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Roadmap for Australian wastewater nutrient recovery – Towards a sustainable circular economy

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ABSTRACT

Tapping into wastewater for nutrient recovery is largely missing from water policy and circular economy (CE) conversations, and in particular, its incorporation of machine learning (ML). Past nutrient roadmap studies have either ignored or largely unaccounted for advancements in AI and ML for CE wastewater treatment plants (WWTP). This nutrient roadmap paper provides technology and ML evaluation guidance, data collection practices to prime the industry for smarter treatment processes, financial opportunities and assessments, social acceptance drivers, and guidance on navigating the current environmental and regulatory landscape for the implementation of ML CE WWTPs. Finally, further policy improvements are needed surrounding CE WWTPs to incentivise local production and recycling of critical nutrients (i.e. phosphorus) which would support the creation of new economic growth opportunities, meet environmental targets while securing and stabilising food supply chains.

1. Introduction

Numerous technologies have been introduced over the years to address the issue of nutrient scarcity and circularity, but nutrient recovery has not reached full commercialisation. The European Union (EU) lately recognised the importance phosphorous plays across the bloc with the introduction of the Critical Raw Materials Act [1] – designating phosphorous alongside phosphate rock as critical materials for the security and stability of its member states. In Australia, phosphorous was not listed in the proposed $23 bn Future Made in Australia framework as a critical mineral [2], instead prioritising net-zero commodities and other critical metals for a low-carbon future. To date, water utility companies across Australia exclude nutrient recovery practices across their treatment operations – instead, opting to remove nutrients instead of recovering it. Australia's Environmental Protection Agency (EPA), provides several guidelines on drinking water qualities and recovery exemption orders, however, none of these listed is specific to that of wastewater and source-separated urine [3]. On the other hand, Australia does reuse sewage sludge as biosolids, where in 2019, approximately 70 % of the recovered biosolids are reused in agriculture, 24 % for landscaping and the remaining 6 % is disposed of [4]. The report mentions preserving water qualities and food supply chains, but the missing link with wastewater is noticeable.

A driving force for nutrient circularity is the finite reserves of phosphorus, stabilisation of food and fertiliser prices, and the prevention of eutrophication across river ecosystems [5-7]. The Australian Circular Economy Framework which was announced on November 2024, recently listed nutrient capture and reuse as a key metric for the sustained recycling of organics through composting and anaerobic digestion, and further investments into artificial intelligence (AI) and automation to support circularity [8]. However, missing from this report is the recovery of nutrients from municipal wastewater passageways. Given that globally, wastewater constitutes about 16.6 billion kg of nitrogen, 3 billion kg of phosphorus, and 6.3 billion kg of potassium, and could offset 13.4 % of global fertiliser consumption and power 158 million households with energy [9]. This research area remains understudied and underrepresented across policy conversations.

Other roadmap papers such as *The Nutrient Roadmap* [10] explores regulations, technologies, wastewater influent characteristics, case studies, operator training and education, financing, planning, stakeholder engagements, process modelling, resources recoverable, and risk management. Previous studies have provided a more generalised

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approach to the framework of WWTP nutrient CE which included stakeholders and different levels of society [11] and extensions of this with ML highlighting the need for more data collection and enablement of the technology in WWTPs [12]. Meanwhile, a recent strategic roadmap paper published for Australia has a large focus on urine-based fertilisers and source-separation systems involving live workshop participants covering socio-cultural, environmental and health, economic and technological drivers and barriers [13]. Moreover, the application of ML for nutrient recovery is an emerging discipline of study with the aim of using predictive analytics to optimise processes and maximise resource recovery [14-16] and for enhancing transparency [17], however, several factors such as the lack of data capture and sharing, and sensor points makes ML implementation across WWTPs difficult.

1.1. Understanding nutrient loading trends and characteristics

To an operator, it is important to become familiar with wastewater characteristics. The standard chemical composition of wastewater influents of interest covers flow rates, pH, total suspended solids (TSS), total dissolved solids (TDS), biological oxygen demand (BOD), chemical oxygen demand (COD), total nitrogen (TN), total phosphorous (TP), ammonia, nitrates, nitrites and metallic elements. These chemical traits can be found in Table 1 below. Alongside these treatment plants and wastewater resource recovery facilities (WRRF), treatment guidelines are present throughout the country to regulate the discharge concentrations of these nutrients into the environment alongside any toxins and metal contaminants. Sydney Water models influent concentrations over several years with Generalised Additive Models (GAM) [18], and has collected extensive data on wastewater TP and TN loadings, but little beyond this.

Environmental protection licences (EPL) apply limits to the influent nutrient loads for wastewater treatment plants with for example, West Camden WWTP has an EPL limit of 6 kg/day of TP, for the West Camden WWTP the TN EPL limit was 252 kg/day [18]. Sydney Water's modelling processes follow Fourier sine and cosine transformations with periods factored into the prediction model, and then streamlined with a prediction interval of 95 % (Fig. 1). The influent nutrient loads vary from year to year, and predictions with best-fit models are required to make accurate data assessments. Geometric means of the nutrient loads were compared between different periods when upgrades were made to the WWTPs with TN, dissolved inorganic nitrogen (DIN) and TP being key interest variables. An EPL sets nutrient loading discharge limits on a case-by-case basis given that different nutrient discharge limits have varying impacts on the environment, however, if the nutrient recovery technology has an extremely high removal rate (for example, 100 %) across all inorganic and organic nutrients, the issues of meeting EPLs are reduced. Compared to biological nutrient removal methods, nutrient recovery prevents nutrients from being discharged into the environment or removed by bacteria and disposed of. These nutrients can be recovered through biological, electrochemical, chemical, thermal and membrane means, and repurposed into useful resources such as fertilisers, water and energy.

There is also immense potential for the data seen in Table 1 for example, to effectively recover valuable resources and to drive process optimisations. Training AI and ML models requires inputs such as the concentration of phosphorus, nitrogen, TSS, TDS and so on, to effectively estimate the treatment or recovery processes that is most efficient and optimal. Recent research has explored the use of ML with microalgae [15,24], hydrochar and biochar production [25-27], struvite precipitation [28,29], membrane [30] for either resource recovery or removal. The data that is collected is fed into ML models to predict and anticipate nutrient loadings with tailored processes. For example,

Table 1
Influent wastewater characteristics across WWTPs in Australia and its guidelines.

References	[19]	[19]	[20]	[21]	[22]	[22]	[22]	[23]
Flow Rate (ML/d)	-	-	90	-	-	-	-	59.6 (max)
Plant	Water Reclamation and Management Schemes	Luggage Point Water Reclamation Plant	Canberra WWTP	Bolivar WWTP SA	N/A (treatment guide for domestic low strength)	N/A (treatment guide for domestic light trade waste)	N/A (treatment guide for domestic high trade waste)	Selfs Point STP
Location	Sydney	Sydney	Canberra	South Australia	N/A	N/A	N/A	Hobart
pH	7.5	7.36	-	6.44	-	-	-	
TSS (mg/L)	200	262	796	980	< 250	220–350	> 300	280
TDS (mg/L)	350	-	-	944	-	-	-	
BOD (mg/L)	200	258	414	35	< 200	200–350	> 300	300
COD (mg/L)	470	583	-	91	< 500	500–700	> 800	684
TN (mg/L)	40	-		9.72	< 45	40–65	50–90	57
Ammonia (mg/L)	30	36.5	37.2		< 40	35–50	40–80	33
Nitrates (mg/L)	0.05	-			< 1	< 1	< 1	-
Nitrites (mg/L)	0.27	-			< 1	< 1	< 1	-
TP (mg/L)	7	10.57	12.1	0.07	8–12	8–12	8–12	9
Aluminium (mg/L)	0.13	0.5		0.97	-	-	-	-
Calcium (mg/L)	99	45		45.1	-	-	-	-
Chlorine (mg/L)	-	-			-	-	-	-
Fluoride (mg/L)	-	-			-	-	-	-
Magnesium (mg/L)	18	46		30	-	-	-	-
Potassium (mg/L)	86	31		44.2	-	-	-	-
Sodium (mg/L)	368	394		244	-	-	-	-
Sulphides (mg/L)	-	6.8		72	-	-	-	-

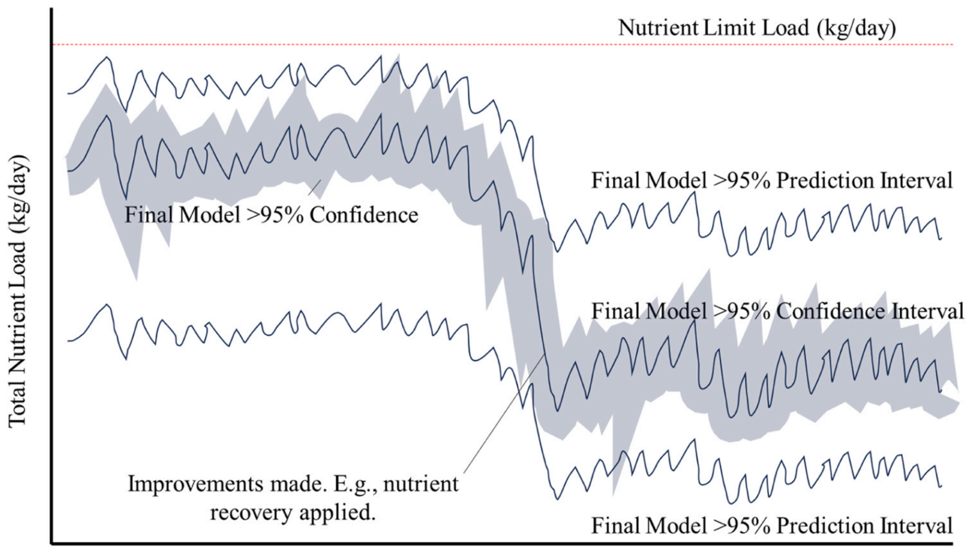

Fig. 1. Nutrient loading models and prediction mapping is done based on historical nutrient loading trends. These include phosphorus and nitrogen nutrient loadings within wastewater.

predicting the concentration of phosphorus and nitrogen loads and altering pH, temperature, magnesium additions and ammonia stripping air flow rates to maximise nutrient recovery economics. Insufficiently, studies across ML for nutrient recovery on WWTPs is largely under-implemented.

Population is factored into nutrient load analysis. However, nutrient loadings differed even from growths in population levels, and buffers were placed on the volatile nutrient loads that varied over the course of the years across TP, Chlorophyll-a, TN, DIN, dissolved oxygen, pH, ammonia, oxidised nitrogen and turbidity. Nutrient leakage from land and agricultural farmlands is factored in the environmental analysis, and proximity to major agricultural activity areas can help improve the distribution and engagement of farmers with nutrient CE WWTPs [31]. It is important to consider what is affecting the variations in nutrient loadings and factor that in data collection and ML model trainings. An estimation model based off the nutrient loadings of the past would lead to upper and lower limits along confidence interval levels of > 95 %. Prediction and model confidence intervals were set based on these nutrient loadings, fit according to reasonably high R^2 values. Nutrient recovery technology effectiveness can be assessed according to the steepness in the curve for the nutrients after implementations have been made along WWTPs at the influent and the effluent monitoring positions. The loadings would be constantly monitored should nutrient levels pick up and breach legal loading limits.

2. Setting the foundations for a nutrient circular economy wastewater treatment plant within Australia with machine learning

Wastewater disciplines can be separated between municipal and industrial wastewater streams. Municipal wastewater streams are heavily concentrated with nutrients at the influent, and come from households. This type of wastewater undergoes a combination of biological and membrane filtration processes to reduce nutrient loads down to an acceptable level to which eutrophication can be prevented. In this linear wastewater economy, none of the nutrients and the useful resources that accompany it are recovered. For example, phosphorous, nitrogen and methane are either emitted or disposed of into the environment. Throughout Australia, the dominant form of nutrient recovery is conventional activated sludge methods and other biological nutrient removal technologies. Nutrient recovery methods are largely unused throughout the WWTP landscape. To prime for ML CE WWTPs, appropriate data collection methods are required, social changes to operator attitudes and management via education and trainings, and commercialisation planning are critical to this success.

2.1. Data collection and monitoring

Data collection on influent nutrient loadings and the quality of the water effluent is important towards training ML and AI models for smart nutrient recovery WWTPs. This could include employing the use of data buoys, loggers, flowmeters, pH and chemical analysers at locations of interest. Not only do these sensors serve to monitor the environmental protection these recovery systems have, but to assess the circular efficiency of nutrient CE WWTPs in a digitised approach that gives policy makers and utility operators a 360-degree view of their operations from waste collection to nutrient redistribution across society. Sampling frequencies differ depending on the severity of the pollutant, with some done monthly and others every 6 days [32]. As specified by various wastewater reports, data accuracy is also important, and this is dependent on the measurement sensor instrument that is used for collecting water data characteristics which can either be automatic or manual.

2.2. Complying to environmental regulations

Within Australia, environmental regulations are stringent for maintaining low levels of nutrient leakage into waterways. These are regulated by the Environmental Protection Agency (EPA) and can differ by states and licenses are issued out. In New South Wales (NSW), the EPA regulates nutrient load limits by sample rates. For example, for phosphorous limits, these vary depending on the WWTP site with an EPL requiring plants to take regular samples. A sample of 1 mg/L of phosphorous concentrations for example, EPL 1725 Castle Hill WWTP has a TN limit of 25 mg/L for 90 % of the samples collected [33], while Picton WWTP EPL 10555 has a TN limit of 15 mg/L per 90 % of samples collected [34]. Therefore, there is no universally defined limit to which nutrients should be set to, as this is dependent on the environment's sensitivity towards eutrophication [35]. While the EPA encourages the recovery of nutrients [36], there is no national framework to support the transition to nutrient CE for WWTPs. Permission exemptions and orders can be applied to state EPAs; however, no state EPA has defined nutrient recovery and reporting guidelines for wastewater [3,37,38], rather, resource recovery applications do require individual assessments by the EPA. This presents a policy gap to which nutrient recovery performances and standards are left up to the operators which can lead to non-uniform recovered products. The exception here is on the large-scale reuse of sewage-sludge biosolids which has been in operation in Australia for over 25 years since the guidelines [39], but given the low nutrient-density of biosolids and the constant emergence of new contaminants [40], biosolids are not commercially viable. NQMS has classified a list of macro and micronutrients including boron, calcium, chloride, iron, sodium, sulphur and magnesium beyond potassium, nitrogen and phosphorous (Table 2).

2.3. Driving social change, trainings, and acceptance

2.3.1. Knowledge dissemination

Disseminating knowledge on the impacts of nutrient recovery is important, as this is under-implemented throughout the wastewater sector. Currently throughout Australia, not many wastewater recovery technologies are known to members of the workforce, given the emerging status of many of these technologies. For example, in Austria, some authorities require smaller WWTP operators to obtain training to manage and maintain their facilities to improve operating reliability [44]. Knowledge transfer among WWTP operators is low in some utility organisations [45] due to an ageing workforce being a contributor. However, in the case of training and education for a nutrient CE WWTP, this problem becomes more of an upskilling one, rather than a knowledge retention challenge. On the contrary, there are upskilling challenges for WWTP operators to manage ML systems for effective nutrient recoveries with smart CE WWTPs [46]. The knowledge of circularity among operators should also be assessed as was the case during Covid-19 on taking samples of the virus from wastewater [47]. When factoring in ML, it becomes even more challenging for WWTP operators to collect necessary data to train predictive models [48]. Therefore, data collection, monitoring, a general understanding of ML parameters and working with process engineers with ML models are crucial for advancing nutrient CE WWTPs.

2.3.2. Incentivising community best practices

Widespread community participation and support are crucial for the success of CE WWTP. This involves providing a compelling value proposition for households – particularly in high density neighbourhoods – to dispose of waste in a manner that is compatible with CE WWTP practices for efficient waste collections. This includes household residential schemes participating in reverse logistics programs which are financially remunerated in the form of strata cost offsets from the recovery of phosphorous and nitrogen treated onsite through, for example, source-separated urine within apartments. These can be driven by harmonised standards for waste disposal, safety regulations and trade facilitations across different jurisdictions and construction codes [49] to drive public trust and participation. For example, the introduction of the European Union Critical Raw Materials Act [1] which aims to retain the circulation of critical minerals across the bloc. There is therefore, an intersectional focus between local communities and resilient circular supply chains that are aligned with CE regulations. However, policies encouraging financial remuneration for those participating in source-separation urine and wastewater nutrient recovery schemes are levers that can be pulled to stimulate desirable consumer behaviours to recycle their waste into profitable fertilisers, while minimising nutrient loadings on WWTPs by combining it with the use of ML. A challenge here is the lack of reliable ML data to train the models on, requiring changes in community behaviours to accept decentralised waste collection methods that can expand the number of connected, data collection sources via connected devices and geographical information systems data sources [46]. Urban designs currently lack the incorporation of source-separation toilets and urinals within residential apartments and public spaces. The behaviours of the communities themselves can be studied through assessments of nutrient ML topics that are being discussed on social media [50,51], with strategies tailored by geographies to increase nutrient CE acceptance and discourse.

2.4. Finance and funding for new CE WWTP projects

2.4.1. Identifying sources of revenue

Nutrients are a valuable source of revenue for WWTPs, and prices are mainly determined by supply and demand for these nutrients, and the operating cost of the WWTP. Several underlying technologies can be used to recover nutrients, for example, struvite precipitation and ammonia stripping processes, and their products may be regulated. In the EU for example, the Fertilizing Products Regulation provides a list of recycled nutrients from wastewater that can be resold onto the market as "precipitated" phosphates and derivatives [52], however, one of the key challenges of this is competitive pricing and lack of regulations in other markets where nutrient circularity is not a critical policy issue [53]. Other valuable sources of revenue that can be recovered and sold transcend beyond nutrients and can cover resales of treated wastewater, biogas and other materials. The sale of nutrients and other valuable resources can help offset the operating costs of the nutrient CE WWTP. Nutrient trading schemes, reverse auctions, grant funding and subsidies were proposed by the OECD as a way to facilitate an economic system that encourages CE [54]. A nutrient CE trading scheme allows nutrient credits to be offset against linear economy WWTPs as the entire sector transitions to a CE one. For example, CE WWTP in Sydney with a higher phosphorous recovery rate can offset lower nutrient removal efficiencies for a WWTP in Melbourne through the sale of nutrient reduction credits to help meet water quality standards. In a reverse auction, nutrient suppliers can bid to outcompete on price compared to synthetic fertilisers. Given that economically, suppliers are motivated to supply more of a good that is profitable and at a higher price, the profit margins for organic nutrients then need to be higher than synthetic fertilisers. ML can improve the price stability, resource efficiency allocations and

Table 2
90 % percentile limit of pollutants allowable for Sydney Water issued EPL [32-34,41,42,43] across different WWTPs.

WWTP	Sampling Frequency		Castle Hill	Picton	Penrith	Rouse Hill	St Mary's	Cronulla
Aluminium	Monthly	μg/L	400		270	340		383
Cadmium		μg/L	0.2		0.2			
BOD	Every 6 days	mg/L	10	10	15	5		20
Ceriodaphnia dubia immobilisation (EC50)	Monthly	% effluent by volume						
Copper	Monthly	μg/L	11		9	7		500
Diazinon	Monthly	μg/L	0.1					2
Faecal coliforms								
Hydrogen sulphide	Monthly	μg/L	60		60			70
Iron	Monthly	μg/L	1100		350	52		
Nitrogen (ammonia)	Every 6 days	mg/L	1.4	1	5	1.4	0.75	52
Total Nitrogen	Every 6 days	mg/L	25	10	15	15	1.5	
Total phosphorous	Every 6 days	mg/L	1	0.4	0.4	0.4	0.1	
TSS	Every 6 days	mg/L	10	15	10	8		15
Zinc	Monthly	μg/L	37		180	39		100

sustainable urban development of CE products on marketplaces and raise the financial efficacy for its resale [55], and capturing investments into digitised CE solutions from businesses can safeguard growth due to elevated supply chain resiliencies and improved economic output and trade [56].

2.4.2. Identifying sources of cost reductions

Resources recovered can be fed back into the CE WWTP to reduce operating costs. This can be done through energy, water and the diversion of biosolids away from landfills (i.e. reduction in waste management costs) [57]. Therefore, there are landfilling and treatment cost savings from identifying and monetising nutrient, water and energy resources that come with CE. Namely, energy recoveries in the form of biogases for plant heating purposes can save on-grid power bills, or using renewable energy. Diverting waste away from landfills offers treatment savings, and the conversion of these waste into useful products offers alternative revenue streams beyond water treatment. Plant operators should see CE as a cost reduction strategy on top of revenue operating opportunities from nutrient resales. ML-driven acceptance of CE programs can yield benefits such as reduced expenses, better time savings and optimisation of human resources [58-60], providing resounding business cases for cost competitive environments, however, not many examples exist within current nutrient CE WWTPs at larger scales where the main focus is on environmental outcomes such as the DARROW project [61].

2.4.3. Understanding the costs of circular supply chains

Undoubtedly, one of the largest cost contributors for nutrient CE operations will come from recovering, processing, logistics and distribution. When transporting urine for nutrient recoveries, volume reduction methods and shipment of high value nutrient products are proposed [62] to cut costs down per unit of nutrient moved. These deliveries have two components behind them – being the transportation of nutrients from the waste collection source to the treatment plant, and from the treatment plant to those who need it [63]. For centralised WWTPs, it is mainly recovery, processing and distribution. For waste that can be treated onsite through decentralised WWTPs, such products can theoretically be transported direct to consumers and farmers provided they meet safety standards. Route optimisations to suppliers or fertiliser manufacturers, nutrient volume compression, increasing the value and quality of fertilisers in a price competitive fertiliser market, are all factors that need to be considered – which can be driven by ML optimisation for green supply chains which can factor in energy consumption, economic growth and recovered product outputs in ML predictions and business decisions [64]. The market value of phosphorous for example is volatile, and processing costs need to adjust buffers to ensure that organic fertilisers are profitable, AI/ML however can stabilise these fluctuations by improving efficient resource matching between buyers and sellers [55], help design effective CE supply chains [65,66], and improve recovery efficiencies [67]. Transportation costs should be measured relatively against the price of phosphorous, and factor in environmental repercussions from GHG emissions depending on the mode of transportation that is used [68]. It is also unknown whether agreements between individual companies towards many different recyclers is the most cost-effective option compared to tailored individual agreements between waste centres and recyclers [69]. What is known, is that the state of AI in nutrient CE supply chains shows promising cost-reduction and operational streamlining potential.

2.4.4. Securing financing and investing opportunities for nutrient recovery

Green financing depends on the level of country-level financial support for CE activities. The formality of investing practices, taxations, government soft loans and grant funding, supporting regulations are all drivers for favourable investment conditions into CE that also factor in the financial integrity of the institutions that facilitate these investments [70]. Self-financing and alternative financing (venture capital, crowdfunding and capital market investing) were proposed as some of the most effective methods of raising funding for CE projects, given the unconventional risks that traditional financial institutions such as banks may not necessarily have a formalised approach to assess and provide loans on [71], however, it has been argued that public financing sits between the higher self-financing and lower debt financing of CE business models [72] in the order of importance, but challenges remain which include ambiguous legal and CE definitions that fail to align financing for CE projects [73]. Several CE state organisations and not-for-profits aim to provide financing opportunities and act as knowledge hubs.

2.4.5. Assessing financial viability of a nutrient recovery project

The financial viability of the nutrient recovery project should consider the inflows and outflows of finance. Moreover, the net present value of the project should always be factored into every nutrient recovery commercial project, the use of the formula is shown below [74]:

$$PV_{GC} = CAPEX + \sum_{t=1}^{T} \frac{OPEX}{(1+i)^t}$$

$$PV_R = \sum_{t=1}^{T} \frac{R}{(1+i)^t}$$

$$NPV = \sum_{t=1}^{T} \frac{R_t - OPEX}{(1+i)^t} - CAPEX$$

Where PV_{GC} is the present value of the gross cost, PV_R is the present value of the revenue to be made from the project, NPV is the net present value of the project, CAPEX is capital expenditure for the plant, $OPEX_t$ is the operating expenditure of the plant for the year, R_t is the revenue for the year, T is the lifetime of the plant, and i is the discount rate for the project. The plant operating lifetime can be 20 years and a discount rate of 5 % [74]. A positive NPV shows that the project is economically feasible, a negative means it is not. Increases in the cost to recover fertiliser nutrients make it more economically feasible [74]. In Mayor et al. [74], the contributions of each nutrient were factored in the as a percentage of the overall gross cost, whether it be the capital contribution or by nutrient recovery process. The inclusion of ML systems into the nutrient CE WWTP NPV process can improve feasibility predictions, costings and calculations for recovery processes [75,76]. AI-assisted nutrient costing predictions can aid planning efforts that can raise the success of nutrient CE WWTP projects, this however, is not widely practiced across industry.

ML has opportunities to estimate the economic benefits of a given CE system and estimate payback periods by providing probabilistic models and results on the success of the NPV [75]. This application can help aid commercial planning stages for upscaling emerging nutrient recovery technologies in the wake of GHG emissions reductions and improving WWTP CE [75,77]. However, most of these studies have a focus on payback periods via energy reuse and resell, for example, biogas and other biofuels, or for reducing costs such as predictive maintenance and corrosion control [78]. AI-assisted technology selection tools for resource recovery can yield significantly positive results through membrane selections and improved payback periods [60]. An example is the application of ML frameworks and designs respectively yielded 4.7–8X and 5.6–83.5X lower costs than non-ML comparisons via geometry optimisations [79], financial modelling for integrated renewable energy costing [80], and reduce testing time and costs for new nutrient recovery technologies [81]. ML applications within WWTPs have proven to accelerate the commercialisation and costing procedures for planners and operators in the academic field, given the emerging nature of ML in WWTPs, its maturity is still in its newfound stages (Table 3).

Table 3
Cases where ML was used to assist in payback period forecasting.

Application	ML	Payback period (yrs)	Source
Waste heat storage and reuse for WWTPs	ANN	4.8	[82]
Waste heat reuse in multi-effect desalination plant	DT	< 2	[83]
Modelling algae-bacteria granular sludge integrated with down-flow hanging sponge on COD removal for effluent quality.	XGB and RF	7.45 (best) 12.81 (negative NPV)	[84]
Modelling biogas recovery (excluding biofertilisers recovery).	MLP and SVR	~3.5	[85]

3. Environmental and safety performance of nutrient CE WWTPs

3.1. Environmental greenhouse gas emissions

CE can be a lower cost alternative method to reducing carbon emissions [89] that can help wastewater operators achieve carbon-neutrality. Microalgae and constructed wetlands for example, are used as effective biological pretreatment methods for nutrient and contamination removal [90,91], and they can behave as carbon neutral processes for bioproduct production [92]. Currently, from 2025 onwards, Australia will mandate the disclosure of scope 1, 2 and 3 carbon emissions from large entities which will begin phasing down reporting requirements to smaller companies [93]. This is inclusive of power and water utility companies. Therefore, CE operations with their low [94] and even carbon negative footprints [95,96] will prove to be invaluable for driving a sustainable nutrient economy. Scope 3 emissions – considered to be both upstream and downstream emissions along the supply chain that an organisation is directly and indirectly responsible for [97] – will play a large part in determining the product carbon footprints of the purchasing of fertilisers, particularly in the Purchased Goods and Services category of the emissions. Where studies have shown organic fertilisers have a lower emission intensity compared to chemical alternatives [98]. Combined with ML and AI, carbon emission trails can be simulated which can effectively lead to AI-driven decarbonisation of CE supply chains [64,99,100] that can be monitored using blockchain [101]. The carbon footprint from using ML/AI systems should also be a consideration in the environmental footprint of smart nutrient CE WWTPs [102]. Therefore, opportunities from decarbonising nutrient CE WWTP supply chains are a sustainability direction that can make nutrient CE less carbon intensive.

3.2. Process safety of recovered nutrients and resources

Several nutrient recovery products such as biochar, hydrochar, biosolids, source-separated urine, and sewage sludge may contain harmful contaminants such as heavy metal traces, active pharmaceutical ingredients (API) and pathogens. The recovery rates of technologies can be very high but this does not necessarily lead to a safer product. For instance, the presence of trace metals in hydrochar such as chromium, cadmium, lead, bismuth and many others [103]. These require selective extraction of P from heavy metal trace contaminants either through acidic or alkaline solutions, and preferably through a sequential process [104,105]. For dealing with APIs, membrane processes have been applied to remove these contaminants, but small residual traces still remain given the challenges of removing water-soluble compounds, and membranes were prone to organic fouling and scaling [106,107]. Further treatments such as oxidation and adsorption mechanisms should be adopted [106,108,109]. Despite treatment from AD, APIs and metal traces continue to remain in the sludge. Reverse osmosis and forward osmosis have shown to be highly promising in removing APIs, but given the concentration of the filtered compounds, biological approaches towards removing APIs are limited due to its bactericidal properties [110].

3.3. Wastewater reuse regulations frameworks and direction

Water effluent regulations dictate the nutrient loading discharge limits that are allowed. The US EPA governs the use of sewage biosolid products across several classes with Class A being the highest. More specifically, EPA 40 CFR Part 503 governs the use of and disposal of sewage including that of land application [111], however, this regulation does not factor in a range of resource recovery technologies for WWTPs [112]. In Australia, the EPA determines biosolid reapplication guidelines, with the latest draft dating back to 1991 citing that biosolid reuse should adhere to the AS4454–1999: Composts, soil conditioners and mulches standard [39]. The guidelines from the EPA's *Environmental Guidelines: Solid Waste Landfills*, in fact, encourage the safe reuse of biosolids from WWTPs. There are fines and penalties applicable to the improper reuse of waste according to the Australian Resource Recovery Framework of up to $2 million for corporations and $500,000 for individuals under Section 286 A of the Protection of the Environment Operations Act [113]. Orders are submitted to supply resources that are recovered from a waste source with the EPA, and suppliers of the nutrient biosolid must comply to these orders. With regards to struvite precipitation, such an order would apply to facilities with dedicated source-separated urine diversion infrastructure in place.

The following standards, guidelines and legislations governing the use of biosolids are summarised as follows applicable within Australia (Table 4):

Recent publications for Australian CE frameworks to recover nutrients appear highly focused on food and organic waste as opposed to wastewater systems [8,86,88]. However, in 2023, the Department of Industry, Science and Resources recently designated phosphorus as a strategic material [114], but recent CE national frameworks have ignored the recovery of this element from wastewater sources, for example, that of source-separated urine systems and wastewater struvite recovery. Meanwhile, the EU has an entire nutrient recovery from wastewater platform to evaluate and invite technology submissions and progress updates for commercialisation [115], such as that of the European Sustainable Phosphorus Platform (ESPP) and competitive green awards [116-118]. Australia's primary nutrient recovery is in the form

Table 4
Comparison between EU and Australia CE regulatory and policy progress. Taken from [1,8,86-88].

Country coverage	AU	EU
CE Framework	Australia's Circular Economy Framework 2024; National Waste Policy Action Plan 2024	Circular economy action plan 2020; Bioeconomy strategy 2020; Bioeconomy action plan
Nutrient CE regulation	None	Critical Raw Materials Act 2023
Phosphorus designated a critical element?	No	Yes
Minimum recoverable target for P?	No	Yes, strategic raw material
Material System Analysis of P	No	Yes
Nutrient recovery a metric	Yes (proposed framework)	
Nutrient CE technology platform	No	Yes
Wastewater a focal point of recovery	No	Yes
Promote track and trace of recycled resources	Yes	Yes
Framework to track and trace nutrients recovered	No	Yes

of biosolids, but this only fills 4 % of the total P-demand with the majority of the nutrients lost in the effluent [119], sludge liquor and dewatering stages of wastewater treatment, with the nutrient ultimately lost into the oceans [120]. While the tracking and tracing of recycled content applies in other areas of waste management, a similar system should be applied for nutrients recovered to ensure transparency, accurate material flow analysis and tracking of phosphorus flows across the economy. However, cited challenges in Australia include the lack of source-separation infrastructure, scalability of emerging technologies, product quality consistencies in a fragmented regulatory environment, and stakeholder drivers [13]. While regulations can provide consistency in practices and standards, its interaction with technologies and stakeholders should remain supportive.

3.4. Water recycling and classifications

Across Australia, there are several classes of recycled water quality grades and their permissible applications, these are Class A, B and C [121]. Class A is recycled water that can be used for toilet flushing, cleaning and garden watering; Class B for irrigating sports fields and industrial washdown procedures that is regulated against human exposure; finally, Class C is water that can be used to water crops. These three categories of water reuse classifications each have contamination guidelines. Water reuse forms a part of the nutrient CE because of its importance in growing crops; therefore, nutrients and irrigation water are mutually complementary towards sustainable agricultural practices. During drought periods, water stress levels are elevated and several desalination and water recycling programs were reactivated in response [122]. Recycled water for irrigation has other benefits such as being cheaper and comes with many government incentives [123]. When framing nutrient CE frameworks and guidelines, water reuse should be factored in as a large part of the regulations to promote circularity [124]. Irrigation is the world's leading source of water consumption, and in 2021–22, irrigation accounted for 74 % of Australia's water consumption [125]. Sydney Water recently launched the Purified Recycled Water Discovery Centre to help treat Quakers Hill WWTP to drinkable standards [126] which will set a precedent to supplement existing drinking water supplies with purified recycled water. There are options to use AI and ML to improve the quality of drinking water through parameters such as chemical dosages, microbes, pH and turbidity [127,128] and determining whether it is drinkable or not [129], however, there are still a lack of regulations for AI-optimisation on drinking water quality for public consumption [127], or commercial applications predicting the quality of fertiliser products made from recovered nutrients - for example, any presence of pharmaceuticals and trace metals.

4. Decision making tools for selecting resource recovery technologies for wastewater

Several wastewater recovery technologies can be outlined for implementation throughout Australia. These include membrane, biological, electrochemical, chemical and thermal approaches to recovering nutrients, water, energy and materials technologies [130,131]. Currently, there are no live nutrient recovery WWTPs in Australia. Several large nutrient recovery plants are already in operation in other parts of the world. These include the Clover Bar Nutrient Recovery Facility in Canada [132] which produces about 1000 bags of Crystal Green® nutrient product using the Evoqua Ostara Pearl® fluidised bed reactor technology that is processed by a fertiliser recovery company and sold directly to farmers. The technology uses struvite precipitation of wastewater by capturing the influent and then treating it by recovering phosphorous, before discharging the nutrient-stripped solution to the plant's effluent.

For co-recovery of other resources, other technologies should be examined as well. These include thermal technologies to recover biogas [133] and biochar [134], membrane technologies to volume reduce source-separated urine and recover water [135], or combined with constructed wetlands for removal of harmful chemicals and production of biomass for food supplements and lipid proteins [136]. Technology selection of nutrient recovery should be assessed along several desired metrics covering cost of capital, economic return on investments, carbon footprint, suitability with waste, community acceptance, and other risks to the environment. These can be distilled across economic, environmental, social and technical sustainability dimensions and performance indicators [137]. Energy, water and food security were other dimensions referred to in other studies [138]. These included accessibility, affordability, applicability, acceptability, utilisation, stability, safety and adaptability. The recovery percentages and efficiencies, economic returns, noise levels, odour, land requirements, affordability, acceptability and flexibility of application are expanded metrics that CE technology evaluators can weigh into [137]. AI can assist in the development of CE policies and technology implementations that can reduce GHG emissions, improve commercial viability, simulate sustainability scenarios to help achieve policy outcomes [139].

Other decision support tools (DST) have been proposed to evaluate the most effective nutrient or resource recovery technology to use for a given wastewater treatment plant (Table 5). The new energy and resources from urban sanitation (NEREUS) developed for public and private use in the Interreg 2 Seas area [137,140], helps evaluate the election of CE technologies. This DST uses a train approach to evaluate the best technology setup to recover the greatest number of resources, covering TP, TN, water and energy. Policy makers and environmentalists can assess the recovery potential of wastewater resources that can address current resource demand through substance flow analysis. The technology readiness level (TRL) of the technologies can be scored and weighted during this planning process, and can be adapted from UK Water Industry Research [141] and CREW [142]. Fuzzy weighting methods and more complex approaches to selecting nutrient recovery technologies were explored [138]. This is done by firstly assigning weights to decision making nodes based on a scale of very unimportant or very important for each of the technologies available. There are other DSTs used including ELECTRE, PROMETHEE, MADM AHP TOPSIS, WMOMINLP NEREUS, MCDM seen in Table 5. Evaluation approaches for resource recovery WWTP technologies would examine preliminary, primary, secondary and tertiary processes throughout the treatment plant's operations [143]. Respectively, treatment stages cover coarse, settleable suspended solids, suspended solids and soluble biological oxygen demand, and useful resources [143]. It is during the secondary and tertiary treatment stages that are the most promising for resource recovery, and therefore, plant designers and operators would begin by assessing every stage of the treatment system to determine where recovery technologies are best applied while evaluating the economic, social and environmental costs and benefits.

4.1. Technology readiness indexes for the selected resource recovery technologies

When selecting the appropriate nutrient recovery technologies, its maturity and place in the wastewater treatment chain is an important consideration. Li et al. [150] explores the barriers of implementing nutrient recovery technologies through Parasuraman's [151] methodology to assess its technological readiness levels (TRL) for commercialisation throughout the wastewater sector. These readiness levels can be summarised in the below Table 6. TRLs alone do not paint the entire picture for economic feasibility, as one report found that the struvite recovery costs were higher in Australia compared to the standard worldwide price [152] (at US$613/Tonne compared to the standard price of mono-ammonium phosphate standard price of US$320/Tonne). Furthermore, treatment sizes, electricity costs, feed-in tariffs, waste disposal costs, trace metals and concentration of valuable nutrients are all other factors affecting economic feasibility for the nutrient recovery

Table 5
Various DSTs used to recover resources from wastewater treatment plants.

Decision Making Indicator	Decision support tools	References
Global warming potential (kg)	Multiple-attribute decision-making (MADM) with analytical hierarchy process (AHP) and similarity to ideal solutions (TOPSIS)	[144,145]
Net present value ($)	MADM + AHP + TOPSIS	[144,145]
Eutrophication potential (kg)	MADM + AHP + TOPSIS	[144,145]
Land requirement (m^2)	MADM + AHP + TOPSIS	[144]
Manpower number of personnel	MADM + AHP + TOPSIS	[144]
System robustness (reliability, durability, flexibility)	MADM + AHP + TOPSIS	[144]
Sustainability (acceptability, participation, replicability, social promotion of the behaviour)	MADM + AHP + TOPSIS; WMOMINLP NEREUS;	[144]
Water security (Access, safety and affordability)	Entropy and linear multi-criteria decision making (MCDM)	[138]
Energy security (Availability, accessibility, affordability, acceptability, applicability and adaptability)	Entropy and linear MCDM	[138]
Food security (availability, access, utilisation, stability)	Entropy and linear MCDM	[138]
Resource weighted scoring (heat, biopolymers, ammonia, struvite, biosolids, biochar, hydrogen, grit, biomethane, biogas, syngas, and oil waste)	Substance flow analysis and material flow analysis, multi-criteria analysis (MCA) with TRL scores.	[146]
Target parameters (removal percentages, recovery percentages, net present value, logarithmic reduction in nutrient loadings, minimum and maximum loadings)	NEREUS (MCDM using weighted multi-objective mixed integer non-linear programming (WMOMINLP))	[137]
Technical features (footprint, lifetime operation, noise emissions, odour emissions, flexibility)	NEREUS (MCDM using WMOMINLP)	[137]
Economical features (capital cost and operational cost)	NEREUS (MCDM using WMOMINLP)	[137]
Social acceptability	NEREUS (MCDM using WMOMINLP)	[137]
Global warming potential, acidification, eutrophication, toxicity, resource depletion, and particulate matter.	EASETECH LCA	[147]
Social, technological, economic, environmental, political, legal, ethical, demographic (STEEPLED) and TRL	MCDM	[148]
Equality Index, net present value, greenhouse gas emissions, and accumulation of effluent quality violations.	MCDM + TOPSIS	[149]

technology [153,154]. Procedural frameworks such as that seen in Fig. 2 are some examples of an evaluation methodology to determine whether the new CE WWTP technology can generate positive environmental, economic and social benefits while considering the TRL maturity of these technologies. Seen in Table 7, thermochemical processes tend to have much higher TRLs in the 9 range, meanwhile, biomass valorisation processes have a TRL range of 4–5 [155]. It is worth noting that some thermal technologies emit higher carbon footprints. TRLs serve to provide the plant designer a gauge on the individual technology's readiness when operated standalone, however, it does not paint its readiness level at the plant system level [156]. Comparing the technology exploration endeavours between the EU and that of Australia (Table 7), struvite precipitation and ammonia stripping technologies are the most mature and readily implementable systems for wastewater nutrient recovery.

Table 6
TRL table based on Parasuraman's [151], adapted by Li et al. [150] with TRL guidelines from Rybicka et al. [157].

TRL	State of Development	TRL Guide
1	Basic principle observed and reported	Low, lab scale
2	Technology concept/application formulated	Low to medium, lab scale
3	Analytical and experimental critical function/Characteristic proof - of - concept	Medium, lab scale
4	Component and/or breadboard validation in lab	Medium, lab scale entering pilot scale
5	Component and/or breadboard validation in relevant environment	High, lab to pilot scale
6	System/subsystem model or prototype demonstration in relevant environment	High, pilot scale
7	System prototype demonstration in relevant environment	High, growth implementation phase at plants
8	Actual system completed and qualified through demonstration	High, maturing implementation at plants
9	Actual system proven through successful mission operations	High, fully mature at plants

4.2. Modelling and simulating processes factoring in impacts

Once the appropriate technologies have been selected, these are simulated through LCA software. ReCIPe and other LCA databases are used to simulate the environmental and recovery performances of a given design system. Numerous factors are considered when constructing an LCA ecosystem for the design of nutrient recovery WWTPs. Data collection is also critical to the operation, particularly when recovery plants are powered with ML and simulated with digital twins to optimise and drive-up recovery of valuable resources [183].

The use of DSTs to select the right technologies can follow the process of identifying the properties of the influent, contaminations, required treatment levels, unit processes and stages such as membrane filtration and sedimentation tanks, and availability of resources for operation [143]. While the article was more focused on treatment technologies, it can be adapted to cover concentration of valuable nutrients during the influent characteristics phase and nutrient recovery technologies to be incorporated during unit operation and process declarations [143].

4.3. Productivity, demand, and supply of recovered resources

Nutrient CE WWTP proximity to relevant stakeholders such as fertiliser manufacturers and farmers, the market price of the nutrients recovered and resold, acceptance of the operation and products, technologies, are considerations for the viability of the nutrient CE WWTP [31]. An NPV of a wide range of nutrient recovery technologies may be necessary including all of the resources from biogas, energy, nutrients and water that are recovered [183], with a wide array of technologies ranging from biological, chemical, physical, physicochemical, and hybrid recovery processes [143]. Lower TRLs are much more prone to negative NPVs stemming from the low economy of scale, poorer reliabilities and higher capital costs as a result of the custom-manufactured prototypes during pilot stages. These types of recovery technologies are unproven on the commercial market and require extensive government and sector funding, particularly when coupled with mature systems in cogeneration and hybrid setups. Combined with ML, nutrient CE products can be matched more efficiently between buyers and suppliers on a marketplace [55] where these interactions can be measured [184]. ML can improve productivity of CE WWTP recovery performances, distribution, augment the social welfare of society under a growing economy [185], improves the flexibility of sustainable supply chains [186], and enhances supply chain transparency and decision making speeds [187].

The greatest resource recovery potential could be within energy,

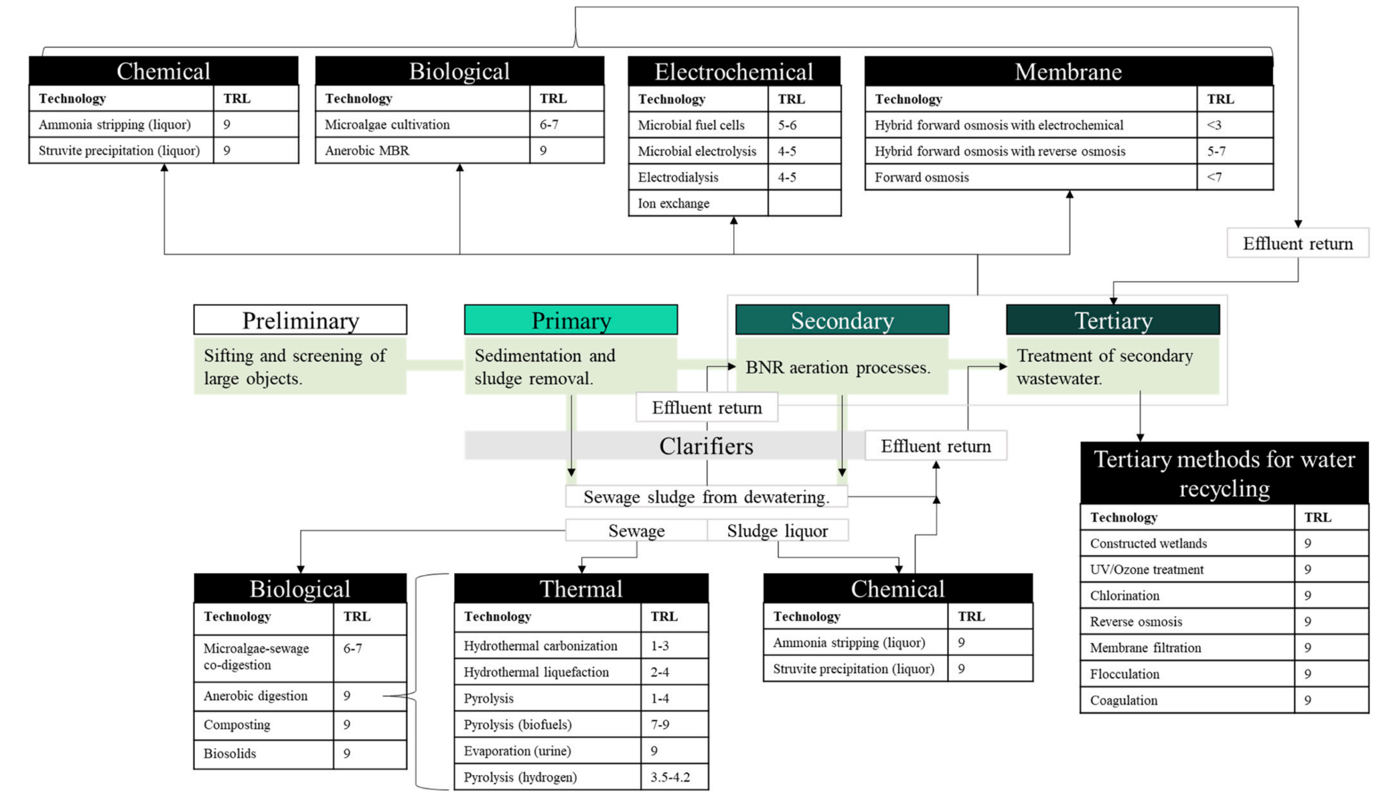

Fig. 2. Selection and evaluation opportunities for a nutrient CE WWTP project with a range of emerging and mature resource recovery technologies. Academic TRLs taken for struvite precipitation and composting [150]; incineration and landfilling [157]; biochar and pyrolysis [169]; hydrothermal liquefaction [170]; pyrolysis (hydrogen) [171]; microbial fuel cells [172]; microbial electrolysis [173,174]; hydrothermal carbonisation (based on lab scale) [175]; constructed wetlands (hybrid with microbial electrolytic carbon capture) [176]; microalgae [177]; struvite precipitation and ammonia stripping [178]; electrodialysis [179]; forward osmosis [180,181], hybrid forward osmosis and electrochemical [180]; and hybrid forward osmosis and reverse osmosis [182].

where according to a study, up to 7 % of Scotland's heat energy use could be met through energy CE WWTP, with an economic value of £ 200 M/year, 5800 GWh/y, and numerous economic, emissions and energy savings [142]. Market value of nutrients can be seen in the below table taken from the World Bank. The assessment of the feasibility for the plant's capacity to recover and distribute enough resources should begin by quantifying the total resources available within the influent, the savings to offset operating costs, and production potential of biogases and other recoverable energies [142]. It appears that the highest potential for wastewater resource recovery is within heat pumps and AD biogas generation. However, despite the lower economic returns on inorganic nutrients that could provide Scotland 5 % of the total fertiliser supply, price fluctuations and the concentration of nutrients in influents can also contribute to lower returns. Seen in Fig. 3, biosolids are an established method of recovering nutrients for farmland application, and the market value for recovering biogas and other forms of energy from wastewater is high, with the TRL maturity being average. Nutrient recovery of P and N directly still lags significantly when recovering from municipal wastewater, however, it does not consider recoveries from source-separated urine.

4.4. Stakeholder feedback on nutrient recovery technologies

Satisfaction levels throughout the community and farmers should be actively monitored in response to the implemented recovery technologies [188-190], and in particular, understanding barriers to adoption [191]. However, with newer recovery technologies, surveys and trust-building are important in the successful, community participation in circular economy programs. For example, under the $25 million Sydney Water's Purified Recycled Water initiative, 64 % of their surveyed customers were open to the idea of drinking recycled water that has been treated to safe, drinkable standards [126]. To date, no widespread survey can be stated similarly for an Australian water utility company on the reuse of nutrients recovered from sewage and urine for human consumption. It is important to survey, understand the concerns, and develop solutions and informational campaigns to demystify and clarify the safety and importance of nutrient recovery on standards of living and food security.

5. Combining machine learning models with nutrient recovery technologies

5.1. Adapting to machine learning for accelerated nutrient CE WWTP

Once the best technologies have been selected, inputs, processes and outputs are established to help train the machine learning model to best predict and optimise the wastewater resource recovery plant (WWRF). Nutrient loadings (such as the inputs parameters seen in Table 8), other characteristics of the wastewater influent which affect recovery performances, environmental and plant operating conditions, and across different model types such as gradient boosting, support vector machine, neural networks, deep learning, k-nearest neighbour (KNN) and random forest [192]. For biogas, the likely input variables include total suspended solids, volatile suspended solids, hydraulic retention time, organic loading rates, pH, and volatile fatty acids to determine its yield [192]. Microalgae-derived biofuels can derive predictions according to RGB values, light intensity, CO_2, air flow rate, C/N ratios, lipids, pH and cultivation time. To date, no machine learning has been applied for source-separated urine nutrient recoveries.

There are other applications of ML for non-resource recovery applications such as plant maintenance, odour and corrosion control [78], membrane fouling [205], environmental monitoring [16,17],

Table 7
List of phosphorous recovery technologies on the EU platform and author determined TRLs as a gauge on progress.

Whatresourceisbeingrecovered?	StruvitePrecipitation(Ostara, Struvia, NuReSys, etc.	AnaerobicDigestion + MagneticSeparation(Vivimag)	ThermalHydrolysis(Lystek)	ContinuousIonExchange(PHOSPHIX)	MechanicalVapourCompression(Varcor)	IonExchange(LayneRT™)	SewageSludgeIncineration(Ash2Phos)	Thermochemical(AshDec – MetsoOutotec)	Aluminium/IronCoagulation(Kemira)	AcidDigestion + Nanofiltration(Rubiphos)	AshChemicalLeaching(Metawater)	Pyrolysis + ChemicalLeaching(Charlene – ReCord)	Solubilisation + P – precipitation(QuickWash)	Coagulation, SolventExtractionthenP – precipitationRavita	SewageSludgeAsh + SolventExtraction(SusPhos)	SludgeHydrolysis, LeachingandAbsorption(TerraNova)	AshAcidLeaching, SolubilisationandIonExchange(Tetraphos)
Technological Readiness Level (1−9)	9	4–5	8–9	3	8	6	6–8	6	6–7	4	9	5–7	6	5–6	6	8–9	8
Phosphorous	×	×	×	×	×	×	×		×	×	×	×	×	×	×	×	×
Nitrogen			×														
Potassium			×													×	
Ammonia					×												
Water				×	×												
Biogas																	
Biofuel												×					
Electricity																	

List of nutrient recovery technologies experimented or commercially available within Australia and perceived TRLs according to published status.

	Aquatec Maxcon Struvite	Membrane electrodialysis	Evoqua Ostara Pearl - Crystal Green	Multiform Fluidized Bed Struvite Reactor	NuReSys Struvite Crystalliser	PhosPAQ Struvite Crystalliser	Hydroflux Epco AirPrex Crystalliser	REMONDIS TetraPhos – Incineration	*C. vulgaris* Photobioreactor	Urine MBR – Sydney Central Park Mall	Alkali metal sludge centrate	Electrodialysis energy recovery from urine	Fertiliser drawn forward osmosis – urine	Urine forward osmosis and distillation	Urine solar evaporation
TRL (1−9)	9	6–7	9	9	9	9	9	8–9	4–5	6–7	4	4	4	4	4
Phosphorous	×	×	×	×	×	×	×	×		×	×	×	×	×	×
Nitrogen			×	×	×	×	×			×		×	×	×	×
Potassium										×		×			×
Ammonia		×	×	×	×	×	×								×
Water														×	
Biogas															
Biomass									×						
Electricity												×			
Reference	[158]	[159]	[160]	[160]	[160]	[160]	[161]	[162]	[163]	[62]	[164]	[165]	[166]	[167]	[168]

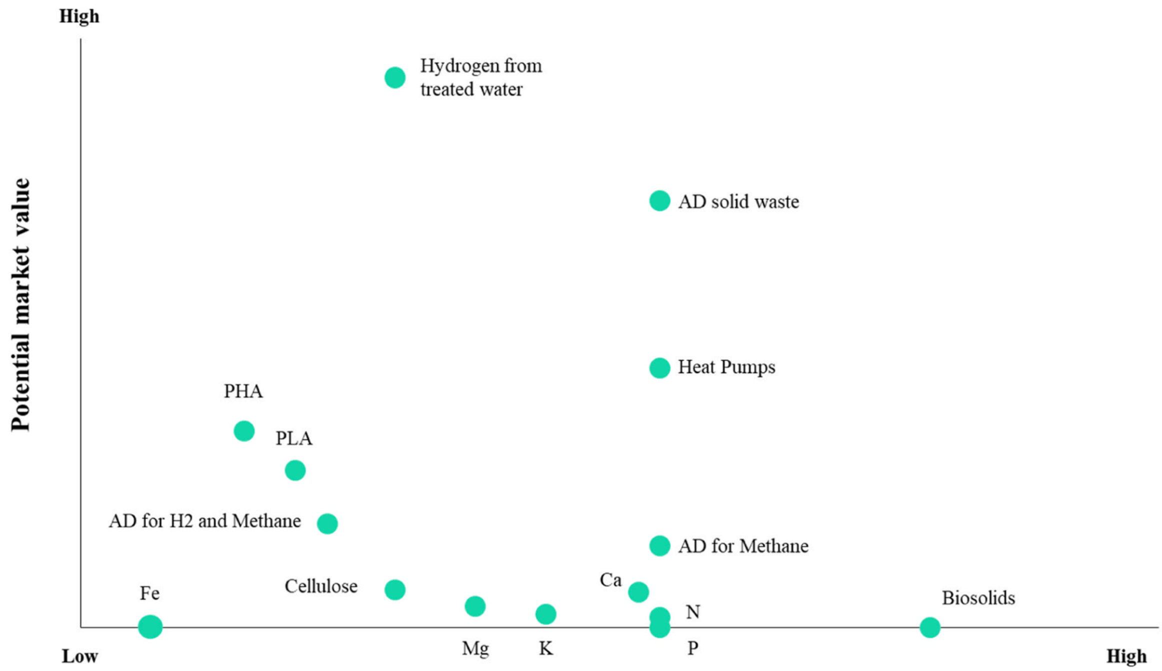

Fig. 3. The market potential of several resources that can be recovered from wastewater. Modified from Dionisi et al. [142].

Table 8
Predictive modelling input parameters and output prediction objectives across the wastewater resource recovery spectrum.

Resource	Data Source	Inputs	Outputs for prediction	Source
Biogas	Anaerobic digestors, benchmark simulations and	Total suspended solids, volatile suspended solids, hydraulic retention time, organic loading rates, pH, volatile fatty acids, substrate biodegradation rate, COD loading, temperature, average flow rate, suspended solid content, effluent (pH, H_2 mole fraction, CH_4 mole fraction and CO_2 mole fraction), fermentation time, food waste concentration, TSS, and CH_4 and CO_2 percentage in content.	Volatile fatty acid yield and production	[193-196]
Nutrients	Vermicomposting	Nutrient influent concentrations (TN and TP), pH, electrical conductivity, C/N ratio, NH_4/NO_3,	Nutrient recovery of P and N	[197]
Biofuel	Photobioreactor	Temperature, light intensity, radius and total area, pH, dissolved oxygen, nitrates, time after harvest, and initial biomass.	Biomass output	[198-200]
Electricity	Microbial fuel cell	Time, substrate concentration, particle size, COD removal efficiencies, cylinder materials and radius, electrode distances, load resistance, cathode size, membrane porosity, flow rates.	Power production	[201-203]
Bioplastics	Mixed microbial communities with mechanistic models and collected datasets	Time dependent data with bacteria, PHA accumulation, external substrate, polydispersity index, molecular weight and other molecular parameters.	Polyhydroxyalkanoates (PHA) concentrations	[204]

wastewater treatment control [206,207], forecasting quarter qualities and effluent discharges [14,208], energy modelling [209], and other treatment processes [210]. ML models used for nutrient recoveries may not synchronise well with predicting plant maintenance outcomes, therefore, multiple ML models may be necessary for the prediction of plant maintenance, membrane and electrode replacements, environmental impacts while coinciding with resource recovery process optimisations and control responses.

5.2. Selecting the best machine learning model

ML models - depending on the application - would ideally have high accuracies, lower processing times, and can factor in outlier data well during predictions. Feature selection and their correlations between the input and output prediction accuracies is one of the more crucial steps in the implementation of effective ML for CE WWTP [211]. The coefficient of determination R^2, root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) are considered during the ML evaluation process. These formulas are given below:

$$R^2 = 1 - \frac{\sum (a_i - p_i)^2}{(a_i - u_a)^2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(a_i - p_i)^2}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|a_i - p_i|$$

$$\mathrm{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{a_i - p_i}{p_i}\right|$$

Where i is the number of observations, n is the total number of records, a_i is the calculated or predicted output, p_i is the actual observed result, and u_a is the mean of the actual values. An R^2 closer to 1 indicates an ML model that has a higher accuracy or where the variation matches as closely to the provided inputs. An R^2 closer to 0 indicates lower correlation with the inputs. The use of the coefficient of determination is simply done to measure how well an ML model best fits to predicting outputs. R^2 only measures the fit of an ML model, RMSE measures the standard deviation of the ML model's prediction values from the actual values, that is, the deviation between the prediction and actual errors. The two are commonly used to explain the best fit and errors between different tested ML models. MAE is the measure of the averages in errors between predicted and actual values for regression ML models, the lower the better.

There are error estimation testing methods that use resubstitution, hold-out, k-interval, cross-validation, bootstrap and leave-one-out [212]. In many WWTP ML models, k-intervals and bootstrapping are commonly used. Earlier models did not factor in false positives, true positives and so on during the evaluation [212]. There are other deep learning models such as recurring neural networks (RNN), long-short term memory (LSTM), convoluted neural networks (CNN), gated recurrent unit (GRU), deep belief network (DBN), deep reinforcement learning (DRL) and generative adversarial network (GAN) [213]. Deep learning requires large sets of data and this can slow down the processing time. Moreover, the quality of the data used to train the ML model is critical [213] and they can either be supervised and unsupervised. Supervised forms of learning are the most commonly used for WWTP ML. Large datasets consequently raises the computational costs of the model. Another challenge is that every WWTP is unique in the recovery processes and the environment it is situated in. This necessitates the need to develop new ML models for every plant, however, it is possible to transfer trained models to another WWTP [214]. Models can be subject to overfitting (overtrained on narrow variations of data) and underfitting (unable to factor in outliers). Generalisations are performed with ML models factoring in unseen data disturbances such as changes in operating conditions, influent nutrient loads exceeding the EPL, contamination within wastewater and different weather conditions [213].

5.3. Application of models to controls and processes

The challenges that lie within smart CE WWTPs are the lack of sensors to collect and monitor data that is relayed to train the ML model used to optimise controls [213]. The lack of high-quality data is another issue, and transfer learning aims to address this, for example, the transfer of river data for water quality predictions [215]. However, this study also found that poorly located measurement instruments could induce further noise into the ML system and may not be suited to transfer learning into other WWTPs. Transfer learning is used with LSTM, and can be used to reduce the RSME of an ML model even with insufficient or unstable, complex datasets [216-218]. These models can be expanded beyond nutrients including energy [219]. Additionally, sensors are expensive, have limited measuring ranges and require constant maintenance [220]. The EU is currently funding and supporting the DARROW project to provide data-driven solutions to reduce energy consumption, promote resource circularity and lower GHG emissions [61]. The goal of the project is to use AI to increase phosphorus recovery by 50 %, nitrogen by 5 %, reduce energy consumption by 20 % and GHG emissions by 20 % [61], and it is estimated to be completed by February 2026. It is one of the forefront pilot plant projects for the Tilburg WWTP – one of the largest WWTPs in the Netherlands to optimise secondary treatment, biogas recovery and anaerobic digestion with AI tools. Interested data points include flow rates pH levels, temperature, chemical concentrations, gas and water quality, pump power and efficiency and meteorological data.

5.4. Simulating with digital twins as best practice

Melbourne Water corporation in 2023 began piloting the use of digital twins, ML and predictive analytics to better manage the quality of recycled water with accuracies reaching approximately 75 % [221]. The use of such technologies can provide greater data transparency and access to companies and stakeholders, who can then use this data to drive technical innovations and new business models for nutrient circularity. The recent launch of the Digital Twin Victoria program in 2024, helps to provide more accurate geospatial mapping of the data, streamlining utility data for improved project partner collaborations, open data, automating construction approval workflows, disaster and environmental response improvements and asset management. Data availability is a challenge for those wishing to innovate and improve wastewater treatment programs and plants to shift the entire industry towards nutrient circularity.

WaterNSW has developed a real-time insights platform since 2020 which provides a birds-eye view of the entire region's water quality [222]. The use of application programming interfaces (APIs) gives developers opportunities to connect into the water network and collect unadulterated data without verification at different intervals ranging from every 15 min to hourly ratings for site located, sensor collections. This presents challenges for ML models which must distinguish between outlier data that was collected and normalised sets. Primarily, influent nutrient data is measured on BOD, phosphorous, ammonia, nitrogen, TP and TN, and data accuracy becomes important given nutrient loads vary periodically. Digital Twin simulations enable greater planning and digital inclusivity for sustainability technology partners to innovate and provide niche CE services to enhance the environmental performance of CE WWTPs.

5.5. Digital standardisation and efforts for water and wastewater in Australia

The Australian Government is making continued efforts to streamline data collection and availability processes for the public. However, these efforts largely exclude resource circularity. For example, the second independent review of the Environment Protection and Biodiversity Conservation Act 1999 (EPBC Act) [223] from 2018/19, largely excludes nutrient circularity with a key focus on water efficiency instead, the paper does however propose for better monitoring and data collection tools [224]. The Digital Restart Fund is currently piloting data collection from smart meters across 250 households to improve better water efficiencies. The recent revamp of the Water Quality Australia website to meet the Digital Service Standard, is one effort of making water data more accessible [225]. Environment Online by the Western Australian government offers tools to access water quality databases to assess operators for their licenses [226,227]. The standardisation of water project management and proposal processes can help those wishing to submit development and retrofitting of CE WWTP facilities for nutrient recoveries. There are several wastewater resource recovery projects with the primary goal of recovering water, including the Resilient Rivers Water Infrastructure Program with the goal of recovering 450 GL of water [228], and the Goondiwindi Hydrogen Project in Queensland using recycled wastewater as the feedstock for the electrolytic process [229].

5.6. Incorporating a risk management framework

The EPA outlines a set of guidelines to the proper classification of risks and mitigation actions to the ongoing operation of a plant [230-232]. This framework can be modified to accommodate the nutrient CE WWTP proposals for the plant retrofitter or builder as outlined in the table below. According to the documents, licensees looking to improve (i.e., retrofit their WWTPs) would need to submit an application to the EPA with attachments detailing their proposed costs, completion date, details of the milestones to be reported and environmental improvements as a result. The licensee can also incur penalties for noncompliance affecting their environmental management scores, for example, formal warnings and clean-up notices. Licensees of nutrient CE WWTPs would ideally have ISO14001 environmental management systems to comply to maintenance procedures, but other risk guidelines such as AS/NZS ISO 31000:2009, AS/NZS 4360:2004 and HB 203:2012

[231]. NSW EPA prescribes a list of scores below on the level of regulatory compliance a proposer is assessed on and Table 9 shows the risks arising from operating resource recovery CE from wastewater that should be factored in.

In Australia, nutrient recovery projects at large scales are not commercially accepted, and require EPA permits and work approvals. Australian BioFert for example, submitted approved grant applications with the EPA to recover poultry organic waste and to establish a nutrient recovery facility following risk assessments [243]. Australia's current policy focus is on recycled water, nor does the country's EPA certify the use of potable drinking water from treated wastewater [244]. The regulations do permit the use of nutrient-rich effluent wastewater that has been treated for farming purposes. On the other hand, the Australian Meat Processor Association has produced a report detailing its design for recovering biogas, phosphorus, nitrogen and CO_2 recovery for red meat wastewater [245], but has not submitted this to the EPA.

5.7. Selecting ML models for training

Depending on the application of the nutrient recovery model, certain ML models will excel one over the other. Dansawad et al. [246] classifies four ML models for the treatment of wastewater, being boosting, classification, regression and clustering algorithms. These models can be combined together, or ensembled, to improve the accuracy of the system. Throughout Australia, WWTPs operate using aerated, conventional activated sludge (CAS) and biological nutrient removal systems prevail the national treatment landscape [247], even more so compared to membrane bioreactors. New WWTPs being constructed in Australia are expected to use ion exchange, activated carbon and oxidation processes [248]. Consequently, the selection of ML models will be impacted. For this to work, rigorous and large amounts of datasets are required to produce reliable predictions and process optimisations. In this scenario, ML optimisations can be applied once current new generation WWTPs are built, following data collection, preparation and training of various ML models for accuracy performance and enhancements [249]. For ANN approaches, larger datasets require longer processing times and computational power [213]. Another red tape cited were approvals from public authorities to certify the reliability of this data which can be used for ML purposes, who act in the best interests of the public, and to make this data publicly available [213]. State water authorities throughout Australia are already disclosing geospatial data for commercial purposes [250,251], however, other state utilities require payment for requesting such data [252]. The emergence of smart metering allows households to view their water consumption data remotely [253]. The biggest challenge in implementing and selecting the best ML for WWRF Australia, is the installation of smart sensors throughout Australian WWTPs, and decentralising this data for public access. Sydney Water has WWTP data spanning back to the early 1990s [18], but the performance of this nutrient management is weakly connected to the processing inputs of the plants spanning decades – a correlation between other characteristics within wastewater, weather and environment, and the plant's operating data.

5.8. Evaluating the performance of ML for nutrient CE WWTP compliance

Accuracy, performance, power consumption and server reliability uptimes are other considerations that ML CE WWTP operators in Australia will need to include. Currently, no standard has been developed within Australia for the acceptance of ML accuracies and robustness for wastewater that can be used to help implement and approve studies on a larger scale. such as those seen in Table 10 and following Fig. 4. Data collection frequencies and the quality of such data will be critical to the effectiveness of an ML CE WWTP [249]. This data is collected, cleaned and structured to work with specific ML models. In WWTPs, most likely, time-based data is used as the input. For example, influent nutrient loads throughout the day, month or year. This data is converted from time to batch series, and then split between training, test and validation data. The plant designer can choose to train the ML model by firstly listing the different processes that happen throughout the nutrient CE WWTP [14]. Table 10 shows the advantages and disadvantages from each ML model being applied. ANN for example, due to improper data preparation, is prone to underfitting and overfitting even if fewer datapoints can be used. XGB exemplifies a great degree of generalisation with missing data. Other challenges for these ML models include the lack of intense kinetic modelling predictions and limited availability on different nutrient types for a given similar recovery set of technologies. Conclusively, the selection of the best ML model requires experimentation by plant operators as different configurations can alter the prediction accuracies and the ML model compatible.

Finally, the cost of servers and additional components integrated into ML processes becomes a factor that must be balanced against economic gains. All of the smart nutrient, ML CE WWTPs, server cloud costs can vary from hundreds to thousands of dollars a year. Given that the cost of

Table 9
Resource recovery risks based on the EPA framework.

Resource recovery technology	Emissions risk	Pollution controls	Highest risk activity or component	Proposed solution sources and assessed risks
Source separated urine struvite precipitation	N_2O emissions; ammonia emissions, allyl methyl disulfide, methyl propyl disulfide, and menthol, hydrogen sulphide.	Water dilution, prevention of stale and fresh urine from mixing, maintaining low temperature of urine, elimination of odour causing compounds, eliminating turbulence in sewage, air-dilution, odour adsorption or incineration, chemical elimination, preventing corrosion and ensuring complete coverage and sealing against odour leakages.	Growth in bacteria, trace metals in urine, active pharmaceutical ingredients, corrosion failure of critical equipment, pipe leakage and cross contaminations.	[233,234]
Anaerobic digestion with soil application	Methane, ammonia, nutrient leakage, micropollutants, biocides, and other harmful chemicals.	Process controls such as temperature and pH, feedstocks, pathogen inactivation, storage time, risk management methodologies such as quantitative microbial risk assessment and probabilistic models, and proper sealing of biogas.	Pathogen contamination, heavy metal traces, manganese toxicity on soil, flammable biogas.	[235-238]
Sewage sludge ash incineration processes	Toxic fumes, volatile organic compounds, biogas leakage, soil contamination, nutrient leaching.	Heat/biological/chemical treatment of sewage sludge, suitable land types for application, testing of groundwater and soil for contamination, gas cleaning or scrubbers, and thermal disposal.	Fire hazard, cross-contamination, heavy metal traces, chemical poisoning, combustion.	[239-242]

Table 10
Machine learning methods for recovering resources from wastewater.

Data Collection Source	ML Model	Method	Dataset	Accuracies	Input output correlations	Source
Effluent	RF and DNN	Collection frequency ranges from 10 min intervals	More than 105,861 samples for a robust model, with 34 variables.	Analysed using Variable Importance Measure and Partial Dependence Plot on RF and DNN model.	Strong relationship between TSS and $PO4_e$ for effluent predictions. Influent temperature affects both TSS and $PO4_e$.	[14]
Effluent	ANN and SVM	1-day interval data collection of effluent, non-linear time series. Over 1- months.	8 input variables of month, volumetric inflow rate, pH, temperature, COD, suspended solids, T-N inflow.	Sensitivity analysis on the 8 input variables, and ranked across ANN and SVM. R^2, NSE and relative efficiency used across training and validation data.	ANN superior for T-N effluent concentration predictions. R^2, NSE, relative efficiency criteria were used across training and validation data for R^2, NSE and relative efficiency criteria.	[249]
Sewage sludge output	KNN, SVR, LR, DT, kernel ridge regression, XGBoost, FCNN, RF.	Top 10 feature selection using Spearman, Pearson, DT feature contribution and maximum information coefficient. Ranked using XGBoost.	2 years' worth of water quality and sludge data. 584 training and 147 test data. Using water quality, rainfall and temperature and volume.	Taylor diagram to map out the correlation coefficients. XGBoost followed by RF were the most accurate tested. RMSE, MAE, MAPE, and R2 values were 2.1169, 1.7032, 0.0415, and 0.8218 for XGBoost respectively.	Top 5 features were volumes of water, TN, TP, BOD and COD across all correlation analysis.	[254]
Influent weather data covering rain, dry and storm.	Bayesian, linear, RF, XGBoost, ANN were tested.	Feature selection to identify predictors targeting ammonia and TN removal in effluent.	Input data collected in 15-minute intervals over two-week period.	Performance enhancing through bootstrapping and bagging. XGBoost and RF models superior.	Self-organising fuzzy inference system and feed-forward control were used to optimise treatment process.	[255]
TAN measurements in full scale anaerobic digester for membrane contactors	Feed forward ANN, RF, SVM and Gaussian Progression Regression (GPR)	TAN value every 20 s. Experiment ran for 45 min to 75 min at a time.	2350 datapoints were collected. 8 batches, 6 training and 2 test data. Inputs were pH, pH derivative and pH intervals. Target being TAN.	ANN was the most accurate boasting R^2 of 0.99, and RMSE of 19.87 mg/L.	75 % and 25 % training and test data respectively. Permutation used to inspect input contributions to output.	[30]
Struvite recovery	RF and GBR models were tested.	Pearson correlation between inputs and target outputs (TN and TP recovery).	504 pieces of data.	RF model achieved R^2 of 0.86–0.94 and RMSE of 5.48–10.17, and was the best performing one. Relative errors for P and N recoveries were respectively 0.18–4.67 % and 0.12–7.32 %.	80:20 training and test data, 5-fold cross validation.	[29]
Effluent	Three ML models were assessed, including RF, multilayer perceptron (MLP), and SVM.	RF, SVM and MLP models were built, feature and permutation importance were used to understand input output relationships. Three scenarios considering seasonal, chemical, and daily data.	Santa Catarina Brewery AMBEV WWTP with collected wastewater data over 752 days.	R^2 of 0.72 for MLP, or the feedforward ANN.	Pearson analysis on input output variables to understand the correlation, and a feature importance analysis. TN, NH, and TKN had 2.2 times more influence on the prediction of TN_{out} than COD + BOD + TSS.	[256]

Wastewater experiments with ML, with R^2, RMSE and MAP errors in the recovery of N and P for mature technologies.

Process (nutrients)	Selection reason	R^2	RMSE	Input	Output	Advantages	Disadvantages

(continued on next page)

Table 10 (*continued*)

Data Collection Source	ML Model	Method	Dataset	Accuracies	Input output correlations		Source
Struvite recovery (N, P and ammonia) (**RF**) [29]	Model 504 data points for synthetic wastewater KH_2PO_4, $MgCl_2$, and NH_4Cl.	086–0.94	5.48–10.17	Stir speed, pH, Mg: P, N:P, temperature, and time, initial P concentration.	Optimise conditions for struvite recovery.	Increase production yield of struvite.	Did not consider P source due to lack of data.
Struvite recovery (N, P and ammonia) (**XGB**) [28]	100 datasets from 85 scientific documents. Missing data imputations. Linear regression.	0.9683 (PO_4^{3-}) and 0.9483 (NH_3)		Mg^{2+} concentration for PO_4^{3-} recovery, reaction temperature for struvite precipitation, and PO_4^{3-} and Mg^{2+} concentrations for NH_4^+ recovery.	Optimise struvite production.	Can factor in many missing data, good generalisation, robustness and can obtain feature importance with feature data.	For RF, more trees meant longer training times. High numbers of inputs made it prone to overfitting.
Ammonia stripping (**ANN**) [30]	75:25 training to test data. ANN captures non-linear predictions.	0.99 (TAN)	< 19.87 mg/L (TAN)	pH, pH increments and the pH derivative.	Low-cost predictions, pH cheap input to measure, and avoids maintenance and training of staff. Maintain pH levels optimally for effective TAN recovery.	ML model trained using real-time data. Only one hidden layer was needed to develop an effective model.	Partial least square method underestimated (concentrations higher than 600 mg NH_4^+-N/L) or overestimated (concentrations lower than 300 mg NH_4^+-N/L) results.
Electrochemical P-recovery (**XGB**) [257]	582 datasets. Wastewater contained Ca^{2+}, Mg^{2+}, Na^+, K^+, PO_4^{3-}, and NH_4^+	0.98 (P)	33.51 (P)	Current density, pH, inter-electrode distance, electrolysis time and initial phosphorus concentration.	Prediction of P-recovery to optimise processes and assist commercialisation.	XGB did not suffer from overfitting.	Limited information on different types of P in the ML model.
Hydrothermal liquefaction sewage sludge for hydrochar P-recovery (**GBR**) [26]	194 data points. Can predict P-content with complex sewage sludge compositions.	> 0.9 (P)	4.66 (P)	Temperature, residence time, and solid content most important inputs for P-recovery.	Prediction of P content in hydrochar.	Good accuracies in predictions.	Does not extensively factor in kinetic models for P conversion at higher temperatures.
Microalgae nutrient recovery (**ANN**) [258]	72 data points. Used for experimental ML validation.	0.98 (Biomass)	0.056 (Biomass)	pH, retention time and COD were most influential inputs.	Prediction of biomass yields, provides foundations for further ML.	High accuracy, low error. Required fewer data points.	Varying the Train ratio by more than 20 % led to severe underfitting.

*Note: Bold font indicates ML model used for the study.

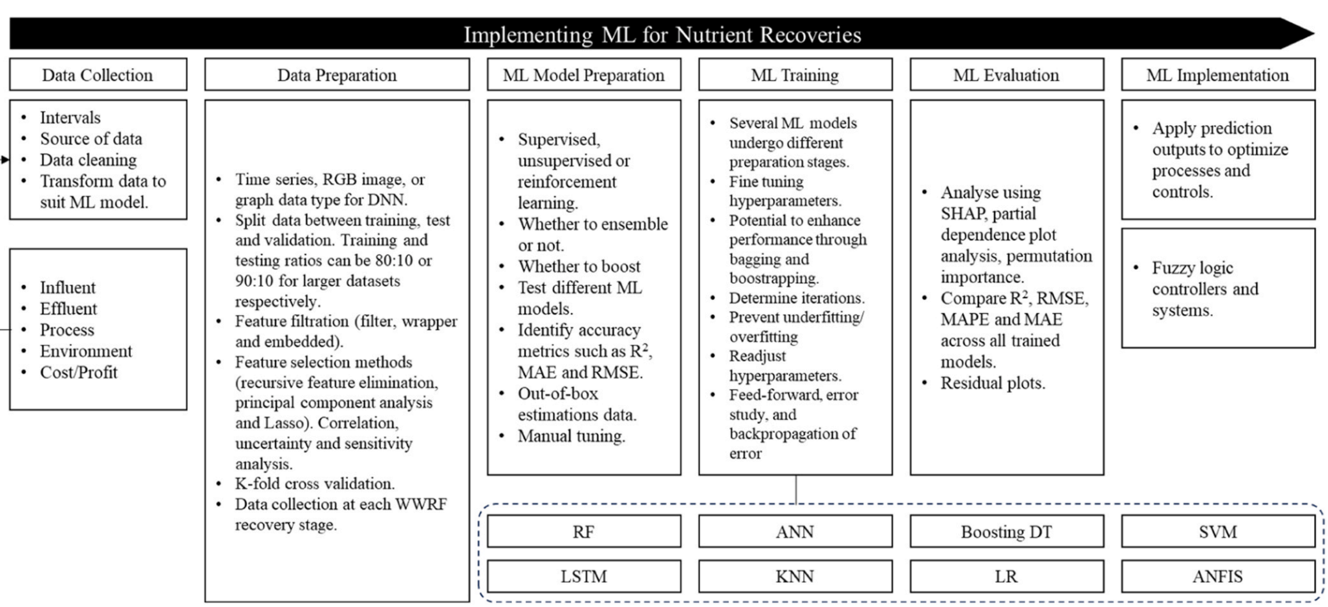

Fig. 4. Aggregated information from [14,30,192,206,249,255,254,256,259] and [260] showing the procedures taken to model ML for nutrient management across WWTPs.

a sensor is more than $US10,000 [261], there are conditions within a nutrient CE WWTP which can corrode and force costly frequent replacements of sensors and other measuring equipment [262]. The benefits of using these sensors can outweigh the costs if it leads to significant labour savings. Furthermore, the fluctuating cost of electricity makes it more difficult to factor in operating costs [263]. The use of five servers for example with a storage capacity over 1000 GB per server, and over a span of 2 weeks can cost 7504 CAD (1900 CAD cost saving divided by 25.32 % achieved cost savings) [263]. Therefore, the higher the computation requirements and power needed, the greater the server costs. These should be factored into the technoeconomic assessment and planning stages for nutrient CE WWTPs. The application of ML in the study [263], however, also explores the power savings of using ML to predict surge prices and to offload data storage to minimise computational requirements (for example, a smart ML CE WWTP can offload data during periods of low wastewater loadings or high-power prices). Despite the high-power consumption of ML servers, these studies have shown that cost savings can still be achieved when applied correctly.

6. Discussion

This roadmap paper examines the steps and research needed to implement a broader, nutrient CE ecosystem across Australia's WWTP that can be graphically summarised for future reference in Fig. 5. The first major evaluation is the readiness of technologies and its compatibility to existing WWTPs, and the extensiveness to which retrofitting and upgrades are required. The EU has already undertaken major strides in evaluating and implementing pilot and commercialisation funding for such plants to recover critical raw materials as a part of its Circular Economy Action Plan and its Critical Raw Materials Act. Presently, Australia's environmental regulatory and legislative landscape is fragmented at the state level, with water guidelines lacking the essence and nuances for nutrient recoveries. There are, however, initiatives to recover water to make the country more drought resistant.

From an ML CE WWTP lens, there are several key points to be made for a nutrient roadmap combining smart systems to optimise and enhance recovery performances and advance high participation rates in wastewater CE. One is the supply chain shocks that have raised the price of phosphorous and food prices, and decreased the standard of living among consumers. In fact, global food prices have risen by 78.6 % in 2021 year-on-year during the pandemic [264]. Australian consumers were not immune to these price shocks, however ironically, an increase in fertiliser prices from disrupted supply chains could make recycling nutrients more profitable [265]. Beyond food, there is also growing demand for phosphorus in the industrial and automotives sector [266], and so, it becomes essential to map out the industries demanding this critical element beyond agriculture as well. Thirdly, investments in AI have increased considerably since the pandemic, and have shown through research that they are effective tools at mitigating supply chain shocks and stabilising prices; however, this topic remains absent across Australian wastewater guidelines, policies and standards. Given recycling systems can be manually intensive, combining ML, automation and resource recovery optimisation with retrofitted or new plants are key sustainability areas that are under-implemented at the state and federal level. Prioritising nutrient removal in favour of water recovery has consequences on securing low-carbon and sustainable fertilisers. While increasing water supply in a drought-prone country may expand irrigation capacities, this has so far, come at the cost of nutrient wastage, increased risks of eutrophication, and forgoing alternative, organic, low-carbon fertilisers.

What is missing from the water framework of Australia is nutrient circularity to support the agribusiness sector for a country where 72 % of agricultural production was exported in 2019–20 [267]. The focus on preventing eutrophication by removal, rather than recovery methods to supplement water supplies, will make Australia's food and phosphorus supply chains more vulnerable to global geopolitical volatility [5]. The lack of economic understanding, high reliance on finite sources of mined phosphate rock, concentration on nutrient removal technologies at the expense of recovery ones, poor investments and lack of training data in AI and ML across utilities in general, and fragmented water guidelines and frameworks are hindrances towards shifting Australia to smarter, CE WWTPs.

7. Conclusions

This roadmap paper specific to Australia highlights and outlines the stages and procedures to transition conventional WWTPs into WWRFs. Technologies, policies, financials, infrastructural, social, regulatory, ML modelling methods and performances were all methodically evaluated through data collection, implementation, regulatory standardisation,

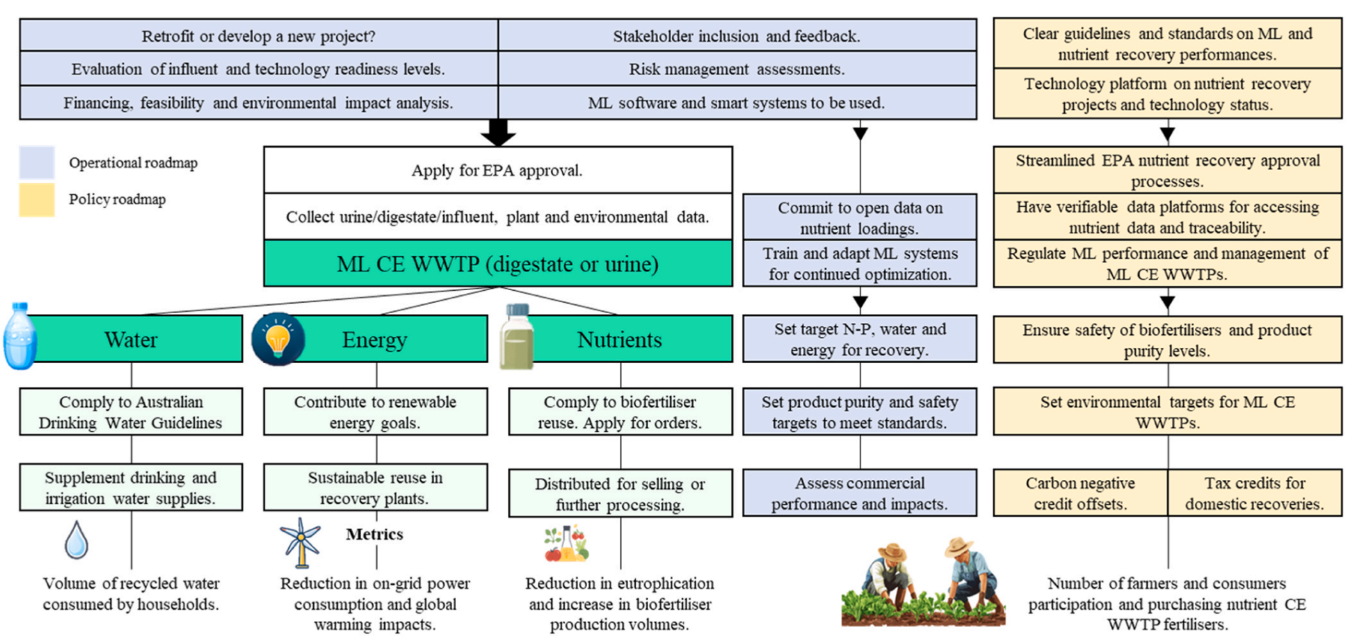

Fig. 5. Roadmap encompassing operational and policy objectives on covering the gap in the current national Australian CE framework.

economic and ML modelling, and social inclusion lenses. Some significant barriers to Australia's transition to ML CE WWTP are the lack of initiatives at the EPA and state water authorities' level, low financial investments and appetite for nutrient CE WWTPs (especially retrofitting and greenfield developments), high reliance on legacy centralised WWTPs for biological nutrient removal technologies, fragmented approval procedures, and lack of consumer awareness. The application of ML for CE WWTPs is still an emerging area of study, and are predominated by studies focusing more on nutrient removal outcomes.

Disseminating and implementing mature nutrient recovery technologies becomes the next major challenge based on readiness levels, given the EU has an open access platform showcasing the current progress and investments made into nutrient recovery from WWTPs. In Australia, the selection of these technologies happens on a case-by-case basis depending on the volume of nutrients in the WWTP influent which requires approval by the EPA following an environmental impact analysis. These technologies will have to replace removal processes in WWTPs, and the issue of plant retrofitting can be prohibitively costly in an environment where nutrient CE economics is poorly understood. Unlike the EU where phosphorus is deemed as a critical raw material, the recent *Made in Australia National Interest Framework* fails to consider this element important. The paper underscores the regulatory and policy challenges in advancing nutrient ML CE WWTPs throughout Australia, and provides a series of considerations on how to overcome and arrive to a smarter, nutrient CE.

CRediT authorship contribution statement

Shon Hokyong: Writing – review & editing, Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Allan Soo:** Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Li Gao:** Writing – review & editing, Investigation, Formal analysis, Conceptualization.

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Data availability

No data was used for the research described in the article.

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