissions from waste collection typically being greater in areas with low household density (Friedrich & Trois, 2013). This point is particularly relevant for Australian locales, given high levels of suburban sprawl and variation in household densities across cities. This makes applying emission intensity factors to estimate emissions from waste collection for a generic region, such as Australia, difficult.

A recent study by Edwards et al. (2016) sought to overcome the aforementioned limitations to estimate fuel requirements for separate organic waste collection for 19 local government areas across Australia. Waste collection vehicle activities in Edwards et al. (2016) were based on *ORWARE* to include travel to and from waste truck depots, and kerbside collection. They extended the modelling approach by also including energy consumption during the hydraulic lifting of bins during collection. Their model incorporated local spatial data in a geographical information system (GIS) to estimate location-specific parameters, for example, distance between stops. Despite these improvements, the model in Edwards et al. (2016) is still limited in that it did not consider transport along existing road networks, instead relying on straight-line Euclidean distances, and it applied simple local averages for distances between bins.

The aim of this study is to estimate emissions associated with the collection and transportation of household organic waste in the Greater Sydney and surrounding areas in New South Wales, Australia, for the 2018-19 financial year. A spatial model was developed utilising high spatial resolution waste generation and road network data to estimate the emissions associated with kerbside collection in addition to transportation to-and-from waste transfer stations, and to points of waste recovery and disposal. The focus of this study is kerbside organic waste derived from households, which made up approximately 46% of all kerbside waste collected in New South Wales in 2018-19 (NSW EPA, 2020b). Organic waste is collected via three different pathways across the study area: separate garden organic waste collection (GO) and separate food and garden organic waste collection (FOGO), both destined for organics recovery via composting; and mixed waste, typically destined for landfill, or for recovery at alternate waste treatment (AWT) facilities (i.e., mechanical biological treatment). There is a current preference for local government areas in NSW to move towards FOGO collection to manage household organic waste. Therefore, this study also aimed to compare the transport emissions intensity associated with each collection pathway, to identify the lowest-carbon collection system for household organic waste diversion.

The main contribution of this paper is in generating accurate and up-to-date emissions data and intensity factors for kerbside organic waste collection in New South Wales for the first time, which has potential application in LCA comparative analyses of different waste collection systems. Findings can further inform decision making towards sustainable and low-carbon waste management, such as in comparing the emissions intensity of different recovery pathways with consideration to transportation, as well as in identifying facility locations minimising transportation (e.g., Karadimas et al. (2007); Comber et al. (2015)); and informing technology selection such as fossil fuel alternatives for collection vehicles (e.g., Pastorello et al. (2011)). The model developed has simple data requirements, making it readily applicable to other jurisdictions where spatial data on road networks and property lot boundaries are available.

5.2. Study area and scope of analysis

Figure 5-1 shows the study area for this analysis. The study area included 43 local government areas (LGAs) across the Sydney Metropolitan Area, Greater Western Sydney, Central Coast & Hunter, and the Illawarra & Shoalhaven regions, which represent the major population centres of NSW. These regions have a combined population of approximately 6.3 million, and approximately 2.3 million households (ABS, 2021). As such, the combined region is a significant source of household waste, generating approximately 2.2 million tonnes of waste across the dry recyclable, organics, and non-recyclable municipal waste fractions in 2018-19 (NSW EPA, 2020b).

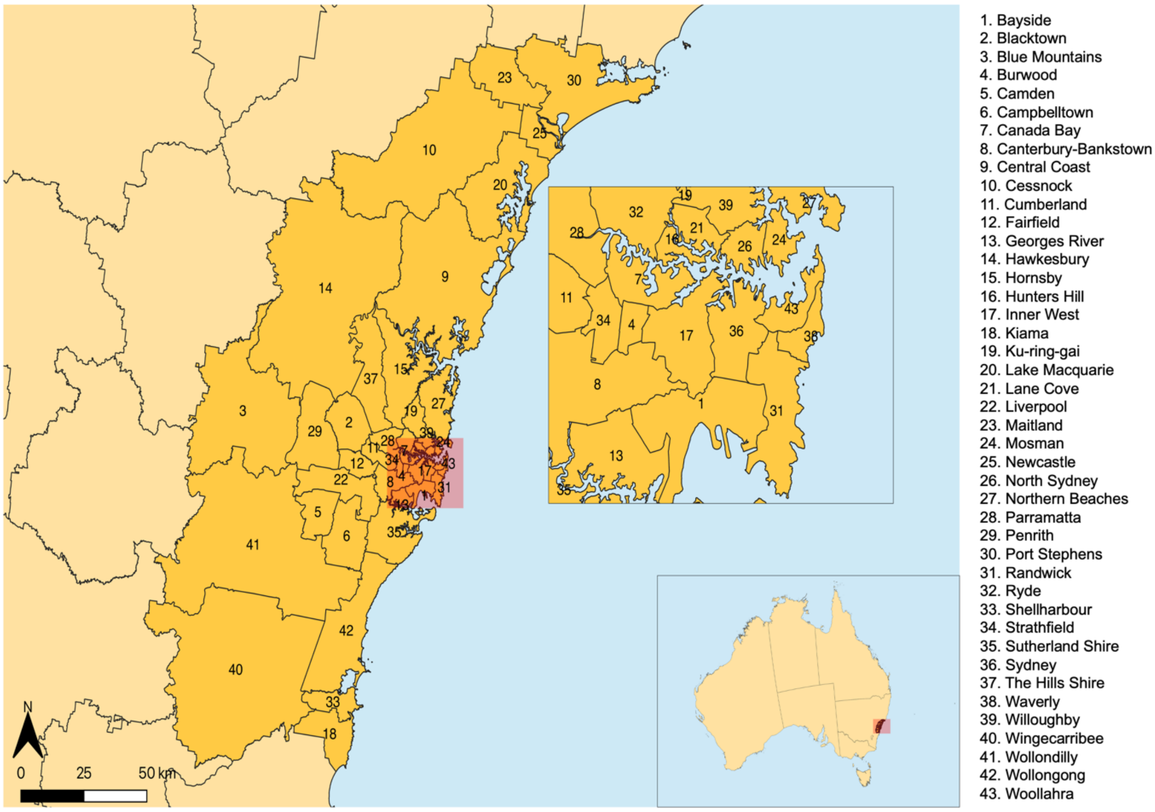


Figure 5-1: Local government areas within the Greater Sydney Area in the Australian state of New South Wales

Table 5-1 summarises LGA organic waste collection pathways employed across LGAs in the study area and included within scope of this analysis. GO and FOGO collections are mutually exclusive, however all LGAs in the study area collect mixed waste. Three LGAs did not have any separate organic collection services during the study time period, with the mixed waste fraction being the only form of organic waste collection for these LGAs. While there is a cost associated with the operation of waste collection vehicles, including for example labour, maintenance, and fuel, cost was not considered within the scope of the analysis. Cost was excluded from the scope, as we are concerned with estimating a baseline performance for GHG emissions from waste collection and transportation only. Future work may incorporate operational costs in studies for improving the efficiency of waste collection routes and transport services.

Table 5-1: Summary of organic waste collection pathways in the study area. Total waste collected quantities includes non-organic waste collected (e.g., plastic, paper etc in mixed waste, and contamination in GO/FOGO)

Organic collection pathway	Number of LGAs with service	Typical frequency of collection	Total waste collected (incl. non-organics) [tonnes, 2018-19]
Separate GO collection	35	Fortnightly	363,436
Separate FOGO collection	5	Weekly	88,116
Mixed waste	43	Weekly (fortnightly for LGAs with FOGO)	1,298,301

The average composition of each organic collection pathway is summarised in Table 5-2. Contamination rates (i.e., non-organic materials) in GO and FOGO collection bins are low, at 2.8% and 2.2% respectively. This contamination is primarily made up of plastics, metals and in the case of FOGO, also non-compliant organic material such as meat (APC, 2019; Rawtec, 2020a, 2020b). Contamination in the municipal organic stream however has been raised as a concern for local organics recyclers (NSW EPA, 2019a). This could indicate some underreporting of contamination in the available kerbside bin audit data, or that small levels of contamination have a significant impact on the quality of recovered organics. The average composition of the mixed waste stream varies depending on the level of separation via GO and FOGO collection, with the proportion of organic waste in mixed waste bins being highest in LGAs without separate collection of organics (61.3%). LGAs with FOGO collection have an average diversion rate for food waste of approximately 44% (Rawtec, 2020a), that is, 56% of all food waste generated in FOGO LGAs remains in the mixed waste bin. Analysis of the collection of the mixed waste stream has been included along with separate organic collection, as considering the high proportion of organic content in this stream, it is still a significant pathway for organic waste management.

Table 5-2: Average composition of organic waste collection pathways. Proportions shown are for the combined organic (i.e., food and garden waste) components only (APC, 2019; Rawtec, 2020a, 2020b)

	Organic waste composition of kerbside bin [%]	
Collection service	**Mixed waste bin**	**Separately collected organics bin**
FOGO collection	36.3%	97.8%
GO collection	51.0%	97.2%
No separate organic collection	61.3%	NA

From Table 5-2, the mixed waste bin is shown to be a significant source of organic waste, which is primarily destined for landfills within and outside of the study area. 22 LGAs in the study area diverted quantities of mixed waste to AWT facilities for recovery of organic waste and other high-valued recyclable material (e.g., metals and rigid plastics) via mechanical biological treatment. Recently however, the NSW waste authority (NSW EPA) has restricted the use of recovered organic materials from AWT and mixed waste streams as a soil amendment product, owing to contaminants present in mixed waste organic outputs (NSW EPA, 2019a). This limits the applicability of AWT as an organic waste management pathway in the future. Despite this, approximately 32% of mixed waste in the study area was diverted to AWTs in 2018-19, at a recovery rate of 41% (NSW EPA, 2020b). Figure 5-2 shows waste collection service by LGA, including AWT diversion.

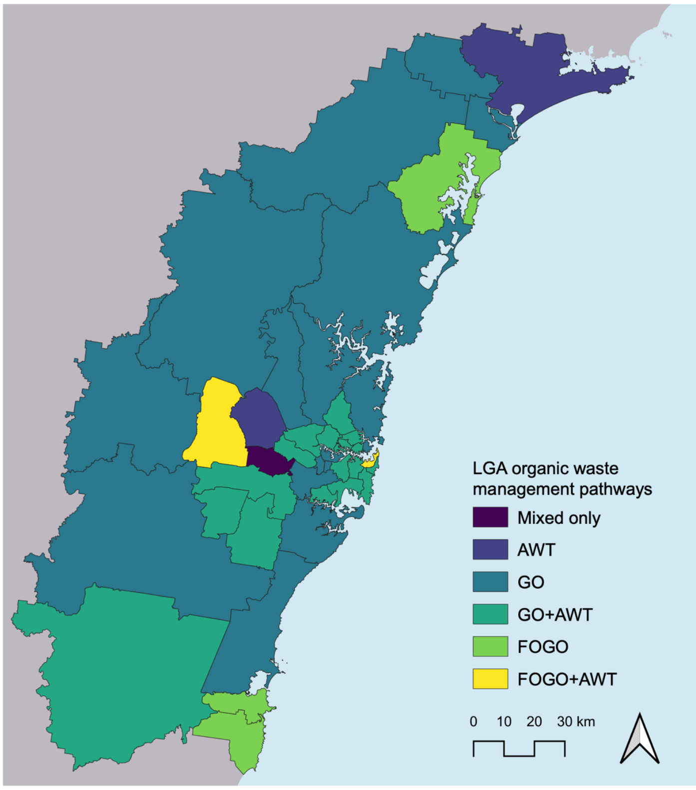


Figure 5-2: Distribution of LGA organic waste management pathways in the study area

Waste is first destined for waste transfer stations and collection, where collection vehicles drop off waste collected on a collection route for aggregation before then being directed to recovery or landfill. AWT facilities, along with organic reprocessing (e.g., industrial-scale windrow composting) and landfills were the destinations of waste collected considered in scope for this analysis. Despite anaerobic digestion (AD) being a preferred recovery pathway for food waste given both bioenergy outputs and stabilised organic matter for soil improvement (Banks et al., 2018), anaerobic digestion is not currently deployed at municipal scale in the study area for household waste, with only small amounts of commercial food waste processed via AD in the study area. Recovery facilities generate residual wastes from their processes due to recovery inefficiencies and contamination, which is also then directed to landfills from these facilities. Figure 5-3 shows the waste system boundary and scope of material flows along the waste management chain considered for this analysis. The figure also shows the sources of emissions considered in scope for the analysis, computed as carbon dioxide equivalent (tonnes CO_2-e).

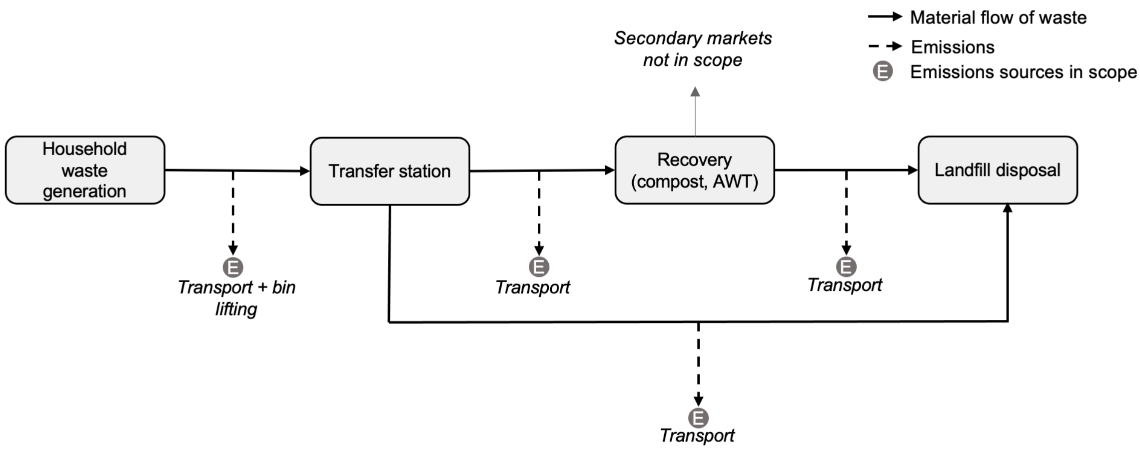


Figure 5-3: Waste management system and sources of emissions in scope

Locations for waste infrastructure were based on data in the national *Waste Infrastructure Database – 2017* (Geoscience Australia, 2020), and in NSW LGA *Waste avoidance and resource recovery* data reports (NSW EPA, 2020b). Figure 5-4 shows a map of infrastructure locations in scope for this analysis.

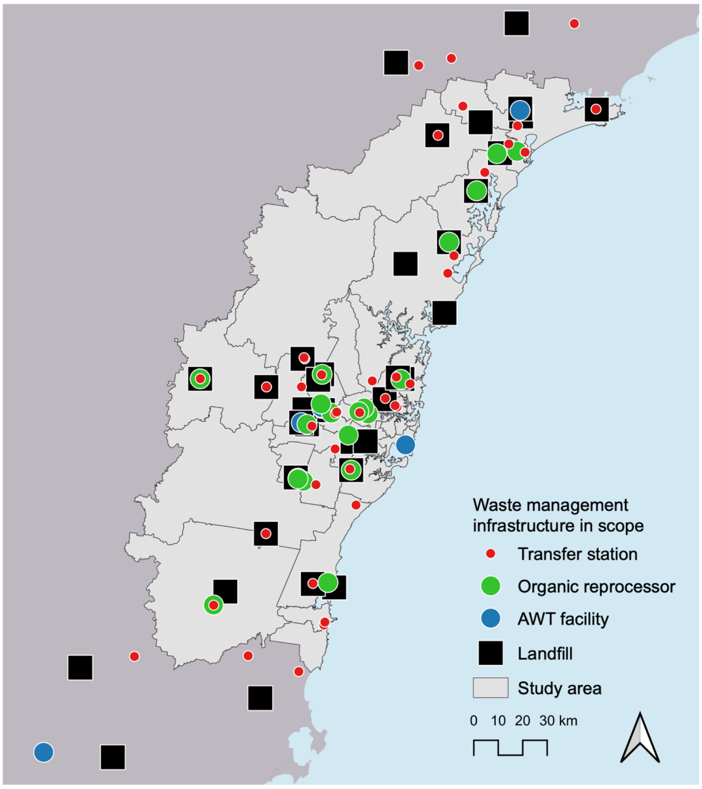


Figure 5-4: Waste management infrastructure in the study area

5.3. Methodology

Analyses of waste management systems using spatial data and geographical information systems (GIS) are common in the literature (Singh, 2019), and have been applied for: identifying optimal locations for landfills and other facilities (Aguilar et al., 2018; Eghtesadifard et al., 2020; Lin et al., 2020; Yadav et al., 2018); service area planning (Hatamleh et al., 2020; Tanguy et al., 2017); and small-area estimation of waste generation (Kontokosta et al., 2018; Liu et al., 2022; Madden et al., 2021; Yazdani et al., 2021). Models utilising spatial data also have a diverse range of applications in the evaluation of waste transport flows. For example, Son (2014) applied a novel optimisation approach within a GIS-based environment to determine optimal collection routes for tricycle waste collection in Danang city, Viet Nam. Lella et al. (2017) utilised GIS to identify optimal collection routes for solid waste collection and disposal in a proposed smart city in India. Utilising road network data, the authors applied network analysis to identify the shortest routes between proposed transfer stations and collection points.

In Vu et al. (2019), the authors applied predictive forecasting of weekly waste generation rates with GIS to analyse the impact of waste characteristics on collection route optimisation in the city of Austin, Texas, USA. The authors used network analysis applied using GIS to solve a vehicle routing problem (VRP)—a generalisation of the classic travelling salesman problem (TSP), whereby solutions were the shortest routes travelled by waste collection vehicles, with constraints such as maximum travel distance and maximum collection time applied. The basic concept of VRPs are to find least cost travel routes from a starting location to service a set of demand points, and then return to the starting location (Du & He, 2012; Hannan et al., 2018). Where vehicle capacity is considered, the problem becomes the capacitated vehicle routing problem, or CVRP, which has particular relevance for evaluating waste collection. Hannan et al. (2018) applied CVRP in the optimisation of waste collection routes to minimise drive time, drive cost, and environmental impacts, solved via particle swarm optimisation (PSO). Akhtar et al. (2017) solved a CVRP using a backtracking search algorithm in the optimisation of fuel usage and GHG emissions from waste collection. Otoo et al. (2014) solved a CVRP using a cluster-first-route-second algorithm in a GIS for finding the lowest cost waste collection routes. Karadimas et al. (2007) also used GIS to solve a CVRP via genetic algorithm to identify cost savings through optimising waste collection routes.

Indeed, the application of CVRP for evaluating waste collection is wide, and the choice of solution methodology is numerous. Mojtahedi et al. (2021) gives a comprehensive review of VRPs more generally including solution methodologies in the context of waste management. Despite the wide application of the VRP and its variants in waste management, it is noteworthy that case studies from the literature are generally at the city scale or smaller.

The approach developed for this study estimated emissions associated with the collection of kerbside GO, FOGO and mixed waste by solving a CVRP for the Greater Sydney and surrounding area—a combined area of approximately 20,000km^2. The modelling approach developed utilised high spatial resolution household waste data derived in Madden et al. (2021), waste infrastructure data from Geoscience Australia (2020), and road network data from the NSW Digital Cadastral Database (DFSI, 2012), integrated with GIS. Our approach extends the work in Edwards et al. (2016) and Sonesson (2000) by utilising higher resolution data to estimate transport flows with greater resolution (for example, between bin distances); and by broadening the scope to also include emissions from transport to waste recovery facilities and landfills.

Figure 5-5 gives an overview of the methodological approach. There were two key components of the model. The *waste collection and transport model* was used to estimate organic waste collection distances, achieved by solving a CVRP using a nearest neighbour search algorithm for waste collection services in each LGA in the study area. Furthermore, waste infrastructure data representing waste recovery facilities and landfills were also integrated with road network data to estimate the flows of waste between facility types as a simpler shortest-path problem, solved using Dijkstra's algorithm (Dijkstra, 1959)—a classic algorithm for finding shortest paths on a graph/network. Outputs from the *waste collection and transport model* were coupled with vehicle data from the literature in a *transport energy analysis* to estimate fuel consumption and emissions from waste collection and transportation for each kerbside service across all 43 LGAs. The following sections describe our approach in further detail.

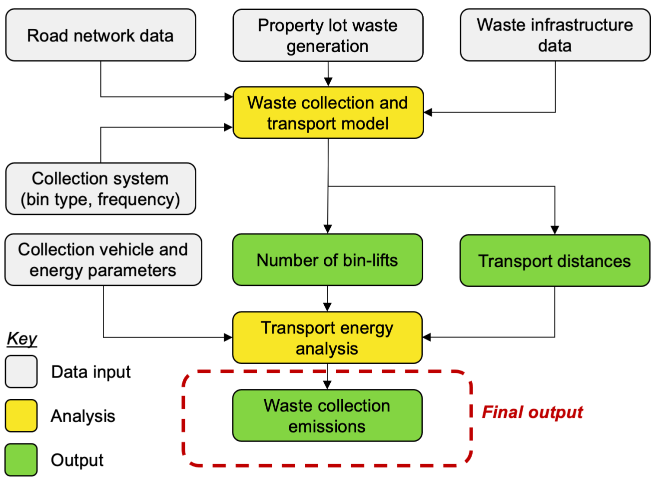


Figure 5-5: Overview of the methodological approach for this study. The approach is applied for each local government area in the study area Figure 5-1

5.3.1. Waste collection and transport model

Figure 5-6 gives an overview of the *waste collection and transport model*, showing the transport flows estimated for each LGA in the study area. Two high-level modes of transport were considered for each waste collection service: kerbside collection, which included the traversal of roads along a collection route (i.e., the collection zone) and the servicing of individual property lots within (i.e., the between bin travel); and recovery and disposal transfer, which included transport of aggregated waste from transfer stations to recovery facilities and landfills, and the transport of residual wastes from recovery facilities to landfills. Estimated travel distances for each LGA were multiplied by waste service collection frequency to calculate annual transport distances for the study timeframe.

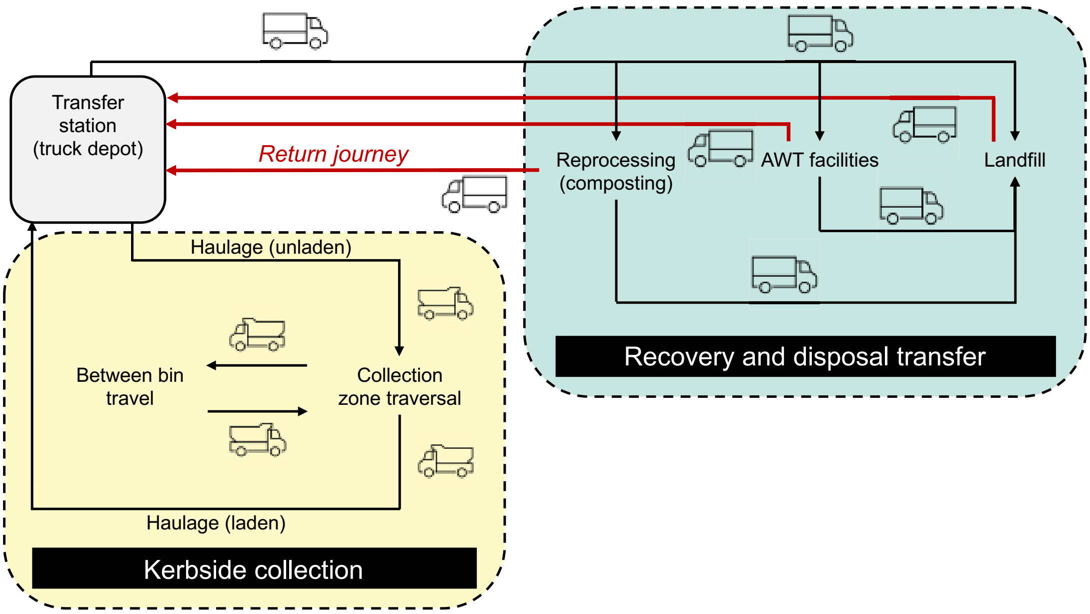


Figure 5-6: High-level overview of the waste collection and transport model

5.3.1.1. Estimating kerbside collection distances

We estimated distances travelled for kerbside collection for each collection stream by solving a CVRP using the nearest neighbour search algorithm on road network data and property lot data derived from the NSW Digital Cadastre Data Base (DFSI, 2012) and Madden et al. (2021). The optimal collection routes in our model were treated as approximations of actual collection routes beginning and ending at transfer stations, where data on such routes are limited. We differentiated collection zone traversal and between bin travel distance as a simplification due to limitations in the road network data, which represents many multi-lane and multi-directional roads as single undirected line segments. Due to this, routing between individual property lots is not feasible, as kerbside bins located on opposite sides of a road may appear as adjacent, thus significantly underestimating the transport distance between them. A further limitation in the road network data, is lack of characteristics of the road segments themselves, including characteristics such as width and slope, which are important considerations for truck traversal. Road segments were filtered by road function which were given in the DFSI (2012) data, with only road segments labelled as arterial/sub-arterial road, local and primary road, distributor road and motorway included in our analysis.

Figure 5-7 gives an overview of the collection zone traversal component, which is performed on an LGA-basis for each waste stream and transfer station servicing the LGA. Figure 5-8 gives an overview of between bin travel, applied to all neighbourhood blocks within an LGA. Both components when summed give the overall kerbside collection distance. The estimation approach is explained in further detail in the following paragraphs.

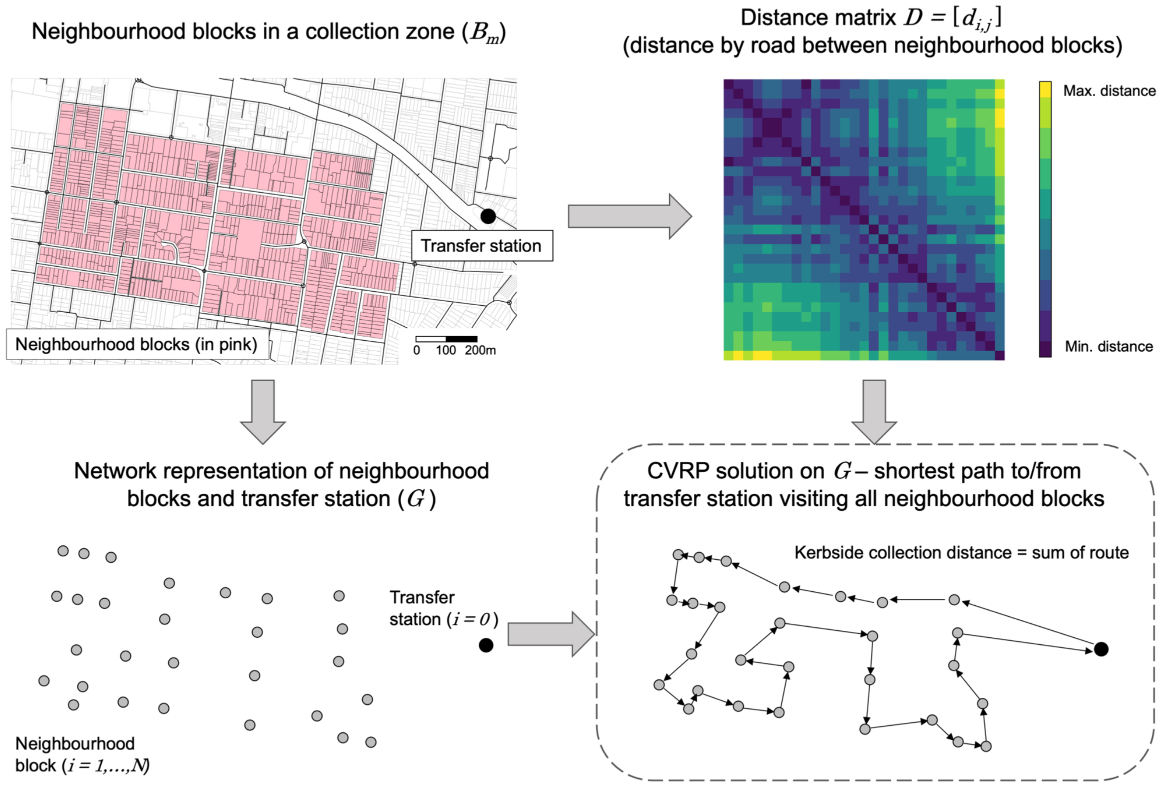


Figure 5-7: Overview of the approach used for estimating collection zone traversal in the kerbside collection component of the waste collection and transport model

Figure 5-8: Overview of the approach used for estimating the between-bin collection travel in the kerbside collection component of the waste collection and transport model

Kerbside collection distances were estimated for each LGA separately. We first generated the set of neighbourhood 'blocks' for each LGA by merging contiguous property lots within an LGA together, bounded by adjacent roads on the road network. Each neighbourhood block consisted of at least one property lot occupied by a residential dwelling, with an expected amount of waste generated $w > 0$ per waste service collection interval. The number of bins to be collected within a block was equal to the number of dwellings, assuming that each dwelling within a property lot had exactly one bin per waste collection service. In the case of multi-unit dwellings located within a property lot, the number of bins was assumed to equal the number of dwellings. While some multi-unit buildings may have larger bin systems servicing multiple individual dwellings, data on this was unavailable during the time of this study. Collection vehicles were assumed to make a single trip to a multi-unit building on a collection route (except where the total waste generated in a building exceeds the assumed capacity of the vehicle, then the number of trips equal $\lceil w/C \rceil$ where C is the truck capacity). Therefore regardless of the bin system employed, the transport requirements (i.e., collection zone traversal and between-bin distance) are the same. The difference however does lie in the hydraulic lifting of bins to the waste vehicle receptacle. Energy efficiency of the hydraulic operation is likely greater for large bin systems compared to smaller sized bins for an equal quantity of waste, however data on this is limited. Section 5.3.2 describes the energy requirements of bin collection in greater detail.

Neighbourhood blocks within an LGA were assumed to be serviced by the nearest transfer station, which were also the assumed waste collection vehicle depot locations. This is a simplification, and allocation of a transfer station to a collection zone can also be dependent on the waste type, and contracts between local councils and waste managers. As transfer stations are distributed across the study area, some LGAs were assumed to be serviced by multiple transfer stations. The CVRP for an LGA was then solved iteratively for each transfer station and corresponding set of neighbourhood blocks serviced.

First, $B_m = \{b_{m,i}\}$ is defined as the set of neighbourhood blocks in an LGA nearest to transfer station m, with $0 < w \leq C$, where $C = 5$ tonnes was the assumed capacity of a collection vehicle, from Edwards et al. (2016). The estimation of kerbside collection for neighbourhood blocks with weekly waste generation greater than truck capacity (for example, where there are a large number of multi-unit dwellings) was simplified by assuming that collection vehicles travel directly to the neighbourhood block from the transfer station and back again via the shortest path. In these instances, distance travelled for collection was the length of this shortest path, multiplied by the number of collection vehicles required to service the neighbourhood block. This same approach was also applied where individual property lots had expected waste generated greater than C, for example, where large apartment complexes were located. Once transport distances were estimated for these property lots and neighbourhood blocks where $w > C$, they were removed from the following analysis to ensure collection from these locations were not counted twice.

For all other neighbourhood blocks with $0 < w \leq C$, we estimated collection distance by solving a CVRP. The objective of the CVRP in our application was to find the optimal collection routes that minimise total travel distance between collection points and transfer station subject to constraints. The CVRP was defined on the undirected graph $G = (V, E)$, where $V = \{v_i\}$ is the vertex set representing locations visited by collection vehicles, and $E = \{(v_i, v_j) : v_i, v_j \in V\}$ is the set of edges between vertices, representing the traversal of roads between locations. The initial vertex $i = 0$ represents transfer station m, where K waste collection vehicles begin and end their journeys. Vertices $i = 1, \dots, n$ correspond to the neighbourhood blocks $b_{m,i}, \dots, b_{m,n}$ where collection of bins takes place. A collection route is then a sequence of vertices $(v_i, v_{i+1}, \dots, v_n)$, where v_i is adjacent to v_{i+1}, and travel distance over the whole route is minimised. The symmetrical matrix $D = [d_{i,j}]$ corresponds to the non-negative travel distance along each edge (v_i, v_j), computed as the shortest road travel distance between locations. This is computed as the shortest travel distance along roads between locations, found using Dijkstra's shortest path algorithm (Dijkstra, 1959) evaluated using the cadastral road network data. Cartesian coordinates of the transfer station and neighbourhood block centroids were mapped to positions on the road network by finding the nearest point on the road network perpendicular to v_i, using the method in Lu et al. (2018), implemented using the *points2network* function from the *shp2graph* library in the *R* statistical computing language. (see Appendix C.1 for a summary of this method). The decision variables of the CVRP model are as follows (Equations. 5.1 and 5.2):

$$X_{i,j,k} = \begin{cases} 1, & \text{if vehicle } k \text{ travels from location } i \text{ to } j \\ 0, & \text{otherwise} \end{cases} \tag{5.1}$$

$$Y_{i,k} = \begin{cases} 1, & \text{if location } i \text{ is visited by vehicle } k \\ 0, & \text{otherwise} \end{cases} \tag{5.2}$$

The objective function of the CVRP is then to minimise the total travel distance of all waste collection vehicle routes visiting collection points to and from transfer stations as follows (Equation 5.3):

$$\text{minimise } Z = \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{k=1}^{K} d_{i,j} X_{i,j,k} \tag{5.3}$$

Subject to the following constraints:

- All waste collection vehicles begin their routes from transfer stations with no load

- Each location (neighbourhood block) with waste generation $0 < w \leq C$ is serviced by a single waste collection vehicle

- Collection vehicles must collect all waste generated at a location

- Collection vehicles visiting a location must also depart from that location

- Waste collected on a route must not exceed the truck capacity (5 tonnes)

- Collection vehicles must return to the transfer station after visiting the final collection point on a route

- Travel distance between two vertices are the same in either direction (i.e., edge distance between two given vertices are symmetrical)

The above constraints are expressed mathematically in Appendix C.2. An additional assumption is also made, in that there are no time restrictions imposed. To solve the CVRP, we used the nearest neighbour algorithm—a greedy search algorithm that attempts to find the optimal solution by first selecting a random starting location $i \neq 0$, and building a route by adding locations nearest the randomised starting location, given the constraints in Equations (5.4) to (5.11). The algorithm is performed over a large number of iterations (10,000) using the *R Statistical Computing* language (R Core Team, 2020), with overall route distance evaluated for each iteration. The optimal collection route is updated for instances resulting in a shorter overall route distance. The nearest neighbour algorithm has been used to solve VRPs previously in the literature for its simplicity and ease of implementation, especially for large-scale problems (Du & He, 2012; Faccio et al., 2011; Kulkarni et al., 2014).

Outputs from this process were the most optimal collection routes to and from a transfer station m, given as a sequence of vertices $(v_i, v_{i+1}, \dots, v_n)$, with distance travelled given by the edge weight between vertices, i.e., $d(v_i, v_{i+1})$. This sequence was decomposed into unladen haulage (travel from the transfer station vertex to the first vertex of a collection route); laden haulage (travel from the last vertex of a collection route back to the transfer station); and collection zone traversal as the remaining vertices of the sequence. We then summed the distances for each component for all waste collection services and transfer stations that service the LGA to determine the total collection zone traversal and haulage distances for an LGA (Eq. 5.4):

$$Z_l^h = \sum_m \sum_x Z_{m,s}^h \tag{5.4}$$

Where $l \in L$ is an LGA in the study area, and $s \in S$ are the collection services active in the LGA, and h are the estimated transport components, i.e. $h \in \{unladen, traversal, laden\}$.

For the between bin travel distance, we found the point perpendicular to the nearest road segment for each property lot in a neighbourhood block, and then calculated the distance travelled along the adjacent road between these points, as visualised in Figure 5-7. The method in Lu et al. (2018) implemented using the *R* library *shp2graph* (Lu et al., 2018) was employed, which maps points of interest (i.e., property lots) to the graph representing road vertices and road edges. We then summed these distances calculated for each neighbourhood block in an LGA to derive the total LGA between bin travel distance for a given waste service.

Final kerbside collection distance for an LGA on which carbon emissions were estimated was the combination of collection zone traversal and between bin travel distances (Equation 5.5):

$$Z_l^{kerbside} = Z_l^{laden} + Z_l^{traversal} + Z_l^{between-bin} + Z_l^{laden} \tag{5.5}$$

5.3.1.2. Estimating recovery and disposal transfer distances

Distances travelled for recovery and disposal transfer were estimated by solving the simpler shortest-path problem on the road network data, and locations of waste infrastructure in Geoscience Australia (2020) using Dijkstra's algorithm. Dijkstra's algorithm performs by calculating the distance between a starting vertex on a graph, and all other vertices. The shortest path from the starting vertex to a destination vertex is then determined by finding the path that minimises the total length between the starting and destination vertices. While the shortest route may not necessarily be the fastest route, which is more likely to be the optimal routing from a transport planning perspective, data was not available to calibrate the model to account for road speed limits. This is a limitation with this work, however minimising transport distance is commonly applied in the literature for identifying optimal (e.g., Hannan et al. 2018; Vu et al., 2019). Further analysis to incorporate speed limits to evaluate fastest vs. shortest routes is an avenue for future work.

We calculated transport distances for five separate facility pairings: transfer station to composter; transfer station to AWT; transfer station to landfill; composter to landfill, and; AWT to landfill. Destination facilities were assigned to source facilities for each pairing based on proximity (e.g., the nearest composter to a transfer station). The exception to this was transfer station to AWT, where destination AWT facilities were assigned to transfer stations that service LGAs sending mixed waste to AWTs from the data (NSW EPA, 2020b). Road travel distance was calculated for each pairing from source location to destination location, mapped to the graph representing road vertices and road edges via the method in Lu et al. (2018), with the shortest path between facilities found using Dijkstra's algorithm (Equation 5.6):

$$Z^{\tau} = \left(\sum_{i,j \in \tau} dist(i,j)\, x_{i,j} \right) \times K_{i,j} \tag{5.6}$$

Where τ is the given facility pairing, $dist(i,j)$ is the length of edge (i,j) between facilities, and $x_{i,j}$ is the decision variable, taking a value of 1 if the edge (i,j) is on the shortest path. $K_{i,j}$ is the number of trucks required to transport aggregated waste between locations i and j, and is calculated from $q'_{i,j}/C_2$, where $q'_{i,j}$ is the total amount of waste to be transported from facility i to facility j during a collection service interval, and C_2 = 15 tonnes is the transport truck capacity. Compaction of aggregated waste material, and a larger truck size compared to waste collection, equivalent to a 3-axle, 22.5 tonne gross vehicle mass rigid truck (NSW RMS, 2019) was assumed for C_2. We attributed distance between facility pairings to individual LGAs by calculating the proportion of waste transported between facilities that was derived from each LGA.

It was assumed that LGAs sending mixed waste to the Woodlawn AWT facility (located approximately 190km outside the Sydney CBD) did so via rail, with waste first being transferred to the Clyde Transfer Station, located in the Parramatta LGA (Veolia, 2022). Distances between nearest transfer station to the Clyde Transfer Station were calculated as described as above. Distance travelled by rail was calculated between the Clyde Transfer Station and Woodlawn AWTs, assuming weekly transfer of AWT destined mixed waste.

5.3.2. Transport energy analysis

The *transport energy analysis* estimated the emissions from waste collection and transport, following the approach and parameters applied in Edwards et al. (2016), which was based on truck activity. These activities were: i) unladen haulage from transfer station to the first collection point on a collection route; ii) 'stop-go' travel between bins; iii) bin-lifting (i.e., emptying of bins into truck receptacle via hydraulic lifting arm); iv) laden haulage back to the transfer station, and; v) laden haulage between facilities. Hydraulic lifting systems are standard practice for waste collection vehicles in the study area, which ensure worker safety and efficiency in loading waste into the vehicle receptacle. It was assumed that all collection vehicles employed utilised the same technology.

Table 5-3 lists the parameters used in the model. Estimated distances (km) for a given activity were divided by the corresponding truck speed (km/h) for that activity (based on LGA classification as metropolitan/metropolitan-fringe, or regional in NSW OLG (2020), and multiplied by the energy intensity (MJ/s) to calculate energy requirements in megajoules. From this, diesel fuel consumption (L) and associated emissions (t CO_2-e) were estimated, based on average CO_2-e emissions for diesel combustion by rigid trucks in National Transport

Commission (2019). Fuel type was consistent with data in ABS (2020) showing 99.8% of the Australian truck fleet consuming diesel fuel in the study period. Proportion of highway travel for haulage and transport between facilities was determined from the cadastral road data (DFSI, 2012). For energy requirements and fuel consumption for bin-lifts, it was assumed that the number of bins per property lot at a collection point was equal to the number of dwellings in that property lot.

Estimated fuel consumption for facility-to-facility haulage of aggregated waste was calculated for each LGA, based on the proportion of waste derived from an LGA. To illustrate, if 10% of waste at a transfer station was derived from LGA1, then 10% of the fuel consumption associated with facility-to-facility haulage was associated with that LGA. For rail transfer of AWT destined waste, a standard diesel-electric locomotive operating at 5,000 horsepower was assumed, based on the Australian Transport Assessment and Planning Guidelines (Transport and Infrastructure Council, 2020).

Table 5-3: Parameters used for modelling fuel consumption of waste collection and transport vehicles. All parameters values taken from values derived from Edwards et al. (2016) unless where stated

Parameter	**Value [unit]**	**Description**
Average time per bin-lift	8.27 [seconds]	Average time for collection vehicle to lift a bin using hydraulic lifting arm
Average speed - bin collection (urban)	7 [km/hr]	Average speed during bin collection (between bin travel) for urban LGAs
Average speed – bin collection (peri-urban)	9 [km/hr]	Average speed during bin collection for peri-urban LGAs
Average speed – haulage (urban)	35 [km/hr]	Average speed for laden/unladen haulage (collection zone traversal, and facility-to-facility transfer) for urban LGAs
Average speed – haulage (peri-urban)	40 [km/hr]	Average speed for laden/unladen haulage for peri-urban LGAs
Average speed – haulage (highway)	82 [km/hr]	Average speed for laden/unladen haulage along highways
CO_2-equivalent emissions from diesel	0.0027 [tonnes/L]	Average CO_2 equivalent emissions per litre of diesel fuel combusted (National Transport Commission, 2019)
Energy from diesel	39 [MJ/L]	Energy content of diesel fuel
Energy during bin lift	0.1 [MJ/s]	Amount of energy consumed by the hydraulic lift per bin lift
Energy during laden haul (urban/peri-urban)	0.176 [MJ/s]	Energy consumed whilst driving laden along roads urban/peri-urban LGAs
Energy during unladen haul (urban/peri-urban)	0.035 [MJ/s]	Energy consumed whilst driving unladen along roads urban/peri-urban LGAs
Energy during laden haul (highway)	0.450 [MJ/s]	Energy consumed whilst driving laden along highways
Energy during unladen haul (highway)	0.183 [MJ/s]	Energy consumed whilst driving unladen along highways
Energy during kerbside bin collection	0.176 [MJ/s]	Energy consumed whilst moving between bin collection locations (between bin travel)
Diesel consumption per kilometer (freight rail)	7.5 [L/km]	Diesel consumption per locomotive kilometre for diesel-electric freight locomotives. From (Transport and Infrastructure Council, 2020)

5.3.3. Model validation

A sensitivity analysis was performed to test the robustness of emissions estimates given variation in key model variables. Variables chosen for evaluation were the selection of kerbside collection routes, given the stochastic nature of the nearest neighbour solution algorithm; waste transport truck capacity, where the actual size of transport trucks was unknown; and waste generation rates.

To test the sensitivity of emissions on kerbside collection routes, we performed 10,000 iterations of the CVRP solution algorithm for 3 LGAs selected from each LGA category from NSW Office of Local Government (2020) (i.e., metropolitan, metropolitan-fringe, and regional). The average coefficients of variation (CV) for each LGA category were computed, and used to estimate CVs on kerbside emissions for each LGA in the study area. This was done due to the large computation times necessary to perform iterations of the CVRP solution algorithm for a single LGA.

To test sensitivity of emissions on transport truck sizes, we estimated overall emissions based on candidate truck sizes in NSW RMS (2019) and Strandgard et al. (2021), assuming either 2-axle rigid, 3-axle rigid (the nominal transport truck size), and semi-trailer, at assumed load weights of 10, 15, 26 tonnes respectively.

To test sensitivity of emissions on variations in waste generation, we performed the model with waste generation rates perturbed by ±20%, and compared against baseline estimates. Sensitivity of overall emissions given percentage-variation in kerbside collection routes, transport truck sizes and waste generation, were then evaluated by comparing the percentage change in emissions, after Acevedo (2013).

A further unknown in our model was the assignment of landfill locations to transfer stations and recovery distances based on proximity. It is possible that some jurisdictions and transfer/recovery facilities may have agreements with particular landfill sites, and that capacity limits at landfills may lead to non-proximal landfill sites being the destination of disposed waste. To explore this uncertainty on the model results, the disposal transfer distance component waste computed, based on randomly assigned landfill facilities in a simulation with 1,000 iterations. Landfills locations were selected randomly from a weighed sample, with landfills in closer proximity to transfer stations and recovery facilities more likely to be selected.

Considering a lack of actual data on waste transport logistics and emissions, validating the accuracy of modelling results is difficult, and is a limitation of this work. To evaluate the accuracy of the model, outputs were compared against available data from the literature. This validation included for example, comparison against waste transport distances per litre of fuel consumption in Agar et al. (2007) and Larsen et al. (2009); litres of fuel consumed per tonne of waste transported in Nguyen and Wilson (2010), Quintili and Castellani (2020), and Jaunich et al. (2016); and emissions intensity per tonne of waste collected from LCA studies summarised in Friedrich and Trois (2013). An avenue of future research related to this work could include the collection of actual waste collection and transport data. Such data collection would most likely involve collaboration with both local governments as well as waste collection service providers.

5.4. Results and discussion

5.4.1. Kerbside collection and facility-to-facility distances travelled, and fuel consumer

Table 5-4 summarises overall distances travelled by waste collection and transport vehicles in the study area for each waste stream (used to estimate transport emissions reported in Section 3.2). Figure 5-9 shows the breakdown of collection and transport distances by component, and by waste stream. Overall, approximately 18 million kilometres were travelled for the management of organic wastes in the study area in 2018-19 by road and rail, equivalent to approximately 694 times around the Earth. Distance travelled by rail were small, at approximately 25,000 km, or 0.1% of total distances travelled in 2018-19. Considering that waste transported by rail makes up approximately 7% of total residual waste managed, rail transport is unsurprisingly the most efficient form of waste transportation.

The average distance travelled per LGA ranged between 208,000 km/year to 1.3 million km/year, with a mean distance of approximately 370,000 km/year travelled. Appendix C.3 gives a breakdown of average-distances travelled by LGAs. The overall intensity of transport per tonne of waste generated across the streams considered was 10.17 km/tonne. The mixed waste stream had the highest transport requirements, accounting for 72% of total mileage. FOGO waste had the lowest transport requirements at 6.2% of total mileage, expected given that FOGO waste collection accounts for only 4.9% of total waste collections. Intensity of transport was highest for the FOGO waste stream, at 12.7 km/tonne, reflecting the large distances travelled for collection, and the relatively small quantities of FOGO waste collected. The mixed waste stream had the lowest intensity at 9.8 km/tonne, which illustrates the efficient location-allocation of mixed waste management facilities, with landfills, AWT facilities and transfer stations located within close proximity with eachother. The exception to this is the Woodlawn AWT facility, however transfer of mixed waste via rail is much more efficient compared to road freight on a tonnes-kilometer basis (5.2 tonnes-kilometer for road compared to 0.26 tonnes-kilometer for rail).

Table 5-4: Summary of estimated annual distances travelled by waste collection and transportation vehicles for the management of organic waste in the study area for 2018-19

	Total distance travelled [km/year]	**Distance travelled – GO waste [km/year]**	**Distance travelled – FOGO waste [km/year]**	**Distance travelled – Mixed waste [km/year]**
Total kerbside collection	*14,028,217*	*3,428,644*	*892,603*	*9,706,971*
Collection zone haulage (unladen)	4,070,921	909,816	206,055	2,955,050
Collection zone traversal	1,736,337	471,109	143,288	1,121,940
Bin pickup	4,286,622	1,172,764	347,231	2,766,628
Collection zone haulage (laden)	3,934,338	874,956	196,029	2,863,353
Total recovery transfer (incl. return)	*2,393,477*	*521,116*	*201,815*	*1,670,546*
Transfer station to composters	722,930	521,116	201,815	0
Transfer station to AWTs (road)	1,645,504	0	0	1,645,504
Transfer station to AWTs (rail)	25,042	0	0	25,042
Total disposal transfer (incl. return)	*1,405,319*	*10,000*	*3,440*	*1,391,878*
Transfer station to landfills	976,060	0	0	976,060
Composters to landfills	13,441	10,000	3,440	0
AWTs to landfills	415,817	0	0	415,817
Total	*17,827,013*	*3,959,760*	*1,097,858*	*12,769,395*

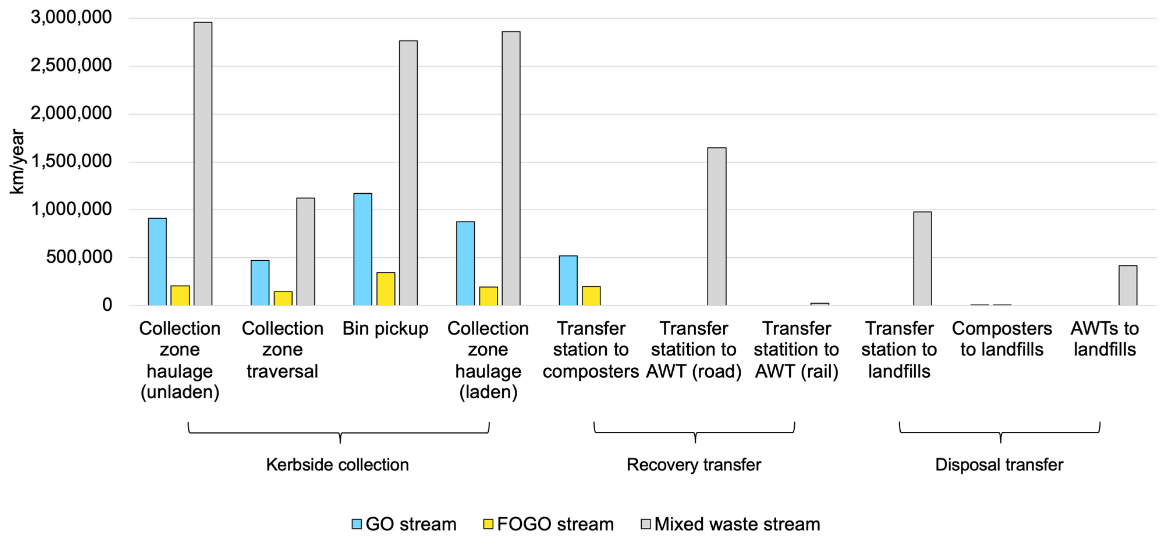


Figure 5-9: Breakdown of waste collection and transport distance by waste stream, and waste component

Kerbside collection contributed the most to overall distances travelled by waste management vehicles, accounting for approximately 79% of total mileage. There was a large variance on LGA kerbside collection mileages, ranging from approximately 68,000km/year to 570,000km/year. Such variance is expected, given LGA sizes range from approximately 6km^2 to 2,800km^2, and number of households per LGA ranging between 16,000 to 97,000. Larger LGAs typically saw greater kerbside collection distances than smaller LGAs, however this effect was most evident in metropolitan LGAs, where LGA size is smaller compared to regional LGAs. Larger, more regional LGAs with less urban development (for example Wingecarribee, Blue Mountains), are characterised by large proportions of national parks and primary produce land, with most residential dwellings located in smaller, less distributed parts of these LGAs. Indeed, the total number of dwellings was a stronger indicator of total kerbside collection distance, with total distances travelled by collection vehicles increasing by approximately 5km for every occupied household in an LGA. Average kerbside collection distance per dwelling ranged from between approximately 3km/dwelling to 10km/dwelling. Dwelling density and dwelling type, and their impact on transport emissions are discussed further in the following section.

A total number of 409,970 waste collection vehicle trips were required to service all households in the study area for 2018-19. Mixed waste collection required the greatest number of truck trips at 288,938, which is expected given that all LGAs in the study area have mixed waste collection services. FOGO waste collection had the fewest number of vehicle trips in 2018-

19, at 19,864, with only 5 LGAs having FOGO collection services. GO collection required 101,168 trips.

Of the kerbside collection travel components summarised in Table 5-4, bin pickup was responsible for the greatest mileage. Table 5-5 shows the average between-bin distances for LGAs by regional classification from NSW OLG (2020). The average between-bin distance for all LGAs was approximately 44 metres, with the metropolitan LGA average being approximately 30 metres. Metropolitan-fringe and regional LGAs had similar between-bin distances of approximately 62 metres and 64 metres respectively. Between bin distances are not reported in Edwards et al. (2016), despite the authors noting that this variable is crucial for modelling fuel consumption for waste collection. Edwards et al. (2016) does however refer to between bin distances of 20-110 meters used in other studies for urban locales.

Table 5-5: Estimated average distance between collection points (i.e., bins) by LGA classification from NSW OLG (2020)

	Average distance between collection points [m] (St.dev.)
All LGAs	43.88 (32.23)
Metropolitan LGAs	30.17 (6.85)
Metropolitan-fringe LGAs	61.58 (35.59)
Regional LGAs	64.25 (12.73)

Total recovery transfer distances were approximately 2.4 million km/year, including 25,000 km via rail. LGA variance was also high for this component, with average mileage ranging from 5,000 km/year to 136,000 km/year. This can mostly be attributed to AWT transfer. Notably, AWT transfer intensity on a km/t basis was significantly greater than compost transfer, at an average of 5.2 km/tonne compared to 1.6 km/tonne.

Landfill disposal transfer made the smallest contribution to overall waste transport distances, at approximately 1.4 million km/year. LGA variance on disposal transfer was relatively small, between 6,400 km/year and 72,000 km/year. Landfills were generally located in proximity to transfer stations and recovery stations, whereas recovery facilities were more dispersed across the study area. This is indicated by the average transport intensity for disposal of 1.3 km/tonnes, with a range of between 0.4—2.3 km/tonne.

Table 5-6 shows estimated fuel consumption for waste collection and transport. Supporting Information D gives a breakdown on LGA average fuel consumption. Overall, approximately 16,300,000 litres of diesel fuel was consumed in 2018-19 for organic waste collection and transportation, with approximately 25,000 litres consumed via rail transport. This is compared to a combined 661 million litres of diesel fuel consumption for rigid, articulated, and non-freight carrying trucks in NSW for the 2018-19 period (ABS, 2020).

Kerbside collection was responsible for approximately 88.6% of all fuel consumed and therefore is a significant contributor to emissions, and also had the highest fuel intensities, at 8.23 L/tonne waste managed, and 1.03 L/km travelled. Recovery transfer to AWT facilities (via road) also had high fuel intensity on a fuel consumed per tonne of waste managed basis compared to recovery transfer to compost facilities. Bin pickup was the most fuel intensive component of kerbside collection, which included both stop-and-go travel at low speeds between collection points, and the lifting of bins into the vehicle receptacle using a hydraulic lifting arm. Stop-and-go travel accounted for approximately 85% of bin pick up emissions (approximately 9,980,000 L), with hydraulic lifting accounting for the remaining 15% (1,760,000 L). Average kerbside collection fuel intensity was highest for FOGO waste collection, at approximately 13 L/tonne collected, compared to 10.4 L/tonne for GO waste collection, and 7.3 L/t for mixed waste collection. While average fuel intensity is highest for FOGO collection, there are only 5 LGAs that have this service, including 3 LGAs classified as regional. As such, fuel intensity for FOGO collection is impacted by other factors, including LGA size as regional LGAs are larger, and have greater between bin distances (see Table 5-6). Overall fuel intensity for organic waste managed in the study area was 8.86 litres per tonne, and 0.87 litres per kilometre travelled. These metrics are compared with validation data from the literature in Section 5.5.

Table 5-6: Estimated annual diesel fuel consumption by waste collection and transport vehicles for the management of organic waste in the study area for 2018-19

	Total annual diesel fuel consumption [L/yr]	**Average fuel per tonne managed [L/t]**	**Average fuel per distance travelled [L/km]**
Total kerbside collection	*14,429,470*	*8.23*	*1.03*
Collection zone haulage (unladen)	361,777	0.21	0.09
Collection zone traversal	705,220	0.40	0.41
Bin pickup	11,739,066	6.69	2.74
Collection zone haulage (laden)	1,623,408	0.93	0.41
Total recovery transfer (incl. return)	*1,178,288*	*0.77*	*0.32*
Transfer station to composters	352,012	0.39	0.24
Transfer station to AWTs (road)	801,234	1.26	0.24
Transfer station to AWTs (rail)	25,042	1.96	7.50
Total disposal transfer (incl. return)	*684,282*	*0.31*	*0.24*
Transfer station to landfills	475,266	0.28	0.24
Composters to landfills	6,545	0.46	0.24
AWTs to landfills	202,471	0.41	0.24
Total	*16,292,040*	*8.86*	*0.87*

5.4.2. Organic waste collection and transport emissions, and emissions intensities by activity

Table 5-7 shows overall waste collection and transport emissions, and average emissions intensity per tonne for each waste stream. Emissions intensity is calculated on a per-tonne waste generated basis, and on a per-tonne waste managed basis, that is, the amount of waste collected or transported for each component. Overall, approximately 43,700 tonnes of CO_2-equivalent emissions were emitted across the study area for 2018-19 through kerbside collection and organic waste transportation. Overall emissions intensity in 2018-19 was 24.9 kgCO_2-e per tonne of waste generated, and 11.8 kgCO_2-e per tonne weighted by quantities managed for each component. The overall impact of waste collection and transport emissions on state-wide emissions from all sources was small. In 2018-19, approximately 136,570,000 tonnes of CO_2-e emissions were reported for NSW across all economic sectors (DISER, 2021a). The overall contribution of waste related transport emissions from the study area was therefore less than 0.01%. Road transport emissions for medium-duty trucks was reported as approximately 2,356,000 tonnes CO_2-e, with waste related transport in the study area contributing approximately 2% to these emissions.

Table 5-7: Annual estimated emissions and emissions intensity for organic waste kerbside collection, and recovery and disposal transfer in the study area by waste stream for 2018-19

Total annual emissions	**Overall GHG emissions [tCO_2-e]**	**GO waste GHG emissions [tCO_2-e]**	**FOGO waste GHG emissions [tCO_2-e]**	**Mixed waste GHG emissions [tCO_2-e]**
Total kerbside collection	*38,671*	*10,271*	*2,997*	*25,403*
Collection zone haulage (unladen)	970	214	47	708
Collection zone traversal	1,890	513	156	1,221
Bin pickup	31,461	8,578	2,579	20,303
Collection zone haulage (laden)	4,351	965	215	3,170
Total recovery transfer (incl. return)	*3,158*	*680*	*263*	*2,214*
Transfer station to composters	943	680	263	0
Transfer station to AWTs (road)	2,147	0	0	2,147
Transfer station to AWTs (rail)	67	0	0	67
Total disposal transfer (incl. return)	*1,834*	*13*	*4*	*1,816*
Transfer station to landfills	1,274	0	0	1,274
Composters to landfills	18	13	4	0
AWTs to landfills	543	0	0	543
Total	*43,663*	*10,964*	*3,265*	*29,434*
Average emissions per tonne of waste	Overall GHG emissions [$kgCO_2$-e/t]	GO waste GHG emissions [$kgCO_2$-e/t]	FOGO waste GHG emissions [$kgCO_2$-e/t]	Mixed waste GHG emissions [$kgCO_2$-e/t]
Total kerbside collection	*22.05*	*27.82*	*34.71*	*19.57*
Collection zone haulage (unladen)	0.55	0.58	0.55	0.55
Collection zone traversal	1.08	1.39	1.81	0.94
Bin pickup	17.94	23.24	29.87	15.64
Collection zone haulage (laden)	2.48	2.62	2.49	2.44
Total recovery transfer (incl. return)	*3.65*	*1.87*	*2.99*	*5.37*
Transfer station to composters	2.09	1.87	2.99	0.00
Transfer station to AWTs (road)	6.78	0.00	0.00	6.78
Transfer station to AWTs (rail)	0.70	0.00	0.00	0.70
Total disposal transfer (incl. return)	*1.68*	*2.70*	*2.03*	*1.67*
Transfer station to landfills	1.16	0.00	0.00	1.51
Composters to landfills	0.02	2.70	2.03	0.00
AWTs to landfills	0.50	0.00	0.00	2.21
Total (tonnes generated basis)	*24.90*	*29.70*	*37.81*	*22.67*
Total (tonnes managed basis)	*11.76*	*14.87*	*18.48*	*10.52*

Management of the mixed waste stream was responsible for approximately 67% of all emissions—expected given the large quantities of mixed waste generated compared to the other streams (approximately 1.3-million tonnes compared to combined 451,000 tonnes for GO and FOGO). Kerbside collection across all waste streams was the activity with the greatest impact on emissions, responsible for approximately 89% of all emissions. This proportion was highest for GO and FOGO waste streams, where kerbside collection was responsible for 94% and 92% of emissions respectively.

The mixed waste stream had the highest proportion of recovery and disposal transfer contributing to overall emissions, at 8% and 6% respectively. Compared to GO and FOGO recovery, mixed waste recovery transfer was more emissions intensive on a per tonnes transported, given the smaller waste quantities and greater distances travelled from transfer stations to AWT facilities, compared to composters. The proportion attributed to disposal transfer is also higher for mixed waste, given that a fraction of mixed waste is diverted to landfill from transfer stations after collection. FOGO was the waste stream with the highest average emissions intensity, expected given the high fuel intensity of kerbside collection of FOGO waste (Section 5.4.1). Recovery transfer emissions intensity is also higher for FOGO compared to GO. This indicates for those LGAs where FOGO is collected, FOGO waste is transported over greater distances to recovery compared to GO. Although this difference in intensity in small, it is likely a regional effect, where 3 out of 5 LGAs with FOGO services are located outside the metropolitan area, where there are fewer recovery facilities located in proximity to transfer stations. Recovery transfer intensity was significantly higher for mixed waste, due quantities of mixed waste for recovery transported to a fewer number of AWT locations distributed through the study area.

Considering that kerbside collection emissions are responsible for the majority of waste management related transport emissions, emissions intensity of kerbside collection is further examined in Figure 5-10. The figure also compares LGA size, and the proportion of dwellings that are multi-units (MUDs) with kerbside collection emissions intensity. A positive correlation was observed between kerbside collection emissions intensity and LGA size, with large LGAs generally located regionally or on the metropolitan-fringe, therefore having greater distances to travel to service properties. A negative correlation was found between the proportion of MUDs and kerbside fuel intensity, which is expected given that average between-bin distances and stop-and-go travel are reduced when servicing MUDs on account of there being several bins located on a single property lot. Dispersal of collection points is therefore an important factor when considering total mileage and fuel intensity, and thus GHG emissions, for kerbside collection services.

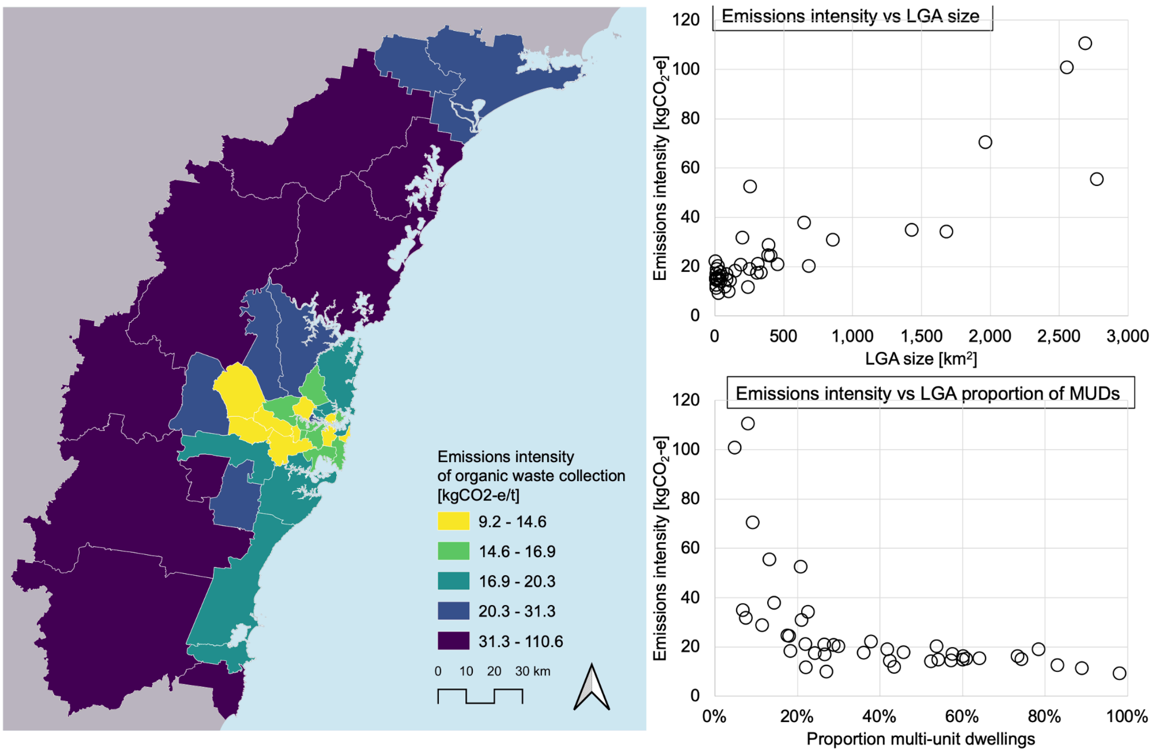


Figure 5-10: Spatial distribution of kerbside collection GHG emissions intensity, and correlations between LGA size and proportion of multi-unit dwellings in LGAs

While population and dwelling density are the important drivers of dispersal of collection points, and driven by urban planning policies and regulations, improving GHG intensity for GO and FOGO collection services could also theoretically be achieved through the deployment of community collection hubs, or other similar systems whereby household organic waste is collected at more centralised locations. Examples of this in the study area include a trial of centralised 'compost huts' servicing between 40-60 households, conducted by Inner West Council in 2017, where participating households could drop-off food scraps at council-managed public drop-off locations for on-site composting (Inner West Council, 2018). Another example was the 9-week trial of 'compost hubs' in Blue Mountains City Council also in 2017, which connected households that do not compost with households that do, in an effort to reduce food waste in the mixed waste bin (Blue Mountains City Council, 2022). Both trials saw reductions in food waste in the mixed waste bin for participating households over the trial period, however reduction in fuel requirements for collection were not objectives of either trial. Nevertheless, centralised collection systems have been shown to reduce fuel requirements of collection due to shorter distances being travelled by collection vehicles for the collection of plastic waste for recycling (Kerdlap et al., 2020).

In the context of organic waste, centralised collection locations could limit collection truck requirements, however would be likely be practical in locations with high density, where collection hubs could be placed in efficient locations limiting the need for vehicle transport. Such systems would also likely only be practical for small amounts of garden waste and food waste due to space limitations, making urban locations ideal candidates. Such a collection system however would place more of the burden of waste management onto waste generators and the general public, which could lead to perverse outcomes including poorer diversion of organic wastes to recycling.

5.4.3. Comparison of emissions intensities between organic waste management pathways

Figure 5-11 compares average kerbside collection and transport emissions across LGAs classified by organic waste management pathways employed. Data presented in this figure is different to data in Table 5-7, which presents emissions by management of each waste stream individually. Kerbside collection intensity was lowest for the single LGA that collected mixed waste as the only pathway for organic collection, which was disposed directly to landfill. This is anticipated, given that only a single bin per-household is collected. For this LGA (Fairfield, located in Sydney's south-west), food waste is collected entirely in the mixed waste stream, with garden waste collected through council drop-offs at waste depots. Only 10 tonnes of garden was reported collected for this LGA in the time period via drop offs. Note that drop-offs are not considered in scope of our analysis.

For the remaining LGAs, those employing AWT, both on its own as the only pathway for organic waste management, and in combination with separate organic waste collection, had the lowest kerbside collection intensities. For the AWT only LGAs, low kerbside emissions are expected given, as noted above, that no separate organic bins are collected on a weekly or fortnightly basis. For GO+AWT and FOGO+AWT LGAs, these LGAs are located in denser areas, with average population densities of 3,639 and 2,687 persons/km^2 respectively, compared to the LGA average of 2,347 persons/km^2. Population (and dwelling) densities have been shown earlier to negatively correlate with fuel intensity and thus emissions intensity of kerbside collection.

Recovery transfer emissions intensity was highest for GO+AWT and FOGO+AWT LGAs. This is anticipated, given that additional transport flows are required compared to GO and FOGO only management.

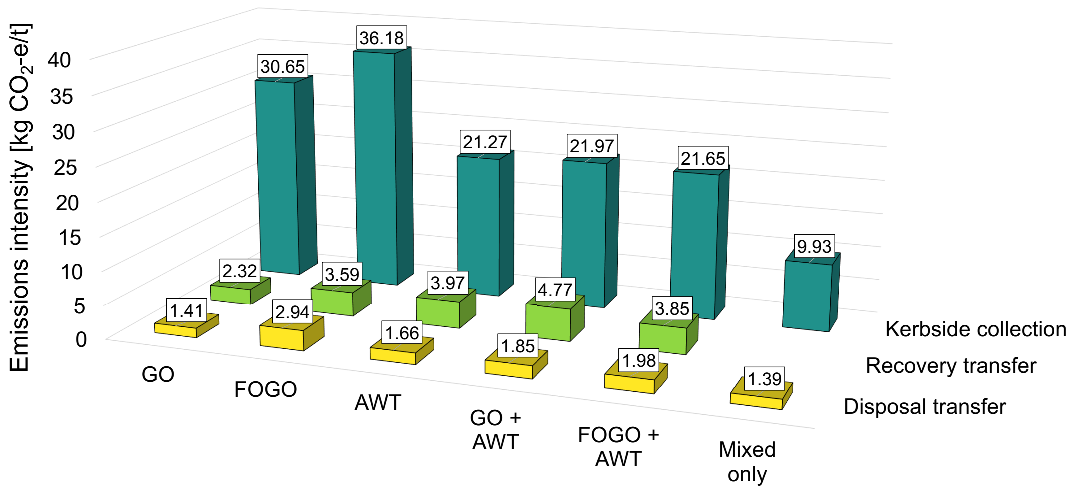


Figure 5-11: Comparison of average emissions intensities of kerbside collection, recovery transfer and disposal transfer for LGAs classified by organic waste management pathways employed

Table 5-8 compares transport emission intensities on a per tonne diverted from landfill basis, and total organics recovered across the organic waste management pathways employed, as a way to compare organic waste management performance across the LGA types observed. Data in Table 5-8 shows a correlation between increased levels of food separation and lower emissions intensity, with councils separating food waste through FOGO having the highest recovery rates, and lowest emissions intensity per tonne diverted. However, given the small number of LGAs for each pathway, variation (reported as standard deviation) in estimated emissions intensities is high. On average, emissions intensities were 96.26 kgCO_2-e per tonne of organic waste diverted. Note that these emissions intensity values do not include emissions generated from landfill disposal, nor do they consider emissions generated through recovery activities.

LGAs with FOGO collection had the highest recovery rates, and lowest emissions intensities of the LGA organic waste management pathways. LGAs with FOGO as the only organic recovery pathway had an average organic waste recovery rate of 68%, and emissions intensity of 73.83 kgCO_2-e per tonne diverted. With the addition of diversion of mixed waste to AWT (FOGO+AWT), average recovery rates increased to 77%, and average emissions intensity improved to 45.35 kgCO_2-e per tonne diverted. This indicates that while FOGO alone is an efficient collection stream for diverting food waste from landfill, there still remains a significant proportion of food waste in the mixed waste stream that can be managed via AWT. While the increase in collection and transport emissions intensity is significant for LGAs adopting AWT along with FOGO, this does not take into account emissions from the AWT recovery process itself, which due to the mechanical nature of AWT separation, would likely be higher than direct emissions from composting of FOGO.

LGAs with GO as the only organic recovery pathway had the lowest average recovery rate at 49% (excluding LGAs with no separate collection of organics or AWT diversion only), and highest average emissions intensity at 124.64 kgCO_2-e per tonne diverted. Figure 5-12 shows the spatial distribution of LGA emissions intensity by tonnes diverted across the study area. Many GO only LGAs were located regionally or on the metropolitan fringe, where kerbside collection distances and fuel consumption were significant. GO only LGAs with emissions intensity below the average for this pathway were located within the Sydney metropolitan area, where kerbside collection fuel intensity was lower, on account of higher dwelling density, and closer proximity of organic recovery facilities. With the addition of AWT diversion (GO+AWT), average recovery rate increases to 63%, and average emissions intensity improves to 80.25 kgCO_2-e per tonne diverted. While an improvement over GO only, the addition of AWT diversion does not improve efficiency to the levels seen with FOGO collection. This indicates that FOGO is the most efficient pathway for food and garden waste diversion in the study area. Based on this analysis, councils would likely be better off transitioning from GO to FOGO as a first step towards improved organic waste management under lower carbon emission policies, assuming composting is the recovery pathway for organic waste.

Table 5-8: Comparison of total organic waste generation and recovery, with average collection and transport emissions intensity per tonne of organic waste diverted for LGAs classified by organic waste management pathway for 2018-19

	Total organics generated, 2018-19 [tonnes]	**Total organics recovered, 2018-19 [tonnes]**	**Average recovery rate [-]**	**Average emissions intensity per tonne diverted [kgCO_2-e/t](St.dev)**
Mixed waste only LGAs (*n = 1*)	30,640	10	<1%	NA
GO only LGAs (*n = 17*)	458,867	226,344	49%	124.64 (98.91)
FOGO only LGAs (*n = 3*)	69,473	47,147	68%	73.83 (24.31)
AWT only LGAs (*n = 2*)	58,813	34,494	59%	83.73 (33.57)
GO + AWT LGAs (*n = 18*)	357,676	227,091	63%	80.25 (66.57)
FOGO + AWT LGAs (*n = 2*)	60,319	46,353	77%	45.35 (2.55)
All LGAs (*n = 43*)	1,035,788	581,428	56%	96.26 (78.6)

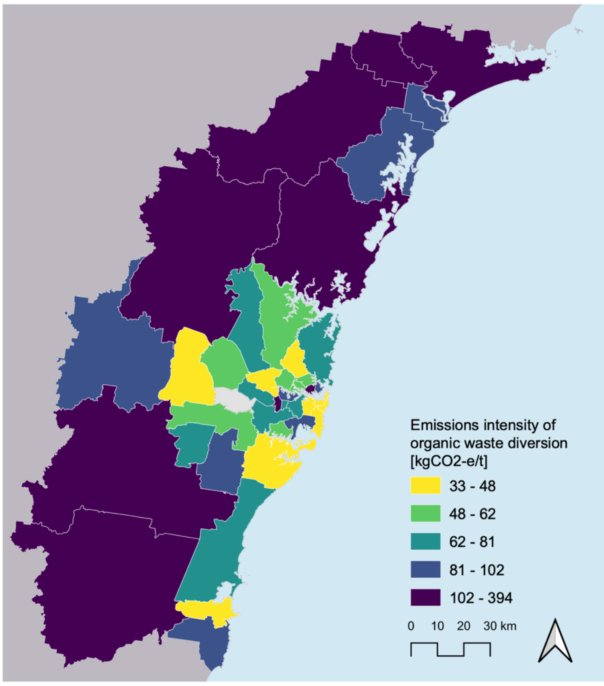


Figure 5-12: Spatial distribution of emissions intensity per tonne of organic waste diverted in the study area for 2018-19

Comparison of the different management pathways employed across the study area however is problematic, given the small sample sizes for each pathway as indicated in Table 5-8. For a fairer comparison, a simple scenario analysis was performed. For this, 3 LGA areas were selected, representing metropolitan, metropolitan-fringe, and regional LGAs: Burwood, Hornsby, and Lake Macquarie respectively. For the scenario analysis, 6 scenarios were analysed, assuming all 3 LGAs employed no separate organic pathway; GO only; FOGO only; AWT only; GO+AWT; and FOGO+AWT. Quantities of FOGO for Burwood and Hornsby were estimated assuming diversion from the mixed waste stream with a constant proportion of food waste in the FOGO bin of approximately 11% (Rawtec, 2020b). With FOGO employed, mixed waste was assumed to be collected at fortnightly instead of weekly intervals. Quantities of mixed waste diverted to AWT was estimated based on the average proportion of mixed waste sent to AWT across the study area. Estimated emissions for this scenario analysis by organic pathway and emissions component, as well as emissions per tonne managed and diverted are summarised in Table 5-9.

Table 5-9: Results of scenario analysis exploring emissions for different LGA organic waste management pathways

LGA scenario	Kerbside collection emissions [tCO_2e]	Recovery transfer emissions [tCO_2e]	Disposal transfer emissions [tCO_2e]	Overall emissions [tCO_2e]	Emissions per tonne waste managed [$kgCO_2e/t$]	Emissions per tonne waste diverted [$kgCO_2e/t$]
No organics	2,299	0	421	2,720	21.43	NA
GO only	3,350	132	261	3,743	29.50	75.22
FOGO only	3,255	150	240	3,644	28.72	64.90
AWT only	2,299	469	145	2,913	22.95	94.42
GO+AWT	3,350	403	93	3,846	30.31	56.23
FOGO+AWT	3,255	395	86	3,736	29.44	51.04

Findings from this scenario analysis were typically consistent with overall findings presented in Table 5-8. Lower emission intensities and higher recovery rates were observed as more of the organic waste stream was diverted from landfill to recovery. On an emission intensity per tonne of waste managed basis, GO pathways had higher emissions intensity than FOGO, by approximately 3%. This result indicates that both reduced volume and less frequent collection of mixed waste has an impact on gross collection and transport emissions, albeit the impact is small. Similar to Table 5-8, the addition of AWT to GO and FOGO management resulted in reductions in emissions intensity.

Results here indicate that improvements to organics recovery and emissions intensity could be achieved through increasing diversion of household food waste into the FOGO stream, through improved household communication and better disposal practices. This may have the effect of reducing the proportion of food waste in the mixed stream, and thereby making diversion to AWT redundant as a pathway for organic waste recovery. This is particularly relevant given recent decisions limiting the application of AWT derived organic products for soil improvement (NSW EPA, 2019a).

5.5. Model validation and limitations

Figure 5-13 compares sensitivity of overall transport emission to variation in kerbside collection distances, transport vehicle load capacities, and waste generation. Variation in kerbside collection distances as a result of stochastic uncertainty in outputs from the CVRP solution algorithm was relatively small, ranging from between approximately ±1%. This suggests that the solution algorithm converges on an optimal solution for each LGA that is roughly equivalent to a minimum distance that must be traversed in the LGA to service all properties. While the nearest neighbour search algorithm can be trapped in local optima, the large number of iterations performed for the CVRP solution gives some confidence that this is unlikely. Performing the CVRP on an even larger number of iterations as performed for this study, or utilising alternative solution approaches that appear in the literature including genetic algorithms, or swarm optimisation, may result in an improved solution. However these approaches were considered impractical for this study owing to the significant additional computational resources required for such a large study area analysed.

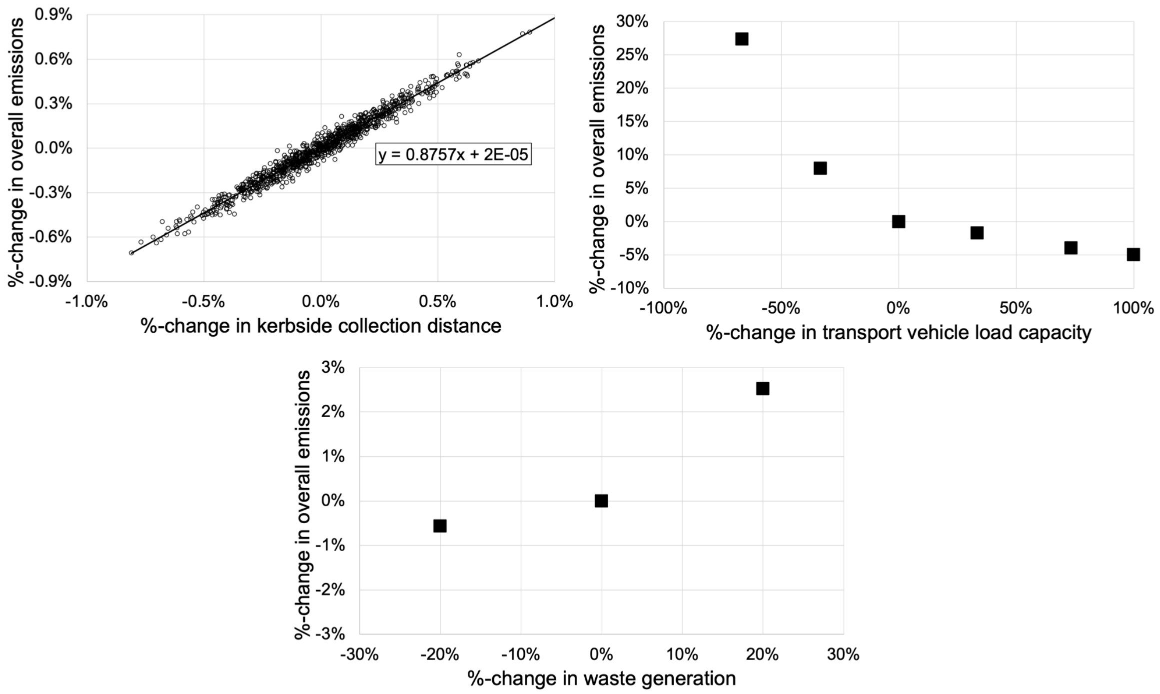


Figure 5-13: Sensitivity plots for change in kerbside collection distance, and change in transport vehicle load capacity

Bin pickup was the most significant component of kerbside collection as indicated in Table 5-7, however emissions from this component were not impacted by the CVRP solution. The mean sensitivity ratio of kerbside collection distance was approximately 0.88%/%, implying for a 1% change in kerbside collection distance, total emissions change by 0.88%. This sensitivity analysis performed for kerbside collection distances was simplified by estimating average variation in route selection by LGA classification—necessary due to the long computation times required for the CVRP solution algorithm. Despite this limitation, Figure 5-13 shows a linear relationship between %-change in kerbside collection route distance and variation in overall emissions, implying that even with a larger variation in these distance for example ±10%, the impact on overall emissions would be in the range of ±8.8%.

Variation in total waste generation (±20%) had a relatively small impact on overall transport emissions, with an approximate variation of between -0.6% and 2.5% in emissions. Results of the sensitivity to transport emissions to variation in waste generation are summarised in Table 5-10. Variation in recovery transfer and disposal transfer emissions were approximately equal to the variation in waste generation, however these components were only responsible for approximately 11% of overall emissions (see Table 5-7). The kerbside collection component exhibited different sensitivities, with both variation in waste generation above and below baseline levels leading to increases in emissions. Lower quantities of waste generated led an increase in kerbside collection emissions of 1.2%. With reduced LGA waste generation, fewer collection routes were required, however the average distance of these routes were longer than baseline in order to meet the constraints of the CVRP approach (i.e., collection trucks aim for approximately 5 tonnes of waste collected per route). The sensitivity analysis showed that a 20% reduction in waste generation across the LGAs resulted in a 1.5% increase in collection zone traversal distance, and a 22% increase in the average route length compared to baseline. For variation in waste generation above baseline, emissions compared to baseline were also higher, but only by approximately 1%. Total collection zone traversal distance increased by approximately 0.2%, and the average length per collection route decreased by approximately 1.4%. This implies that the CVRP estimation approach performs as expected with variation in waste generation across the LGAs, and gives confidence in the approach utilised.

Table 5-10: Summary of sensitivity of emissions to variation in LGA waste generation. Values in the table are compared to baseline

Variation in waste generation (% change)	**Variation in kerbside collection emissions (% change)**	**Variation in recovery transfer emissions (% change)**	**Variation in disposal transfer emissions (% change)**	**Variation in overall transport emissions (% change)**
+20%	+1.0%	+19.8%	+20.1%	+2.5%
-20%	+1.2%	-20.1%	-20.2%	-0.6%

Variation in transport truck sizes was found to be the more sensitive variable compared to variation in kerbside collection distances and waste generation. Small truck sizes (moving from the nominal value of 15 tonnes to 10 tonnes) lead to an average increase in emissions of approximately 8%. Larger truck sizes (moving from 15 tonnes to 26 tonnes) lead to an average decrease in emissions of 4%. The relationship between change in transport vehicle size and change in overall emissions is not linear as indicated in the figure. This suggests that transport truck sizes greater than 26 tonnes would have a reduced impact on overall emissions. Truck sizes smaller than 10 tonnes would have a greater impact on overall emissions, however this would imply little difference between waste collection vehicles and trucks used for transporting waste.

A further unknown in our model was the assignment of landfill locations to transfer stations and recovery distances based on proximity. To evaluate sensitivity on emissions, 3 candidate LGAs were selected (Burwood, Hornsby, Lake Macquarie) representing metropolitan, metro-fringe and regional LGA classifications. A simulation was performed whereby landfills were allocated to transfer stations and recovery facilities randomly over 1,000 iterations. Landfill locations were randomly selected from a weighted sample, whereby random selection of landfills at large distances from transfer stations and recovery facilities was less likely. Results of this showed that disposal transfer distances could vary by up to 85% higher than baseline distances. The impact of this variation on overall transport emissions however was small, at approximately 4%.

The sensitivity analysis performed highlights some limitations in our model. Transport vehicles are a significant unknown in our model, with little data on the fleet of vehicles used for transporting aggregated waste quantities available. A comprehensive account of waste vehicles in operation in the study area would be required to further calibrate our model to give more certainty around overall transport emissions. While sensitivity of kerbside collection route selection is relatively small, calibration data including actual waste collection route data, or information on LGA waste collection zones would improve our model and give more confidence that our CVRP solutions are sensible and reflect actual waste collection routes in the study area. Sensitivity on landfill selection was small, and how likely non-proximal landfills are likely to be selected for disposal from transfer stations and recovery facilities is unknown. Data on specific landfills to which waste is destined by jurisdiction and recovery facility would improve accuracy of the results.

A further limitation of our model is in the treatment of apartment complexes in the estimation of kerbside collection distances. While data is available on the estimated distribution of dwelling types at the property lot level, data is limited on the bin systems for multi-unit dwelling types. The model presented here assumes that most apartment style buildings have bin collection systems similar to detached dwelling types, and have their bins collected on the same route as detached dwellings. This is not strictly true, especially for larger apartment complexes, which are more likely to have separate waste collection agreements with the local waste management authorities, and different bin collection systems. These buildings therefore may not be managed via the same kerbside system that detached dwellings and smaller apartment buildings are serviced by. However data on the management of large apartment complexes on an LGA level for the study area is limited, and is problematic to obtain given privacy issues, and contractual agreements between apartment buildings, local council, and waste management service providers. It seems plausible however that regardless of the waste collection arrangement, waste collection vehicle travel between apartment complexes and transfer station, and hydraulic bin lifting requirements would be on the same scale as what is estimated here. Further analysis on apartment complex bin systems, and how individual LGAs manage apartment dwelling wastes would help to improve the certainty of model estimates, however was outside the scope of this work.

Despite these limitations, an analysis of calculated performance metrics from data generated from our model compared with literature data, gives confidence that our estimates are reasonable. Table 5-11 summarises this analysis. Literature cited in the table refer to studies performed across jurisdictions in a number of different countries, including South Africa, Taiwan, Denmark, Canada and the USA. Performance metrics compared to literature values were calculated from overall study area level estimates for emissions intensity of waste collected; and fuel economy of waste collection in terms of litres per kilometre travelled, and litres per tonne of waste collected. In general, performance metrics calculated from our model fall within, or close to, the ranges found in the literature, giving confidence that estimates from our model are realistic compared to other studies. This analysis also illustrates that emissions intensity and fuel intensity for waste collection in the study area are similar to values reported in the literature globally.

Table 5-11: Comparison of mean value performance metrics from this study, compared with data from literature sources

Performance metric	Mean value ±uncertainty from this study	Value range in the literature	Literature reference
Emissions per tonne collected [kgCO_2-e/t]	22.1±1.0	3.7 – 40.3 48.8 19.5-32.3 27.8±2.0	Friedrich & Trois (2013) Chen & Lin, 2008 Larsen et al. (2009) Nguyen & Wilson (2010)
Fuel economy of vehicles during collection [km/L]	1.12±0.05	0.6 – 1.4 0.46 – 1.34	Jaunich et al., (2016) Agar et al. (2007)
Litres of fuel per tonne waste collected [L/t]	8.2±0.4	1.4 – 10.1 10.1±0.7 7.1 – 10.6	Larsen et al. (2009) Nguyen & Wilson (2010) Quintili & Castellani (2020)
Litres of fuel per tonne diverted (FOGO) [L/t]	13.2±0.7	~17±5	Edwards et al. (2016)

5.6. Conclusion

This study developed a spatial model for the estimation of emissions associated with kerbside collection and transportation of household organic wastes in the Greater Sydney and surrounding areas for 2018-19. The estimation of waste collection emissions supports improved emissions accounting in the study area, which is essential for benchmarking and comparing against future waste collection systems and their impact on GHG emissions. The model developed was used to estimate waste related transport emissions of approximately 43,700 tonnes of CO_2-e for the management of kerbside organic waste. The modelling was novel, with the application of the capacitated vehicle routing problem applied to estimate GHG emissions being an innovative contribution of this work.

Kerbside collection, specifically the between-bin travel and lifting of bins to waste vehicle receptacles, was found to be the most emissions intensive activity completed during organic waste collection and transportation. Findings from the study indicate that kerbside collection emissions are lower for more population dense areas—suggesting that collection emissions might be reduced by moving towards more centralised waste collection models, where greater quantities of waste are collected per collection point. The practicalities of such collection systems however were not assessed in this work. The separation of food waste from mixed waste via the co-collection of garden and food waste, with additional diversion of mixed waste to AWT facilities, was found to be the most efficient collection model in the study area, in terms of tonnes of organic waste diverted, and lowest emissions intensity. Collection of food and garden organic waste should be prioritised for LGAs in the future in support of emission reduction strategies, given recent restrictions on the application of AWT recovered products applied to land. Findings from this study also indicate that organic waste collection and transport emissions do not contribute significantly to state-wide transport emissions.

The model presented here has value in assessing the environmental impacts of waste collection and management for waste streams in the study area. Moreover, the modelling and analysis supports progress towards United Nations Sustainable Development Goal (SDG) 11 – *sustainable cities and communities*. Specifically, SDG 11.2: *Safe, affordable, accessible, and sustainable transport systems*; and SDG 11.6: *Reducing the adverse per capita environmental impact of cities, including by paying special attention to air quality and municipal and other waste management* are addressed in this study.

Further work could incorporate this study's findings into a more comprehensive analysis of emissions over the entire waste management chain, including net emissions from the recovery of organic wastes, and emissions from landfill disposal. Moreover, results presented could be parameterised in order to estimate transport emissions from key variables, including population density, road network complexity, waste generation rates, and waste collection systems employed. The model presented could also be utilised to explore aspects of the waste management logistics chain, including more efficient routing to reduce labour costs, and also fuel costs—important when considering future scenarios exploring the electrification of the waste vehicle fleet. Future studies could also utilise the methodology developed for estimating emissions for collection and transport of non-organic materials including dry-recyclables to obtain a more complete estimation of waste-related emissions for the municipal waste stream in the study area.

Chapter 6.
Emissions from household organic waste management

While Chapter 5 presents estimates for the emissions intensity of household organic waste collection and transportation, the emissions associated with OFMSW over the entire waste management chain are still unclear. This can impact decision making on which areas along the waste management chain to prioritise when seeking the most impactful emissions reductions. This chapter presents yet-to-be-published research and analysis that helps fill this important gap in the knowledge, by addressing the following thesis research question:

Research question 4: What are the emissions associated with the recovery of household organic waste in NSW?

This thesis focuses on well-established recovery pathways internationally, that are either also established in Australia or under consideration for municipal scale deployment, namely: industrial composting, mechanical biological treatment, and anaerobic digestion, and are reviewed in the context of resource recovery and emissions potential in the following Section. While other recovery pathways such as combustion, pyrolysis, and to a lesser degree fermentation are utilised internationally, these are not considered in this PhD.

The research in this chapter extends the analysis in Chapter 5 on waste transportation emissions, to include emissions associated with organic waste recovery via the above mentioned pathways; lifetime landfill emissions; and avoided emissions from landfill diversion. Data generated from this study can help inform decision making towards lower-carbon waste management for the organic and other waste streams, including in technology and feedstock selection, optimal locations for infrastructure deployment, and in prioritising low-emissions pathways for optimal waste recovery.

The rest of this chapter is structured as follows: a comprehensive review of emissions associated with different organic waste management pathways is presented, to provide background on available organic recovery and management pathways in NSW, and their potential impact on emissions. A review of household organic waste management in NSW is also provided, to give background information on existing household organic waste management and baseline performance. The research approach undertaken for this analysis is then described in detail. Baseline results for the 2019-20 financial year are then presented, and implications of the research are discussed, and conclusions are made.

6.1. Organic waste recovery and impacts on GHG emissions

The management of organic waste carries an emissions burden from fuel and energy consumed, and from landfill gas emitted from disposal. This burden can be balanced by potential avoided emissions brought on by organic waste recovery. Selection of organics recovery technology is then important when considering net emissions in the context of the sustainable management of OFMSW (Yoshida et al., 2012). As mentioned in the introduction to this chapter, industrial composting, mechanical biological treatment, and anaerobic digestion are applied at varying scales in Australia for organic waste recovery. Other recovery pathways including combustion, pyrolysis, and to a lesser degree fermentation are utilised internationally, however are not deployed at scales necessary to address municipal organic waste. In the case of combustion or incineration, perverse outcomes including air emissions, and lack of demand for distract scale heating locally, has meant an overall lack of social acceptance for energy recovery, limiting its deployment at scale. In the case of more advanced recovery technologies including pyrolysis, gasification, and others, the lack of maturity at large scales necessary for treating OFMSW, and high capital costs, limits the commercial potential of these technologies in Australia in the short term for OFMSW scale waste.

6.1.1. Composting as a resource recovery pathway

Composting is a biochemical process, where under aerobic conditions and mediated by microbes, organic waste is degraded to form a stabilised material rich in nutrients, to be applied to land (Vergara & Silver, 2019). Industrial scale composting is the most widespread recovery pathway for OFMSW internationally (Asquer et al., 2017; Babu et al., 2021). Products obtained from composting are high in key nutrients required for plant growth, including nitrogen, phosphorus and potassium (NPK), and is also a pathway for capturing carbon in soils (Boldrin et al., 2009). As such, composted organic material can be used as fertiliser or as a soil additive, improving soil characteristics including pH buffering capacities, porosity and structure, nutrient retention, and bacterial diversity (Babu et al., 2021; Fernández-Delgado et al., 2020; Ferreira et al., 2010). Production of high-quality compost for organic fertiliser and soil improvers does not depend on the availability of mineral and fossil-derived resources or energy-intensive processes, and is therefore a significant advancement towards the circular economy where waste organics are reincorporated into the production cycle (Fernández-Delgado et al., 2020; Friedrich & Trois, 2013; Paungfoo-Lonhienne et al., 2019). Table 6-1 gives an overview of typical composting process types used in the recovery of OFMSW, adapted from Maturi et al. (2022), US EPA (2022) and DAWE (2012).

Table 6-1: Overview of composting technologies, adapted from DAWE (2012); Maturi et al. (2022); US EPA (2022)

Composting technology	Aeration	Investment cost	Land area required	Accepted materials
Windrow	Mechanical turning, passive	Low	Very large	Food waste; garden waste; fats, oils and greases; animal by-products
Vermi-composting	Passive	Low to medium	Large to medium	Food waste; garden waste; paper
Aerated static pile	Forced aeration	Medium	Medium	Food waste; garden waste; paper
In-vessel composting	Agitation, mechanical turning, forced aeration	Large	Medium to small	Food waste; urban sludge
Fully enclosed composting	Agitation, mechanical turning, forced aeration	Very large	Medium to small	Food waste; garden waste

Windrow composting, where compostable material is arranged in long rows in open-air, is the most common type of municipal scale organics composting, due to its low investment cost, and capacity to process large volumes of organic waste (Zhu-Barker et al., 2017). Composting windrows are typically laid out in lengths of 15 to 120 metres, and are 2 to 5 meters wide (Andersen et al., 2010), making the land requirements large. Diesel powered windrow turners are used to aerate compost to maintain optimal temperatures and introduce oxygen to the compost pile, performed up to every 3 days however turning frequency can vary dramatically from facility to facility (Zhu-Barker et al., 2017). Typical composting time can vary depending on the material being composted (woody biomass taking longer), size of windrows, and turning frequency. Compost time can be short, from weeks to around 3 months for immature compost; to 14 months for mature compost including higher proportions of woody biomass (ten Hoeve et al., 2019).

The net emissions from the composting of OFMSW is highly variable in the literature, likely a result of diverse municipal waste transport systems and characteristics of the waste stream, which can have a large impact on the overall emissions balance for the process. A flow diagram of windrow composting, including main processing steps and sources of emissions is shown in Figure 6-1, adapted from ROU (2006).

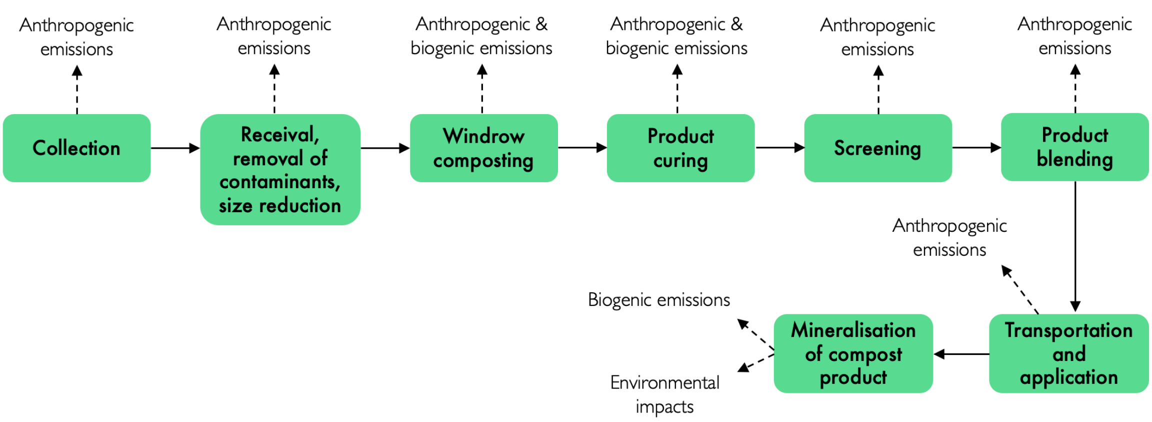


Figure 6-1: Flow chart of the windrow composting process, adapted from ROU (2006)

The direct CO_2 emissions from OFMSW composting and maturing (that is, from the aerobic decomposition of organic material) is biogenic in origin, and does not contribute to GHG emissions in most accounting frameworks (e.g., (DISER, 2021b)). Direct emissions of biogenic CO_2 however do account for over 90% of all direct emissions from windrow composting (Sayara & Sánchez, 2021). Several studies have evaluated the emissions associated with

OFMSW composting, finding that the process is overall a net emitter of GHGs (Friedrich & Trois, 2013; Komilis et al., 2004; Sayara & Sánchez, 2021; Scheutz et al., 2009; ten Hoeve et al., 2019). Friedrich and Trois (2013) for example found that composting 1 tonne of OFMSW in South Africa resulted in between 172 and 186 kg CO_2-e of emissions for in-vessel and windrow composting respectively. Overall net emissions accounted for in the literature typically come from direct methane and nitrous oxide emissions (between 220-370 kg CO_2-e in Komilis et al. (2004)), consumption of diesel fuel during feedstock preparation and compost pile turning, and the consumption of electricity on-site (Friedrich & Trois, 2013; Scheutz et al., 2009; ten Hoeve et al., 2019). Transportation of waste, including collection and transfer to recovery facilities can also be a significant part of overall emissions related to compost recovery, shown in studies including Friedrich and Trois (2013) and Yoshida et al. (2012). Emissions from OFMSW collection depend heavily on the spatial distribution of collection sites, which contribute to greater transportation distances, and thus fuel consumption and associated emissions.

Emissions savings from the mitigation of primary resource consumption and from avoided landfill emissions varies in the literature, dependent on the types of landfills utilised, and the composition of waste. In Friedrich and Trois (2013), emissions reductions were approximately 60-65 kgCO_2-e per tonne of OFMSW treated, however only the mitigation of fossil-fuel derived fertiliser and the capture of carbon in the soil is considered. This level of emissions savings is heavily dependent on the reliance of petrochemical-based fertilisers and the substitution rate of recovered organics. For example, in Boldrin et al. (2009) and Friedrich and Trois (2013), the substitution rate varies between 20-60%. Figure 6-2 shows a schematic representation of emissions savings from composting, assuming substitution of mineral based fertiliser and peat soil production, as per Boldrin et al. (2009). Note that recovered organics from OFMSW are not utilised for peat substitution in NSW as according to ROU (2006). Peat substitution is also not considered in Friedrich and Trois (2013).

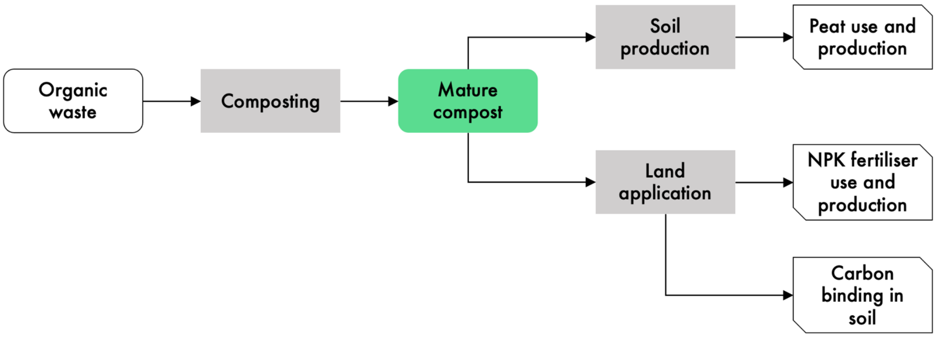


Figure 6-2: Schematic of system of analysis in Boldrin et al. (2009), showing compost substituting peat and mineral based fertiliser use and production, leading to emissions savings.

Besides the potential for emissions savings, there are numerous additional benefits of composting of organic waste beyond fertiliser substitution and landfill diversion that is outside the scope of this work. ROU (2006) in their LCA study of NSW composting, found several positive post-application benefits from compost derived from OFMSW when applied to cotton and grape cropland. These benefits included: reduced irrigation water use of up to 0.95ML per hectare, due to the improved soil retention properties of compost; reduction in herbicide (glyphosate) use of up to 6L per hectare; improvements in soil sodicity, reducing the need for gypsum by up to 5 tonnes per hectare; reduction of soil erosion by up to 4 tonnes per hectare annually; and increase in harvest yields for cotton and grapes by up to 22% and 27% respectively.

Considering the above, composting of OFMSW is beneficial from an emissions perspective when compared to the alternative of landfilling, and also offers numerous additional benefits to soil management. Even when accounting for the large land requirements, it is generally low-capital cost and resource (e.g., labour) intensive. The limitations of composting OFMSW for recovery are primarily concerned with applications of the end compost product. High recovery rates can typically be achieved with industrial scale windrow composting of up to 99% (NSW EPA, 2021), depending on the composition of the OFMSW, namely the presence of non-compostable materials and contaminants. In studies evaluating the composition of OFMSW streams, contaminants are typically up to 5% of the total waste stream (Hla & Roberts, 2015; NSW EPA, 2014a; Rawtec, 2020a), however contaminants measured at the input at composting facilities may be higher, as indicated in Wilkinson et al. (2021). Other feedstock characteristics affecting end-product quality include moisture content outside the ideal range of 50-60% for aerobic digestion (Wang et al., 2018); C:N ratio outside the ideal range of 25:1 to 30:1 (Babu et al., 2021); and sub-optimal pH, particle size, and control parameters including temperature during the composting process (Asquer et al., 2017). Compost quality however is most impacted by feedstock composition, including the presence of non-organics especially for MSW derived organics, illustrating the importance of source separation, and collection of clean organic feedstock. A recent review of recycled organics standards in Australia (Wilkinson et al., 2021) noted that challenges related to contamination in household garden waste have been addressed to varying levels of success by local governments, which is illustrated by the high recovery rates for separately collected organic waste in NSW (NSW EPA, 2021). The contamination challenges however are far greater with the co-collection of food and garden organics (FOGO). Indeed, as Wilkinson et al. (2021) found, the key challenges for existing and future organic recycling schemes especially in regards to FOGO collection, are not of a technological nature, but rather an effect of household waste disposal behaviours. This is an important challenge to address, as poor quality compost has fewer applications, with many jurisdictions limiting the application of poor-quality compost for food production (NSW EPA, 2019a). Instead, poor 'industrial' quality compost is typically applied as soil stabilisers, backfilling in construction and landscaping projects, and as an overlay or soil cap for sanitary landfills (Stunzenas & Kliopova, 2018). While still a benefit in comparison to landfill, these poorer quality recovery pathways have less of an impact in a circular economy perspective than via nutrient recycling.

6.1.2. Mechanical biological treatment as a resource recovery pathway

Locally referred to as 'dirty' material recovery facilities (MRFs), or alternate waste treatment (AWT) in Australia, mechanical biological treatment (MBT) is a process that combines the sorting and recovery of dry recyclable materials (e.g., metals, plastics, paper, glass), with composting or digestion of organic materials for mixed waste streams (Bourtsalas & Themelis, 2022; Połomka & Jędrczak, 2019). MBT is typically employed both as a recovery pathway, and for volume reduction and stabilisation of the waste before landfilling, which provides better sanitary and emissions outcomes than landfilling untreated mixed waste to landfill (Rigamonti et al., 2019). This makes the MBT pathway especially relevant for jurisdictions where there is poor source separation of MSW, or where organic waste is typically collected in mixed streams; and where there is a lack of mixed waste treatment infrastructure (Tyagi et al., 2021). Where municipal energy from waste is employed, MBT can also be utilised as a pre-treatment process—reducing moisture and low energy content material to improve energy recovery yields for processes including pyrolysis, or co-combustion with other high-calorific valued materials (Rigamonti et al., 2019; Tyagi et al., 2021).

MBTs are typically classified as single-stream or separate stream MBTs, with configuration typically determined by input stream characteristics and desired end-products, for example refuse derived fuels (RDF), or recovered organics products (Bourtsalas & Themelis, 2022). Material streams that cannot be easily recovered have value as a source of RDF, for example, for the cement industry, where emission reductions can be achieved through the replacement of fossil derived fuels for heat generation (Bourtsalas & Themelis, 2022). Figure 6-3 shows a schematic diagram of a typical single-stream MBT treating incoming mixed waste, derived from Ng et al. (2021). Recovery rates for dry recyclables through MBT can reach around 30-50% locally (NSW EPA, 2021; Pressley et al., 2015), however these rates are considerably lower than 'cleaner' dedicated dry recyclable MRFs (Pressley et al., 2015). The dry fraction is typically mechanically sorted/refined (Pressley et al., 2015; Rigamonti et al., 2019), while the organic fraction is treated via composting or AD (Ng et al., 2021). Outputs from treated organics via MBT are stabilised, but are typically of a poor quality, limiting application for industrial purposes only, due to presence of undesirable materials including plastics, metals and other contaminants (NSW EPA, 2019a; Stunzenas & Kliopova, 2018).

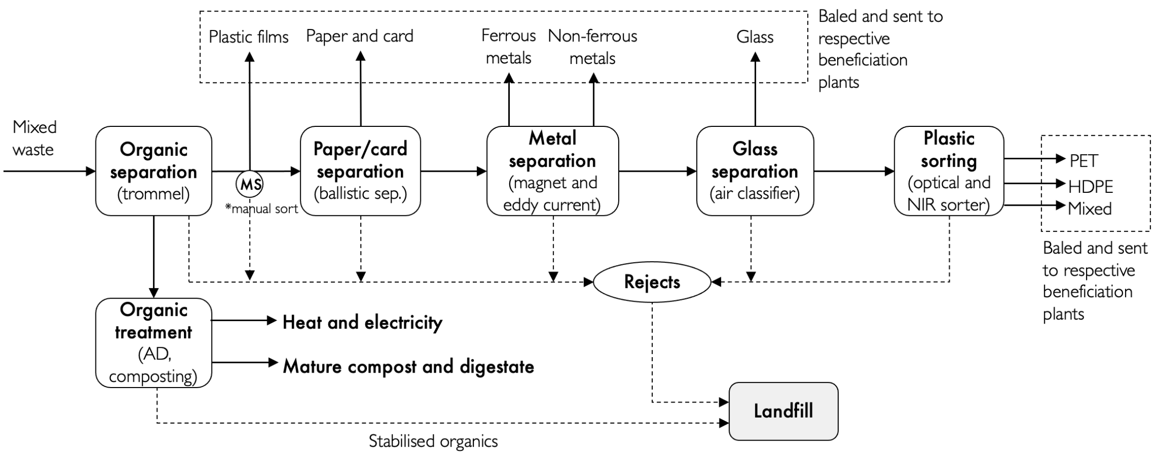


Figure 6-3: Schematic diagram of a typical MBT/AWT treatment facility, adapted from Ng et al. (2021)

Bourtsalas and Themelis (2022) found net emission reductions of between 0.2 to 0.6 tonnes CO_2-e per tonne of feedstock, dependent on the level of diversion from landfill, and if fuel (as biogas) was generated if AD is employed for organic treatment. In the case of Australia, where anaerobic digestion is not utilised at scale for OFMSW, composting is the pathway of organic waste recovery in AWT facilities. As such, emissions associated with organic recovery from the mixed stream, including avoided emissions, would be similar to that of composting. However, the additional mechanical sorting performed at MBT facilities would potentially lead to a greater emissions intensity per tonne of feedstock treated, given that the organic fraction must first be separated from the mixed waste to be further treated.

6.1.3. Anaerobic digestion as a resource recovery pathway

Anaerobic digestion is a complex biochemical process, where organic matter is degraded through a series of reactions into a methane rich (approx. 50-75%) biogas and concentrated solids, mediated by several micro-organics in oxygen-free conditions (Babu et al., 2021; Franca & Bassin, 2020; Jain et al., 2015). Figure 6-4 shows a generic schematic of the AD process for OFMSW, adapted from Gadaleta et al. (2021).

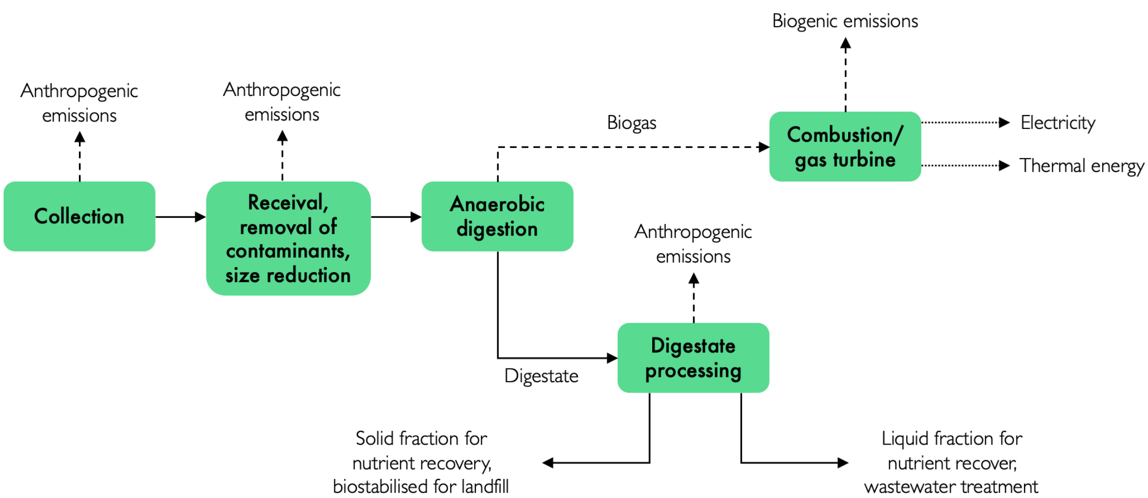


Figure 6-4: Overview of the anaerobic digestion process for OFMSW, adapted from Gadaleta et al. (2021)

Products from the digestion of OFMSW have valuable applications as a renewable clean energy source, and as fertiliser and soil conditioner rich in NPK (Babu et al., 2021; Campuzano & González-Martínez, 2016; Demichelis et al., 2022; Zamri et al., 2021). As such, the emissions reduction potential of digestion for the OFMSW stream is significant, especially when quality biogas is generated. Biogas from AD is high in methane content, and as such is a suitable alternative for fossil fuels in the generation of heat and electricity. Cudjoe et al. (2020) for example describe the environmental impacts of AD yields, reporting that AD could reduce global warming potential of OFMSW across China by up to 92.7%, through diversion of organic waste from landfill, and mitigation of fossil-fuel derived fertiliser and energy. Yields from the AD of OFMSW are however variable, dependent on a range of factors including feedstock characteristics, and digestion technology employed. Nevertheless, rising global nutrient prices, as well as landfill diversion directives and challenges associated with transitioning to fossil fuel alternatives, make AD a competitive option for organic waste treatment, compared to alternatives such as composting (Franca & Bassin, 2020).

AD technology is typically characterised by the operating temperatures, i.e., mesophilic at 35˚C operating temperature, and thermophilic at 55˚C (Kumar & Samadder, 2020); processing feeding mode, i.e., continuous, and batch; moisture characteristics of the substrate, i.e., wet or dry; and number of digestion stages (Franca & Bassin, 2020). Table 6-2 summarises digestor technology characteristics, derived from Kumaran et al. (2016). Dry mesophilic AD is most associated with OFMSW, and is classified where the feedstock has solids content in the range of 20-40% (Rocamora et al., 2020). Dry AD has been shown to be more robust and flexible in terms of feedstock input characteristics and in feedstock handling compared to wet AD, which is typically utilised for wastewater treatment, in addition to having greater biogas yields up to 10 times that of wet AD (Chiu & Lo, 2016; Rocamora et al., 2020; Zamri et al., 2021). Dry AD systems have large scale commercialisation in Europe, proving to be more efficient and often exhibit smaller costs than wet systems, given reduced requirement for dewatering after AD treatment (Franca & Bassin, 2020).

Table 6-2: Types of anaerobic digestion systems used in the treatment of OFMSW, adapted from (Kumaran et al., 2016)

Digester type	Description
Wet	Feedstock is diluted to make a substrate 10-15% solid content. Substrate must be continuous stirred for optimum gas production
Dry	Feedstock with solid content 20-40%. Dry anaerobic digestion is cheaper as the organic loading rate is higher, and thus more gas production per unit of the feedstock
Batch	Reactors are loaded with organic raw feedstock and inoculums from other digesters. Once all the organic material has been degraded, the reactor is emptied, cleaned and a new batch for digestion is added
Continuous	Most digesters for waste products are operated as continuous flow as restarting the system when economical is unfavourable. This system gives higher amounts of biogas per unit of feedstock, and the operating cost is also lower due to the reduction in start-up time
Single stage	Easy to operate, cheaper to construct compared to a multi-stage system. Limitations do exist since optimum conditions for all participating micro-organisms cannot be achieved in a single system, but methanogenic population in the system can be managed efficiently by controlling the feeding rate and ensuring through mixing, buffering, and additions of nutrients
Multi-stage	The digestion occurs in separate stages, allowing provision of optimum environmental conditions for each microbial group. Usually two digesters are employed, and separation of acetogenesis stage from methanogenesis stage often results in increased process efficiency

Feedstock availability and quality is an important consideration for substrate selection, and therefore technology selection. In Europe, most AD plants are mainly operating using livestock and other agricultural residues and energy crops (Grando et al., 2017; Zamri et al., 2021). In Australia and also the United States, on the other hand, AD is mostly utilised in the treatment of wastewater sludge (Lou et al., 2013; Zamri et al., 2021), although some capacity, albeit small, exists for AD of municipal- and commercial-sourced dry organics in Australia (e.g., at Camelia in Sydney's West (EarthPower, 2022)). Pre-treatment, including grinding and screening of feedstock, is especially relevant for the AD of OFMSW, due to the presence of sub-optimal characteristics, including non-organic wastes and other materials that inhibit microbial activity (Zamri et al., 2021). When pre-treatment is employed, the energy requirements for AD correspondingly increase, however typically so do biogas and digestate yields.

From an emissions perspective, AD can have significant potential impacts on emissions avoidance from landfill diversion, and by offsetting emissions intensive fossil fuel consumption. In Lou et al. (2013), the authors estimated a potential 1,915 GWe, or 20,272 TJ of potential energy generation from food waste across Australia via AD. This potential energy generation could theoretically offset approximately 1.8 million tonnes of CO_2-e, or approximately 1% of total electricity sector emissions in Australia in 2013-14 (the year of that study). In Liu et al. (2017), the authors found that AD of OFMSW in China could lead to reduction in overall carbon intensity of waste management between approximately –27.7 kgCO_2-e/t to –54.8 kgCO_2e/t; finding that AD was the optimal technical route for MSW for source separated organic fractions. Findings in Cudjoe et al. (2020) showed that deploying AD for OFMSW across 31 provinces in China could reduce the carbon intensity of OFMSW management by up to 92%, resulting from landfill diversion and fossil fuel mitigation.

Despite the benefits, AD of OFMSW also faces some limitations. As noted previously, AD is sensitive to feedstock characteristics, including non-organic materials, which can inhibit microbial activity responsible for anaerobic degradation (Abad et al., 2019). Co-digestion of two or more substrates, including sewage sludge, can overcome this, however uncertainty in quality feedstock supply makes investment in AD a risk (Zamri et al., 2021). Indeed, biogas and digestate yield and quality, and process efficiency, is highly dependent on feedstock characteristics. Ensuring ample supply of quality organic substrate is then critical for commercial deployment of AD at scales necessary for OFMSW treatment, and for the realisation of the GHG reduction potential of AD.

6.1.4. Emissions from landfill disposal

While not an OFMSW recovery pathway, landfill is currently the primary management pathway for the OFMSW fraction in NSW. Emissions from landfill disposal in the form of landfill gas (LFG) are a significant contributor to emissions globally accounting for up to 5% of all global GHG emissions (Zhang et al., 2019), and an estimated 2% of all GHG emissions in NSW (DPIE, 2021). Therefore, LFG emissions are an important consideration when assessing the emissions intensity of waste management. Considering that OFMSW recovery ensures a proportion of organic waste generated is not disposed to landfill (or at least, a proportion of disposed material is bio-stabilised), diversion of waste to landfill is a significant part of overall emissions avoidance from OFMSW recovery.

Landfill technology has advanced over many decades, with contemporary sanitary landfills being designed to store waste, and to some degree, to also treat wastes in order to minimise the impact of disposal on the environment, including for example impacts of leachate on groundwater supplies (Vaverková, 2019). Figure 6-5 shows a diagram of a typical sanitary landfill, adapted from Scheutz and Kjeldsen (2019), and Figure 6-6 shows an example sanitary landfill located in Wollert, Victoria, taken from the *National Waste Report 2020* (Blue Environment, 2020). Modern sanitary landfills are engineered structures, consisting of bottom liners typically of non-permeable clay, plastic, or concrete (Pathak et al., 2016); leachate and LFG collection and removal systems; and a final organic soil layer cover. Leachate is formed from precipitation interacting the deposit wastes, and although the unmitigated impact of leachate on groundwater can be severe, leachate emissions are not in scope of this work.

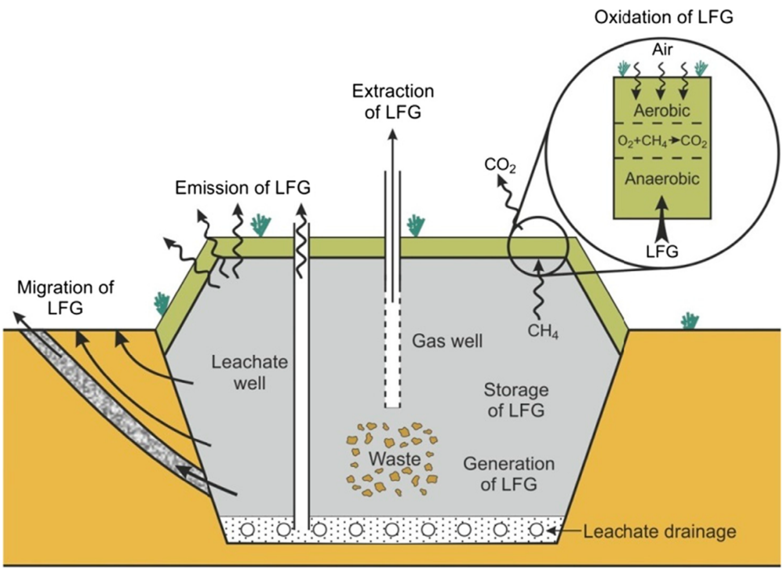


Figure 6-5: Process affecting the fate of methane generated in a sanitary landfill, adapted from Scheutz and Kjeldsen (2019)

Figure 6-6: Sanitary landfill in Wollert, Victoria, from Blue Environment (2020)

LFG produced in MSW landfills is high in methane (between 45-60%) on account of the high proportions of organic waste in MSW streams, and is produced via a number of biological process over several years as the disposed waste degrades. Figure 6-7 shows the production and composition of landfill gas generation over time, taken from the Centres for Disease Control and Prevention primer on landfill gas (CDC, 2008). The 4 phases in the diagram refer to the primary process that produces landfill gas, with Phase I being dominated by aerobic microbial activity; Phases II and III dominated by anaerobic microbial activity; and Phase IV corresponding to a stabilisation of gas production.

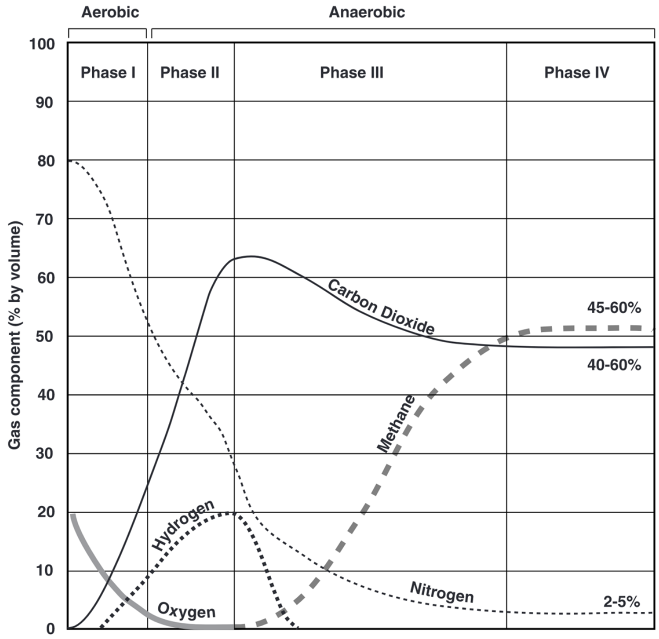


Figure 6-7: Changes in typical landfill gas composition over time, after waste placement, from CDC (2008)

While CO_2 is also produced from the aerobic degradation of waste as well as from oxidation of methane through the upper layers of the landfill, the CO_2 portion of LFG is considered biogenic and part of the natural carbon cycle. As such, these emissions are not typically considered in landfill emissions accounting, as is the case in Australia (DISER, 2021b). LFG that is captured on site and combusted to form CO_2 and water vapor, and the oxidation of methane to CO_2 through filtration of the LFG through the soil cap are also considered biogenic. Therefore what is considered in GHG accounting of landfill emissions is the non-captured methane and nitrous oxide portion of the LFG, which have global warming factors factor of approximately 28 and 265 respectively (DISER, 2021b). That is to say, methane/nitrous oxide are approximately 28/265 times more potent as a GHG to anthropogenic climate change than CO_2. With up to 30% of methane emissions from OFMSW occurring within 2 years of landfill disposal (Liu et al., 2017), avoiding landfill emissions of organic wastes is a priority for waste management for many jurisdictions around the world, including in Australia (DPIE, 2021).

Combustion of LFG, both as a form of energy conversion, and flaring of LFG to the less impactful CO_2, are crucial components of low-carbon waste management with respect to landfills. As indicated in Ayisi et al. (2022), LFG capture and energy conversion systems are mature globally. Indeed, some environmental regulations require that LFG be captured and flared or converted to energy, such is the case in the European Union, where the Landfill Directive, which regulates the management of landfills in the EU, states:

> "[LFG] shall be collected from all landfills receiving biodegradable waste and the [LFG] must be treated and used. If the gas collected cannot be used to produce energy, it must be flared" (Directive 1999/31/EC, 2018, p. 21).

Similar regulations exist in Australia, including the NSW Protection of the Environment Act (1997), which stipulates that landfills must minimise the emissions of untreated LFG to the atmosphere and minimise offensive odours. LFG capture has also been incentivised under the Clean Energy Regulator's Emissions Reduction Fund, which provides credits for the flaring and generation of energy from LFG capture (Clean Energy Regulator, 2021). Given these mandatory conditions and incentives, approximately 85% of Australian landfills capture LFG (LMS Energy, 2021) with around 40-50% of captured gas recovered for energy (Blue Environment, 2020).

Some recent studies have evaluated the impact of LFG management on low carbon and circular economy transitions for the waste management sector. Kurniawan et al. (2022) for example showed LFG can be utilised to generate approximately 0.04 kWh/tonne of landfilled waste at a sanitary MSW landfill in Jakarta, Indonesia—equivalent to 26,000,000 Mt of CO_2-e avoidance over a 100 year timeframe. Winslow et al. (2019) performed an economic and environmental assessment on LFG to vehicle fuel conversion in the USA, with their findings indicating that emissions reductions can be achieved due to mitigating fossil fuel consumption and methane emissions from LFG, however the financial viability was found to rely on government financial incentives. LCA studies performed (e.g., Damgaard et al. (2011); Lee et al. (2017)) have shown that proper LFG management including flaring and conversion to energy can have a significant reduction on the environmental impact potential of landfills, with overall emissions for LFG capture and conversion up to 44% lower than MSW without such technology (Lee et al., 2017). The estimation of landfill gas emissions is discussed in further detail in Section 6.3.

6.1.5. Emissions from other sources

Waste related emissions accounts in Australia consider only the emissions from landfilling and from the breakdown of organic material via composting (DISER, 2021b). Emissions from recovery processes together with waste transportation emissions (i.e., from the combustion of vehicle fuel) are not attributed directly to waste management in Australian emissions accounts. Indeed, the emissions attributed to waste collection and transport are significant, and should be considered as part of any carbon footprint analysis or emissions accounting for resource recovery activities.

While some studies exploring the carbon footprints of waste treatment pathways have also considered the impact of waste collection and transportation on overall emissions intensity, these studies are limited. Yoshida et al. (2012) for example, found waste collection and transportation accounted for approximately 69% of the overall net emissions intensity of organic waste composting in Madison County, Wisconsin USA, using an assumed average 50km collection and transport distance. The transport component (that is, transportation of collected waste to composting facility), accounted for approximately 6% of the overall net emissions intensity. This is a similar finding to Friedrich and Trois (2013), which found waste transport accounted for approximately 4% of the overall emissions intensity of OFMSW composting. Importantly, Friedrich and Trois (2013) did not account for waste collection in their study, and used an average 30km transportation distance. LCA studies often employ average collection and transport distances or impact factors (e.g., Sonesson (2000)) however these are typically based on default values and not necessarily relevant to the region being investigated—a criticism raised in Edwards et al. (2016). Indeed, Boldrin et al. (2009), an influential study exploring emissions associated with OFMSW management, did not consider waste collection or transportation at all in their study, citing lack of data required to estimate associated emissions. While other studies do explore waste collection and transport from fuel consumption (e.g., Edwards et al. (2016)); optimal collection routing (Hannan et al., 2018); and cost (Karadimas et al., 2007) perspectives, studies evaluating waste collection and transportation emissions, and comparing these to overall waste-related emissions are limited. Ultimately, without accounting for waste collection and transport emissions, the carbon footprint of waste systems or processes investigated may be significantly under-estimated. This is especially true in locales such as NSW and around Australia, which are characterised by large transport distances between regional centres, and high levels of suburban sprawl on the periphery of cities. Moreover, the potential emissions reductions can also be inaccurate by not accounting for collection and transport—especially if a recovery process considered has considerably greater collection or transport requirements (e.g., FOGO collection, or transportation to a facility not in proximity to locations of waste generation).

6.2. Household organic waste management in NSW

This section provides a short review of the management of household organic waste in NSW during the study time frame (2019-20). Household organic waste is typically managed via kerbside waste collection services in NSW, with some organics managed through household 'drop-offs' at specified organic collection points, including transfer stations, and landfills. Separately collected (that is, not comingled) organic waste is collected at the kerbside via separate garden organics (GO) fortnightly bin collection, or for some council areas, food organics and garden organics (FOGO) weekly bin collection (mutually exclusive with GO), where food and garden waste are comingled. The number of council areas employing FOGO collection has increased in recent years, however this expansion in services has mostly been in regional areas of NSW, with a slow uptake in Sydney and other metropolitan areas (Surdo & Gupta, 2021). Despite this, expanded FOGO collection to cover all households in NSW has been identified as a key part of future organic waste management in the *NSW Waste and Sustainable Materials Strategy* (DPIE, 2021). Table 6-3 gives a summary of the number of households with each kerbside collection service in NSW, and overall volumes collected across all NSW for 2019-20.

Table 6-3: Summary of number of households and quantities of waste collected for waste streams containing organic wastes, from NSW EPA (2021)

Waste collection service	Households serviced in 2019-20 (state-wide) [hhlds]	Quantities of waste collected at kerbside in 2019-20 [tonnes]
Separate GO collection	1,514,948	405,717
Separate FOGO collection	550,435	215,899
Mixed waste	2,952,576	1,718,474

Generally for FOGO bins in NSW, food makes up approximately 12% of what is collected (Rawtec, 2020a). Each council area across NSW also has a mixed waste weekly bin collection service which is typically disposed to landfill, or for a few councils in NSW (23 in 2019-20), is sent to AWT/MBT facilities for recovery (NSW EPA, 2021). Note that councils with FOGO services typically collect mixed waste bins at fortnightly instead of weekly intervals. Figure 6-8 shows the breakdown of total household organic waste collected in NSW by waste collection service. The proportion of organic waste in the mixed waste bin is high, and typically consists of food waste (e.g., kitchen scraps), and is thus the main source of household organic waste that is disposed to landfill. The proportion of food waste in the mixed waste stream is on average between 23% and 38% (Rawtec, 2020b); and councils with FOGO services typically seeing smaller proportions of food waste in the mixed waste bin. As such, council areas with FOGO services have average food waste diversion rates of up to 44% (Rawtec, 2020a).

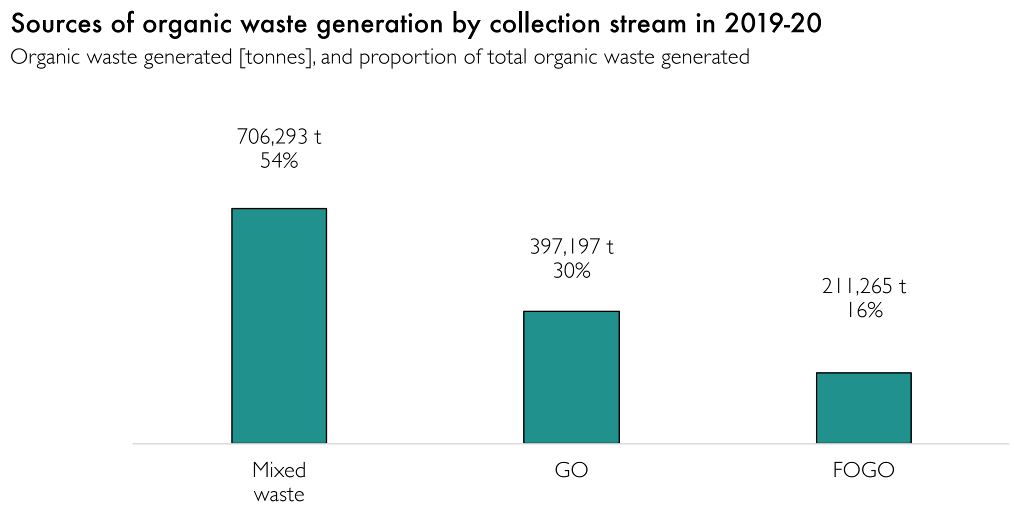


Figure 6-8: Breakdown of organic waste collected by waste collection stream in 2019-20, derived from data in NSW EPA (2021), Rawtec (2020b), and Rawtec (2020a)

Separately collected household organic waste (i.e., GO and FOGO wastes) are typically managed through compost facilities for organic waste recovery. As is the case internationally, windrow composting is utilised for large scale compost processing for the majority of collected household organics, with in-vessel composting and aerated static pile composting also employed at smaller scales (DEC, 2007). AD is currently not utilised at large scale for household organics in NSW, however is identified as an important future recovery pathway in the *NSW Waste and Sustainable Materials Strategy* (DPIE, 2021). Table 6-4 gives a summary of recovered quantities of organic waste and recovery rates by waste stream for all of NSW in 2019-20. Compost recovery of GO and FOGO have high rates of recovery, at approximately 99% and 96% respectively. Differences in recovery rates for these streams can mostly be attributed to higher levels of non-organic or non-compliant organic material (e.g., meat) in the FOGO stream compared to the GO stream (Rawtec, 2020a). Organic waste recovered from the mixed waste stream is done so via AWT. Overall organics recovery from the mixed waste stream is low, at approximately 7% in 2019-20. In total, approximately 122,900 tonnes of mixed waste (organic and non-organic waste) was recovered at AWT facilities, with an average AWT recovery rate of approximately 27% of incoming waste, or approximately 49% of incoming organic waste (NSW EPA, 2021). An important consideration with AWT is the quality of the recovered material stream. The NSW Environment Protection Authority recently restricted the application of AWT derived secondary organics to land, due to problems with contamination levels of the recovered stream (NSW EPA, 2019a; Wilkinson et al., 2021). Despite this, AWT is still seen to be an important part of the municipal waste management system moving towards 2030 and beyond, at least for contributing towards landfill diversion and mitigating the need for future landfill expansions, and subsequent emissions reductions (DPIE, 2021). As a pathway for organics waste recovery however, system intervention is needed beyond AWT recovery for the mixed waste stream, where the majority of household organics waste is found.

Table 6-4: Organic waste management performance in NSW for 2019-20 (NSW EPA, 2021)

Waste collection service	Total waste recovered in 2019-20 [tonnes]	Recovery rate [%]
Separate GO collection	400,334	98.67%
Separate FOGO collection	208,201	96.39%
Mixed waste	122,855	7.15%

6.3. Approach for estimating emissions from household organic waste management

The aim of the research presented in this chapter was to examine the waste recovery and GHG emissions potential of the household organic waste stream in the Greater Sydney and surrounding areas in NSW, Australia (note that the geographical scope of this work is the same as in Chapter 5). GHG emissions as CO_2-equivalent associated with the management of household organic waste, including collection, recovery and disposal were estimated, along with the emissions reduction potential in terms of avoided landfill gas emissions, and fossil fuel mitigation.

Other studies appearing in the literature examine emissions for recovery pathways for OFMSW. For example, Paes et al. (2020) examined the transition towards eco-efficient management of municipal waste across regions in Brazil, by estimating the emissions generation and prevention for several organic (and dry recyclable) waste management pathways. The authors found that a mix of 70% composting and 30% landfilling with methane capture was the most eco-efficient pathway for municipal organics when factoring in emissions reductions and recovery, and investment and operational costs. The authors also found that this outcome was sensitivity to socioeconomic factors, reflected in the composition of the municipal waste stream, which can have a significant positive impact on recovery efficiency, and recovered products (e.g., biogas) yields. Stunzenas and Kliopova (2018) assessed a number of organic municipal waste management options for regions in Lithuania in terms of organics (nutrient) recovery and biogas output. The authors found that improved source separation of organics at the household, coupled with treatment via anaerobic digestion at mechanical biological treatment facilities, could result in improved compost yields and quality, compared to existing composting management for OFMSW. Moreover, improved source separation was shown to lead to greater potential yields of biogas (4.7 times compared to non-source separated OFMSW), leading to significant potential net-emission reductions through mitigation of fossil fuel-derived fuels. Thanh et al. (2015) evaluated the potential environmental benefits from the introduction of composting of OFMSW on indicators including organic fertiliser production, landfill life extension, and GHG emission reduction. The authors found that composting of OFMSW in Hanoi can lead to landfill life extension from 0.5 to 8.7 years; and estimated GHG emission reduction between 15% to 98% compared to current practices prioritising landfill disposal.

Studies analysing the recovery and emissions reduction potential from OFMSW management pathways in detail for Australia and NSW are however limited, where energy recovery and advanced OFMSW recovery beyond composting are not applied at municipal scales. Lou et al. (2013) for example examined the theoretical maximum benefit of the digestion of municipal food waste in Australia in terms of energy recovery, and landfill diversion. That study found that multiple decentralised AD facilities across Australia could generate approximately 20.3 PJ of heating potential, or 1,915 GWe in electricity generation annually from OFMSW—equivalent to ~3.5% of Australian energy supply in 2013. Considering Australia's reliance on fossil fuel for electricity as well as prevalence of landfilling of organic wastes, OFMSW could contribute to important GHG emissions reductions in Australia as a source of renewable energy and as a pathway for landfill diversion. The study in Lou et al. (2013) however is limited for evaluating AD and OFMSW management pathways aligned with recent NSW circular economy strategy, as that study was Australian-wide, focussing on theoretical potential of AD of food waste from all sources. Dastjerdi et al. (2019) in their study of residual waste energy recovery potential, found that AD of municipal food waste in the mixed waste stream could have an emissions reduction potential of up to 634,000 tonnes of CO_2-e in NSW, from landfill diversion and mitigation of fossil fuels. That study however was focused only on the mixed waste (or residual) waste collection fraction, and did not consider separately collected organic waste, or the emissions associated with waste collection and transportation.

For this study, a modelling framework was developed in order to estimate these emissions associated with organic waste management and recovery, and is shown in flowchart form in Figure 6-9. The *waste collection and transport model* is based on the models developed in Chapters 4 and 5, with updated waste generation data for the 2019-20 financial year (NSW EPA, 2021). Data on organic waste throughputs at recovery facilities and landfills were integrated with energy requirements and emissions factors from the literature in an *organic waste recovery model* to estimate the net emissions associated with recovery of household organic waste at dedicated recovery facilities. For this component, a mass-balance model was developed based on Ng et al. (2021) and Pressley et al. (2015), whose work involved material flow analysis of various organic and non-organic waste sorting and recovery processes. The mass balance model was used to estimate the energy requirements of mixed waste sorting at AWT facilities, and associated emissions (scope 2 and 3). Literature data was utilised to estimate direct and indirect emissions for the organic waste recovery process at AWTs, and for recovery at dedicated composting facilities for the GO and FOGO streams. Avoided emissions were estimated based on quantities of waste diverted from landfill. A final modelling step, the *landfill emissions model* was used to estimate the lifetime emissions from organic waste disposed to landfill. For this, the accounting method employed in the Australian National Greenhouse Accounts (DISER, 2021b) was employed. Finally, estimates of waste collection, transport, recovery, and disposal emissions from the described modelling steps were combined, to give the overall net waste-related emissions for organic waste management in the study area. The following sub-sections describe these modelling steps and scenario analysis performed in further detail.

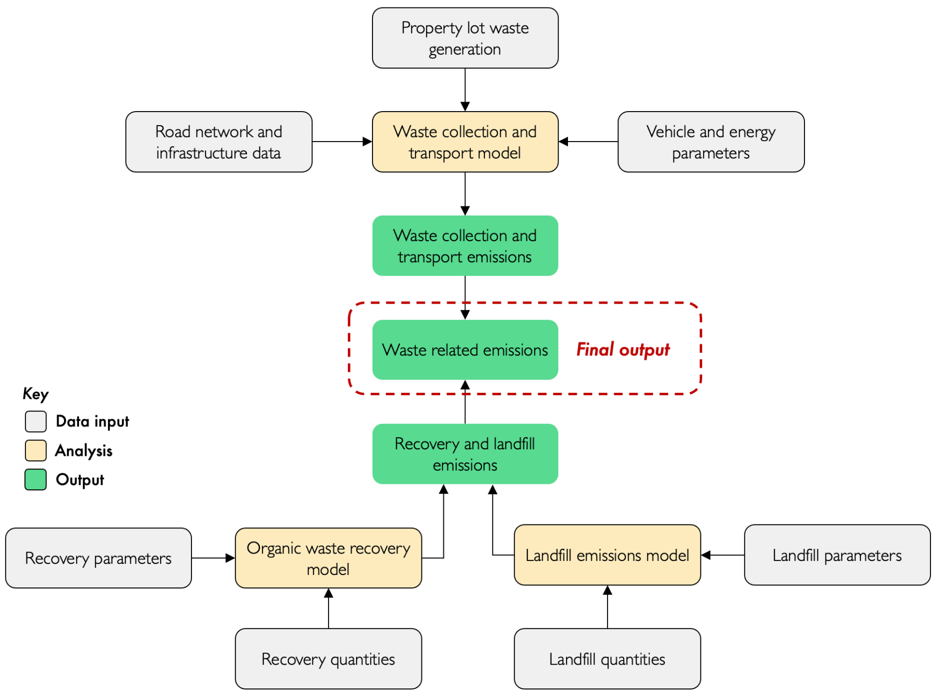


Figure 6-9: Methodological overview for this study

6.3.1. Study area and scope of analysis

Figure 6-10 shows the study area for this analysis, representing the Greater Sydney and surrounding areas, consistent with the geographical scope in Chapter 5. The study area includes 43 local government areas (LGAs) across the Sydney Metropolitan Area, Greater Western Sydney, Central Coast & Hunter, and the Illawarra & Shoalhaven regions, and is home to a combined population of approximately 6.3 million residents (ABS, 2021). With approximately 2.3 million households, the study area is a significant source of household organic waste, with approximately 1.8 million tonnes of waste collected in 2019-20 across the mixed waste, GO and FOGO streams (NSW EPA, 2021).

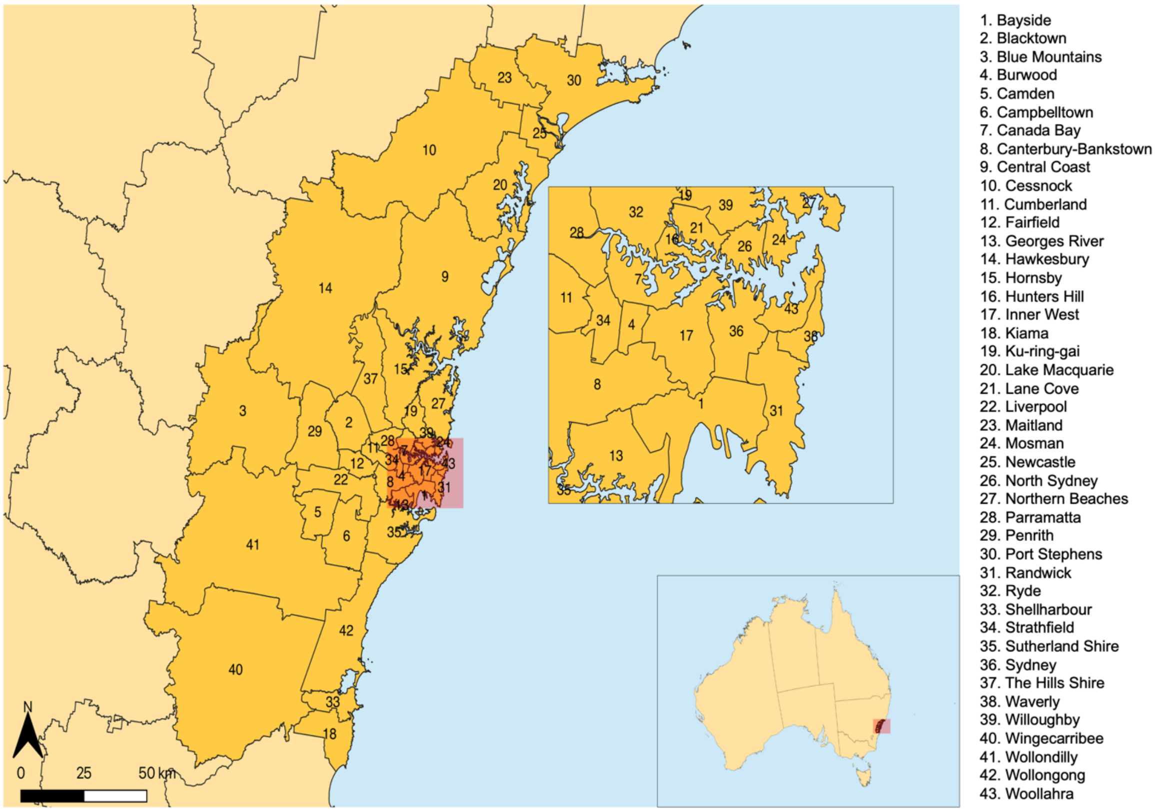


Figure 6-10: Study area for this analysis

Table 6-5 summarises the LGA organic waste collection pathways in the study area for study timeframe (2019-20). For this study, the OFMSW included GO, FOGO and mixed waste services. As household organics are commingled and treated along with non-organic waste as well as non-compliant organics, collection and treatment of the entire mixed waste stream was considered in scope.

Table 6-5: Summary of organic waste collection pathways in the study area, from NSW EPA (2021)

Organic collection pathway	**Number of LGAs with service**	**Typical frequency of collection**	**Total waste collected (incl. non-organics in mixed) [tonnes, 2019-20]**
Separate GO collection	35	Fortnightly	377,465
Separate FOGO collection	5	Weekly	90,047
Mixed waste	43	Weekly	1,374,095

The average composition of waste bins collected are summarised in Table 6-6. Data on the composition of GO and FOGO bins were derived from NSW EPA (2014a) and Rawtec (2020a) audit reports respectively. In both streams, an average contamination rate of 2.1% was observed, consisting primarily of non-compliant organics, building materials and plastic wastes. The composition of the mixed waste stream varies depending on the level of organic waste separation. LGAs that separately collect FOGO have the smallest proportion of organics in the mixed waste stream, followed by LGAs collecting GO separately. Other variations in mixed waste composition are attributed to LGA level variation, observed in Rawtec (2020b).

Table 6-6: Material composition of the NSW municipal waste stream by collection pathway, derived from NSW EPA (2014a); Rawtec (2020a, 2020b)

Waste material	GO stream composition	FOGO stream composition	Mixed waste stream composition (LGAs w/GO)	Mixed waste stream composition (LGAs w/FOGO)	Mixed waste stream composition (LGAs w/ no organic collection)
Garden waste	97.9%	86.3%	3.5%	2.1%	26.7%
Food waste	-	11.5%	37.6%	22.7%	26.9%
Textiles	-	-	3.1%	3.5%	2.4%
Wood	-	-	2.2%	2.5%	1.7%
Rubber/leather	-	-	4.7%	5.4%	3.6%
Cardboard	-	-	10.4%	11.7%	7.9%
Paperboard	-	-	6.1%	6.8%	4.6%
Other paper	-	-	2.4%	2.7%	1.8%
Plastic film	-	-	5.3%	7.1%	3.8%
HDPE	-	-	3.6%	4.9%	2.6%
PET	-	-	1.7%	2.3%	1.2%
Other plastic	-	-	2.1%	2.9%	1.5%
Ferrous metals	-	-	2.1%	2.9%	1.9%
Non-ferrous metals	-	-	0.8%	0.7%	0.7%
Glass	-	-	3.3%	3.3%	3.1%
Other materials/ contamination	2.1%	2.1%	11.1%	18.4%	9.6%

Waste treatment pathways in scope of this analysis were broadly described in Section 6.1, and include windrow composting of GO and FOGO collected organics; AWT for mixed waste collections; and landfill disposal for non-AWT directed mixed waste and residual wastes from the compost and AWT processes.

In terms of GHG emissions accounted for, Figure 6-11 includes an overview of the primary emissions and material flows in scope from the management and recovery of organic wastes in the study area. Table 6-7 gives further detail of the indirect and direct emissions in scope from upstream, processing, and downstream sources. Biogenic CO_2 emissions through the decomposition of organic emissions at landfills and through the aerobic composting process were not considered in scope of this analysis, following guidance from DISER (2021b). However, emissions of methane and nitrous oxide (both converted to CO_2-equivalent using factors in the NGA) were considered. Furthermore, emissions avoided from material being diverted from landfill due to recovery is considered in this analysis. Emissions avoided from the application of recovered compost to land as substitution for mineral-based fertilisers were not considered in scope. This was due to a number of reasons: i) large uncertainty around the substitution rate of mineral-based fertiliser, ranging from as low as 30% in ROU (2006), to up to 80% in Friedrich and Trois (2013). Most studies in the literature assume emissions savings from both the reduction in mineral-based fertiliser production, and from their application to land. It was assumed to be unlikely that compost derived from the study area would offset mineral-based fertiliser production nationally, nor offset importing of mineral-based fertilisers from overseas; ii) limitations in the application of OFMSW derived compost to land, due to contamination fears, which applies to both mixed waste-derived and FOGO-derived recovered organics NSW EPA (2019a); and iii) the assumption that landfill gas diversion is the most significant source of emissions reductions.

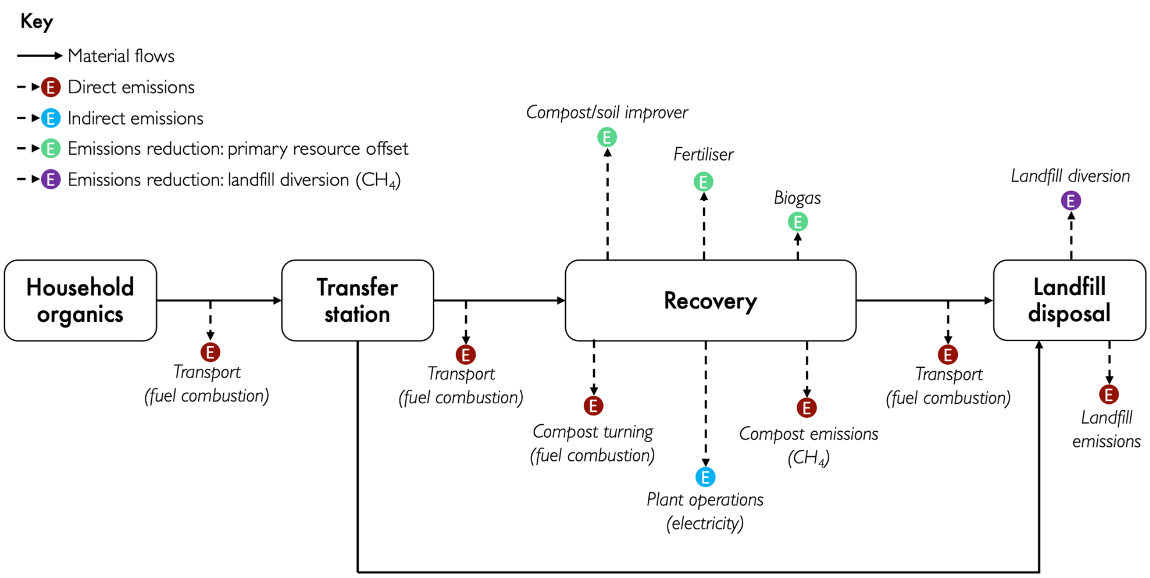


Figure 6-11: Overview of emissions and major material flows in scope for this analysis

Table 6-7: Sources of emissions and emissions savings in scope of this analysis

Sources of emissions in scope	Sources of emissions savings in scope
Upstream	
Emissions from organic waste collection and transportation (fuel combustion)	NA
Processing	
Electricity consumed during recovery processes (e.g., mechanical sorting equipment, office lighting, etc.) Fuel consumed during recovery processes (e.g., shredding of material, windrow turning, etc.)	NA
Downstream	
Landfill emissions (methane and N_2O)	Landfill emissions avoided (methane and N_2O)

6.3.2. Waste collection and transport model

The *waste collection and transport model* is a route-optimisation model integrated with GIS, used to estimate the collection of household waste from the kerbside for the 1.8 million property lots in the study area. Described in detail in Chapter 5 of this thesis, the model estimates the transportation (in kilometres per year) for kerbside waste collection, and the transport of collected waste between waste management infrastructure. The components of transport considered in the *waste collection and transport model* are: (1) kerbside collection, from households to transfer stations; (2) recovery transfer from transfer stations to waste recovery facilities, and (3) disposal transfer. For component (3), residues from recovery processes are transported from recovery facilities to landfill sites. Mixed waste not directed to AWT facilities is transfer from transfer stations to landfill. See Chapter 5 for a full description of this approach.

6.3.3. Organic waste recovery model

Emissions from industrial composting of organic waste, and sorting and recovery of organics in the mixed waste stream at AWTs were considered in the *organic waste recovery model*, and apportioned to LGAs from where the waste was originally derived. Direct and indirect emissions were estimated for the consumption of fuel and grid-supplied electricity at recovery facilities, and methane and nitrous oxide emitted during the composting process, as per Figure 6-11 and Table 6-7. Direct emissions of CO_2 from the composting process were not considered, due to these emissions being biogenic, and not considered in the National Greenhouse Accounts.

For industrial composting, windrow composting with a 12-month composting time was assumed, based on ROU (2006). Electricity consumption for operational activities (e.g., offices, lighting, etc.), and diesel consumption for feedstock loading, shredding and windrow turning were considered, based on factors in ten Hoeve et al. (2019) and ROU (2006). Emissions intensity factors (scope 2 and 3) were used to estimate the emissions associated with electricity consumption, based on intensity factors published in the National Greenhouse Accounts (DISER, 2021b), specific to the NSW energy supply mix in the study time period. It was assumed that all organic waste composting facilities had sufficient capacity to treat all incoming organic waste during the study timeframe. Recovery rates for garden waste and food waste recovery were based on GO and FOGO waste recovery rates in NSW EPA (2021).

Mature compost and residual waste were the assumed outputs of the composting process, with residual waste transferred to landfills for disposal (transport for which was considered in the *waste collection and transport model*). For landfill diversion, the *landfill emissions model* described in the following section was utilised, to estimate the landfill gas (methane and nitrous oxide) emissions avoided from waste recovery. Table 6-8 includes parameters from the literature utilised in the *organic waste recovery model* for composting.

Table 6-8: Parameters used for the estimation of emissions from composting of household organic wastes in the study area for 2019-20

Parameter	Value	Reference
Fuel (diesel) for feedstock receival and compost dispatch	0.51 L/t	ROU (2006)
Fuel for shredding, windrow formation and screening	5.02 L/t	ROU (2006)
Electricity for operations (lighting etc.)	0.04 kWh/t	ten Hoeve et al. (2019)
Emissions per litre of diesel fuel consumed	0.00258 tCO_2e/L	NTC (2019)
Emissions (scope 2 and 3) from electricity supply	0.85 $kgCO_2e/kWh$	DISER (2021b)
Emissions of methane from the composting process	4 $kgCH_4/t$ (wet)	US EPA (2010)
Emissions of nitrous oxide from the composting process	0.3 kgN_2O/t (wet)	US EPA (2010)

For AWT facilities, electricity consumption for mechanical sorting of the incoming mixed waste stream was estimated. This was achieved using a mass-balance model, based on the work in Ng et al. (2021) and Pressley et al. (2015). This approach estimated the energy consumption of the equipment in use at AWTs during sorting and recovery operations individually (e.g., conveyers, trommel screens, etc.). Figure 6-12 shows the assumed system diagram of AWT sorting. While the focus of this study is on organic waste recovery, the electricity requirements for both organic and non-organic waste at AWTs were estimated. This was done as accounting for only the organic processing electricity consumption would underestimate the total electricity requirements for treating the incoming mixed waste stream, considering that organics and non-organics are comingled. Separation efficiencies for each sorting equipment (i.e., the proportion of material moving from one equipment to the next in the figure) were estimated based on efficiencies in Ng et al. (2021), adjusted via optimisation for each LGA such that overall AWT separation is consistent with AWT recovery rates in NSW EPA (2021).

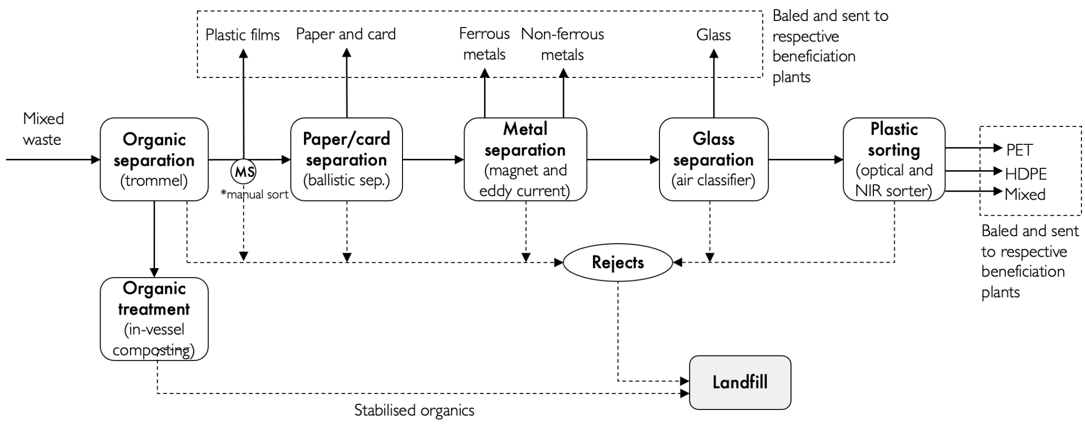


Figure 6-12: Assumed system scope of AWT sorting

Average equipment sorting rates used are summarised in Table 6-9. Note that sorting rates in the table are for material entering a process step, and are averaged over LGAs sending waste to AWT facilities. Also in the table are sorting efficiency values in Ng et al. (2021) for comparison. Average sorting equipment efficiencies from the described approach are considerably lower than efficiencies reported in Ng et al. (2021). Overall AWT recovery rates in the study area and timeframe are low, ranging from no recovery (i.e., 0% recovery rate), to approximately 60%.

Table 6-9: Estimated AWT sorting equipment sorting efficiencies. Numbers in brackets are baseline efficiencies found in Ng et al. (2021)

	AWT sorting equipment						
Waste material	**Trommel (organics separation) [%]**	**Trommel (non-organics separation) [%]**	**Manual sorting [%]**	**Ballistic separator [%]**	**Metals separation [%]**	**Glass separation [%]**	**Plastic sorting [%]**
Garden waste	49.2% (85%)						
Food waste	49.2% (85%)						
Textiles		0.9% (5%)					
Wood		0.9% (5%)					
Rubber/leather		0.9% (5%)					
OCC				2.1% (60%)			
Non-OCC				2.1% (60%)			
Other fibre				2.1% (60%)			
Plastic film		0.9% (5%)	55.7% (81%)				
HDPE							10.6% (83%)
PET							10.6% (83%)
Other plastic		0.9% (5%)	55.7% (81%)				10.6% (83%)
FE					14.4% (88%)		
Al					14.2% (87%)		
Glass		1.7% (10%)				59.2% (87%)	
Other		1.7% (10%)					

Energy intensity factors from Ng et al. (2021) and Pressley et al. (2015) were applied to estimate the energy consumed by each piece of sorting equipment. Overall energy consumption for each facility was then estimated as the sum of electricity consumption estimated for all sorting equipment. Sorted organic waste was assumed to be composted on site via in-vessel composting following Połomka and Jędrczak (2019), Ng et al. (2021), and described in Jacobs (2019). Emissions of methane and nitrous oxide (again assuming all CO_2 emissions are biogenic) from the in-vessel composting process were based on windrow composting emissions factors in US EPA (2010), adjusted for the reduced emissions via in-vessel composting found in Friedrich and Trois (2013) and Sharma and Chandel (2017). The same assumptions around shredding and feedstock loading fuel requirements for windrow composting were used, based on intensities in ROU (2006) and ten Hoeve et al. (2019). As the application of organic products from AWT to land have been restricted by the NSW waste authority NSW EPA (2019a), it was assumed that the final destination of recovered organics from AWT was as bio-stabilised material sent to landfill. As such, emissions savings from landfill diversion are assumed to still apply. Parameters used to estimate AWT emissions are summarised in Table 6-10.

Table 6-10: Parameters used for the estimation of emissions from AWT processing of household organic wastes in the study area for 2019-20

Parameter	Value	Reference
Trommel energy usage	0.81 kWh/t	Ng et al. (2021)
Vacuum (manual separator) energy usage	0.294 kWh/t	Ng et al. (2021)
Ballistic separator energy usage	0.431 kWh/t	Ng et al. (2021)
Magnet separator energy usage	1.176 kWh/t	Ng et al. (2021)
Eddy current separator energy usage	0.441 kWh/t	Ng et al. (2021)
Air classifier energy usage	2.68 kWh/t	Ng et al. (2021)
Optical/NIR sorter – PET energy usage	0.765 kWh/t	Ng et al. (2021)
Optical/NIR sorted – HDPE/mixed rigid energy usage	2.353 kWh/t	Ng et al. (2021)
Conveyer energy usage	0.11 kWh/t	Ng et al. (2021)
Emissions of methane from the composting process	3.84 $kgCH_4$/t (wet)	US EPA (2010)
Emissions of nitrous oxide from the composting process	0.29 kgN_2O/t (wet)	US EPA (2010)
Fuel for shredding, vessel turning, and screening	5.02 L/t	ROU (2006)

6.3.4. Landfill emissions model

Emissions from waste degrading in landfills are estimated in the *landfill emissions model*. For this, the method and parameters from the Australian National Greenhouse Accounts (DISER, 2021b) were utilised. With this method, expected lifetime emissions from the decay of materials disposed to landfill were estimated as tonnes CO_2-equivalent for GO and FOGO waste disposed (i.e., residual waste from composting); and from mixed waste disposed (i.e., direct to landfill disposal; and organic and non-organic residues from AWT recovery). Material disposed to landfill decays over decades, therefore the emissions estimated for waste disposed in the study timeframe are the assumed lifetime emissions, given by Equation 6.1:

$$\text{Lifetime GHG } (tCO_2e) = \{[(Q \cdot DOC \cdot DOC_f \cdot F_1 \cdot C_{CH_4}) - R] \times (1 - OX)\} \times GWP \quad 6.1$$

Where Q is the quantity of municipal solid waste disposed to landfill in a given timeframe; DOC is the proportion of degradable organic carbon; DOC_f is the fraction of degradable organic carbon dissimilated; F_1 is the methane fraction of landfill gas; C_{CH_4} is the conversion rate of carbon to methane; R is the amount of landfill gas recovered or flared in the given year; OX is the oxidation factor; and GWP is the global warming potential used to estimate CO_2-e from methane. Parameter values from DISER (2021b) are summarised in Table 6-11. Estimates for landfill gas capture rates were based on LMS Energy (2021), where 85% of landfill gas is estimated to be captured across landfills in Australia. Note that for methane gas captured and flared at landfills, the CO_2 emissions are not counted as emissions, but considered as part of the natural carbon cycle (DISER, 2021b).

Table 6-11: Landfill emissions model parameters, from DISER (2021b)

Parameter	Value
Degradable organic content (*DOC*):	
- Food waste	0.15
- Paper and cardboard waste	0.4
- Garden waste	0.20
- Wood waste	0.43
- Textile waste	0.24
- Rubber and leather waste	0.39
- Inert waste	0
- AWT residues	0.08
Fraction of DOC dissimilated (DOC_f)	
- Food waste	0.84
- Paper and cardboard waste	0.49
- Garden waste	0.47
- Wood waste	0.10
- Textile waste	0.50
- Rubber and leather waste	0.50
- Inert waste	0
- AWT residues	0.50
Methane fraction of landfill gas (F_1)	0.50
Oxidation factor (*OX*)	0.10
Methane global warming potential (*GWP*)	28

6.3.5. Sensitivity analysis

A sensitivity analysis was performed to test the robustness of emissions estimates given variation in key model variables. Key uncertain variables were the methane gas capture rate (*R* in Equation 6.1), where data on this is limited for the study area; AWT sorting equipment energy requirements (Table 6-10), where some variation between technology selection between

Ng et al. (2021) and technology in Australia may exist; and composting parameters (Table 6-8). For composting parameters, fuel requirements for feedstock preparation and pile turning, and operations energy requirements varied considerably in the literature. Methane and nitrous oxide emissions from the composting process were also considered uncertain, based on remarks in US EPA (2010) indicating that these parameters are uncertain owing to measurement uncertainty, and large variation in compost pile composition. Sensitivity of parameters for the estimation of kerbside collection and transport emissions were examined in Chapter 5, Section 5.2.5.

For this analysis, the sensitivity of overall net emissions to recovery emissions and landfill emissions parameter uncertainty were evaluated following a combined Latin hypercube sampling-Monte Carlo simulation approach. Latin hypercube sampling (LHS) makes sensitivity analysis with a large number of parameters practical, providing a convenient approach for dimension reduction by generating random samples of multiple parameters from known probability distributions, spaced evenly over a sample space (McKay et al., 1979). In this approach, parameter values are drawn randomly from the LHS, and net emissions are computed. This was performed 10,000 times for this analysis, to generate a distribution of estimated net emissions from which sensitivity could be evaluated. A similar method was employed for analysing uncertainty in aluminium material flows in China (Li et al., 2021). Value ranges for uncertain parameters were assumed to be uniformly distributed in a range ±10% of the baseline parameter value.

Outputs from the sensitivity analysis is a distribution of estimated net emissions for the study area. Sensitivity of emissions estimates to variation in uncertain parameters was evaluated by comparing the percentage change in emissions given percentage change in parameter value using regression analysis, after Acevedo (2013).

6.4. Results and discussion

6.4.1. Overall organic waste recovery and emissions for 2019-20

Table 6-12 shows the total amount of waste generated, recovered and landfilled by waste collection stream. This data forms the basis of the emissions footprint performance indicators reported later in this section. Over 1.8 million tonnes of OFMSW was generated by households in the study area in 2019-20, at an overall per-household generation rate of 956 kg per household. Approximately 582,000 tonnes of waste was recovered from the GO, FOGO and mixed waste streams, at an overall recovery rate of 31.6% of waste generated. This recovery rate does include the estimated recovery of a small proportion of non-organic waste in the mixed waste stream. Excluding this proportion of non-organic waste, approximately 580,000 tonnes of OFMSW was recovered, at a recovery rate of 55.3%. Together, waste collected via GO and FOGO streams accounted for approximately 25% of all waste generated in the study area in 2019-20.

Table 6-12: Summary of waste generation and recovery by waste collection stream for 2019-20

Waste stream	Waste generated, 2019-20 [tonnes]	Waste recovered, 2019-20 [tonnes]	Waste landfilled, 2019-20 [tonnes]	Waste recovery rate
GO stream	377,465	373,873	3,592	99.0%
FOGO stream	90,047	88,273	1,773	98.0%
Mixed waste stream	1,374,096	119,377	1,254,718	8.7%
Organics in mixed waste	*578,668*	*116,995*	*461,673*	*20.2%*
Non-organics in mixed waste	*795,427*	*2,382*	*793,045*	*0.3%*
Overall	1,841,607	581,523	1,260,084	31.6%

Overall emissions and their sources are summarised for each waste stream in Figure 6-13. Overall gross emissions across all waste streams in 2019-20 were estimated at approximately 391,000 tCO_2-e. This was balanced by an approximate 146,000 tCO_2-e of emissions avoidance, resulting in overall net emissions of 245,000 tCO_2-e. The mixed waste stream was the largest contributor to overall emissions. Landfilling of mixed waste alone was responsible for approximately 55% of total gross emissions—expected given the poor waste recovery rates for this stream, as indicated in Table 6-12. The GO stream was responsible for approximately 64% of all recovery emissions, and approximately 60% of all emissions avoidance. This is also expected, given the large quantities of waste recovered via this collection stream, thereby avoiding lifetime landfill emissions. The contribution of the FOGO stream to overall emissions is low, with the stream responsible for only 5% of waste collected in the study area.

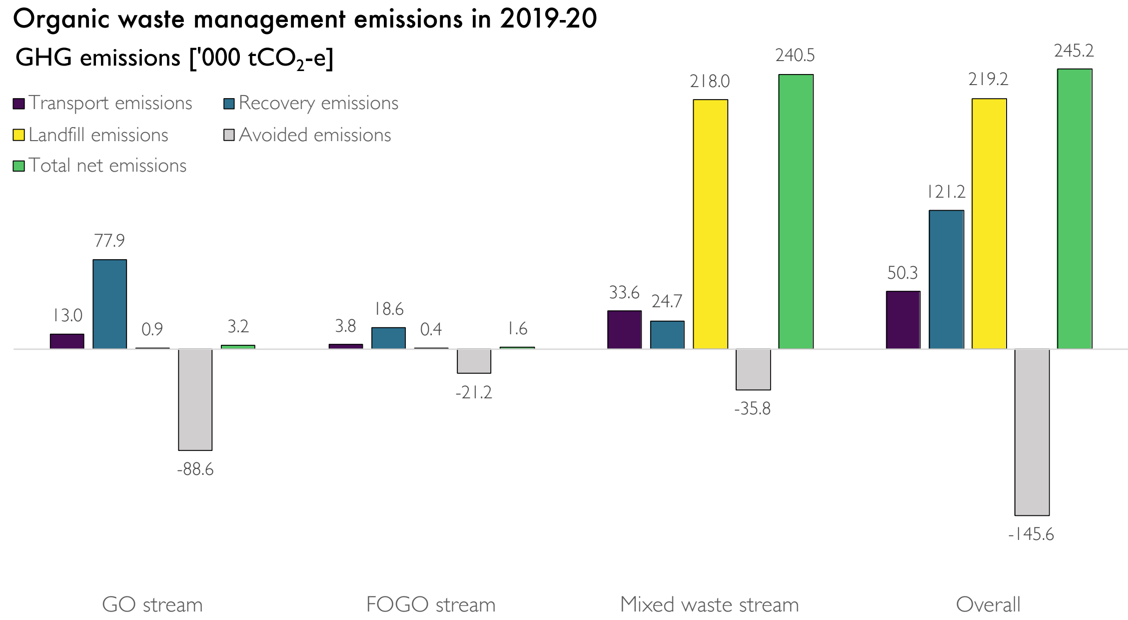


Figure 6-13: Estimated emissions by waste stream in the study area for 2019-20

Figure 6-14 shows the breakdown of estimated gross emissions by source and waste stream. Lifetime landfill emissions were the largest contributor to overall gross emissions, accounting for approximately 56% of all OFMSW management emissions in 2019-20. For the mixed stream, lifetime landfill emissions accounted for 79% of emissions for that stream. Such large emissions from landfill disposal again are expected for this stream, considering the large quantities of mixed waste disposed to landfill. Conversely, landfill emissions contributed only 1% and 2% to GO and FOGO stream emissions respectively, consistent with the small quantities of these streams disposed to landfill. Transport emissions were relatively consistent across the streams, ranging between 12% to 17% of emissions. Overall, transport emissions contributed 13% to gross emissions, which addresses an identified gap in knowledge from the analysis in Chapter 5, in that this contribution was unknown for OFMSW management in the study area. Although small, the contribution of transport emissions should not be ignored in holistic evaluations of the emissions intensities of OFMSW management. This is especially true for the mixed waste stream, where transport emissions were approximately a third higher than emissions associated with the AWT recovery process. This is expected, given the large quantities of mixed waste collected compared to the small quantities of mixed waste sent to AWT for recovery.

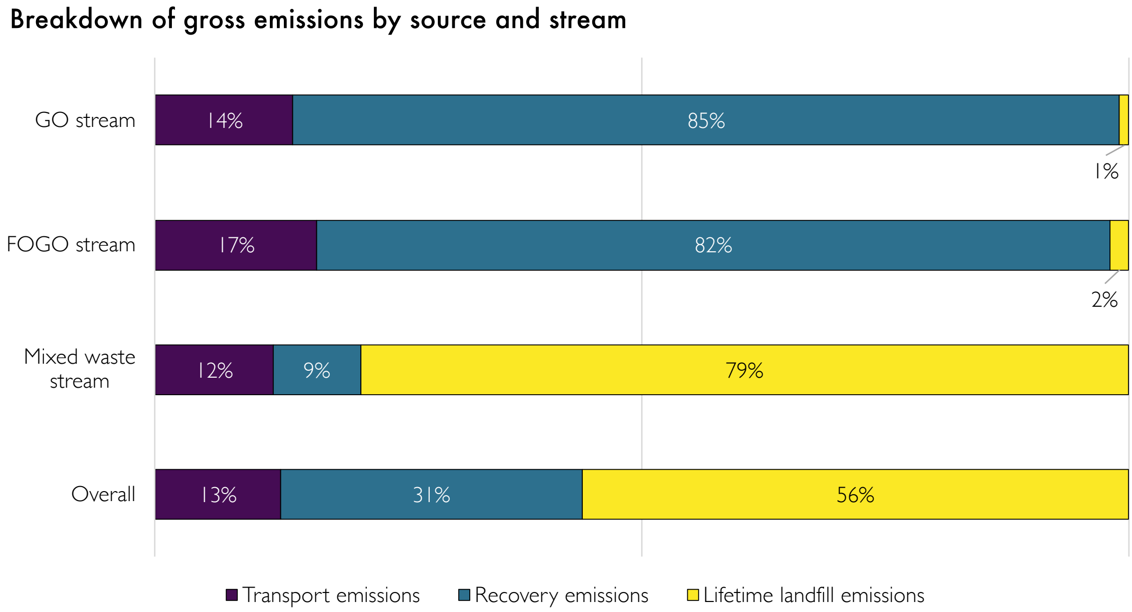


Figure 6-14: Breakdown of emissions by source and stream for 2019-20

Table 6-13 summarises emissions intensity for each waste stream and overall. The net emissions per tonne of waste diverted is the chosen emissions intensity performance indicator. This is an important metric used for accounting and evaluating emissions of different resource recovery systems (Gavrilescu, 2022; Iacovidou et al., 2017a). Compared to a gross emissions intensity metric, net emissions better characterise the emissions balance by considering avoided emissions. Compared to net emissions on a per tonne managed basis, the chosen metric also factors in resource recovery efficiency. This means that emissions intensity performance is impacted both by the quantity of waste recovered, and the balancing of emissions and avoided emissions, thereby better reflecting the principles of low carbon resource recovery than net emissions on a per tonne managed basis. Overall, net emissions were approximately 423 kgCO_2-e per tonne of waste diverted in the study area. Emissions intensity was lowest for the GO stream, at approximately 8.5 kgCO_2-e per tonne of waste diverted from landfill. As indicated in Figure 6-13, avoided emissions were significant, which mostly offset gross emissions. FOGO stream intensity was higher than GO stream intensity, due to greater transport emissions intensity for FOGO collections (confirmed in Chapter 5), and lower stream recovery compared to the GO stream. Mixed waste stream emissions intensity was very high, at approximately 2 tCO_2-e per tonne of waste diverted. This can be attributed to poor stream recovery rates leading to significant quantities of waste disposed to landfill. Improving mixed waste recovery and reducing the quantities of waste collected via mixed waste (e.g., via FOGO collections) would likely have significant impacts on reducing overall emissions intensity, based on these findings.

Table 6-13: Summary of net emissions intensity for each waste stream for 2019-20

Waste stream	**Net emissions intensity per tonne diverted [kgCO_2-e/t]**
GO stream	8.5
FOGO stream	17.7
Mixed waste stream	2,055.6
Overall	423.4

6.4.2. Spatial distribution of waste related emissions

Table 6-14 summarises LGA level waste and emissions intensity statistics across the study area. LGAs generated on average approximately 43,000 tonnes of GO/FOGO and mixed waste per year, with an average recovery rate of 31.3%. LGA variation on these estimates were high, with recovery rates ranging between 19% to 50%. Net emissions were on average approximately 5,700 tCO_2-e, with average emissions intensity of 500 tCO_2-e per tonne diverted. Variation in LGA emissions intensity was high, ranging from 100 to 959 tCO_2-e. This variation is explored further in the following paragraphs.

Table 6-14: Summary of LGA-level waste and emissions intensity statistics for the study area in 2019-20

	LGA average	**95^{th} percentile range**
Waste generated 2019-20 [tonnes]	42,828.1	8,091 – 109,499
Waste recovered 2019-20 [tonnes]	13,468.4	1,559 – 34,473
Recovery rate [%]	31.3%	19% - 50%
Net emissions [tCO_2-e]	5,702.9	760 – 16,052
Net emissions intensity (diverted) [kgCO_2-e/t]	504.4	101 - 959

Figure 6-15 shows the spatial distribution of net emissions intensities over the study area. The figure also shows the locations of organic waste recovery facilities, including AWTs. There is some visual correlation between emissions intensities and proximity to recovery facilities, with LGAs further away from recovery facilities having higher emissions intensities. However, LGA recovery rates were found to be more strongly correlated with net emissions intensities (see Figure 6-16), which is consistent with findings in Section 6.4.1 suggesting that waste diversion has the greatest contribution to net emissions.

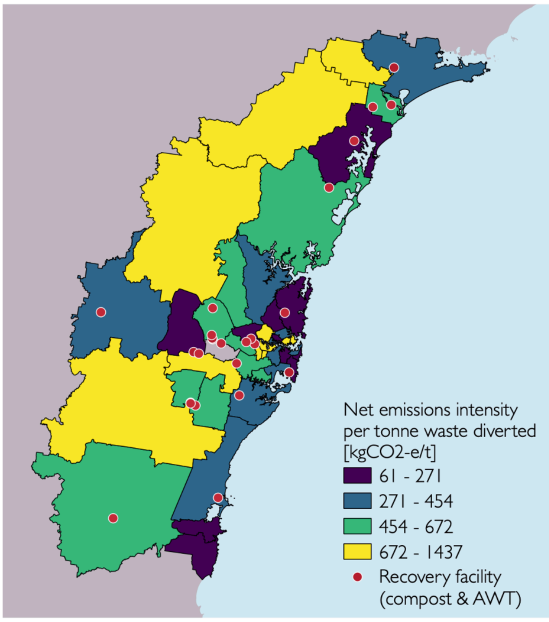


Figure 6-15: Spatial distribution of net emissions intensities

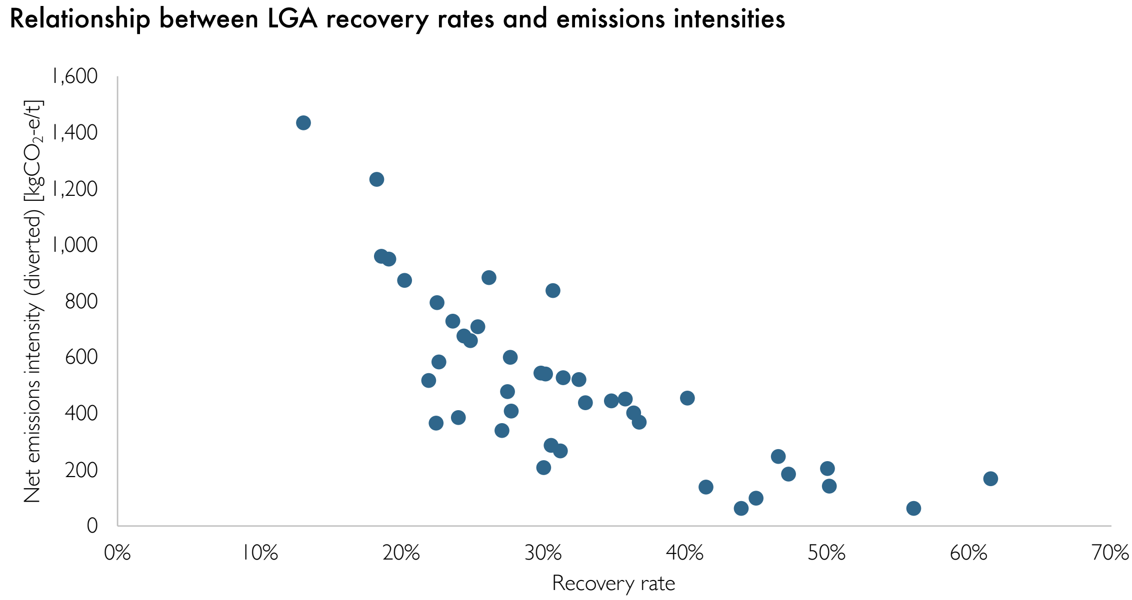


Figure 6-16: Relationship between LGA recovery rates and net emissions intensity on a per tonne diverted basis

A weak correlation can be seen in Figure 6-15 between LGA size and emissions intensities. This is explored in more detail in Figure 6-17. Generally, there is a weak correlation across all LGAs between LGA size and net emissions intensities. However when broken down by LGA region classification, derived from NSW Office of Local Government (NSW OLG, 2020), a stronger correlation emerges.

LGA size is a determinant for net emissions intensities, whereby larger LGAs have higher net emissions intensities, although this relationship is stronger for metro-fringe LGAs compared to regional LGAs. For metropolitan LGAs, no such correlation emerges. Table 6-15 further summarises emissions and waste statistics by LGA type that may help explain these correlations, indicating that metro-fringe and regional LGAs have on average almost double the transport emissions intensity of metropolitan LGAs. This is expected given the greater dispersal of households and the greater distances to waste infrastructure in these LGAs, contributing to greater waste collection and waste transport requirements. This is consistent with findings in Chapter 5. The metro-fringe classification is characterised more by suburban sprawl, and as Chapter 5 identified, LGAs with lower spatial density of households (i.e., households per km^2) result in greater waste collection requirements compared to LGAs with higher household spatial densities. Further evaluation of data in Table 6-15 shows that regional LGAs had the highest rates of waste recovery as well as the lowest emissions intensities—consistent with findings in Figure 6-16. Despite metro-fringe LGAs having higher recovery rates, net emissions were also higher than metropolitan LGAs. This indicates that for metro-fringe LGAs, transportation emissions are a significant contributor to overall emissions—more so than for metropolitan LGAs.

These findings on the spatial distribution of net emissions are important, with implications for waste management policy. For example, infrastructure needs may be different depending on the level of urbanisation. Findings here indicate that metropolitan LGAs may require intervention in improving waste diversion rates. Indeed, as indicated in Figure 5-2 in Chapter 5, FOGO collection services are less prevalent in metropolitan LGAs. Furthermore, findings also indicate the importance of addressing transportation when prioritising net emissions reductions in more suburban and regional locations. Practical ways for addressing transportation emissions in these locations may include alternate fuels for waste collection vehicles, more optimal waste collection routing, or the electrification (with renewable energy) of waste collection vehicles.

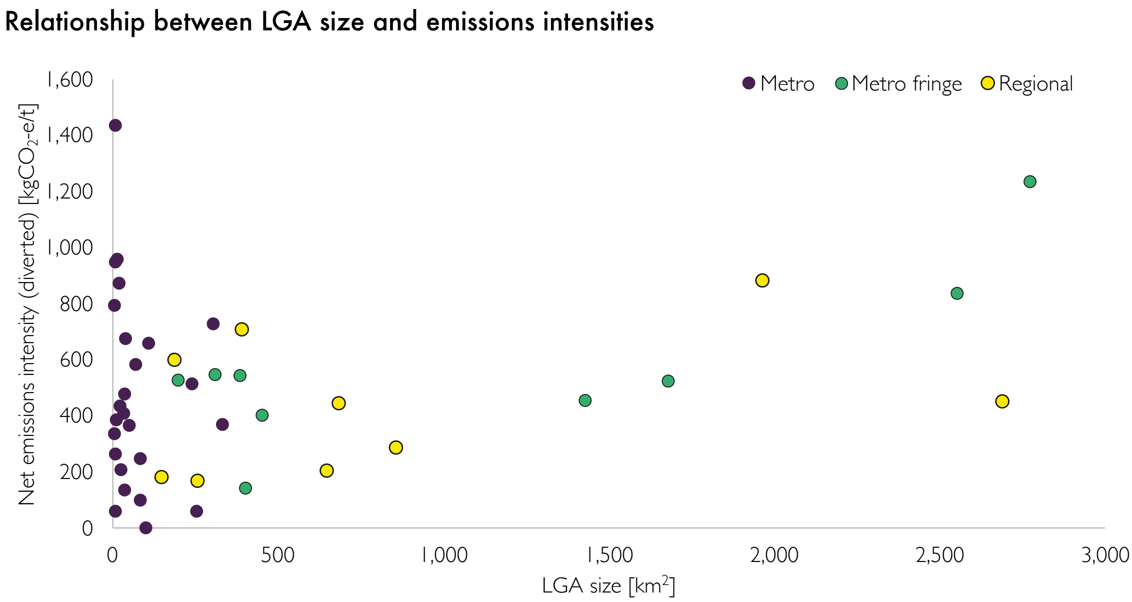


Figure 6-17: Relationship between size and net emissions intensity on a per tonne diverted basis, by LGA type

Table 6-15: Summary of waste recovery and emissions statistics by LGA classification, from NSW OLG (2020)

LGA type	Average organic waste generation [t/year]	Average organic waste recovery rate	Contribution to gross emissions	Contribution to emissions reductions	Average transport emissions [tCO_2-e]	Average net emissions intensity per tonne diverted [$kgCO_2$-e/t]
Metro	44,180.7	29.4%	55.7%	56.8%	820.0	501.9
Metro-fringe	48,550.4	32.8%	26.5%	24.5%	1,857.1	578.0
Regional	33,348.4	38.2%	17.8%	18.6%	1,456.5	437.6

6.4.3. Emissions from composting

Table 6-16 summarises estimated composting emissions for GO and FOGO waste streams. Total gross emissions for composting were approximately 96,500 tCO_2-e, and avoided emissions from landfill diversion were estimated at 109,800 tCO_2-e, making composting a negative net emissions process at -13,300 tCO_2-e. When considering emissions associated with collection and transportation, overall net emissions becoming positive, at 3,500 tCO_2-e. Of the emissions occurring from the compost process itself, approximately 93% were attributed to direct emissions of methane and nitrous oxide. Compost turning, using diesel fuel, contributed approximately 7% to composting emissions, and facility operations (e.g., lighting and office equipment), less than 1%. GO stream composting contributed 81% to overall composting emissions—expected given the larger quantities of GO stream waste collected for composting.

Table 6-16: Estimated composting emissions

Waste stream	Compost turning emissions [tCO_2-e]	Compost operations emissions [tCO_2-e]	Direct emissions (CH_4 & N_2O) [tCO_2-e]	Total compost emissions [tCO_2-e]	Emissions reductions via diversion [tCO_2-e]
GO	5,594	12.83	72,285	77,892	88,563
FOGO	1,335	9.95	17,244	18,588	21,235
Overall composting	6,929	22.78	89,529	96,480	109,798

Table 6-17 summarises estimated emissions intensities for composting, including emissions associated with transport. Approximately 242 $kgCO_2$-e per tonne of waste managed was emitted via composting of GO and FOGO. On a net emissions basis, emissions intensity was approximately 8 $kgCO_2$-e per tonne of waste diverted from landfill. Differences in intensities between the organic streams were minor, with differences owing to the greater transport requirements for the FOGO stream identified in Chapter 5. Focusing on the compost process itself by excluding transport emissions, gross intensity per tonne managed was 206 $kgCO_2$-e/t, and net emissions per tonne diverted of -29 $kgCO_2$-e/t.

Table 6-17: Estimated composting emissions intensities

Waste stream	Gross composting emissions per tonne managed [$kgCO_2$-e/t]	Net composting emissions per tonne diverted [$kgCO_2$-e/t]
GO	240.78	6.21
FOGO	248.39	12.83
Overall composting	242.24	7.47

These estimates of composting emissions do not include downstream emissions associated with the final utilisation of mature compost. As noted in the literature (e.g., Boldrin et al. (2009); Fernández-Delgado et al. (2020); Friedrich and Trois (2013)), mature compost can offset the use of mineral based fertilisers, which can have considerable life-cycle emission considerations. Boldrin et al. (2009) and Friedrich and Trois (2013) for example assume the 3.76 kg of nitrogen in OFMSW derived compost would offset 1.88 kg of nitrogen from mineral sources (assuming a substitution of mineral fertiliser at a rate of 50%), resulting in approximately 24 $kgCO_2$-e savings per tonne of compost produced. Moreover, as noted in ROU (2006) and Friedrich and Trois (2013), the application of mature compost to land also carries and emissions burden, mainly from the consumption of fuel required by transporting of compost and from farm equipment applying it to land, as well as emissions savings from carbon bound to soil (Friedrich & Trois, 2013).

These emissions were not considered in this analysis for several reasons. Firstly, as indicated in NSW EPA (2019a), the application of municipally derived compost is restricted in its application to land for food crops, due to contamination concerns. The rate of substitution of mineral based fertilisers for OFMSW compost is also an unknown, and is wide ranging in the literature, making estimation difficult. Boldrin et al. (2009) for example assumes a substitution rate of 20-60%. The level of potential substitution however would likely be dependent on the application to land, with food and other high value crops likely having lower substitution rates, as fertiliser inputs must be consistent to guarantee crop yields. This point however does require further analysis to verify. Future applications of this modelling could incorporate an expanded system scope, to include the emissions savings from mineral-based fertiliser substitution. Data on the existing rates of fertiliser consumption would be needed, as well as current utilisation levels of secondary organics, to accurately assess the potential of emissions avoidance.

6.4.4. Emissions from AWT recovery

Table 6-18 summarises total AWT throughout and recovered quantities and recovery rates for the study area for 2019-20. Quantities of AWT throughput and waste recovered are derived from NSW EPA (2021). A total of approximately 464,000 tonnes of mixed waste was diverted to AWTs for recovery in 2019-20, originating from 19 LGAs in the study area. The recovery rate of LGA mixed waste ranged from 0% to 50%, with a total recovery rate of approximately 26%. Some LGAs sent mixed waste to AWTs, however recovery rates of 0% were reported in NSW EPA (2021), namely Georges River, Hunters Hill, Lane Cover, Penrith and Woollahra . Reasons for this 0% recovery are unclear. Notably, 2 of the listed LGAs had FOGO collection, therefore organic waste in the mixed stream may have been insufficient for AWT recovery processes prioritising organic waste recovery. In total, AWT diversion represented approximately 34% of total mixed waste generated across the study area, and AWT recovery represented approximately 9% of total mixed waste.

Table 6-18: AWT throughputs, and recovered quantities

Mixed waste fraction	AWT throughput, 2019-20 [tonnes]	Waste recovered via AWT, 2019-20 [tonnes]	AWT recovery rate [%]
Organic waste	197,606	116,995	59.2%
Non-organic waste	266,484	2,382	0.9%
Total	464,090	119,377	25.7%

Table 6-19 summarises some key statistics from the *organic waste recovery model*. Approximately 43% of the AWT throughput stream was organic waste, primarily consisting of food waste. Organic waste accounted for 98% of total waste recovered from the mixed stream at AWTs. Total gross emissions from AWT recovery including transportation was approximately 36,200 tCO_2-e. Approximately 67% of these emissions were attributed to the in-vessel composting process.

Table 6-19: Summary of key AWT statistics

	Value
Waste sent to AWTs 2019-20 [tonnes]	464,090
Fraction of input that is organic	42.6%
Mixed waste recovered at AWTs in 2019-20 [tonnes]	119,377
Fraction of recovered that is organic	98.0%
Mechanical sorting energy [MWh]	711.4
Mechanical sorting energy intensity [kWh/t]	1.53
Mechanical sorting emissions [tCO_2-e]	604.7
Organic recovery emissions*[tCO_2-e]	36,240
Emissions reductions via diversion [tCO_2-e]	35,774
Net emissions [tCO_2-e]	466
Net emissions intensity (diverted) [$kgCO_2$-e/t]	3.9

*Includes compost turning, operations and direct emissions

The mechanical sorting component accounted for only 2% of overall AWT emissions. The energy intensity of mechanical sorting operations were estimated at 1.53 kWh per tonne of material throughput. This is compared to a value of 1.32 kWh/t in Ng et al. (2021), from which the AWT sorting component of the *organic waste recovery model* waste based. Considering only the organic waste recovered at AWT facilities, AWT outperformed composting in terms of net emissions intensity on a per tonne diverted basis. This can be attributed to the much higher proportion of food waste in the mixed waste stream diverted to AWT, than food waste in the FOGO stream. Food waste accounted for approximately 38% of mixed waste diverted to AWT, compared to approximately 12% in the FOGO stream. This indicates that better management of the food waste stream might lead to significant impacts on emissions reductions. Expansion of FOGO services to more households and LGAs is planned for NSW, which would lead to greater quantities of food waste diverted from landfill. However considering restrictions on AWT derived compost (NSW EPA, 2019a), diverting more of the food waste in the mixed stream to the FOGO stream (i.e., increasing the proportion of food in FOGO) would be more beneficial from a compost utilisation perspective, and the potential downstream emissions reductions.

6.4.5. Sensitivity analysis and comparison with emissions intensities from the literature

Figure 6-18 shows the distribution of overall net emissions estimates, derived from a Monte-Carlo simulation (10,000 iterations) with random values for selected variables as described in Section 6.3.5. Variation in overall net emissions was estimated at approximately ±18% at the 95% confidence level. Table 6-20 summarises results from a regression analysis on the generated outputs of the Monte-Carlo simulation, used to evaluate sensitivity on variation in selected variable values, based on Acevedo (2013). Equation 6.2 shows the functional relationship analysed:

$$y = \beta_0 + \beta_n x_n + \epsilon \qquad 6.2$$

Where y is the estimated percentage variation in net emissions compared to baseline with nominal variable values; β_0 is the estimated model intercept; β_n is the coefficient value for the n^{th} variable; x_n is the variation of the n^{th} variable compared to the nominal value; and ϵ is the error term.

Of the variables assessed in the sensitivity analysis, variation in waste generation quantities; landfill gas capture rate; compost turning fuel requirements; and direct methane and nitrous oxide emissions from the composting process were found to have a significant impact on variation in net emissions. Of these variables, the overall net emissions in the study area were most sensitive to variation in the landfill gas capture rate, with a doubling of landfill gas capture resulting in an approximately 170% reduction in net emissions. This is expected, given that lifetime landfill emissions have been shown through this analysis to be the most significant contributor to waste-related emissions. This identifies that better landfill data will help improve model accuracy. Future research, including identifying methane emissions from landfill via satellite data, and implications for better estimating landfill emissions, are elaborated in Chapter 8.

Variability in waste generation had a statistically significant impact on net emissions, with a doubling of waste generation across the study area resulting in an approximately 80% increase in net emissions. The impact of waste generation variation on transport emissions were explored in Chapter 5, where it was found a 20% change in waste generation resulted in 2.5%

increase in transportation emissions. Considering that transport emissions make up approximately 13% of overall gross emissions, the impact of waste generation variability is more significant on recovery and landfill emissions.

The impact of variability in compost emissions variables on net emissions was relatively low, however still significant. Results indicate a doubling of the parameter values for methane and nitrous oxide emissions from windrow composting, would result in an approximate 27% and 20% increase in net emissions respectively. The impact of variability in electricity requirements for composting was statistically significant, however very small, with a doubling of parameter value resulting in an approximately 3% change in net emissions.

The impact of variability on AWT processes emissions was found to not impact the overall net emissions estimates. This is somewhat expected, given that emissions from AWT sorting account for a relatively small proportion of overall emissions from the management of the mixed waste stream.

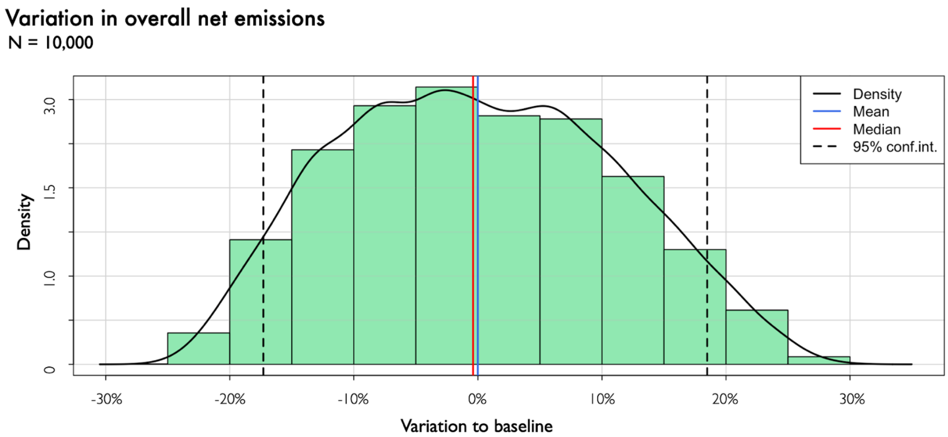


Figure 6-18: Distribution of overall net emissions estimate given variable uncertainty, based on a Monte-Carlo simulation with 10,000 iterations.

Table 6-20: Summary of regression analysis used to evaluate variable sensitivity on overall net emissions

Variable	β-coefficient	*p*-value
Intercept	-0.0000683	0.240
Waste generation	**0.7946286**	**<0.005**
Landfill gas capture rate	**-1.7024166**	**<0.005**
Compost fuel requirements	**0.0353115**	**<0.005**
Compost energy	0.0008206	0.415
Compost CH_4 emissions	**0.2675333**	**<0.005**
Compost N_2O emissions	**0.1913701**	**<0.005**
Trommel energy	0.0013947	0.166
Vacuum sorting energy	0.0001036	0.918
Ballistic sorting energy	0.0010762	0.286
Metal separation energy	-0.0008182	0.417
Air knife separation energy	0.0001406	0.889
Optical sorting energy	0.0006554	0.515
Conveyer belt energy	0.0001219	0.904
R^2 value	0.9972	
Adjusted R^2 value	0.9972	
Model *p*-value	<0.005	

The sensitivity analysis performed does reveal some limitations with the modelling in this analysis, which can be addressed through targeted data collection, for example, more specific landfill gas capture rates for NSW. Estimating direct methane and nitrous oxide from composting has been noted as being difficult, due to complexities in the composting process, and wide variation in compost technology and feedstock composition (US EPA, 2010). Despite these limitations, comparison with metrics from data generated through this analysis with data from the literature, gives confidence to the baseline estimates described in this section. Table 6-21 summarises this comparison, showing key indicators calculated from data generated from this analysis, compared to data from the literature. Data was selected from the literature that could be aligned with data generated from this analysis, and not be biased towards technology or management systems inconsistent with the management system for this study. Metrics from this analysis are generally consistent with values in the literature, illustrating that the emissions intensity of OFMSW management estimated are similar to values reported in the literature elsewhere. Values in the literature however, especially with respect to emissions intensity per tonne managed, vary widely. This can be attributed to variation in the composition of OFMSW internationally, as well as the different composting and recovery technologies employed. Coupled with the results of the sensitive analysis described above, this gives confidence to the results.

Table 6-21: Comparison of mean value performance metrics from this analysis, compared with some data points from literature sources

Metric	Value (this analysis)	Value from literature	Reference
Net emissions intensity per tonne managed	179 kg/t	172 kg/t	Friedrich and Trois (2013)
Gross compost emissions intensity	245 kg/t	218 kg/t	Dastjerdi et al. (2019)
per tonne managed		402.3kg/t	Friedrich and Trois (2013)
		170kg/t	Martínez-Blanco et al. (2009)
		98.4kg/t	Martínez-Blanco et al. (2009)
		172.2kg/t	Zhu-Barker et al. (2017)
		75-150kg/t	Vergara and Silver (2019)
Landfill emissions per tonne disposed	238 kg/t	259.5kg/t	Liu et al. (2017)
(organics)		569.8kg/t	Thanh et al. (2015)
AWT/MBT mechanical sorting energy	1.53 kWh/t	1.32kwh/t	Ng et al. (2021)

6.4.6. Summary of 2019-20 emissions intensities

A final summary of estimated emissions intensities by LGA organic management pathway is presented in Table 6-22, along with average recovery rates. Here, 'GO only' and 'FOGO only' refer to LGAs that have GO and FOGO composting as the only organic waste recovery pathways, and estimated intensities also includes emissions associated with mixed waste management. 'AWT only' refer to LGAs that do not separately collect organics, but send a proportion of mixed waste to AWTs for recovery. 'GO+AWT' and 'FOGO+AWT' refer to LGAs that separately collect GO and FOGO waste for composting as well mixed waste to AWTs (including also emissions associated with the management of non-AWT mixed waste). A single LGA did not separately collect GO or FOGO, or send mixed waste to AWTs for recovery.

Of these different organic management pathways, 'FOGO only' and 'FOGO+AWT' LGAs had the lowest net emissions intensities, at approximately 197 kgCO_2-e/t and 167 kgCO_2-e/t respectively. Interestingly, LGAs that divert mixed waste to AWT as the only recovery pathway, had lower net emissions intensities than 'GO only' LGAs. In addition, 'GO+AWT' LGAs had lower emissions than 'AWT only', but higher than LGAs with FOGO collection. Given that the only pathways for food recovery are via FOGO collections or AWT recovery, these findings support that increasing the diversion of food waste from landfill leads to improved overall emissions performance. Although this finding is useful from a waste management planning perspective, results should be treated with a degree of caution, given that sample sizes for the different LGA pathways are low. Further analysis on state-wide waste related emissions and organic waste recovery, would give greater certainty to these finding and allow further exploration of trends in emissions intensities between the organic management pathways. This is discussed further in Chapter 8 in the context of future work related to this research.

Table 6-22: Emissions intensity factors for different LGA organic waste pathways. Percentage uncertainty is derived from the standard deviation of LGA level estimates, and should be treated with caution due to small sample sizes

LGA organic waste pathway	**Average waste recovery rates [%]**	**Net emissions intensity factor, per tonne managed [kgCO$_2$-e/t]**	**Net emission intensity factor, per tonne diverted [kgCO$_2$-e/t]**
GO only (N=20)	29.7%	165.9 ±19.4%	557.8 ±41.1%
FOGO only (N=3)	50.2%	98.8 ±9.4%	196.6 ±9.5%
No organics + AWT (N=2)	23.3%	109.5 ±16.7%	470.2 ±40.5%
GO + AWT (N=15)	34.7%	96.9 ±52.3%	279.7 ±54.7%
FOGO + AWT (N=2)	45.0%	75 ±21.1%	166.8 ±65.9%
No organics (N=1)	0.0%	216.8 ±17.3%	NA

6.5. Conclusions

This chapter presented a modelling framework and results on the emissions associated with OFMSW management in the Greater Sydney and surrounding areas for 2019-20. The aim of the analysis was to address thesis research question 4, on the accounting of emissions associated with the recovery of household organic waste in NSW. In this regard, a review of the literature supported that any holistic accounting of emissions associated with waste recovery should also include upstream (i.e., transportation) and downstream (i.e., landfill disposal) emissions and potential emissions avoidance. The analysis found that total emissions associated with OFMSW recovery in the study area including upstream and downstream management, was approximately 245,000 tCO$_2$-e, with emissions from landfill disposal accounting for approximately 56% of all emissions generated. Management of the mixed waste stream, which also accounts for the majority of organic waste generated by households in the study area, had the largest impact on overall emissions, and the highest emissions intensity on a per tonne diverted basis. The analysis also addressed an important knowledge gap identified in Chapter 5, on the accounting of OFMSW management emissions beyond transportation; finding that emissions from transportation account for approximately 13% of overall OFMSW management emissions.

The analysis highlights that landfill diversion of organics, especially food waste in the mixed stream, is crucial in the context of achieving good low carbon resource recovery performance.

Increasing the diversion of food waste from the mixed stream to separate FOGO collections, and increasing quantities of mixed waste treated via AWTs were shown to have a positive impact on landfill diversion. These strategies are also aligned with the *NSW Waste and Materials Strategy 2041*, and would likely have significant impacts on transitioning to low carbon resource recovery.

The modelling approach can be further adapted, to investigate other OFMSW management strategies and their impacts on low carbon resource recovery, including for example, the impacts of anaerobic digestion as a recovery pathway. This is further explored in the context of a scenario analysis in Chapter 7. The modelling approach utilised also performed well from an uncertainty and parameter sensitivity perspective, and analysis identified where improvements could be made to give further confidence in the accuracy of results. Namely, better data on landfill capture rates, and direct emissions of methane and nitrous oxide from the composting process could improve the accuracy and certainty of results. Future analysis may also explore expanding the system boundaries, to include the emissions potential of the utilisation of secondary organics to land, including from carbon capture in soil, and from offsetting mineral based fertiliser consumption. Future utilisation of this modelling approach is elaborated further in Chapter 8.

Chapter 7.
Evaluation of low carbon resource recovery pathways

This chapter utilises the modelling approach described in the previous chapter for exploring and evaluating the impacts of a number of potential OFMSW management pathways from a low carbon resource recovery perspective, in order to address the following research question:

Research question 5: What are the optimal low carbon resource recovery pathways for household organic waste in NSW, and how may they be identified?

Addressing the above research question is done so via two parts in this chapter. First, a scenario analysis is performed, which utilises the modelling approach from Chapter 6, and explores some potential organic management pathways derived from the *NSW Waste and Sustainable Materials Strategy 2041* (DPIE, 2021). Secondly, data generated from this scenario analysis is analysed through a multi-criteria analysis, the objectives which are twofold: i) to test and evaluate a simple multi-criteria method for assessment of low carbon pathways for decision makers; and ii) to identify from the data generated, what OFMSW management pathways are most optimal from a low carbon resource recovery perspective.

The concept of optimality from a low carbon resource recovery perspective was introduced earlier in Chapter 2, and is reintroduced here briefly. Evaluating and identifying pathways that are most optimal from a low carbon resource recovery perspective is complex. While one management pathway may lead to emissions reductions, for example through improving transportation efficiency, it may not have a significant impact on recovery rates. In contrast, a pathway may be directed at improving waste separation and collection rates, leading to improved recovery rates but at a higher emissions intensity. From a low carbon resource recovery perspective, it is not always clear what pathways are most optimal, or how they should be prioritised by decision makers.

The analysis in this chapter is motivated by potential organic waste management pathways that appear in the *NSW Waste and Sustainable Materials Strategy* (DPIE, 2021). While the strategy does prioritise some pathways for organic waste management to 2030, for example anaerobic digestion and mandatory FOGO collection, identifying what pathway or combination of pathways is most optimal from a low carbon resource recovery perspective, is unclear. Literature analysing waste management pathways and systems from the perspective of multi-criteria optimisation is widespread, and is useful for addressing this problem. A brief review of some of these studies is provided in Chapter 2. Many studies attempt to find optimal pathways or system configurations based on a set of criteria informed by stakeholders or waste management experts. While criteria including costs (e.g., revenue and operational/capital costs), social licencing, and other socio-economic factors can be significant in determining what pathways to prioritise for a given waste system, this analysis is focused only on the techno-environmental domain as described in Iacovidou et al. (2017a). This is because prioritisation of environmental impact reduction (i.e., emissions) and waste recovery fall under the techno-environmental value domains (Iacovidou et al., 2017a). The analysis in this chapter therefore attempts to identify optimal low carbon resource recovery pathways in an effort to help inform future organic waste management decision making, aligned with waste recovery strategies and carbon reduction priorities.

The remainder of this chapter is organised as follows: firstly, a description of the scenario development and evaluation approach is given, including an introduction to the *NSW Waste and Sustainable Materials Strategy*, and details of scenario assumptions. Results of the scenario analysis are given, including net emissions intensities of the different management pathways and comparison across the scenarios, and against intensities derived from Chapter 6. Results of the multi-criteria analysis are then given, followed by an evaluation of the approach tested.

7.1. Scenario development and evaluation approach

A scenario analysis was performed to evaluate the waste recovery and potential emissions intensities of a number of alternate organic waste management and recovery pathways, utilising the modelling approach described in Chapter 6. Scenarios are evaluated to optimise low carbon resource recovery performance, and are compared against baseline (i.e., Chapter 6 results) in a multi-criteria analysis.

For this analysis, scenarios are derived from the *NSW Waste and Sustainable Materials Strategy* (DPIE, 2021). This strategy is an outline of planned actions and reforms to be undertaken by the NSW Government in transitioning to a more circular economy in the state around waste and materials management. With respect to OFMSW management, the strategy also targets the halving of organic waste sent to landfill by 2030, as well as achieving net zero emissions from organics to landfill, also by 2030. These targets are largely driven by the environmental benefits and economic opportunities brought about by better management of NSW waste streams, but also the need to address growing requirements for landfill expansion in the near future. Several planned actions are identified in the strategy, including mandating FOGO collection for all NSW households, and incentivising biogas generation from waste materials via anaerobic digestion. However the strategy also indicates that significant investment in new OFMSW management infrastructure is required—not just to manage a growing FOGO waste stream or to harness potential bioenergy from the stream, but also to keep pace with growing populations in NSW specifically in urban areas. Findings from this scenario analysis can therefore help inform the trajectory of OFMSW recovery and related emissions towards the objectives of the *NSW Waste and Sustainable Materials Strategy*, and can also assist decision making around selection of optimal pathways and infrastructure. Although not within scope of this analysis, the modelling utilised (i.e., from Chapter 6) can be utilised to identify optimal locations for infrastructure, as well as catchment areas for feedstock. This is discussed further in the context of future work in Chapter 8.

Table 7-1 summarises the scenarios modelled for this analysis. Waste generation rates in each scenario were based on 2019-20 (baseline year) levels, as described in Chapter 6. This allows for the simple comparison between current waste management practices, and the impact of the various scenario interventions tested in this analysis. Estimating future waste generation (e.g., for 2030 or beyond) is outside the scope of analysis, given the large uncertainties related to changing household waste disposal and generation behaviours, and future household distributions. For each scenario, organic waste recovery rates and net emissions per tonne of waste diverted are compared with baseline 2019-20 performance. Modelled scenarios and assumptions are described in detail in the following section.

Table 7-1: Overview of scenarios modelled

Scenario		Description
Mandatory FOGO collection scenarios	Scenario 1.1	- Mandatory weekly FOGO collection for all councils - Mixed waste collected fortnightly - FOGO collected treated at existing composting facilities
	Scenario 1.2	- Mandatory weekly FOGO collection for all councils - Mixed waste collected fortnightly - Food waste diverted from mixed waste to FOGO increased - FOGO collected treated at existing composting facilities
Standalone anaerobic digestion scenarios	Scenario 2.1	- Mandatory weekly FOGO collection for all councils - Mixed waste collected fortnightly - Standalone AD facility deployed in Western Sydney - FOGO not treated via AD is treated at composting facilities
	Scenario 2.2	- Mandatory weekly FOGO collection for all councils - Mixed waste collected fortnightly - 3 standalone AD facilities deployed in Western Sydney, Hunter, & South Coast - FOGO not treated via AD is treated at composting facilities
	Scenario 2.3	- Mandatory weekly FOGO collection for all councils - Mixed waste collected fortnightly - 3 standalone AD facilities deployed in Western Sydney, Hunter, & South Coast - Food waste diverted from mixed waste to FOGO increased - FOGO not treated via AD is treated at composting facilities
Anaerobic digestion deployed at AWTs scenarios	Scenario 3.1	- Mandatory weekly FOGO collection for all councils - Mixed waste collected fortnightly - Organic waste sent to AWT facilities is digested on site - FOGO not treated via AD is treated at composting facilities
	Scenario 3.2	- Mandatory weekly FOGO collection for all councils - Mixed waste collected fortnightly - Organic waste sent to AWT facilities is digested on site - Food waste diverted from mixed waste to FOGO increased - FOGO not treated via AD is treated at composting facilities
	Scenario 3.3	- Mandatory weekly FOGO collection for all councils - Mixed waste collected fortnightly - Organic waste sent to AWT facilities is digested on site - 3 standalone AD facilities deployed in Western Sydney, Hunter, & South Coast - Food waste diverted from mixed waste to FOGO increased - FOGO not treated via AD is treated at composting facilities

7.1.1. Description of scenarios

Scenario 1.1 – mandatory FOGO collection

Scenario 1.1 examines the impact on emissions from the mandatory collection of household FOGO across NSW. The *NSW Waste and Sustainable Materials Strategy* (DPIE, 2021) identifies mandatory FOGO across NSW households as being a key implementation for improved organic waste diversion by 2030. For this scenario, all LGAs in the study area are assumed to collect FOGO at the kerbside at weekly intervals, with mixed waste being collected fortnightly instead of weekly. As such, FOGO collection must be modelled for LGAs without FOGO services in the baseline year. For LGAs in the baseline case with GO collection services (note that GO and FOGO are mutually exclusive), the garden waste proportion of FOGO is assumed to be equal to quantities of GO collection in the baseline. The food waste proportion of FOGO is then estimated, based on the proportion of food waste in the FOGO stream reported in Rawtec (2020a), equal to approximately 12% by mass. Estimated quantities of food waste collected via FOGO for these LGAs are then removed from the total quantity of waste collected via the mixed waste stream, to ensure food waste collections via FOGO were not double counted. For LGAs without separate organics collection in the baseline case, quantities of FOGO collection were estimated based on the baseline average proportion of FOGO collection to total (FOGO + mixed) waste collection for LGAs with FOGO in the baseline year, equal to approximately 47% of total waste generated. Garden and food waste apportioned to FOGO collection was then removed from quantities of mixed waste collection for these LGAs, to ensure FOGO collections were not double counted.

Scenario 1.2 – mandatory FOGO collection with increased food diversion

Scenario 1.2 also examines mandatory FOGO collection for NSW households, however assumes a higher diversion of food waste from the mixed waste to FOGO stream for all LGAs. The diversion rate of food waste from the mixed waste stream to FOGO (that is, the proportion of total food waste that is collected via FOGO) is doubled compared to the baseline and Scenario 1.1, and is assumed to occur based on improved household disposal practices and increased awareness of eligible organic materials accepted in FOGO waste bins. Additional quantities of food waste diverted to FOGO are removed from the mixed waste stream, and added to the FOGO stream, resulting in an increased proportion of food waste in

FOGO. Detailed assumptions on the composition of the FOGO and mixed waste streams are summarised in Table 7-2.

Table 7-2: Average proportion of food waste in FOGO and mixed waste stream for baseline 2019-20, and Scenarios 1.1 and 1.2

Scenario	Food waste in FOGO stream	Food waste in Mixed waste stream
Baseline	11.5%	22.7%
Scenario 1.1	11.5%	22.7%
Scenario 1.2	20.6%	17.4%

Scenario 2.1 – standalone OFMSW digestion (low-demand)

Scenario 2.1 explores the potential impact of the deployment of anaerobic digestion on waste related emissions in the study area. The *NSW Waste and Sustainable Material Strategy* notes the potential for anaerobic digestion in the Greater Sydney area, identifying 3 general locations where digestion technology may be deployed in the future. Scenario 2.1 is a low-demand scenario, where a single dry OFMSW digester is deployed in Western Sydney for treatment of FOGO waste collections. Collection assumptions from Scenario 1.1 are used for this scenario, assuming mandatory FOGO collection would be necessary to ensure sufficient feedstock for commercialisation. The Eastern Creek location was chosen as the location of the digestion facility, given it is currently the site of other waste recovery infrastructure, including AWT. A dry digester system of 50,000 tonnes per year throughput capacity, with organic loading of 80% food waste and 20% garden waste was chosen as the technology for examination, based on assumptions for OFMSW digestion in Perin et al. (2020) and Peces et al. (2014). Separation of FOGO for digestion is modelled to occur at transfer stations, with FOGO not directed to digestion instead transported to existing composting facilities.

In order not to bias the scenario towards a particular council supplying feedstock to the digestion facility, it was instead assumed that feedstock for the digester would be sourced from nearby transfer stations rather than directly from councils (although acknowledging that quantities of waste at transfer stations are derived from local council areas). For this, a feasible transport distance was determined between the digester and nearby transfer stations such that sufficient FOGO waste was available for digestion. When examining the distance between the digester and all transfer stations in the area, a median distance of approximately 50 km was observed. A feasible distance of approximately 30 km was chosen, which was calibrated such that sufficient organic waste was available (assuming 80% of the feedstock is food waste). All transfer stations within this transport radius of the digester were identified, and it was assumed feedstock for the digester would be drawn evenly from these transfer stations (i.e., if 5 transfer stations were in proximity, 10,000 tonnes of total waste would be sourced from each transfer station). To avoid double counting, quantities directed to digestion for applicable LGAs were removed from FOGO collections destined for composting. Figure 7-1 shows the assumed location of the digestion facility, transfer stations within the assumed collection zone, and LGAs where waste sent to the AD facility is derived. Assumptions on AD processing and biogas generation common across all scenarios are described in detail further in Section 7.1.2.

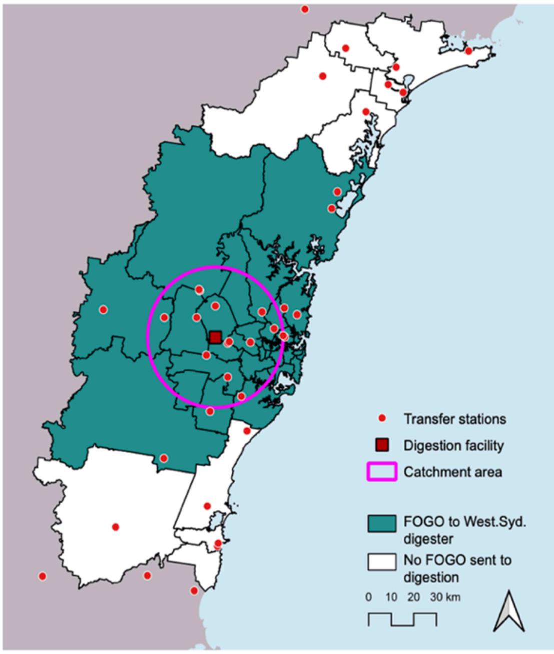


Figure 7-1: Location of the Western Sydney digester and LGAs sending waste to digestion for Scenario 2.1

Scenario 2.2 – standalone OFMSW digestion (high-demand)

Scenario 2.2 examines OFMSW digestion deployment in Western Sydney, and in the Hunter and Shoalhaven regions, based on potential locations noted in the *NSW Waste and Sustainable Materials Strategy*. The Eastern Creek location from Scenario 2.1 is used for the Western Sydney digester. For the Hunter region, Raymond Terrace was selected as a location for a digester, given it is the site of an existing AWT facility. For the Shoalhaven digester, South Nowra was selected as a candidate location, as it is the site of a significant resource recovery park. Digesters in the Hunter and Shoalhaven however were assumed to operate at reduced throughput, given the reduced quantities of available feedstock for operation of 50,000 tonnes per year scale digesters at these locations compared to the Eastern Creek location. Pre-analysis found that given the assumed organic loading rates of 80% food and 20% garden waste, there is only sufficient feedstock from the FOGO stream alone for approximately 90,000 t/year capacity of digestion across the entire study area. Given the 50,000 t/year sized digester in Western Sydney, the remaining 40,000 t/year of theoretical capacity was apportioned to facilities in the Hunter and Shoalhaven. As such, the Hunter-based digester was assumed to have a throughput of 25,000 t/year, and the Shoalhaven facility 15,000 t/year, reflecting that waste generated across LGAs in the Hunter is approximately 1.5-times that of LGAs in the Shoalhaven and surrounding regions. The same approach used to calculate the origin of FOGO feedstock as applied to the Western Sydney digester in Scenario 2.1, was applied for Scenario 2.2. For the Western Sydney digester, the transport radius of 30km was used, consistent with Scenario 2.1. For the Hunter, a transport radius of approximately 130km was required to supply sufficient feedstock for the digester. For the Shoalhaven facility, a radius of 105km was required. Although it is likely that feedstock could be incorporated from other areas outside the study area, and indeed from other waste sources such as agriculture, this was outside the scope, and is discussed in the context of future research in Chapter 8. Figure 7-2 shows the assumed location of the digestion facilities, transfer stations within the assumed collection zones, and LGAs where waste sent to each AD facility is derived. Note that there are some overlaps where LGAs effectively send waste to more than one AD facility.

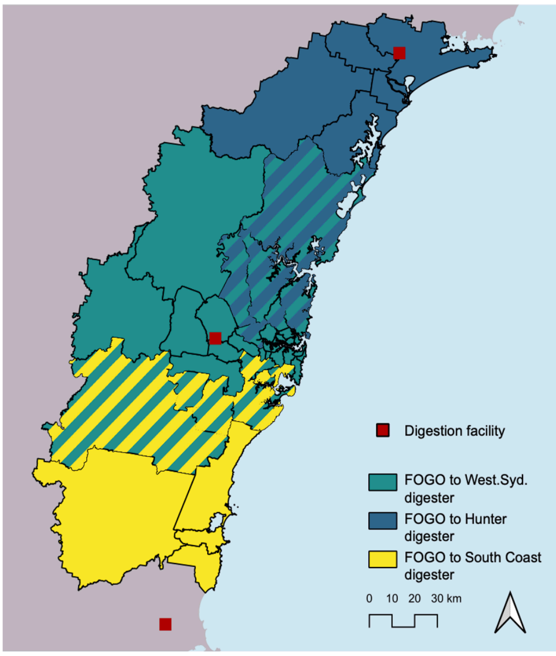


Figure 7-2: Location of the Western Sydney, Hunter and Shoalhaven digesters, and LGAs sending waste to digestion for Scenario 2.2. Note that there is overlap in catchment areas for the different digesters

Scenario 2.3 – standalone OFMSW digestion (high-demand) with increased food diversion

Scenario 2.3 examines the deployment of the same facilities as assumed in Scenario 2.2, but with assumptions for increased diversion of food waste to FOGO collection as used for Scenario 1.2. In this scenario, reduced transport radii to ensure sufficient feedstock were possible, with a radius of 16km used for the Western Sydney facility; 70km used for the Hunter facility; and 95km for the Shoalhaven facility. Table 7-3 summarises transport distances assumptions for Scenarios 2.1, 2.2 and 2.3; and Figure 7-3 shows collection zones for each digester under Scenario 2.3 conditions. Note digester throughput capacities are the same as Scenario 2.2.

Table 7-3: Summary of transport distance assumptions for Scenarios 2.1, 2.2 and 2.3

Scenario	Digester catchment transport distance assumptions
Scenario 2.1	Western Sydney digester – 30km
Scenario 2.2	Western Sydney digester – 30km Hunter region digester – 130km South Coast region digester – 105km
Scenario 2.3	Western Sydney digester – 15km Hunter region digester – 70km South Coast region digester – 95km

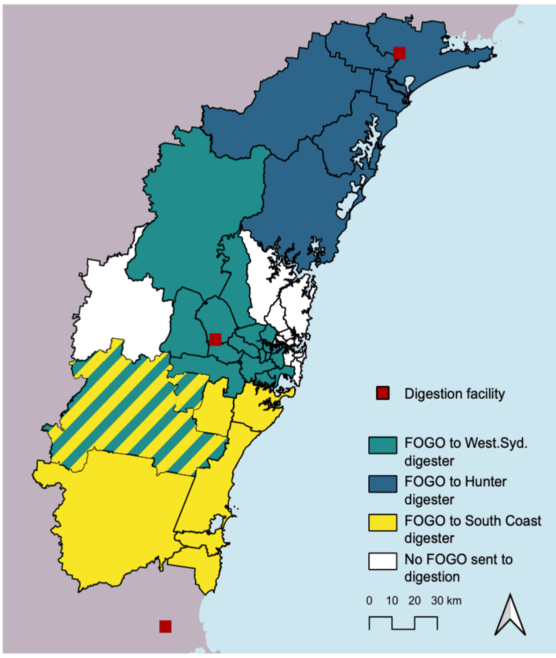


Figure 7-3: Location of the Western Sydney, Hunter and Shoalhaven digesters, and LGAs sending waste to digestion for Scenario 2.3

Scenario 3.1 – anaerobic digestion at AWT facilities

Scenario 3.1 explores the adapting of existing AWT facilities to incorporate anaerobic digestion in place of in-vessel composting. Anaerobic digestion is commonly deployed at AWT/MBT facilities abroad, and is assessed as viable OFMSW treatment options in Ng et al. (2021); Stunzenas and Kliopova (2018); and Rigamonti et al. (2019). Scenarios 2.1, 2.2 and 2.3 assume some upheaval of the existing FOGO composting pathway by diverting feedstock away from existing composting facilities. Scenario 3.1 assumes that feedstock from AD comes only from the mixed waste streams at AWT facilities, consisting of food waste only, therefore does not impact existing compost recovery. An additional benefit from this scenario is the potential for greater AD capacity, with approximately 150,000 tonnes of food waste sent to AWT via the mixed stream in the baseline year, and 105,000 tonnes under mandatory FOGO conditions. Mandatory FOGO collection assumptions for this scenario are consistent with Scenario 1.1 assumptions. AWT mechanical sorting energy intensity assumptions are the same as in the baseline case. Assumptions and parameters used to estimate AD energy requirements and biogas generation are the same used for Scenarios 2.1, 2.2 and 2.3, which are described in detail later in this section.

Scenario 3.2 – anaerobic digestion at AWT facilities, with increased food waste diversion

Scenario 3.2 explores adapting of existing AWT facilities with AD capabilities, however also includes assumptions around increased diversion of food waste from mixed waste to FOGO streams. Although increased diversion means less food waste in the mixed stream available for AD at AWT facilities, this scenario tests the combined impact on emissions intensity of these two interventions. Food waste diversion assumptions are consistent with Scenarios 1.2 and 2.3, and assumptions around AD recovery at AWTs are the same as Scenario 3.1. The difference between these scenarios, is a reduced quantity of food waste available at AWTs, given the increased redirection of food waste from the mixed stream to FOGO.

Scenario 3.3 – standalone OFMSW digestion with AD deployed at AWTs, and increased food waste diversion

Scenario 3.3 examines the potential of the system to prioritise energy recovery from organic streams, and is the final scenario evaluated. Scenario 3.3 assumes the deployment of the 3 digesters located in Western Sydney, the Hunter and Shoalhaven areas, with the added assumption of increased food waste diversion (Scenario 2.3). All AWTs are also assumed to deploy AD for treatment of the organic fraction entering AWTs. The overall AD capacity for this scenario is therefore approximately 184,000 tonnes per year (90,000 tonnes standalone AD; 94,000 tonnes AD at AWT facilities).

7.1.2. Estimating anaerobic digestion emissions and avoidance

Figure 7-4 illustrates the anaerobic digestion process assumed for all scenarios utilising AD as recovery pathway, adapted from Wang et al. (2021). Mesophilic digestion is the assumed digester type, which operates at temperatures between 20°C and 40°C, and represents more than 90% of OFMSW digesters in use worldwide (Li et al., 2018; Wang et al., 2021). Feedstock collected for digestion is delivered to the digestion facility, where it is first pre-treated on site. Pre-treatment is performed to improve the quality of the feedstock entering the digester, and pre-treatment processes can vary. Fan et al. (2018) performed a review of different pre-treatment processes utilised for AD for different feedstocks. Mechanical grinding was common for the digestion of OFMSW, and therefore is the assumed pre-treatment process.

Grinding of the feedstock reduces the feedstock to a consistent particle size, where smaller particle sizes of the digestion substrate leads to improved microbial activity and methane generation (Pilli et al., 2020).

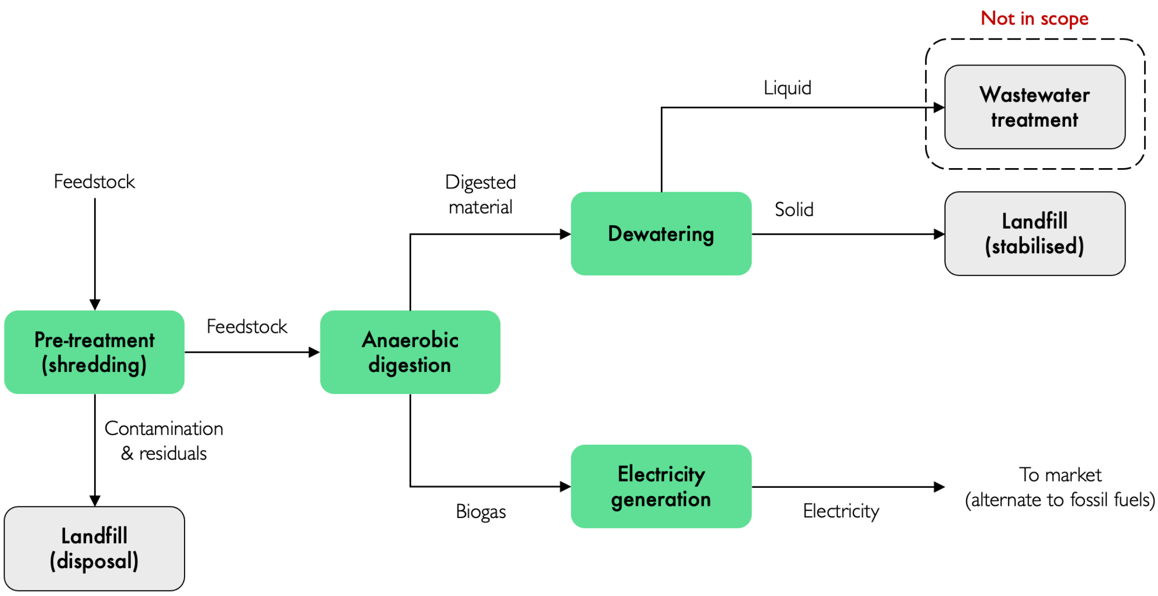


Figure 7-4: Illustration of the assumed OFMSW anaerobic digestion process, adapted from Wang et al. (2021)

Contamination is also removed at this step. For the purpose of this model, feedstock that is pre-treated and ready for digestion is considered recovered—consistent with how compost is treated in accounting for organic waste recovery in *organic waste recovery model* described in Chapter 6. Contamination within the feedstock stream (i.e., at the input of the recovery process) is treated as residual, and is transported to landfill for disposal. After digesting (for 21 days as per Wang et al. (2021), although this does not have bearing on the model estimates), the digestate is then treated to remove water ('dewatering'), before being utilised as a soil amendment. For this model, the application of digestate to land and the treatment of the liquid component are not considered in scope, consistent with compost recovery assumptions. Biogas generated from the digestion process is assumed to be combusted to generate electricity as per Lou et al. (2013). Before combustion, the biogas is assumed to be treated to improve its quality and utilisation potential via chemical scrubbing (Andriani et al., 2014; Fan et al., 2018; Niesner et al., 2013). Table 7-4 includes parameters used to estimate energy requirements of the digestion process. Emissions from AD treatment are calculated by multiplying estimated electricity consumption by emissions factors (scope 2 and 3) from DISER (2021b), specific to the NSW energy supply for 2019-20.

Table 7-4: Anaerobic digestion parameters

Parameter	Value	Reference
Pre-treatment (grinding)	10.7334 kWh/t-input	Average of values given in Zhang and Banks (2013); Izumi et al. (2010); Fan et al. (2018) and Wang et al. (2021)
Dewatering	0.67 kWh/t-output	Average of values given in Wang et al. (2021)
Post-treatment (chemical scrubbing)	0.43 kWh/m^3	Average of values given in Fan et al. (2018)

It was assumed that digesters produce methane-rich biogas, based on the model in Lou et al. (2013), which is combusted for the generation of electricity in a generic gas combustion engine, with an assumed electricity conversion efficiency of 34%. It is assumed that digestate produced is biostabilised and sent to landfill, given municipal waste derived recovered organics are currently restricted from land application (NSW EPA, 2019a). Electricity generated from biogas was assumed to offset fossil fuel derived electricity, resulting in emissions reductions (assuming CO_2 generated from combustion is biogenic). While AD deployed in Europe often utilise combined heat and power (CHP) systems, given the lack of demand for district heating in NSW due to milder temperatures than in Europe, it was assumed that only electricity is generated from combustion. Future analysis could explore the application of AD-derived biogas for trigeneration systems which produce cooling derived from the thermal energy of the system. For the purpose of this analysis, it was assumed that biogas was combusted at the AD facilities, which are assumed to also be connected to the local electricity network, given proximity to existing industrial sites around the selected digester locations. A more detailed analysis in identifying optimal facility locations based on proximity to existing electricity transmission networks, and scenarios exploring transportation of biogas for electricity generation at other locations, is beyond the scope of this analysis, but is discussed in the context of future work in Chapter 8. The authors in Lou et al. (2013) estimated the theoretical biogas generation potential from municipal food waste in Australia, using the model in Equation 7.1, which was also utilised for this analysis:

$$G_{AD} = q \cdot f_{vs} \cdot b \cdot g \cdot c_{CH_4} \qquad 7.1$$

Where G_{AD} is biogas generated from AD (in m^3); q is the quantity of feedstock treated (in tonnes); f_{vs} is the ratio of volatile solids to total solids; b is the volatile solids biodegradability for OFMSW; g is the biogas yield (m^3 per tonne of volatile solids destroyed); and c_{CH_4} is the volume concentration of methane in biogas (m^3m^{-3}). A proportion of biogas generated from

AD is lost to the environment through leakages in the system (i.e., containment leakage). This leakage is based on data in Fei et al. (2022), who reported 1.5% of the methane generated was lost to the atmosphere over the digestion process, in addition to approximately 0.015 kg of nitrous oxide per tonne of feedstock. These factors were used to estimate leakages of methane and nitrous oxide, and were multiplied by their respective global warming potentials from DISER (2021b) to estimate emissions in CO_2-equivalent. These values are summarised in Table 7-5.

Table 7-5: Summary of parameters used for direct GHG emissions from anaerobic digestion of OFMSW

Parameter	Value	Reference
Methane leakage	1.5% of total methane generated	Fei et al. (2022)
Nitrous oxide leakage	0.015 kg/t feedstock	Fei et al. (2022)
Methane global warming potential	28	DISER (2021b)
N_2O global warming potential	265	DISER (2021b)

The electricity generated from combusting biogas derived from AD is also estimated, based on the model in Lou et al. (2013). The energy generation potential from the biogas generated is estimated from Equation 7.2:

$$E_{AD} = G_{AD} \cdot Q_{CH_4} \cdot \eta_e \qquad 7.2$$

Where E_{AD} is the energy generation potential (MJ); Q_{CH_4} is the volumetric heating value of methane (MJ m^{-3}); and η_e is the efficiency of the combustion engine generator. Parameter values used in the analysis are shown in Table 7-6.

Table 7-6: Parameter values used in the estimation of biogas and electricity generation from digestion, from Lou et al. (2013), and Demichelis et al. (2022) (for f_{vs})

Parameter	Value
f_{vs}	0.84
b	0.83
g	0.55
c_{CH_4}	0.71
Q_{CH_4}	36.3 [MJ m^{-3}]
η_e	34%

Electricity generated from the combustion of biogas generated is assumed to substitute fossil fuel derived electricity in NSW. Emissions reductions are therefore calculated based on offsetting emissions associated with fossil-fuel derived electricity utilised in NSW, using the emissions intensity of fuel combustion. For this, the emissions offset is calculated by applying emissions factors for fuel combustion to the quantity of electricity generated in MJ from AD derived biogas (i.e., from Equation 7.2). Fuel combustion emissions factors from DISER (2021b) were then multiplied by E_{off} to estimate the emissions offset. Data on the distribution of fossil fuel energy sources for NSW in 2019-20 (DECCEEW, 2022) were used to estimate the emissions offset, weighted to the NSW energy mix. Approximately 96% of fossil fuel energy is derived from black coal in NSW, with the remainder from natural gas sources. Emissions offsets were balanced by the direct emissions from the combustion of AD derived biogas, also estimated from the emissions factors from DISER (2021b), which are subtracted from the estimated emissions offsets to calculate the net emissions offset (Equation 7.3):

$$GHG_{net\,offset} = \left(\sum_{j}\sum_{k} E_{AD}\cdot\varphi_{j,k}\right) - \left(\sum_{j} E_{AD}\cdot\varphi_{j,biogas}\right) \qquad 7.3$$

Where $GHG_{net\,off}$ is the estimated GHG emissions offset from AD in CO_2-e; $\varphi_{j,k}$ is the emissions factor for fuel source $k = \{coal, gas\}$ and greenhouse gas $j = \{CO_2, CH_4, N_2O\}$. Table 7-7 summarises emissions factors for fuel combustion used in this analysis. Total emissions for AD treatment at AD facilities (i.e., not including transportation) are then calculated as per Equation 7.4. Note that transport emissions are calculated following the approach described in Chapter 5 and applied in Chapter 6.

$$GHG_{total\,netAD} = \left(GHG_{pre} + GHG_{op} + GHG_{dewater} + GHG_{post}\right) - GHG_{net\,offset} \qquad 7.4$$

Where GHG_{pre} is the emissions associated with AD pre-treatment; GHG_{op} is the emissions associated with AD plant operations; $GHG_{dewater}$ are emissions associated with dewatering of the digestate, and GHG_{post} are emissions associated with post-treatment. Energy consumption for pre- and post-treatment, operations, and dewatering are converted to CO_2-e emissions by applying scope 2 and 3 emissions factors from DISER (2021b), specific to the NSW energy supply in the study timeframe.

Table 7-7: Emissions factors from fuel combustion, from DISER (2021b)

	Emissions factor (kgCO_2-e/GJ)		
Energy source	**CO_2**	**CH_4**	**N_2O**
Black coal	90	0.04	0.2
Natural gas	51.4	0.1	0.03
Biogas	0	6.4	0.03

Findings from the scenario analysis may help inform the strategic planning of organic waste management in the study area, including in optimal household collection systems (e.g., FOGO vs GO) and the impact of identified key future technologies (i.e., anaerobic digestion).

7.1.3. Evaluation approach

Evaluating organic management pathways from a low carbon resource recovery perspective is complex. Pathways considered optimal might depend on a range of factors, including technical and environmental criteria (e.g., waste recovery rates and net emissions), as well as factors representing ease of implementation, cost of implementation, and social licencing among others. Various tools and approaches exist for identifying or evaluating pathways from the perspective of optimality (i.e., which pathways are most optimal for a given set of criteria), as is summarised in Section 2.3. For this study, the simple additive model (SAM) approach was utilised to evaluate the modelled scenarios from a low-carbon resource recovery perspective. This approach is the recommended multi-criteria analysis (MCA) approach for evaluating infrastructure projects in the *Guide to Multi-Criteria Analysis* (Infrastructure Australia, 2021), due to its ease of implementation, flexibility, and few data requirements. It is also a method that is widespread in the literature, as indicated in Vlachokostas et al. (2021), and has been used in the evaluation of MSW energy recovery technologies (Almanaseer et al., 2020; Joseph & Prasad, 2020; Khan & Kabir, 2020); and organic waste management pathways (Makarichi et al., 2018) in a variety of developed and developing-world countries.

The SAM approach can be summarised as a method that takes a measure against a set given criteria, which are then weighted based on the relative importance of the criteria for the decision maker, and combined to compute a weighted score for each scenario. This weighted score is then ranked and evaluated. This simple approach requires only data on measures related to the chosen criteria, and the weightings characterising the relative importance of each criteria (each weighting must be between 0 and 1, and all weightings must sum to 1). For this analysis, the criteria of organic waste recovery rate (that is, the proportion of organic waste generated that was recovered), and net emissions intensity on a tonnes diverted basis were utilised. Following Vafaei et al. (2022), who notes that measures used in SAM must be normalised to overcome scale differences, each measure was normalised using max-min normalisation. Equations 7.5 and 7.6 show the measures used for this analysis:

$$M_{1,i} = \frac{a_i - \min(\boldsymbol{a})}{\max(\boldsymbol{a}) - \min(\boldsymbol{a})};\ a_i = Q_{rec,i} / Q_{gen,i} \quad (7.5)$$

$$M_{2,i} = 1 - \frac{b_i - \min(\boldsymbol{b})}{\max(\boldsymbol{b}) - \min(\boldsymbol{b})};\ b_i = GHG_{net,i} / Q_{div,i} \quad (7.6)$$

Where **a** and **b** are vectors of criteria values for each scenario; $Q_{rec,i}$ and $Q_{gen,i}$ are the total quantity of organic waste recovered and generated for scenario i across the entire study area (i.e., all LGA organic waste recovered and generated summed); $Q_{div,i}$ is total quantity of waste (including some non-organic waste from AWT recovery) diverted for landfill for scenario i; and $GHG_{net,i}$ is the total net GHG emissions (tCO_2-e) for scenario i across the entire study area. Values for measure 2 are normalised and then subtracted from 1, to give higher scoring to scenarios with lower net emissions (and conversely, lower scoring for scenarios with higher emissions). Once M_1 and M_2 are calculated, the final weighted score can be computed (Equation 7.7):

$$S_i = \sum_n M_{n,i} \cdot \gamma_n \quad (7.7)$$

Where γ_n is the relative importance of criteria n. For this application, it was assumed that both recovery performance and net emissions performance were of equal importance, therefore γ_n = 0.5.

Results from this approach is a weighted score S_i computed for each scenario, with higher scores indicating more optimal scenarios/pathways from a low-carbon resource recovery perspective—that is, where waste recovery is maximised, and net emissions minimised.

The approach utilised here is overly simplified, accounting only for the techno-environmental factors of waste recovery rates and net emissions. Further criteria including for example economic considerations, as well as more complex evaluation approaches that account for stakeholder preferences in selecting values for γ_n, are discussed in the context of future work in Chapter 8.

7.2. Scenario analysis results and discussion

This section presents results of the scenario analysis. Results on direct emissions and avoided emissions are first presented for each scenario, before an analysis comparing net emissions intensity for overall OFMSW management for each scenario against baseline estimates. Note that scenario estimates are based on 2019-20 waste generation quantities, to allow for a more direct comparison of the evaluated intervention against the baseline.

7.2.1. Mandatory FOGO collection (Scenarios 1.1 and 1.2)

Figure 7-5 shows the comparison of emissions by source for Scenarios 1.1 and 1.2 compared to baseline. For reference, both scenarios assume all LGAs in the study area have FOGO collection across all households, with Scenario 1.2 having a greater level of diversion of food waste from the mixed waste stream to FOGO. A reduction in total net emissions of approximately 23% compared to baseline was observed for both Scenario 1.1 and 1.2, which can be attributed to higher quantities of organic waste diverted to landfill. Both scenarios 1.1 and 1.2 show higher emissions associated with waste transport compared to baseline. Despite mixed waste being collected at less frequent fortnightly intervals, the increase in transport emissions can be attributed to greater quantities of separately collected organics via FOGO at weekly interval collection. Chapter 5 showed that the emissions intensity of transport is higher for FOGO and GO streams compared to mixed waste, due to these streams being transported to recovery facilities at a higher rate than the mixed waste stream. For the baseline case, approximately 468,000 tonnes of separately collection organics via GO and FOGO were collected, compared to 628,000 tonnes of FOGO in Scenario 1.1, and 700,000 tonnes of FOGO in Scenario 1.2. Recovery emissions are also higher for Scenarios 1.1 and 1.2 compared to baseline, which is expected due to the greater quantity of organic waste treated at composting facilities.

Between Scenarios 1.1 and 1.2, transport and recovery emissions were higher in Scenario 1.2, however these emissions were balanced by lower landfill emissions and greater emissions avoidance. Differences in overall net emissions for Scenarios 1.1 and 1.2 were marginal, with net emissions in Scenario 1.2 less than 1% lower than Scenario 1.1, at approximately 188,300 tCO_2-e (note that the figure show the same quantities of total net emissions due to rounding).

Net emissions intensity on a per tonne basis is examined further for these scenarios in Section 7.2.4.

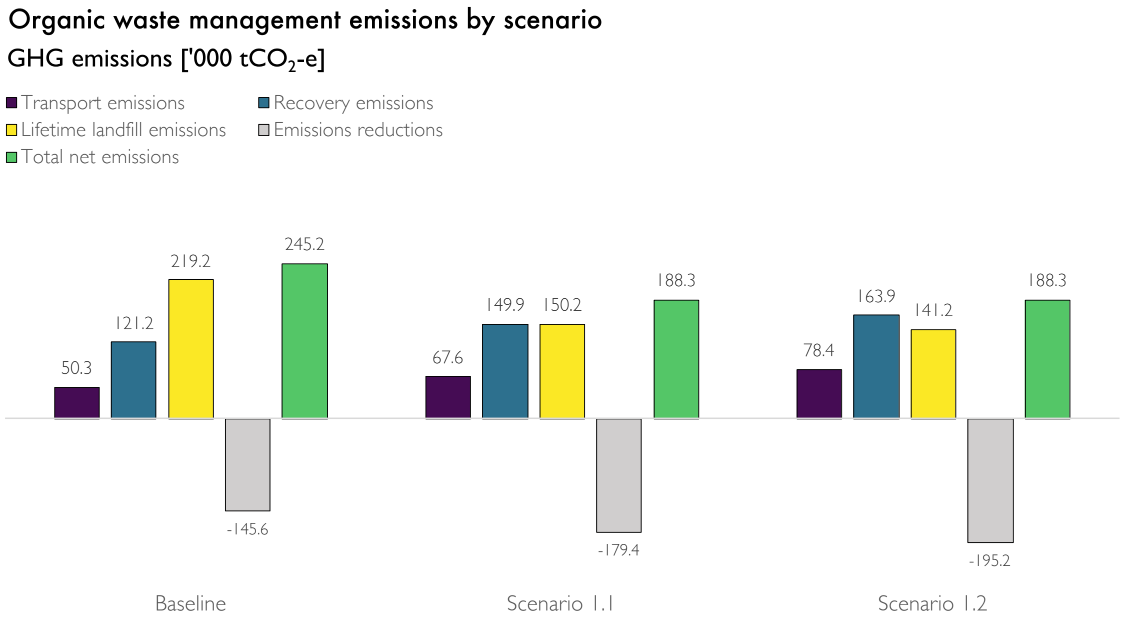


Figure 7-5: Summary of overall emissions by source for mandatory FOGO collection scenarios compared to baseline

7.2.2. Standalone anerobic digestion (Scenarios 2.1, 2.2 and 2.3)

Scenarios 2.1, 2.2 and 2.3 evaluate the implementation of standalone AD as a OFMSW recovery pathway, along with FOGO collection across the entire study area. Table 7-8 summarises quantities of organic waste recovery by pathway for each of the above scenarios and compared to baseline. The addition of standalone AD as a treatment pathway does create competition for feedstock between AD and existing composting pathways. However even with a proportion of OFMSW being diverted to digestion, mandatory FOGO results in a greater quantity of feedstock availability for composting in Scenarios 2.1, 2.2 and 2.3 compared to baseline. This indicates that it would be unlikely for the potential deployment of AD in the study area to have a significant impact on existing composting. Given the preference for food waste for AD, and that the addition of food waste can introduce suboptimal parameters in the composting of garden waste (Babu et al., 2021), future deployment of AD may consider further separation of food and garden waste at the household. Kerbside collections of dedicated food waste (that is, not comingled with garden organics) may ensure that composters would have ample access to optimal garden organics as a compost feedstock, with dedicated food waste collections treated via AD. A system such as this may see benefits in terms of higher quality compost outputs, and more efficient pre-treatment at compost and AD facilities, leading to reduced emissions intensities.

Table 7-8: Summary of composting and digestion throughputs for each scenario compared to baseline

Scenario	Organic waste treated via composting [tonnes]	Organic waste treated via AD [tonnes]	Total organic waste treated (input) [tonnes]
Baseline*	467,512	0	467,512
Scenario 2.1	577,651	50,000	627,651
Scenario 2.2	537,651	90,000	627,651
Scenario 2.3	609,996	90,000	699,996

*Includes FOGO and GO streams

Table 7-9 summarises estimated AD digestion outputs from Scenarios 2.1, 2.2 and 2.3. Potential biogas generation from AD is significant, with 13,600 dam^3 and 24,500 dam^3 generated in Scenario 2.1 and 2.2/2.3 respectively (note that Scenarios 2.2 and 2.3 assume the same quantity of AD throughput, therefore the same potential biogas generation). From the combustion of biogas generated, the electricity generation potential from AD was estimated as 46,700 MWh and 84,000 MWh respectively for Scenarios 2.1 and 2.2/2.3. Considering plant electricity requirements, the net electricity generation potential was estimated as 40,200 MWh and 72,400 MWh respectively. As a proportion of NSW renewable energy supply in 2019-20, this potential represents less than 1% of total electricity generation from renewable sources. However as a proportion of NSW electricity supply from biogas in 2019-20, the potential generation from OFMSW AD represents between 10-20% of total generation (DISER, 2021a). This shows that AD of OFMSW in the study area can augment existing biogas supply, and also identifies the significant potential that OFMSW AD may have as a renewable energy source, especially if AD is deployed across other parts of NSW as well.

The quantity of dewatered digestate produced was also estimated in this analysis, at 35,400 tonnes to 63,700 tonnes for Scenarios 2.1 and 2.2/2.3 respectively. While small compared to windrow composting yields, this digestate has potential applications as a soil conditioner, augmenting existing compost and soil improver supply in the region. Digestate can also be further improved and upgraded, including producing NPK rich liquid fertiliser (Fernández-Delgado et al., 2020; Stunzenas & Kliopova, 2018). This highlights one of the advantages of AD from the literature as a flexible organic resource recovery pathway, with multiple high-valued potential process outputs.

Table 7-9: Summary of digestion throughput and estimated outputs

Scenario	Digestion input [tonnes]	Potential biogas generation [dam³]	Potential electricity generation (gross) [MWh]	Potential electricity generation (net) [MWh]	Dewatered digestate produced* [tonnes]
Scenario 2.1	50,000	13,612.8	46,669.3	40,244.0	35,390
Scenario 2.2 & 2.3	90,000	24,503.1	84,004.8	72,439.2	63,703

*Assumed 40% moisture content (MC) of final product from Wang et al. (2021); initial MC of input derived from Hla and Roberts (2015)

Figure 7-6 shows the comparison of emissions by source for Scenarios 2.1, 2.2 and 2.3 against baseline emissions. Net emissions were approximately 173,400 tCO_2-e for Scenario 2.1; 167,300 tCO_2-e for Scenario 2.2; and 153,500 tCO_2-e for Scenario 2.3. Overall, the implementation of standalone AD would see a significant reduction in net emissions compared to baseline between 29-37% across the scenarios evaluated. Emissions reductions are higher in Scenario 2.2 compared to Scenario 2.1, as a result of the greater quantity of organic waste recovered via AD leading to greater offsetting of emissions from fossil fuel supplied electricity. However, the difference in emissions reductions between Scenarios 2.1 and 2.2 are marginal, representing reductions compared to baseline of 33% and 36% respectively. While Scenario 2.3 assumes the same amount of recovery via AD as Scenario 2.2, the increase in diversion of food waste from mixed waste to FOGO results in higher landfill emissions avoidance compared to the other scenarios.

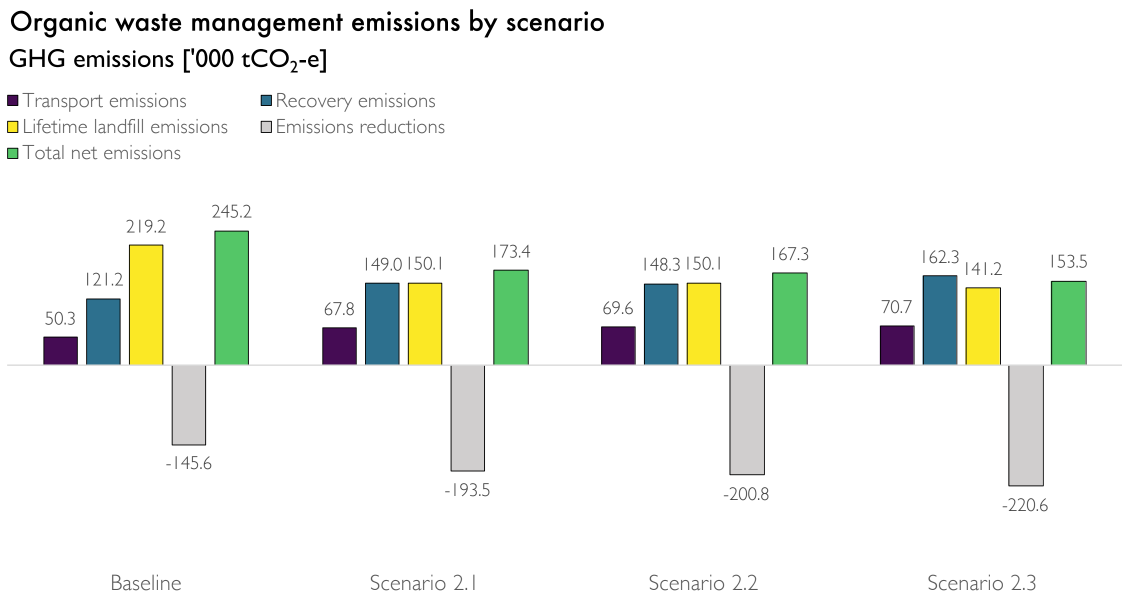


Figure 7-6: Summary of overall emissions by source for standalone anaerobic digestion scenarios compared to baseline

Recovery emissions across all scenarios are higher than baseline, given the greater quantities of organic waste collected for recovery due to the implementation of mandatory FOGO. Recovery emissions in these AD scenarios are lower than in Scenario 1.1 and 1.2, showing that the gross emissions from digestion are lower than windrow composting. This can be attributed to the direct emissions of methane and nitrous oxide through windrow composting, which are greater contributors to CO_2-e emissions than from operational electricity usage and leaked biogas emissions at AD facilities. Transport emissions are higher for these AD scenarios compared to baseline also, due to added transportation links between transfer stations and AD locations. Interestingly, Scenario 2.3 transport emissions are lower than Scenario 1.2, with both scenarios assuming increased diversion of food waste from mixed waste to the FOGO stream. This indicates that more centralised recovery locations as explored in Scenario 2.3 may potentially lead to more efficient transportation, compared to more distributed recovery facilities (e.g., composters) assumed in Scenario 1.2.

7.2.3. Digestion deployed at AWT facilities (Scenarios 3.1, 3.2 and 3.3)

Table 7-10 summarises quantities of organic recovery throughputs for Scenarios 3.1, 3.2, 3.3 and compared to baseline quantities. In Scenario 3.1, approximately 99,300 tonnes of organic waste from the mixed stream (food waste) is treated at AWTs via digestion. Scenarios 3.2 and 3.3 see a reduced quantity of organic waste treated at AWTs, due to increased diversion of food waste from the mixed waste stream to the FOGO stream. Quantities of organic waste treated at AWTs is approximately 94,200 tonnes in Scenarios 3.2 and 3.3, however Scenario 3.3 also assumes that standalone digestion is deployed, consistent with Scenario 2.3. Despite Scenario 3.3 diverting some feedstock away from composting to standalone AD treatment, compost recovery for this scenario is still significantly higher than baseline, on account of mandatory FOGO and increased mixed to FOGO diversion assumptions.

Table 7-10: Summary of organic recovery throughputs for scenarios evaluating digestion deployed at AWT facilities

Scenario	**Organic waste treated via composting [tonnes]**	**Organic waste treated via AWT (compost) [tonnes]**	**Organic waste treated via AWT (biogas) [tonnes]**	**Organic waste treated via standalone AD [tonnes]**	**Total organic waste treated [tonnes]**
Baseline	467,512	197,606	0	0	665,118
Scenario 3.1	627,651	0	99,319	0	726,971
Scenario 3.2	699,996	0	94,208	0	794,203
Scenario 3.3	609,996	0	94,208	90,000	794,203

Table 7-11 summarises quantities of digestion throughput and estimated outputs for Scenarios 3.1, 3.2 and 3.3. Total digestion throughput is higher across all 3 scenarios in comparison with Scenarios 2.1, 2.2 and 2.3. This is due to there being greater quantities of food waste in the mixed waste stream being available for digestion at AWT facilities compared to FOGO—even with mandatory FOGO collection and increased diversion of food waste from mixed to FOGO. As a result, potential biogas and electricity generation is significantly higher in Scenarios 3.1 to 3.3 compared to 2.1 to 2.3. Scenario 3.3 had the greatest quantities of potential biogas generation at approximately 50,000 dam^3, corresponding to a potential electricity generation of 171,300 MWh. Scenario 3.3 assumes deployment of AD at existing AWTs, in addition to the 3 standalone AD facilities in Scenario 2.3 (in addition to increased rates of food waste diversion). Scenario 3.1 had the next highest potential biogas generation, at approximately 26,100 dam^3. Scenario 3.2 had lower quantities of potential biogas generation than Scenario 3.1. This can be attributed to smaller quantities of food waste entering AWTs for this scenario, on account of assumed increases in food waste diversion from mixed waste to the FOGO stream. Potential (net) electricity generation across these scenarios represent an estimated 20-38% of total electricity generation from biogas sources in NSW in 2019-20 (DISER, 2021a).

Table 7-11: Summary of digestion throughput and estimated outputs for Scenarios 3.1, 3.2 and 3.3

Scenario	**Total digestion throughput [tonnes]**	**Potential biogas generation [dam^3]**	**Potential electricity generation (gross) [MWh]**	**Potential electricity generation (net)^ [MWh]**	**Dewatered digestate produced* [tonnes]**
Scenario 3.1	99,319	26,110.0	89,513.7	77,188.9	68,608
Scenario 3.2	94,208	24,860.0	85,228.5	73,493.8	65,324
Scenario 3.3	184,208	49,980.0	171,348.0	147,756.5	130,647

^For digestion at AWT, includes only the energy requirements for the digestion process
* Assumed 40% moisture content (MC) of final product from Wang et al. (2021); initial MC of input derived from Hla and Roberts (2015)

Figure 7-7 summarises overall emissions by source for Scenarios 3.1 to 3.3, compared with baseline. Overall net emissions across the 3 scenarios were significantly less than the baseline. Scenario 3.3 had the lowest net emissions, at an estimated 124,400 tCO_2-e—an approximately 49% reduction on baseline net emissions. Scenarios evaluated are compared in greater detail in the following section.

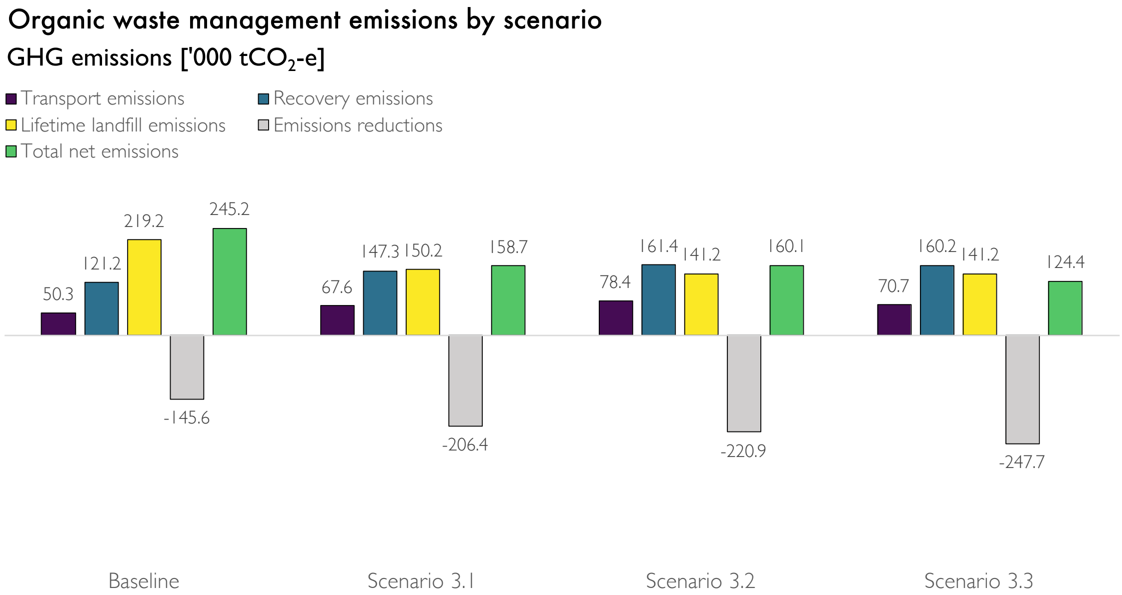


Figure 7-7: Summary of overall emissions by source for AWT deployment of anaerobic digestion scenarios compared to baseline

7.2.4. Comparison of scenarios

Table 7-12 shows a summary of estimated recovery rates for the baseline case, compared with mandatory FOGO and increased diversion of food to FOGO scenarios. Note that recovery rates for digestion are assumed to be consistent with compost recovery for the purpose of this analysis. As such, only variation in the quantities of FOGO collected, and food waste diverted from the mixed stream, have an impact on organic recovery rates. Mandatory FOGO was estimated to increase the organic recovery rate from 55% in the baseline to 69%. With the addition of increased diversion of food waste to the FOGO stream, organic waste recovery was estimated at approximately 75%. These increases in recovery compared to baseline are expected, given that a large proportion of organic waste (food) is in the mixed stream and destined for landfill in the baseline. Interventions that focus on diverting food waste from the mixed waste stream will have a significant impact on increasing the overall organic recovery rate for the waste system. Other interventions not analysed here, such as home composting programs and food waste only collections, may also significantly contribute to diverting food waste from the mixed stream. In the case of food waste only collections, deployment of municipal scale AD could be a driver for this type of collection system, as AD operators would have preference a 'cleaner' food waste stream as a digestion feedstock.

Table 7-12: Summary of estimated recovery rates for baseline and scenarios

Scenario	**Recovery rate [% of total waste generated]**	**Organic recovery rate [% of organic waste generated]**
Baseline	31.6%	55.4%
Mandatory FOGO collection	39.0%	68.5%
Increased diversion of food to FOGO	42.7%	74.9%

Figure 7-8 shows a breakdown of organic waste recovery by pathway across all scenarios, compared to baseline. Quantities of recovered organics as compost varied across the scenarios. Scenarios 1.1 and 1.2 had the greatest quantity of organic waste recovered as compost, at approximately 719,000 and 786,000 tonnes respectively. While quantities of recovered organics derived from AWT facilities are restricted in their application to land in NSW (NSW EPA, 2019a), the FOGO stream is also subject to high amounts of contamination which can limit its application as a soil amendment especially for food production (Wilkinson et al., 2021). This is an important consideration across all scenarios which assume mandatory FOGO collection as per the *NSW Waste and Sustainable Materials Strategy* (DPIE, 2021). Nevertheless, non-food applications including for example energy crops; and industrial applications for example in construction and as bio-stabilised landfill cap, are beneficial end-uses for contaminated compost (Stunzenas & Kliopova, 2018) that are far better outcomes from a circular economy and resource recovery perspective, than simply depositing organic waste to landfill untreated. Despite AD deployment creating competition for composting feedstock in Scenarios 2.1 to 2.3, quantities of organic waste recovered for composting are still higher than in the baseline case. However, compost recovery in the baseline is primarily sourced from the GO stream, which has lower rates of contamination compared to FOGO, and therefore having a greater likelihood of application as a soil amendment compared to recovered compost derived from other municipal sources.

Recovery for biogas was highest in Scenarios 3.1 to 3.3. Higher quantities of food waste are present in the mixed waste stream than FOGO, therefore potential feedstock quantities for AD are higher at AWT facilities compared to standalone AD facilities sourcing feedstock from the FOGO stream. Furthermore, considering the small proportion of food waste in the FOGO stream (~12%), and the assumed AD organic loading rate of 80% food 20% garden waste, AD feedstock derived from FOGO must go through a separation process in order to extract the food waste component. This then highlights that further separation of food waste is required for households, and that FOGO collection may not be the most efficient approach for recovering food waste as a feedstock for AD. Based on these findings, FOGO collections may not be necessary, considering the amount of biogas potentially generated at AWT facilities with AD. Rather, FOGO could present a burden to waste managers, if additional sorting is required in order to extract food waste feedstock for AD. Alternatively, FOGO collection does increase the total volume of organic waste collected and made available for composting which is an important resource recovery pathway. Although EPA restrictions on the application of OFMSW derived compost does diminish this opportunity. Having a separate food waste only bin collected weekly at the kerbside could ensure a greater proportion of food waste would be available as feedstock for AD, while retaining significant volumes of garden organics for composting applications. However contamination issues, especially those related to food packaging and non-compliant organics, may still be present, and transport costs (including emissions) would be greater.

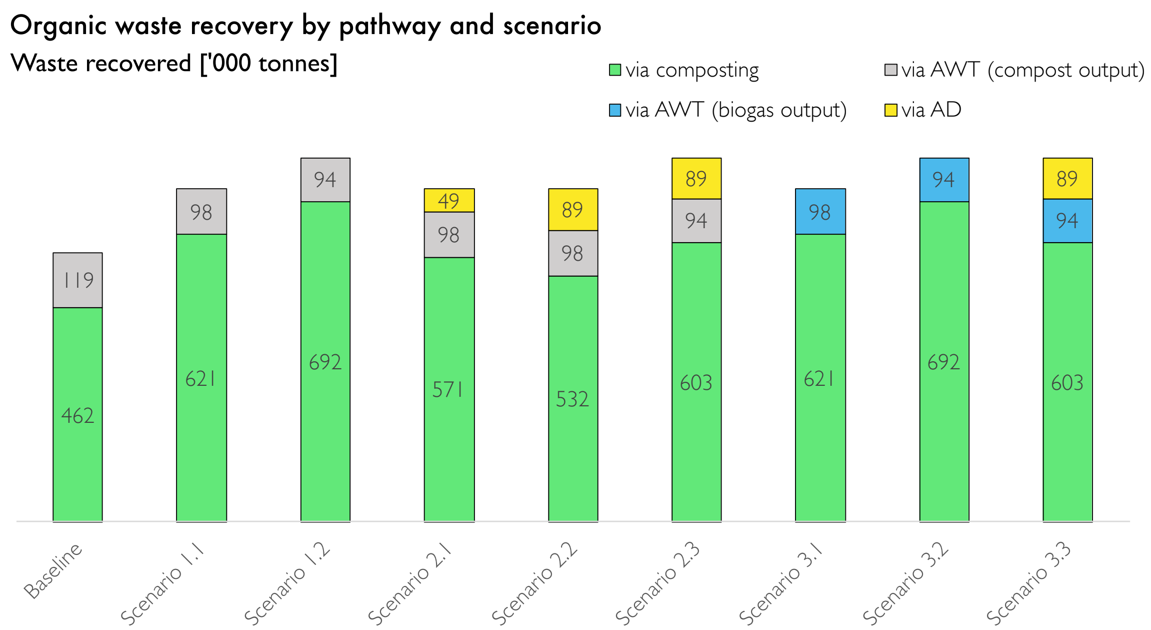


Figure 7-8: Breakdown of organic waste recovery by pathway and scenario

Figure 7-9 shows a comparison of net emission intensities on a per tonne diverted basis for each scenario evaluated, compared to baseline. Emissions intensities for all scenarios were significantly lower than baseline. Mandatory FOGO and increased diversion of food waste to the FOGO stream in Scenarios 1.1 and 1.2, led to reductions in net emissions intensity of 38% and 43% respectively. This reduction in intensity can be attributed to the avoidance of landfill emissions, as greater quantities of food waste are collected for recovery.

Standalone anaerobic digestion saw net emissions intensities of 242 kg CO_2-e/t for a single 50,000 t digester in Western Sydney—a reduction of approximately 43% compared to baseline. Additional digestion facilities in the Hunter and Shoalhaven regions with 90,000 tonnes total throughput, brought estimated intensity down to 228 kg CO_2-e/t—a reduction of 46%. The addition of increased diversion of food waste to the mixed stream made more food waste available across the study area for digestion in Scenario 2.3, with estimated intensity of 196 kgCO_2-e—a reduction of 54% against baseline. For these digestion scenarios, the rate of organic waste recovery was kept constant with FOGO composting, that is, recovery is estimated as the proportion of organic material not including contamination that is treated via composting/digestion. Therefore, the greater reductions in intensities for Scenarios 2.2 and 2.3 compared to Scenarios 1.1 and 1.2, can be attributed to the offsetting of fossil fuel-derived electricity supply.

The implementation of anaerobic digestion at AWTs had the lowest net emissions intensities of the scenarios evaluated. As indicated in Table 7-11, total food waste throughput across all AWT facilities was significantly higher than what was determined to be available for standalone AD facilities. Total digestion throughput was approximately 99,000 tonnes in Scenario 3.1 and 3.2, at an average throughput of approximately 14,000 tonnes per AWT facility, with Scenario 3.3 also assuming digestion at the 3 standalone facilities at 90,000 tonnes assumed throughput. Scenario 3.3 had the lowest net emissions intensity across all scenarios evaluated, at 158 kgCO_2-e/t diverted—a reduction of approximately 63% compared to baseline.

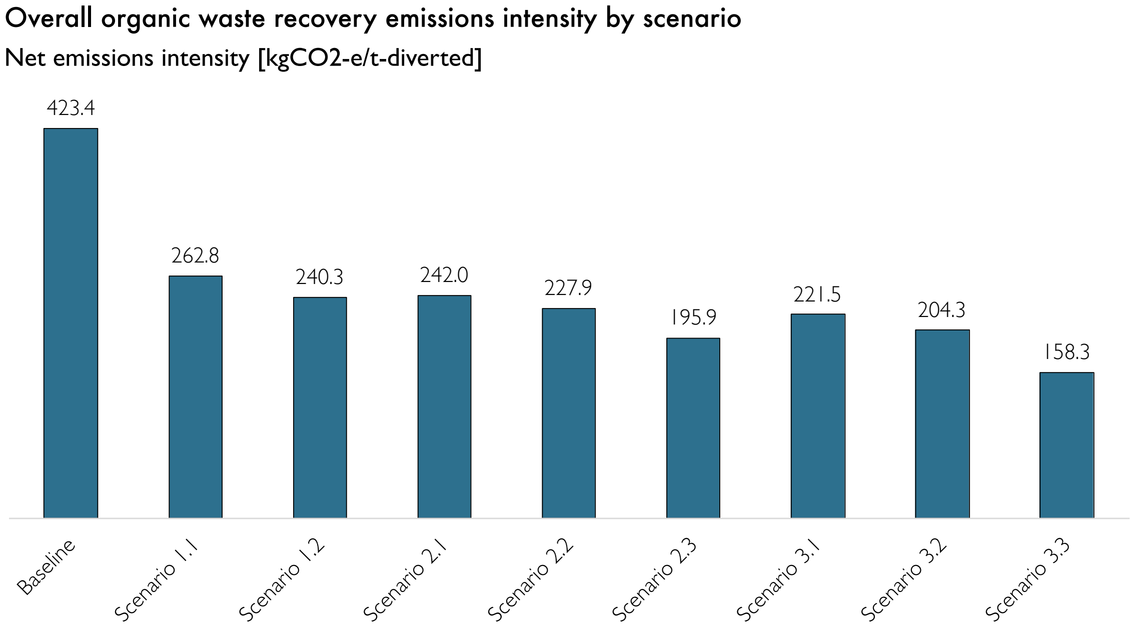


Figure 7-9: Comparison of net emissions intensities across the scenarios evaluated

Findings from the scenario comparison in Figure 7-9 identify a trend in net emissions intensity, whereby as the proportion of organic waste recovered via digestion increases, net emissions intensity reduces. This relationship is elaborated in Figure 7-10, and implies that large scale anaerobic digestion is the highest performing pathway when compared to composting from a low carbon resource recovery perspective, which is consistent with findings in the literature (e.g., Cudjoe et al. (2020)). As noted previously in this section, increased rates of FOGO collection will better enable AD at large scale, however the co-collection of food and garden together does present a problem for dry digestion, where the maximum proportion of garden as feedstock from the literature is around 20%. This does make digestion at AWT facilities a potentially attractive option: organic waste is still collected via the mixed stream at high rates, even with FOGO services available; there is little garden waste in the mixed waste stream; and it is too contaminated for recovery as a high valued (e.g., food crop) compost. Alternatively, the introduction of food waste only collection as noted previously would provide an ample and clean stream for AD, however higher diversion rates would need to be achieved to realise this potential. With respect to the *NSW Waste and Sustainable Materials Strategy,* the findings here imply that initiatives aimed at mandating FOGO collection and deploying municipal scale digestion will have positive impacts on resource recovery and emissions reductions. Addressing identified infrastructure requirements in the strategy, namely FOGO specific treatment facilities and organics specific transfer stations, may further enable system performance improvements towards achieving landfill diversion and net emissions targets. However, no plans have been identified that directly addresses increasing the diversion rates of food waste to dedicated food waste collection streams, which as these results show, may have a significant impact on feedstock availability for future AD deployment, and for landfill minimisation.

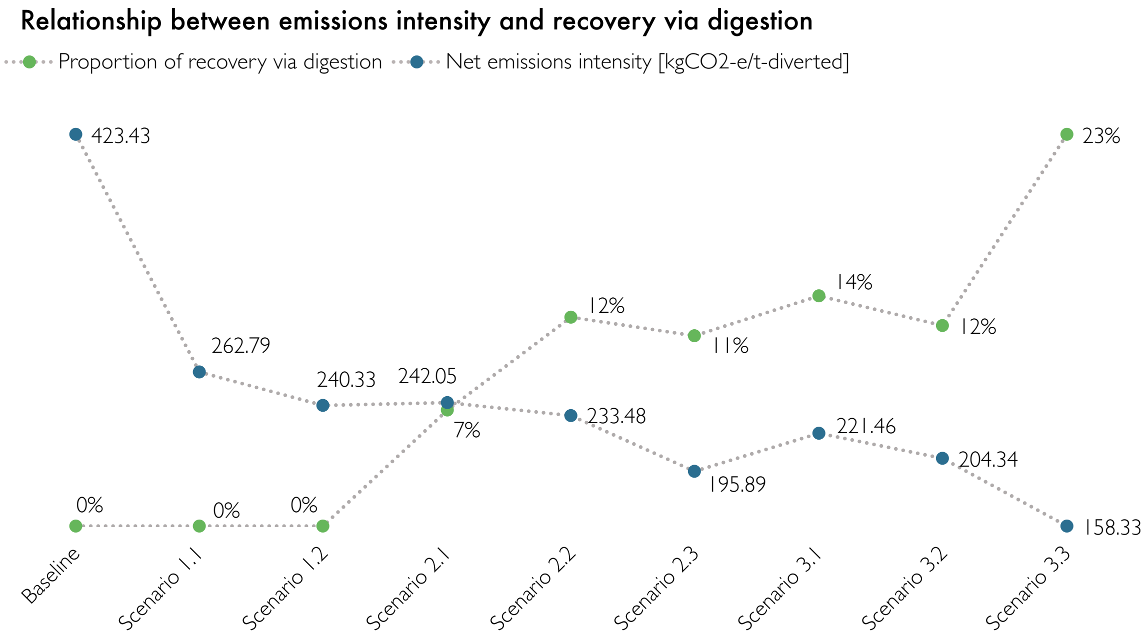


Figure 7-10: Relationship between net emissions intensity and proportion of organics recovery via digestion

7.3. Evaluation results and discussion

Table 7-13 shows the results of the MCA using the SAM method for each modelled scenario compared to baseline. Note that performance for each scenario is based on performance across the study area as a whole. The table shows the normalised scores for organic recovery rate and net emissions intensity (M_1 and M_2 from Equations 7.5 and 7.6); the combined weighted score (S_i in Equation 7.7), with even relative importance for the two measures (i.e., γ_n = 0.5); and the rank for each pathway based on the weighted score, with rank 1 corresponding to the highest performing (and thus most optimal) scenario.

Table 7-13: Summary of MCA results, following the SAM method. Scenarios are ordered by rank, based on the weighted score.

Scenario	Normalised organic recovery rate	Normalised net emissions intensity	Weighted score	Rank
Scenario 3.3	1.00	1.00	1.00	1
Scenario 2.3	1.00	0.86	0.93	2
Scenario 3.2	1.00	0.83	0.91	3
Scenario 1.2	1.00	0.69	0.85	4
Scenario 3.1	0.67	0.76	0.72	5
Scenario 2.2	0.67	0.72	0.69	6
Scenario 2.1	0.67	0.68	0.68	7
Scenario 1.1	0.67	0.61	0.64	8
Baseline	0.00	0.00	0.00	9

The SAM method is simple, and ensures that the scenarios with the highest normalised recovery rate and lowest emissions intensity will have the highest weighted score. As expected, the baseline scenario had the lowest score and therefore was the lowest ranked scenario. Scenario 3.3, where mandatory FOGO collection, improved diversion of food waste to the FOGO stream, and with AD deployed at both standalone facilities and at AWT facilities, was the highest performing scenario. This result is also expected given that increased diversion of food waste to the FOGO stream led to the highest organic recovery rates observed (see Table 7-12); and that the deployment of AD at both standalone facilities (3 locations for Scenario 3.3) and at AWT, led to the greatest potential for GHG offsets via the generation of electricity from recovered biogas. The method applied here was simple, however complexity can be added by incorporating additional normalised measures into the analysis. For example, expected net costs of deployment for pathways, and factors characterising the ease of implementation could be incorporated into future analysis, which may alter the findings reported in this thesis. For example, such analysis may balance the high performance of the AD at AWT facilities pathway, if deploying AD at existing facilities is costly or otherwise difficult to implement (e.g., from a facility integration perspective). Chapter 8 further elaborates on expanding the MCA to include additional criteria.

Figure 7-11 further explores the results of the MCA shown in Table 7-13. Here, actual (i.e., not normalised) performance for organic recovery rate and net emissions intensity (per tonne diverted) are compared for each of the modelled scenarios and the baseline case, with rankings shown. The scenarios that achieved the highest weighted score (ranks 1-4) are the 4 scenarios that have an assumed increase in diversion of food waste from the mixed stream to FOGO. Notably, this also includes Scenario 1.2, which assumed only mandatory FOGO collections and increased diversion to the FOGO stream, without the deployment of AD for source separated food waste recovery. The increase in diversion is assumed to come from improved household disposal practices for organic waste, which could be enabled via initiatives including better information on correct disposal practices for households, a food waste only collection service, and better food packaging materials (e.g., compostable) and labelling. This finding is important, highlighting the significance of improved source separation, and is consistent with findings in Chapters 5 and 6 identifying increasing levels of source separation have a significant impact on relative net emission reductions at an LGA level. Targeting households to improve source separation and diversion of food waste from the mixed stream to the correct organic waste bin, should be a priority for achieving low carbon resource recovery aligned with the targets in the *NSW Waste and Sustainable Materials strategy*.

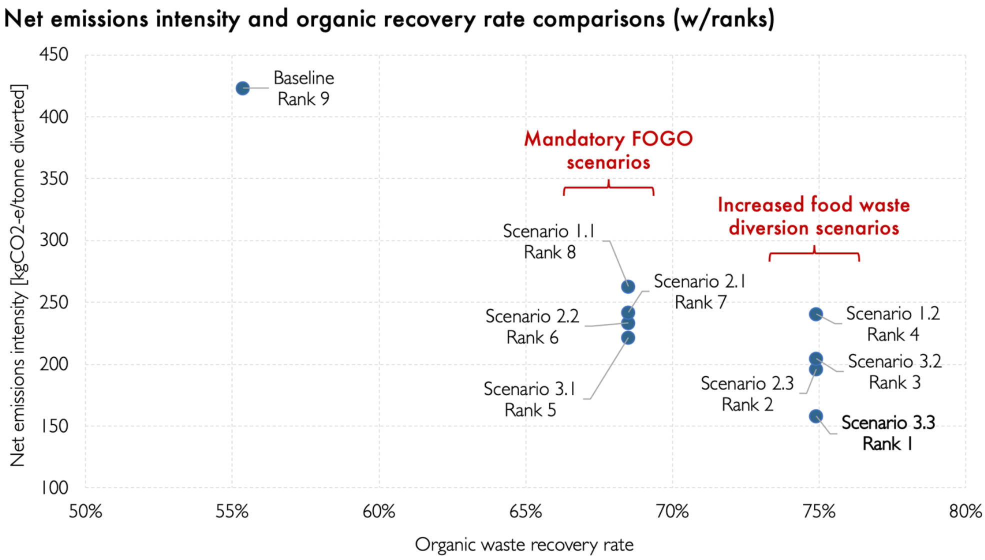


Figure 7-11: Comparison of net emissions intensities and organic waste recovery rates for the modelled pathways, with rankings from the MCA shown

7.4. Conclusions

The analysis in this chapter modelled a number of potential OFMSW management pathways, based on the *NSW Waste and Sustainable Materials strategy*, and evaluated them from the perspective of low carbon resource recovery. The scenario analysis showed a trend, where increasing the diversion of organic waste from mixed waste to separately collected organic streams, and increasing the scale of deployment of AD, results in improved low carbon resource recovery performance compared to the current system. The analysis therefore addressed thesis research question 5, identifying that large scale deployment of anaerobic digestion (at standalone and AWT facilities), with mandatory FOGO collection and increased mixed waste diversion rates, is the most optimal pathway for OFMSW management from a low carbon resource recovery perspective. These finding is also consistent with similar analyses from the literature, including Lou et al. (2013), Liu et al. (2017), and Cudjoe et al. (2020); who have identified the effectiveness of municipal scale AD for net emission reductions; and Bourtsalas and Themelis (2022) and Stunzenas and Kliopova (2018), who identified MBT/AWT is effective for waste streams with poor separation from a resource recovery perspective.

From the analysis, the mandating of FOGO collections for all households in NSW as identified in the *NSW Waste and Sustainable Materials strategy* will lead to improvements in performance compared to the current system. However, more can be done to improve the emissions intensity of OFMSW management; namely via increasing diversion of food waste from the mixed waste to source separated streams including FOGO. The analysis also showed that AD deployment as identified in the strategy, has the potential for significant emissions mitigation via biogas utilisation, and in promoting the circular utilisation of resources via digestate utilisation. The scenario analysis showed that ample food waste feedstock would exist for AD to be deployed at existing AWT facilities throughout the study area. This may be an attractive option for future OFMSW management, given the large proportion of food waste that is present in the mixed waste stream, even with mandatory FOGO collections and increased diversion rates from the mixed to FOGO stream. However, AWT upgrade costs and other factors that might impact on deployment at AWT facilities, were not considered in the analysis, and could be a considerable obstacle for the deployment of this pathway. This finding also indicates that increased levels of FOGO collection may not be necessary for the deployment of AD, and in fact, may be a practical obstacle for AD, given that food waste would need to be sorted out of the FOGO stream to be utilised as feedstock. This then raises the potential of a food-only kerbside collection system, which could encourage diversion of food waste out of the mixed waste stream and landfill, and could provide a more appropriate feedstock source for AD than FOGO. Such a collection system would lead to higher transport-related emissions, however the analysis in this chapter and in Chapter 6 indicates that potential avoidance of landfill emissions would offset any increase in transportation emissions. Moreover, mixed waste and GO collection frequency could potentially be further reduced to offset increased transport requirements. Contamination would also likely be a significant issue for food-only collections, however this could be potentially minimised by local government decision makers through household education, and pre-treatment.

The analysis presented here also tested a simple method for evaluating OFMSW management pathways from a low carbon resource recovery perspective, as part of addressing thesis research question 5. Following Iacovidou et al. (2017a), the metrics of organic waste recovery rate and net emissions intensity per tonne diverted were used to evaluate pathways. The analysis showed that the method tested is simple and gives expected outputs. Additional complexity, namely costs and ease of implementation for the selected pathways under investigation, would improve the method.

Chapter 8.

Conclusions

Greenhouse gas emissions must be curtailed across all sectors of society to limit the impacts of anthropogenic climate change. Food waste is also a global issue, and Australia in particular is a poor performer when it comes to the management of household organic waste. Managing household organics through sustainable waste management practices informed by circular economy principles, can address both of these issues. Indeed, recent policy and strategic planning in NSW is beginning to align emissions reductions and sustainable waste management from a decision making perspective. However data on the emissions intensity of NSW waste streams is limited, making decision making around the most optimal pathway for waste that addresses landfill diversion and emissions reduction objectives difficult.

This thesis explored optimal pathways for household organic waste in NSW from a low carbon resource recovery perspective. This is defined in the thesis as a maximisation of the recovery of waste into secondary resources, with minimal impact on GHG emissions. The research questions addressed in this thesis were:

i) What is the spatial distribution of waste generation in NSW, and is regional variability significant?

ii) How can waste generation data be modelled at high resolitions, where data is limited?

iii) What are the emissions associated with kerbside organic waste collection and transportation?

iv) What are the emissions associated with the recovery of household organic waste in NSW?

v) What are the optimal low carbon resource recovery pathways for household organic waste in NSW, and how may they be identified?

Conclusions derived from addressing each of the above are summarised in the following section.

8.1. General thesis conclusions

8.1.1. 'What is the spatial distribution of waste generation in NSW, and is regional variability significant?'

NSW is a large state, with varied populations and socioeconomic characteristics, such as economic opportunities, education levels and employment—all of which can have a significant contribution to the quantities and composition of wastes generated.

To address the research question, a spatial model was developed to explore regional variation in waste generation drivers across NSW. To explore this problem more deeply, the model, a form of geographically weighted regression, was used to examine an open problem in the waste management literature: whether or not the Kuznet's curve relationship exists for waste. The Kuznet's curve relationship characterises a decoupling of waste generation and income, and although examining its existence is not specifically related to the overarching thesis problem of low carbon resource recovery, it is an opportunity to explore statistically regional variation in waste generation drivers, and justify the methodological approach.

Conclusions drawn from this analysis are:

i) Variation in waste generation drivers do exist across LGAs in NSW. This indicates that exploring the thesis problems from a spatial modelling perspective at a high resolution that can account for LGA-by-LGA variation is appropriate.

ii) The modelling approach utilised (geographically weighted regression) is useful for exploring spatially varying drivers for waste generation, but was not applied further in the context of this thesis. The approach however does have further applications for estimating regional level or LGA level waste generation where data is not available, including in the context of estimating future waste generation.

iii) Related to the Kuznet's curve hypothesis, evidence supporting the existence of the waste Kuznet's curve was found over the 2011 to 2015 period. The analysis showed that the region to the west of the Sydney metropolitan area exhibited the waste Kuznet's curve relationship when accounting for spatially varied socioeconomic and structural factors. Findings indicated that LGAs conforming to the Kuznet's curve relationship had higher rates of per-capita waste generation, and lower proportions of waste collected as recycling compared to other LGAs. This suggests that the conforming LGAs had poorer performing waste systems and disposal practices on average compared to other LGAs. Findings related to the Kuznet's curve hypothesis show that regional LGAs have different waste generation behaviours, and should not necessarily be treated the same as metropolitan LGAs in waste management decision making and strategic planning.

8.1.2. 'How can waste generation data be modelled at high resolutions, where data is limited?'

Some specific knowledge gaps limiting the accurate accounting of waste related emissions, namely emissions from waste collection and transport, require higher spatial resolution waste data to overcome. For example, data on the quantities of waste generated at collection points (i.e., at the kerbside) is needed to accurately model collection routs of waste collection vehicles.

To address the above, a novel, probabilistic spatial model was developed for estimating the spatial distribution of waste generation at a high resolution. Data on the distribution of waste generation is limited for NSW, with council area waste generation data the highest resolution data available. Estimating the emissions from waste collection however requires data on quantities of waste generated at the kerbside. Therefore, the spatial model was applied to estimate quantities of organic and non-organic waste generated at over 1.2 million property lots across the Sydney metropolitan area.

The model had modest data inputs, relying only on LGA level waste generation statistics, and high resolution census dwelling data. Validation of the high resolution estimates was performed by aggregating estimated dwelling numbers in property lots to lower resolution (SA1 scale), and comparing with census dwelling count data. This showed that the model was accurate, especially with respect to detached dwellings. Accuracy was poorer for property lots with multi-unit dwellings, however variation between model estimation and the validation data was only approximately 5%.

The significance of the model developed in addressing this research question is ultimately illustrated through the application of the data generated in estimating emissions from waste collection and transport. An important innovation of this work was the modest data requirements, utilising cadastral data, census data and council-level waste statistics, enabling the approach to be applied to varied locations and spatial scales.

High spatial resolution data on waste generation has multiple additional uses from a waste management and planning perspective, including in identifying optimal areas for waste management facilities, or whereabouts a particular waste management strategy could be implemented.

8.1.3. 'What are the emissions associated with kerbside organic waste collection and transportation?'

To address this research question, a route optimisation model was developed, using the high resolution data generated from the model in Chapter 4/Madden et al. (2021). Waste collection routes and transport to and from transfer stations, recovery facility and landfill sites were modelled, and emissions estimated from quantities of diesel fuel consumed by collection and transportation vehicles. This model was applied to estimate transport emissions for collection and management of household organic waste in the Greater Sydney and surrounding area.

The study had several important conclusions:

i) Collection and transport emissions for household organic waste in 2018-19 was estimated at approximately 43,700 tonnes of CO_2-e. Emissions made a small contribution to overall NSW emissions from rigid trucks (<2%), however the relative importance of transport emissions to overall waste related emissions was still unclear based on this analysis.

ii) Kerbside collection, specifically travel between kerbside bins and the lifting of bins to waste vehicle receptables, was the most emissions intensive activity completed during organic waste collection and transportation. Related to this, LGAs with a higher proportion of multi-unit dwellings had lower transport emissions intensity, as more bins are collected per stop at multi-unit dwellings compared to detached dwellings. Although multi-unit dwelling types are becoming more widespread in the study area, affecting housing and urban planning policy is outside the bounds of waste managers. Therefore improving vehicle efficiency, and using less emissions intensive vehicle fuels, would be necessary to reduce overall transport emissions intensity.

iii) Related to the above, kerbside collection emissions are lower in more population dense areas, which suggests that collection emissions might also be reduced by moving towards more centralised waste collection models, where greater quantities of waste could be collected per collection point. The practicalities of this however were not examined in this work, but could include such pathways as community organic collection sites, for example, 'compost hubs' such as those employed in Inner West and Blue Mountains council areas.

iv) Diversion of food waste from mixed waste to dedicated organic collection (i.e., FOGO), and diversion of mixed waste to AWT facilities, was found to be the most efficient management model with respect to transport emissions intensity on a tonnes diverted basis. This can be attributed to higher recovery rates for LGAs that have FOGO collections and AWT as a pathway compared to other LGAs. Collection of food and garden organic waste is prioritised for LGAs in the future in support of emission reduction strategies, for example in the *NSW Waste and Sustainable Materials Strategy*

8.1.4. 'What are the emissions associated with the recovery of household organic waste in NSW?'

The above research question was addressed via a modelling framework developed, incorporating waste collection and transport estimates from Chapter 5, with mass balance modelling and emissions factors derived from available data. The modelling developed accounted for emissions over the whole waste management chain in addition to transport emissions, including emissions from recovery processes, namely windrow composting and AWT, and lifetime landfill emissions.

Key findings from this study are summarised as follows:

i) Overall net emissions for household organic waste management in the study area (Greater Sydney and surrounding areas) was approximately 245,000 tCO_2-e. Overall net emissions intensity was approximately 133 $kgCO_2$-e per tonne of waste managed, and approximately 423 $kgCO_2$-e per tonne of waste diverted to landfill.

ii) Net emissions intensity on both a per tonne managed and per tonne diverted basis was highest for the mixed waste stream, due to lower levels of waste recovery and therefore, high landfill emissions. Net emissions intensity for the mixed waste stream was approximately 175 $kgCO_2$-e per tonne managed, and 2,056 $kgCO_2$-e per tonne diverted. The garden waste stream had the lowest emissions intensity, at approximately 8 $kgCO_2$-e per tonne on both a per tonne managed and diverted basis. FOGO intensity was also significantly lower than the mixed waste stream, at approximately 17 $kgCO_2$-e per tonne.

iii) Landfill emissions were the greatest contributor to overall emissions, accounting for approximately 56% of all emissions generated. Efforts that divert organic waste from landfill will have the biggest impact on low carbon resource recovery performance, assuming that material diverted from landfill, is in fact recovered for resources, energy, and/or nutrients.

iv) Transport emissions accounted for only approximately 13% of overall gross OFMSW management emissions. There was a relationship between LGA classification (metropolitan, metropolitan-fringe, and regional) and transport emissions. Metropolitan LGAs had the lowest proportion of transport emissions to total gross emissions, at 11%. This proportion was higher for metropolitan-fringe (18%) and regional (22%). Lower emissions intensive fuels and/or vehicle electrification may be necessary to reduce transport related emissions for large LGAs with lower population densities that have large waste collection and transportation requirements.

v) Overall findings highlight that landfill diversion of organics, especially food waste in the mixed stream is crucial in the context of achieving good low carbon resource recovery performance. Increasing diversion of food waste from the mixed stream to separate FOGO collections, and increasing quantities of mixed waste treated via AWT were shown to have a positive impact on landfill diversion and thus emissions intensities.

8.1.5. 'What are the optimal low carbon resource recovery pathways for household organic waste in NSW, and how may they be identified?'

The above research question was addressed using modelling developed in Chapters 5 and 6. Several potential household organic management pathways were evaluated based on the *NSW Waste and Sustainable Material Strategy*. A simplified multi-criteria analysis was performed in order to identify the most optimal pathways from those analysed in terms of organic waste recovery rates and net emissions intensity.

Key findings from addressing the above research question were as follows:

i) Large scale deployment of anaerobic digestion (both standalone, and at AWT facilities), with mandatory FOGO collection and increased mixed waste diversion rates, was the most optimal pathway for OFMSW management.

ii) Pathways with mandatory FOGO and increased rates of diversion of organic waste in the mixed waste stream to dedicated organic collection streams, were the pathways with highest performance. Even with increased rates of diversion, there is still a substantial quantity of food waste in the mixed waste stream. Increasing rates of diversion further may have significant impacts on low carbon resource recovery performance, however the current *NSW Waste and Sustainable Material Strategy* does not specifically target this.

iii) Anaerobic digestion deployment has the potential for significant emissions mitigation via biogas utilisation, and for promoting the circular utilisation of resources via digestate utilisation. Potential electricity generation from biogas from digestion ranged from approximately 40,000 MWh, to 171,000 MWh—representing between 10% and 38% of NSW biogas generation in 2019-20.

iv) Potential biogas generation was greater for digestion deployed at AWT compared to standalone digestion facilities treating FOGO. This is because quantities of food waste treated at AWT facilities is greater than available food waste through FOGO collections. Digestion at AWT facilities may be an attractive option for future OFMSW management, which could also including expanding the number of LGAs that direct mixed waste to AWT. However AWT upgrade costs and whether some facilities are upgradable, was not within scope of the analysis, and may be significant barriers to deployment. There was an estimated 90,000 tonnes per year available capacity for standalone digestion, treating FOGO waste (20% garden waste, 80% food waste); compared to over 94,000 tonnes of food waste embedded in the mixed stream available at AWT facilities.

v) Findings indicate that food waste only kerbside collection may encourage further diversion of food waste out of the mixed waste stream and landfill, and may provide a more appropriate feedstock source for digestion compared to FOGO. This is due to food waste making up only approximately 12% of the FOGO stream. Such a collection system would likely lead to higher transport related emissions, however landfill emissions avoidance and mitigating emissions from fossil fuel derived electricity could potential offset any increase in transportation emissions.

8.2. General discussion

Although waste related emissions are not major contributors to overall emissions in NSW, it is still important to consider emissions intensity when evaluating potential waste management pathways. The circular economy framework, which is motivating waste management decision making in NSW, encourages waste managers towards pathways that lead to increased waste recovery and minimal environmental impact outcomes. Assessing waste management pathways from the perspective of low emissions and maximised resource recovery fits within the scope of the circular economy framework, and is aligned with emission reduction strategies, namely the *Net Zero by 2030* plan.

The work in this thesis has explored the concept of optimal low carbon resource recovery pathways for household organic waste management. From the findings highlighted in this concluding chapter, the most optimal pathways can be characterised by the following:

i) **Increased diversion of organic waste from landfill**: with mixed waste being the primary contributor to landfill disposal and thus emissions, increasing diversion from landfill could be achieved through improved separation of food waste from the mixed waste stream to dedicated organic waste collection systems, and also through efficient recovery processes. The co-collection of food and garden organics via FOGO collections was shown in this study to lead to landfill diversion and improvements in emissions intensity over garden organics-only and mixed waste collections. However depending on the recovery pathway, for example digestion, FOGO collections could in fact be a hindrance, potentially requiring additional pre-treatment in order to separate the food and garden waste components. Additionally, increasing the quantities of mixed waste diverted to AWT facilities could lead to increases in landfill diversion, however AWT facility capacities and capabilities in processing significantly larger quantities of mixed waste is unclear.

ii) **Offsetting of emissions intensive primary resources**: the research illustrated this point with biogas derived from digestion, however any secondary resource utilisation that significantly offsets primary resources is important from a low carbon resource recovery perspective. Combined with the above point, this is where the greatest potential emissions reductions compared to the current system occur. Considering also the current reliance on fossil fuels for the NSW electricity supply, biogas derived from organic solid waste can help support the greater uptake of renewable energy in NSW, supporting the *Net Zero by 2030* plan.

While the research for this thesis has addressed a number of important knowledge gaps in regards to low carbon resource recovery in NSW, there are some limitations, which are described in each relevant chapter in the thesis. The most significant limitations are:

i) There is limited data to validate modelled estimates. Although data from the literature has been used to confirm that estimates for emissions intensities are comparable, location specific data is limited. This is especially relevant to transport emissions, and the emissions associated with AWT recovery.

ii) Data limitations on downstream compost applications. While data does exist on emissions reductions from the application of compost to land, much of this data assumes some substitution of mineral-based fertilisers. It is unclear how compost derived from municipal organics would offset the production and application of mineral-based fertilisers, and has therefore not been considered in this analysis. As a result, other downstream positive impacts of secondary compost utilisation have been ignored, including the binding of carbon to soil. The potential emissions reduction from compost applications are therefore underestimated in this work.

8.3. Recommendations for future work

There are many avenues for future work, motivated by the thesis findings as well as through the methodological development. Some of these avenues could address specific data limitations, for example, using satellite imagery to better calibrate the landfill gas estimation, or developing a robust model for estimating the downstream impact of compost utilisation of mineral-based fertiliser consumption in NSW. Additional insights can be gained by applying the modelling approach presented in a number of new areas as a priority, which are described in the following subsections.

8.3.1. Expanding the geographical scope of analysis

The geographical scope varies across the work presented in this thesis. This is primarily due to constraints in the modelling especially in regards to transportation emissions, where computation of solutions to the route optimisation model for all of NSW would take an excessive amount of time, adversely impacting completion of this thesis. While the insights gained from this work can be applied across NSW, there is benefit for replicating the modelling for areas outside of the Greater Sydney and surrounding areas. Although this region accounts for the majority of the state's population and therefore household waste generated, estimating waste related emissions for the entire state following the approaches developed would allow for a complete evaluation of state wide emissions. Practically, this can achieved with the existing modelling approaches and data sources used throughout the thesis, however as noted above, is time intensive. Re-evaluating the solution algorithm for the route optimisation model may yield a more efficient algorithm, however the algorithm selected for solving the CVRP as described in Chapter 5, was chosen due to its usefulness when evaluating large scale networks.

The estimation of waste related emissions could also potentially be expanded nation-wide. Several of the data sets relied on are from the national census (e.g., population and dwelling counts, and dwelling type distributions), as well as from the national database for waste infrastructure data (Geoscience Australia, 2020). However, state specific data including cadastral data, road network data, and LGA level waste generation would be required.

8.3.2. Expanding scope to include additional waste streams

The modelling developed could be expanded to include additional waste streams. Estimating emissions associated with the collection of dry recyclables was not performed for this thesis, however could be incorporated into the modelling, given that dry recyclable generation was estimated at the property lot level for Chapter 4. Estimating these emissions would give a clearer picture of the overall emissions associated with the management of municipal waste in NSW. Moreover, specific management pathways for dry recyclables and non-organic wastes, including for example packaging waste and soft plastics collection pathways and advanced recycling, could be examined from a low carbon resource recovery perspective.

The modelling could also incorporate other organic waste streams. These could include commercial and industrial derived organic wastes (e.g., restaurant food waste; fats, oils and greases; tradewaste); agricultural waste (e.g., slurry; crop residues); and wastewater. Considering that anaerobic digestion has been identified both in the *NSW Waste and Sustainable Materials Strategy* and findings from this thesis as an important organic recovery pathway, examining the impact of digestion utilising a range of feedstock could be beneficial from an state energy planning perspective.

8.3.3. Exploring additional low carbon resource recovery pathways

The modelling approach presented in this thesis can be applied to explore a broader range of scenarios and management pathways from a low carbon resource recovery perspective using the method developed through the thesis. These might include:

- Additional recovery technology, including different energy recovery pathways (e.g., pyrolysis, waste-to-fuel), and different composting technologies such as large scale in-vessel composting (especially relevant considering the significance of direct methane emissions from windrow composting)

- Different waste collection systems, including food waste only collections; detached dwelling and multi-unit dwelling specific collection systems; different bin sizes and collection frequencies, and regional specific collection systems

- Household activities and their impacts on low carbon resource recovery, including further improved household separation of wastes, and at-home composting

- Efficiency improvements for waste collection and transport vehicles, including more efficient bin-lift mechanisms, lower emissions intensity fuels, and vehicle electrification

8.3.4. Expanded complexity in multi-criteria evaluation

Chapter 7 presented a simplified approach for evaluating recovery pathways from a low carbon resource recovery perspective, factoring in only technical (i.e., waste recovery) and environmental (i.e., net emissions intensity) factors. Incorporating additional complexity, for example cost and revenue factors, ease of implementation, additional technical criteria (e.g., fuel, electricity and labour requirements), and social licence, may give a more robust prioritisation of resource recovery pathways that may yield different results to those presented.

The literature on multi-criteria evaluation for waste management pathways is widespread, and many studies do incorporate these additional complexities. Vlachokostas et al. (2021) for example reviewed over 100 studies in the field of waste management utilising multi-criteria evaluation. Many studies incorporate the priorities of various stakeholders in the evaluation as well, through approaches such as the analytical hierarchy process (AHP), which is very common in the literature.

8.3.5. Further applications of the modelling

The modelling developed has potential applications in exploring problems outside of those examined in this thesis. Some of these applications include:

- **Identifying optimal facility locations and feedstock allocations**: many studies have used high resolution spatial data to evaluate optimal locations for waste management infrastructure, including for example landfills (Demesouka et al., 2019), anaerobic digestion facilities (Comber et al., 2015), and energy recovery facilities more generally (Shi et al., 2008). The methods employed in the literature generally can be considered spatial multi-criteria evaluation. Not too dissimilar to the multi-criteria evaluation discussed at several times in this thesis, these models evaluate candidate locations or potential areas for deployment, based on a range of selected criteria, that might include appropriate land attributes (e.g., slope, precipitation), distance to infrastructure, and proximity to areas of exclusion (e.g., residential or protected areas). Also often considered, especially with respect to recovery facilities, is the spatial distribution of available feedstock. The modelling in this thesis can be used to estimate available feedstock derived from household waste (and is illustrated in Chapter 5). Spatial multi-criteria analysis can be performed, by combining this data with selected criteria that is spatially resolved. Applications could including refining the selected locations of digestion facilities used in Chapter 7, by identifying where the most optimal locations are in the Greater Sydney area for digestion deployment.

- **Deeper analysis of waste transportation and infrastructure**: the analysis in the thesis models waste transport between facilities in an effort to estimate transportation emissions, however does not further evaluate the transport system. The data generated from the route optimisation however can be further analysed, and provide insights into more efficient waste collection routing, and in waste infrastructure planning. For example, in the context of waste infrastructure planning, transport distances and quantities of waste transported along a route can be inputs in a spatial interaction analysis, to explore what facilities and points of infrastructure may need augmenting or may have spare capacity. This type of analysis is based on the Boltzmann-Lotka-Volterra predator-prey model, and is well studied in the context of exploring evolution in spatial structure based on flows along a network, and has use in evaluating the growth and decline of retail centres and urban development (Dearden et al., 2019; Wilson, 2007). Although this type of analysis has not been published in a waste management context, some examples from the literature are analogous to waste management, and may provide some key insights that combined with other findings from this thesis, may further inform optimal facility locations, transport routes, and as a way to estimate facility capacity where data is limited.

8.4. Final remarks

The work presented here makes a number of key contributions in advancing low carbon resource recovery for household organic waste. These contributions can be summarised as follows:

Contribution 1: Model for estimating high resolution household waste generation with limited data

The model presented in Chapter 4 of the thesis is a novel approach for estimating waste generation at fine spatial scales, where data is non-existent. The approach developed is general, requiring limited data that is typically available in other jurisdictions. Outputs from the model can inform waste management planning around optimal waste collection pathways, and can enable further analysis of the high-resolution waste resource supply—important for facility planning and feasibility of waste recovery pathways, as well as estimating waste collection and transportation emissions accurately.

Contribution 2: Model for estimating waste collection and transport fuel requirements and emissions

The model presented in Chapter 5 of the thesis provides an estimate of the fuel requirements and the emissions associated with kerbside waste collection and transport in the Greater Sydney and surrounding areas, for the first time. Data from this model can be utilised as emissions factors in further studies analysing the emissions associated with transport, including in life cycle assessment studies, with better consideration to the urban and suburban structure in NSW. The model presented in Chapter 5 can be further utilised for waste collection route optimisation, and in studying the impacts of alternative fuels and electrification of the waste collection vehicle fleet on overall waste transport emissions.

Contribution 3: Data on the emissions intensity of organic waste recovery in NSW

The analysis in Chapter 6 of the thesis provides data on the direct, indirect and avoided emissions associated with OFMSW management in Greater Sydney and surrounding areas for the first time. Data generated from this analysis can be used in characterising emissions factors for OFMSW management pathways in use in NSW, and is also important for evaluating potential OFMSW pathways and policies from a low carbon resource recovery perspective.

Contribution 4: Framework for evaluating optimal resource recovery for waste and environmental performance objectives

Chapter 7 presents a framework for evaluating OFMSW recovery pathways in NSW from a low carbon resource recovery perspective, that utilises only technical (waste recovery) and environmental (net emissions intensity) measurements. Analysis in Chapter 7 can inform waste management decision making in NSW in the selection of recovery pathways to address waste recovery and GHG emission reduction priorities.

This work has ultimately focused on generating data that can be used to evaluate and identify optimal management pathways for household organics, that maximise landfill diversion, and minimise emissions intensity. In order to influence change to improve the low carbon resource recovery performance, decision makers including the NSW state waste authority, state environmental departments, and local governments can utilise data and modelling presented here to inform their decision making processes.

References

Abad, V., Avila, R., Vicent, T., & Font, X. (2019). Promoting circular economy in the surroundings of an organic fraction of municipal solid waste anaerobic digestion treatment plant: Biogas production impact and economic factors. *Bioresource Technology*, *283*, 10-17. https://doi.org/10.1016/j.biortech.2019.03.064

Abdallah, M., Hamdan, S., & Shabib, A. (2021). A multi-objective model for strategic waste management master plans. *Journal of Cleaner Production*, *284*, 124714. https://doi.org/10.1016/j.jclepro.2020.124714

ABS. (2016a). *12701.0.55.001 - Australian Statistical Geography Standard (ASGS), July 2016*.

ABS. (2016b). *20171.0 - Census of Population and Housing*.

ABS. (2017). *Australian Statistical Geography Standard (ASGS): Volume 4 - Non-ABS Structures*.

ABS. (2018). *Data by Region, 2012-17*.

ABS. (2020). *Survey of Motor Vehicle Use, Australia*. https://www.abs.gov.au/statistics/industry/tourism-and-transport/survey-motor-vehicle-use-australia

ABS. (2021). *Regional population by age and sex, 2020*.

Acevedo, M. F. (2013). *Simulation of Ecological and Environmental Models*. CRC Press, Boca Raton. https://doi.org/10.1201/b12922

Agar, B. J., Baetz, B. W., & Wilson, B. G. (2007). Fuel consumption, emissions estimation, and emissions cost estimates using global positioning data. *Journal of Air & Waste Management Association*, *57*(3), 348-354. https://doi.org/10.1080/10473289.2007.10465328

Aguilar, J. A. A., Aguilar, H. A. N., Hernandez, R. F. G., & Valencia, M. N. R. (2018). Emplacement of solid waste management infrastructure for the Frailesca Region, Chiapas, Mexico, using GIS tools. *The Egyption Journal of Remote Sensing and Space Sciences*, *21*, 391-399. https://doi.org/10.1016/j.ejrs.2018.01.004

Akhtar, M., Hannan, M. A., Begum, R. A., Basri, H., & Scavino, E. (2017). Backtracking search algorithm in CVRP models for efficient solid waste collection and route optimization. *Waste Management*, *61*, 117-128. https://doi.org/10.1016/j.wasman.2017.01.022

Al-Garni, H., & Awasthi, A. (2017). Solar PV power plant site selection using a GIS-AHP based approach with application in Saudi Arabia. *Applied Energy*, *206*, 1225-1240. https://doi.org/10.1016/j.apenergy.2017.10.024

Albright, D., Lee, H., McDaniel, J., Kroner, D., Davis, J., Godfrey, K., & Li, Q. (2019). Small area estimation of human papillomavirus vaccination coverage among school-age children in Alabama counties. *Public Health*, *177*, 120-127. https://doi.org/10.1016/j.puhe.2019.08.006

Allwood, J. M. (2011). Material efficiency: a white paper. *Resources, Conservation & Recycling*, *55*(3), 362-381. https://doi.org/10.1016/j.resconrec.2010.11.002

Almanaseer, N., Abbassi, B., Dunlop, C., Friesen, K., & Nestico-Semianiw, E. (2020). Multi-criteria analysis of waste-to-energy technologies in developed and developing countries. *Environmental Research, Engineering and Management*, *76*(1), 32-43. https://doi.org/10.5755/j01.erem.76.1.25254

Andersen, J. K., Boldrin, A., Samuelsson, J., Christensen, T. H., & Scheutz, C. (2010). Quantification of greenhouse gas emissions from windrow composting of garden waste. *Journal of Environmental Quality*, *39*(2), 713-724. https://doi.org/10.2134/jeq2009.0329

Andriani, D., Wresta, A., Atmaja, T. D., & Saepudin, A. (2014). A review on optimization production and upgrading biogas through CO2 removal using various techniques. *Applied Biochemistry and Biotechnology*, *172*, 1909-1928. https://doi.org/10.1007/s12010-013-0652-x

Antonopoulos, I. S., Perkoulidis, G., Logothetis, D., & Karkanias, C. (2014). Ranking municipal solid waste treatment alternatives considering sustainability criteria using the analytical hierarchical process tool. *Resources, Conservation & Recycling*, *86*, 149-159. https://dx.doi.org/10.1016/j.resconrec.2014.03.002

APC. (2008). *SSROC Regional Waste Audit Report - 2007.*

APC. (2019). *SSROC Kerbside Waste Audit: Regional Report.*

Arena, U. (2015). From waste-to-energy to waste-to-resources: The new role of thermal treatments of solid waste in the Recycling Society. *Waste Management*, *37*, 1-2. http://dx.doi.org/10.1016/j.wasman.2014.12.010

Asefi, H., Lim, S., & Maghrebu, M. (2015). A mathematical model for the municipal solid waste location-routing problem with intermediate transfer stations. *Australasian Journal of Information Systems*, *19*, 21-35. https://doi.org/10.3127/ajis.v19i0.1151

Asquer, C., Cappai, G., Gioannis, G., Muntoni, A., Piredda, M., & Spiga, D. (2017). Biomass ash reutilisation as an additive in the composting process of organic fraction of municipal solid waste. *Waste Management*, *69*, 127-135. https://doi.org/10.1016/j.wasman.2017.08.009

Assamoi, B., & Lawryshyn, Y. (2012). The environmental comparison of landfilling vs. incineration of MSW accounting for waste diversion. *Waste Management*, *32*, 1019-1030. https://doi.org/10.1016/j.wasman.2011.10.023

Ayisi, P. A., Ngonda, T., & Kanyarusoke, K. (2022). Current landfill technologies and the prospects of developing landfill-based biogas generators for African countries. *Materials Today: Proceedings*, *56*, 1865-1871. https://doi.org/10.1016/j.matpr.2021.11.055

Babu, R., Prieto Veramendi, P. M., & Rene, E. R. (2021). Strategies for resource recovery from the organic fraction of municipal solid waste. *Case Studies in Chemical and Environmental Engineering*, *3*, 100098. https://doi.org/10.1016/j.cscee.2021.100098

Balwada, J., Samaiya, S., & Mishra, R. P. (2021). Packaging plastic waste management for a circular economy and identifying a better waste collection system using analytical hierarchy process (AHP). *Procedia CIRP*, *98*, 270-275. https://doi.org/10.1016/j.procir.2021.01.102

Banks, C. J., Heaven, S., Zhang, Y., & Baier, U. (2018). *Food waste digestion: anaerobic digestion of food waste for a circular economy* (J. D. Murphy, Ed.). IEA Bioenergy Task 37.

Belsley, D., Kuh, E., & Welsch, R. (1980). *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. Wiley, New York.

Berrens, R., Bohara, A., Gawande, K., & Wang, P. (1998). Testing the unverted U hypothesis for US hazardous waste. An application of the generalised gamm model. *Economic Letters*, *55*, 435-440. https://doi.org/10.1016/S0165-1765(97)00088-8

Bivand, R., Pebesma, E., & Gómez-Rubio, V. (2013). *Applied Spatial Data Analysis with* R (Second edition ed.). Springer, New York.

Bivand, R., & Rundel, C. (2020). *regeos: Interface to Geometry Engine - Open Source ('GEOS'). R package version 0.5.3.* . https://CRAN.R-project.org/package=rgeos

Blue Environment. (2020). *National Waste Report 2020.*

Blue Mountains City Council. (2022). *Food Waste and Composting - The Compost Hub.* https://www.bmcc.nsw.gov.au/composthub

Boldrin, A., Andersen, J. K., Møller, J., Christensen, T. H., & Favoino, E. (2009). Composting and compost utilization: accounting of greenhouse gases and global warming contributions. *Waste Management & Research*, *27*(8), 800-812. https://doi.org/10.1177/0734242X09345275

Bourtsalas, A. C., & Themelis, N. J. (2022). Materials and energy recovery at six European MBT plants. *Waste Management*, *141*, 79-91. https://doi.org/10.1016/j.wasman.2022.01.024

Brunner, P. H., & Rechberger, H. (2016). *Handbook of Material Flow Analysis: For Environmental, Resource and Waste Engineers, Second Edition (2nd ed.)*. CRC Press. https://doi.org/10.1201/9781315313450

Buil-Gil, D., Medina, J., & Shlomo, N. (2019). The geographies of perceived neighbourhood disorder. A small area estimation approach. *Applied Geography*, *109*, 102-113. https://doi.org/10.1016/j.apgeog.2019.102037

Bunker, R. (2014). How is the compact city faring in Australia. *Planning Practice and Research*, *29*, 440-460. https://doi.org/10.1080/02697459.2014.945376

Campuzano, R., & González-Martínez, S. (2016). Characteristics of the organic fraction of municipal solid waste and methane production: A review. *Waste Management*, *54*, 3-12. https://doi.org/10.1016/j.wasman.2016.05.016

CDC. (2008). Chapter 2: Landfill Gas Basics. In *Landfill Gas Primer - An Overview for Environmental Professionals*. Centers for Disease Control and Prevention, Washington D.C. https://www.atsdr.cdc.gov/HAC/landfill/PDFs/Landfill_2001_ch2mod.pdf

Chandra, H., Salvati, N., Chambers, R., & Tzavidis, N. (2012). Small area estimation under spatial nonstationarity. *Computational Statistics and Data Analysis*, *56*, 2875-2888. https://doi.org/10.1016/j.csda.2012.02.006

Chang, N. B., & Pires, A. (2015). *Sustainable solid waste management: a systems engineering approach*. John Wiley & Sons.

Chapman, A., Shigetomi, Y., Ohno, H., McLellan, B., & Shinozaki, A. (2021). Evaluating the global impact of low-carbon energy transitions on social equity. *Environmental Innovation and Societal Transitions*, *40*, 332-347. https://doi.org/10.1016/j.eist.2021.09.002

Chen, T. C., & Lin, C. F. (2008). Greenhouse gases emissions from waste management practices using life cycle inventory model. *Journal of Hazardous Materials*, *155*(1-2), 23-31. https://doi.org/10.1016/j.jhazmat.2007.11.050

Chen, Y. C., & Liu, H. M. (2021). Evaluation of greenhouse gas emissions and the feed-in tariff system of waste-to-energy facilities using a system dynamics model. *Science of the Total Environment*, *792*. https://doi.org/10.1016/j.scitotenv.2021.148445

Chiu, S. L. H., & Lo, I. M. C. (2016). Reviewing the anaerobic digestion and co-digestion process of food waste from the perspectives on biogas production performance and environmental impacts. *Environmental Science and Pollution Research*, *23*, 24435-24450. https://doi.org/10.1007/s11356-016-7159-2

Churchman, C. W., & Ackoff, R. L. (1954). An approximate measure of value. *Journal of the Operations Research Society of America*, *2*(2), 172-187. http://www.jstor.org/stable/166603.

Clean Energy Regulator. (2021). *Emissions Reduction Fund - Landfill gas method*. Australian Government, Clean Energy Regulator. https://www.cleanenergyregulator.gov.au/ERF/Choosing-a-project-type/Opportunities-for-industry/landfill-and-alternative-waste-treatment-methods/Capture-and-combustion-of-landfill-gas

COAG. (2020). *Phasing out exports of waste plastic, paper, glass and tyres - response strategy to implement the August 2019 agreement of the Council of Australian Governments*.

Coban, A., Ertis, I. F., & Cavdaroglu, N. A. (2018). Municipal solid waste management via multi-criteria decision making methods: a case study in Istanbul, Turkey. *Journal of Cleaner Production*, *180*, 159-167. https://doi.org/10.1016/j.jclepro.2018.01.130

Cockx, K., & Canters, F. (2015). Incorporating spatial non-stationarity to improve dasymetric mapping of population. *Applied Geography*, *63*, 220-230. https://doi.org/10.1016/j.apgeog.2015.07.002

Comber, A., Dickie, J., Jarvis, C., Phillips, M., & Tansey, K. (2015). Locating bioenergy facilities using a modified GIS-based location-allocation-algorithm: considering the spatial distribution of resource supply. *Applied Energy*, *154*, 309-316. https://doi.org/10.1016/j.apenergy.2015.04.128

Concu, N. (2000). *La tirannia del trade off sconfitta? Turismo, ambiente naturale e rifuti solidi urbani: La ricerca di una EKC. Is the tyranny of the trade-off defeated? Tourism, environment, and municipal solid waste: Finding an EKC*.

Contreras, F., Hanaki, K., Aramaki, T., & Connors, S. (2008). Application of analytical hierarchy process to analyze stakeholders preferences for municipal solid waste management plans, Boston, USA. *Resources, Conservation & Recycling*, *52*, 979-991. https://dx.doi.org/10.1016/j.resconrec.2008.03.003

Čuček, L., Klemeš, J. J., & Kravanja, Z. (2015). Chapter 5 - Overview of environmental footprints. In J. J. Klemeš (Ed.), *Assessing and Measuring Environmental Impact and Sustainability*. https://doi.org/https://doi.org/10.1016/C2013-0-13586-6

Cudjoe, D., Han, M. S., & Nandiwardhana, A. P. (2020). Electricity generation using biogas from organic fraction of municipal solid waste generation in provinces of China: Techno-economic and environmental impact analysis. *Fuel Processing Technology*, *203*, 106381. https://doi.org/10.1016/j.fuproc.2020.106381

Damgaard, A., Manfredi, S., Merrild, H., Stensøe, S., & Christensen, T. H. (2011). LCA and economic evaluation of landfill leachate and gas technologies. *Waste Management*, *31*, 1532-1541. http://dx.doi.org/10.1016/j.wasman.2011.02.027

Das, A., Mazumder, T. N., & Gupta, A. K. (2012). Pareto frontier analyses based decision making tool for transportation of hazardous waste. *Journal of Hazardous Materials*, *227-228*, 341-352. http://dx.doi.org/10.1016/j.jhazmat.2012.05.068

Dastjerdi, B., Strezov, V., Kumar, R., & Behnia, M. (2019). An evaluation of the potential of waste to energy technologies for residual solid waste in New South Wales, Australia. *Renewable and Sustainable Energy Reviews*, *115*, 109398. https://doi.org/10.1016/j.rser.2019.109398

DAWE. (2012). *Food and Garden Organics Best Practice Collection Manual*.

DAWE. (2021). *Tackling Australia's food waste*. https://www.awe.gov.au/environment/protection/waste/food-waste

Dearden, J., Gong, Y., Jones, M., & Wilson, A. (2019). Using the state space of a BLV retail model to analyse the dynamics and categorise phase transitions of urban development. *Urban Science*, *3*(31). http://dx.doi.org/10.3390/urbansci3010031

DEC. (2007). *TBL Assessment of (Domestic) Food Organics Management*. https://www.epa.nsw.gov.au/-/media/epa/corporate-site/resources/waste/070153-tbl-food-organics-mgt.pdf?la=en&hash=3546A924E30EED051A4563580E6B5A213ACCD3BB

DECCEEW. (2022). *Australian electricity generation - fuel mix calendar year 2021*. Australian Government, Department of Climate Change, Energy, the Environment and Water. https://www.energy.gov.au/australian-electricity-generation-fuel-mix-2020

Demesouka, O. E., Anagnostopoulos, K. P., & Siskos, E. (2019). Spatial multicriteria decision support for robust land-use suitability: The case of landfill site selection in Northeastern Greece. *European Journal of Operations Research*, *272*, 574-586. https://doi.org/10.1016/j.ejor.2018.07.005

Demetrious, A., & Crossin, E. (2019). Life cycle assessment of paper and plastic packaging in landfill, incineration, and gasification-pyrolysis. *Journal of Material Cycles and Waste Management*, *21*, 850-860. https://doi.org/10.1007/s10163-019-00842-4

Demichelis, F., Tommasi, T., Deorsola, F. A., Marchisio, D., Mancini, G., & Fino, D. (2022). Life cycle assessment and life cycle costing of advanced anaerobic digestion of organic fraction municipal solid waste. *Chemosphere*, *289*, 133058. https://doi.org/10.1016/j.chemosphere.2021.133058

Deshpande, P. C., Skaar, C., Brattebø, H., & Fet, A. M. (2020). Multi-criteria decision analysis (MCDA) method for assessing the sustainability of end-of-life alternatives for waste plastics: A case study of Norway. *Science of the Total Environment*, *719*, 137353. https://doi.org/10.1016/j.scitotenv.2020.137353

DFSI. (2012). *NSW Digital Cadastre Data Base* https://sdi.nsw.gov.au/catalog/search/resource/details.page?uuid=921D6586-8594-4473-A923-A446DEBF3336

Di Foggia, G., & Beccarello, M. (2021). Designing waste management systems to meet circular economy goals: The Italian case. *Sustainable Production and Consumption*, *26*, 1074-1083. https://doi.org/10.1016/j.spc.2021.01.002

Dieterle, M., Schäfer, P., & Viere, T. (2018). Life cycle gaps: interpreting LCA results with a circular economy mindset. *Procedia CIRP*, *69*, 764-768. https://doi.org/10.1016/j.procir.2017.11.058

Dijkstra, E. W. (1959). A note on two problems in connexion with graphs. *Numerische Mathematik*, *1*, 269-271. https://doi.org/10.1007/BF01386390

Council directive 1999/31/EC of 26 April 1999 on the landfill of waste, (2018).

DISER. (2021a). *Australian Energy Update 2021*. https://www.energy.gov.au/sites/default/files/Australian%20Energy%20Statistics%202021%20Energy%20Update%20Report.pdf

DISER. (2021b). *National Greenhouse Accounts Factors*. https://www.dcceew.gov.au/climate-change/publications/national-greenhouse-accounts-factors-2021

DISER. (2021c). *National Inventory Report 2019: The Australian Government Submission to the United Nations Framework Convention on Climate Change*. https://www.dcceew.gov.au/climate-change/publications/national-greenhouse-accounts-2019/national-inventory-report-2019

DISER. (2021d). *National Inventory Report 2019: The Australian Government Submission to the United Nations Framework Convention on Climate Change*. Department of Industry, Science, Energy and Resources, Australian Government.

DISER. (2022a). *National Greenhouse Gas Inventory - Paris Agreement Inventory*. Department of Industry, Science, Energy and Resources. Retrieved April 17 from https://ageis.climatechange.gov.au/

DISER. (2022b). *Tracking and reporting greenhouse gas emissions*. Department of Industry, Science, Energy and Resources, Australian Government. Retrieved April 17 from https://www.dcceew.gov.au/climate-change/emissions-reporting/tracking-reporting-emissions

DoEE. (2018). *National Waste Report 2018*. https://www.dcceew.gov.au/sites/default/files/documents/national-waste-report-2018.pdf

DPIE. (2021). *NSW Waste and Sustainable Materials Strategy 2041, Stage 1: 2021-2027*. https://www.dpie.nsw.gov.au/__data/assets/pdf_file/0006/385683/NSW-Waste-and-Sustainable-Materials-Strategy-2041.pdf

Drożdż, W., Bilan, Y., Rabe, M., Streimikiene, D., & Pilecki, B. (2022). Optimizing biomass energy production at the municipal level to move to low-carbon energy. *Sustainable Cities and Society*, *76*. https://doi.org/10.1016/j.scs.2021.103417

Du, L., & He, R. (2012). Combining nearest neighbor search with Tabu search for large-scale vehicle routing problems. *Physics Procedia*, *25*, 1536-1546. https://doi.org/10.1016/j.phpro.2012.03.273

Du, Z., Wu, S., Zhang, F., Liu, R., & Zhou, Y. (2018). Extending geographically and temporally weighted regression to account for both spatiotemporal heterogeneity and seasonal variations in coastal seas. *Ecological Informatics*, *43*, 185-199. https://doi.org/10.1016/j.ecoinf.2017.12.005

Dyson, B., & Chang, N. B. (2005). Forecasting municipal solid waste generation in a fast-growing urban region with system dynamics modelling. *Waste Management*, *57*, 669-679. https://doi.org/10.1016/j.wasman.2004.10.005

EarthPower. (2022). *About EarthPower Technologies Sydney*. EarthPower Technologies Sydney, Camlia. https://earthpower.com.au/about-us/

Eberth, J., McLain, A., Hong, Y., Sercy, E., Diedhiou, A., & Kilpatrick, D. (2018). Estimating county-level tobacco use and exposure in South Carolina: a spatial model-based small area estimation approach. *Annals of Epidemiology*, *28*, 481-488. https://doi.org/10.1016/j.annepidem.2018.03.015

EcoRecycle. (1997). *Australian Waste and Recycling Cost Model (WRCM), User Guide*.

Edwards, J., Othman, M., Burn, S., & Crossin, E. (2016). Energy and time modelling of kerbside waste collection: Changes incurred when adding source separated food waste. *Waste Management*, *56*, 454-465. http://dx.doi.org/10.1016/j.wasman.2016.06.033

Eghtesadifard, M., Afkhami, P., & Bazyar, A. (2020). An integrated approach to the selection of municipal solid waste landfills through GIS, K-means and multi-criteria decision analysis. *Environmental Research*, *185*, 109348. https://doi.org/10.1016/j.envres.2020.109348

Ellen MacArthur Foundation. (2013). *Towards the Circular Economy - Economic and Business Rationale for an Accelerated Transition*. Retrieved April from http://www.feve.org/OPENDAY-FEVE-2013/120130_EMF_CE_Full%20report_final.pdf.

Ellen MacArthur Foundation. (2015). *Delivering the Circular Economy: A toolkit for policymakers*.

EpE. (2013). *Protocol for the quantification of greenhouse gas emissions from waste management activities*.

Ercolano, S., Gaeta, G., Ghinoi, S., & Silvestri, F. (2018). Kuznets curve in municipal solid waste production: an empirical analysis based on municipal-level panel data from the Lombardy region (Italy). *Ecological Indicators*, *93*, 397-403. https://doi.org/10.1016/j.ecolind.2018.05.021

Essin, T., & Cosgun, N. (2007). A study conducted to reduce construction waste generation in Turkey. *Building and Environment*, *42*, 1667-1674. https://doi.org/10.1016/j.buildenv.2006.02.008

European Commission. (2015). *Communication from the commission to the parliament, the council and the European economic and social committee and the committee of the regions: closing the loop - an EU action plan for the Circular Economy*. https://www.eea.europa.eu/policy-documents/com-2015-0614-final

European Commission. (2019). *Guidelines on small area estimation for city statistics and other function geographies*. https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/ks-gq-19-011

Eurostat. (2020). *Greenhouse gas emissions from waste*. https://ec.europa.eu/eurostat/web/products-eurostat-news/-/DDN-20200123-1

Fabrizi, E., & Trivisano, C. (2016). Small area estimation of the Gini concentration coefficient. *Computational Statistics and Data Analysis*, *99*, 223-234. https://doi.org/10.1016/j.csda.2016.01.010

Faccio, M., Persona, A., & Zanin, G. (2011). Waste collection multi objective model with real time traceability data. *Waste Management*, *31*, 2391-2405. https://doi.org/10.1016/j.wasman.2011.07.005

Fan, Y. V., Klemeš, J. J., Lee, C. T., & Perry, S. (2018). Anaerobic digestion of municipal solid waste: energy and carbon emission footprint. *Journal of Environmental Management*, *223*, 888-897. https://doi.org/10.1016/j.jenvman.2018.07.005

Fei, X., Jia, W., Chen, T., & Ling, Y. (2022). Life cycle assessment of food waste anaerobic digestion with hydrothermal and ionizing radiation pretreatment. *Journal of Cleaner Production*, *338*, 130611. https://doi.org/10.1016/j.jclepro.2022.130611

Fernández-Delgado, M., del Amo-Mateos, E., Lucas, S., García-Cubero, M. T., & Coca, M. (2020). Recovery of organic carbon from municipal mixed waste compost for the production of fertilizers. *Journal of Cleaner Production*, *265*, 121805. https://doi.org/10.1016/j.jclepro.2020.121805

Ferrão, P., & Fernández, J. (2013). *Sustainable Urban Metabolism*. MIT Press, Cambridge.

Ferreira, A., Jose, W., & Singh, R. (2010). Municipal solid waste compost amendment in agricultural soil: changes in soil microbial biomass. *Reviews in Environmental Science and Bio/Technology*, *9*, 41-49. https://doi.org/10.1007/s11157-009-9179-6

Fischer-Kowalski, M., & Amann, C. (2001). Beyond IPAT and Kuznets curves: Globalization as a vital factor in analyzing the environmental impact of socioeconomic metabolism. *Population and the Environment*, *23*, 7-47. https://doi.org/10.1023/A:1017560208742

Fletcher, R., & Rammelt, C. (2017). Decoupling: a key fantasy of the post-2015 sustainable development agenda. *Globalizations*, *14*, 450-467. https://doi.org/10.1080/14747731.2016.1263077

Fortin, M., Boots, B., Csillag, F., & Remmel, T. (2003). On the role of spatial stochastic models in understanding landscape indices in ecology. *Oikos*, *102*, 203-212. https://www.jstor.org/stable/3547872

Fotheringham, A., Brundson, C., & Charlton, M. (2002). *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. John Wiley & Sons, United Kingdom.

Fotheringham, A., Crespo, R., & Yao, J. (2015). Geographical and temporal weighted regression (GTWR). *Geographical Analysis*, *47*, 431-452. https://doi.org/10.1111/gean.12071

Franca, L. S., & Bassin, J. P. (2020). The role of dry anaerobic digestion in the treatment of the organic fraction of municipal solid waste: A systematic review. *Biomass and Bioenergy*, *143*, 105866. https://doi.org/10.1016/j.biombioe.2020.105866

Friedrich, E., & Trois, C. (2013). GHG emission factors developed for the recycling and composting of municipal waste in South African municipalities. *Waste Management*, *33*, 2520-2531. http://dx.doi.org/10.1016/j.wasman.2013.05.010

Fuqua, M., & Doty, J. (2012). *Data-driven stochastic model development for unknown data sources* 50th AAIA Aerospace Sciences Meeting, Nasville, Tennessee, USA.

Gadaleta, G., De Gisi, S., & Notarnicola, M. (2021). Feasibility analysis on the adoption of decentralized anaerobic co-digestion for the treatment of municipal organic waste with energy recovery in urban districts of metropolitan areas. *International Journal of Environmental Research and Public Health*, *18*. https://doi.org/10.3390/ijerph18041820

Gavrilescu, D. (2022). Footprint assessment of solid waste management systems. In C. Teodosiu, S. Fiore, & A. Hospido (Eds.), *Assessing progress towards sustainability:*

frameworks, tools and case studies. Elsevier. https://doi.org/https://doi.org/10.1016/B978-0-323-85851-9.00016-X

Geoscience Australia. (2020). *Waste Management Facilities - 2017*. Government of Australia, Canberra. https://data.aurin.org.au/dataset/au-govt-ga-ga-waste-management-facilities-2017-na

Ghisellini, P., Cialani, C., & Ulgiati, S. (2016). A review on circular economy: the expected transition to a balanced interplay of environmental and economic systems. *Journal of Cleaner Production*, *114*, 11-32. https://doi.org/10.1016/j.jclepro.2015.09.007

Glavič, P., Lesjak, M., & Hirsbak, S. (2012). *European training course on eco-efficiency* 15th European Roundtable on Sustainable Consumption and Production, Bregenz, Austria.

Goerndt, M., Wilson, B., & Aguilar, F. (2019). Comparison of small area estimation methods applied to biopower feedstock supply in the Northern U.S. region. *Biomass and Bioenergy*, *121*, 64-77. https://doi.org/10.1016/j.biombioe.2018.12.008

Gohlke, O. (2009). Efficiency of energy recovery from municipal solid waste and the resultant effect on the greenhouse gas balance. *Waste Management & Research*, *27*, 894-906. https://do.org/10.1177/0734242X09349857

Gollini, I., Lu, B., Charlton, M., Brundson, C., & Harris, P. (2015). GWmodel: An R package for exploring spatial heterogeneity using geographically weighted models. *Journal of Statistical Software*, *63*, 1-50. http://dx.doi.org/10.18637/jss.v063.i17

Goodchild, M. (1992). Geographical information science. *International Journal of Geographical Information Systems*, *6*, 31-45. https://doi.org/10.1080/02693799208901893

Google. (n.d.). *Google Maps Burwood search area.*

Goovaerts, P. (1997). *Geostatistics for Natural Resources Evaluation*. Oxford University Press, New York.

Grando, R. L., de Souza Antune, A. M., de Fonseca, F. V., Sánchez, A., Barrena, R., & Font, X. (2017). Technology overview of biogas production in anaerobic digestion plants: A European evaluation of research and development. *Renewable and Sustainable Energy Reviews*, *80*, 44-53. https://doi.org/10.1016/j.rser.2017.05.079

Haight, F. (1967). *Handbook of the Poisson Distribution*. John Wiley and Sons.

Hannan, M., Akhtar, M., Begum, R., Basri, H., Hussain, A., & Scavino, E. (2018). Capacitated vehicle-routing problem model for scheduled solid waste collection and route optimization using PSO algorithm. *Waste Management*, *71*, 31-41. https://doi.org/10.1016/j.wasman.2017.10.019

Hatamleh, R. I., Jamhawi, M. M., Al-Kofahi, S. D., & Hijazi, H. (2020). The use of a GIS system as a decision support tool for municipal solid waste management planning: the case study of Al Nuzha district, Irbid, Jordan. *Procedia Manufacturing*, *44*, 189-196. https://doi.org/10.1016/j.promfg.2020.02.221

Haupt, M., Vadenbo, C., & Hellweg, S. (2017). Do we have the right performance indicators for the circular economy? Insight into the Swiss waste management system. *Journal of Industrial Ecology*, *21*, 615-627. https://doi.org/10.1111/jiec.12506

Hayes, J., Wilson, T., Brown, C., Deligne, N., Leonard, G., & Cole, J. (2021). Assessing urban disaster waste management requirements after volcanic eruptions. *International Journal of Disaster Risk Reduction*, *52*. https://doi.org/10.1016/j.ijdrr.2020.101935

Hijmans, R. (2020). raster: Geographic Data Analysis and Modeling. R package version 3.1-12, https://CRAN.R-project.org/package=raster. In.

Hla, S. S., & Roberts, D. (2015). Characterisation of chemical composition and energy content of green waste and municipal solid waste from Greater Brisbane, Australia. *Waste Management*, *41*, 12-19. http://dx.doi.org/10.1016/j.wasman.2015.03.039

Huang, B., Wu, B., & Barry, M. (2010). Geographically and temporally weighted regression for modeling spatio-temporal variation in house prices. *International Journal of Geographical Information Science*, *24*, 383-401. http://dx.doi.org/https://doi.org/10.1080/13658810802672469

Iacovidou, E., Velis, C. E., Purnell, P., Zwirner, O., Brown, A., Hahladakis, J., Millward-Hopkins, J., & Williams, P. T. (2017a). Metrics for optimising the multi-dimensional value of resources recovered from waste in a circular economy: a critical review. *Journal of Cleaner Production*, *166*, 910-938. https://doi.org/10.1016/j.jclepro.2017.07.100

Ichinose, D., Yamamoto, M., & Yoshida, Y. (2011). *GRIPS Discussion Paper 11-07: The decoupling of affluence and waste discharge under spatial correlation: do richer communities discharge more waste?*

IEA. (2022). *Global Energy Review: CO2 Emissions in 2021*.

Infrastructure Australia. (2021). *Guide to multi-criteria analysis - Technical guide of the Assessment Framework*.

Inghels, D., Dullaert, W., Aghezzaf, E. H., & Heijungs, R. (2019). Towards optimal trade-offs between material and energy recovery for green waste. *Waste Management*, *93*, 100-111. https://doi.org/10.1016/j.wasman.2019.05.023

Inner West Council. (2018). *First compost huts in Australia*. https://www.innerwest.nsw.gov.au/about/news/media-releases/2017-media-releases/first-compost-huts-in-australia

IPCC. (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J. B. R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, & B. Zhou, Eds.). Cambridge University Press.

Islam, M., Kashem, S., & Morshed, S. (2020). Integrating spatial information technologies and fuzzy analytic hierarchy process (F-AHP) approach for landfill siting. *City and Environment Interactions*, *7*, 100045. http://dx.doi.org/10.1016/j.cacint.2020.100045

Izumi, K., Okishio, Y., Nagao, N., Niwa, C., Yamamoto, S., & Toda, T. (2010). Effects of particle size on anaerobic digestion of food waste. *International Biodeterioration & Biodegradation*, *64*(7), 601-608. https://doi.org/10.1016/j.ibiod.2010.06.013

Jackson, T. (2009). *Prosperity Without Growth: Economics for a Finite Planet*. Taylor and Francis LTD.

Jacobs. (2019). *Process and technology options for treatment of municipal solid waste.* https://www.epa.nsw.gov.au/-/media/epa/corporate-site/resources/recycling/mwoo/process-and-technology-options-for-treatment-of-msw.pdf?la=en&hash=D4798CBF610AC11B7F15EBF854A19B0AB59748D5

Jain, S., Jain, S., Wolf, I. T., Lee, J., & Tong, Y. W. (2015). A comprehensive review on operating parameters and different pretreatment methodologies for anaerobic digestion of municipal solid waste. *Renewable and Sustainable Energy Reviews*, *52*, 142-154. https://doi.org/10.1016/j.rser.2015.07.091

Jaligot, R., & Chenal, J. (2018). Decoupling municipal solid waste generation and economic growth in the canton of Vaud, Switzerlanf. *Resources, Conservation & Recycling*, *130*, 260-266. https://doi.org/10.1016/j.resconrec.2017.12.014

Jaunich, M. K., Levis, J. W., DeCarolis, J. F., Gaston, E. V., Barlaz, M. A., Barelt-Hunt, S. L., Jones, E. G., Hauser, L., & Jaikumar, R. (2016). Characterization of municipal solid waste collection operations. *Resources, Conservation & Recycling*, *114*, 92-102. https://doi.org/10.1016/j.resconrec.2016.07.012

Joseph, J. P., & Prasad, R. (2020). Assessing the sustainable municipal solid waste (MSW) to electricity generation potentials in selected Pacific Small Island Developing Stats (PSIDS). *Journal of Cleaner Production*, *249*, 119222. https://doi.org/10.1016/j.jclepro.2019.119222

Jouhara, H., Czajczynska, D., Ghazal, H., Krzyzynska, R., Anguilano, L., Reynolds, A., & Spencer, N. (2017). Municipal waste systems for domestic use. *Energy*, *139*, 485-506. https://doi.org/10.1016/j.energy.2017.07.162

Kalmykova, Y., Sadagopan, M., & Rosado, L. (2018). Circular economy - from review of theories and practices to development of tools. *Resources, Conservation & Recycling*, *135*, 190-201. https://doi.org/10.1016/j.resconrec.2017.10.034

Kannangara, M., Dua, R., Ahmadi, L., & Bensebaa, F. (2018). Modeling and prediction of regional municipal solid waste generation and diversion in Canada using machine learning approaches. *Waste Management*, *74*, 3-15. https://doi.org/10.1016/j.wasman.2017.11.057

Karadimas, N. V., Papatzelou, K., & Loumos, V. G. (2007). Genetic algorithms for municipal solid waste collection and routing optimization. In C. Boukis, I. Pnevmatikakis, & I. Polymenakos (Eds.), *IFIP International Federation for Information Processing, Volume 247, Artificial Intelligence and Innovations 2007: From Theory to Applications*.

Kerdlap, P., Purnama, A. R., Low, J. S. C., Tan, D. Z. L., Barlow, C. Y., & Ramakrishna, S. (2020). Environmental evaluation of distributed verses centralized plastic waste recycling: integrating life cycle assessment and agent-based modelling. *Procedia CIRP*, *90*, 689-694. https://doi.org/10.1016/j.procir.2020.01.083

Keser, S., Duzgun, S., & Aksoy, A. (2012). Application of spatial and non-spatial data analysis in determination of the factors that impact municipal solid waste generation rates in Turkey. *Waste Management*, *32*, 359-371. https://dx.doi.org/10.1016/j.wasman.2011.10.017

Khalil, M., Northey, G., Septianto, F., & Lang, B. (2022). Hopefully that's not wasted! The role of hope for reducing food waste. *Journal of Business Research*, *147*, 59-70. https://doi.org/10.1016/j.jbusres.2022.03.080

Khan, D., Kumar, A., & Samadder, S. R. (2016). Impact of socioeconomic status on municipal solid waste generation rate. *Waste Management*, *49*, 15-25. https://dx.doi.org/10.1016/j.wasman.2016.01.019

Khan, I., & Kabir, Z. (2020). Waste-to-energy generation technologies and the developing economies: a multi-criteria analysis for sustainability assessment. *Renewable Energy*, *150*, 320-333. https://doi.org/10.1016/j.renene.2019.12.132

Kim, Y., Tanaka, K., & Ge, C. (2018). Estimating the provincial environmental Kuznets curve in China: a geographically weighted regression approach. *Stochastic Environmental Research and Risk Assessment*, *32*, 2147-2163. https://doi.org/10.1007/s00477-017-1503-z

Kirchherr, J., Reike, D., & Hekkert, M. (2017). Conceptualizing the circular economy: An analysis of 114 definitions. *Resources, Conservation & Recycling*, *127*, 221-232. http://dx.doi.org/10.1016/j.resconrec.2017.09.005

Kolekar, K., Hazra, T., & Chakrabarty, S. (2016). A review on prediction of municipal solid waste generation models. *Procedia Environmental Sciences*, *35*, 238-244. https://doi.org/10.1016/j.proenv.2016.07.087

Komilis, D. P., Ham, R. K., & Park, J. K. (2004). Emission of volatile organic compounds during composting of municipal solid wastes. *Water Research*, *38*, 1707-1714. http://doi.org/10.1016/j.watres.2003.12.039

Kontokosta, C., Hong, B., Johnson, N., & Starobin, D. (2018). Using machine learning and small area estimation to predict building-level municipal solid waste generation in cities. *Computers, Environment and Urban Systems*, *70*, 151-162. https://doi.org/10.1016/j.compenvurbsys.2018.03.004

Kravchenko, A. (2003). Influence of spatial structure on accuracy of interpolation methods. *Soil Science Society of America Journal*, *67*, 1564-1571. https://doi.org/10.2136/sssaj2003.1564

Kulkarni, S., Sohani, N., & Sehta, N. (2014). Capacitated vehicle routing using nearest neighbour algorithm in supply chain. *International Journal of Engineering Research & Technology*, *3*(5), 1331-1334.

Kumar, A., Mangla, S. K., Kumar, P., & Karamperidis, S. (2020). Challenges in perishable food supply chains for sustainability management: a developing country perspective.

Business Strategy and the Environment, *29*(5), 1809 - 1831. https://doi.org/10.1002/bse.2470

Kumar, A., & Samadder, S. R. (2017). An empirical model for prediction of household solid waste generation rate - A case study of Dhanbad, India. *Waste Management*, *68*, 3-15. https://doi.org/10.1016/j.wasman.2017.07.034

Kumar, A., & Samadder, S. R. (2020). Performance evaluation of anaerobic digestion technology for energy recovery from organic fraction of municipal solid waste: A review. *Energy*, *197*, 117253. https://doi.org/10.1016/j.energy.2020.117253

Kumaran, P., Hephzibah, D., Sivasankari, R., Saifuddin, N., & Shamsuddin, A. H. (2016). A review on industrial scale anaerobic digestion systems deployment in Malaysia: opportunities and challenges. *Renewable and Sustainable Energy Reviews*, *56*, 929-940. https://doi.org/10.1016/j.rser.2015.11.069

Kurniawan, T. A., Liang, X., Singh, D., Othman, M., Goh, H. H., Kern, A. O., Kusworo, T. D., & Shoqeir, J. A. (2022). Harnessing landfill gas (LFG) for electricity: a strategy to mitigate greenhouse gas (GHG) emissions in Jakarta (Indonesia). *Journal of Environmental Management*, *301*, 113882. https://doi.org/10.1016/j.jenvman.2021.113882

Kuznets, S. (1955). Economic growth and income inequality. *American Economics Review*, *45*, 1-28.

Larsen, A. W., Vrgoc, M., Lieberknecht, P., & Christensen, T. H. (2009). Diesel consumption in waste collection and transport and its environmental significance. *Waste Management & Research*, *27*, 652-659. https://doi.org/10.1177/0734242X08097636

Lasdon, L., Warren, A., Jain, A., & Ratner, M. (1978). Design and testing of a generalized reduced gradient code for nonlinear programming. *ACM Transactions on Mathematical Software*, *4*, 34-50.

Lebersorger, S., & Beigl, P. (2011). Municipal solid waste generation in municipalities: quantifying impacts of household structure, commercial waste and domestic fuel. *Waste Management*, *9-10*, 1907-1915. https://doi.org/10.1016/j.wasman.2011.05.016

Lee, U., Han, J., & Wang, M. (2017). Evaluation of landfill gas emissions from municipal solid waste landfills for the life-cycle analysis of waste-to-energy pathways. *Journal of Cleaner Production*, *166*, 335-342. http://dx.doi.org/10.1016/j.jclepro.2017.08.016

Lella, J., Mandla, V. R., & Zhu, X. (2017). Solid waste collection/transport optimization and vegetation land cover estimation using Geographic Information System (GIS): a case study of a proposed smart-city. *Sustainable Cities and Society*, *35*, 336-349. https://doi.org/10.1016/j.scs.2017.08.023

Lewandowska-Gwarda, K. (2018). Geographically weighted regression in the analysis of unemployment in Poland. *International Journal of Geo-Information*, *7*, 1-16. https://doi.org/10.3390/ijgi7010017

Li, Q., Dai, T., Gao, T., Zhong, W., Wen, B., Li, T., & Zhou, Y. (2021). Aluminium material flow analysis for production, consumption, and trade in China from 2008 to 2017.

Journal of Cleaner Production, *296*, 126444. https://doi.org/10.1016/j.jclepro.2021.126444

Li, T., Pullar, D., Corcoran, J., & Stimson, R. (2007). A comparison of spatial disaggregation techniques as applied to population estimation for South-East Queensland (SEQ), Australia. *Applied GIS*, *3*, 1-16.

Li, Y., Manandhar, A., Li, G., & Shah, A. (2018). Life cycle assessment of integrated solid state anaerobic digestion and composting for on-farm organic residues treatment. *Waste Management*, *76*, 294-305. https://doi.org/10.1016/j.wasman.2018.03.025

Lin, C., Wen, L., & Tsai, Y. (2010). Applying decision-making tools to national e-waste recycling policy: an example of analytical hierarchy process. *Waste Management*, *30*, 863-869. http://dx.doi.org/10.1016/j.wasman.2009.11.012

Lin, Z., Xie, Q., Feng, Y., Zhang, P., & Yao, P. (2020). Towards a robust facility location model for construction and demolition waste transfer stations under uncertain environment: The case of Chongqing. *Waste Management*, *105*, 73-83. https://doi.org/10.1016/j.wasman.2020.01.037

Liu, Y., Ni, Z., King, X., & Liu, J. (2017). Greenhouse gas emissions from municipal solid waste with a high organic fraction under different management scenarios. *Journal of Cleaner Production*, *147*, 451-457. http://dx.doi.org/10.1016/j.jclepro.2017.01.135

Liu, Y., Song, L., Wang, W., Jian, X., & Chen, W. Q. (2022). Developing a GIS-based model to quantify spatiotemporal pattern of home appliances and e-waste generation - a case study in Xiamen, China. *Waste Management*, *137*, 150-157. https://doi.org/10.1016/j.wasman.2021.10.039

LMS Energy. (2021). *The role of landfill biogas capture, Australia's largest source of carbon abatement, in a changing policy landscape*. LMS Energy. https://www.wmrr.asn.au/common/Uploaded%20files/ALTS/2021/Tiana%20Nairn.pdf

Lombardi, L., Carnevale, E., & Corti, A. (2015). A review of technologies and performances of thermal treatment systems for energy recovery from waste. *Waste Management*, *37*, 26-44. http://dx.doi.org/10.1016/j.wasman.2014.11.010

Lou, X., Nair, J., & Ho, G. (2013). Potential for energy generation from anaerobic digestion of food waste in Australia. *Waste Management & Research*, *31*(3), 283-294. https://doi.org/10.1177/0734242X12474334

Lou, Z., Cai, B. F., Zhu, N., Zhao, Y., Geng, Y., Yu, B., & Chen, W. (2017). Greenhouse gas emission inventories from waste sector in China during 1949-2013 and its mitigation potential. *Journal of Cleaner Production*, *157*, 118-124. http://dx.doi.org/10.1016/j.jclepro.2017.04.135

Lozano-García, D., Santibañez-Aguilar, J., Lozano, F., & Flores-Tlacuahuac, A. (2020). GIS-based modeling of residual biomass availability for energy production in Mexico. *Renewable and Sustainable Energy Reviews*, *120*, 109610. https://doi.org/10.1016/j.rser.2019.109610

Lu, B., Sun, H., Harris, P., Xu, M., & Charlton, M. (2018). Shp2graph: Tools to convert a spatial network into an Igraph in R. *International Journal of Geo-Information*, *7*(8), 293. https://doi.org/10.3390/ijgi7080293

Lu, G., & Wong, D. (2008). An adaptive inverse-distance weighting spatial interpolation technique. *Computers and Geosciences*, *34*, 1044-1055. https://doi.org/10.1016/j.cageo.2007.07.010

Ma, J., Scott, N. R., DeGloria, S. D., & Lembo, A. J. (2005). Siting analysis of farm-based centralized anaerobic digester systems for distributed generation using GIS. *Biomass and Bioenergy*, *28*, 591-600. https://doi.org/10.1016/j.biombioe.2004.12.003

Madden, B., Florin, N., Mohr, S., & Giurco, D. (2021). Spatial modelling of municipal waste generation: deriving property lot estimates with limited data. *Resources, Conservation & Recycling*, *168*, 105442. https://doi.org/10.1016/j.resconrec.2021.105442

Maddison, D. (2006). Environmental Kuznets curves: A spatial econometric approach. *Journal of Environmental Economics*, *51*, 218-230. https://doi.org/10.1016/j.jeem.2005.07.002

Maia, A., Ferreira, E., Oliveira, M., Menezes, L., & Andrade-Campos, A. (2017). Numerical optimization strategies for springback compensation in sheet metal forming. *Computation Methods and Production Engineering*, 51-82. https://doi.org/10.1016/B978-0-85709-481-0.00003-3

Makarichi, L., Techato, K., & Jutidamrongphan, W. (2018). Material flow analysis as a support tool for multi-criteria analysis in solid waste management decision-making. *Resources, Conservation & Recycling*, *139*, 351-365. https://doi.org/10.1016/j.resconrec.2018.07.024

Malczewski, J. (2018). 1.15 - Multicriteria Analysis. In B. Huang (Ed.), *Comprehensive Geographic Information Systems*. Elsevier. https://doi.org/https://doi.org/10.1016/B978-0-12-409548-9.09698-6

Marrucci, L., Marchi, M., & Daddi, T. (2020). Improving the carbon footprint of food and packaging waste management in a supermarket of the Italian retail sector. *Waste Management*, *105*, 594-603. https://doi.org/10.1016/j.wasman.2020.03.002

Martínez-Blanco, J., Muñoz, P., Antón, A., & Rieradevall, J. (2009). Life cycle assessment of the use of compost from municipal organic waste for fertilization of tomato crops. *Resources, Conservation & Recycling*, *53*, 340-351. https://doi.org/10.1016/j.resconrec.2009.02.003

Maturi, K. C., Haq, I., & Kalamdhad, A. S. (2022). 4 - Composting techniques: utilization of organic wastes in urban areas of Indian cities. In C. M. Hussain & S. Hait (Eds.), *Advanced Organic Waste Management - Sustainable Practices and Approaches*. Elsevier Inc.

Mavrotas, G., Gakis, N., Skoulaxinou, S., & Katsouros, V. (2015). Municipal solid waste management and energy production: consideration of external cost through multi-objective optimization and its effect on waste-to-energy solutions. *Renewable and Sustainable Energy Reviews*, *51*, 1205-1222. http://dx.doi.org/10.1016/j.rser.2015.07.029

Mazzanti, M., Montini, A., & Zoboli, R. (2008). Municipal waste generation and socioeconomic drivers - evidence from comparing northern and southern Italy. *Journal of Environmental Development*, *17*, 51-69. https://doi.org/10.1177/1070496507312575

Mazzanti, M., & Zoboli, R. (2009). Municipal waste Kuznets curves: evidence on socio-economic drivers and policy effectiveness from the EU. *Environmental Resource Economics*, *44*, 203-230. https://doi.org/10.1007/s10640-009-9280-x

McKay, M. D., Beckman, R. J., & Conover, W. J. (1979). A comparison of three methods for selecting input variables in the analysis of output from a computer code. *Technometrics 21*(2), 239-245. https://doi.org/10.2307/1268522

Meys, R., Frick, F., Westhues, S., Sternberg, A., Klankermayer, J., & Bardow, A. (2021). Towards a circular economy for plastic packaging wastes - the environmental potential of chemical recycling. *Resources, Conservation & Recycling*, *162*, 105010. https://doi.org/10.1016/j.resconrec.2020.105010

Mojtahedi, M., Fathollahi-Fard, A. M., Tavakkoli-Moghaddam, R., & Newton, S. (2021). Sustainable vehicle routing problem for coordinates solid waste management. *Journal of Industrial Information Integration*, *23*, 100220. https://doi.org/10.1016/j.jii.2021.100220

Monteiro, J., Martins, B., Murrieta-Flores, P., & Pires, J. (2019). Spatial disaggregation of historical census data leveraging multiple sources of ancillary information. *International Journal of Geo-Information*, *8*, 327. https://doi.org/10.3390/ijgi8080327

Montello, D., & Sutton, P. (2012). *An introduction to scientific research methods in geography and environmental studies*. Sage Publishing, London.

Montevecchi, F. (2016). Policy mixes to achieve absolute decoupling: a case study of municipal waste management. *Sustainability*, *8*, 442-464. http://dx.doi.org/doi:10.3390/su8050442

Movahed, Z. P., Kabiri, M., Ranjbar, S., & Joda, F. (2020). Multi-objective optimization of life cycle assessment of integrated waste management based on genetic algorithms: a case study of Tehran. *Journal of Cleaner Production*, *247*, 119153. https://doi.org/10.1016/j.jclepro.2019.119153

Mueller, T., Pierce, F., Schabenberger, O., & Warncke, D. (2001). Map quality for site-specific fertility management. *Soil Science Society of America Journal*, *65*, 1547-1558. https://doi.org/10.2136/sssaj2001.6551547x

Münster, M., Ravn, H., Hedegaard, K., Juul, N., & Söderman, M. L. (2015). Economic and environmental optimization of waste treatment. *Waste Management*, *38*, 486-495. http://dx.doi.org/10.1016/j.wasman.2014.12.005

National Transport Commission. (2019). *Carbon Dioxide Emissions Intensity for New Australian Light Vehicles 2018 - Information Paper June 2019*.

NATSEM. (2008). *A review of small area estimation problems and methodological developments*. https://researchoutput.csu.edu.au/ws/portalfiles/portal/25229570/A_Review_of_Small_Area_Estimation.pdf

Nautiyal, H., & Goel, V. (2021). Chapter 3 - Sustainability assessment: metrics and methods. In J. Ren (Ed.), *Methods in Sustainability Science: Assessment, Prioritization, Improvement, Design and Optimization*. Elsevier. https://doi.org/https://doi.org/10.1016/B978-0-12-823987-2.00035-0

Ng, K. S., Phan, A. N., Iacovidou, E., & Ghani, W. A. W. A. K. (2021). Techno-economic assessment of a novel integrated system of mechanical-biological treatment and valorisation of residual municipal solid waste into hydrogen: A case study in the UK. *Journal of Cleaner Production*, *298*, 126706. https://doi.org/10.1016/j.jclepro.2021.126706

Nguyen, T. T. T., & Wilson, B. G. (2010). Fuel consumption estimation for kerbside municipal solid waste (MSW) collection activities. *Waste Management & Research*, *28*(4), 289-297. https://doi.org/10.1177/0734242X09337656

Niesner, J., Jecha, D., & Stehlik, P. (2013). Biogas upgrading technologies: state of art review in European region. *Chemical Engineering Transations*, *35*, 517-522. https://doi.org/10.3303/CET1335086

NSW EPA. (2014a). *Domestic kerbside waste and recycling in NSW: results of the 2011 waste audits*. https://www.epa.nsw.gov.au/~/media/EPA/Corporate%20Site/resources/warrlocal/140442-audits-2011.ashx

NSW EPA. (2014b). *NSW Waste Avoidance and Resource Recovery Strategy 2014-21*.

NSW EPA. (2017). *NSW Local Government Waste and Resource Recovery Data Report 2015-16*. https://www.epa.nsw.gov.au/-/media/epa/corporate-site/resources/warrlocal/19p1628-nsw-local-government-warr-data-report-2015-16.pdf?la=en&hash=3DF11FC62B910C80CDD548C966FCC257FB86FE5D

NSW EPA. (2019a). *The future use of Mixed Waste Organic Outputs in NSW*. NSW Environment Protection Authority. Retrieved July 31 2022 from https://www.epa.nsw.gov.au/newsletters/epa-connect-newsletter/spring-november-2019/the-future-use-of-mixed-waste-organic-outputs-in-nsw

NSW EPA. (2019b). *NSW Circular Economy Policy Statement: Too Good To Waste*. https://www.epa.nsw.gov.au/-/media/epa/corporate-site/resources/recycling/19p1379-circular-economy-policy-final

NSW EPA. (2020a). *20-Year Waste Strategy for NSW*. State of NSW and NSW Environment Protection Authority.

NSW EPA. (2020b). *Local Government Waste and Resource Recovery Data Report 2018-19*. https://www.epa.nsw.gov.au/-/media/epa/corporate-site/resources/wastestrategy/20p2373-waste-resource-recovery-report-2108-19.pdf

NSW EPA. (2021). *NSW Local Government Waste and Resource Recovery Data Report 2019-20*. https://www.epa.nsw.gov.au/-/media/epa/corporate-site/resources/wastestrategy/21p3136-2019-20-lg-waste-resource-recovery-data.pdf?la=en&hash=C9538E0011B247C3D31A332E9BDCF312219E97E9

NSW EPA. (2022). *Emissions impacts of food waste recovery technologies - fact sheet*, https://www.epa.nsw.gov.au/-/media/epa/corporate-site/resources/wasteregulation/fogo/22p4168-emissions-impacts-food-waste-recovery-technologies.pdf?la=en&hash=54897B2223F64252BA77A9F1ED982C1D39EB72EC

NSW Government. (2020). *Net Zero Plan Stage 1: 2020-2030*. https://www.environment.nsw.gov.au/-/media/OEH/Corporate-Site/Documents/Climate-change/net-zero-plan-2020-2030-200057.pdf

NSW OLG. (2020). *Australian Classification of Local Governments and OLG group members*. NSW Office of Local Government, NSW Government Sydney. https://www.yourcouncil.nsw.gov.au/wp-content/uploads/2020/05/Australian-Classification-of-Local-Government-and-OLG-group-numbers.pdf,

(1997). https://legislation.nsw.gov.au/view/html/inforce/current/act-1997-156

NSW RMS. (2019). *Mass limits for heavy vehicles*. https://roads-waterways.transport.nsw.gov.au/business-industry/partners-suppliers/lgr/other-information/heavy-vehicles/mass-limits.html

NTC. (2019). *Carbon dioxide emissions intensity for new Australian light vehicles 2018 - information paper June 2019*. https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&cad=rja&uact=8&ved=2ahUKEwigqpa_89L6AhWIwnMBHU8mA0MQFnoECB0QAQ&url=https%3A%2F%2Fwww.ntc.gov.au%2Fsites%2Fdefault%2Ffiles%2Fassets%2Ffiles%2FCarbon%2520dioxide%2520emissions%2520intensity%2520for%2520new%2520Australian%2520light%2520vehicles%25202018.pdf&usg=AOvVaw1S220ICjEWZdEAZcctlJkW

Obersteiner, G., Gollnow, S., & Eriksson, M. (2021). Carbon footprint reduction potential of waste management strategies in tourism. *Environmental Development*, *39*, 100617. https://doi.org/10.1016/j.envdev.2021.100617

OECD. (2018). *OECD Global Material Resources Outlook to 2060 - Economic Drivers and Environmental Consequences*. P. OECD Publishing.

Oribe-Garcia, I., Kamara-Esteban, O., Martin, C., Macarulla-Arenaza, A., & Alonso-Vicario, A. (2015). Identification of influencing municipal characteristics regarding household waste generation and their forecasting ability in Biscay. *Waste Management*, *39*, 26-34. https://doi.org/10.1016/j.wasman.2015.02.017

Otoo, D., Amponash, S. K., & Sebil, C. (2014). Capacitated clustering and collection of solid waste in Kwadaso estate, Kumasi. *Journal of Asian Scientific Research*, *4*(8), 460-472.

Paes, M. X., de Medeiros, G. A., Mancini, S. D., Gasol, C., Pons, J. R., & Durany, X. G. (2020). Transition towards eco-efficiency in municipal solid waste management to reduce GHG emissions: The case of Brazil. *Journal of Cleaner Production*, *263*, 121370. https://doi.org/10.1016/j.jclepro.2020.121370

Papargyropoulou, E., Colenbrander, S., Sudmat, A. H., Gouldson, A., & Tin, L. C. (2015). The economic case for low carbon waste management in rapidly growing cities in the developing world: The case of Palembang, Indonesia. *Journal of Environmental Management*, *163*, 11-19. http://dx.doi.org/10.1016/j.jenvman.2015.08.001

Parzen, E. (2015). *Stochastic Processes*. Courier Dover Publications.

Pastorello, C., Dilara, P., & Martini, G. (2011). Effect of a change towards compressed natural gas vehicles on the emissions of the Milan waste collection fleet. *Transportation Research Part D*, *16*, 121-128. https://doi.org/10.1016/j.trd.2010.09.002

Pathak, P., Kumari, K., & Bodawala, A. (2016). Mitigation of environmental pollution by a sanitary landfill: a review. *International Journal of Technical Research and Applications*, *4*(3), 206-209.

Paungfoo-Lonhienne, C., Redding.M., Pratt, C., & Wang, W. (2019). Plant growth promoting rhizobacteria increase the efficiency of fertilisers while reducing nitrogen loss. *Journal of Environmental Management*, *233*, 337-341. https://doi.org/10.1016/j.jenvman.2018.12.052

Peces, M., Astals, S., & Mata-Alvarez, J. (2014). Assessing total and volatile solids in municipal solid waste samples. *Environmental Technology*, *35*(24), 3041-3046. https://doi.org/10.1080/09593330.2014.929182

Perin, J. K. H., Borth, P. L. B., Torrecilhas, A. R., de Cunha, L. S., Kuroda, E. K., & Fernandes, F. (2020). Optimization of methane production parameters during anaerobic co-digestion of food waste and garden waste. *Journal of Cleaner Production*, *272*, 123130. https://doi.org/10.1016/j.jclepro.2020.123130

Pilli, S., Pandey, A. K., Katiyar, A., Pandey, K., & Tyagi, R. D. (2020). Pre-treatment technologies to enhance anaerobic digestion. In B. K. Taşeli (Ed.), *Sustainable Sewage Sludge Management and Resource Efficiency*. IntechOpen. https://doi.org/https://doi.org/10.5772/intechopen.80201

Pires, A., & Martinho, G. (2019). Waste hierarchy index for circular economy in waste management. *Waste Management*, *95*, 298-305. https://doi.org/10.1016/j.wasman.2019.06.014

Połomka, J., & Jędrczak, A. (2019). Efficiency of waste processing in the MBT system. *Waste Management*, *96*, 9-14. https://doi.org/10.1016/j.wasman.2019.06.041

Pressley, P. N., Levis, J. W., Damgaard, A., Barlaz, M. A., & DeCarolis, J. F. (2015). Analysis of material recovery facilities for use in life-cycle assessment. *Waste Management*, *35*, 307-317. http://dx.doi.org/10.1016/j.wasman.2014.09.012

Quintili, A., & Castellani, B. (2020). The energy and carbon footprint of an urban waste collection fleet: a case study in Central Italy. *Recycling*, *5*(4), 25. https://doi.org/10.3390/recycling5040025

R Core Team. (2020). R: A language and environment for statistical computing. In: R Foundation for Statistical Computing, Vienna.

Ramanathan, R. (2004). Multicriteria analysis of energy. In C. J. Cleveland (Ed.), *Encyclopedia of Energy*. Elsevier. https://doi.org/https://doi.org/10.1016/B0-12-176480-X/00240-0

Rawtec. (2020a). *Analysis of NSW Kerbside Green Lid bin audit data report - March 2020.*

Rawtec. (2020b). *Analysis of NSW Kerbside Red Lid Bin Audit Data Report - Results of the 2011-2019 audits.*

Rich, J. (2018). Large-scale spatial population synthesis for Denmark. *European Transport Research Review*, *10*. https://doi.org/10.1186/s12544-018-0336-2

Rigamonti, L., Borghi, G., Martignon, G., & Grosso, M. (2019). Life cycle costing of energy recovery from solid recovery fuel produced in MBT plants in Italy. *Waste Management*, *99*, 154-162. https://doi.org/10.1016/j.wasman.2019.08.030

Roberts, M. B., Bruce, A., & MacGill, I. (2019). Opportunities and barriers for photovoltaics on multi-unit residential buildings: reviewing the Australian experience. *Renewable and Sustainable Energy Reviews*, *104*, 95-110. https://doi.org/10.1016/j.rser.2018.12.013

Rocamora, I., Wagland, S. T., Villa, R., Simpson, E. W., Fernández, O., & Bajón-Fernández, Y. (2020). Dry anaerobic digestion of organic waste: a review of operational parameters and their impact on process performance. *Bioresource Technology*, *299*, 122681. https://doi.org/10.1016/j.biortech.2019.122681

Rood, T., & Hanemaaijer, A. (2017). *Opportunities for a circular economy*. https://themasites.pbl.nl/o/circular-economy/

ROU. (2006). *Life Cycle Inventory and Life Cycle Assessment for Windrow Composting Systems*. Department of Environment and Conservation, State of NSW.

Saaty, T. L. (1970). How to make a decision: the analytical hierarchy process. *European Journal of Operations Research*, *48*, 9-26. http://dx.doi.org/10.1016/0377-2217(90)90057-I

Sarmah, S., Yadav, R., & Rathore, P. (2019). Development of vehicle routing model in urban solid waste management system under periodic variation: a case study. *IFAC PapersOnLine*, *52*, 1961-1965. https://doi.org/10.1016/j.ifacol.2019.11.490

Sayara, T., & Sánchez, A. (2021). Gaseous emissions from the composting process: controlling parameters and strategies of mitigation. *processes*, *9*, 1844. https://doi.org/10.3390/pr9101844

Scheutz, C., & Kjeldsen, P. (2019). Guidelines for landfill gas emission monitoring using the tracer gas dispersion method. *Waste Management*, *85*, 351-360. https://doi.org/10.1016/j.wasman.2018.12.048

Scheutz, C., Kjeldsen, P., & Gentil, E. (2009). Greenhouse gases, radiative forcing, global warming potential and waste management - an introduction. *Waste Management & Research*, *27*, 716-723. https://doi.org/10.1177/0734242X09345599

Schittkowski, K. (1988). Solving constrained nonlinear least squares problems by a general purpose SQP-method. In K. H. Hoffman, J. Zowe, J. B. Hiriart-Urruty, & C. Lemarechal (Eds.), *Trends in Mathematical Optimization. 4th French-German Conference on Optimization*.

Shahnazari, A., Rafiee, M., Rohani, A., Nagar, B. B., Ebrahiminik, M. A., & Aghkhani, M. H. (2020). Identification of effective factors to select energ recovery technologies from municipal solid waste using multi-criteria decision making (MCDM): a review of thermochemical technologies. *Sustainable Energy Technologies and Assessments*, *40*, 100737. https://doi.org/10.1016/j.seta.2020.100737

Sharma, B. K., & Chandel, M. K. (2017). A life cycle assessment to compare composting schemes for the treatment of municipal solid waste in Mumbai, India. Sixteenth International Waste Management and Landfill Symposium, Cagliari, Italy.

Sharma, H. B., Vanapalli, K. R., Samal, B., Cheela, V. R. S., Dubey, B. K., & Bhattacharya, J. (2021). Circular economy approach in solid waste management system to achieve UN-SDGs: Solutions for post-COVID recovery. *Science of the Total Environment*, *800*, 149605. https://doi.org/10.1016/j.scitotenv.2021.149605

Shepard, D. (1968). A two-dimensional interpolation function for irregularly-spaced data. Proceedings of the 1968 ACM National Conference,

Shi, X., Elmore, A., Li, X., Gorence, N., Jin, H., Zhang, X., & Wang, F. (2008). Using spatial information technologies to select sites for biomass power plants: a case study in Guangdon Province, China. *Biomass and Bioenergy*, *32*, 35-43. https://doi.org/10.1016/j.biombioe.2007.06.008

Singh, A. (2019). Remote sensing and GIS applications for municipal waste management. *Journal of Environmental Management*, *243*, 22-29. https://doi.org/10.1016/j.jenvman.2019.05.017

Singh, R., Murty, H. R., Gupta, S. K., & Dikshit, A. (2012). An overview of sustainability assessment methodologies. *Ecological Indicators*, *15*(1), 281-299. https://doi.org/10.1016/j.ecolind.2011.01.007

Sliz-Szkliniarz, B., & Vogt, J. (2012). A GIS-based approach for evaluating the potential of biogas production from livestock manure and crops at a regional scale: a case study for the Kujawsko-Pomorskie Voivodeshop. *Renewable and Sustainable Energy Reviews*, *16*, 752-763. https://doi.org/10.1016/j.rser.2011.09.001

Son, L. H. (2014). Optimizing municipal solid waste collection using chaotic particle swarm optimization in GIS based environments: a case study at Danang City, Vietnam. *Expert Systems with Applications*, *41*, 8062-8074. https://doi.org/10.1016/j.eswa.2014.07.020

Sonesson, U. (2000). Modelling of waste collection - a general approach to calculate fuel consumption and time. *Waste Management & Research*, *18*(2), 115-123. https://doi.org/10.1034/j.1399-3070.2000.00099.x

Strandgard, M., Acuna, M., Turner, P., & Mirowski, L. (2021). Use of modelling to compare the impact of roadside drying of Pinus radiata D.Don logs and logging residues on delivered costs using high capacity trucks in Australia. *Biomass and Bioenergy*, *147*, 106000. https://doi.org/10.1016/j.biombioe.2021.106000

Stunzenas, E., & Kliopova, I. (2018). Optimizing municipal biodegradable waste management system to increase biogas output and nutrient recovery: a case study in Lithuania. *Energy Procedia*, *147*, 641-648. https://doi.org/10.1016/j.egypro.2018.07.083

Suárez-Eiroa, B., Fernández, E., Méndez-Martínez, G., & Soto-Oñate, D. (2019). Operational principles of circular economy for sustainable developing: linking theory and practice. *Journal of Cleaner Production*, *214*, 952-961. https://doi.org/10.1016/j.jclepro.2018.12.271

Sun, N., & Chungpaibulpatana, S. (2017). Development of an appropriate model for forecasting municipal solid waste generation in Bangkok. *Energy Procedia*, *138*, 907-912. https://doi.org/10.1016/j.egypro.2017.10.134

Surdo, D. L., & Gupta, K. (2021). Household food waste program fails to catch on among Sydney councils. *Sydney Morning Herald*. https://www.smh.com.au/national/nsw/household-food-waste-program-fails-to-catch-on-among-sydney-councils-20210917-p58slz.html

Tabata, T., Onishi, A., Saeki, T., & Tsai, P. (2019). Earthquake disaster waste management reviews: prediction, treatment, recycling and prevention. *International Journal of Disaster Risk Reduction*, *36*, 101119. https://doi.org/10.1016/j.ijdrr.2019.101119

Tanguy, A., Villot, J., Glaus, M., Laforest, V., & Hausler, R. (2017). Service area size assessment for evaluating the spatial scale of solid waste recovery chains: a territorial perspective. *Waste Management*, *64*, 386-396. https://doi.org/10.1016/j.wasman.2017.03.027

ten Hoeve, M., Bruun, S., Jensen, L. S., Christensen, T. H., & Scheutz, C. (2019). Life cycle assessment of garden waste management options including long-term emissions after land application. *Waste Management*, *86*, 54-66. https://doi.org/10.1016/j.wasman.2019.01.005

Thanh, H. T., Yabar, H., & Higano, Y. (2015). Analysis of the environmental benefits of introducing municipal organic waste recovery in Hanoi city, Vietnam. *Procedia Environmental Sciences*, *28*, 185-194. https://doi.org/10.1016/j.proenv.2015.07.025

Tirkolaee, E. B., Mahdavi, I., Esfahani, M. M. S., & Weber, G. W. (2020). A robust green location-allocation-inventory problem to design an urban waste management system under uncertainty. *Waste Management*, *102*, 340-350. https://doi.org/10.1016/j.wasman.2019.10.038

Trang, P., Dong, H., Toan, D., Hanh, N., & Thu, N. (2017). The effects of socio-economic factors on household solid waste generation and composition: A case study in Thu Dau Mot, Vietname. *Energy Procedia*, *107*, 253-258. https://doi.org/10.1016/j.egypro.2016.12.144

Transport and Infrastructure Council. (2020). *Australian Transport Assessment and Planning Guidelines: M3 - Freight Rail*. https://www.atap.gov.au/sites/default/files/documents/atap-1622-m3-pv3-freight-rail-public-consultation-draft-v4.2-2020-10-06.pdf

Truong, P., & Stein, A. (2019). Model-based small area estimation at two scales using Moran's spatial filtering. *Spatial and Spatio-temporal Epidemiology*, *31*, 100303. https://doi.org/10.1016/j.sste.2019.100303

Turner, A., Fam, D., Madden, B., & Liu, A. (2017). *Pyrmont-Ultimo Precinct (PUP) Scale Organics Management Scoping Study*.

Tyagi, V. K., Kapoor, A., Arora, P., Banu, J. R., Das, S., Pipesh, S., & Kazmi, A. A. (2021). Mecahnical-biological treatment of municipal solid waste: Case study of 100 TPD Goa plant, India. *Journal of Environmental Management*, *292*, 112741. https://doi.org/10.1016/j.jenvman.2021.112741

UNEP. (2021). *Food Waste Index Report 2021*. United Nations Environment Programme.

US EPA. (2010). *Greenhouse gas emissions estimation methodologies for biogenic emissions from selected source categories: solid waste disposal, wastewater treatment, ethanol fermentation*. https://www3.epa.gov/ttnchie1/efpac/ghg/GHG_Biogenic_Report_draft_Dec1410.pdf

US EPA. (2022). *Types of compsting and understanding the process*. United States Environmental Protection Agency. Retrieved June 2022 from https://www.epa.gov/sustainable-management-food/types-composting-and-understanding-process

Vafaei, N., Ribeiro, R. A., & Camarinha-Matos, L. M. (2022). Assessing normalization techniques for simple additive weighting method. *Procedia Computer Science*, *199*, 1229-1236. https://doi.org/10.1016/j.procs.2022.01.156

van Eygen, E., Laner, D., & Fellner, J. (2018). Circular economy of plastic packaging: current practice and perspectives in Austria. *Waste Management*, *72*, 55-64. https://doi.org/10.1016/j.wasman.2017.11.040

van Leeuwen, R. P., de Wit, J. B., & Smit, G. J. M. (2017). Review of urban energy transition in the Netherlands and the role of smart energy management. *Energy Conversion and Management*, *150*, 941-948. https://doi.org/10.1016/j.enconman.2017.05.081

Vanotti, M. B., Garcia-González, M. C., Molinuevo-Salces, B., & Riaño, B. (2019). Editorial: New processes for nutrient recovery from wastes. *Frontiers in Sustainable Food Systems*, *3*. https://doi.org/10.3389/fsufs.2019.00081

Vaverková, M. D. (2019). Landfill impacts on the environment - review. *Geosciences*, *9*(10), 431-447. https://doi.org/10.3390/geosciences9100431

Veolia. (2022). *Clyde Transfer Station, NSW*. https://www.veolia.com/anz/our-services/our-facilities/transfer-stations/clyde-transfer-station

Vergara, S. E., & Silver, W. L. (2019). Greenhouse gas emissions from windrow composting of organic wastes: patterns and emissions factors. *Environmental Research Letters*, *14*, 124027. https://doi.org/10.1088/1748-9326/ab5262

Vlachokostas, C., Michailidou, A. V., & Achillas, C. (2021). Multi-criteria decision analysis towards promoting waste-to-energy management strategies: a critical review. *Renewable and Sustainable Energy Reviews*, *138*, 110563. https://doi.org/10.1016/j.rser.2020.110563

Vu, H., Bolingbroke, D., Ng, K., & Fallah, B. (2019). Assessment of waste characteristics and their impact on GIS vehicle collection route optimization using ANN waste forecasts. *Waste Management*, *88*, 118-130. https://doi.org/10.1016/j.wasman.2019.03.037

Wang, F. (2001). Deterministic and stochastic simulations for solid waste collection systems - a SWIM appraoch. *Environmental Modeling and Assessment*, *6*, 249-260.

Wang, J., Okopi, S. I., Ma, H., Wang, M., Chen, R., Tian, W., & Xu, F. (2021). Life cycle assessment of the integration of anaerobic digestion and pyrolysis for treatment of municipal solid waste. *Bioresource Technology*, *338*, 125486. https://doi.org/10.1016/j.biortech.2021.125486

Wang, P., Bohara, A., Berrens, R., & Gawande, K. (1998). A risk based environmental Kuznets' cruve for US hazardous waste sites. *Applied Economics Letters*, *5*, 761-763. https://doi.org/10.1080/135048598353970

Wang, Q., Awasthi, M. K., Ren, X., & Zhao, J. (2018). Recent advances in composting of organic and hazardous waste: a road map to safer environment. In S. J. Varjani, B. Parameswaran, S. Kumar, & S. S. Khare (Eds.), *Biosynthetic Technology and Environmental Challenges*. Springer, Singapore. https://doi.org/https://doi.org/10.1007/978-981-10-7434-9

Ward, J., Sutton, P., Werner, A., Constanza, R., Mohr, S., & Simmons, C. (2016). Is decoupling GDP growth from environmental impact possible? *PLoS ONE*, *11*. https://doi.org/10.1371/journal.pone.0164733

Waste Management Review. (2020). *The MUD dilemma*. https://wastemanagementreview.com.au/the-mud-dilemma/

Wichapa, N., & Khokhajaikiat, P. (2017). Solving multi-objective facility location problem using the fuzzy analytical hierarchy process and goal programming: a case study on infectious waste disposal centers. *Operations Research Perspectives*, *4*, 39-48. http://dx.doi.org/10.1016/j.orp.2017.03.002

Wiedmann, T., Schandl, H., Lenzen, M., Moran, D., Suh, S., West, J., & Kanemoto, K. (2016). The material footprint of nations - reassessing resource productivity. *Proceedings of the National Academy of Sciences*, *112*, 6271-6276. http://dx.doi.org/10.1073/pnas.1220362110

Wilkinson, K., Price, J., Biala, J., & McDonald, D. (2021). *Review of Regulations and Standards for Recycled Organics in Australia*. Frontier AG & Environment. https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&cad=rja&uact=8&ved=2ahUKEwj8mvym9dL6AhUs9zgGHbqAB6kQFnoECBoQAQ&url=https%3A%2F%2Fwww.dcceew.gov.au%2Fenvironment%2Fprotection%2Fwaste%2Fpublications%2Freview-regulations-standards-recycled-organics-in-australia&usg=AOvVaw0KR0LcsVL3v3-B74LZCnWs

Wilson, A. (2007). Boltzmann, Lotka and Volterra and spatial structural evolution: an integrated methodology for some dynamical systems. *Journal of the Royal Society Interface*, *5*, 865-871. https://doi.org/10.1098/rsif.2007.1288

Winslow, K. M., Laux, S. J., & Townsend, T. G. (2019). An economic and environmental assessment on landfill gas to vehicle fuel conversion for waste hauling operations.

Resources, Conservation & Recycling, *142*, 155-166. https://doi.org/10.1016/j.resconrec.2018.11.021

World Trade Organization. (2017). *18 July 2017 Committe on Technical Barriers to Trade.*

Wu, B., Li, R., & Huang, B. (2014). A geographically and temporally weighted autoregressive model with application to housing prices. *International Journal of Geographical Information Science*, *28*, 1186-1204. https://doi.org/10.1080/13658816.2013.878463

Wu, Y. H., & Hung, M. C. (2016). Comparison of spatial interpolation techniques using visualization and quantitative assessment. In M. C. Hung (Ed.), *Applications of Spatial Statistics*. IntechOpen.

Yadav, P., Yadav, S., Singh, D., & Giri, B. S. (2022). Sustainable rural waste management using biogas technology: an analytical hierarchy process decision framework. *Chemosphere*, *301*, 134737. https://doi.org/10.1016/j.chemosphere.2022.134737

Yadav, V., Bhurjee, A., Karmakar, S., & Dikshit, A. (2017). A facility location model for municipal solid waste management system under uncertain environment. *Science of the Total Environment*, *603-604*, 760-771. https://doi.org/10.1016/j.scitotenv.2017.02.207

Yadav, V., Karmakar, S., Dikshit, A., & Bhurjee, A. (2018). Interval-valued facility location model: an appraisal of municipal solid waste management system. *Journal of Cleaner Production*, *171*, 250-263. https://doi.org/10.1016/j.jclepro.2017.09.233

Yaman, C. (2020). Investigation of greenhouse gas emissions and energy recovery potential from municipal solid waste management practices. *Environmental Development*, *33*. https://doi.org/10.1016/j.envdev.2019.100484

Yazdani, M., Kabirifar, K., Frimpong, B. E., Shariati, M., Mirmozaffari, M., & Boskabadi, A. (2021). Improving construction and demolition waste collection service in an urban area using a simheuristic approach: a case study in Sydney, Australia. *Journal of Cleaner Production*, *280*, 124138. https://doi.org/10.1016/j.jclepro.2020.124138

Yoshida, Y., Gable, J. J., & Park, J. K. (2012). Evaluation of organic waste diversion alternatives for greenhouse gas reduction. *Resources, Conservation & Recycling*, *60*, 1-9. https://doi.org/10.1016/j.resconrec.2011.11.011

Yu, Z., Khan, S. A. R., Ponce, P., Zia-ul-haq, H. M., & Ponce, K. (2022). Exploring essential factors to improve waste-to-resource recovery: a roadmap towards sustainability. *Journal of Cleaner Production*, *350*, 131305. https://doi.org/10.1016/j.jclepro.2022.131305

Zamri, M. F. M. A., Hasmady, S., Akhiar, A., Ideris, F., Shamsuddin, A. H., Mofijur, M., Fattah, I. M. R., & Mahlia, T. M. I. (2021). A comprehensive review on anaerobic digestion of organic fraction of municipal solid waste. *Renewable and Sustainable Energy Reviews*, *137*, 110637. https://doi.org/10.1016/j.rser.2020.110637

Zavadskas, E. K., Antucheviciene, J., & Kar, S. (2019). Multi-objective and multi-attribute optimization for sustainable development decision aiding. *Sustainability*, *11*, 3069. http://dx.doi.org/10.3390/su11113069

Zhang, C., Hu, M., Di Maio, F., Sprecher, B., Yang, X., & Tukker, A. (2022). An overview of the waste hierarchy framework for analyzing the circularity in construction and demolition waste management in Europe. *Science of the Total Environment*, *803*, 149892. https://doi.org/10.1016/j.scitotenv.2021.149892

Zhang, C., Xu, T., Feng, H., & Chen, S. (2019). Greenhouse gas emissions from landfills: a review and biblometric analysis. *Sustainability*, *11*. https://doi.org/10.3390/su11082282

Zhang, Y., & Banks, C. J. (2013). Impact of different particle size distributions on anaerobic digestion of the organic fraction of municipal solid waste. *Waste Management*, *33*(2), 297-307. https://doi.org/10.1016/j.wasman.2012.09.024

Zhu-Barker, X., Bailey, S. K., Paw, K. T. U., Burger, M., & Horwath, W. R. (2017). Greenhouse gas emissions from green waste composting windrow. *Waste Management*, *59*, 70-79. http://dx.doi.org/10.1016/j.wasman.2016.10.004

Appendices

A. Appendices for Madden et al., 2019 (Chapter 3)

A.1. Variation in β coefficient and t-value estimates for values of λ

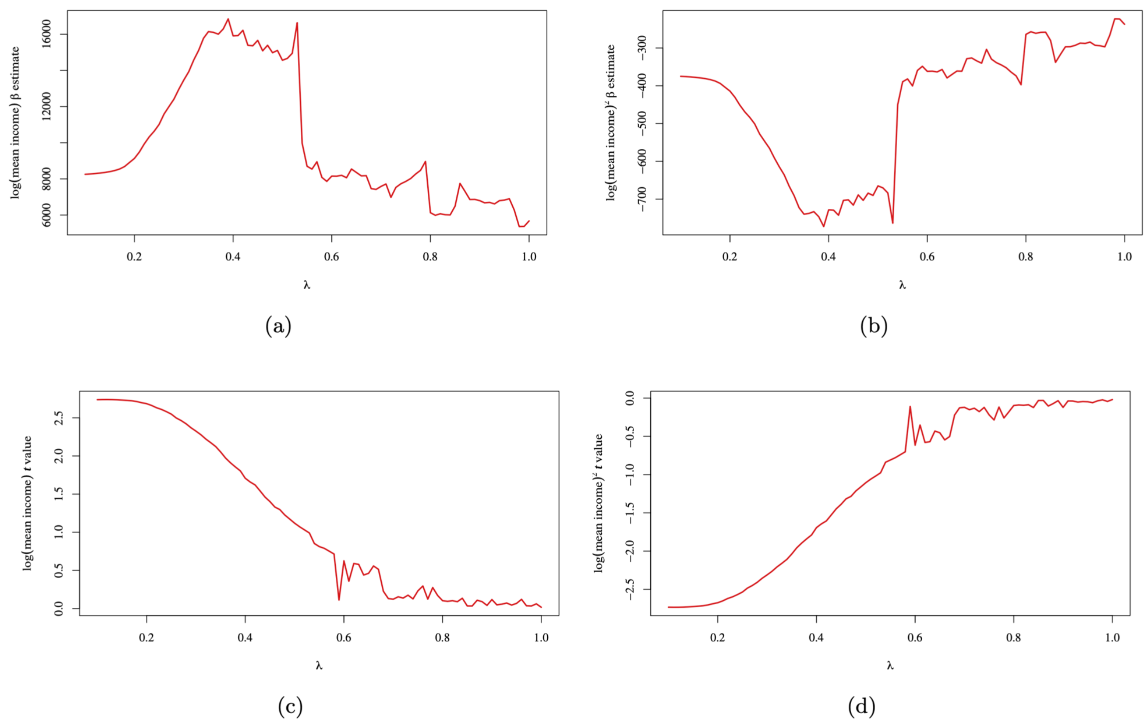


Figure A-0-1: Variation in β coefficient and t-value estimates for values of λ. (a) and (b) are the β estimates for the log(mean income) and log(mean income)^2 variables and (c) and (d) are t-value estimates

B. Appendices for Madden et al., 2021 (Chapter 4)

B.1. Algorithm 1 - Estimation of detached dwellings at the property lot

Here, $X_{det,\mathcal{S}}$ is the set of all values of $X_{det}(l)$ for an SA1 $\mathcal{S}$.

Algorithm 1 Estimation of $X_{\mathrm{det},\mathcal{S}}$

Require: k, p, L^a, $n = |L^a|$, $N_{\mathrm{det}}(\mathcal{S})$

  Let $\Gamma = \emptyset$ be a container set

  Set maximum iterations $max.iter = 1000$

  Set counter $i = 0$

  while $i \leq max.iter$ **do**

    $i = i + 1$

    Estimate $\bar{X}_{\mathrm{det},\mathcal{S}}$ for lots in L^a

    Append $\bar{X}_{\mathrm{det},\mathcal{S}}$ to the container: $\Gamma \cup \bar{X}_{\mathrm{det},\mathcal{S}}$

    Calculate $\hat{N}_{\mathrm{det}}(\mathcal{S}) = \sum_l \bar{X}_{\mathrm{det}}(l)$

    Calculate $\delta_i = |N_{\mathrm{det}}(\mathcal{S}) - \hat{Y}_{\mathrm{det}}(\mathcal{S})|$

    if $\delta_i = 0$ **then**

      $X_{\mathrm{det},\mathcal{S}} = \bar{X}_{\mathrm{det},\mathcal{S}}$

      return $X_{\mathrm{det},\mathcal{S}}$

    else if $i = max.iter$ **then**

      $j = \arg\min_i \delta_i$

      $X_{\mathrm{det},\mathcal{S}} = \Gamma_j$

      return $X_{\mathrm{det},\mathcal{S}}$

    end if

  end while

B.2. Algorithm 2 - Estimation of multi-unit dwellings at the property lot

Here $X_{mul,\mathcal{S}}$ is the set of all values of $X_{det}(l)$ for an SA1$\mathcal{S}$.

Algorithm 2 Estimation of $X_{\mathrm{mul},\mathcal{S}}$

Require: λ, L^b, $N_{\mathrm{mul}}(\mathcal{S})$

Let $\Gamma = \emptyset$ be a container set

Set maximum iterations $max.iter = 1000$

Set counter $i = 0$

while $i \leq max.iter$ **do**

  $i = i + 1$

  Estimate $\bar{X}_{\mathrm{mul},\mathcal{S}}$ for lots in L^b

  Append $\bar{X}_{\mathrm{mul},\mathcal{S}}$ to the container: $\Gamma \cup \bar{X}_{\mathrm{mul},\mathcal{S}}$

  Calculate $\hat{N}_{\mathrm{mul}}(\mathcal{S}) = \sum_l \bar{X}_{\mathrm{mul}}(l)$

  Calculate $\delta_i = |N_{\mathrm{mul}}(\mathcal{S}) - \hat{N}_{\mathrm{mul}}(\mathcal{S})|$

  if $\delta_i = 0$ **then**

    $X_{\mathrm{mul},\mathcal{S}} = \bar{X}_{\mathrm{mul},\mathcal{S}}$

    return $X_{\mathrm{mul},\mathcal{S}}$

  else if $i = max.iter$ **then**

    $j = \arg\min_i \delta_i$

    $X_{\mathrm{mul},\mathcal{S}} = \Gamma_j$

    return $X_{\mathrm{mul},\mathcal{S}}$

  end if

end while

B.3. Estimated per-dwelling waste generation rates

	Residual waste		Dry recyclables		Garden waste	
LGA	Detached	Multi-unit	Detached	Multi-unit	Detached	Multi-unit
Blacktown	1371.8	1227.6	231.3	206.9	566.0	391.3
Botany Bay	749.1	592.5	314.1	248.5	86.9	68.7
Burwood	793.6	677.4	256.9	219.3	225.9	192.8
Camden	864.3	536.5	376.0	233.4	449.5	279.0
Campbelltown	836.3	618.6	331.9	245.5	376.6	278.6
Canada Bay	735.3	552.1	330.6	248.2	192.0	144.2
Canterbury-Bankstown	920.8	760.9	287.4	237.5	281.0	232.2
Cumberland	1122.3	945.4	264.8	223.0	161.3	135.9
Fairfield	1265.3	997.3	206.1	162.4	31.4	24.7
Georges River	724.6	593.9	267.5	219.2	276.5	226.6
Hornsby	763.6	558.2	328.8	240.3	393.3	287.5
Hunters Hill	752.7	469.9	296.5	185.1	288.5	180.1
Inner West	739.7	562.3	337.4	256.5	143.2	108.8
Ku-ring-gai	706.6	483.0	360.8	246.7	504.6	345.0
Lane Cove	636.0	422.1	274.0	181.8	537.4	356.7
Liverpool	993.5	716.2	327.1	235.8	304.3	219.4
Mosman	810.7	511.7	321.5	202.9	271.6	171.5
Northern Beaches	587.5	406.9	308.4	213.6	74.7	51.7
North Sydney	768.8	503.5	400.1	262.0	497.6	325.8
Parramatta	796.8	644.7	242.2	196.0	251.4	203.4
Penrith	595.2	411.5	352.6	243.8	566.0	391.3
Randwich	735.1	525.8	336.1	240.4	162.2	116.0
Rockdale	1210.5	933.2	328.0	252.9	2.0	1.5
Ryde	744.0	533.7	292.8	210.0	291.7	209.3
Strathfield	861.4	697.2	254.9	206.3	148.6	120.2
Sutherland Shire	810.1	533.9	364.4	240.1	411.7	271.3
City of Sydney	735.4	543.8	244.9	181.1	28.4	21.0
The Hills Shire	896.8	692.6	318.7	246.1	392.5	303.1
Waverley	843.5	584.3	491.4	340.4	127.0	87.9
Willoughby	709.3	530.9	311.9	233.5	305.2	228.4
Woollahra	838.3	554.3	428.9	283.6	258.1	170.6

C. Appendices for Madden et al., 2022 (Chapter 5)

C.1. Method applied for integrating points of interest with road network data for the evaluation of road travel distance

Estimating road travel distance between two locations of interest on a road network requires that the locations of interest be represented as nodes/vertices on the network/graph. This however rarely occurs in practice. For example, a spatial point representing a property lot may be located at the property lot boundary, or as the property lot centroid—neither of which are necessarily vertices on the graph representing the road network. Integration of spatial points of interest and the road network therefore may be required when analysing road travel distance between points of interest.

For our study, we seek to find the shortest path between two pairwise points along the road network, represented as a graph with vertices being road junctions/intersections, and edges representing road segments. Points of interest are transfer stations and neighbourhood blocks for the solution of the capacitated vehicle routing problem for waste collection estimation; and waste infrastructure pairings (e.g., transfer station to landfill; composter to landfill, etc). The *shp2graph* library (Lu et al., 2018) for the *R* computing language was utilised to integrate the points of interest with the road network data. In this library, four approaches for integrating points with network data are implemented in the *points2network* function from *shp2graph*, which are summarised as follows and visualised in Figure C-1: (1) points of interest are represented on the network as the nearest vertex on the network (i.e., road junctions/intersections) to the point of interest; (2) the point of interest is represented as a new vertex on the road network, which is the its nearest geometric point to the point of interest on the network (3) a pseudo edge is added to the network connecting the point of interest with the nearest vertex on the network; and (4) a pseudo edge is added to the network connecting the point of interest with its nearest geometric point on the network, with a new vertex added as the junction of the road segment, and the pseudo edge.

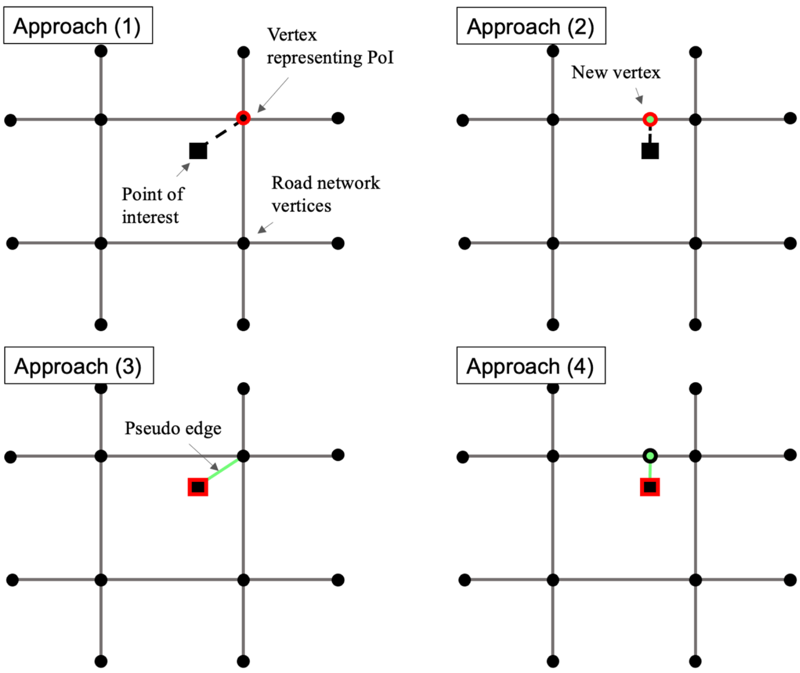


Figure C-1: Overview of point integration approaches for spatial networks in shp2graph, adapted from Lu et al., 2018

In our application, we integrated points of interest with road network data via the second approach in Lu et al. (2018), whereby points of interest are represented as new vertices on the road network equivalent to the nearest geometric point to the point of interest on the network. This is expressed as follows (Equation. C.1), adapted from Lu et al. (2018):

$$Pt_i(x_i, y_i) \leftarrow V_{pos_{min} \in LS_{min}} \leftarrow \underset{LS \in E(G)}{\arg\min} \left\{ dist(Pt_i, LS) = \right.$$

$$\left\{ \begin{array}{ll} \dfrac{\left|(y_{LS_2} - y_{LS_1})x_i - (x_{LS_2} - x_{LS_1})y_i + (y_{LS_1}x_{LS_2} - y_{LS_2}x_{LS_1})\right|}{\sqrt{\left((y_{LS_2} - y_{LS_1})^2 + (x_{LS_2} - x_{LS_1})^2\right)}} & \text{if } x_\perp, y_\perp \in range(x_1, x_2) \\ \min\left\{ d_j \mid d_j = \sqrt{(y_j - y_i)^2 + (x_j - x_i)^2}, i = 1,2 \right\} & \text{otherwise} \end{array} \right\} \tag{C.1}$$

Where Pt_i is the point of interest with Cartesian coordinates (x_i, y_i); (x_{LS_1}, y_{LS_1}) and (x_{LS_2}, y_{LS_2}) are the coordinates of the endpoints of any line segment LS in the network; pos_{min} is the nearest position on the closest line segment LS_{min}, and is taken as the vertex to be added to the network representing Pt_i. $(x_\perp, y_\perp)$ are the coordinates of the foot point from Pt_i to the nearest segment, and are found from the following (Equation C.2):

$$\begin{cases} x_{\perp} = \dfrac{(x_2, x_1)^2 x_i + (y_2 - y_1)(x_2 - x_1) y_i - (y_2 - y_1)(y_1 x_2 - y_2 x_1)}{(y_2 - y_1)^2 + (x_2 - x_1)^2} \\ y_{\perp} = \dfrac{(y_2 - y_1)(x_2 - x_1) x_i + (y_2 - y_1)^2 y_i + (x_2 - x_1)(y_1 x_2 - y_2 x_1)}{(y_2 - y_1)^2 + (x_2 - x_1)^2} \end{cases} \qquad (C.2)$$

C.2. Elaboration of the CVRP formulation

Note: The section reproduces text from the main paper that is elaborated to include constraints expressed mathematically.

Kerbside collection distances were estimated for each LGA separately. We first generated the set of neighbourhood 'blocks' for each LGA by merging contiguous property lots within an LGA together, bounded by adjacent roads on the road network. Each neighbourhood block consisted of at least one property lot occupied by a residential dwelling, with an expected amount of waste generated $w > 0$ per waste service collection interval. The number of bins to be collected within a block was equal to the number of dwellings, assuming that each dwelling within a property lot had exactly one bin per waste collection service. Neighbourhood blocks within an LGA were assumed to be serviced by the nearest transfer station, which were also the assumed waste collection vehicle depot locations. As transfer stations are distributed across the study area, some LGAs were assumed to be serviced by multiple transfer stations. The CVRP for an LGA was then solved iteratively for each transfer station and corresponding set of neighbourhood blocks serviced.

First, $B_m = \{b_{m,i}\}$ is defined as the set of neighbourhood blocks in an LGA nearest to transfer station m, with $0 < w \leq C$, where $C = 5$ tonnes was the assumed capacity of a collection vehicle, from Edwards et al., (2016). The estimation of kerbside collection for neighbourhood blocks with weekly waste generation greater than truck capacity (for example, where there are a very large number of multi-unit dwellings) was simplified by assuming that collection vehicles travel directly to the neighbourhood block from the transfer station and back again via the shortest path. In these instances, distance travelled for collection was the length of this shortest path, multiplied by the required number of collection vehicles.

For all other neighbourhood blocks with $0 < w \leq C$, we estimated collection distance by solving a CVRP. The objective of the CVRP in our application was to find the optimal collection routes that minimise total travel distance between collection points and transfer station subject to constraints. The CVRP was defined on the undirected graph $G = (V, E)$, where $V = \{v_i\}$ is the vertex set representing locations visited by collection vehicles, and $E = \{(v_i, v_j) : v_i, v_j \in V\}$ is the set of edges between vertices, representing the traversal of roads between locations. The initial vertex $i = 0$ represents transfer station m, where K waste collection vehicles begin and end their journeys. Vertices $i = 1, \dots, n$ correspond to the neighbourhood blocks $b_{m,i}, \dots, b_{m,n}$ where collection of bins takes place. A collection route is then a sequence of vertices $(v_i, v_{i+1}, \dots, v_n)$, where v_i is adjacent to v_{i+1}, and travel distance over the whole route is minimised. The symmetrical matrix $D = [d_{i,j}]$ corresponds to the non-negative travel distance along each edge (v_i, v_j), computed as the shortest road travel distance between locations. This is computed as the shortest travel distance along roads between locations, found using Dijkstra's shortest path algorithm (Dijkstra, 1959) evaluated using the cadastral road network data. Cartesian coordinates of the transfer station and neighbourhood block centroids were mapped to positions on the road network by finding the nearest point on the road network perpendicular to v_i, using the method in Lu et al. (2018). The decision variables of the CVRP model are as follows (Equations. C.3 and C.4):

$$X_{i,j,k} = \begin{cases} 1, & \text{if vehicle } k \text{ travels from location } i \text{ to } j \\ 0, & \text{otherwise} \end{cases} \tag{C.3}$$

$$Y_{i,k} = \begin{cases} 1, & \text{if location } i \text{ is visited by vehicle } k \\ 0, & \text{otherwise} \end{cases} \tag{C.4}$$

The objective function of the CVRP is then to minimise the total travel distance of all waste collection vehicle routes visiting collection points to and from transfer stations as follows (Equation C.5):

$$\text{minimise } Z = \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{k=1}^{K} d_{i,j} X_{i,j,k} \tag{C.5}$$

Subject to the following constraints:

$$\sum_{j=1}^{n} X_{0,j,k} = 1, \qquad \forall k \in \{1, \dots, K\} \tag{C.6}$$

$$\sum_{j=1}^{n} q_{0,j,k} = 0, \qquad \forall k \in \{1, \dots, K\} \tag{C.7}$$

$$\sum_{i=0}^{n} \sum_{k=1}^{K} X_{i,j,k} = 1, \qquad \forall j = 1, \dots, n \tag{C.8}$$

$$\sum_{j=1}^{n} X_{i,j,k} = \sum_{j=1}^{n} X_{j,i,k} = Y_{ik}, \qquad \forall i = 0, \dots, n;\ k \in \{1, \dots, K\} \tag{C.9}$$

$$q_{j,i,k} - q_{i,j,k} = w_j, \qquad \forall j = 1, \dots, n \tag{C.10}$$

$$\sum_{i=1}^{n} w_i X_{i,j,k} \leq C, \qquad \forall j = 0,1, \dots, n;\ k \in \{1, \dots, K\} \tag{C.11}$$

$$\sum_{j=1}^{n} X_{i,0,k} = 1, \qquad \forall k \in \{1, \dots, K\} \tag{C.12}$$

$$d_{i,j} = d_{j,i}, \qquad \forall i, j \tag{C.13}$$

Equations C.6 and C.7 ensure that a waste collection vehicle will begin its route from the transfer station with no load, where $q_{i,j,j}$ is the load of truck k between v_i and v_j. Equation C.8 ensures that each location is serviced by only one vehicle, and equation C.9 determines the ingoing and outgoing edge for each location. Equation C.10 specifies that a truck must collect all waste generated at a location, and Equation C.11 specifies that waste collected on a route must not exceed the truck capacity. Finally, Equations C.12 and C.13 ensure that a truck returns to the transfer station after visiting the final collection point, and that the travel distance between location i and j is the same in both directions of travel.

C.3 Summary of average LGA waste collection and transport distances by waste stream, and transport component

	GO waste			FOGO waste			Mixed waste			Overall waste		
	LGA average [km/year]	LGA range ['000 km/year]	Distance per tonne waste managed [km/t]	LGA average [km/year]	LGA range ['000 km/year]	Distance per tonne waste managed [km/t]	LGA average [km/year]	LGA range ['000 km/year]	Distance per tonne waste managed [km/t]	LGA average [km/year]	LGA range ['000 km/year]	Distance per tonne waste managed [km/t]
Total kerbside collection	*97,961*	*13.1 - 185.4*	*2.18*	*178,521*	*50.9 - 362.7*	*0.60*	*225,744*	*41 - 373.5*	*6.03*	*326,238*	*68.1 - 565.8*	*8.80*
Collection zone haulage (unladen)	25,995	2.3 - 52.9	0.51	41,211	10.5 - 86.3	0.13	68,722	9.8 - 123.6	1.71	94,673	14.6 - 188.8	2.34
Collection zone traversal	13,460	2.1 - 23.8	0.34	28,658	8 - 58.5	0.10	26,092	4.4 - 48.2	0.77	40,380	6.6 - 72.5	1.21
Bin pickup	33,508	5.4 - 64.8	0.85	69,446	21.1 - 135.6	0.26	64,340	11.1 - 124.7	1.92	99,689	16.6 - 191.3	3.03
Collection zone haulage (laden)	24,999	2.1 - 51.5	0.48	39,206	9.7 - 82.2	0.12	66,590	8.9 - 120.8	1.63	91,496	12.8 - 183.7	2.23
Total recovery transfer	*14,889*	*2 - 27.2*	*1.45*	*40,363*	*13.6 - 76*	*0.15*	*77,578*	*10.2 - 137.4*	*1.37*	*55,662*	*5 - 136.6*	*4.84*
Transfer station to composters	14,889	2 - 27.2	1.45	40,363	13.6 - 76	0.15	0	0	0.00	17,632	1.6 - 32	1.76
Transfer station to AWTs (road)	0	0	0.00	0	0	0.00	74,796	10.2 - 137.4	1.37	74,796	10.2 - 137.4	1.37
Transfer station to AWTs (rail)	0	0	0.00	0	0	0.00	2,782	378.7 - 2971	0.13	2,782	378.7 - 2971	0
Total disposal transfer	*435*	*0 - 1.2*	*1.00*	*1,147*	*0.4 - 2*	*0.06*	*46,788*	*6.4 - 72*	*1.84*	*32,682*	*6.4 - 72*	*1.33*
Transfer station to landfills	0	0	0.00	0	0	0.00	27,887	1.6 - 58.8	0.96	27,887	1.6 - 58.8	0.96
Composters to landfills	435	0 - 1.2	1.00	1,147	0.4 - 2	0.06	0	0	0.00	517	0 - 1.6	1.13
AWTs to landfills	0	0	0.00	0	0	0.00	18,901	2.6 - 36.8	0.88	18,901	2.6 - 36.8	0.88
Total	*105,549*	*30.66 - 460.2*	*6.07*	*199,046*	*115.3 - 827.78*	*5.92*	*261,062*	*109.48 - 1182.2*	*4.72*	*370,118*	*202.58 - 1632.8*	*4.87*