Word count of the manuscript: 14, 699

A systematic review of empirical methods for modelling sectoral carbon emissions in China

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Abstract:

A number of empirical methods have been developed to study China's sectoral carbon emissions (CSCE). Measuring these emissions is important for climate change mitigation. While several articles have reviewed specific methods, few attempts conduct a systematic analysis of all the major research methods. In total 807 papers were published on CSCE research between 1997 and 2017. The primary source of literature for this analysis was taken from the Web of Science database. Based on a bibliometric analysis using knowledge mapping with the software CiteSpace, the review identified five common families of methods: 1) environmentally-extended input-output analysis (EE-IOA), 2) index decomposition analysis (IDA), 3) econometrics, 4) carbon emission control efficiency evaluation and 5) simulation. The research revealed the main trends in each family of methods and has visualized this research into ten research clusters. In addition, the paper provides a direct comparison of all methods. The research results can help scholars quickly identify and compare different methods for addressing specific research questions.

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Keywords: climate change; carbon emissions; China; knowledge mapping; literature review; modelling

List of abbreviations

Abbreviation	Description
ABM	agent-based model
ARIMA	autoregressive integrated moving average model
CBE	consumption-based emissions
CGE	computable general equilibrium
CSCE	China's sectoral carbon emissions
DEA	data envelopment analysis
DMU	decision-making unit
EE-IOA	environmentally-extended input-output analysis
ELC	environmental learning curve
ETS	emissions trading scheme
FDI	foreign direct investment
GIS	geographic information system
GMM	generalized method of moments
GPS	Global Positioning System
IAM	integrated assessment models
IDA	index decomposition analysis
IOA	input-output analysis
IO-LCA	input-output life cycle assessment
IPAT	Impact = Population × Affluence × Technology
IPCC	Intergovernmental Panel on Climate Change
LCA	life cycle assessment
LLR	log-likelihood ratio
LMDI	logarithmic mean Divisia index
MRIO	multi-region input-output
MRIO-LCA	multi-region input-output models and their integration with life-cycle assessment models
MSIO	multi-scale input-output tables
PBE	production-based emissions
SCE	sectoral carbon emissions
SD	system dynamics
SDA	structural decomposition analysis
SRIO	single-region input-output
STIRPAT	Stochastic Impacts by Regression on Population, Affluence, and Technology
WoS	Web of Science

1. Introduction

Interest in formulating and applying analytical or modelling techniques to understand carbon emissions has profoundly increased since the Kyoto Protocol was introduced in 1997. In

China the largest source of CO_2 emissions comes from intermediate production processes, which are attracting the attention of policy makers, researchers and the international community wishing to curb growth in emissions. Several commentators have also given China the title as the "factory of the world" owing to the significant proportion of global manufactured goods originating in China (Liu and Diamond, 2005; X. Tang et al., 2015; Zhang et al., 2016). Given the growing importance of full life-cycle accounting and the associated embodied emissions in products – particularly for products consumed in developed countries that were manufactured in emerging markets – China's national emissions inventory is continuing to attract global attention. The need to understand and operationalise emissions reductions targets is demonstrated by the wide range of methods and approaches that are being embraced and developed in the rapidly growing number of published research papers looking at China's Sectoral Carbon Emissions (CSCE). This has been particularly evident since 2007 when China became the largest carbon emitting country in the world. Today, around one-third of global sectoral carbon emissions (SCE) research focuses on emissions generated in China. A number of novel modelling techniques have been developed and deployed to address complex SCE issues specific to the Chinese context.

Tackling the CSCE problem is complex and requires diverse research approaches. While several attempts have been made to review specific methods in their own contexts, few, if any, research papers have provided an analysis of the main research methods that provide an overall picture of the multiple methods that have been developed to answer different research questions. For example, in one family of methods under the broad umbrella of CSCE, the method known as environmentally-extended input-output analysis (EE-IOA) was reviewed by Hoekstra (Hoekstra, 2010) and updated by Hawkins et al. (Hawkins et al., 2015). In another, a total of 80 papers were reviewed using index decomposition analysis (IDA), by Xu

and Ang (Xu and Ang, 2013). Data envelopment analysis (DEA) was reviewed by Meng et al. (Meng et al., 2016) who compared five widely used DEA efficiency methods. In addition, in papers that review or apply to a specific method or family of methods, it is rare for authors to explain why they chose a particular method to address their research problem.
While scholars from particular fields are naturally familiar with one method or another, such as economists using econometrics, scholars would be in a much better position to approach the problem if they were aware of, and could compare, the strengths and weaknesses of the main methods that have been used to answer similar research questions. This review paper addresses this problem through a direct comparison of the strengths and weaknesses of each of the main research methods. It also highlights the relationships between methods and research themes, recent trends, the popularity of different methods as well as research gaps and opportunities for further research. This paper aims to fill an important gap by providing an analysis of all major CSCE-related methods so that scholars and policy-makers can quickly identify and compare different methods for answering their research needs.

Instead of focusing on the detailed techniques or models that are used in a particular method, we outline the main methods that have been applied and the types of research questions that each method can answer. We use bibliometric analysis and knowledge mapping with the software CiteSpace to create an overall picture of the ongoing activity in CSCE research, and to assess the similarities and differences between the adopted methods. The paper reviews five families of methods that are commonly used to model and assess carbon emissions, and it examines the pros and cons of each method. The families of methods identified include: (1) environmentally-extended input-output analysis (EE-IOA), (2) index decomposition analysis (IDA), (3) econometrics, (4) carbon emission control efficiency evaluation and (5) simulation. While we draw on carbon emissions research in China, the findings can be applied to carbon emissions research worldwide.

The rest of this paper is structured as follows. Section 2 (Methods) describes the boundaries of the literature reviewed and how the research papers were analysed using bibliometric analysis and knowledge mapping. Section 3 (Review of methods) describes each of the representative methods and discusses the pros and cons for each of them. Section 4 (Bibliometric analysis) provides a quantitative analysis which compares the main trends and approaches for each family of methods. Section 5 (Knowledge mapping) presents a number of graphical visualisations of the main research themes and summarizes the main points of comparison between the methods. This section also identifies key milestone papers in the development of the CSCE field over the last 20 years. Section 6 (Discussion) critiques the representative methods and explores what can be done to further develop and grow CSCE research. Finally, Section 7 (Conclusion) summarizes the gaps in the present literature and the main findings and limitations.

2. Method

2.1 Search strategy and selection of papers

A systemic review of the literature was undertaken using Thomson Reuters's Web of Science (WoS) database. The WoS database covers approximately 12,000 leading journals worldwide. It includes the Science Citation Index Expanded, the Social Sciences Citation Index, and the Arts and Humanities Citation Index databases. The quality and quantity of papers included are therefore sufficient for conducting a systemic review.

We searched for papers in the CSCE field using the following steps. Papers were filtered using key words "China", "carbon emission*" and "industr* OR sector*" in titles, abstracts or indexing terms. The period selected for this analysis was from 1997 to 2017 because of the growing importance of CSCE since the introduction of the Kyoto Protocol in 1997. The most recent paper was published on 20 July, 2017. In total 1,057 papers were identified under the CSCE umbrella published between 2001 and 2017. The number of papers was reduced to 807 by filtering by document type to only include articles and reviews and exclude proceedings papers, book chapters, reprints, meeting abstracts, editorial material and retracted publications.

The five families of methods listed in the introduction to this paper were identified after we manually reviewed the 807 papers. When we searched for articles that use a particular family of methods such as environmentally-extended input-output analysis, we would add relevant method descriptions in the search terms such as "input-output analysis", "IOA" or "SDA". For more information about the search terms for each method, see Table 1.

Method		Topic Search Terms
Environmentally-Extended Input-Output Analysis		IO *OR* input-output *OR* embodied *OR* "structural decomposition" *OR* SDA
Index Decomposition Analysis		LMDI *OR* "index decomposition" *OR* "Logarithmic mean divisia index" *OR* decoupling
Econometrics		Regression *OR* "panel data" *OR* econometrics *OR* correlation *OR* STIRPAT *OR* IPAT *OR* statistics
Carbon emission control efficiency evaluation		DEA *OR* "data envelopment analysis" OR Malmquist
Simulation	Computable General Equilibrium	CGE *OR* "computable general equilibrium"
	Integrated Assessment	"integrated assessment" *OR* "integrated-assessment" *OR* IAM
	System Dynamics	"system dynamic" *OR* "system-dynamic" *OR* SD
	Agent-Based	"agent-based model" OR "agent-based modelling" *OR* ABM
	Optimization	Optimization
	Multi-Criteria	"multi criteria" OR "multi-criteria"
	Techno-Economic	"techno economic" OR "techno-economic"

Table 1 Search terms for the representative methods

2.2 Methods used for bibliometric analysis and knowledge mapping

Bibliometric analysis and knowledge mapping were used to analyse the search results. The bibliometric analysis revealed subject areas as well as publication and citation trends for each of the five families of methods. In the literature, knowledge mapping is commonly used to uncover and visualise groups of similar ideas or unusual features and trends by showing how knowledge within a field has evolved over time in a comprehensive and transparent manner (X. Li et al., 2017). Compared with bibliometric analysis, which mostly focuses on providing a general understanding of the field by undertaking a descriptive analysis, knowledge mapping aims to reveal structural and dynamic aspects of studies by charting, mining, analysing, sorting, and displaying knowledge (Shiffrin and Börner, 2004).

The software used for this analysis, CiteSpace, is a popular choice for conducting knowledge mapping. Chen (2004) developed this software based on bibliometric analysis, data mining algorithms and visualization methods. We used CiteSpace in this paper to visualize research clusters and detect milestone developments in CSCE research. To this end, CiteSpace was used to explicitly establish the intellectual base for each research method and track its evolution based on co-citation network. The co-citation network was derived using graph-theories, in which the vertices represent the reference papers of the 807 papers, on the basis of the CSCE search results from the WoS database. If two papers were cited in a third paper, they were co-cited, and a link was formed in the co-citation network. The co-citation network was further clustered by using the expectation maximization algorithm (Chen, 2014) based on a series of attributes, including citation frequency, first author, year of publication and the source of the publication. See Figure 1 for the conceptual framework of the co-citation network. The clustering analysis provided insights into the underlying knowledge structure by detecting fundamental and distinctive research papers in the field. In addition, CiteSpace uses Kleinberg's (2003) burst-detection algorithm[1] for identifying sharp increases of interest in a particular topic, thereby providing insights on the critical evolving paths in a timely manner.

[1] The burst-detection algorithm is used to find features which have high intensity over a period of time and then fade away through analysing document streams arriving continuously (Kleinberg, 2003). The 'bursty' event which is uncharacteristically frequent, and the corresponding time period can be identified by using this algorithm.

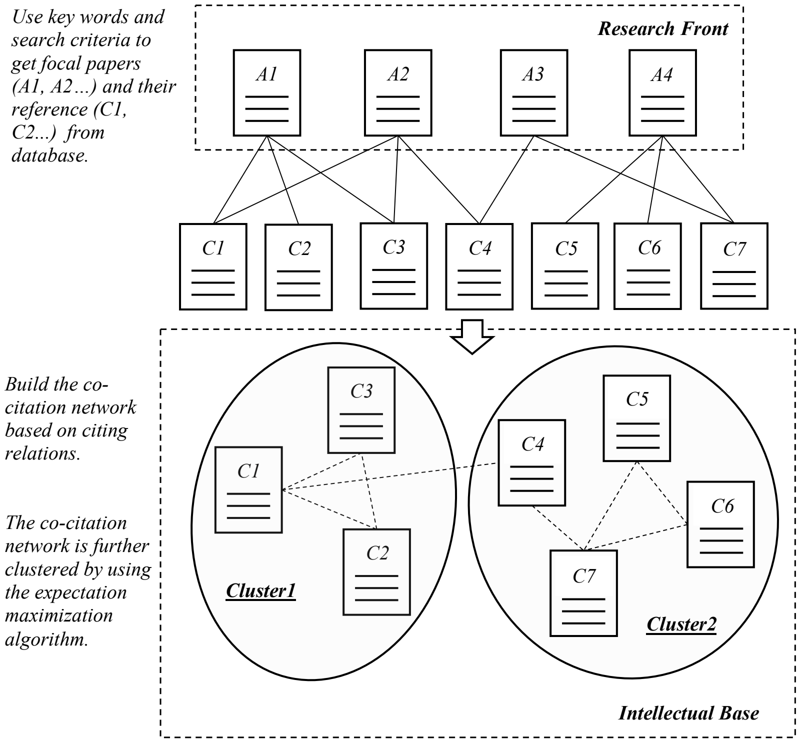


Figure 1 The conceptual frame work of the co-citation network

Previous literature review papers published in the CSCE field have usually been expert-dependent, and such papers cannot avoid subjectivity and individual preferences. Our analysis using CiteSpace was driven by bibliometric data, and no subjective preferences were involved in the clustering and visualisation process for identifying unique research groups.

3. Review of methods

In this section, five families of methods within the CSCE field are reviewed. For each method, we provide a brief introduction to show how it has been applied, followed by a short discussion of its pros and cons.

3.1 Environmentally-extended input-output analysis (EE-IOA)

Over the last ten years EE-IOA has been increasingly used to study the regional and sectoral effects of carbon emissions in China. It allows for the assessment of carbon emissions from both a production and a consumption perspective (Leontief, 1970). EE-IOA is particularly useful for examining the embodied carbon flows of industries both within China and internationally (Liu et al., 2012; Su and Ang, 2014) and provides a good foundation for "common but differentiated" responsibilities for tackling carbon abatement.

Within EE-IOA, both the direct and indirect effects of economic activities on the environment are examined in the entire supply chain and production system. The influence of changes to production, technology and final demand on China's carbon emissions are frequently examined through multiplier effect analysis (Su and Ang, 2014; Zhang et al., 2015) and structural decomposition analysis (SDA) (Shan et al., 2017; Su and Thomson, 2016). It is straightforward to integrate EE-IOA with other methods to provide more solutions to research problems in the CSCE field. For example, the integration of EE-IOA with life cycle assessment (LCA) enables a much more detailed account of total life-cycle carbon emissions, and makes it possible to adopt a cradle-to-grave approach for industries and regions (Bilec et al., 2010; Thiesen et al., 2008).

Although EE-IOA offers several benefits, it also has several limitations. The data used to construct EE-IOA tables is variable and depends on the assumptions and data collection methods used. Significant differences can arise simply from the accounting and collection methods that are used. For example, estimates of consumption-based carbon emissions for China varied from 1,841 Mt to 4,030 Mt in 2012 with a 54% difference rate (Zhang et al., 2017). Moreover, due to the large datasets required to conduct EE-IOA at high sectoral and regional resolution, there is a significant time lag between each new release of input-output data tables.

3.2 Index decomposition analysis

Index decomposition analysis (IDA) has been used to examine the driving forces of carbon emissions in China over time. IDA starts with the macro-variable of carbon emission change (Ang, 2004). It is commonly decomposed into “activity effect” indicators such as GDP, the “structure effect” indicators such as industrial structure, and the “intensity effect” indicators such as carbon emissions per unit of GDP (Liu et al., 2007). Through an “ideal decomposition” process (i.e. there is no residual term), such as the logarithmic mean Divisia index (LMDI) decomposition approach (Ang and Choi, 1997), IDA produces a deterministic result to trace the effect of each indicator used in the analysis.

The popularity of this method can be attributed to its minimal data requirements, and the ease of application and result interpretation. The data sources available for conducting IDA are relatively abundant, as only aggregate sector-level data are required. In China, such data is readily available and is provided on an annual basis at high spatial resolution by regional and national bureaus of statistics. IDA has proven to be flexible in problem formulation and is generally easy to apply. Using this method it is possible to work with both multidimensional and multilevel emissions data over both time and space (Su and Ang, 2012). For example, the latest publications in the field cover an analysis time span of over twenty years and range from the city to the international level, and they can incorporate data from specific industry sectors and economy-wide emissions trends (Zhao et al., 2016; Zhen et al., 2017).

One limitation of this method is that it fails to represent the linkages between industries and it is therefore unable to capture the spill-over effects of changing demand across different industry sectors (Hoekstra and van der Bergh, 2003). Another limitation is that IDA is only able to reveal changes to macro-variables owing to the limited number of predefined factors. Because IDA requires factors to be introduced that cancel each other out, it is not easy to incorporate new variables such as weather into the analysis. Moreover, because IDA looks at change over time for specific macro-variables, it is generally necessary to have a time-series over the period of interest.

3.3 Econometrics

Econometrics is used as an analytical tool to describe the contributions of multiple factors or policies to carbon emissions. Most of the econometrics models in the field of CSCE research are derived from STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) framework. Based on the estimated relationship, STIRPAT also serves as a starting point to simulate carbon emissions under different scenarios (Y. Liu et al., 2015; Wang et al., 2013). For a more precise specification of the sensitivity of the carbon emissions to the driving factors, researchers have attempted to improve this approach, by using different model specifications or by adding more variables of interest.

Panel data is the most frequently used econometrics method in CSCE. It attempts to provide quantitative evidence of the connections between carbon emissions and influencing factors across different industries in the observed period. Several changes have been introduced in an attempt to enable more precise measurement. Firstly, to avoid multicollinearity issues among socioeconomic variables, partial least squares or ridge estimation procedures are widely applied (Wang and Zhao, 2015; D. Yan et al., 2017). Secondly, the Tobit model has been adopted to analyze the factors affecting energy-environment efficiency (Pan et al., 2013; Yang et al., 2014). Thirdly, because economic behavior exhibits some continuity, it is essential to introduce the lagged level of carbon emissions to ensure that the model coefficients are calculated consistently and effectively (Omri and Nguyen, 2014). To solve the endogeneity problem causing by the dynamic lag term of the explained variables, the generalized method of moments (GMM) using a set of instrumental variables is applied to estimate the dynamic panel data model (Guo, 2017; Zhang and Xu, 2017).

A key advantage of econometrics is its versatility due to the wide variety of methods and techniques that can be used. For example, spatial econometrics has introduced the concept of 'economic distance' into carbon emissions research to provide a new perspective on the impact of geospatial factors (Conley and Ligon, 2002). In addition, many other previously less-discussed variables have been incorporated into the econometric analysis, such as financial development (Mahdi Ziaei, 2015; Zhang, 2011), urbanization (Ding and Li, 2017; Xu and Lin, 2015), climate change (Cai et al., 2017; Hao et al., 2016), the relationship between CO_2 and other pollutants (X. Li et al., 2015), land use and distribution (Zhang and Xu, 2017; Zhou et al., 2015). Moreover, due to the versatility of econometrics, it is relatively straightforward to find the data required to answer the research question of interest.

The disadvantages of econometrics can be categorized according to the analysis procedure undertaken. In the data gathering phase, it is sometimes difficult to observe some variables, such as financial development and proxy data is often chosen, such as the amount of foreign direct investment (FDI). This may result in concerns about validity and reliability. In addition, owing to the complexity of this type of analysis, it is challenging to choose the most appropriate method and conduct the right statistical tests. Even when the same data is used for analysis, the magnitude of an effect can vary depending on the method and the variables used. For example, Hang and Tu (2007) found that energy prices had a significant impact on energy efficiency in China, while Zhao et al. (2014) reached the opposite conclusion. In some cases, it can be difficult to explain why certain variables are significant, and it can be difficult to interpret the effects of different coefficients.

3.4 Carbon emission control efficiency evaluation

Measuring the efficiency of carbon emission control measures has been an active research topic in recent years. The aim is to improve productivity at levels ranging from the micro to the macro. The most common approach is data envelopment analysis (DEA). DEA models can be classified according to their reference technologies and efficiency measures (see Figure 2 for details). It investigates and compares the CO_2 emissions across regions and sectors and across time (Li and Lin, 2015; Meng et al., 2016). For regions in China, most studies focus on measuring the carbon emission efficiency of 28–30 provinces and regions. For sectors, DEA either investigates specific sectors, usually energy intensive sectors, or adopts a comprehensive perspective which includes all the main sectors. The research spans the period from 1992 to 2012, especially the 2000–2010 period (Zhou et al., 2008).

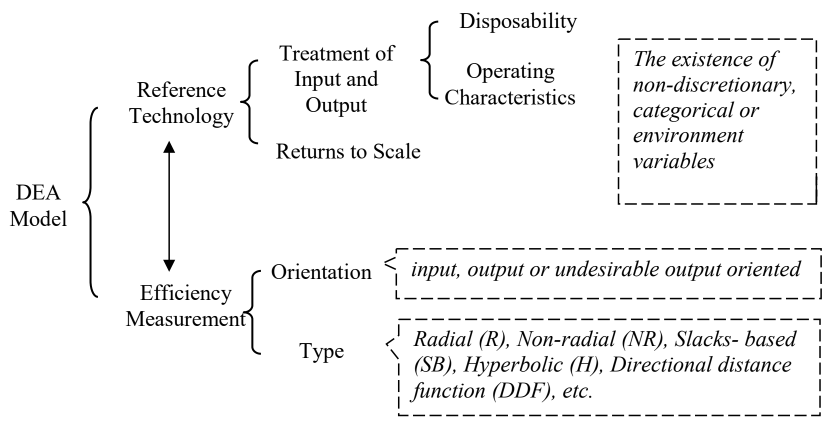


Figure 2 The general structure of a DEA model adapted from (Zhou et al., 2008)

DEA is a non-parametric method and does not assume the production 'technology' function determining the relationship between inputs and outputs of each decision-making unit (DMU) (Seiford and Thrall, 1990; Zhou et al., 2008). Instead, it takes each DMU as a whole, without considering the details internal production procedures (Kao, 2014). The method therefore allows hidden relationships to be uncovered.

In regard to disadvantages, the model selection and choice of variables can affect the results dramatically. Meng et al. (2016) reviewed 18 studies using DEA to estimate carbon emission efficiency in China from 2006 to 2015. The analysis showed that there are five main model types and several variable schemes available. Meng et al. found substantial differences in the outputs due to different choices of models and variables. In addition, due to the unspecific production function, the end result of DEA is an efficiency index rather than an estimate of carbon emissions. When the scope of the research changes, the efficiency values also change.

3.5 Simulation and other methods

Commented [SK1]: Optimisation and techno economic are not simulation models

In the context of CSCE, simulation is usually employed to predict carbon emission trends when policies, technologies, or other influential factors change. This paper identifies the following simulation methods: computable general equilibrium models (CGEs), integrated assessment models (IAMs), system dynamics (SD), agent-based modeling (ABM), optimization and multi-criteria optimization, and techno-economic models. These methods are adopted worldwide to address carbon emission abatement problems.

3.5.1 Computable general equilibrium models and integrated assessment models

Computer general equilibrium models (CGEs) and integrated assessment models (IAMs) come from the same family of economic optimization models. They use real data and rely on a series of equations that are either empirically or theoretically derived to determine projections from the present state to some future equilibrium state where the system has been optimized. While CGE models describe the sectoral interrelationships of the whole economy with a focus on cost optimization, IAMs are more integrated and include not only socio-economic activities, but also the physical relationships that drive climate change (Parson, 1995). CGEs and IAMs are frequently used to predict how carbon emissions and economies will react to emissions trading schemes (Babatunde et al., 2017; W. Li et al., 2017; Wang et al., 2015), carbon taxes (Guo et al., 2014; Tang et al., 2017), low-carbon policies (Cheng et al., 2016; Kishimoto et al., 2014), technology diffusion (Hübler, 2011) and energy consumption (Chi et al., 2014), in order to find the 'optimal' option.

The primary advantage of IAMs and CGEs is their ability to incorporate the complex relationships between the world economy and environmental policy to tackle climate change mitigation problems. When the effect of a specific policy is evaluated, the effects of 'exogenous' variables on economic, social and environmental systems can also considered (Cantore, 2009). By providing simulation results based on different scenarios, the consequences of policy choices are presented in a clear and easy to understand way.

A key output of IAMs and CGE models is forecasts of model variables under very specific conditions and assumptions. These models are often criticized for their unrealistic assumptions, such as homogenous products or services and full employment of labor (Böhringer and Löschel, 2006). Different models may therefore give contrasting simulation results, due to different modeling assumptions. In addition, for IAMs, because the physical mechanisms underlying climate change are complex and partly unknown, it is difficult to set convincing parameter values with a sound theoretical or empirical foundation (Pindyck, 2013).

3.5.2 System dynamic models

While CGE and IAM produce scenario analysis results as snapshots, system dynamics (SD) models reflect the dynamic evolution of systems. SD models take several simulations over a given period of time (Anand et al., 2005). The dynamic of system consists of two components: a causal loop diagram and a flow diagram. The causal loop diagram is developed by incorporating various subsystems, such as socio-economic factors, energy consumption, technologies (Anand et al., 2006), and other factors associated with industries which produce CO_2 emissions. They reveal the interactive and reinforced causality relationships among the subsystems and influential factors. Research into the factors driving carbon emissions focus mainly on energy consumption (Feng et al., 2013), population and economic growth (Al-Mulali et al., 2013; Du et al., 2018), energy and economic structure upgrades (Mao et al., 2013; Zheng and Luo, 2013), technological progress (Lai et al., 2017; Liu, 2015), and policies (Xiao et al., 2016). Based on the causal loop diagram, a flow diagram is created to demonstrate the measurable elements in each subsystem and the intricacies of the interacting processes.

One advantage of SD models is their capacity to explicitly model dynamic feedbacks. The two-way relationships among the driving factors in subsystems provide a holistic cause-and-effect interpretation of the evolving trend of sector carbon emissions and their changes under different polices and social and economic conditions. Another advantage is that system dynamics models are easy to use for policy analysis. Researchers can directly identify the direction and magnitude of carbon emission changes due to policy changes from causal and flow diagrams. However, the evolution ability of SD models depends on the variations in the values used in feedback loops and equations. Once the input values of all parameters and constants are fixed, the feedback mechanism itself cannot change. This creates difficulties in the interpretation of research results. For example, the marginal impact of a technology upgrade on carbon emissions will fluctuate in response to changes in market competition or governmental subsidies, but, such impacts are usually modeled as fixed auxiliary variables. This leads to biased estimates when simulations of more than ten years are conducted.

3.5.3 Agent-based models

IAM, CGE, and SD models estimate carbon emissions and identify the factors driving them from a macroscopic perspective by dealing with aggregated variables and parameters. Agent-based models (ABMs), on the other hand, focus on the dynamic behavior at the individual or "agent" level. In agent-based models, final aggregate carbon emissions emerge as a result of the dynamic interactions of those agents. These interactions are considered to occur at each simulation step according to predefined decision-making rules. In the context of sector carbon emissions, agent-based models are most frequently used in research about strategy and mechanism design for carbon emissions trading. The main purpose is to understand how carbon emissions at an aggregate level change from the bottom up.

Agent-based models are defined using two main components: (1) the selection of agents, and (2) the interactions between agents which lead to emergent outcomes. Firms, industries and governments, as carbon trading scheme participants, are the most common agents chosen (Jiang et al., 2016; L. Tang et al., 2015). Firms and industries usually aim at profit maximization. Governments, on the other hand, set carbon prices, allocate emissions quotas and ensure fair trade by imposing penalties and subsidies. From these interactions between these agents, researchers can examine how total carbon emissions emerge from micro-level behavior.

The main advantage of agent-based models lies in their ability to capture dynamic decision-making process which involve adaptive and evolutionary learning. This provides a more realistic representation of the behaviors of bounded rational firms and governments, because the preferences and strategies underpinning their decision-making can change when new information is obtained. Another advantage is that no prior knowledge about the macro interdependencies and dynamics is required. However, the interactions in agent-based models sometimes cannot always be easily articulated to reflect reality (Bonabeau, 2002). Moreover, the granular information fed into the model implies that if the number of parameters involved is large, this may introduce sensitivities to the emergent outcomes at an aggregated level (Filatova et al., 2013). This calls for vigorous validation with respect to the soundness of model construction.

3.5.4 Optimization and multi-criteria optimization models

Optimization is defined as finding universal solutions of a function that minimizes or maximizes its value while being subjected to constraints (Banos et al., 2011). Optimization can be categorized as being either single- or multiple objective problems. The latter is sometimes called a multi-criteria optimization model, which more likely deals with several conflicting objectives (Odu and Charles-Owaba, 2013). When it comes to sectoral carbon emissions, optimization models are most frequently used to formulate carbon mitigation policies (Chang et al., 2017; C. Wang et al., 2014; Zhang et al., 2013), design carbon trading systems, compare different taxing strategies (Wei et al., 2014; Zhou et al., 2013), upgrade and optimize industrial infrastructure (Chang, 2015; Chen et al., 2016; L. Li et al., 2015), and analyze the mechanisms of inter-regional carbon emissions transfer (Guo et al., 2016; Sun et al., 2017; Tan et al., 2013).

The optimization or multi-criteria optimization models require the specification of objective functions and constraints to which the objective function is being subjected. Minimizing the total production costs, minimizing carbon emissions, and maximizing economic growth are the most frequent but conflicted objectives (Chang, 2015). In addition, several other constraints, such as: meeting energy demand; reaching energy and emission control targets; energy resource availability; and manufacturing and construction budgets are also identified as constraints across different research themes. For example, to find the best carbon mitigation policy, Zhang et al. (2012) take three distinct carbon tax policies as constrains for scenario analysis.

Optimization or multi-criteria optimization models rely on the capacity to provide an optimal pathway to achieve carbon emission targets under different sets of assumptions about technologies, the economy, and energy systems. However, the establishment of the optimization system requires detailed prior information on the functions and parameters which are used. In addition, it is sometimes not feasible to find a solution for the optimization function.

3.5.5 Techno-economic model

Rather than estimate sectoral carbon emissions directly, techno-economic models use a decision-making process to compare available technological options, especially for CO_2 reduction and carbon capture technologies (Cau et al., 2018; Cormos and Cormos, 2017; Klemeš et al., 2007). Techno-economic models approach research problems from both a technical and an economic perspective. From the technical perspective, productivity performance is assessed with reference to different configurations with and without applying new CO_2 reduction and capture technologies under predefined operational parameters (Pettinau et al., 2017). The technical assessment aims to evaluate the extent to which the new technologies improve productivity or reduce energy consumption. From an economic perspective, potential benefits and costs, including investment, operation and maintenance, are quantified for the life of the technology (Huang et al., 2010). Techno-economic models employ sensitivity analysis of the key factors included in the model, such as fuel costs, technological growth and environmental impacts, to provide uncertainty bounds on the final estimation. The economic assessment aims to ensure that profits can be achieved.

For estimating sector carbon emissions, the primary advantage of techno-economic models is that assessing new technologies from two independent perspectives enables researchers to evaluate their benefits in a more practical and objective manner. However, the full implementation of a techno-economic model is a major undertaking. Significant effort is required to evaluate existing and future technical options, and to work out meaningful parameters. Moreover, techno-economic models rely on the synthesis of technological and economic expertise, which is usually very challenging for researchers.

4. Bibliometric analysis

As indicated in Figure 3, since China overtook the USA as the largest carbon emitter in 2007, CSCE research has attracted increasing attention. Over the last six years, the annual number of CSCE publications has increased from 14 in 2010 to 230 in 2016, with an average annual growth rate of 63%. The annual number of citations has also increased markedly, growing from 97 in 2010 to 2,716 in 2016, equating to an average annual growth rate of 47%. Though the number in 2017 only covers seven months of the year, the increasing trend for both publications and citations is evident. This compares with an estimated average annual growth rate of 8%–9% in global scientific output since the end of WWII, making CSCE research a very active area of research which is growing four times as fast (McKerlich et al., 2013).

CSCE research attracts scholars from a diverse range of disciplines. The number of published subject areas has increased from 2 in 1997 to 25 in 2017. While the disciplines of environmental science, energy, engineering and technology have dominated the CSCE field, research in economics, meteorology, atmospheric sciences, thermodynamics, water resources and public management has increased significantly. Initially, CSCE research was primarily conducted in science subjects, but it is increasingly being conducted in fields such as urban studies, government, law and international relations.

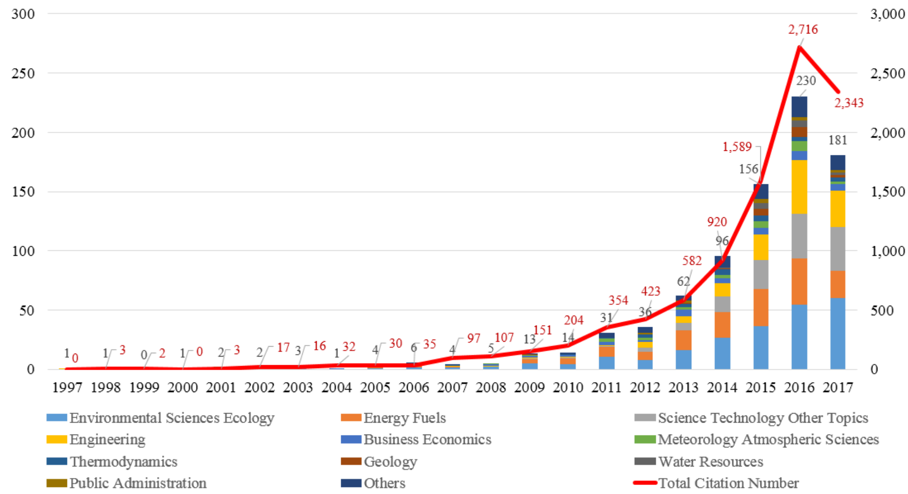


Figure 3 Publications and citations of papers published from 1 January 1997 to 20 July 2017

Notes:

1. The data for 2017 only covers the first 7 months of the year.

2. Because one paper can belong to more than one subject area, the stacked column shows the relative proportion for each subject. It does not indicate the publication or citation number for each subject.

Table 2 indicates that IOA, IDA and econometrics are the three main methods adopted in the CSCE field. Around 50% of CSCE papers cite at least one of these three methods

Method		WoS search results	Percentage
Environmentally-extended input-output analysis		182	22.55%
Index decomposition analysis		121	14.99%
Econometrics		135	16.73%
Data envelopment analysis		35	4.34%
Simulation and other methods	Computable general equilibrium	38	4.71%
	Integrated assessment	10	1.24%
	System dynamics	6	0.74%
	Agent-based	3	0.37%
	Optimization	6	0.74%
	Multi-criteria	1	0.12%
	Techno-economic	1	0.12%

Table 2 Percentages of published CSCE journal papers using each method

Note: More than one method may be used in the same CSCE paper.

Figure 4 (publications) and Figure 5 (citations) show the increasing use of the main methods applied in the CSCE field. Between 2010 and 2016, the number of publications grew at an average annual rate of 85%, with the number of citations growing at an average annual rate of 68%. For 2017, only papers that were published before 20th July were included in the analysis. However, the trend is still evident. In addition, while IOA, IDA and Econometrics are still the dominant methods in this research field, DEA, IAM and CGE methods have become increasingly popular, taking up a larger share of the total percentage.

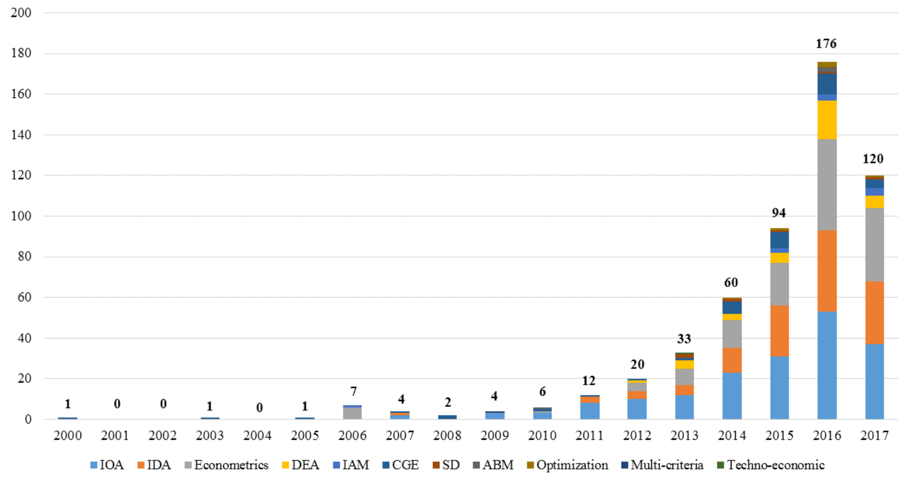


Figure 4 Publication per method from 1997 to 2017

Note: The stacked columns show the relative proportion of each family of methods in each year.

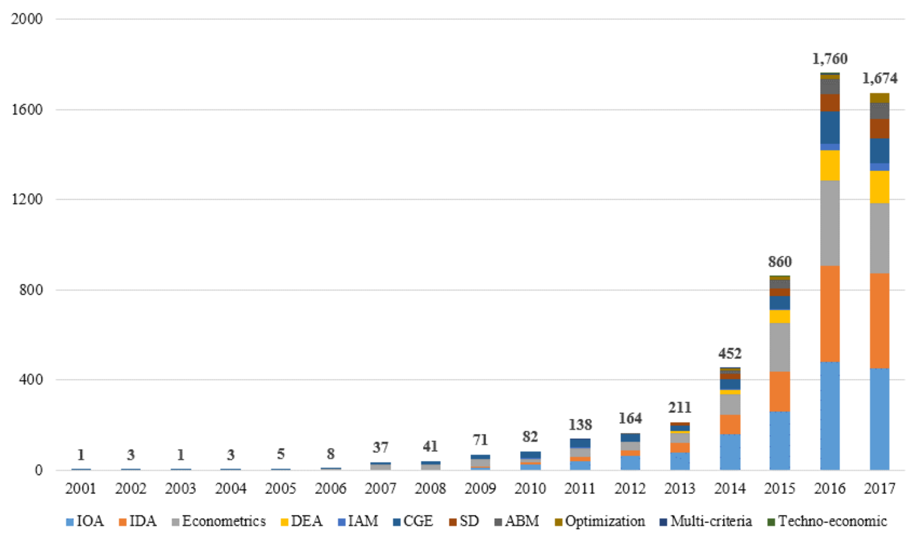


Figure 5 Citation per method from 1997 to 2017

Note: The stacked columns show the relative proportion of each family of methods in each year.

5. Knowledge mapping through CiteSpace

Figure 6 presents a landscape view of the CSCE field, generated by CiteSpace. It is based on 807 papers and 24,744 citations between 2001 and 2017. The top 50 most-cited publications in each year are used to construct a network of citations for that year. Each individual network is then synthesized so that each node on the map represents a cited paper, and the node size represents the number of citations for that paper. If two papers are both cited in a third paper, there is considered to be a link connecting the two cited papers. The assumption is that if two papers are cited together, the two references are associated in some ways (Chen et al., 2012). The nodes with red tree-rings are references with “citation bursts”, which indicate dramatic increases in their citations over one year or multiple years. These bursts were detected using Kleinberg's (2003) algorithm. The colour of the cluster areas indicates the time when co-citation links in one area of research appeared for the first time (Chen, 2017). Areas in green were generated earlier than areas in yellow.

We used CiteSpace to cluster references that are commonly cited in CSCE research. Each cluster corresponds to an underlying research speciality. The co-citation network was found to have a high modularity Q of 0.7799. Modularity Q measures the extent to which a network can be grouped into clusters with distinct boundaries (Chen et al., 2010; Martin III, 2012). The high modularity Q suggests that the specialties of the CSCE network are clearly defined in terms of co-citation clusters.

While the cited papers in the reference provide the knowledge base, citing papers present the frontier of certain subjects. In other words, the paper which cites the papers in a cluster reveals the latest research topic of the underlying research speciality. The clusters were labelled using terms in the titles of citing papers and a log-likelihood ration (LLR) weighting algorithm (Chaomei Chen et al., 2010). LLR algorithms are used to create labels for clusters by identifying the core concepts in the cluster using keywords and phrases from the titles of papers. In order to better reveal the focus of each cluster, we have adjusted the labels according to the titles and abstracts of the citing papers as shown in Figure 6.

In Figure 6, it can be seen that Cluster 4 is distinct from the other clusters. Cluster 4 concentrates on organic and black carbon emissions, while all other clusters focus on carbon dioxide emissions, which comprise 81% of greenhouse gas emissions (United States Environmental Protection Agency, 2018). Organic and black carbon emissions are components of particulate matter, produced by the incomplete combustion of carbonaceous fuels (Chow et al., 2012). They have a different effect on the climate and they are studied using different research methods. In addition, Clusters 9 and 10 are less connected with other clusters due to their distinct research interests. The rest of the clusters are closely connected, with some areas of overlap.

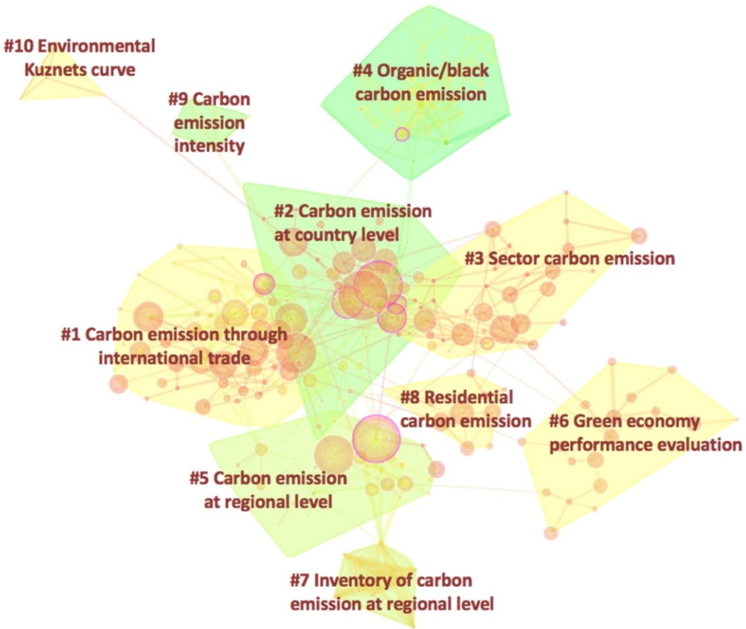


Figure 6 A landscape view of the co-citation network from 1997 to 2017

In Table 3, a 'silhouette score' is calculated for each cluster to measure the quality of a cluster as indicated by its homogeneity and consistency (Chen et al., 2010; Rousseeuw, 1987). The closer the silhouette score is to 1.0, the more homogeneous the cluster is thought to be. As indicated in Table 3, the silhouette scores for most of the largest ten clusters are above 0.78. These high scores suggest that the content of each paper is well matched to its own cluster, and poorly matched to neighbouring clusters. In addition, the Mean (Cite Year) column in Table 3 is the average year of publication within a single cluster, indicating whether a cluster generally comprises old or recent papers (Chen, 2014). It can be seen that Clusters 2, 4 and 9 are relatively old clusters that contain papers with an average year of publication of 2007 or 2008. Clusters 3, 6, 8 and 10 are relatively new clusters that contain papers with an average year of publication of 2012 or later.

Cluster ID	Size	Silhouette score	Cluster Label	Mean (Cite Year)
1	54	0.883	Carbon emissions through international trade	2010
2	44	0.775	Carbon emissions at country level	2008
3	36	0.788	Sector carbon emission	2012
4	35	0.988	Organic/black carbon emission	2007
5	31	0.807	Carbon emissions at regional level	2009
6	20	0.933	Green economy performance evaluation	2012
7	14	0.983	Inventory of carbon emission at regional level	2009
8	10	0.963	Residential carbon emissions	2012
9	5	0.994	Carbon emission intensity	2008
10	4	0.977	Environmental Kuznets curve	2014

Table 3 Summary of the largest 10 clusters

Size: The number of reference that a cluster contains

Figure 7 presents the timeline of co-citation clusters. The clusters are arranged according to size. The clusters, “carbon emissions through international trade”, “carbon emissions at country level” and “sector carbon emissions”, are the most active clusters, and they have been active for more than 10 years. In addition, there have been continuous breakthrough achievements in these clusters. This can be seen from the large nodes in red indicating ‘bursts in citations’. The clusters, “carbon emissions at regional level”, “green economy performance evaluation” and “residential carbon emission” were formed later, but are now active clusters.

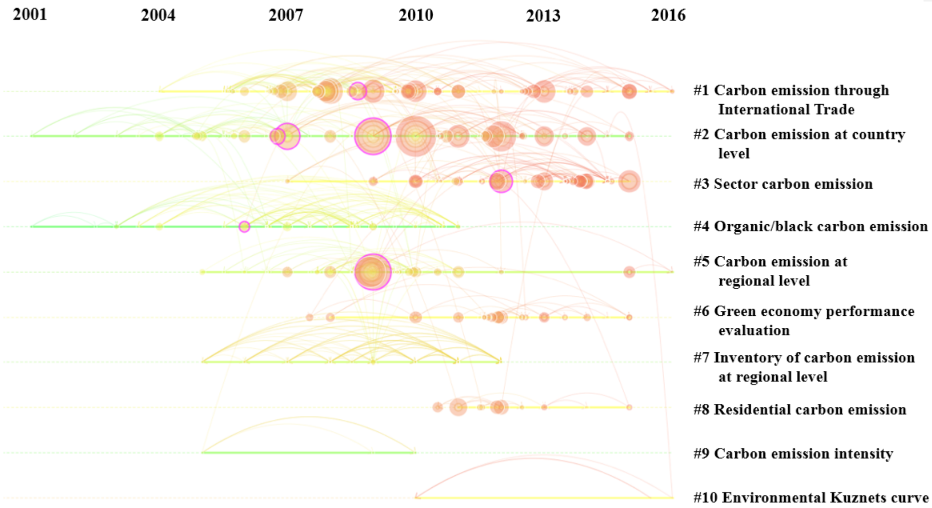


Figure 7. The timeline of co-citation clusters from 1997 to 2017

In Table 4 below, the main methods adopted in each cluster are identified by manually reviewing the top 20 citing papers in each cluster. Co-citation analysis has been criticized for not being able to identify whether a citation gives supportive arguments or offers a critique (Cheng, 2016; Kunz and Hogreve, 2011). Through a manual review, the potential bias of co-citation analysis is minimized. Each cluster is reviewed to confirm the research focus and identify the main analysis methods used, creating a more precise presentation of CSCE field.

The clusters are arranged in order according to the average year of publication of the cluster. The three clusters 'carbon emissions at country level', 'organic/black carbon emissions' and 'carbon emissions intensity' are the earliest clusters, with average publication years of 2007 and 2008 respectively. The initial research interest was in carbon emissions at the country level. A bottom-up inventory method was adopted to produce the direct carbon emissions inventory, and there have been many efforts to improve its accuracy. In addition, the effect of the main influencing factors, especially carbon emissions intensity, on national carbon emissions, has attracted significant interest. IOA, IDA and econometrics were all used for the impact analysis. Some comparative analysis was also conducted to compare the different impact factors across countries and across regions in China. Based on the inventory and impact factors research, some simulation models, such as the environmental learning curve (ELC) model, were developed to predict trends in carbon emission activities.

The research focus moved to the regional level around 2009 due to concerns about the large size and imbalanced development of the Chinese economy. The ‘Inventory of carbon emissions at regional level’ cluster and the ‘Carbon emissions at regional level’ cluster focus on this topic. Similar methods were used to construct emissions inventories, analyse impact factors and predict future trends. In addition, this area of research also looks at carbon footprints across different regions and the spatial distribution of carbon emissions using life-cycle and spatial analysis. For the emissions inventory, analysis went beyond direct emissions to create an embodied carbon emissions inventory based on input-output tables. The examination of linkages between different regions has grown in popularity.

Research on embodied carbon emissions due to international trade has emerged as an important area of study which is clarifying the role that China should play in mitigating global carbon emissions. Although China has been the largest carbon emissions country since 2007, as a world factory, much of these carbon emissions are induced by demand from other countries. While input-output databases serve to construct embodied carbon emissions, IOA and IDA techniques and models are frequently used to analyse the relevant impact factors.

Research interest was gradually drawn to the sector level around 2012. Although embodied emissions inventory construction and impact analysis are still at the core of sector-level research, much of the discussion has shifted to providing policy suggestion for curbing future emissions. Policies discussed have included establishing a carbon tax and constructing an emissions trading scheme (ETS). CGE models are frequently used to forecast the impact of these policies in different contexts.

The green economy performance evaluation cluster is distinct in terms of its research content and methods. The main aim of studies in this cluster is to assess the performance and efficiency of the carbon emission control policies of regions, industries or countries. DEA, Malmquist index analysis, directional distance function or their hybrids are usually used to assess efficiency levels and to measure green total factor productivity. In addition, econometrics are used to analyse the impacts of particular factors on carbon emission efficiency.

A growing area of research is attempting to model residential carbon emissions, due to the constantly increasing amounts of emissions produced by residents. In this line of research, two new research topics are being used. One draws on the behaviour of residents using survey methods and the other uses network analysis models to examine urban carbon emissions. The reason for this growing interest in residential emissions is that the control of emissions is more complete when the residential sector is considered. Network analysis could provide a new perspective for considering both the linkages between industries and final demand using a residential model.

The most recent research cluster focuses on analysing the factors impacting carbon emissions by investigating the existence of environmental Kuznets curves.[2] This is a relatively small cluster, formed around 2014. The research content itself is not new, but the cluster provides a new perspective based on the use of the Kuznets curve.

[2] The environmental Kuznets curve (EKC) proposes an inverted-U relationship between pollution and economic development (Grossman and Krueger., 1995). In other words, pollution increases with economic development to a certain income level, and after that it declines.

Table 4 Methods used by the top 20 citing papers for each cluster

Cluster ID	**Adjusted label**	**Mean (Year)**	**Research focus**	**Main Method** **IOA**	**IDA**	**Econometrics**	**Simulation**	**Efficiency**	**Others**
1	Carbon emission through international trade	2010	1) Inventory of embodied carbon emissions through international trade at industry, region and country level 2) Analysis of impact factors on the embodied carbon emissions through international trade	✓ IOA/SDA: construct the embodied inventory; analyse impact factors	✓ analyse impact factors on embodied carbon emission through international trade				1) Hybrid between SDA and IDA: to clarify the effect of impact factors on embodied carbon emissions through international trade
2	Carbon emissions at country level	2008	1) National carbon emissions inventory and accuracy improvement 2) Analysis of impact factc on carbon emissions in China at regi and industry lev 3) Comparative analysis factors impacting carb emissions acro countries/regions in China 4) Prediction for futu scenarios	✓ IOA/SDA: analyse the impact factors on carbon emission	✓ IDA / LMDI: analyse the impact factors on domestic carbon emission	✓ Econometrics/ STIRPA: analyse the impact factors on domestic carbon emission	✓ Environ-mental learning curve (ELC) model: predict carbon intensity reduction potentials		1) Bottom-up inventory: to construct direct emissions inventory at country level using official statistical data, latest emission factor, collected activity data and emissions sources 2) Path analysis model: to analyse the impact factors on domestic carbon emission 3) Comparative analysis: to compare the different emission amounts and impact factors in different regions 4) Use Individual sector prices indices used instead of one general GDP deflator for improvement in decomposition analysis

Cluster ID	Adjusted label	Mean (Year)	Research focus	Main Method					
				IOA	IDA	Econometrics	Simulation	Efficiency	Others
3	Sector carbon emission	2012	1) Inventory of each industry's carbon emissions 2) Analysis of impact factors on each industry's carbon emissions 3) Development of emissions trading scheme (ETS), including the allocation of carbon emissions among industries, the impact of ETS on certain industries	✓ construct the emissions inventory of industries	✓ IDA / LMDI: analyse the impact factors on each industry's carbon emission		✓ CGE/IAM/ Optimization /System Dynamic/ ABM To provide policy suggestion for ETS design, carbon tax and examine its impact		1) Literature review: to provide policy suggestion for ETS design
4	Organic/ black carbon emission	2007	1) Emissions inventory of black carbon emissions at city, region and country levels 2) Prediction of black emission amounts				✓ Monto Carlo simulation model, global chemical transport model, MOZART-4 model		1) Bottom-up inventory: To construct emissions inventory of black/organic carbon using official statistical data, latest emission factor, collected activity data such as vehicle activity data, and major emission sources in cities

Cluster ID	Adjusted label	Mean (Year)	Research focus	Main Method					
				IOA	IDA	Econometrics	Simulation	Efficiency	Others
5	Carbon emission at regional level	2009	1) Carbon footprint through different industrial spaces 2) Impact factor analysis at city level 3) Spatial analysis 4) Prediction for future scenarios of low-carbon cities		✓ IDA / LMDI: analyse the impact factors on regional carbon emission	✓ analyse the impact factors on regional carbon emission	✓ Long-Range Energy Alternatives Planning model and others: predict future scenarios of cities		1) Life-cycle model: to simulate the carbon emissions, amount of fossil energy and rural biomass energy of different regions of China 2) Spatial analysis: to analyse the spatial distribution of carbon emissions
6	Green economy performance evaluation	2012	1) Assessment of carbon emissions performance at industry, city, province and country levels 2) Measure China's green total factor productivity (TFP) growth 3) Analysis of impact factors on carbon emission levels in different stages and regions			✓ Econometrics/ STIRPAT/SEM: analyse impact factors on carbon emission efficiency in different regions/ development stages		✓ DEA/ Malmquist index/ DDF: compare carbon emission performance of industries or regions	1) Hybrid among DEA, Malmquist index and DDF: to estimate the changes in carbon emission performance as well as their driving forces at industry and whole economy level, such as the meta-frontier non-radial Malmquist CO2 emissions performance index model
7	Inventory of carbon emissions at regional level	2009	1) Carbon emissions inventory of cities	✓ construct the embodied inventory at city level					1) Bottom-up inventory: to construct direct emissions inventory at city level using official statistical data, latest emission factor, collected activity data and emission sources

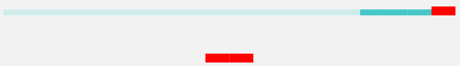
Cluster ID	Adjusted label	Mean (Year)	Research focus	Main Method: IOA	IDA	Econometrics	Simulation	Efficiency	Others
8	Residential carbon emission	2012	1) Emissions inventory of the residents 2) Analysis of impact factors on the carbon emissions of the residents 3) Prediction for future scenarios of residential carbon emission 4) Analysis of residential carbon emission behaviour 5) Mitigating urban carbon emissions through network perspective	✓ construct the embodied inventory of residents		✓ Econometrics/ STIRPAT: analyse impact factors on the carbon emissions of residents	✓ AIM (Asia-Pacific Integrated Model)/End use model/others: predict future scenarios of residential carbon emission		1) Bottom-up inventory: to construct direct emissions inventory of residents using official statistical data, latest emissions factor, collected activity data and emission sources 2) Divisia index decomposition method: to analyse impact factors on the carbon emissions of residents 3) Survey study: to investigates the energy consumption behaviours of households 4) Network analysis: to mitigate carbon emissions in a holistic way
9	Carbon emissions intensity	2008	1) Analysis of impact factors on carbon emission intensity change		✓ IDA / LMDI				
10	Environmental Kuznets curve	2014	1) Analysis of factors impacting carbon emissions through investigation of the existence of an environmental Kuznets curve			✓ Econometrics/ STIRPAT/GMM: analyse impact factors on the carbon emissions from various angles			

Important milestone papers in the development of CSCE research can be identified from the list of references with citation bursts (Table 5) and they reflect the dynamics of the field. A citation burst means that the reference it is associated with has received a sharp increase in the number of citations over a year or multiple years. The detection of citation bursts in CiteSpace is based on Kleinber's algorithm (Kleinberg, 2003). The size of the increase in citations is indicated by the strength of the citation burst, which takes account of both the number of citations and the length of the period over which the citations occur. From 1997 to 2017, there were 37 reference papers with citation bursts in CSCE research. Table 4 lists the 10 references with the largest citation burst strength values. The table is arranged according to the strength of the citation bursts. The colour along the timeline from 1997 to 2017 indicates the number of citations the paper received. The stronger the colour, the greater the number of citations. The red part represents the period when the citation burst happened.

As can be seen from the method column, four out of five families of methods have been adopted as the main methods by the top 10 papers. The earliest two bursts, which started in 2009 and ended in 2012, focused on decomposing carbon emission changes at the national level with IDA (Ang, 2004) and particularly with LMDI (Wang et al., 2005). Subsequently, two other bursts from 2014 to 2015 addressed consumption-based national emissions inventory construction with input-output databases and the analysis of the forces driving carbon emissions using SDA (Peters et al., 2007). From 2015 to 2017, researchers focused on: decomposing carbon emissions changes in the cement and transportation industries using LMDI (Wang et al., 2011; Xu et al., 2012); constructing residential carbon emissions inventories and analysing impact factors with IOA (Zhu et al., 2012); examining total factor carbon emissions performance with DEA (Zhu et al., 2012) and Malmquist index analysis

(Zhou et al., 2010); and predicting the impact of household consumption patterns on carbon emissions with CGE (Dai et al., 2012).

Table 5 Top 10 papers with the strongest citation bursts

Strength of burst	Start of burst	End of burst	1997 - 2017	Pub. Year	Author	Title	Journal	Method	Times cited
7.1695	2015	2017		2012	Xu J., Fleiter T., Eichhammer W., and Fan Y.	Energy consumption and CO2 emissions in China's cement industry: A perspective from LMDI decomposition analysis	Energy Policy	IDA/ LMDI	83
5.8507	2009	2012		2004	Ang B.W.	Decomposition analysis for policymaking in energy: which is the preferred method?	Energy Policy	IDA	543
5.6039	2014	2015		2008	Peter G.P.	From production-based to consumption-based national	Ecological Economics	IOA	327

Strength of burst	Start of burst	End of burst	1997 - 2017	Pub. Year	Author	Title	Journal	Method	Times cited
						emission inventories			
5.4458	2015	2017		2012	Zhu Q., Peng X., and Wu K.	Calculation and decomposition of indirect carbon emissions from residential consumption in China based on the input–output model	Energy Policy	IOA	38
4.9897	2009	2012		2005	Wang C., Chen J., and Zou J.	Decomposition of energy-related CO_2 emission in China: 1957–2000	Energy Policy	IDA/LMDI	222
4.8829	2014	2015		2007	Peters G. P., Weber C., Guan D., and	China's Growing CO_2 Emissions -	Environmental Science and Technology	IOA/SDA	263

Strength of burst	Start of burst	End of burst	1997 - 2017	Pub. Year	Author	Title	Journal	Method	Times cited
					Hubacek K.	A Race between Increasing Consumption and Efficiency Gains			
4.7592	2015	2017		2012	Wang Z., Zeng H., Wei Y. and Zhang Y.	Regional total factor energy efficiency: An empirical analysis of industrial sector in China	Applied Energy	DEA	194
4.7592	2015	2017		2012	Dai H., Masui T., Matsuoka Y., and Fujimori S.	The impacts of China's household consumption expenditure patterns on energy demand and carbon emissions towards 2050	Energy Policy	CGE	41

Strength of burst	Start of burst	End of burst	1997 - 2017	Pub. Year	Author	Title	Journal	Method	Times cited
4.6897	2015	2017		2011	Wang W. W., Zhang M., and Zhou M.	Using LMDI method to analyse transport sector CO2 emissions in China	Energy	IDA/LMDI	71
4.4166	2015	2017		2010	Zhou P., Ang B.W., and Han J.Y.	Total factor carbon emission performance: A Malmquist index analysis	Energy Economics	Malmquist index analysis	174
7.1695	2015	2017		2012	Xu J., Fleiter T., Eichhammer W., and Fan Y.	Energy consumption and CO2 emissions in China's cement industry: A perspective from LMDI	Energy Policy	IDA/ LMDI	83

Strength of burst	Start of burst	End of burst	1997 - 2017	Pub. Year	Author	Title	Journal	Method	Times cited
						decomposition analysis			
5.8507	2009	2012		2004	Ang B.W.	Decomposition analysis for policymaking in energy: which is the preferred method?	Energy Policy	IDA	543
5.6039	2014	2015		2008	Peter G.P.	From production-based to consumption-based national emission inventories	Ecological Economics	IOA	327
5.4458	2015	2017		2012	Zhu Q., Peng X., and Wu K.	Calculation and decomposition of indirect carbon emissions from residential consumption	Energy Policy	IOA	38

Strength of burst	Start of burst	End of burst	1997 - 2017	Pub. Year	Author	Title	Journal	Method	Times cited
						in China based on the input–output model			
4.9897	2009	2012		2005	Wang C., Chen J., and Zou J.	Decomposition of energy-related CO2 emission in China: 1957–2000	Energy Policy	IDA/LMDI	222
4.8829	2014	2015		2007	Peters G. P., Weber C., Guan D., and Hubacek K.	China's Growing CO2 Emissions - A Race between Increasing Consumption and Efficiency Gains	Environmental Science and Technology	IOA/SDA	263
4.7592	2015	2017		2012	Wang Z., Zeng H., Wei Y. and Zhang Y.	Regional total factor energy efficiency:	Applied Energy	DEA	194

Strength of burst	Start of burst	End of burst	1997 - 2017	Pub. Year	Author	Title	Journal	Method	Times cited
						An empirical analysis of industrial sector in China			
4.7592	2015	2017		2012	Dai H., Masui T., Matsuoka Y., and Fujimori S.	The impacts of China's household consumption expenditure patterns on energy demand and carbon emissions towards 2050	Energy Policy	CGE	41
4.6897	2015	2017		2011	Wang W. W., Zhang M., and Zhou M.	Using LMDI method to analyse transport sector CO2 emissions in China	Energy	IDA/LMDI	71
4.4166	2015	2017		2010	Zhou P., Ang B.W., and Han J.Y.	Total factor carbon emission performance:	Energy Economics	Malmquist index analysis	174

Strength of burst	Start of burst	End of burst	1997 - 2017	Pub. Year	Author	Title	Journal	Method	Times cited
						A Malmquist index analysis			

6. Discussion

6.1 Critique of methods

Methods cannot be discussed in isolation from the research questions they are used to address. As indicated in Table 3, different methods were adopted in different clusters. However, although the research was conducted from distinct perspectives ranging from the residential sector to international trade, there are three common topics: the emissions inventory, impact analysis, and predictions for carbon emission trends. The five families of methods are discussed below, in relation to these three common topics. In addition, there are special topics for some clusters, such as carbon trading schemes in the 'sector carbon emissions cluster'. The relevant methods shall also be discussed.

6.1.1 Carbon emissions inventory

For the carbon emissions inventory topic, the two main methods used are the bottom-up approach and input-output analysis. Emissions inventories have been constructed at the household, industry, city, province, country and international trade levels. The bottom-up approach is generally used for calculating direct carbon emissions, using official statistical data, the latest emission factors, collected activity data and information about major emissions sources. Input-output analysis, and more specifically the databases of MRIO, SRIO and MSIO, are used to calculate the embodied carbon emissions of industry sectors and regions. In addition, the IOA database is frequently used in conjunction with other methods, such as life-cycle assessment, computable general equilibrium, and network analysis. While the direct carbon emissions inventory can be updated on an annual basis, the embodied inventory is updated less frequently, due to the large data requirement. Inventory construction provides support to clarify the responsibilities of regions and countries for carbon emissions from both a production and a consumption perspective. Inventory construction could also be used to make decisions about how to allocate the initial quotas of certificates for an emissions trading scheme (ETS) in China, and how to share responsibilities for emissions reduction internationally.

In addition, it is important to note the large fluctuation in both production-based emissions (PBE) and consumption-based (CBE) emissions. Zhang et al. (2017) compared ten PBE and CBE results for 1995, 2000, 2002 and 2005. They found significant differences in the quantities of carbon emissions and the differences tended to increase over time. Such discrepancies may result from the different assumptions that are associated with the different methods being used. These methods include single-region input-output models, bi-regional input-output models, as well as multi-region input-output models and their integration with life-cycle assessment models (MRIO-LCA).

The different data sources on which these models are based also contribute to differences in results. For example, Guan et al.'s (2012) research on China concluded there was a gigatonne gap between the national carbon dioxide inventory and the summation of provincial inventory data between 1997 to 2010. More transparency is therefore urgently needed for data collection, processing and validation of statistical procedures. In addition, the data collected by statistical bureaus and agencies within China is only as reliable as the sources of the data, and these sources are susceptible to political pressure. Statistical agencies and bureaus are frequently pressured to conceal data to achieve a political goal, which further reduces the quality of the data being collected. However, with increasing awareness about data accuracy due to commentary by domestic and international critics, attempts have been made by the Chinese government and scholars to address the problem. For instance, research by Z. Liu et al. (2015) refined carbon emissions inventories with independently assessed activity data and two new sets of measured emission factors for Chinese coal based on 602 coal samples.

6.1.2 Impact analysis

In the process of impact analysis, the methods of input-output analysis, index decomposition analysis and econometrics all come into play. The main advantage of IOA techniques lies in the examination of system-wide effects, including the direct and indirect effects on the entire supply chain. However, in contrast to its wide application in emissions inventory construction, input-output analysis techniques were only used frequently in carbon emissions research at the country (Cluster 1) and international trade (Cluster 2) levels. Two lines of research are adopted for assessing the impacts of the factors which affect carbon emission levels. The first approach is based on the assumption that there is a stable technological structure. When the flow of outputs in any part of the system is altered, this changes the input requirements in all sectors in fixed proportions, leading to a multiplier effect across the economy (Su and Ang, 2014; Zhang et al., 2015). The second approach, known as structural decomposition analysis (SDA), relaxes the assumption of fixed technology coefficients and allows the sensitivity of changes to technical coefficients to be explored to assess their relative impacts (Tarancon and Del Río, 2012; J. Yan et al., 2017). Using SDA, it is possible to apply a disaggregated comparative statistical approach to both final demand and technological structure (Cellura et al., 2012; Su and Thomson, 2016).

Index decomposition analysis has been used extensively for impact analysis at various levels of carbon emissions, including at the industry, city, province, country and international trade levels. IDA produces deterministic results through an "ideal decomposition" with no residual term. With the development of several extensions of the LMDI method such as LMDI-I, the number of pre-defined factors is increased from five to eleven, and the application areas are expanded from specific industry sectors to economy-wide energy trends (Ang and Wang, 2015). In addition, various decomposition schemes have been proposed to satisfy a range of different macro-level variables, with corresponding formulas to carry out the decomposition (Ang, 2005; Su and Ang, 2012).

IDA is especially useful for examining the effects of changes in carbon emissions intensity on carbon emission levels. Moreover, in the international trade research cluster, IDA is used in conjunction with SDA methods, such as multiplicative SDA, to clarify the roles of different impact factors. The popularity of IDA comes mainly from its ideal decomposition and annually updated data resources. Because there is no residual term in the formula, it is easy to interpret results. However, while IDA works well at macro and meso levels of analysis, it is rare for attempts to be made to use IDA at micro levels, such as the firm and household levels.

Econometrics has increasingly been used in almost all the research clusters due to its versatility. Apart from impact factor analysis at the macro and meso levels, econometrics is also used for micro-level analysis, including at the firm and household levels. Moreover, for research evaluating green economy performance (cluster 6), econometrics is also used to investigate the driving forces behind changes to carbon emissions control efficiency. The

Kuznets curve cluster, focusing primarily on research that analyses the Kuznets curve, also takes economics as its main method.

An important development in using econometrics in CSCE is to take the regional spillover effect and the heterogeneity of provinces into consideration. It is particularly evident in the research about carbon emissions at the country level (cluster 2) and regional level (cluster 5). The spatial autoregressive model (Zhang and Xu, 2017), spatial lag model (Chuai et al., 2012), and exploratory spatial data analysis (Chuai et al., 2012) are usually the starting points for this approach. Those models assume the carbon emissions in one place manifest an increased likelihood of emissions in neighboring places. They capture the spillover effect by adding the spatial lag of the dependent variable, namely carbon emissions. In addition, considering that the determinants of carbon emissions such as population, income and technology are also directly affected by neighboring places, The Spatial Durbin Panel Data Model (Liu et al., 2016; Y. Liu et al., 2014) was adopted to add the spatial autocorrelation coefficients of the explanatory variables. This kind of random coefficient geographically weighted regression model effectively captures both nonstationary and spatial heterogeneities by relaxing the assumption of global estimators of invariant parameters (Brunsdon et al., 1996). However, it is applicable only when high-solution and balanced data is available. The spatial correlation effect is statistically significant across all research, which indicates a remarkable spillover effect existing in China's sectoral carbon emissions processes.

In addition, the provincial heterogeneity is also considered for impact factor analysis in recent studies. Given China has a vast territory with significant provincial differences in resources distribution and economic growth, the relationships between socioeconomic variables and carbon emissions is nonlinear, and this may result in a biased estimation (Lin and Wang, 2015). Quantile regression was attempted to solve the problem and this line of research demonstrated that the effects of explanatory variables are not constant across the spectrum of the dependent variable (carbon emission). For example, Lin and Benjamin (2017) found that urbanization was only significant at the tail ends (10^{th} percentile and 90^{th} percentile respectively) of the carbon emissions distribution while the gross domestic product, energy intensity, carbon intensity was statistically significant across the entire spectrum of carbon emissions. However, for the factors exerting consistent impacts across all the carbon emission groups, the magnitude of effects would be biased at the tail ends. This calls for better understanding for how the effects of explanatory variables are different across the distribution.

6.1.3 Predictions for carbon emission trends

The prediction of carbon emissions is active in national carbon emissions research (Cluster 2), sectoral carbon emissions research (cluster 3), regional carbon emissions research level (Cluster 5), and residential carbon emissions research (Cluster 8). Apart from the prediction methods reviewed in part 3.5 simulation, more models and techniques within IOA, IDA and econometrics, which are not traditionally used for predictions, have been developed for forecasting. Take the increasingly used time-series econometrics models for example. They focus more on the simulation or prediction of carbon emissions under different scenarios, including GM (1,1) grey model (Tang et al., 2016), autoregressive integrated moving average model (ARIMA) (L. Liu et al., 2014) and the vector-error correction model (Zheng and Luo, 2013). Although time series models are helpful for understanding the long-term trend of sectoral carbon emissions, historical data lasting more than two decades are required to obtain a robust estimation. Data availability is another challenge in this group of study. In addition, in consistent with the impact analysis research, IOA, IDA and econometrics usually predict carbon emissions under the impact of final demand, population, economic growth, technology progress, energy consumption, industrial structural change.

The influence of ETS, carbon tax and other low-carbon policies on future carbon emissions have attracted much attention. CGE, IAM, SD and ABS are mainly adopted to evaluate these initiatives based on forecast analysis. CGE, IAM and SD take a top-down approach. While CGE and IAM focus on scenario analysis results, SD focuses on the dynamic evolution of the system. The dependency and dynamics among economic, social and environmental systems are assumed from macro perspective. Correspondingly, the parameters of equations are predefined according to existing literatures, empirical evidences, expert judgements, or intuitive assumptions. While the research results are straightforward, which is easy for interpretation, it is challenging to set appropriate and convincing parameters. On the other hand, ABM takes a bottom-up approach from a micro perspective, and several simulations were taken over a given period of time to reflect the dynamic. It focuses on the interaction at individual level, such as firms and industries, and approaches the changes in carbon emissions as an aggregated result from bottom up.

The adoption of IAM and Tech-economic models encourages multi-disciplinary research. Apart from examining the influence of socio-economic activities, IAM considers the physical relationships that drive climate change while the techno-economic model considers the productivity performance of newly introduced technology. These integrated models make prediction from a more comprehensive perspective and yield a more convincing result. However, it is very extensive undertaking. In addition, drawing on data simulation based on different model assumptions, IAMs seek to provide information on climate change policy choices, rather than advancing the understanding for knowledge’s sake (Kolstad, 1998).

6.1.4 Carbon control efficiency measurement

The green economy performance evaluation cluster is distinct from other clusters. The common methods used in this cluster include DEA, the Malmquist index and the directional distance function. Econometrics is usually used in conjunction with the above methods for efficiency assessment. Hybrid approaches and econometrics are increasingly being used to estimate the changes in carbon emissions performance and to identify the driving forces at the industry and whole economy levels. The meta-frontier non-radial Malmquist CO_2 emissions performance index model is a good example of this (Lin and Tan, 2016).

6.1.5 Method summary

Table 6 summarises the key features of the main methods that have been reviewed in this paper. Apart from these primary methods, several other less popular methods have been introduced for fulfilling different research purposes. For example, Moran I is has been introduced to analyse the spatial distribution of carbon emissions. The use of surveys was introduced to investigate the energy consumption behaviours of households, and network analysis was introduced to study carbon emissions control in a more holistic way.

Table 6. Comparison of the main methods in CSCE field

	IOA	***IDA***	***Econometrics***	***DEA***	***IAM/CGE***	***SD***	***ABM***	***Optimization***	***Tech-Economic***
General and specific purpose	Carbon emissions inventory; influencing factor analysis	Influencing factor analysis	Influencing factor analysis	Efficiency evaluation	Simulation for forecast ETS design	Simulation for forecast Influencing factors analysis	Simulation for forecast ETS design	Simulation for forecast Policies making	Simulation for forecast Evaluation of new technology
Type of variables	Production effect variables, such as GDP; technology change variables in terms of intermediate input structure or carbon emissions intensity; final demand variables	Activity effect variables such as GDP; Structure effect variables, such as industrial structure; intensity effect variables such as carbon emissions per unit GDP	Various social economic variables, including population, GDP, GDP per capital, technology, energy structure, industrial structure, energy price, geography, urbanisation, financial development	Major input variables: labour force, capital stock and total energy consumption Major output variables: GDP and CO_2	Various Social economic variables and physical variables driving climate change	Energy consumption, population, economic growth, energy and economic structure upgrading, technologies progress, policies	Rules or strategies used for interaction among the agents Adaptive learning mechanism of agents	Energy demanding, energy and emissions control targets, energy resources availability, manufacture and construction budget, carbon tax policies	Predefined operation parameters of new technologies, measurement of productivity efficiency Cost and benefit components

	IOA	***IDA***	***Econometrics***	***DEA***	***IAM/CGE***	***SD***	***ABM***	***Optimization***	***Tech-Economic***
Key assumptions	Input-output linkages among the industries can be quantified	Total effects can be decomposed into several influencing factors without residuals	High accuracy of variables measurement; the relationship between dependent and independent variables are correctly quantified by the selected models	Optimal productivity frontier exists	Globally Pareto equilibrium exists	Whole system can be represented by subsystems with causal and feedback loops	Autonomous and heterogenous agents with adaptive learning ability exist	Global optimal solution can be reached under nonlinear constraints	Changes if applying new technologies are measurable
Analytical approach	Top-down	Top-down	Top-down	Top-down	Top-down	Top-down	Bottom-up	Top-down	Top-down
Mathematical approach	Linear algebra, statistics	System decomposition, partial derivative	Statistics, econometrics	Envelopment analysis	Simultaneous equations	Differential equations	Statistics and differential equations	Convex optimization and nonlinear programming	Statistics
Geographical Coverage	Global, national, regional, local	Global, national, regional, local	Global, national, regional, local, project	Global, national, regional, local, project	Global, national, regional, local	National, regional, local	Local	National, regional	Local
Sectoral coverage	High	High	High	Medium	High	High	Low	Medium	Low
Time horizon	Short	Short	Short	Medium	Long-term	Long-term	Short	Medium	Short
Data requirement	High	Medium	Medium	Low	High	Medium	Medium	Medium	High
Static analysis	Yes	No	Yes	Yes	No	No	No	No	N/A
Time-series	No	Yes	Yes	Yes	N/A	N/A	N/A	N/A	N/A

	IOA	***IDA***	***Econometrics***	***DEA***	***IAM/CGE***	***SD***	***ABM***	***Optimization***	***Tech-Economic***
High Geo spatial	Medium	Low	High	Medium	Medium	Low	Low	Medium	N/A
Residual terms	No	No	Yes	No	No	No	N/A	No	N/A
Integration with other methods	✓✓✓	✓✓	✓✓✓	✓✓	✓✓	✓	✓✓	✓	N/A
Prediction	✓	✓	✓✓	✓	✓✓✓	✓✓✓	✓✓	✓	N/A
Flexibility to incorporate variables	✓✓	✓✓	✓✓✓	✓	✓✓✓	✓✓	✓✓✓	✓✓	✓
Parametric	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Main Limitations	High resolution data requirement; limited flexibility to incorporate new variables	Overlook systemic effect; limited flexibility to incorporate new variables	Hardly avoidable bias in parameter calculation; overlook systemic effect	Non-parametric	Based on logically inconsistent assumptions to some extent	Structured equations with limited evolving capacity	Interactions hardly be articulated to reflect the reality; Highly sensitive to parameters	Detailed prior information required; End up as a NP-hard problem	Heavily relies on the synthesis of technologies and economic expertise
Future directions	Improve data quality and update frequency of database; prediction techniques development; hybrid model	Prediction techniques development; hybrid model	Incorporate more impact factors; overcome bias	Hybrid model; more consideration about the international structure of DMU	Improve scenario forecast accuracy	Integrate more meaningful subsystems with more accurate measurements	Vigorous validation with respect to the soundness of model constructions	Integrate more micro-level constraints	Modular-based design of evaluation process

6.2 Emerging trends and gaps for method usage in CSCE field

The emerging trends and gaps can be summarized according to the three common research topics of carbon emissions inventory, impact analysis and predictions.

For carbon emissions inventory construction, there have been continuous improvements in data quality and update frequency, partly driven by the dramatic 'big data' capture and analysis that has evolved over recent years. The data sources used by these models have also become increasingly diversified. For example, Ma et al. (Ma et al., 2015) used an activity survey and a geographical information system (GIS) based on land use data to compile data on emissions from work and non-work trips. Global positioning system (GPS) data and GIS data are used to analyse the spatial-temporal features of emissions from taxis (Luo et al., 2017). Remote-sensing data is increasingly used to monitor and verify carbon emissions in factories and workplaces in real time, for example by monitoring carbon that is released from burning coal (Jiang et al., 2017).

There have also been recent attempts to improve the resolution and accuracy of carbon emissions data. For bottom-up research relating to direct emissions, efforts are being made to improve and update the important factors for calculation, including emissions factors, oxidation rates and the quality of fossil fuels. The variations of these factors within and among provinces need to be considered for a comprehensive and accurate understanding. Liu et al. (Z. Liu et al., 2015) found that the IPCC default emissions factor for coal is on average 40 percent higher than Chinese coal, based on on-site sampling from Chinese coal mines. For the MRIO database relating to embodied carbon emissions, scholars have been increasing the update frequency and data resolution. Wang et al. (Y. Wang et al., 2014) demonstrated a new approach to constructing time series data from an MRIO database for China from 1997 to 2011 covering 30 provinces and 135 industries, as well as linkages to 185 countries. In addition, the introduction of multi-scale input-output tables (MSIO) (Shao et al., 2016) also serves as an efficient tool when MRIO data is not available.

For impact analysis a multi-disciplinary perspective is needed for advancing the understanding of climate change and identifying more relevant variables accordingly. The ultimate goal of carbon emissions abatement is to mitigate climate change. The CSCE research is a multi-disciplinary field. The knowledge sharing among scholars will bring out more relevant variables and make better use of the increasingly rich data. For example, sectoral carbon emissions reduction is closely connected with social and economic development. More socioeconomic and governance information can provide extra value, such as income inequity, financial development, low carbon awareness of residents, regional economic collaboration, development concepts bearing by municipal governments and geopolitics around China. Moreover, the climate and geographic information are another source of variables to be considered.

In addition, the development of techniques within each family of methods provides new perspectives to tackle impact analysis problems, and to improve the validity and veracity of model results. Benefiting from the its versatility, econometrics is increasingly being used to include these new variables. In addition, there is also a trend for IDA to be decomposed into more factors. Though IOA is frequently used as a database, the IOA analysis techniques should be valued more for examining the systemic effect of variables. In addition, the gap between IOA and IDA with regards to decomposition methods has been narrowed. For example, multiplicative decomposition used to only be used by IDA, but is now being increasingly used by SDA (Su and Ang, 2012). DEA and LMDI are integrated to better assess energy efficiency (Olanrewaju et al., 2012). Several new methods and techniques have been introduced in the CSCE filed. For example, network analysis has recently been combined with IOA to track and control embodied carbon flows (Chen and Chen, 2016; Wang et al., 2017).

For prediction, within the family of simulation, more efforts could be made to bridge the gap between micro- and macro-level analysis. From the comparison of the main methods in CSCE field (see table 6), it is found that most of the methods are undertaken at the macro-level. To understand the micro-meso-macro pipeline of CSCE, further research is called for linking microscopic behaviours modelled by agent-based models with macroscopic emission patterns modelled by the ones such as econometrics, IAM/CGE, and system dynamics, by learning from other disciplines (Eppstein et al., 2011; Geertman and Stillwell, 2009; LeBaron, 2012; Miller et al., 2004).

For other families of methods, more techniques can be also introduced for the prediction of emissions. While IOA and IDA are traditionally adopted to analyse past developments, the trend is to do more prospective analysis. For example, the sensitivity analysis of IOA, sometimes combined with other techniques such as Monte Carlo, is increasingly used for future scenario analysis (Cao et al., 2017; Tarancon and Del Río, 2012). This trend is even more obvious for IDA. The projections can be based either on retrospective analysis or on different quantifications of the underlying drivers (Ang, 2015). IDA can also be used to analyse how reduced emissions can be realized through decomposing the difference between the projected emission levels and the business-as-usual scenario (Ang, 2015; Smit et al., 2014).

From an overall perspective, an integration of multiple methods could play a crucial role in enhancing research developments of all the CSCE clusters. For example, building a hybrid estimation model by integrating econometrics with hierarchical clustering techniques, machine learning, induced ordered weighted harmonic averaging operator and LMDI are some of the new endeavours (Bai et al., 2016; Liang et al., 2016; Song et al., 2014). Yet another area of ongoing research activity combines spatial and geographic modelling that use computer vision techniques with deep learning methods, which offer additional insights by analysing the images from a meteorological satellite system.

The integration of EE-IOA with other methods is another good example. It is now possible to integrate EE-IO with life cycle assessment, including input-output life cycle assessment (IO-LCA) (Bilec et al., 2010; Thiesen et al., 2008) and hybrid life cycle assessment (hybrid LCA) (Finnveden et al., 2009; Suh et al., 2004). The use of hybrid approaches enables a much more detailed account of total life-cycle carbon emissions and makes it possible to adopt a cradle-to-grave philosophy for industries and regions. By incorporating the strengths of bottom-up approaches that use LCA, and of top-down approaches offered by IOA, the benefits of both approaches can be maximised. Recently there have been several attempts to fuse IOA with index decomposition analysis (IDA) (Hoekstra and van der Bergh, 2003; Su and Ang, 2012), scenario analysis (Hubacek and Sun, 2001; Liu et al., 2010; Xuan and Yue, 2017), computable general equilibrium (CGE) (Dervis et al., 1982; Guo et al., 2014) and network analysis (Chen and Chen, 2016; Wang et al., 2017) to achieve different complementary purposes where I-O analysis on its own would not have given the solution required.

From a research content perspective, while the carbon emissions at a national and provincial level dominated CSCE research for almost a decade, a recent trend has been a focus on the role played by cities, firms and residents in carbon emissions reduction. To estimate embodied carbon emissions, the industrial connections between provinces/cities, rather than connections at a regional level, have begun to be the focus of attention in the search for opportunities to reduce carbon emissions. While the Chinese government has demonstrated its determination to curb carbon emissions, more discussion on relevant policies, such as a carbon emissions trading scheme and carbon tax, provide another important area for future research.

7. Conclusions and recommendations

China has been playing a leading role in tackling climate change in recent years. China's 13th Five-Year Plan for Economic and Social Development (2016-2020) and its 13th Five-Year Plan on Energy Development, set specific climate and energy targets, which demonstrate China's determination to curb carbon emissions within the country. The national carbon trading scheme launched in 2017 is a good example of putting policy into action. In addition, the Three-Year Action Plan for Winning the Blue Sky, released in 2018 by China State Council, asked for a reduction in carbon emissions in coordination with a reduction in emissions of pollutants. The CSCE research is important for tackling global climate change and has still been an active research field.

This paper presents a systematic and objective review of the main research methods adopted in CSCE field through a survey of 807 papers published from 1997 to 2017. It compares five primary 'families of methods' and assessed their pros and cons. In addition, the knowledge mapping exercise undertaken for this study clarifies where the methods sit within different research clusters. The five families of methods have different focuses and they complement each other to solve the current and future research problems under different research themes. The CSCE field is a very active cross-disciplinary research area. All the methods have been modified and improved through problem solving in realities. From the analysis, all the methods aim to answer three fundamental problems. They are (i) carbon inventory construction, (ii) analysis of carbon emissions influencing factors and (iii) future trend prediction. The research results provide relevant Chinese departments with practical methods for carbon emissions trend prediction, low-carbon path design and environmental innovation. In addition, they also offer reference to similar research in other countries and regions.

When it comes to identifying the most suitable method for assessing carbon emission, methods have their advantages from different perspectives. If the direct carbon emission amount produced by sectors is the research focus, the bottom-up approach is recommended for calculating the amount considering all the emission sources. If the carbon emission is assessed from consumption perspective, IOA is more suitable for examining the embodied carbon flows among sectors through the entire supply chain and production system.

When the role played by different factors on carbon emission are assessed, IOA, IDA, econometrics and DEA prevail in different contexts. If the research is interested in finding out both the direct and indirect effects of economic activities on environment, multiplier effect analysis, linkage analysis and SDA developed from IOA are recommended. On the other hand, IDA plays a better job when the research focus is on the deterministic effect of macro-variables with no residual terms. While many previously less-discussed variables have been included into the impact analysis such as economic distance and weather data, econometrics is recommended due to its versatility. Moreover, DEA is recommended when the research focus is on evaluating the carbon emission control efficiency of regions and sectors.

Among simulation methods, different methods have their own advantages in predicting carbon emission trend. When the option of introducing a new carbon reduction /capture technology is considered, techno-economic model is a more appropriate option. When it comes to formulating carbon mitigation policies, optimization models are recommended for carbon emission prediction under different constraints, such as meeting energy demand and manufacturing budgets. When a specific policy such as carbon tax or ETS is evaluated, CGE/IAM is appropriate for predicting the carbon emission trend based on different scenarios from a top-down perspective. In addition, if the dynamic evolution of systems affecting future carbon emission is the primary research interest, SD is recommeded. On the other hand, if the research focus is on how future carbon emission will change from bottom-up perspective, ABM is advised for its ability to reveal the interaction among different micro-level agents behind the emission change.

Although CSCE studies have made great progress in many disciplines over the last two decades, there are still substantial gaps that urgently need to be filled. First, the quality of the fundamental data needed for CSCE research have to be improved constantly. GPS, GIS and remote-sensing data technology, as well as onsite surveys could be employed to collect real-time, accurate and high-resolution raw data. In addition, some new approaches need to be developed for constructing MRIO at higher resolutions and with higher update frequencies. Second, the iteration of data and new research results can help modify models and construct dynamic optimization models.

At the same time, the research needs of CSCE based researchers has been changing. While researchers in the past were happy to apply historically collected data, the current trend is to use dynamic real-time data for analysis purposes. While in the past data was sampled, the current tends is to use complete data. In addition, models are increasingly being integrated and adapted, benefiting from the advantages of increased computing power and advances in new methods such machine learning, deep learning, Monto-Carlo and agent-based models. Recent developments aim to improve carbon emissions efficiency measurement and low-carbon policy design through analysing large-scale complex relationships among different driving factors for carbon emissions.

The focus of research methods used for CSCE has been gradually moving away from technological development, to innovation in social governance systems. For example, new research trends are increasingly incorporating (i) the establishment of environmental policies; (ii) the analysis of adjustments to industrial structure, energy structure and transportation structure; and, (iii) the analysis of constructing efficient low-carbon energy system. In addition, while the CSCE used to be approached from national and provincial perspective, it has now expanded into regional economic zones which cross several administrative divisions. From regional perspective, the research focus is on the carbon emissions transfer caused by urbanisation, trade and population immigration, and its influence on optimizing the industrial structure and recognizing carbon abatement responsibilities. Moreover, it is a complex environmental problem to reduce carbon emissions. Efficient response mechanism needs to be formed to deal with problems at different levels, from non-disciplined enterprise-level emissions to large-scale excessive regional carbon emissions. Lastly, the emissions trading scheme (ETS) as well as research and innovation in carbon tax, carbon efficiency improvement and low-carbon policy should be further enhanced to form a solid foundation for reducing greenhouse gases as quickly as possible.

This research was impacted by several limitations. First, this it is limited to the Web of Science database of English peer-reviewed journal papers. The grey literature and non-English journal articles could add another layer of insights to this paper. In addition, while this paper focuses on method review, other knowledge mapping visualisation techniques or methods could be combined to explore and explain developments from other perspectives, such as the author collaboration network and more qualitative or policy-focused analysis.

Acknowledgements

This work was supported by National Natural Science Foundation of China (Grant no. 71774108) and China Scholarship Council (Grant no. 201606890043). The authors thank the editors and three anonymous reviewers for their constructive suggestions.

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