Science of the Total Environment 783 (2021) 147074

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Review

Review on pollution damage costs accounting

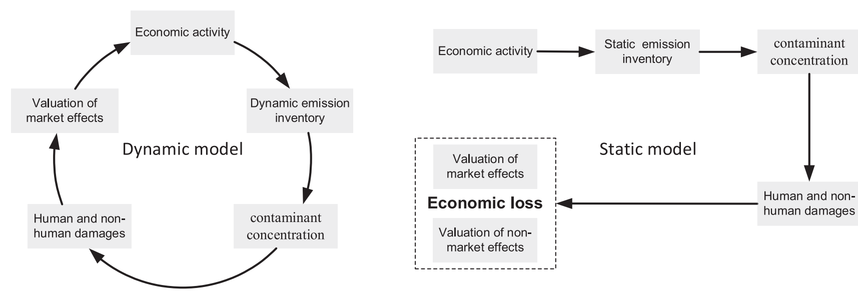
Yashuang Feng [a], Gengyuan Liu [a,b,*], Lixiao Zhang [a,b,*], Marco Casazza [c]

[a] State Key Joint Laboratory of Environment Simulation and Pollution Control, School of Environment, Beijing Normal University, 100875 Beijing, China
[b] Beijing Engineering Research Center for Watershed Environmental Restoration & Integrated Ecological Regulation, 100875 Beijing, China
[c] Department of Engineering, University of Naples "Parthenope", 80143 Naples, Italy

HIGHLIGHTS

- Pollution damage cost accounting helps to evaluate appropriate emission reduction policies.
- There is an urgency of implementing database of exposure-response relationships.
- Research on water, soil and other pollution damage accounting is still inadequate.
- System alternatives should be incorporated into models to achieve accurate damage assessment.
- Environmental policy relevance at different spatial scales is discussed for future decision support.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 2 December 2020
Received in revised form 2 February 2021
Accepted 7 April 2021
Available online 14 April 2021

Editor: Kuishuang Feng

Keywords:
Environmental pollution
Damage cost accounting
Methods
Spatial-temporal variability

ABSTRACT

Although the concept of damage cost accounting is already well-studied and applied, its application to pollution still lacks of an integrated accounting framework, while the spatial-temporal variability of accounting results has not been fully discussed. To fill this gap, this review frames the existing models and their limitations into static and dynamic categories, outlining the characteristics of different methods, which consider both human and non-human damages caused by pollution. Existing data sources, that could be used for accounting purposes, are detailed. Finally, this work discusses the relevance of spatial scales for the computation process, in order to obtain a more detailed information support for environmental policies for future compensatory actions. Conclusions highlights the need to develop a more comprehensive database of exposure-response relationships and to incorporate system alternatives into models to achieve a more accurate damage assessment.

© 2021 Elsevier B.V. All rights reserved.

Contents

1. Introduction . . . 2
2. Framework and methods of environmental cost accounting . . . 2
   2.1. Theory and framework. . . . 2
   2.2. Damage accounting methods . . . 3
   2.3. Economic cost accounting methods . . . 4

* Corresponding authors at: State Key Joint Laboratory of Environment Simulation and Pollution Control, School of Environment, Beijing Normal University, 100875 Beijing, China.
E-mail addresses: liugengyuan@bnu.edu.cn (G. Liu), zhanglixiao@bnu.edu.cn (L. Zhang).

https://doi.org/10.1016/j.scitotenv.2021.147074
0048-9697/© 2021 Elsevier B.V. All rights reserved.

3. Spatial-temporal variability of the environmental cost accounting . . . 6
3.1. Closed system vs open system . . . 6
3.2. Short-time vs long-time . . . 6
3.2.1. Human health . . . 6
3.2.2. Property . . . 6
3.2.3. Ecosystem . . . 6
3.3. Small-scale vs large-scale . . . 7
4. Data resources for an integrated accounting model . . . 7
5. Method application and implementation to multi-scale costs assessment . . . 7
5.1. Global studies . . . 7
5.2. Macroregional studies . . . 9
5.3. National studies . . . 9
5.4. Subnational studies . . . 9
5.5. Urban studies . . . 9
6. Conclusions . . . 9
Declaration of competing interest . . . 9
Acknowledgements . . . 9
References . . . 9

1. Introduction

The deterioration of environmental quality, the destruction of ecological balance, and the adverse impacts on public health are some of the problems caused by anthropic emissions. These key factors, among others, limit a sustainable economic growth and social development (Chen and He, 2014; Janse et al., 2015; Simkin et al., 2016). For example, atmospheric pollutants can cause a variety of physical and mental illnesses and even death (Vicedo-Cabrera et al., 2020; Wang et al., 2019b; Xue et al., 2019). Water pollutants impact on humans' health through drinking water or by contaminating food (Chen et al., 2019; Schwarzenbach et al., 2010). Climate change and rising ozone concentrations reduce crop yields, as well as the quality of agricultural products, increasing the risk of malnutrition worldwide, particularly in developing countries (Hong et al., 2020; Li et al., 2019b; Myers et al., 2014). According to the United Nations Environment Programme (UNEP), global warming, water and atmospheric pollution costed 6.3 trillion dollars in 2008, accounting for 10.48% of global GDP (UNEP-Financing Initiative, 2010). World Bank (2016) estimated the "human welfare costs" in terms of 5.5 million people died, in 2013, from diseases related to air pollution, costing 5.1 trillion dollars globally (World Bank, 2016). Governmental agencies are also investing for implementing emission reduction policies. These factors are making pollution environmental cost accounting a necessary research hotspot, in relation to the definition of suitable and informed emission reduction policies.

Many researchers approached the study of pollution environmental cost accounting for single and multiple items (Antheaume, 2004; Fang et al., 2016; Feng et al., 2019; Kim et al., 2004; Muller et al., 2011; Qin et al., 2011). Two approaches were generally used: pollution restoration cost method and environmental degradation cost accounting (PRCEE, 2006). The former evaluates the costs of recovering the environmental benefits lost by degradation, while the latter focuses on the negative impacts (or damages) of pollution emission or discharge, quantifying the impacts from a macrocosm perspective, such as the impacts on product output, human health, and ecological environment (Wang et al., 2019a).

In particular, damage cost accounting method is a key part of environmental cost accounting of pollution. Xie et al. (2016) estimated that China will reduce its health expenses from a 2% of GDP to a 1.17% due to environmental improvements by 2030, after implementing $PM_{2.5}$ pollution control policy. Chen et al. (2019) quantified the economic losses to human health and ecosystems caused by wastewater discharge in China at macro scale. They identified the main emission links, showing the most effective way to implement the existing environmental emission reduction policies. Air pollution damage cost accounting was also applied to quantify the ecosystem services related to pollutant removal in the case of forest, wetland and other ecosystems (Nowak et al., 2014; Yang et al., 2019). These studies allowed including the effects of natural capital and ecosystem services into the accounting process. In addition, pollution damage cost accounting provides an important reference for ecological compensation policies, cross-regional emission trading, environmental risk assessment, as well as environmental loss identification and assessment (Zhang et al., 2016).

However, there are still limitations and inaccuracies in the application and comparison of methods at different temporal and spatial scales. Moreover, existing works are still relatively scattered and independent. Finally, there is a lack of comprehensive analysis on the advantages and disadvantages of different damage cost accounting methods and their application domains.

The evaluation of economic losses caused by environmental pollution depends on the selected model, which should be based on the discipline approaches of economy, health, agriculture, biodiversity, etc. (Feng et al., 2019; Huijbregts et al., 2017; Jones et al., 2018; Miao et al., 2017; Muller et al., 2011). Thus, there is an urgent need of implementing a complete unified accounting framework (Wang et al., 2019a). Second, pollution damage cost accounting has different gaps in relation to its spatial and temporal scales (Zeng et al., 2019). In particular, spatial-temporal heterogeneity should be fully considered as a key boundary condition, when conducting damage cost accounting (Sun et al., 2019b). This would allow adapting the existing and future environmental policy measures to different spatial and temporal scales (van der Kamp and Bachmann, 2015). Moreover, in order to improve the damage accounting process, data sources with higher spatial-temporal resolution would be highly necessary, becoming the basis for a more detailed assessment. With this respect, further work is required to improve the existing knowledge gaps.

This review attempts to provide a reference in the field of environmental damage cost accounting by sorting out different methods for existing types of damages caused by pollutants. The review starts from a section, outlining a damage cost accounting framework, methods and components, that should be involved in the accounting process. The following section discusses the spatial-temporal variability of factors impacting the accounting results. Then, a list of existing databases is given, based on their spatial-temporal resolution, that can be used for the assessment of damage costs. Following, the policy relevance of damage cost accounting and its application at different spatial scales is discussed.

2. Framework and methods of environmental cost accounting

2.1. Theory and framework

Methods for pollution damage cost accounting can be classified as dynamic and static ones. Fig. 1 shows a simplified scheme of a complete

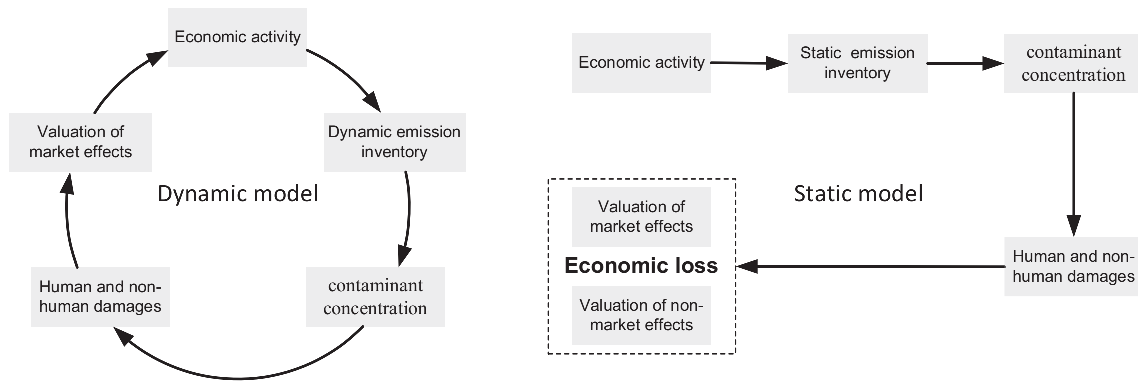


Fig. 1. The integrated economy-environmental accounting dynamic and static model for pollution. Revised by (Bai et al., 2018; Chen and He, 2014; Rosendahl, 1998).

chain, from anthropic emissions to final socio-economic losses, in terms of the two perspectives.

According to the purpose and requirements of different stakeholders, each method can be implemented into different hybrid versions. The accounting logic can be developed from two perspectives, namely, the source-specific emissions and the contaminant concentration. The latter estimates the damage cost caused by pollutants from all sources, while the former is only a part of the latter. Many of the previous estimates of damage cost from pollution focused on total damage caused by anthropic and non-anthropic emissions (Hu et al., 2020; Muller et al., 2011; Wang et al., 2019a). However, such an aggregate number does not estimate the contributions of different source types. Other studies focused on specific emission sources, such as direct emitters, primary suppliers, and final consumers (Chen et al., 2019). For example, some scholars studied the damage cost of air pollution from coal-fired power plants as direct emitters (Ewald, 2018; Thanh and Lefevre, 2000). Other studies estimated the marginal economic damage of atmospheric pollutants emitted by different industries, such as the Air Pollution Emission Experiments and Policy (APEEP) model, developed by Muller et al. (2011). This study, based on the marginal damage perspective, provided a useful reference for damage cost from different industries in the United States. In addition, consumption in a particular country or region may also lead to damage cost in other regions through global or national supply chains (Wilting et al., 2017). For example, Zhang et al. (2018a) estimated the economic benefits and losses of developed and underdeveloped regions in China due to international exports. The study proved that the underdeveloped regions export more energy-intensive products, such as metal and nonmetal products, chemical products and electricity, resulting in more export-related damage cost.

The integrated economy-environmental accounting static model for pollution follows a linear accounting process. The source-specific emissions are taken as the starting point of accounting process. Then, the contaminant concentration can be determined by establishing a diffusion model of air, water and soil pollution to simulate the process of pollutants entering into different media, until a stable concentration level is reached (Goedkoop and Spriensma, 2001). When the contaminant concentration in a region is used as the starting point, data usually derive from monitoring stations of the region, community monitoring data or pollutant concentration simulated by a model (see Section 3.1) (Mo et al., 2018).

Based on the impact pathway in the static model, the European Commission funded the development of ExternE model and Ecosense software, USEPA developed BenMap software, and WHO European Centre for Environment and Health (ECEH) introduced AirQ/AirQ+ software, which are widely applied to estimate health damage cost caused by air pollution at national (Ding et al., 2019), urban (Ansari and Ehrampoush, 2019; Kim et al., 2019) and regional (Carvour et al., 2018; Thanh and Lefevre, 2000) scales. In addition, Life Cycle Assessment (LCA) methods quantifies the analysis results in terms of damage endpoint, such as health and ecosystem, through damage pathways. Methods and databases commonly used include eco-indicator 99, ReCiPe developed in Europe, LUCAS developed in Canada, and LIME developed in Japan (Goedkoop and Spriensma, 2001; Huijbregts et al., 2017; Sabeen et al., 2018).

Damages from emissions have both a direct impact on the economy, as the static model illustrates, and feedbacks on economic growth, i.e. market losses from environmental damage, which, in turn, reduce production. The Computable General Equilibrium (CGE) model, which forms a closed loop process, represents a standard type of integrated economy-environmental accounting dynamic model for pollution. This model was frequently used to estimate the socio-economic costs caused by pollutants. For example, Chen and He (2014) assessed that China experienced a staggering GDP loss of 361 billion Yuan and a welfare loss of about 227 billion Yuan. Other studies applied the model to smaller-scale areas. Xie et al. (2016) simulated the comparison of governance costs and GDP benefits before and after implementing $PM_{2.5}$ pollution control policies at the provincial level. The study found that, in areas with high-level pollution and dense population distribution, $PM_{2.5}$ pollution control could bring positive benefits, while control investment in less developed areas was higher than GDP benefits.

2.2. Damage accounting methods

Damages caused by pollutants can include health, property and ecosystem damages. These three categories involve the calculation of several indexes, which are listed in Table 1. According to the definition by World Health Organization (WHO), human health refers to a state of good physical, psychological and social adaptability, not merely the absence of disease and infirmity (World Health Organization, 2003). Based on this definition, indicators of health impairment in this review include physical index, i.e. mortality, morbidity, Disability Adjusted Life Years (DALYs), Restrained Activity Days (RADs), subclinical symptoms, and psychological index, i.e. disutility.

Property damage refers to the value reduction directly caused by environmental pollution and the necessary expenses incurred to protect the property from loss (Ministry of Ecology and Environment of the People's Republic of China, 2014). The damage to crops and forestry caused by atmospheric pollutants, especially O_3, aroused the interest of researchers (Hong et al., 2020; Hu et al., 2020). The direct economic and cultural heritage losses caused by the housing price decline and building materials damage caused by pollution cannot be ignored (Hou and Lu, 2018; Kim et al., 2004; Kumar and Imam, 2013). Ecosystem damage refers to the observable or measurable adverse changes in the physical, chemical or biological characteristics of the ecological environment directly or indirectly caused by pollution, as well as the damages to the ability of a given ecosystem to provide ecosystem services (Ministry of Ecology and Environment of the People's Republic of

Table 1
Damage indexes for health, property and ecosystem caused by pollution.
Sources from: (Alkemade et al., 2009; Goedkoop and Spriensma, 2001; Ministry of Ecology and Environment of the People's Republic of China, 2014; Science for Environment Policy, 2018; Xia, 2011; Yin et al., 2017).

Damage category	Index	Unit	Description
Health	Mortality	Incidence	The frequency of deaths due to a cause or all causes within a given period of time in a given population.
	Morbidity	Incidence	The incidence of a disease in a particular at-risk population over a period of time.
	DALYs	yr./case	The total number of years of healthy life lost from onset.
	RADs	Day	The bed disability days, work or school loss days and minor restricted activity days.
	Subclinical symptoms	–	Refers to changes in lung function, immune function, etc.
	Disutility	–	The loss of the utility of good health, with respect to life expectancy, pain, suffering, distress or lost opportunity.
Property	Damage to buildings and infrastructure	μm, mg, currency	Corrosive damage or reduction in the price of buildings and facilities caused by environmental degradation.
	Forestry and crop production	m^3, kg	The reduction in forestry and crop yields caused by environmental pollution.
	Damage to fishery	m^3, kg	The direct damage to fisheries caused by surface water pollution.
	Extra cost for decontamination of property	Currency	The cost of decontamination of property to prevent further damage caused by environmental pollution.
Ecosystem	Potentially Disappeared Fraction of species (PDF)	PDF $\times$ m^2 $\times$ yr	The fraction of all species in the region disappearing from 1 m^2 in a year due to 1 kg of pollutants, or 10% of all species in the region disappearing from 10 m^2 in a year.
	Mean Species Abundance (MSA)	MSA-loss·ha	The average number of original species in a disturbed state to measure the health of an ecosystem.
	Biological pathological damage	–	The pathological level of damage that occurs in an organism as a result of the influence of a regional polluted environment.

China, 2014). The indicators used to describe ecosystem damage can be divided into biodiversity loss, species loss and pathological damage of individual organisms.

The calculation of all damage indicators and a related economic analysis are still very difficult to obtain. For example, some subclinical symptoms of health damage and the bio-pathological damage in the indicators of ecosystem damage are not recommended for accounting, because it is currently difficult to assess the long-term impact of such changes on human health and ecosystems (Hong et al., 2004). An inappropriate selection of damage indicators leads to double counting. For example, RADs is a general index, exclusively used for assessing the health damage of atmospheric pollutants. RAD could be caused by respiratory or non-respiratory conditions. The addition of RADs cost and other health damage indexes, such as morbidity, could cause double accounting (Yin et al., 2017).

Since most of damage indicators are non-specific and non-pollution factors can also cause the same damages, it is crucial to determine the relationship between contaminant concentration and damage indicators (Xia, 2011). This quantitative relationship is known as dose-response function (or damage function). Researchers have several explanations on the functional relationship between contaminant concentration and health damage indicators. In LCA methods, health damage factors, being the quantification of pollutants adverse effects on health are supposed to be linear (Goedkoop and Spriensma, 2001). Thus, health damage factors in LCA methods are adaptable to slow changes in pollutants concentration rather than large emissions fluctuations (Liu et al., 2013). In epidemiological methods, researchers usually use linear, log-linear and linear-log functions to calculate the burden of disease due to human exposition to atmospheric pollutants (Atkinson et al., 2014). However, linear functions represent only the typical condition of developed countries with low pollutants concentration background (Atkinson et al., 2014; Samet et al., 2000). Instead, under high concentration background condition, dose-response function tends to be non-linear. Thus, a linear model may underestimate the mortality burden caused by short-term exposure (Li et al., 2019a).

Many studies explored the need for different dose-response functions to estimate health damage in the context of different atmospheric pollution concentrations (Daniels et al., 2004; Ostro, 2004; Ritz et al., 2000). In general, in areas with low concentration background, health damage cost is more likely to be represented by a linear function. Otherwise, a nonlinear model is more suitable. Specific applications vary, due to differences in background concentration, target pollutants and health damage indicators etc. (Nansai et al., 2020; Yin et al., 2017). Several studies revealed also a close statistical association between air pollution, depression and suicide (Braithwaite et al., 2019; Shin et al., 2018). However, the exact mechanism describing how pollution affects human brain is not completely clear and the corresponding dose-response function is lacking.

The dose-response function for outdoor exposed material corrosion and crop damage caused by air pollution was explored through field and laboratory simulation experiments (Feng et al., 2019; Kim et al., 2004). Other researchers determined the damage by ozone to crops, by establishing a correlation between the ozone concentration, obtained through monitoring station data and crop yield estimated by government agencies. However, other variables, such as the impact of temperature on the final results, should not be ignored (Hong et al., 2020). There are few studies on the functional relationship between pollutants and ecosystem damage, mainly in the field of ecotoxicology. On one hand, in LCA methods, the relationship between pollutants and biodiversity damage is similar to that between health damage. This implies a model based on a linear function which is inconsistent with the logistic model of biological population growth (Liu et al., 2013). On the other hand, ecological damage factors are increasingly based on Species Sensitivity Distributions (SSD) to express the non-linear dose-response function of PDF and contaminant concentration (Goedkoop et al., 2009). However, it is difficult to establish dose-response functions between specific pollutants and biodiversity, because relatively few species are covered by studies on the effects of pollutants on organisms (Huijbregts et al., 2011).

2.3. Economic cost accounting methods

While most damage accounting types have no market or incomplete market reference, economic damage accounting is reflected by market values (Rosendahl, 1998). The economic cost accounting methods can roughly be divided into Direct Market Method (DMM), Revealed Preference Method (RPM), Stated Preferences Method (SPM) and Benefit Transfer Method (BTM). All the methods have their own disadvantages, advantages and specific areas of application, as shown in Table 2.

DMM is a method to evaluate the damage cost by using changes in productivity (Ministry of Ecology and Environment of the People's Republic of China, 2014). Being applied in the health damage accounting, Dose-Response Technique (DRT) can be used to calculate values from the perspective of labor loss and medical costs caused by

Table 2
Economic methods in the accounting model and their application domain. Indicators for health, property and ecosystem.
Sources: (Bai et al., 2018; Kougea and Koundouri, 2011; Ministry of Ecology and Environment of the People's Republic of China, 2014; Zhao et al., 2015).

Method	Approach	Description	Domain		
			Health	Property	Ecosystem
Direct Market Method	Market Value Approach	Assesses changes in environmental conditions using changes in productivity.		√	
	Dose-Response Technique	Links output to different levels of inputs to factors of production such as land, labor, capital, raw materials.	√	√	
	Human Capital Approach	Estimates the productivity loss measured in workdays due to illness.	√		
	Cost Of Illness Approach	Estimates the total cost associated with disease treatment, as well as lost earnings related to disease.	√		
Revealed Preference Method	Hedonic Pricing Approach	Estimates the value of environmental quality based on the price people pay for the enjoyment of a good environment.		√	√
	Defensive Expenditure Approach	The sum of the costs of defense and prevention that an individual is willing to spend in order to avoid or reduce the risk of adverse effects of environmental pollution.	√	√	√
	Travel Cost Approach	Evaluates the value of natural attractions or environmental resources that have no market price.			√
	Shadow Project Approach	The cost of project that might be constructed to complement the function of the original ecosystem is considered as the loss.		√	√
Stated Preferences Method	Contingent Value Method	Creates a hypothetical market and respondents express their willingness to pay contingent on some hypothetical change in the future state of environmental conditions.	√	√	√
Benefit Transfer Method		Applies original or adjusted information from prior study to target study.	√	√	

pollution-induced diseases, by using Human Capital Approach (HCA) and Cost Of Illness Approach (COI) (Greco et al., 2019; Yao et al., 2020; Yin et al., 2017; Zhang et al., 2018b). However, due to the absence of market prices for some factors, these methods cannot account for intangible costs, such as psychological ones (Pascal et al., 2013). Similarly, since there is a direct market for agricultural and forestry products and building materials, in the cost accounting of property damage, the amount of physical loss caused by pollutants is usually calculated on DRT. Then, the economic loss is estimated based on the market price (Feng et al., 2019; Hu et al., 2020; Miao et al., 2017; Wang et al., 2019a).

RPM relies on market observations to capture the value of an environmental good, that it is not itself traded in any market but is connected with other marketed goods (Kougea and Koundouri, 2011). Hedonic Pricing Approach (HPA) was applied to the impact of environmental quality deterioration on property value, starting point from the value of a property, that implicitly includes its quality (Ministry of Ecology and Environment of the People's Republic of China, 2014). For example, Harmful Algal Bloom (HAB) pollution affects human welfare by reducing the willingness of people to go to the beach. Using HPA, Osseni et al. (2019) found that, in order to reduce HAB to the lowest levels in the Breton Coast (in France), residents living 20 km from the contaminated beach were willing to pay approximately EUR 208/person/year. Generally, Defensive Expenditure Approach (DEA) underestimates damage costs (Bai et al., 2018). However, it can directly use the observable market prices (Kougea and Koundouri, 2011). Shadow Project Approach (SPA) is a special form of DEA that facilitates the accounting of economic value by replacing ecosystem services with artificial systems. Based on SPA, Li (2013) took the environmental treatment cost and sewage charge as shadow price and estimated the value of forest purification pollution and oxygen release in China in 2001 as CNY 1461 billion. This method is most used in the process of ecosystem damage cost accounting. However, it is necessary to determine whether the artificial system can accurately replace ecosystem services. Otherwise the replacement is imperfect. For example, the establishment of hydropower stations cannot replace the functions of recreation, biodiversity maintenance, carbon sequestration and oxygen release in such a water area (Yang et al., 2006). Travel Cost Approach (TCA) is mainly suitable for tourists to evaluate the entertainment service value of natural attractions for unitary site and single purpose (Zhang et al., 2013). It has obvious advantages in terms of basic data collection, authenticity of market economy model and applicability (Yin et al., 2009). However, there are many difficulties in the evaluation of quality changes related to attractions. Therefore, there are few applications in the estimation of ecosystem damage caused by pollutants in this context.

SPM bases damage costs on the basis of questionnaires and field interviews. Based on a hypothetical reference market, people response determine the willingness to pay or to accept a compensation (Kougea and Koundouri, 2011). According to the Contingent Value Method (CVM), respondents' Willingness To Pay (WTP) for an increased environmental utility or Willingness To Accept (WTA) a compensation for environmental degradation are directly surveyed and calculations are based on utility maximization principle (Bai et al., 2018). WTP is considered the best approach for valuing human health damages related costs, determining the Value of Statistical Life (VSL), an aggregation of individual values for small changes on risk of death. However, Cost Of Illness Approach (COI) is often recommended when determining the VSL for morbidity (Miao et al., 2017). A large number of studies applied market and non-market approaches to the valuation of ecosystems, and have also advocated the inclusion of non-economic values for biodiversity (De Valck and Rolfe, 2019). Economic cost accounting is the most direct way to quantify the economic costs of ecosystem losses. WTP method (Jones et al., 2018) is an economic cost accounting method, which calculates the people's willingness to pay through their actual experience of the evaluation content. However, it is usually difficult and unrealistic to carry out such large-scale experiments.

Based on the environmental and economic information of existing regions, BTM uses numerical and functional transfer methods to obtain the evaluation results of new similar environmental products and services. Economic cost accounting methods have an accuracy ranking, from large to small, ranging from DMM to RPM and SPM (Zhao et al., 2015). Compared with these methods, BTM can overcome the limitation of time, cost and research environment. Thus, it is a simpler and more feasible approach, under the condition of having a lot of reliable empirical research results for value estimation (Bai et al., 2018). Developing countries, for example, because of lacking domestic research, usually use the dose-response function using developed countries as a reference, which generates a high variability of calculation results.

3. Spatial-temporal variability of the environmental cost accounting

Pollutants can have environmental effects at different spatial scales, from regional to global ones. For example, spatial-temporal impact of point sources and diffused sources of chemical pollution on water quality will range from short-term local areas to long-term global areas (Schwarzenbach et al., 2010). Then, damage costs of a specific pollutant are variable on different spatial-temporal ranges (Eckelman et al., 2018; Goedkoop and Spriensma, 2001; La Notte and Dalmazzone, 2018). Spatial-temporal heterogeneity is an important factor affecting the variability of damage cost accounting results. Thus, this review will discuss key steps of spatial-temporal variability in damage cost accounting from the perspective of models, temporal heterogeneity of damages and spatial scale of accounting.

3.1. Closed system vs open system

Since it is obvious that pollutant damages have an inter-regional heterogeneity, damage cost in areas with rapid economic growth and dense population will be seriously underestimated, if this factor is ignored (Nam et al., 2019). The integrated economy-environmental accounting static model for pollution is primarily concerned with damages caused by emissions in a closed economy (focus on a specific period, such as a given year). This approach uses different pollutants to simulate impacts of changes in a certain sector or region on the entire economic system. Then, the value of pollution damage is estimated to measure the economic status of macro region. For example, a recent study applying static model indicated a 7% GDP loss in 2015 due to human health, in relation to forest productivity and crop yield damages induced by O_3 pollution in Chinese rural and urban areas (Feng et al., 2019). In another example, the cost of agricultural losses caused by the air polluting industrial enterprises located in 899 Chinese areas was estimated at US$ 1.43 billion, accounting for 0.66% of the total agricultural value in the polluted area (Wei et al., 2014). However, accounting results from a single economic sector do not necessarily reflect the whole truth, since the pollutant damage from an economic activity can be undertaken by other regions or countries and future generations, i.e. the spatial and intergenerational transfer of pollution and its damage. Based on this consideration, a large number of studies explored the relation between environmental pollution and economic growth from a variety of open macro perspectives (Lu et al., 2017) and trade (Chen et al., 2019; Nansai et al., 2020), employment (Zhang et al., 2018b) and population migration (Price and Feldmeyer, 2012; Squalli, 2010), trying to reveal the hidden environmental inequalities.

The dynamic analysis of open systems focuses on the cumulative effect of environmental pollution damage over time and the related linkage effect, then estimating the social and economic losses. For example, Wilting et al. (2017) quantified the biodiversity loss caused by the production and consumption of goods and services traded between countries related to GHG emissions to 45 countries and regions around the world. (Nam et al., 2010) assessed the long-term cumulative economic effects of air pollution on health in Europe during 1970–2005, using MIT Emissions Prediction Policy Analysis (EPPA) model, a dynamic CGE model describing economic dynamics and resource reallocation implications.

Because economic growth and environmental quality are mutually affecting, estimating the economic loss of environmental damage when the economic system is considered to be single and closed can be biased. For example, the static model was used to estimate the proportion of health economic loss related to air pollution in China's GDP as 3.5% to 5.9%, while the figure obtained by the dynamic model is 6%–9% (Bai et al., 2018). (Zhang et al., 2016) estimated that, once water pollution occurred in the Yangtze River Delta basin of China, the indirect economic loss (dynamic loss) suffered by Shanghai was about 3.5 times that of its direct economic loss (static loss). Compared to the static model, the dynamic model can better depict negative impacts caused by pollution, as it effectively reduces the possibility of underestimation (Bai et al., 2018).

3.2. Short-time vs long-time

3.2.1. Human health

The effects of pollutants on human health can be divided into the damage to individuals and to a group. Nonetheless, health damage cost accounting tends to focus on the damage to the group, usually ignoring individual's time-activity behavioral patterns (Dias and Tchepel, 2018). For example, the exposure-response relationship, based on health damage cost accounting, is obtained from population epidemiological studies and does not include the information of individual hazards due to different levels of exposure.

Considering the temporal heterogeneity of health damage, short-term damages refer to the effects of pollutants on population health in a short period, usually taken as days. Long-term damages are long-period effects of pollutants on human health, usually calculated on a monthly or yearly time scale (Barzeghar et al., 2020; Liu and Song, 2016).

At present, a large number of epidemiological and ecological studies on the damages of pollutants are worthy of reference, most of which focus on the short- and long-term damages of air pollution on human health in the form of exposure-response functions (Li et al., 2020; Salimi et al., 2018). However, studies on the short- and long-term damages of natural water chemical pollution on human health remain limited (Schwarzenbach et al., 2010). Some of these epidemiological studies showed that the dose-response relationship parameters between the annual mean concentration and mortality were much higher than the dose-response relationship parameters between the daily mean and mortality (Atkinson et al., 2012; Shi et al., 2016). If only short-term damages of air pollutants on human health are calculated, the health damage caused by air pollutants is bound to be greatly underestimated. In this case, it is more appropriate to carry out air pollution health damage assessment on an annual time scale (Liu and Song, 2016).

3.2.2. Property

The corrosion rate of building materials is closely related to its location and corrosion time. For example, a study of materials corrosion in China, Japan, and Korea shown that bronze, copper, steel, and marble have the highest average corrosion rates in coastal areas of China and Japan, where concentrations of SO_2 and SO_4^{2-} are high (Kim et al., 2004). Different from the temporary and intense damage caused by the drastic change of pollutant concentration, materials damages are long-term and slow (Kumar and Imam, 2013). This means that the damage of pollutants to materials is related to the pollution degree of the region. In the materials damage cost accounting, dose-response function at local or regional scales should be selected to ensure the accuracy of the accounting. For crop damage, dose-response functions obtained from most field and experimental studies are only used to estimate yield loss at regional scale, while statistical models are more likely to be used to infer larger regional and long-term damages. For instance, the change in yields of perennial crops on historical (1980–2015) and future (project to 2050) trends was assessed in California on the basis of statistical modelling of historical data of O_3 concentration and crop yields (Hong et al., 2020).

3.2.3. Ecosystem

The dynamics of pollutants damages to ecosystems includes transient and long ecological processes. Various acute toxic reactions caused by pollutants generate transient ecological processes, while toxic dilution process, chronic poisoning process and pollutant bioaccumulation and amplification process require a longer period (Zhou and Sun, 2000). For example, land and sea species loss due to global climate change caused by GHG is a long-term ecosystem damage. Studies considered the damage of pollutants or related environmental problems to ecosystems on different time scales. LCA methods, such as ReCiPe, calculate biodiversity loss on different time scales (20, 50, 100 and 500 years) caused by acidification and eutrophication in Europe through different cultural perspectives (Goedkoop et al., 2009). The Biodiversity Footprint and the GLOBIO Model/GLOBIO-Aquatic Model measure the integrity degree of ecosystems by comparing the species richness of ecosystems in undisturbed and disturbed states, and assess the long-term time-scale biodiversity loss of terrestrial and marine ecosystems caused by GHG (Alkemade et al., 2009; Janse et al., 2015). With respect to pollutants, such as long-term and chronic leavers, damages to the value of entertainment, aesthetics and comfort caused by pollution it is difficult to resolve in the short-term, while damages are irreversible. For example, the nuclear leakage accident in Fukushima induced a permanent damage and this scenario will persist for a long period (Sun et al., 2019a; Wang et al., 2018).

3.3. Small-scale vs large-scale

In previous studies, health damage cost tends to select annual, monthly average concentrations of air pollutants as starting point. However, from an explicitly-spatial perspective, areas with different pollutant concentration in the same city are not identical (Zeng et al., 2019). Based on the region's pollution and population average data, health damage cost tends to deviate from the true value. At present, the methods and models used to estimate the spatial distribution of pollutant concentration include remote sensing based approaches to estimate the concentration of atmospheric pollutants (Chu et al., 2015; Kim et al., 2019), spatial interpolation techniques using real-time concentration data at monitoring points (Chen et al., 2017), land use regression model (Henderson et al., 2007), diffusion models (Thanh and Lefevre, 2000; van Zelm et al., 2016) and artificial neural network models (Cabaneros et al., 2019). The spatial distribution of pollutant concentrations estimated by these methods can be very precise and real-time or annual data can be obtained. For example, atmospheric diffusion models can be used to estimate atmospheric pollution concentrations either through bottom-up emission inventories or top-down input-output models. Input-output tables were accounted at national or regional levels, almost excluding the spatial information. In particular, they are a product of the pollutants discharge average with a given spatial resolution, omitting a clear spatial information and the space-time dynamic adjustment and optimization that would be required to tailor appropriate environmental policy measures (Wilting et al., 2017). Similarly, LCA methods cannot reflect the spatial information of the results (Goedkoop and Spriensma, 2001; Huijbregts et al., 2017). However, in recent years, a larger amount of available explicit spatial data allowed the implementation of higher-resolution accounting results (see Table 3).

There are two methods to correlate Input-Output (IO) or LCA data with these spatial databases (Sun et al., 2019b). Mapping emissions between the production models or LCA and emissions identified spatially from the spatial databases. For example, a research distributed the concentration into the grid cells, based on the atmospheric diffusion model to get the specific spatial distribution (Wang et al., 2020). Consumption-related emissions at regional level are determined from IO statistics on regional consumption. For example, (Eckelman et al., 2018) matched Canada's national health care expenditure with the sector emitting pollutants in IO Model, based on which the LCA methods were used to calculate the damage to human health. Such attempts would overcome spatial variability of emissions and enhance precision of damage cost accounting results as far as possible.

In LCA methods, different spatial scales of biodiversity loss depends on the environmental impacts of pollutants and climate change at regional and global scales, considering the evaluation of species richness at global level (Verones et al., 2016; (Asselin et al., 2020). However, some scholars believe that biodiversity is a characteristic of an ecosystem. Thus, diversity should be more relevant than single-species richness (Bartkowski, 2017). Therefore, more attention should be paid to the global level when calculating biodiversity loss caused by pollutants using LCA methods. With regard to pollutants as long-term and chronic damage triggers of entertainment, aesthetics and comfort damages, short-term values are difficult to assess, considering the irreversible nature of generated impacts. This was the case of damages generated by Fukushima nuclear leakage accident (Sun et al., 2019a; Wang et al., 2018).

4. Data resources for an integrated accounting model

Key available data resources in accounting are summarized in Table 3. For procedure 'Economic Activity-Emission', apart from the data covered in the table, real-time hourly average concentrations of pollution can also be detected by environmental monitoring stations in major cities around the world. For example, the Ministry of Environmental Protection of China set up 1497 air quality monitoring stations, which provide the concentration data of major atmospheric pollutants across the country (web platform: http://106.37.208.233:20035/) (Hu et al., 2020). In addition, researchers proposed several available global multi-regional input-output databases, including EORA (Lenzen et al., 2012), EXIOBASE 3 (Stadler et al., 2018), GRAM (Bruckner et al., 2012), GTAP 9 (Aguiar et al., 2016) or WIOD (Dietzenbacher et al., 2013), that can be used in order to obtain comprehensive and explicit results. In the case of 'Emission-Concentration' assessment, upper-air and surface land or sea meteorological data, topography, land use and other parameters may be required. Accounting damage-Economic Loss, finer spatial-resolution data are needed to improve precision of accounting result.

5. Method application and implementation to multi-scale costs assessment

Pollution-related environmental policies are divided into short-term plans, designed to respond to specific activities or emergencies, and long-term plans, designed to reduce one or multiple types of damage. The classic example of the former is the Olympic Games, a planned and organized activity. For example, in order to ensure a low environmental impact of 2008 Beijing Olympic Games, the Chinese government adopted a series of new environmental standards, closure of heavy polluters in Beijing and surrounding provinces and restrictions on pollution emission reduction, etc. These measures effectively reduced the health losses caused by air pollution during the Olympic Games (Hou et al., 2010). The latter example is COVID-19, which appeared suddenly and spread around the world in 2020. Nearly 30 countries closed their entrance to curb further spread of the virus. Studies compared the available data in four cities (Delhi, London, Paris and Wuhan) under the blockade background, revealing the social impacts of policies dealing with emergencies in different urban economic contexts (Bherwani et al., 2020). Based on resolution of final pollution damage accounting results, this review further divided the representative studies into five spatial categories: global, macroregional, national, subnational and urban studies, discussing the main highlights of these studies and their policy relevance.

5.1. Global studies

Currently, production and final consumption sites are often viewed as disconnected, in contrast with the connections of global supply chain (Sun et al., 2019b). Current national policy strategies focus primarily on reducing health, property and ecosystems losses within countries. However, consumption in one particular country or region can also lead to a loss elsewhere through globally-dispersed supply chains. For example, (Wilting et al., 2017) quantified the biodiversity loss caused by the production and consumption of goods and services traded

Table 3
Information on data resource, precision and time range related to the integrated accounting model in this study.

Procedure	Data	Spatial and temporal resolution	Year	Source/website
Economic activity-emission	Regional emission inventory in Asia	0.25° × 0.25°, Asia; monthly	1950–2015	https://www.nies.go.jp/REAS/
	Anthropogenic emissions of air pollutants and greenhouse gases	0.1° × 0.1°, global; annual	1970–2015	https://www.eea.europa.eu/themes/air/links/data-sources/emission-database-for-global-atmospheric
	National air pollution trends	US; annual	1980–2019	https://www.epa.gov/air-trends
	Emission of pollutants	China; annual	1999–2019	http://www.stats.gov.cn/tjsj/ndsj/
Emission-concentration	MODIS AOD	1° × 1°, global; daily	2012–2020	https://earthdata.nasa.gov/eosdis/daacs/laads
	Land surface temperature	0.5° × 0.5°, global; monthly	1948–2020	https://psl.noaa.gov/data/gridded/data.ghcncams.html
		varying, from 0.5° × 0.5° to 5° × 5°, global; monthly	1850–2020	https://climatedataguide.ucar.edu/climate-data/global-temperature-data-sets-overview-comparison-table
	Sea surface temperature	2° × 2°, global; monthly	1854–2020	https://www.ncdc.noaa.gov/data-access/marineocean-data
	Global topographic data	30-, 15-, and 7.5-arc-second, global; —	2010	https://www.usgs.gov/products/data-and-tools/gis-data
	Land cover	30 × 30 m, global; —	2010	https://www.webmap.cn/commres.do?method=globeIndex
Health damage-economic loss	International classification of diseases	–	–	https://www.cdc.gov/nchs/icd/icd10.htm
	Global population distribution	1 × 1 km, global; annual	2000–2018	https://landscan.ornl.gov/index.php/landscan-datasets
		1 × 1 km, global; ten-year interval	2010–2100	https://sedac.ciesin.columbia.edu/data/set/popdynamics-1-km-downscaled-pop-base-year-projection-ssp-2000-2100-rev01
	Global burden of disease	Global; annual	1990–2017	http://www.healthdata.org/gbd
	GDP per capita	Global; annual	1990–2017	https://ourworldindata.org/grapher/gdp-per-capita-worldbank?year=latest
	Thresholds for the health effects of air pollution	–	–	https://www.who.int/publications/list/who_sde_phe_oeh_06_02/zh/
	Average annual wages	36 countries; annual	2000–2019	https://stats.oecd.org/Index.aspx?DataSetCode=AV_AN_WAGE
Property damage-economic loss	Global cropland area distribution	1 × 1 km, global; annual	2007–2012	https://lpdaac.usgs.gov/products/gfsad1kcdv001/
		30 × 30 m, global; annual	2015	https://lpdaac.usgs.gov/products/gfsad30valv001/
	Market prices of crops	Global; annual	1991–2018	http://www.fao.org/faostat/en/#data
	Market prices of woods	Global; monthly	2014–2020	http://www.globalwood.org/index.htm
	Dose-response functions of various materials towards air pollutants	–	–	(Kumar and Imam, 2013)
	Dose-response functions of crop yield towards air pollutants	–	–	(Wei et al., 2014)
	Dose-response functions of materials towards air pollutants	–	–	https://www.unece.org/?id=2721
Ecosystem damage-economic loss	Global mammal distribution	1 × 1 km, global; annual	2000–2050	https://globalmammal.org/activities/data-sets/
	Global species distribution	Global; annual	2009–2020	https://www.iucnredlist.org/resources/spatial-data-download

between countries related to GHG emissions at global scale, using the concept of biodiversity footprint. The study found that more than 50% of the consumption-related biodiversity loss occurred outside the country. (Nansai et al., 2020) assessed the health and economic losses of five major consumer countries in the world (the United States, China, Japan, Germany and the United Kingdom) to Asian countries due to consumption-related $PM_{2.5}$ emissions. Results proved that affected countries were trapped in a vicious circle, in which developing countries generated value through international trade, while increasing health risks ultimately delayed their economic development. Consequently, this study recommends the introduction of clean energy and other types of technical assistance to redress this inequity. Adopting appropriate technical solutions, however, doesn't necessarily reduce the indirect losses in parallel to the reduction of human health and environmental damages caused by air pollution (Chantret et al., 2020). Many countries implemented their environmental policies aimed at reducing pollution damage, such as the Clean Air Policy Package proposed by the European Commission, the U.S. National Ambient Air Quality standards for ground-level O_3 to protect crops and other sensitive vegetation, etc. An improved assessment of various losses based on consumption provides a starting point for policies to reduce the potential for damage from pollutants globally.

5.2. Macroregional studies

A typical example of a macro-regional scale application is the use of EU data to investigate the spatial variations of consumption-driven pollution damage costs. For example, a EU program shows that, positive feedback effects on human health and crop production from the implementation of the Clean Air Policy by 2030 can totally offset the cost of pollution (Vrontisi et al., 2016).

5.3. National studies

The use of common assessment methods is key to allowing countries to compare the costs of pollution damages from a closed- system perspective. (Van Dingenen et al., 2009) found that the air quality loss generated by China and developed countries will be reduced under the existing legislation, while in less-industrialized countries, the existing legislation wouldn't be enough to improve air quality by 2030. Jones et al. (2018) applied a spatially-explicit method to assess the benefits of biodiversity improvements resulting from current policy initiatives to reduce nitrogen emissions. Understanding lost spatial information can help design interventions to reduce pollution pressures in specific locations or areas.

5.4. Subnational studies

These studies are very useful for interregional management, especially for a large country. For example, because of environmental inequality in China between provinces, rural and urban areas, studying the implications of environmental policy can provide valuable policy insights for different levels of development. Compared to more developed areas, air pollution control technologies adopted by less developed provinces in China may have a larger economic burden, which requires the Government to adopt appropriate compensation policies (Xie et al., 2016).

5.5. Urban studies

Different from the dynamic macroeconomic loss estimates based on IO and CGE models, the cost of pollution damage at the city level is based on highly localized statics of pollutant emission concentration measurements and statistics to meet the requirements of different stakeholders. For example, (Thanh and Lefevre, 2000), in the study on the external cost of Thailand's power plants, assessed the health damages caused by an increased concentration of atmospheric pollutants at different receptor locations, providing a reference for the technical selection and siting of new power plants. Ewald (2018) calculated the health cost related to sulphur dioxide emissions from coal-fired electricity generation in New South Wales to provide a suitable price for pricing pollutants under the pollution permit system.

In general, most dynamic studies of economic loss estimation models focused on global, macro-regional and national levels, while static economic loss estimation models were applied to a variety of spatial scales. There are two forms of policy insights for research at different spatial scales. The first is to estimate the health, property and ecosystem damage costs of different industries, sectors or other source-specific emissions, based on the existing pollution situation. Such an approach allows to identify the key linkage causing the damage based on the results and to provide a reference for the formulation of environmental policies, technologies and pollutant pricing related to pollutant reduction emission. Another application form is the validation of environmental policies effectiveness, known as accountability (Bell et al., 2011). Such application assesses the benefits or the cost-benefits of policies implementation to simulate the remove the possible unfairness of regional policies and to promote the cooperation between different administrative areas of governance. Most of the existing works in this field focused on the quantification of damage costs related to atmospheric pollutants to health, crops, and biodiversity. Less attention was paid to the consequences of the overall damages. The costs of pollution damage or the benefits of environmental policies in this field are still under estimated. Thus, future studies should focus on the impact of environmental damage costs caused by air, water and soil pollution on open economies, using an explicitly-spatial information to implement appropriate environmental policy measures and their spatial-temporal adjustment.

6. Conclusions

This review considered different environmental damage cost accounting frameworks and methods. Existing databases and the application of different spatial scales were considered, together with short- and long-term planning impacts. The study evidenced the urgency of implementing a database of exposure-response relationships suitable for each country and region, considering the spatial-temporal heterogeneity of exposure-response relationships leading to inaccurate accounting results. Although epidemiological studies explored the relationship between pollutants and health damages around the world, research on water, soil and other pollution damage accounting is still inadequate.

The introduction and implementation of big data could allow, in the future, obtaining more accurate information on environmental impacts, that might enhance the accuracy of environmental pollution damage cost accounting results. This is the case of mobile phone data collection for spatial-temporal population movement monitoring. In fact, such data allow developing more accurate dynamic exposure models, that could support the implementation of future spatial-temporal dynamic health damage assessment. Several methods, models and software are currently available to calculate the damage costs under a closed-system economic perspective. However, with the growth of studies based on supply chains and consumption, feedbacks at macro- and national level are now possible.

In order to adapt the environmental policies to the dynamic of environmental damages, closed and open system alternatives should be valued and incorporated into models to achieve a more accurate damage assessment. This is why, in future studies, appropriate accounting methods, containing relevant spatial-temporal information, should be selected according to the requirements of different stakeholders.

Declaration of competing interest

All the co-authors, including Yashuang Feng, Gengyuan Liu, Lixiao Zhang, and Marco Casazza, declare that they have no conflict of interest.

Acknowledgements

This work is supported by the National Natural Science Foundation (No. 52070021) and the 111 Project (No. B17005).

References

Aguiar, A., Narayanan, B., McDougall, R., 2016. An overview of the GTAP 9 data base. Journal of Global Economic Analysis 1, 28.

Alkemade, R., van Oorschot, M., Miles, L., Nellemann, C., Bakkenes, M., ten Brink, B., 2009. GLOBIO3: a framework to investigate options for reducing global terrestrial biodiversity loss. Ecosystems 12, 374–390.
Ansari, M., Ehrampoush, M.H., 2019. Meteorological correlates and AirQ+ health risk assessment of ambient fine particulate matter in Tehran, Iran. Environ. Res. 170, 141–150.
Antheaume, N., 2004. Valuing external costs–from theory to practice: implications for full cost environmental accounting. Eur. Account. Rev. 13, 443–464.
Asselin, A., Rabaud, S., Catalan, C., Leveque, B., L'Haridon, J., Martz, P., Neveux, G., 2020. Product biodiversity footprint–a novel approach to compare the impact of products on biodiversity combining life cycle assessment and ecology. J. Clean. Prod. 248, 119262.
Atkinson, R.W., Cohen, A., Mehta, S., Anderson, H.R., 2012. Systematic review and meta-analysis of epidemiological time-series studies on outdoor air pollution and health in Asia. Air Qual. Atmos. Health 5, 383–391.
Atkinson, R.W., Kang, S., Anderson, H.R., Mills, I.C., Walton, H.A., 2014. Epidemiological time series studies of PM2.5 and daily mortality and hospital admissions: a systematic review and meta-analysis. Thorax 69, 660–665.
Bai, R., Lam, J.C.K., Li, V.O.K., 2018. A review on health cost accounting of air pollution in China. Environ. Int. 120, 279–294.
Bartkowski, B., 2017. Are diverse ecosystems more valuable? Economic value of biodiversity as result of uncertainty and spatial interactions in ecosystem service provision. Ecosyst. Serv. 24, 50–57.
Barzeghar, V., Sarbakhsh, P., Hassanvand, M.S., Faridi, S., Gholampour, A., 2020. Long-term trend of ambient air PM10, PM2.5, and O3 and their health effects in Tabriz city, Iran, during 2006–2017. Sust. Cities Soc. 54, 101988.
Bell, M.L., Morgenstern, R.D., Harrington, W., 2011. Quantifying the human health benefits of air pollution policies: review of recent studies and new directions in accountability research. Environ. Sci. Pol. 14, 357–368.
Bherwani, H., Nair, M., Musugu, K., Gautam, S., Gupta, A., Kapley, A., Kumar, R., 2020. Valuation of air pollution externalities: comparative assessment of economic damage and emission reduction under COVID-19 lockdown. Air Qual. Atmos. Health 13, 683–694.
Braithwaite, I., Zhang, S., Kirkbride, J.B., Osborn, D.P.J., Hayes, J.F., 2019. Air pollution (particulate matter) exposure and associations with depression, anxiety, bipolar, psychosis and suicide risk: a systematic review and meta-analysis. Environ. Health Perspect. 127, 126002.
Bruckner, M., Giljum, S., Lutz, C., Wiebe, K.S., 2012. Materials embodied in international trade–global material extraction and consumption between 1995 and 2005. Glob. Environ. Change-Human Policy Dimens. 22, 568–576.
Cabaneros, S.M., Calautit, J.K., Hughes, B.R., 2019. A review of artificial neural network models for ambient air pollution prediction. Environ. Model. Softw. 119, 285–304.
Carvour, M.L., Hughes, A.E., Fann, N., Haley, R.W., 2018. Estimating the health and economic impacts of changes in local air quality. Am. J. Public Health 108, S151–S157.
Chantret, F., Chateau, J., Dellink, R., Durand-Lasserve, O., Lanzi, E., 2020. Can Better Technologies Avoid all Air Pollution Damages to the Global Economy? Clim. Change, pp. 1–18.
Chen, S.-M., He, L.-Y., 2014. Welfare loss of China's air pollution: how to make personal vehicle transportation policy. China Econ. Rev. 31, 106–118.
Chen, L., Shi, M., Gao, S., Li, S.H., Mao, J., Zhang, H., Sun, Y., Bai, Z., Wang, Z., 2017. Assessment of population exposure to PM2.5 for mortality in China and its public health benefit based on BenMAP. Environ. Pollut. 221, 311–317.
Chen, L., Liang, S., Liu, M., Yi, Y., Mi, Z., Zhang, Y., Li, Y., Qi, J., Meng, J., Tang, X., Zhang, H., Tong, Y., Zhang, W., Wang, X., Shu, J., Yang, Z., 2019. Trans-provincial health impacts of atmospheric mercury emissions in China. Nat. Commun. 10, 1484.
Chu, H.-J., Huang, B., Lin, C.-Y., 2015. Modeling the spatio-temporal heterogeneity in the PM10-PM2.5 relationship. Atmos. Environ. 102, 176–182.
Daniels, M.J., Dominici, F., Zeger, S.L., Samet, J.M., 2004. The national morbidity, mortality, and air pollution study. Part III: PM10 concentration-response curves and thresholds for the 20 largest US cities. Research report (Health Effects Institute), 1–21.
De Valck, J., Rolfe, J., 2019. Comparing biodiversity valuation approaches for the sustainable management of the Great Barrier Reef, Australia. Ecosyst. Serv. 35, 23–31.
Dias, D., Tchepel, O., 2018. Spatial and temporal dynamics in air pollution exposure assessment. Int. J. Environ. Res. Public Health 15, 558.
Dietzenbacher, E., Los, B., Stehrer, R., Timmer, M., de Vries, G., 2013. The construction of world input-output tables in the WIOD project. Econ. Syst. Res. 25, 71–98.
Ding, D., Xing, J., Wang, S., Liu, K., Hao, J., 2019. Estimated contributions of emissions controls, meteorological factors, population growth, and changes in baseline mortality to reductions in ambient PM 2.5 and PM 2.5-related mortality in China, 2013–2017. Environ. Health Perspect. 127, 067009.
Eckelman, M.J., Sherman, J.D., MacNeill, A.J., 2018. Life cycle environmental emissions and health damages from the Canadian healthcare system: an economic-environmental-epidemiological analysis. PLoS Med. 15, e1002623.
Ewald, B., 2018. The value of health damage due to sulphur dioxide emissions from coal-fired electricity generation in NSW and implications for pollution licences. Aust. N. Z. Publ. Health 42, 227–229.
Fang, G., Wang, T., Si, X., Wen, X., Liu, Y., 2016. Discharge fee policy analysis: a Computable General Equilibrium (CGE) model of water resources and water environments. Water 8, 413.
Feng, Z., De Marco, A., Anav, A., Gualtieri, M., Sicard, P., Tian, H., Fornasier, F., Tao, F., Guo, A., Paoletti, E., 2019. Economic losses due to ozone impacts on human health, forest productivity and crop yield across China. Environ. Int. 131, 104966.
Goedkoop, M., Spriensma, R., 2001. The Eco-Indicator 99: A Damaged Oriented Method for Life Cycle Impact Assessment. PRé Consultants BV Amersfoort, The Nitherland.
Goedkoop, M., Heijungs, R., Huijbregts, M., De Schryver, A., Struijs, J., van Zelm, R., 2009. ReCiPe 2008: a life cycle impact assessment method which comprises harmonised category indicators at the midpoint and the endpoint level.
Greco, S.L., Belova, A., Haskell, J., Backer, L., 2019. Estimated burden of disease from arsenic in drinking water supplied by domestic wells in the United States. J. Water Health 17, 801–812.
Henderson, S.B., Beckerman, B., Jerrett, M., Brauer, M., 2007. Application of land use regression to estimate long-term concentrations of traffic-related nitrogen oxides and fine particulate matter. Environ. Sci. Technol. 41, 2422–2428.
Hong, C., Kan, H., Chen, B., 2004. Methods for health risk assessment of urban air pollution (continued 5). Journal of Environment and Health 22, 3.
Hong, C., Mueller, N.D., Burney, J.A., Zhang, Y., AghaKouchak, A., Moore, F.C., Qin, Y., Tong, D., Davis, S.J., 2020. Impacts of ozone and climate change on yields of perennial crops in California. Nature Food 1, 166–172.
Hou, B., Lu, D., 2018. Corrosion cost and preventive strategies in China. Strategy & Policy Decision Research 33, 601–609.
Hou, Q., An, X.Q., Wang, Y., Guo, J.P., 2010. An evaluation of resident exposure to respirable particulate matter and health economic loss in Beijing during Beijing 2008 Olympic Games. Sci. Total Environ. 408, 4026–4032.
Hu, T., Liu, S., Xu, Y., Feng, Z., Calatayud, V., 2020. Assessment of O3-induced yield and economic losses for wheat in the North China Plain from 2014 to 2017, China. Environ. Pollut. 258, 113828.
Huijbregts, M.A.J., Hellweg, S., Hertwich, E., 2011. Do we need a paradigm shift in life cycle impact assessment? Environ. Sci. Technol. 45, 3833–3834.
Huijbregts, M.A.J., Steinmann, Z.J.N., Elshout, P.M.F., Stam, G., Verones, F., Vieira, M., Zijp, M., Hollander, A., van Zelm, R., 2017. ReCiPe2016: a harmonised life cycle impact assessment method at midpoint and endpoint level. Int. J. Life Cycle Assess. 22, 138–147.
Janse, J.H., Kuiper, J.J., Weijters, M.J., Westerbeek, E.P., Jeuken, M.H.J.L., Bakkenes, M., Alkemade, R., Mooij, W.M., Verhoeven, J.T.A., 2015. GLOBIO-aquatic, a global model of human impact on the biodiversity of inland aquatic ecosystems. Environ. Sci. Pol. 48, 99–114.
Jones, L., Milne, A., Hall, J., Mills, G., Provins, A., Christie, M., 2018. Valuing improvements in biodiversity due to controls on atmospheric nitrogen pollution. Ecol. Econ. 152, 358–366.
van der Kamp, J., Bachmann, T.M., 2015. Health-related external cost assessment in Europe: methodological developments from ExternE to the 2013 Clean Air Policy Package. Environ. Sci. Technol. 49, 2929–2938.
Kim, S.-T., Maeda, Y., Tsujino, Y., 2004. Assessment of the effect of air pollution on material damages in Northeast Asia. Atmos. Environ. 38, 37–48.
Kim, D., Kim, J., Jeong, J., Choi, M., 2019. Estimation of health benefits from air quality improvement using the MODIS AOD dataset in Seoul, Korea. Environ. Res. 173, 452–461.
Kougea, E., Koundouri, P., 2011. Air quality degradation: can economics help in measuring its welfare effects? A review of economic valuation studies. Indoor Outdoor Air Pollution 105.
Kumar, P., Imam, B., 2013. Footprints of air pollution and changing environment on the sustainability of built infrastructure. Sci. Total Environ. 444, 85–101.
La Notte, A., Dalmazzone, S., 2018. Sustainability assessment and causality nexus through ecosystem service accounting: the case of water purification in Europe. J. Environ. Manag. 223, 964–974.
Lenzen, M., Kanemoto, K., Moran, D., Geschke, A., 2012. Mapping the structure of the world economy. Environ. Sci. Technol. 46, 8374–8381.
Li, B., 2013. Assessment of air purification, carbon fixation and oxygen release of plain forestry in China. Science of Soil Water Conservation 7.
Li, T., Guo, Y., Liu, Y., Wang, J., Wang, Q., Sun, Z., He, M.Z., Shi, X., 2019a. Estimating mortality burden attributable to short-term PM2.5 exposure: a national observational study in China. Environ. Int. 125, 245–251.
Li, Y., Yu, Z., Yang, S., Wang, G., Liu, X., Wang, C., Xie, Z., Jin, J., 2019b. Impact of elevated CO2 on C:N:P ratio among soybean cultivars. Sci. Total Environ. 694, 133784.
Li, J., Liu, F., Liang, F., Huang, K., Yang, X., Xiao, Q., Chen, J., Liu, X., Cao, J., Chen, S., Shen, C., Yu, L., Lu, F., Wu, X., Zhao, L., Wu, X., Li, Y., Hu, D., Huang, J., Liu, Y., Lu, X., Gu, D., 2020. Long-term effects of high exposure to ambient fine particulate matter on coronary heart disease incidence: a population-based Chinese cohort study. Environ. Sci. Technol. 54, 6812–6821.
Liu, S., Song, G., 2016. Evaluation of PM2.5's adverse human health effect in cities. Acta Sci. Circumst. 36, 1468–1476.
Liu, G., Yang, Z., Chen, B., Zhang, Y., Su, M., Zhang, L., 2013. Emergy evaluation of the urban solid waste handling in Liaoning province, China. Energies 6, 5486–5506.
Lu, Z.-N., Chen, H., Hao, Y., Wang, J., Song, X., Mok, T.M., 2017. The dynamic relationship between environmental pollution, economic development and public health: evidence from China. J. Clean. Prod. 166, 134–147.
Miao, W., Huang, X., Song, Y., 2017. An economic assessment of the health effects and crop yield losses caused by air pollution in mainland China. J. Environ. Sci. 56, 102–113.
Ministry of Ecology and Environment of the People's Republic of China, 2014. Recommended methods for environmental damage assessment (2nd Edition).
Mo, Y., Li, N., Xu, C., Dongqun, X., 2018. Review of survey method for human time-activity pattern and its application in the exposure assessment of air pollutants. Chinese journal of preventive medicine 52.
Muller, N.Z., Mendelsohn, R., Nordhaus, W., 2011. Environmental accounting for pollution in the United States economy. Am. Econ. Rev. 101, 1649–1675.
Myers, S.S., Zanobetti, A., Kloog, I., Huybers, P., Leakey, A.D.B., Bloom, A.J., Carlisle, E., Dietterich, L.H., Fitzgerald, G., Hasegawa, T., Holbrook, N.M., Nelson, R.L., Ottman, M.J., Raboy, V., Sakai, H., Sartor, K.A., Schwartz, J., Seneweera, S., Tausz, M., Usui, Y., 2014. Increasing CO_2 threatens human nutrition. Nature 510, 139–142.

Nam, K.M., Selin, N.E., Reilly, J.M., Paltsev, S., 2010. Measuring welfare loss caused by air pollution in Europe: a CGE analysis. Energy Policy 38, 5059–5071.

Nam, K.-M., Zhang, X., Zhong, M., Saikawa, E., Zhang, X., 2019. Health effects of ozone and particulate matter pollution in China: a province-level CGE analysis. Ann. Reg. Sci. 63, 269–293.

Nansai, K., Tohno, S., Chatani, S., Kanemoto, K., Kurogi, M., Fujii, Y., Kagawa, S., Kondo, Y., Nagashima, F., Takayanagi, W., Lenzen, M., 2020. Affluent countries inflict inequitable mortality and economic loss on Asia via PM2.5 emissions. Environ. Int. 134, 105238.

Nowak, D.J., Hirabayashi, S., Bodine, A., Greenfield, E., 2014. Tree and forest effects on air quality and human health in the United States. Environ. Pollut. 193, 119–129.

Osseni, A.F., Bareille, F., Dupraz, P., 2019. Hedonic valuation of harmful algal bloom pollution: why econometrics matters? Land Use Pol., 104283

Ostro, B., 2004. Outdoor Air Pollution: Assessing the Environmental Burden of Disease at National and Local Levels, in: Woodward, A.P.-U.D.C.-L.C.C.A. (Ed.), Environmental burden of disease series, No. 5. World Health Organization.

Pascal, M., Corso, M., Chanel, O., Declercq, C., Badaloni, C., Cesaroni, G., Henschel, S., Meister, K., Haluza, D., Martin-Olmedo, P., Medina, S., 2013. Assessing the public health impacts of urban air pollution in 25 European cities: results of the Aphekom project. Sci. Total Environ. 449, 390–400.

PRCEE, 2006. Experience Report on International Environmental and Economic Accounting. Policy Research Center for Environmental and Economy, State Environmental Protection Administration of China, Fondazione Eni Enrico Mattei (FEEM), ECON The World Bank-Italian Trust Fund Project, Beijing (No: TF054326).

Price, C.E., Feldmeyer, B., 2012. The environmental impact of immigration: an analysis of the effects of immigrant concentration on air pollution levels. Popul. Res. Policy Rev. 31, 119–140.

Qin, C., Bressers, H.T.A., Su, Z., Jia, Y., Wang, H., 2011. Assessing economic impacts of China's water pollution mitigation measures through a dynamic computable general equilibrium analysis. Environ. Res. Lett. 6, 044026.

Ritz, B., Yu, F., Chapa, G., Fruin, S., 2000. Effect of air pollution on preterm birth among children born in Southern California between 1989 and 1993. Epidemiology 11, 502–511.

Rosendahl, K.E., 1998. Social Costs of Air Pollution and Fossil Fuel Use–A Macroeconomic Approach. Statistisk sentralbyrå.

Sabeen, A.H., Noor, Z.Z., Ngadi, N., Almuraisy, S., Raheem, A.B., 2018. Quantification of environmental impacts of domestic wastewater treatment using life cycle assessment: a review. J. Clean. Prod. 190, 221–233.

Salimi, F., Morgan, G., Rolfe, M., Samoli, E., Cowie, C.T., Hanigan, I., Knibbs, L., Cope, M., Johnston, F.H., Guo, Y., Marks, G.B., Heyworth, J., Jalaludin, B., 2018. Long-term exposure to low concentrations of air pollutants and hospitalisation for respiratory diseases: a prospective cohort study in Australia. Environ. Int. 121, 415–420.

Samet, J.M., Zeger, S.L., Dominici, F., Curriero, F., Coursac, I., Dockery, D.W., Schwartz, J., Zanobetti, A., 2000. The national morbidity, mortality, and air pollution study. Part II: morbidity and mortality from air pollution in the United States. Research report (Health Effects Institute) 94, 5.

Schwarzenbach, R.P., Egli, T., Hofstetter, T.B., von Gunten, U., Wehrli, B., 2010. Global water pollution and human health. Annu. Rev. Environ. Resour. 35, 109–136.

Science for Environment Policy, 2018. What are the health costs of environmental pollution? Future Brief 21. Brief produced for the European Commission DG Environment by the Science Communication Unit, UWE, Bristol.

Shi, L., Zanobetti, A., Kloog, I., Coull Brent, A., Koutrakis, P., Melly Steven, J., Schwartz Joel, D., 2016. Low-concentration PM2.5 and mortality: estimating acute and chronic effects in a population-based study. Environ. Health Perspect. 124, 46–52.

Shin, J., Park, J.Y., Choi, J., 2018. Long-term exposure to ambient air pollutants and mental health status: a nationwide population-based cross-sectional study. PLoS One 13, e0195607.

Simkin, S.M., Allen, E.B., Bowman, W.D., Clark, C.M., Belnap, J., Brooks, M.L., Cade, B.S., Collins, S.L., Geiser, L.H., Gilliam, F.S., Jovan, S.E., Pardo, L.H., Schulz, B.K., Stevens, C.J., Suding, K.N., Throop, H.L., Waller, D.M., 2016. Conditional vulnerability of plant diversity to atmospheric nitrogen deposition across the United States. Proc. Natl. Acad. Sci. U. S. A. 113, 4086.

Squalli, J., 2010. An empirical assessment of U.S. state-level immigration and environmental emissions. Ecol. Econ. 69, 1170–1175.

Stadler, K., Wood, R., Bulavskaya, T., Södersten, C.-J., Simas, M., Schmidt, S., Usubiaga, A., Acosta-Fernández, J., Kuenen, J., Bruckner, M., Giljum, S., Lutter, S., Merciai, S., Schmidt, J.H., Theurl, M.C., Plutzar, C., Kastner, T., Eisenmenger, N., Erb, K.-H., de Koning, A., Tukker, A., 2018. EXIOBASE 3: developing a time series of detailed environmentally extended multi-regional input-output tables. J. Ind. Ecol. 22, 502–515.

Sun, J., Zhang, J.-H., Wang, C., Duan, X., Wang, Y., 2019a. Escape or stay? Effects of haze pollution on domestic travel: comparative analysis of different regions in China. Sci. Total Environ. 690, 151–157.

Sun, Z., Tukker, A., Behrens, P., 2019b. Going global to local: connecting top-down accounting and local impacts, a methodological review of spatially explicit input–output approaches. Environ. Sci. Technol. 53, 1048–1062.

Thanh, B.D., Lefevre, T., 2000. Assessing health impacts of air pollution from electricity generation: the case of Thailand. Environ. Impact Assess. Rev. 20, 137–158.

UNEP-Financing Initiative, 2010. Universal Ownership-Why externalities matter to institutional investors.

Van Dingenen, R., Dentener, F.J., Raes, F., Krol, M.C., Emberson, L., Cofala, J., 2009. The global impact of ozone on agricultural crop yields under current and future air quality legislation. Atmos. Environ. 43, 604–618.

Verones, F., Hellweg, S., Azevedo, L.B., Laurent, A., Mutel, C.L., Pfister, S., 2016. Freshwater eutrophication. In LC-Impact Version 0.5: A Spatially Differentiated Life Cycle Impact Assessment Approach. In: Verones, F., Hellweg, S., Azevedo, L.B., Chaudhary, A., Cosme, N., Fantke, P., Goedkoop, M., Hauschild, M., Laurent, A., Mutel, C.L., et al. (Eds.), European LC-IMPACT Project Report: Trondheim, Norway Available online: http://www.lc-impact.eu/.

Vicedo-Cabrera, A.M., Sera, F., Liu, C., Armstrong, B., Milojevic, A., Guo, Y.M., Tong, S., Lavigne, E., Kyselý, J., Urban, A., Orru, H., Indermitte, E., Pascal, M., Huber, V., Schneider, A., Katsouyanni, K., Samoli, E., Stafoggia, M., Scortichini, M., Hashizume, M., Honda, Y., Ng, C.F.S., Hurtado-Diaz, M., Cruz, J., Silva, S., Madureira, J., Scovronick, N., Garland, R.M., Kim, H., Tobias, A., Íñiguez, C., Forsberg, B., Åström, C., Ragettli, M.S., Röösli, M., Guo, Y.-L.L., Chen, B.-Y., Zanobetti, A., Schwartz, J., Bell, M.L., Kan, H.D., Gasparrini, A., 2020. Short term association between ozone and mortality: global two stage time series study in 406 locations in 20 countries. BMJ-British Medical Journal 368, m108.

Vrontisi, Z., Abrell, J., Neuwahl, F., Saveyn, B., Wagner, F., 2016. Economic impacts of EU clean air policies assessed in a CGE framework. Environ. Sci. Pol. 55, 54–64.

Wang, L., Fang, B., Law, R., 2018. Effect of air quality in the place of origin on outbound tourism demand: disposable income as a moderator. Tourism Manage. 68, 152–161.

Wang, M.-X., Liang, L.-N., Siu, W.S., Fan, D., Sun, H.-R., Zhao, H.-H., Zhou, G.-J., Wu, W.-J., 2019a. Loss accounting of environmental pollution within Pearl River Delta region, South China. Environ. Pollut. 249, 676–685.

Wang, M., Aaron, C.P., Madrigano, J., Hoffman, E.A., Angelini, E., Yang, J., Laine, A., Vetterli, T.M., Kinney, P.L., Sampson, P.D., Sheppard, L.E., Szpiro, A.A., Adar, S.D., Kirwa, K., Smith, B., Lederer, D.J., Diez-Roux, A.V., Vedal, S., Kaufman, J.D., Barr, R.G., 2019b. Association between long-term exposure to ambient air pollution and change in quantitatively assessed emphysema and lung function. JAMA-J. Am. Med. Assoc. 322, 546–556.

Wang, Y., Li, X., Sun, Y., Zhang, L., Qiao, Z., Zhang, Z., Zheng, H., Meng, J., Lu, Y., Li, Y., 2020. Linkage analysis of economic consumption, pollutant emissions and concentrations based on a city-level Multi-Regional Input–Output (MRIO) model and atmospheric transport. J. Environ. Manag. 270, 110819.

Wei, J., Guo, X., Marinova, D., Fan, J., 2014. Industrial SO_2 pollution and agricultural losses in China: evidence from heavy air polluters. J. Clean. Prod. 64, 404–413.

Wilting, H.C., Schipper, A.M., Bakkenes, M., Meijer, J.R., Huijbregts, M.A.J., 2017. Quantifying biodiversity losses due to human consumption: a global-scale footprint analysis. Environ. Sci. Technol. 51, 3298–3306.

World Bank, 2016. The cost of air pollution: strengthening the economic case for action, Washington, DC.

World Health Organization, 2003. Mental health in emergencies.

Xia, B., 2011. Health Damage Evaluation System for Environmental Pollution. Huazhong University of Science and Technology, Wuhan, Hubei, China.

Xie, Y., Dai, H., Dong, H., Hanaoka, T., Masui, T., 2016. Economic impacts from PM2.5 pollution-related health effects in China: a provincial-level analysis. Environ. Sci. Technol. 50, 4836–4843.

Xue, T., Zhu, T., Zheng, Y., Zhang, Q., 2019. Declines in mental health associated with air pollution and temperature variability in China. Nat. Commun. 10, 1–8.

Yang, G., Li, W., Min, Q., 2006. Review of foreign opinions on evaluation of ecosystem services. Acta Ecol. Sin. 26, 205–212.

Yang, Q., Liu, G., Casazza, M., Hao, Y., Giannetti, B.F., 2019. Emergy-based accounting method for aquatic ecosystem services valuation: a case of China. J. Clean. Prod. 230, 55–68.

Yao, M., Wu, G., Zhao, X., Zhang, J., 2020. Estimating health burden and economic loss attributable to short-term exposure to multiple air pollutants in China. Environ. Res. 183, 109–184.

Yin, H., Xu, J., Kong, F., 2009. Impact of the amenity value of urban green space on the price of house in Shanghai. Acta Ecol. Sin. 8.

Yin, H., Pizzol, M., Xu, L.Y., 2017. External costs of PM2.5 pollution in Beijing, China: uncertainty analysis of multiple health impacts and costs. Environ. Pollut. 226, 356–369.

van Zelm, R., Preiss, P., van Goethem, T., van Dingenen, R., Huijbregts, M., 2016. Regionalized life cycle impact assessment of air pollution on the global scale: damage to human health and vegetation. Atmos. Environ. 134, 129–137.

Zeng, X., Ruan, F., Peng, Y., 2019. Health effects' spatial distribution analysis of PM2.5 pollution in China based on spatial grid scale. China Environ. Sci. 39, 2624–2632.

Zhang, H., Cao, D., Yu, F., Wang, J., Qi, J., Jia, Q., Zhang, T., Luo, Y., 2013. Environmental damage assessment: international regulations and revelation to China. Environmental Science 34.

Zhang, W., Liu, Y., Jiang, L., Wang, J., Wu, W., Bi, J., 2016. Evaluating the economic loss induced by water pollution based on multi-regional CGE model: a case study of Yangtze River Delta Basin. China Environ. Sci. 36, 2849–2856.

Zhang, W., Wang, F., Hubacek, K., Liu, Y., Wang, J., Feng, K., Jiang, L., Jiang, H., Zhang, B., Bi, J., 2018a. Unequal Exchange of Air Pollution and Economic Benefits Embodied in China's Exports. Environ. Sci. Technol. 52, 3888–3898.

Zhang, Z., Hao, Y., Lu, Z.-N., 2018b. Does environmental pollution affect labor supply? An empirical analysis based on 112 cities in China. J. Clean. Prod. 190, 378–387.

Zhao, H., Zhang, Y., Wang, M., 2015. Research progress of environmental damage assessment methods in China. Environmental science and management 40, 27–30.

Zhou, Q., Sun, T., 2000. Current situation of pollution eco-chemistry and its prospects. Chin. J. Appl. Ecol. 795–798.