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Estimating Air Pollution and Health Loss Embodied in Electricity Transfers: An Inter-Provincial Analysis in China

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Abstract:

Electricity generation may create high levels of pollution, but its consumption is completely clean. Long-distance electricity transfers make the allocation of environmental externalities caused by electricity generation unfair at the regional level. This paper provides a generalized approach that can be used to evaluate air pollution and health loss embodied in electricity transfers. Impact pathway approach is combined with a network approach to evaluate embodied direct health loss and a sophisticated evaluation of air pollution diffusion is implemented to assess indirect environmental impacts between regions. Using China's inter-provincial power transmission as an example, this paper also reveals various air pollutant and health loss transfer patterns among the nation's provinces. The results emphasize the importance of characterizing the embodied environmental effects in electricity transfer through health losses rather than air pollution emissions. The inter-regional indirect

impacts due to the diffusion of pollutants must be considered when examining the embodied health losses, which is even higher than the direct impact on the local. Several central regions in China, adjacent to the major electricity-export provinces, do not export a large amount of electricity, yet their health losses have increased significantly due to nationwide power transfers. The direct external health costs of electricity generation in China's major power-exporting provinces are relatively low. However, when indirect impacts are considered, external costs in the central and northern regions increase significantly. Therefore, the regional environmental benefits of shifting electricity generation to resource-rich remote areas are greatly reduced for many pairs of provinces.

Key words**:** Environment; Electricity transfer; Health loss; GAINS; Economic valuation

1. INTRODUCTION

Long-distance electricity transmission is a crucial energy transfer mode in a number of regions, including Europe, South Asia, China, and the United States (Wright and Kanudia, 2014). The method can facilitate electricity trade and help integrate energy sources efficiently (Yi et al., 2019a). In recent years, China has built a large number of ultra-high voltage lines, making long-distance and large-scale electricity transmission possible (Yi et al., 2016). Its inter-provincial electricity transfer volumes reached approximately 900 TWh in 2015, an increase of 52% compared to 2010 (CEC, 2011, 2016).

Electricity generation may create high levels of pollution, but its consumption is completely clean (Abrell and Rausch, 2016). Consumers enjoy the convenience of electricity, while suppliers face environmental problems that are by-products of its generation.

Inter-regional electricity transfers significantly affect environmental quality on both the supply and demand side, making the allocation of environmental externalities caused by electricity generation unfair at the regional level (Peters and Hertwich, 2008; García-Gusano et al., 2018; Yang et al., 2019). Therefore, it is necessary to examine the air pollution emissions embodied in electricity transfer and their associated environmental impact, and to explore how to share the external environmental costs among regions equitably.

Estimations of environmental or ecological impacts embodied in inter-regional electricity transfer have gradually attracted the attention of researchers, but the related literature focuses on CO_2 (Voorspools and D'haeseleer, 2006; Kang et al., 2012; Bai et al., 2014) and water resources (Zhang et al., 2017). Lindner et al. (2013) use a bottom-up model to evaluate direct CO_2 emissions embodied in Chinese province-specific electricity transfers. Su et al. (2017) analyze the spatiotemporal characteristics of CO_2 emissions from the consumption perspective based on detailed interprovincial electricity transfer data. Qu et al. (2017) develop a network approach to account for embodied CO_2 emissions of purchased electricity in China, and compare the results with the traditional direct trade-adjustment method. Finally, Zhang et al. (2017) investigate the virtual water resources embodied in electricity transfer, and introduce a water stress index into the framework. These studies provide valuable information about the assessment method, but they all ignore air pollution embodied in regional electricity transfers.

Due to the significant regional characteristics of environmental pollution, it is vital to consider air pollutants and their associated environmental impact when studying embodied emissions in electricity transfers (Huang et al., 2012). Greenhouse gases have a lesser relationship to the location of emission sources; their hazards are global. Watcharejyothin and Shrestha (2009) assess the environmental impact of electricity transfers between Laos and Thailand through several pollutants such as nitrogen oxides (NO_X) and sulfur dioxide (SO_2). Chen et al. (2010) evaluate the environmental impact of China's West–East Electricity Transmission Project on each region. Li et al. (2018) use the Yangtze River Delta region as an example to calculate air pollution emissions embodied in provincial power transmission. These studies concentrate on pollutant emissions, but do not specifically evaluate the effect of emissions on air quality and human health. Many studies address the health effects of electricity generation (Büke and Köne, 2011; Partridge and Gamkhar, 2012; Machol and Rizk, 2013); however, none combine these effects with detailed power transmission data to study the embodied health loss in long-distance electricity transfers.

Here, we not only combine impact pathway approach with a network approach to account for embodied direct health loss, but also conduct a sophisticated evaluation of air pollution diffusion to reflect indirect environmental impacts between regions. Indirect impacts mean that the pollutants discharged in one region will not only affect the health of local people, but also affect people in other regions, especially the neighboring areas. We construct an inter-regional health loss impact matrix and combine it with a regional electricity generation-consumption matrix to capture the indirect impacts embodied in electricity transfers. As such, this study advances the literature related to embodied health losses.

The purpose of this paper is to present a generalized approach to evaluate air pollution and health loss embodied in electricity transfers. It outlines how to account for embodied air pollutants and related health losses, and demonstrates how to incorporate the diffusion of pollutants at the regional level into this framework. Using China's inter-provincial power transmission as an example, this paper also analyzes which electricity transfer channels incorporate more health losses in China, and discusses the difficulties in sharing external environmental costs equitably among provinces.

This study builds upon previous studies by: 1) adopting the impact pathway approach to calculate health losses embodied in electricity transfers based on the Greenhouse Gas–Air Pollution Interactions and Synergies (GAINS) model; 2) constructing an inter-regional health loss impact matrix to capture indirect effects embodied in electricity transfers; and 3) using detailed inter-provincial power transfers and provincial pollutant emission factors data to present various air pollutant and health loss transfer patterns among Chinese provinces. These improvements in method and data provide a more accurate assessment of the impact of long-distance power transmission on regional health and environmental quality. They also reveal insights and challenges overlooked in previous studies.

This paper is organized as follows. Section 2 describes the estimation framework for embodied air pollution and health loss. The detailed data are presented in Section 3. Section 4 discusses embodied air pollution and health loss in provincial electricity transfers in China. Section 5 presents the conclusions.

2. METHODS

This study presents a generalized approach to evaluate air pollution and health loss embodied in electricity transfers. The conceptual framework differs from common methods for assessing embodied CO_2 emissions, as seen in Fig. 1.

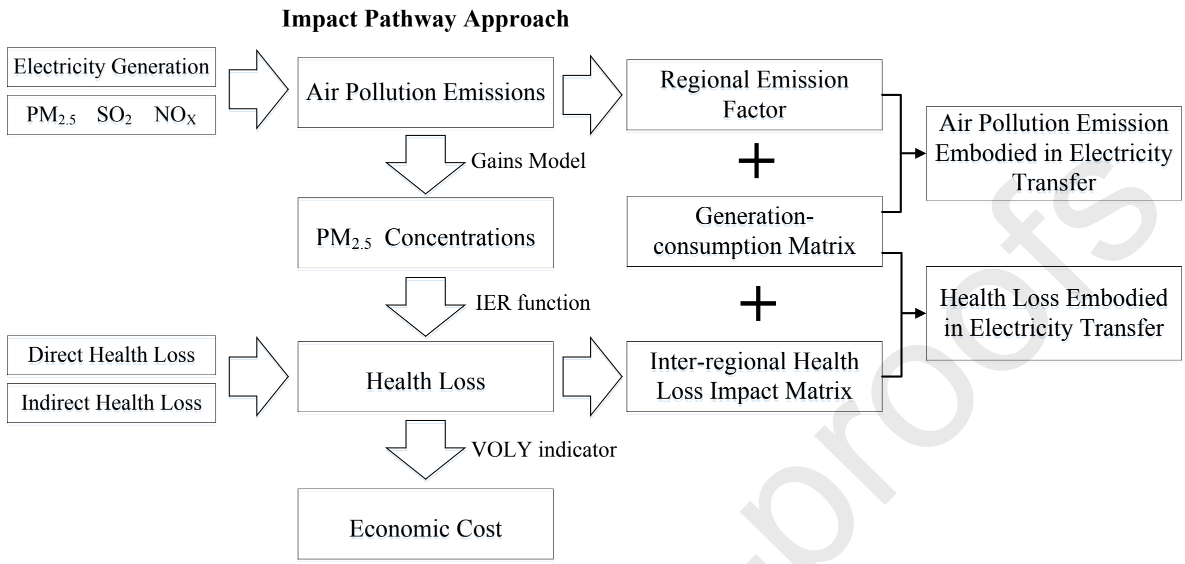


Fig. 1. The conceptual framework of this method.

2.1. Generation-consumption matrix

The core of accounting for emissions embodied in electricity transfers is to clarify the source of electricity consumption, because emission factors vary widely from region to region. The traditional direct trade-adjustment method assumes all electricity exports are attributed to local generation; this overlooks regions that function as intermediate nodes in multilateral trade (Soimakallio and Saikku, 2012). This study applies Qu et al.'s (2017) network approach to solve this issue, which considers both direct and indirect electricity flow in interconnected grid networks.

This approach treats all electricity flows as a network and assumes *n* nodes exist within the network. It first fixes the total electricity inflow of each node, that is, the sum of the imported electricity and local generation, and then determines whether the electricity is consumed locally or exported to other nodes, as shown in Eq. (1).

$$z_j = p_j + \sum_{i}^{i \neq j} T_{i,j} = c_j + \sum_{j}^{j \neq i} T_{j,i} \tag{1}$$

where i, j, i represent the region, and $i, j \in \{1,2,3,...,n\}$. $T_{i,j}$ represents electricity transfer from region i to j, which refers to the amount of electricity delivered in the electricity exporting region. This method assumes that transmission losses are borne by the electricity importing region. p_j and c_j stand for electricity generation and consumption, respectively. z_j is the total electricity inflow or outflow.

The key to the network approach is to assume exported electricity is proportionally derived from local generation and imported electricity. We define the direct outflow matrix $A = [a_{i,j}]_{n \times n}$, an n-order square matrix composed of element $a_{i,j}$ as shown in Eq. (2). $a_{i,j}$ represents the proportion of electricity transmitted from i to j in the total electricity inflow of region i, which is the same as the proportion of local electricity generation directly transferred to region j.

$$a_{i,j} = \begin{cases} \dfrac{T_{i,j}}{z_i}, & i \neq j \\ 0, & i = j \end{cases} \Rightarrow A = [a_{i,j}]_{n \times n} = \begin{bmatrix} 0 & \dfrac{T_{1,2}}{z_1} & \cdots & \dfrac{T_{1,n}}{z_1} \\ \dfrac{T_{2,1}}{z_2} & 0 & \ddots & \vdots \\ \vdots & \ddots & 0 & \dfrac{T_{n-1,n}}{z_{n-1}} \\ \dfrac{T_{n,1}}{z_n} & \cdots & \dfrac{T_{n,n-1}}{z_n} & 0 \end{bmatrix} \tag{2}$$

In addition to direct transfer, we must consider multiple pass-throughs. The total outflow matrix B quantifies the sum of direct and indirect electricity transfers through the operation of matrix A in Eq. (3). $b_{i,j}$ represents the proportion of electricity generation in region i to be transmitted to j.

$$B = [b_{i,j}]_{n\times n} = A + A^2 + A^3 + A^4 + \cdots \tag{3}$$

Then, we define the generation-consumption matrix $T = [T^*_{i,j}]_{n\times n}$ to link electricity generation and consumption between regions. T^*_{ij} indicates the amount of electricity generated by region *i* consumed in region *j*, as shown in Eq. (4).

$$T^*_{i,j} = p_i \cdot b_{i,j} \cdot \frac{c_j}{z_j} \tag{4}$$

2.2. Air pollution emissions embodied in electricity transfer

Air pollution emissions embodied in electricity transfers ($E^{AP}_{i,j}$) can be calculated using the generation-consumption matrix and regional emission factors (ef_i), as shown in Eq. (5).

$$E^{AP}_{i,j} = T^*_{i,j} \cdot ef_i \tag{5}$$

The calculation of air pollution emissions is different from that of carbon dioxide. Rather than being based on the consumption of various types of fuels, it considers the type of power generation and terminal emission control technologies. Therefore, it is necessary to account for air pollution emissions from the technology perspective. The annual average emission factor for region *i* is calculated as shown in Eq. (6).

$$ef_i = \frac{\sum_v \left(p_{i,v} \cdot ef_{i,v}\right)}{p_i} \tag{6}$$

where *v* represents power generation technology.

2.3. Health loss assessment

We adopt the impact pathway approach to account for health losses caused by air pollution emissions. This approach was designed within the ExternE project funded by the European Commission, which is a step-by-step procedure linking a burden to an impact

(Hainoun et al., 2010; Silveira et al., 2016). First, air pollution emissions are converted to concentrations using the GAINS model developed by the International Institute for Applied Systems Analysis (IIASA).[1] The GAINS model is widely used to determine air quality, pollutant emissions, and health effects, which covers the grid-specific particulate matter ($PM_{2.5}$) transfer coefficients and population distribution (Kiesewetter et al., 2015; Qin et al., 2017). It describes the responses of $PM_{2.5}$ concentrations to changes in primary $PM_{2.5}$ emissions and secondary inorganic aerosols formed from emissions of SO_2, NO_X, and NH_3 based on the global-regional chemistry transport model TM5 with a 1*1 degree spatial resolution. The model simulation results are periodically calibrated with real observation data by IIASA. This study also verifies the validity of the model by comparing $PM_{2.5}$ concentrations generated by GAINS with the observed data in China (see the Appendix A). More information on the methodology of the GAINS model can be found in Amann et al. (2008, 2011).

Second, human health losses from exposure to various concentrations of pollutants are assessed based on epidemiological principles. This study only addresses the effect of $PM_{2.5}$ on human health, because it is often considered the main cause of death (Gao et al., 2018). In addition, concentrations of various pollutants are correlated to a certain extent. As such, the inclusion of all pollutant emissions into the accounting category would lead to an overestimation of health loss (Künzli, 2002).

The integrated exposure-response (IER) function is used to estimate epidemiological

[1] GAINS model is available at "http://gains.iiasa.ac.at/models/index.html".

relative risk (RR), which can examine the mortality burden attributable to $PM_{2.5}$ exposure (Burnett et al., 2014). Referring to Global Burden of Disease (GBD), we calculate premature mortality linked to four diseases in adults ≥30 years old, namely chronic obstructive pulmonary disease (COPD), ischemic heart disease (IHD), stroke (STK), and lung cancer (LC), and for one illness among infants <5 years old, acute lower respiratory infection (LRI). The RR calculation for each disease is shown in Eq. (7).

$$RR_{a,k}(C_i) = \begin{cases} 1 + \alpha_{a,k}(1 - e^{-\beta_{a,k}(C_i - C_0)^{\gamma_{a,k}}}), & C_i \geq C_0 \\ 1 & , C_i < C_0 \end{cases} \tag{7}$$

where C_i represents annual $PM_{2.5}$ concentration calculated from the GAINS model, and C_0 represents the minimum-risk concentration threshold, which is set at 5.9 μg/m^3 (Apte et al., 2015). a and k represent age group and disease group, respectively; α, β, and γ are the parameters used to reflect the shape of the IER function.

The impact of $PM_{2.5}$ exposure on population health loss is indicated by years of life lost (YLL), as shown in Eq. (8) (Vienneau et al., 2015).

$$YLL_i = \sum_a \sum_s \left(\sum_k \left(\frac{RR_{a,k}(C_i) - 1}{RR_{a,k}(C_i)} \cdot y_{a,s,k} \cdot POP_{i,a,s} \right) \cdot el_{a,s} \right) \tag{8}$$

where s represents sex group; y is the current age-sex-specific mortality rate for disease k; POP is the size of the exposed population; and el is the expectation of life at age a in s.

2.4. Health loss embodied in electricity transfer

The calculation of embodied health loss is different to that of embodied air pollution or CO_2 emissions, as there is significant diffusion of pollutants in the process of emission-concentration conversion. Pollutants discharged in one region affect both the health of local people and that of those in other regions, especially the neighboring areas. Such inter-regional diffusion must be considered when accounting for embodied health loss. Therefore, we use three categories to describe impact patterns: direct health loss (DHL), indirect health loss (IDHL), and total health loss (THL). DHL includes only the impact of local power generation on local health, while IDHL depicts the effect of local power generation on other regions. THL is the sum of DHL and IDHL.

We explore the impact of power generation on health loss through a series of simulations based on the GAINS model. “BASE” includes all anthropogenic emission sectors and biogenic emissions. “noPOW” excludes power plant emissions in region i, while other settings are the same as in BASE. The difference between BASE and noPOW is considered the impact of the power sector on regional health loss. This approach is similar to that applied in Gao et al. (2018), which aims to separate the contributions of various sectors to determine air pollution concentrations.

Based on these simulations, we construct an inter-regional health loss impact matrix $H=[tl_{i,j}]_{n\times n}$ to reflect the total impact. The calculation of each element is shown in Eq. (9), which indicates YLL in region j caused by unit power generation in region i. Vector (dl_i) consisting of the main diagonal elements of the matrix, reflects the direct impacts, while other elements indicate the indirect impacts.

$$tl_{i,j}=\frac{\left(\frac{C_j^{BASE}-C_j^{noPOW,i}}{C_j^{BASE}}\right)\cdot YLL(C_j^{BASE})}{p_i} \tag{9}$$

where C_j^{BASE} and $C_j^{noPOW,i}$ denote annual $PM_{2.5}$ concentration in region j from the BASE and noPOW simulations

It is crucial to recognize that the contribution of the power industry to health loss is determined by its share of $PM_{2.5}$ concentration compared to total concentration in Eq. (9), not by its share of mortality. Due to the nonlinearity of the IER function, as the $PM_{2.5}$ concentration increases, marginal RR is decreases, so the result obtained by concentration decomposition is significantly larger. Gao et al. (2018) uses the similar approach, which is suitable for determining what fraction of $PM_{2.5}$-related mortality is caused by a single sector's emissions.

The DHL embodied in electricity transfer ($E_{i,j}^{DL}$) is calculated using the generation-consumption matrix and direct impact vector, as shown in Eq. (10).

$$E_{i,j}^{DL} = T_{i,j}^{*} \cdot dl_i \tag{10}$$

The THL embodied in electricity transfer ($E_{i,j}^{TL}$) is equal to the transpose of the total impact matrix multiplied by the generation-consumption matrix, as shown in Eq. (11). The THL of region i caused by power consumption in region j must sum up the impact of power generation in all regions, that transmit electricity to region j, on region i. For example, region a transmits electricity to b, and power generation in region a leads to an increase in health loss in region c. We surmise that part of the health loss in region c is caused by power consumption in region b.

$$E_{i,j}^{TL} = (H^T T)_{ij} \quad \Rightarrow \quad H^T T = \begin{bmatrix} dl_1 & tl_{2,1} & \cdots & tl_{n,1} \\ tl_{1,2} & dl_2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & tl_{n,n-1} \\ tl_{1,n} & \cdots & tl_{n-1,n} & dl_n \end{bmatrix} \begin{bmatrix} 0 & T_{1,2}^{*} & \cdots & T_{1,n}^{*} \\ T_{2,1}^{*} & 0 & \ddots & \vdots \\ \vdots & \ddots & 0 & T_{n-1,n}^{*} \\ T_{n,1}^{*} & \cdots & T_{n,n-1}^{*} & 0 \end{bmatrix} \tag{11}$$

2.5. Economic valuation estimation

Value of a life year (VOLY) is a widely used indicator to assess the monetary value of change in life expectancy due to air pollution (Desaigues et al., 2011). While studies evaluate VOLY in specific areas, the range of such assessment remains limited. A common way to address missing data is to adjust health costs by per capita GDP based on the VOLY of a reference area (Maji et al., 2018). This cost transfer method is shown in Eq. (12).

$$VOLY_i = VOLY_{ref} \cdot \left(\frac{G_i}{G_{ref}} \right)^{\theta} \tag{12}$$

where *ref* denotes the reference region; G is the per capita GDP; and θ is the income elasticity of health cost.

The calculation of the total economic cost embodied in electricity transfer ($E_{i,j}^{TC}$) is shown in Eq. (13). We determine direct economic cost by replacing $E_{i,j}^{TL}$ with $E_{i,j}^{DL}$.

$$E_{i,j}^{TC} = E_{i,j}^{TL} \cdot VOLY_i \tag{13}$$

3. DATA

Based on the assessment framework in Section 2, we take China as the research object to analyze air pollution and health loss embodied in inter-provincial electricity transfers. This study covers the 31 provinces in China, excluding Hong Kong, Macao, and Taiwan due to data limitations. The time periods are set at 2010 and 2015.

3.1. Inter-provincial electricity transfers

Inter-provincial electricity transfers data in 2010 and 2015 are obtained from the "Compilation of Statistical Data of Electric Power Industry" studies published by the China

Electricity Council (CEC, 2011, 2016). These data constitute a 31-order square matrix. Provincial electricity generation and consumption data are from the China Electric Power Yearbook (Fig. B1, Appendix B) (CEPYEB, 2011, 2016). Transmission loss is not considered due to data limitations.[2]

3.2. Air pollution emission factors

We incorporate three major air pollutants caused by electricity generation: NO_X, SO_2, and $PM_{2.5}$. Provincial air pollution emissions are calculated based on electricity generation structure and corresponding emission factors.

This study includes ten electricity generation technologies, categorized by fuel type, capacity, and construction time. The penetration rates of emission control technologies and the sulfur content of coal in various provinces are included when calculating emission factors. The specific technology set is listed in Table B1 of Appendix B. Provincial electricity generation structure and corresponding pollutant emission factors in 2010 and 2015 are from the database of WEO2017 scenario in the GAINS model, as shown in Table B2.

3.3. Health loss parameters

The parameters used for the RR curve of each disease are taken from Apte et al. (2015). Table B3 in Appendix B lists the parameters for COPD, LC, LRI, and age-specific

[2] We test the impact of transmission losses based on literatures. The loss ratio between Fujian and East China is 2% (Cheng et al., 2015). According to this data, we estimate the loss ratios between all provinces, which are set to be in proportion to the transmission distance. We find that the losses contribute between 1% and 5% in different electricity importing regions in 2015. However, due to data limitations, we do not distinguish the embodied pollutants emissions caused by losses in Section 4, but assume that all transmission losses are borne by the electricity importing regions.

modification parameters for IHD and STK. National age–sex–specific mortality rates for the years 2010 and 2015 are derived from the GBD study 2016, as shown in Table B4 and Table B5.[3] The life expectations for Chinese men and women at various ages are from the World Health Organization annual life table. The China Statistical Yearbook (NBS, 2016) provides the age–sex–province population size.

3.4. Economic costs

Desaigues et al. (2011) recommend a European VOLY of 40,000 euros based on a contingent valuation survey of nine European countries. According to the national GDP per capita in PPP and the average exchange rate, we calculate China's VOLY in 2010 at 100,600 Chinese yuan (CNY). The provincial GDP per capita is derived from the China Statistical Yearbook (NBS, 2011, 2016). The income elasticity of health cost is set to 0.8, as suggested by Maji et al. (2018).

4. RESULTS AND DISCUSSION

4.1. Air pollution emissions embodied in provincial electricity transfer

Fig. 2 presents air pollution emission inflows and outflows embodied in provincial electricity transfers in China. The transfer trends of $PM_{2.5}$, SO_2, and NO_X are generally the same. The only difference is the SO_2 emissions embodied in the electricity exports of several southern provinces such as Sichuan, Guizhou, and Hubei are relatively high due to the high sulfur content of coal in southern China.

[3] Data source is the website of Institute for Health Metrics and Evaluation (https://vizhub.healthdata.org/cod/).

At the provincial level, the net outflows of pollutants embodied in electricity transfer from Inner Mongolia and Shanxi are far higher than other major electricity export provinces. The transfer mode of pollutant emissions is quite different from the electricity transfer mode (Appendix, Fig. B1). For example, Sichuan and Yunnan export large volumes of electricity, but the corresponding air pollutant emissions are not high. Most electricity generation in these provinces is from clean hydropower, while thermal power dominates in Inner Mongolia and Shanxi. As our research period is restricted to 2010 and 2015, the share of non-hydro renewable energy is quite limited, but the power supply structure of Inner Mongolia may change in the future (Yi et al., 2019b). The major net air pollutant inflow provinces are Hebei, Guangdong, and Beijing, which is closely related to the sources of imported power in these provinces. For example, electricity imports in Hebei and Beijing are mainly from Inner Mongolia and Shanxi. Meanwhile, several provinces like Jilin and Hunan manage to nearly balance their imports and exports.

Although nationwide, inter-provincial electricity transfer volumes in 2015 are 1.52 times greater than 2010, embodied air pollution emissions, especially of SO_2 and NO_X, are significantly reduced. This is likely due to the large-scale installation of desulfurization and denitrification equipment during the 12th Five-Year Plan (2010–2015). However, $PM_{2.5}$ emissions have barely changed. In particular, the absolute volume of air pollutants embodied in Sichuan's electricity exports are higher in 2015, as the State Grid built many new power transmission channels during this period to promote hydropower consumption.

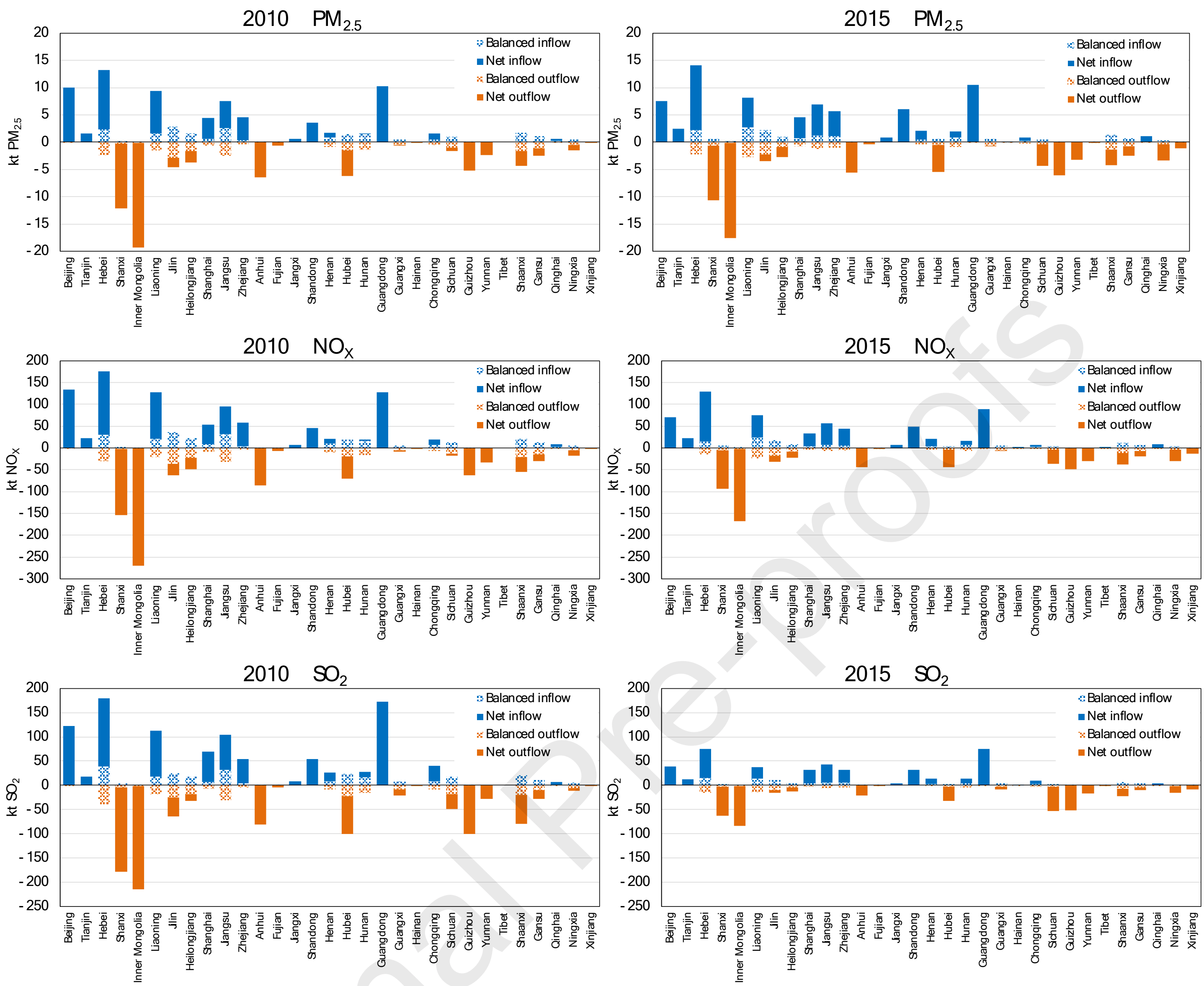


Fig. 2. Air pollution emission inflows and outflows embodied in electricity transfer.

Fig. 3 shows the largest 30 $PM_{2.5}$ flows, reflecting the main transfer network of embodied pollutants. The provincial abbreviations are presented in Table B2 of Appendix. In 2010, the largest inter-provincial $PM_{2.5}$ flows were from Inner Mongolia to Hebei and Beijing (5.9 kt and 5.4 kt),[4] Shanxi to Hebei (5.1 kt), Jilin to Liaoning (4.4 kt), and Guizhou to Guangdong (4.3 kt). The five largest flows in 2015 are from Shanxi to Hebei (5.2 kt), Inner

[4] kt is the unit of emissions, representing the thousand tons.

Mongolia to Hebei, Liaoning, and Beijing (5.1 kt, 4.6kt, and 3.5 kt), and Guizhou to Guangdong (5.0 kt). The main transfer network did not change significantly during the 12th Five-Year Plan, although the order of top flows is somewhat different.

Most $PM_{2.5}$ transfers occur in the North and Northeast power grids, because inter-provincial power transmissions in these grids are relatively large and the power supply structure is dominated by thermal power. The Northwest power grid is rich in renewable energy resources, but until 2015, it lacked many power transmission channels, so it is not a major $PM_{2.5}$ export region. The East and Southern power grids primarily import electricity from Sichuan, Guizhou, Yunnan, and Hubei, where electricity generation is relatively clean. This transfer mode is similar to the CO_2 transfer mode given in Qu et al. (2017). A strong correlation exists between air pollutant emissions and carbon dioxide emissions.

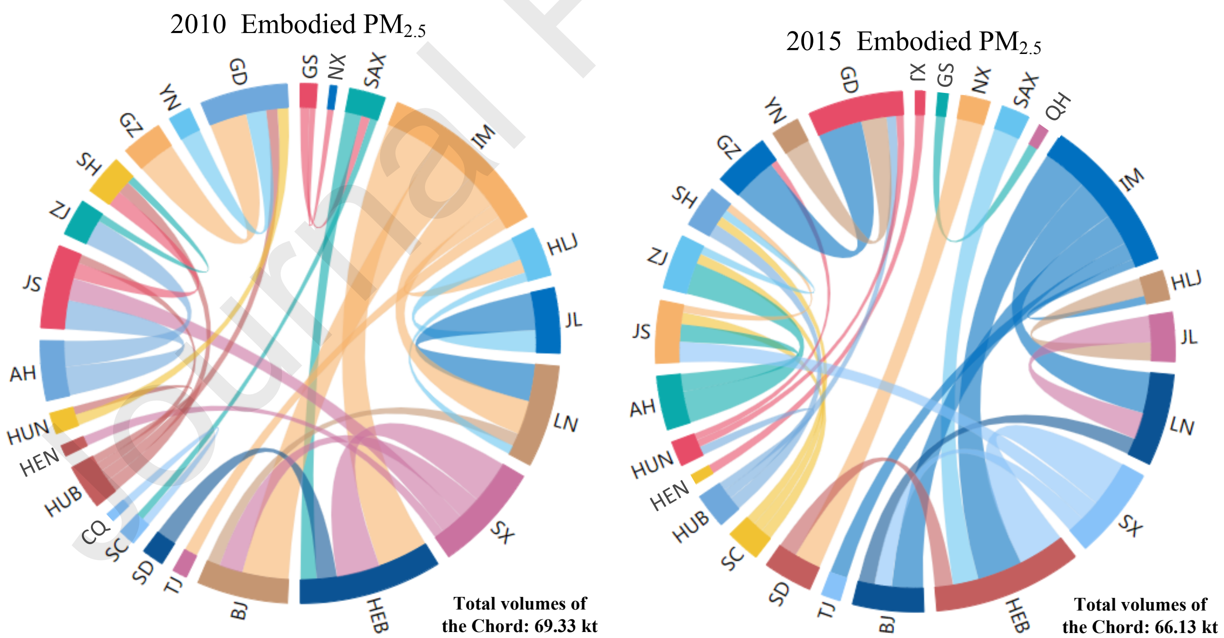


Fig. 3. Province-specific $PM_{2.5}$ emissions embodied in electricity transfer.

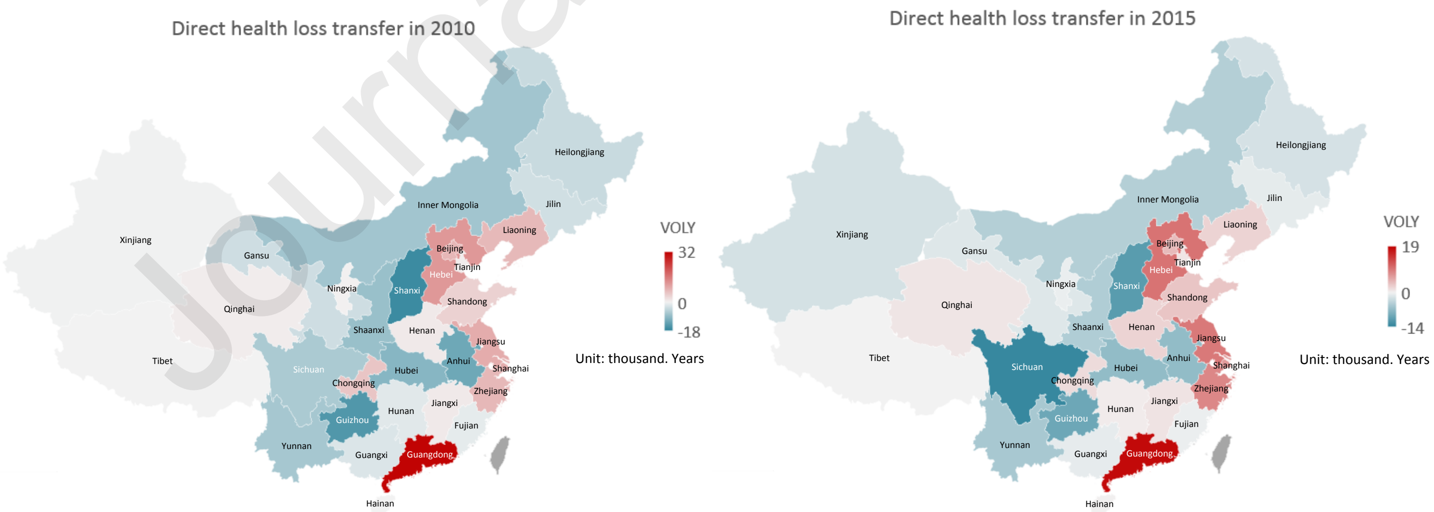
4.2. Health loss embodied in provincial electricity transfers

Fig. 4 presents the health loss embodied in China's provincial electricity transfers. YLL is used as the indicator of health loss. A positive number represents the loss embodied in the electricity inflow, while a negative number represents the outflow.

From the direct loss perspective, the health losses embodied in electricity exports from Sichuan, Shanxi, and Guizhou are the highest. This is significantly different from the results of embodied air pollution emissions. In Inner Mongolia, emission factors of various pollutants are high, but it is sparsely populated and has a vast territory, meaning local health loss caused by air pollution emissions is low. In contrast, Sichuan is densely populated, and its geographical characteristics make air pollutants more likely to accumulate in its basin. Therefore, although Sichuan relies primarily on clean hydropower, local health loss caused by its power generation is still very high. Our analysis indicates that although certain correlations occur between air pollutants and health losses, the differences, which are highly dependent on regional population density and pollutant diffusion level, are obvious.

Guangdong province exhibits the highest DHL inflow, followed by Shanghai, Jiangsu, Zhejiang, and Hebei. Several northern provinces, such as Beijing, Liaoning, and Shandong, are able to import electricity with modest direct losses. Compared to 2010, most health losses associated with inter-provincial electricity transfers decreased significantly in 2015, due to a reduction in $PM_{2.5}$ concentration. The large-scale pollutant emission control during the 12th Five-Year Plan period resulted in a decrease in secondary inorganic aerosols formed from NO_X and SO_2 emissions, which lowered electricity generation's contribution to $PM_{2.5}$ concentrations (Fig. B2, Appendix B). This result is not evident when only $PM_{2.5}$ emissions are considered, as these remained almost unchanged between 2010 and 2015.

When considering total losses, embodied health loss in electricity transfer are much higher than direct losses cases, because the former includes the indirect effects of pollutant diffusion. The biggest difference is that several provinces, such as Henan, have significantly higher health losses despite not exporting electricity; this is due to electricity transfers between other provinces. In addition, including indirect losses increases health losses due to nationwide inter-provincial electricity transfers in Hubei, Anhui, Hunan, Jiangxi, and Sichuan. These provinces are adjacent to, and downwind from, major electricity-export provinces. For example, a large percentage of health losses in Henan, Hubei, and Anhui are due to the diffusion of pollutants in Inner Mongolia and Shanxi. Diffusion's indirect effects are sometimes higher than direct effects. Inner Mongolia, for instance, emits a large amount of pollutants, but the direct health loss from electricity generation is not high due to the low local population density. However, pollutants in Inner Mongolia spread to densely populated central provinces, resulting in more serious losses.



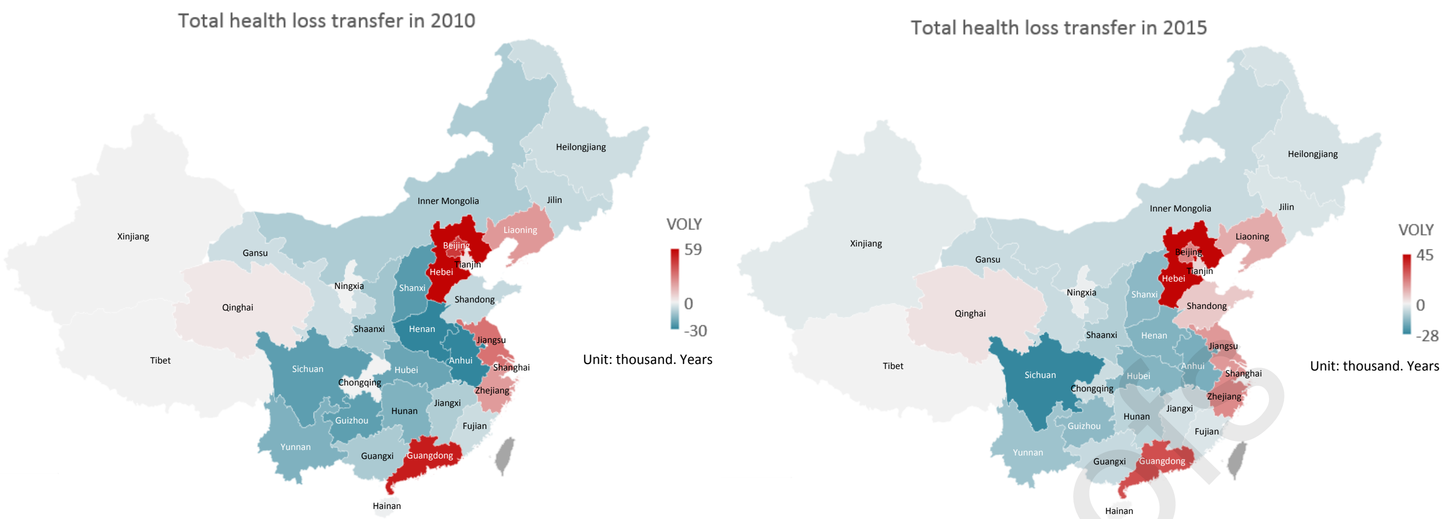


Fig. 4. Health loss embodied in electricity transfer.

Fig. 5 shows the 30 largest embodied health loss flows in 2015. The top five DHL flows are from Guizhou to Guangdong (8.0 ky),[5] Shanxi to Hebei (5.5 ky), Yunnan to Guangdong (4.7 ky), Anhui to Zhejiang (4.5 ky), and Shaanxi to Hebei (4.4 ky), while the highest THL flows are from Guizhou to Guangdong (9.0 ky), Yunnan to Guangdong (8.5 ky), Shanxi to Hebei (7.2 ky), Henan to Hebei (6.8 ky), and Shaanxi to Hebei (6.1 ky). Most health loss transfers occur in the Southern, East, and Central power grids, unlike what is seen in the air pollutant or carbon dioxide transfer modes.

When considering indirect impacts, the embodied health losses in the electricity import of Hebei increase significantly, and this increment mainly comes from Henan. This is because a large part of the electricity consumed in Hebei is generated in Inner Mongolia and Shanxi, and the pollutants produced by these two provinces have spread to Henan and caused great health losses. From the consumption perspective, the increase in health loss in Henan is

[5] ky is the unit of YLL, representing the thousand years.

caused by electricity consumption in Hebei. Although Henan does not directly transmit electricity to Hebei, in 2015 the loss flow between them is 6.8 ky, the fourth-highest flow.

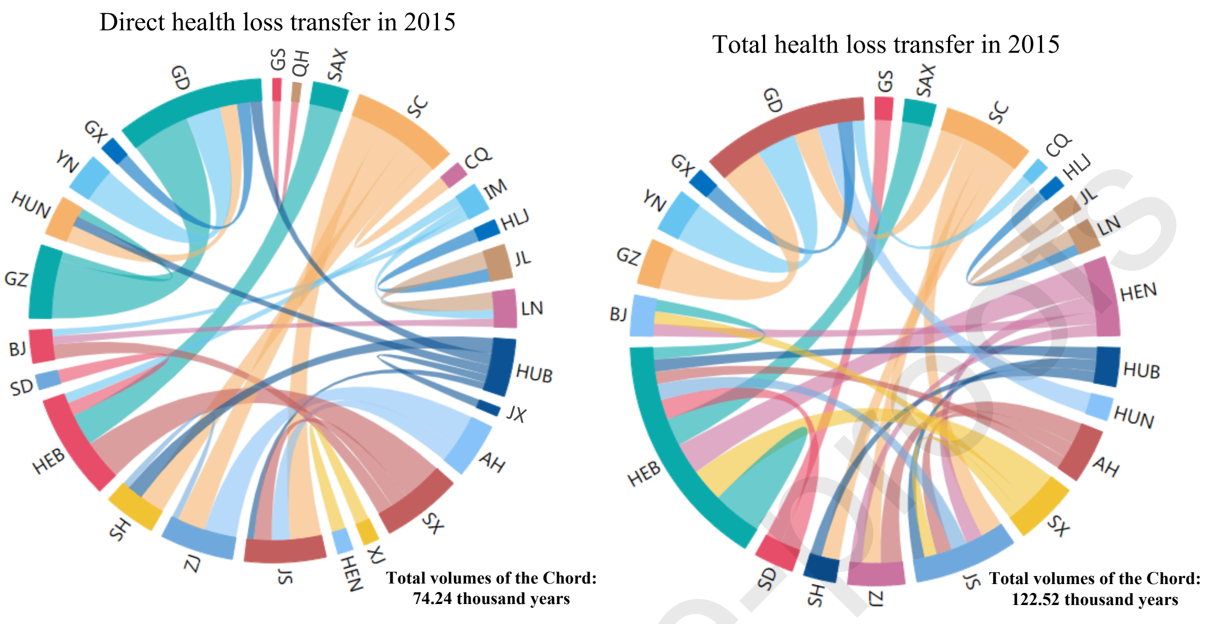


Fig. 5. Province-specific health loss embodied in electricity transfer.

4.3. Health external costs

Different studies value VOLY quite differently (Yang et al., 2013; Xie et al., 2016); as such, we primarily use YLL to estimate health loss. The purpose of introducing economic valuation is to provide a more intuitive external cost that can be used by policymakers. We do not examine economic cost embodied in electricity transfers, but rather calculate the direct and total external costs of electricity generation in each province, as shown in Fig. 6.

The direct external health cost in major electricity-export provinces is below 0.04 CNY per kWh; typically it is below 0.02 CNY. Due to pollution control enhancements, national external costs decreased in 2015. Electricity generation costs of various provinces in China fluctuate between 0.25 and 0.45 CNY per kWh, indicating direct external costs generally account for less than 10% of electricity generation costs.

Total external health costs in each province are at least twice as high as direct external costs. After considering the indirect effects between regions, external costs in several major electricity-export provinces increase significantly, especially in Inner Mongolia and Ningxia, as well as Shanxi and Anhui. Indirect external costs are relatively high in the northern and central regions and relatively low in the southwest regions. Total external costs in Xinjiang, Qinghai, Sichuan, and Yunnan are relatively low in 2015, which is suitable for increasing electricity exports. However, Sichuan and Yunnan have limited hydropower resources that will be almost fully developed by 2030. Xinjiang and Qinghai are far from the eastern high-load areas, so the cost of power transmission is high. As such, future optimal electricity transmission modes incorporating health externalities should be further analyzed by a more complex optimization model.

Although the results indicate indirect impacts can cause significant changes to the estimated effects of electricity generation on health, it is difficult to apply such findings at the policy level. Quantifying the extent of pollutant diffusion between provinces through a recognized standard is challenging. However, the more troublesome issue is separating the transaction subject and the affected subject. Suppose we set an environmental tax on electricity trades to compensate for health loss in power export areas. “Health loss” here would equate to “direct loss” as used in this article. If region *a* transmits electricity to region *b*, *b* pays *a* a certain environmental tax. Yet if electricity generation in *a* leads to health loss to region *c*, then *b* should also compensate *c*; however, a policy forcing *b* to pay a region with which it has no direct dealings might be nearly impossible.

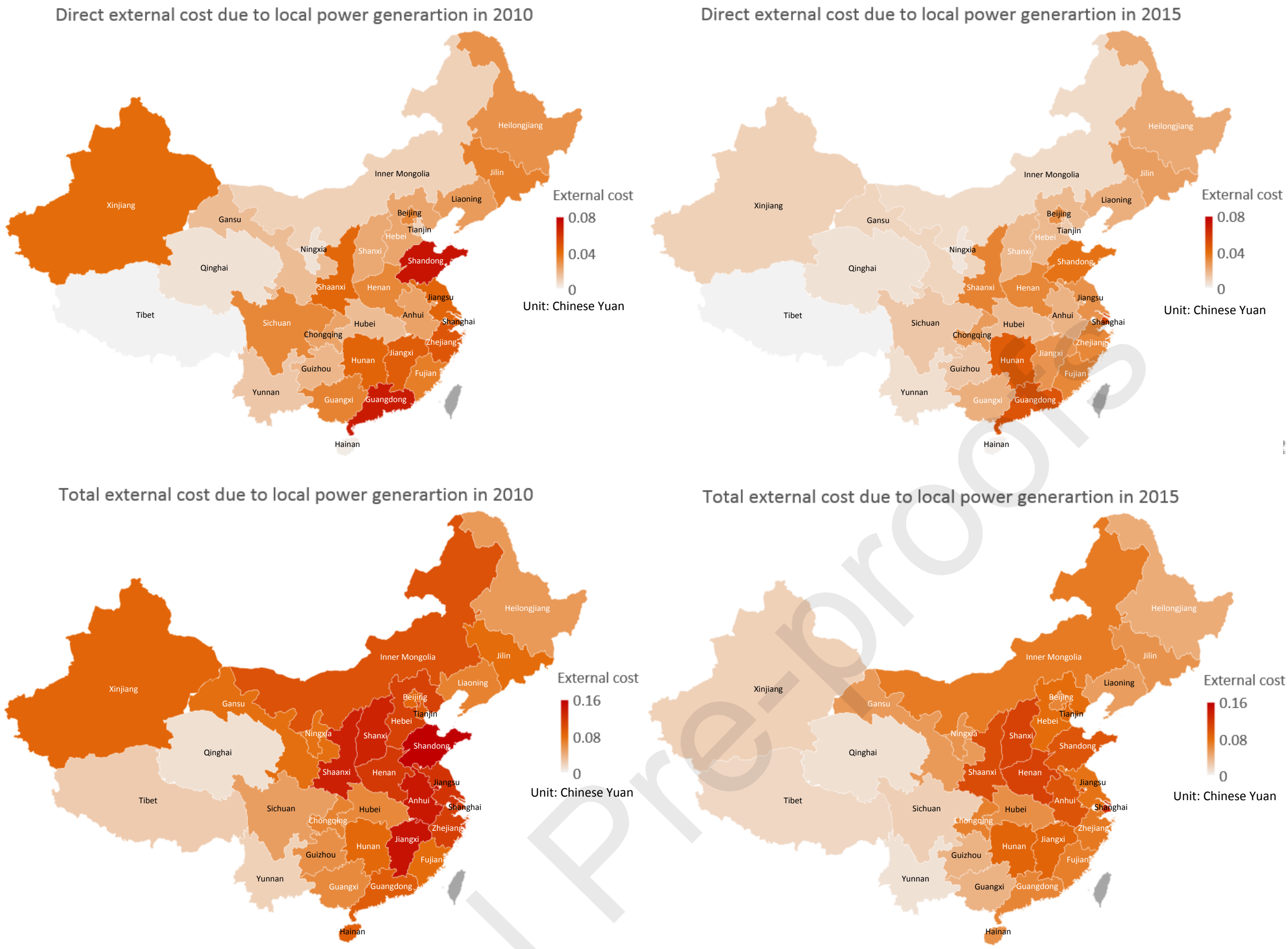


Fig. 6. Provincial health external cost of electricity generation.

5. CONCLUSIONS

This paper provides a generalized approach that can be used to evaluate air pollution and health loss embodied in electricity transfers. Impact pathway approach is combined with a network approach to evaluate embodied direct health loss and a sophisticated evaluation of air pollution diffusion is implemented to assess indirect environmental impacts between regions. Using China's inter-provincial power transmission as an example, this paper also reveals various air pollutant and health loss transfer patterns among the nation's provinces, and discusses the difficulties in sharing external environmental costs equitably among them.

This study emphasizes the need to characterize the embodied environmental effects in electricity transfer through health losses rather than air pollution emissions. The results produced by these two indicators differ significantly, primarily due to regional differences in population density and pollutant diffusion. Sichuan and Inner Mongolia, two of China's biggest electricity exporters, reflect these differences. The direct health loss embodied in the electricity export from Sichuan is high, although its power supply relies primarily on clean hydropower, while Inner Mongolia is the opposite.

The inter-regional indirect impacts due to the diffusion of pollutants must be considered when examining the health losses embodied in electricity transfer, which is even higher than the direct impact on the local. This is one of the biggest differences between the study of embodied pollutant transfers and water or carbon dioxide transfers. The environmental impacts of pollutants have obvious regional and diffusible properties. Several central regions in China, adjacent to the major electricity-export provinces, do not export a large amount of electricity, yet their health losses have increased significantly due to nationwide power transfer. The most typical example is Henan.

The direct external health costs of electricity generation in major power-exporting provinces are relatively low, accounting for less than 10% of the production costs. However, when indirect impacts are considered, external costs in the central and northern regions such as Inner Mongolia, Shanxi, Ningxia, and Anhui increase significantly. Therefore, the regional environmental benefits of shifting electricity generation to resource-rich remote areas are greatly reduced for many pairs of provinces. The southwestern regions where hydropower resources are concentrated, such as Sichuan and Yunnan, are still the first choice for electricity exports. Although local direct health loss caused by electricity generation in these provinces are not insignificant, the associated indirect losses are small. Relatively high direct losses enable the implementation of more accurate environmental tax policies that compensate for external costs in electricity-exporting areas.

This study is the first step in developing a useful approach to evaluate health loss embodied in electricity transfers. We suggest several directions for further research. First, the research accuracy of this study is not enough. The GAINS 1*1 degree resolution for China has certain limitations in studying health benefits. Considering a more detailed grid data for population distribution and $PM_{2.5}$ concentrations will serve better for evaluating health impacts. Second, this study assumes that transmission losses are borne by the electricity importing region. If relevant data is available, it is meaningful to analyze the impact of transmission losses on the air pollution and health loss embodied in electricity transfers.

ACKNOWLEDGEMENT

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APPENDIX A. VALIDITY TEST

The annual average $PM_{2.5}$ concentrations generated by GAINS are compared with the observed data in 2010 and 2015 to verify the validity of the model. The 2015 observations come from air quality reports from 74 major cities announced by the Ministry of Environmental Protection (MEP, 2016). In 2010, due to the lack of official monitoring data, we select the reported $PM_{2.5}$ measurements for more than 20 provinces based on literatures for comparison (Yao and Lu, 2014; Liu et al., 2018).

The model-measurement comparison is presented in Fig. A1. Although not perfect, the agreement with available observations shows considerably less bias.

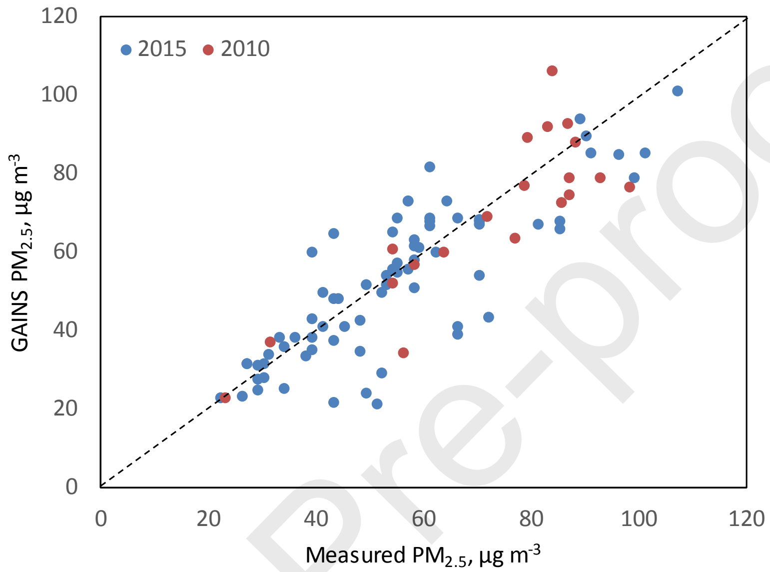

Fig. A1. Comparison of GAINS estimates of $PM_{2.5}$ with observation data.

APPENDIX B. KEY DATA SET

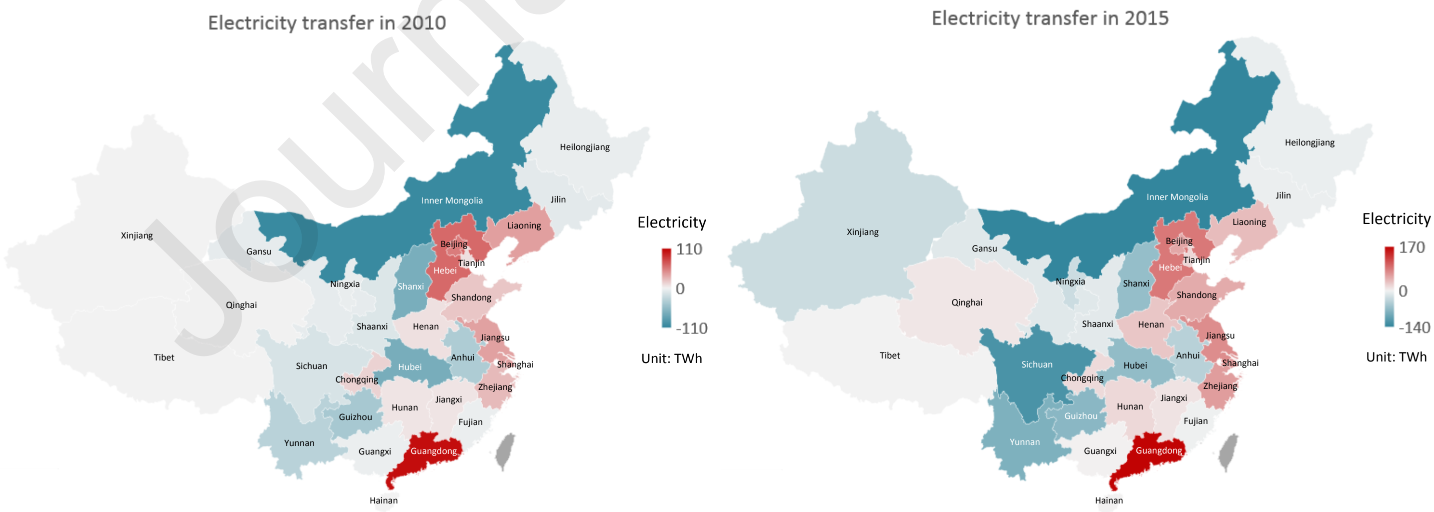

Fig. B1. Provincial electricity transfer in 2010 and 2015.

Table B1
Electricity generation technology category.

Technology	Fuel	Technology	Fuel
Ultra & supercritical power	Coal	Combined-cycle gas turbine	Natural gas
Integrated gasification combined cycle	Coal	Other gas-fired power	Natural gas
Other coal-fired power after 1995	Coal	Biomass power	Biomass
Coal-fired power before 1995 (⩾50 MW)	Coal	Diesel generator sets	Diesel oil
Coal-fired power before 1995 (<50 MW)	Coal	Gasoline generator sets	Gasoline

Table B2
Provincial integrated air pollution emission factors (g/kWh).

Province	Abbreviate	2010			2015		
		$PM_{2.5}$	SO_2	NO_X	$PM_{2.5}$	SO_2	NO_X
Beijing	BJ	0.243	1.469	2.993	0.138	0.583	0.801
Tianjin	TJ	0.200	2.137	2.752	0.189	0.928	1.084
Hebei	HEB	0.180	3.035	2.351	0.149	0.999	0.974
Shanxi	SX	0.169	2.478	2.133	0.147	0.872	1.296
Inner Mongolia	IM	0.183	2.026	2.552	0.126	0.601	1.209
Liaoning	LN	0.234	2.743	3.126	0.180	0.901	1.629
Jilin	JL	0.236	3.279	3.184	0.208	0.939	1.899
Heilongjiang	HLJ	0.266	2.246	3.384	0.211	0.978	1.691
Shanghai	SH	0.190	2.092	2.367	0.215	1.006	1.129
Jiangsu	JS	0.173	2.139	2.151	0.126	0.610	0.738
Zhejiang	ZJ	0.170	2.310	2.101	0.145	0.701	0.832
Anhui	AH	0.168	2.104	2.229	0.132	0.492	1.044
Fujian	FJ	0.135	1.056	1.512	0.106	0.437	0.819
Jiangxi	JX	0.178	2.500	2.021	0.116	0.470	0.893
Shandong	SD	0.201	4.350	2.611	0.123	0.767	1.144
Henan	HEN	0.189	2.023	2.226	0.164	0.844	1.335
Hubei	HUB	0.079	1.263	0.879	0.074	0.431	0.593
Hunan	HUN	0.135	1.508	1.566	0.125	0.610	1.002
Guangdong	GD	0.140	1.590	1.767	0.119	0.605	0.644
Guangxi	GX	0.084	2.626	1.101	0.068	0.731	0.588
Hainan	HN	0.146	1.576	1.699	0.097	0.450	0.795
Chongqing	CQ	0.124	1.906	1.589	0.082	0.918	0.901
Sichuan	SC	0.075	2.275	0.870	0.035	0.423	0.296
Guizhou	GZ	0.121	2.366	1.478	0.080	0.680	0.643
Yunnan	YN	0.073	0.846	1.002	0.039	0.202	0.362
Tibet	TB	0.130	1.235	1.385	0.087	0.447	0.611
Shaanxi	SAX	0.179	3.290	2.267	0.154	0.840	1.377
Gansu	GS	0.150	1.699	1.809	0.111	0.425	0.879
Qinghai	QH	0.038	0.203	0.520	0.028	0.117	0.282
Ningxia	NX	0.179	1.334	2.149	0.106	0.470	0.944
Xinjiang	XJ	0.158	6.355	2.552	0.040	0.278	0.457

Table B3
RR parameters for each disease.

Disease	α	β	γ	Disease	α	β	γ
COPD	2.175	0.00632	0.748	LC	3.725	0.00397	0.803
LRI	1.902	0.00219	1.283	STK 30-34	2.936	0.0145	1.086
IHD 30-34	2.535	0.0635	0.679	STK 35-39	2.583	0.0155	1.080
IHD 35-39	2.225	0.0671	0.673	STK 40-44	2.288	0.0154	1.093
IHD 40-44	1.942	0.0723	0.658	STK 45-49	2.020	0.0154	1.109
IHD 45-49	1.549	0.1013	0.540	STK 50-54	1.745	0.0162	1.110
IHD 50-54	1.366	0.0935	0.585	STK 55-59	1.477	0.0174	1.103

IHD 55-59	1.178	0.0936	0.599	STK 60-64	1.243	0.0188	1.094
IHD 60-64	1.004	0.0947	0.609	STK 65-69	0.993	0.0217	1.043
IHD 65-69	0.842	0.0972	0.611	STK 70-74	0.807	0.0222	1.067
IHD 70-74	0.688	0.1010	0.610	STK 75-79	0.642	0.0233	1.074
IHD 75-79	0.548	0.1048	0.609	STK 80+	0.490	0.0243	1.085
IHD 80+	0.416	0.1094	0.607				

Table B4
Age-sex-specific mortality rate for each disease in 2010 (%).

Age	IHD(M)	IHD(F)	COPD(M)	COPD(F)	STK(M)	STK(F)	LC(M)	LC(F)	LRI(M)	LRI(F)
0-1	_	_	_	_	_	_	_	_	0.2847	0.1485
1-5	_	_	_	_	_	_	_	_	0.0094	0.0119
30-34	0.0091	0.0033	0.0010	0.0007	0.0078	0.0030	0.0023	0.0014	_	_
35-39	0.0147	0.0050	0.0016	0.0011	0.0139	0.0056	0.0046	0.0029	_	_
40-44	0.0275	0.0097	0.0037	0.0023	0.0296	0.0133	0.0113	0.0065	_	_
45-49	0.0472	0.0181	0.0078	0.0045	0.0548	0.0271	0.0262	0.0122	_	_
50-54	0.0697	0.0287	0.0160	0.0089	0.0875	0.0482	0.0469	0.0210	_	_
55-59	0.1114	0.0520	0.0367	0.0206	0.1514	0.0866	0.0910	0.0355	_	_
60-64	0.1982	0.1125	0.0991	0.0545	0.2962	0.1720	0.1620	0.0593	_	_
65-69	0.318	0.203	0.215	0.119	0.507	0.308	0.238	0.089	_	_
70-74	0.582	0.415	0.501	0.281	0.942	0.596	0.358	0.138	_	_
75-79	1.068	0.784	1.009	0.580	1.670	1.088	0.500	0.193	_	_
80-84	2.266	1.726	2.198	1.313	3.070	2.148	0.637	0.243	_	_
85+	3.992	3.272	3.521	2.300	4.440	3.344	0.658	0.270	_	_

Notes: M represents male, and F represents female.

Table B5
Age-sex-specific mortality rate for each disease in 2015 (%).

Age	IHD(M)	IHD(F)	COPD(M)	COPD(F)	STK(M)	STK(F)	LC(M)	LC(F)	LRI(M)	LRI(F)
0-1	_	_	_	_	_	_	_	_	0.1792	0.1249
1-5	_	_	_	_	_	_	_	_	0.0058	0.0056
30-34	0.0104	0.0034	0.0008	0.0006	0.0086	0.0029	0.0024	0.0016	_	_
35-39	0.0137	0.0042	0.0012	0.0008	0.0124	0.0044	0.0040	0.0028	_	_
40-44	0.0251	0.0076	0.0027	0.0016	0.0247	0.0096	0.0093	0.0058	_	_
45-49	0.0543	0.0188	0.0070	0.0038	0.0577	0.0254	0.0273	0.0134	_	_
50-54	0.0916	0.0332	0.0159	0.0080	0.1045	0.0509	0.0600	0.0238	_	_
55-59	0.1029	0.0421	0.0266	0.0133	0.1270	0.0629	0.0833	0.0330	_	_
60-64	0.2205	0.1170	0.0870	0.0437	0.3050	0.164	0.1934	0.0688	_	_
65-69	0.392	0.246	0.214	0.112	0.593	0.350	0.316	0.112	_	_
70-74	0.570	0.422	0.406	0.230	0.875	0.572	0.374	0.148	_	_
75-79	0.994	0.814	0.780	0.485	1.450	1.033	0.480	0.212	_	_
80-84	1.978	1.722	1.583	1.315	2.464	1.914	0.582	0.263	_	_
85+	3.304	3.100	2.453	1.778	3.320	2.800	0.568	0.291	_	_

Notes: M represents male, and F represents female.

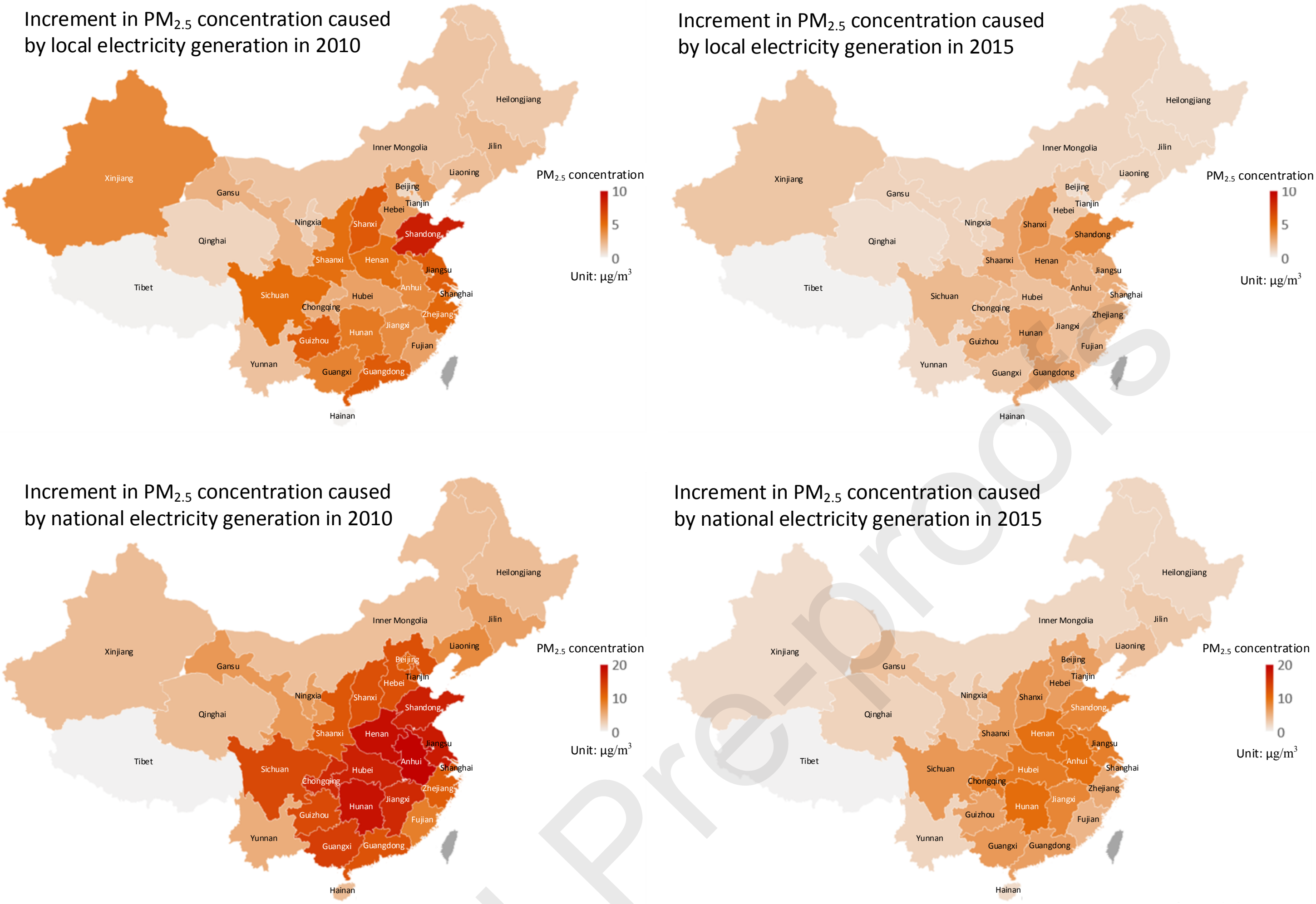

Fig. B2. Electricity generation's contribution to $PM_{2.5}$ concentrations.

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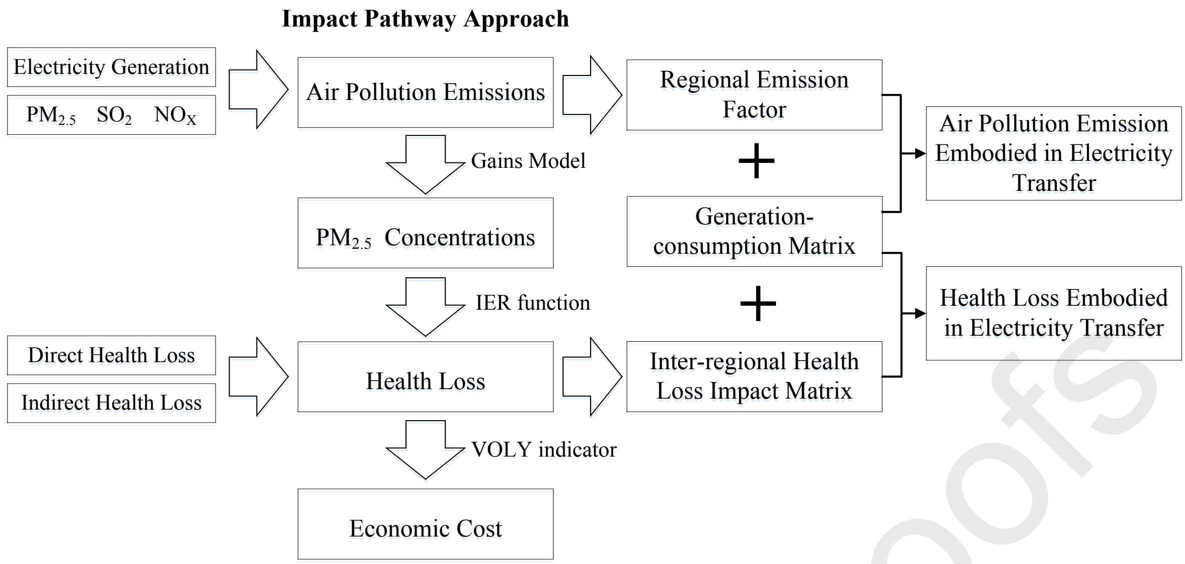

Highlights

- Embodied air pollution and health loss in electricity transfer is evaluated
- Impact pathway approach is combined with an electricity transfer network
- Air pollution diffusion is considered to assess indirect health impacts
- An example about China's inter-provincial power transfer is analysed