ENVIRONMENTAL RESEARCH
LETTERS

LETTER • OPEN ACCESS

Reduced health burden and economic benefits of cleaner fuel usage from household energy consumption across rural and urban China

To cite this article: Chenxi Lu *et al* 2022 *Environ. Res. Lett.* **17** 014039

ENVIRONMENTAL RESEARCH
LETTERS

CrossMark

OPEN ACCESS

RECEIVED
4 September 2021

REVISED
9 December 2021

ACCEPTED FOR PUBLICATION
21 December 2021

PUBLISHED
6 January 2022

LETTER

Reduced health burden and economic benefits of cleaner fuel usage from household energy consumption across rural and urban China

Chenxi Lu[1,2,*], **Shaohui Zhang**[3,4], **Chang Tan**[1], **Yun Li**[5], **Zhu Liu**[1], **Karyn Morrissey**[6], **W Neil Adger**[2], **Taochun Sun**[1], **Hao Yin**[7,8] **and Jiahong Guo**[9]

[1] Department of Earth System Science, Ministry of Education Key Laboratory for Earth System Modeling, Institute for Global Change Studies, Tsinghua University, Beijing, People's Republic of China
[2] Geography, College of Life and Environmental Sciences, University of Exeter, Exeter, United Kingdom
[3] School of Economics and Management, Beihang University, Beijing, People's Republic of China
[4] International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria
[5] Faculty of Engineering Science, Department of Architecture, KU Leuven, Leuven, Belgium
[6] Sustainability Division, Department of Technology, Management and Economics, Technical University of Denmark, Lyngby, Denmark
[7] School of population and public health, University of British Columbia, Vancouver, Canada
[8] Department of Economics, University of Southern California, Los Angeles, CA, United States of America
[9] School of Economics, Minzu University of China, Beijing, People's Republic of China
[*] Author to whom any correspondence should be addressed.

E-mail: **luchenxicc1023@163.com** **and** **cl651@exeter.ac.uk**

Keywords: household energy consumption, health burden, health co-benefits, economic benefits, region, China

Supplementary material for this article is available online

Abstract

Energy consumption in the residential sector is increasing rapidly in China. This study applies an integrated assessment model to investigate the adverse impacts of household energy consumption by various fuel types across rural and urban areas on age- and sex-specific premature deaths associated with $PM_{2.5}$ pollution at provincial levels for 2015. We further estimate the economic and health co-benefits of a switch from solid fuels to electricity within households. We find that energy consumed by Chinese urban households is nearly 1.6 times than that of rural households. However, premature deaths due to household energy usage is 1.1 times higher in rural areas compared to urban areas due to direct use of coal for heating in rural households. The majority of household consumption-related premature deaths are predominately in the Southern area of China due to the population size and aging population. By replacing coal and biomass with electricity, this paper estimates economic benefits equal to 0.09% (95% CI: 0.08%–0.1%) GDP for rural areas and 0.006% (0.005%–0.007%) of GDP for urban areas of China. The results suggest that mitigation measures such as the promotion and subsidization of cleaner fuels, modern stove within rural households would yield these potential significant economic benefits.

1. Introduction

The residential sector is one of largest energy consumers in China (Fan *et al* 2013) and as such has a profound impact on the production activities, energy consumption and greenhouse gas emissions (Liu *et al* 2011). With increasing living standards and wealth across the Chinese population, residential energy consumption is forecast to continually grow in the short and medium term (Fan *et al* 2013). In China, solid fuels specifically coal and biomass (mainly wood and crop residues) are still important sources of energy for heating and cooking, largely in rural areas (Zhang and Smith 2007, Archer-Nicholls *et al* 2016, Yun *et al* 2020). Combustion of solid fuels by households cause both indoor air pollution (Zhang and Smith 2007, Clark *et al* 2013) and ambient air pollution at a local or regional scale (Chen *et al* 2018). The emitted pollutants interact to produce a mixture of hundreds of different and hazardous chemicals known as secondary pollutants through physical processes and chemical reactions in the atmosphere (Li *et al* 2017).

Although household energy consumption is one of major anthropogenic contributors of atmospheric pollutants in China, studies on the impact of the household energy consumption on air quality remain limited (Du *et al* 2018, Zhao *et al* 2019, Yun *et al* 2020). The current evidence base has focused on elements of spatial and policy issues (Chen *et al* 2018, Du *et al* 2018, Zhao *et al* 2018, 2019, Yun *et al* 2020) but has not fully accounted for the effect of household consumption on the health profile of different population groups at different spatial scales or across rural and urban areas. There is some evidence that while rural households have lower energy consumption compared to urban areas, they have higher rates of coal usage. And it is this element of fuel mix that may result in a higher burden for rural areas in terms of emissions and associated economic and public health outcomes. The difference in lifestyles, income, and population distribution between the rural and urban areas of China are pronounced (Hubacek *et al* 2009). Hence analyzing the impact of different activities and lifestyles across urban and rural populations, across different demographic groups may help to explain differential health outcomes (Pachauri *et al* 2004).

This study therefore undertakes an integrated assessment of the adverse impacts of household energy consumption by various fuel types across rural and urban areas on age- and sex-specific premature deaths as a key outcome from $PM_{2.5}$ pollution at the Chinese provincial levels for 2015. It does so through a modelling framework based on an existing integrated assessment model calibrated with data and submodels for population, spatial distribution of population, and air pollution loading. This paper then explores the health co-benefits and economic benefits of switching from coal and biomass to electricity since primary energy tend to be more and more transferred into electricity for usage in China.

2. Data and method

The definition of rural and urban households is based on China Bureau of Statistics definition, whereby urban households are those who have been living within the governance of a village (xiang) or town authority over 1 year and urban households are those who has been living in those areas where local governments of the county level or higher are located (www.stats.gov.cn/tjsj/ndsj/2015/html/zb06.htm). Land use in China is predominately rural: 91% of Chinese territory defined as rural (figure S1 (available online at stacks.iop.org/ERL/17/014039/mmedia)), excluding Taiwan, Hongkong and Macao). The analysis here focuses on households—these are, following standard definitions, individuals or groups of resident individuals who share the same living accommodation, and consume goods and services collectively (Ding *et al* 2017). 56.5% of the total population of China lived in 9.5% of the territory of China, with 775 million urban households and 596 million rural households (excluding Taiwan, Hongkong and Macao) (NBSC 2016). Sub-national data is provided for 30 provinces, cities and autonomous regions (Tibet is excluded due to a lack of energy inventory data). Fifteen fuel types are included in this study. These include electricity, gasoline, raw coal, heat, natural gas, liquefied petroleum gas, diesel oil, briquettes, other energy, other washed coal, coke oven gas, other gas, kerosene, fuel oil and coke. Heat as a form of energy usage, is additional energy produced by primary energy, such as coal combustion. Heat as a form of energy usage is predominately the result of coal combustion in China and is recorded in the Chinese energy balance table and as part of the energy inventory collected by China Emission Accounts and Datasets (CEADs, www.ceads.net). All data is from 2015 unless otherwise specified.

2.1. Household energy consumption

The calculation of household energy consumption is shown below:

$$E_{f,r,i,t} = \sum_{f=1}^{20} \mathrm{AD}_{f,r,i,t} \times \mathrm{NCV}_f. \qquad (1)$$

$E_{f,r,i,t}$ refers to sum of energy consumption from each fuel type f, from household in urban or rural area r, at provincial level i, in year t. The energy unit is petajoule, PJ. $\mathrm{AD}_{f,r,i,t}$ refers to the activity data of the combustion volume of each fuel type f. NCV_f represents the net caloric value, that is heat value produced per physical unit of fossil fuel combustion. Here, data for the $\mathrm{AD}_{f,r,i,t}$ is taken from the energy inventory data from China Emission Accounts and Datasets (CEADs, www.ceads.net), which is collected from China Energy Statistical Yearbook. Data of NCV_f is taken from Shan *et al* (2018).

2.2. Pollutant emissions and $PM_{2.5}$ concentration from household consumption activities

Estimates from the household energy consumption model (equation (1)) are treated as the input to the Greenhouse Gas and Air pollution Interactions and Synergies (GAINS)-ASIA model. The GAINS model includes all key emission sources, with approx. 2000 end of control options (Amann *et al* 2011). The model is applied for estimating air-pollutants and $PM_{2.5}$ concentration based on $E_{f,r,i,t}$ (PJ). Emissions are calculated through a combination of three data categories: activity data, uncontrolled emission factors, the removal efficiency of emission control measures. Equation (2) represents the emissions estimates:

$$E_{p,i} = \sum_a \sum_m A_{a,i} ef_{a,m,p,i} X_{a,m,p,i} \qquad (2)$$

where $E_{p,i}$ represents emissions of pollutants p, in province i; $A_{a,i}$ is the activity level of type a (e.g. coal consumption in residential sector) in province i; $ef_{a,m,p,i}$ is the emission factor of pollutant p for activity a in province i after application of control measure m; $X_{a,m,p,i}$ is the share of total activity of type a in province i to which a control measure m for pollutant p is applied.

The resulting emissions are inputted into an atmospheric dispersion model, the EMEP Chemistry Transport Model (http://webdab.emep.int/) to compute annual mean ambient $PM_{2.5}$ concentration. GAINS employs reduced-form source-receptor relationships that have been derived from the EMEP atmospheric chemistry-transport model with a spatial resolution of $0.1° \times 0.1°$ (Amann *et al* 2020). The $PM_{2.5}$ concentration are defined via:

$$C(\mathrm{PM}_{2.5})_i = \sum [\pi_i \times Em(\mathrm{PPM}) + \sigma_i \times Em(\mathrm{SO}_2) + \alpha_i \times Em(\mathrm{NO}_X) + \beta_i \times Em(\mathrm{NH}_3) + \gamma_i \times Em(\mathrm{VOC}_i)] + \mu_i \quad (3)$$

where $C(\mathrm{PM}_{2.5})_i$ is the $PM_{2.5}$ concentration in grid cell i. $Em(\mathrm{PPM})$ represents the total primary $PM_{2.5}$. The constants π, σ, α, β, γ are the source-receptor matrices for the corresponding pollutants contribution to the $PM_{2.5}$ concentration and the constants μ_i are grid cell specific. More details of GAINS model can be found in Amann *et al* (2011).

2.3. $PM_{2.5}$ related health impact assessment

We consider the long-term exposure to $PM_{2.5}$ concentration on mortality as measured by premature deaths using the Global Exposure Mortality Model (GEMM) (Burnett *et al* 2018). Developed by Burnett *et al* (2018), the GEMM assess excess mortality attributable to ambient air pollution on a global scale.

Here we focus on the five leading causes of the $PM_{2.5}$-related premature mortality: ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD), lung cancer (LC), and lower respiratory infections (LRI). The premature deaths under scenarios are measured by sex (female and male) and age group (25–29, 30–34, 35–39, 40–44, 45–49, 50–54, 55–59, 60–64, 65–69, 70–74, 75–79, 80+). For the purpose of this paper, we refer to the 'elderly' are individuals aged 65 years or more, in line with the World Health Organization definition (Orimo *et al* 2006, WHO 2010).

The number of health outcomes are estimated by multiplying the relative risk (RR) with the population by sex and age and reported cause-specific incidence rate by sex and age, along with the corresponding uncertainties (95% confidence interval (CI)) and normally the percentage of exposed population is assumed to be 1 (Zhang *et al* 2017b):

$$M_{k,e,a,g,t} = (\mathrm{RR}_{k,e,a} - 1)/\mathrm{RR}_{k,e,a} \times I_{e,a,g,t} \times P_{a,g,i,t} \quad (4)$$

where $M_{e,a,g,s,t}$ is mortality in grid cell, k for each health endpoint, e by age, a and sex, g in year t due to $PM_{2.5}$. $\mathrm{RR}_{k,e,a}$ is the RR of a given $PM_{2.5}$ concentration in grid cell k at health endpoint e for age specific a, which is obtained from the GEMM (Burnett *et al* 2018). $I_{e,a,g,t}$ is the mortality rate for health endpoint, e by age, a and sex, g in year t obtained from the GBD Results Tool (http://ghdx.healthdata.org/gbd-results-tool) (figure S2). $P_{k,a,g,t}$ is the exposed population for age, a and sex, g in grid cell k, *in* year t. The spatial distribution of the population as a $0.1° \times 0.1°$grid in China in 2015 is taken from Xu (2017). Population data (NBSC 2011) and death rates (Chen *et al* 2020) by age group (5 year-old segments) and sex for 2010 are obtained at the provincial level. Following similar research, $PM_{2.5}$ intake is assumed to be equally harmful irrespective of the $PM_{2.5}$ composition and source and fuel of origin (Liu *et al* 2017).

The GEMM is expressed as:

$$\mathrm{RR}_{e,a}(C_i) = \begin{cases} \exp\left\{ \dfrac{\theta_{e,a}\log\left(\dfrac{C_i - C_0}{\alpha_{e,a}} + 1\right)}{1+\exp\left\{-\dfrac{C_i - C_0 - \mu_{e,a}}{V_{e,a}}\right\}} \right\} & \text{if } C_i > C_0 \\ 1 & \text{if } C_i \leqslant C_0 \end{cases} \quad (5)$$

where $\mathrm{RR}_{e,a}(C_i)$ is the RR of a given $PM_{2.5}$ concentration in grid cell i *for* age, a and health endpoint, e. C_0 is the threshold $PM_{2.5}$ concentration below which there is no additional risk, in terms of counterfactual $PM_{2.5}$ concentration (2.4 μg m^{-3} in this study). And $\theta_{e,a}$, $\alpha_{e,a}$, $\mu_{e,a}$ and $V_{e,a}$ are parameters describing the overall shape of the concentration-response curve, provided by Burnett *et al* (2018).

2.4. Attribution of premature death to household consumption activities

As per the GBD (2016), given the nonlinear relationship of the GEMM functions, the direct proportional approach was used to estimate premature deaths attributed to the emissions related to a region's production and consumption. The direct proportional approach assumes that the health impact of one pollution source is directly proportional to its contribution to the ambient $PM_{2.5}$ concentration. This proportional approach has also been applied to estimate the pollution health impacts related to household cooking (Chafe *et al* 2014), coal consumption (GBD 2016), road transportation (Anenberg *et al* 2017), and international trade (Zhang *et al* 2017a).

For a given region, premature deaths due to different activity-based emissions (e.g. household consumption activities) can be calculated by multiplying the contributions of each to baseline ambient $PM_{2.5}$ concentrations by the total $PM_{2.5}$-related mortalities for each grid cell.

$$M_{r,e,a,g,t} = \sum_k M_{k,e,a,g,t,\text{base}} \times \frac{C_{k,t,\text{base}} - C_{k,t,r}}{C_{k,t,\text{base}}}. \quad (6)$$

$M_{r,e,a,g,t}$ is the premature death of household consumption of rural or urban regions r for health endpoint e by age, a and sex, g in year t. $M_{k,e,a,g,t,base}$ is the premature death of baseline scenario for health endpoint e by age, a and sex, g in year t in grid cell k. The baseline scenario uses modeled $PM_{2.5}$ concentration is taken from the GAINS model which has been validated against $PM_{2.5}$ monitoring data. Please see www.gains.iiasa.acat for more information. $C_{k,t,\text{base}}$ is the modelled $PM_{2.5}$ concentration for grid cell k in the baseline scenario in year t. $C_{k,t,r}$ is the modeled $PM_{2.5}$ concentration of grid cell k in alternative scenarios where the emissions related to household consumption of rural or urban regions r in year t.

2.5. Avoided premature deaths of replacing coal and biomass fuels into electricity

For the scenario analysis, we assume that households replace all coal and biomass fuels including cleaned coal, other washed coal, briquettes, coke, coke oven gas, other gas, other coking products and other energy (large part is biomass) with electricity but the total amount of household energy consumption remained the same. The GAINS model was used to calculate the number of avoided premature deaths across urban and rural area if current levels of coal and biomass consumption shifted to electricity consumption:

$$A_{r,e,a,g,t} = \sum_k M_{k,e,a,g,t,base} - R_{k,e,a,g,t,r} \quad (7)$$

where $A_{r,e,a,g,t}$ is avoided premature death by rural or urban populations, r for health endpoint e, by age, a and sex, g in year t. $R_{k,e,a,g,t,r}$ is the premature death attributable to household energy consumption without coal and biomass consumption but more electricity consumption of rural or urban regions r for health endpoint e by age a and sex g in year t in grid cell k.

2.6. Economic benefit of replacing coal and biomass fuels into electricity

This paper uses the monetary value statistical life (VSL) approach to reflect health gains in monetary terms. The VSL defines the monetary value of a mortality risk reduction that would prevent one statistical death (Andersson and Treich 2011). The Chinese age-adjusted VSL for 2015, which takes account of the effects of variations in life expectancy, wealth distribution and life quality over the lifecycle is obtained from Yin *et al* (2021) (see figure S3). The calculation of economic benefit is shown:

$$B_{r,e,a,g,k,t} = \text{VSL}_{a,g,i,t} \times A_{r,e,a,g,t} \quad (8)$$

where B is the economic benefit value of household consumption of rural or urban regions r in grid cell k for each health endpoint, e by age a and sex g in year t. $\text{VSL}_{a,g,i,t}$ is the value of a statistical life for age a and sex g in province i in year t. The exchange rate for US dollar and Chinese Yuan for 2015 was taken as 1 US dollar equals 6.2284 Chinese Yuan (https://data.stats.gov.cn/easyquery.htm?cn=C01%26zb=A060J%26sj=2019). Uncertainty analysis is presented in appendix text 1.

3. Results

3.1. Household energy consumption

In 2015, the total household energy consumption in China was 10 500 PJ; nearly 1.6 times greater than rural household energy consumption (6700 PJ) (figure 1(A)). Heat (21.1%), electricity (21%), and gasoline (20.5%) accounted for 63% of total urban household energy consumption. In contrast, raw coal accounted for 34% of the total rural household energy consumption (1300 PJ), representing 2.8 times the amount of coal consumed by urban households. Electricity was the second largest fuel type used by both rural and urban households, that accounted for 1100 PJ and 1400 PJ, respectively (figure 1(B)). Figure 1(B) indicates that fuel type usage is more homogenous than urban households, with the top three fuel types representing 77% of the total rural household energy consumption, whereas in urban areas, the top three fuel types represented 63% of the fuel used.

To examine regional differences between urban and rural dominated regions, we divide China into eight economic zones according to a definition developed by the Development Research Center of the State Council (Wu 2014) (table S2) . These eight zones comprise the Northern coastal, Eastern coastal, Southern coastal, Northeastern, Northwestern, and Southwestern economic zones, as well as two economic zones defined to cover the middle reaches of the Yellow River and the middle reaches of the Yangtze River. Higher household energy consumption is more located in the Northern coastal, Eastern costal, Southern coastal and middle reaches of the Yellow River economic zone (figures 2(A) and (B)). Rural household energy consumption is highest in Hebei, Guangdong, Shandong, Henan and Hunan, that were 448, 293, 265, 243 and 202 PJ, respectively. For urban household energy consumption, consumption is highest in Guangdong, Liaoning, Shandong, Hunan and Heilongjiang, 553, 472, 433, 392 and 386 PJ, respectively. Regrading energy intensity, rural households located in Hebei, Shanxi, Gansu, Guizhou and Chongqing, 3.3, 2.7, 2.7, 2.6 and 2.6 GJ/US$ had the highest energy intensities. Urban households in Xinjiang, Heilongjiang, Shanxi, Inner Mongolia and Qinghai, 2.6, 2.1, 1.6, 1.4 and 1.3 GJ/US$, respectively, on average, energy intensity of rural households are larger than urban households and the Northern coastal, Northeastern, Northwestern, Eastern coastal and Southern coastal economic zone had higher energy intensities of household consumption.

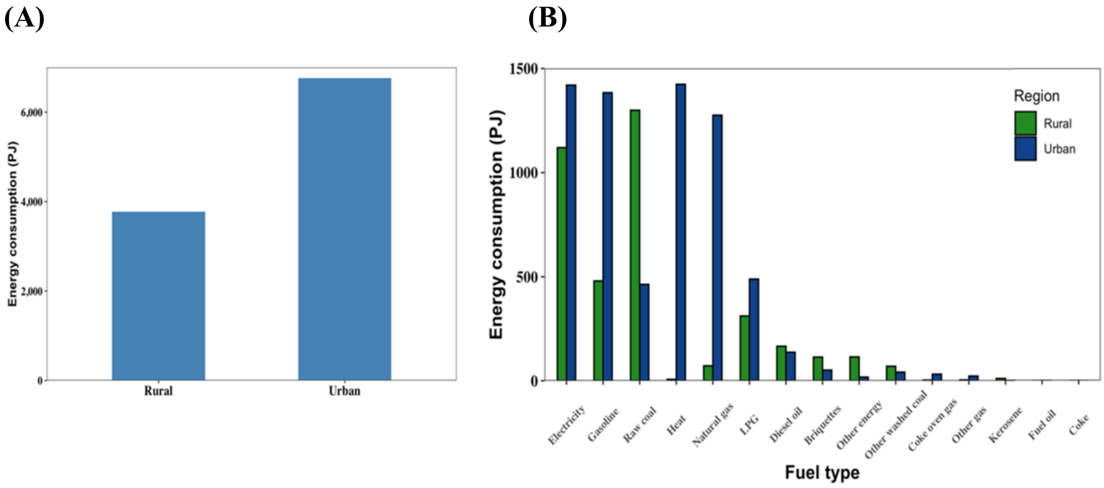

Figure 1. Energy consumption of rural and urban household in China in 2015. (A) The total energy consumption of rural and urban household (PJ). (B) Different fuel types of energy consumption of rural and urban household.

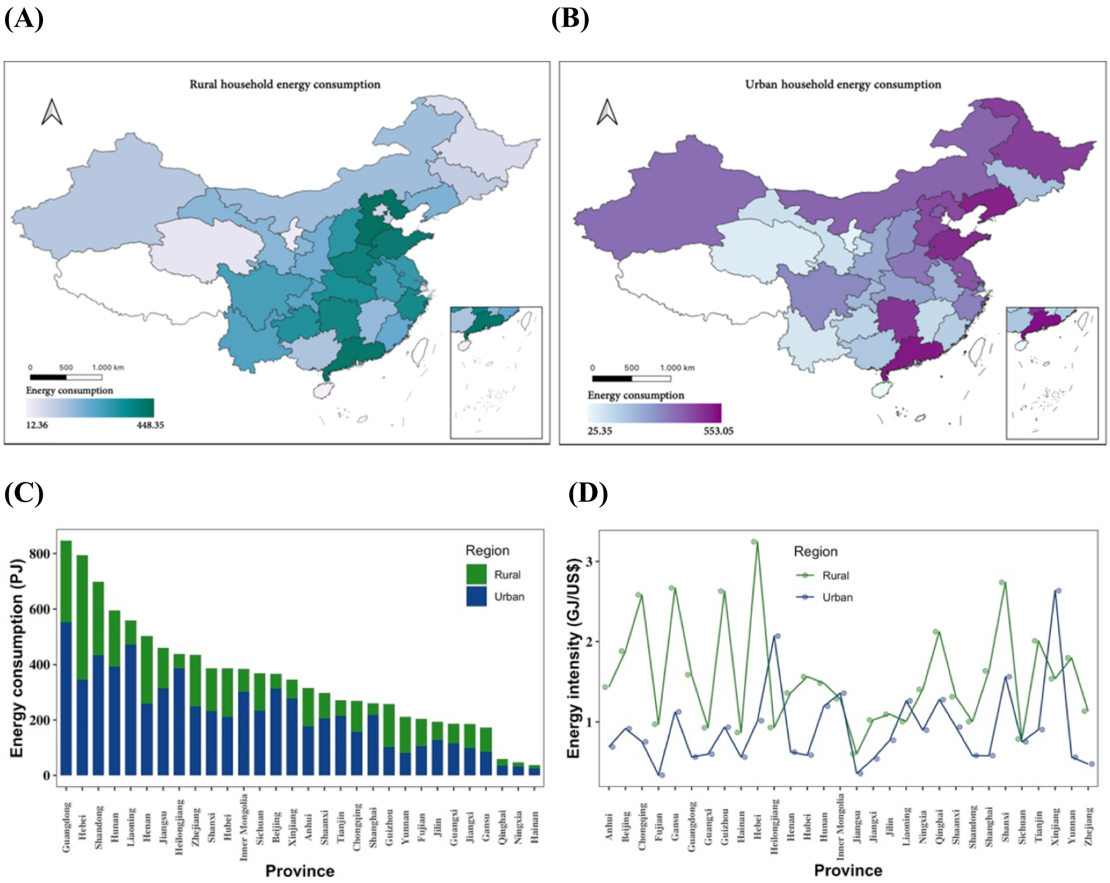

Figure 2. Energy consumption and energy intensity of provinces of rural and urban households in China in 2015. (A) Provincial distribution of energy consumption of rural households. (B) Provincial distribution of energy consumption of urban households. (C) Energy consumption of 30 provinces of rural and urban households. (D) Energy intensity of 30 provinces of rural and urban households; the energy intensity of rural or urban households = energy consumption of households in the rural or urban area /GDP in the rural or urban area in 2015.

3.2. $PM_{2.5}$ concentration of China

Figure 3 presents the average population weighted $PM_{2.5}$ concentration calculated by the GAINS model (the comparison between ambient $PM_{2.5}$ concentration from the GAINS and 941 observation data from observing sites is shown in figure S4). The average population weighted concentration of $PM_{2.5}$ was 37 μg m^{-3} in China in 2015, which has exceeded the national ambient air quality standard (NAAQ) (35 μg m^{-3}) of China and World

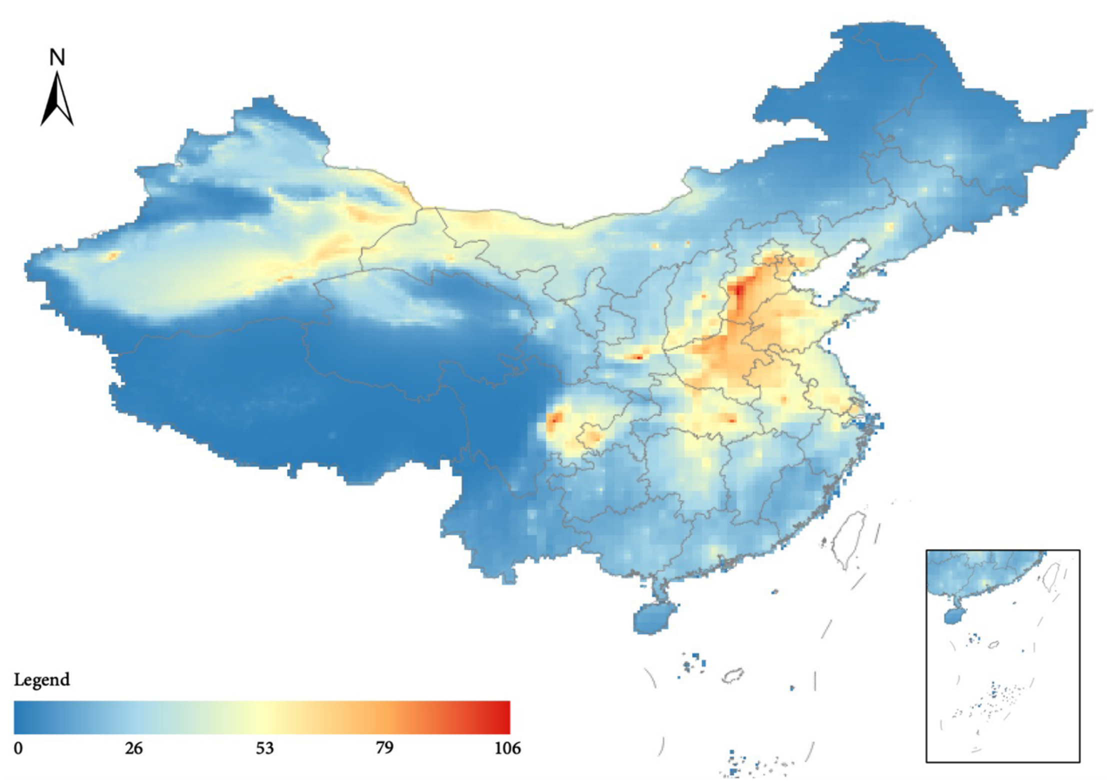

Figure 3. The average population weighted $PM_{2.5}$ concentration in China in 2015.

Health Organization (WHO) air quality guideline (10 μg m^{-3}).

$PM_{2.5}$ concentration was generally higher the Northern coastal economic zone (Jing-Jin-Ji area) with the highest average population weighted $PM_{2.5}$ concentration, middle reaches of the Yellow River economic zone, middle reaches of the Yangtze River economic zone, Eastern coastal economic zone, Southern coastal economic zone, Sichuan Basin area in the Southwestern economic zone and Tarim Basin in the Northwestern economic zone and especially in urban areas. The five provinces with the highest population weighted $PM_{2.5}$ concentration were Henan (68 μg m^{-3}), Hebei (67 μg m^{-3}), Beijing (66 μg m^{-3}), Tianjin (65 μg m^{-3}) and Shandong (58 μg m^{-3}) (figure 3). 55% of the population is exposed to annual average $PM_{2.5}$ concentration of more than 35 μg m^{-3} in 2015.

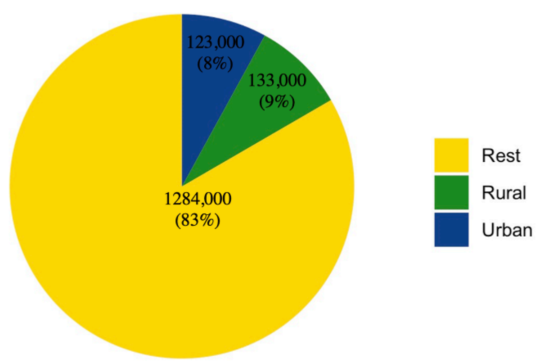

Figure 4. Premature deaths attributable to $PM_{2.5}$ concentration and $PM_{2.5}$-related premature deaths attributable to rural and urban household energy consumption in China in 2015.

3.3. Premature deaths of household consumption

The total premature mortality attributable to $PM_{2.5}$ concentration in China across five health endpoints of interest, COPD, IHD, LC, LRI and Stroke were 1540 000 (95% CI:1270 000–1789 000).

Rural household energy consumption activities resulted in 133 000 (95% CI: 104 476–159 389) premature deaths, representing 9% of the total premature deaths in China in 2015. Although, the total energy consumption of urban households was higher than that of rural households (figure 4), urban household energy consumption was associated with fewer premature deaths, 123 000 (95% CI: 96 136–147 450) premature deaths. In total, 256 000 (95% CI: 200 612–306 839) premature deaths was lost due to household consumption in China in 2015.

The age- and sex-specific premature deaths attributable to $PM_{2.5}$ pollution associated with household energy consumption to varies across rural and urban areas. Premature deaths attributable to $PM_{2.5}$ pollution are greater in rural than urban households (figure 5(A)). Figure 5 shows that IHD was the largest health burden attributable to household sourced $PM_{2.5}$ exposure (between 37.5% and 37.8% premature deaths). The population aged over

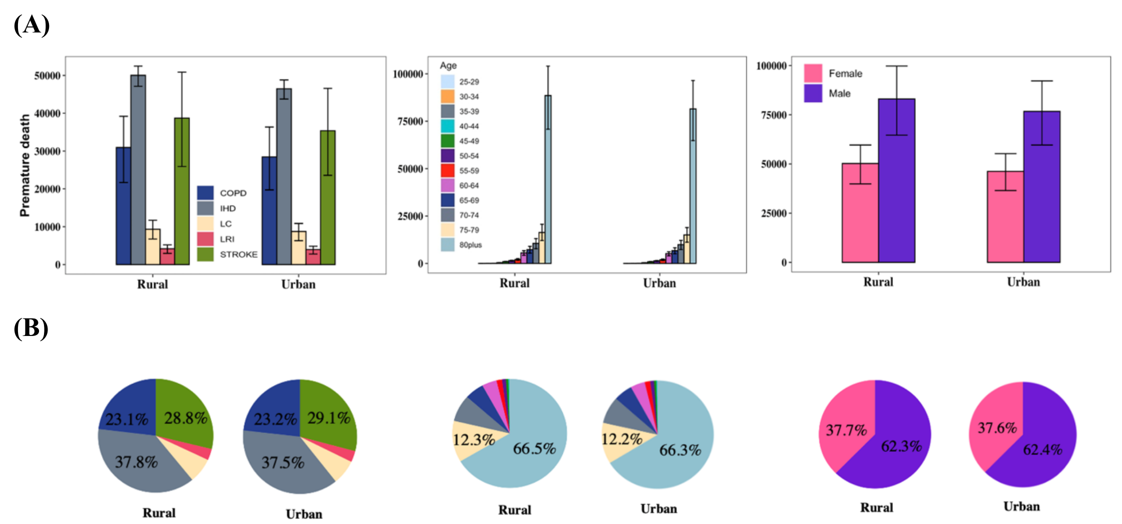

Figure 5. Health endpoint-, age- and sex-specific premature deaths attributable to $PM_{2.5}$ pollution by rural and urban household energy consumption in China in 2015. (A) Value of health endpoint-, age- and sex-specific premature deaths attributable to $PM_{2.5}$ pollution by rural and urban household energy consumption in China in 2015. (B) Percentage of health endpoint-, age- and sex-specific premature deaths of the total premature deaths attributable to $PM_{2.5}$ pollution by rural and urban household energy consumption in China in 2015.

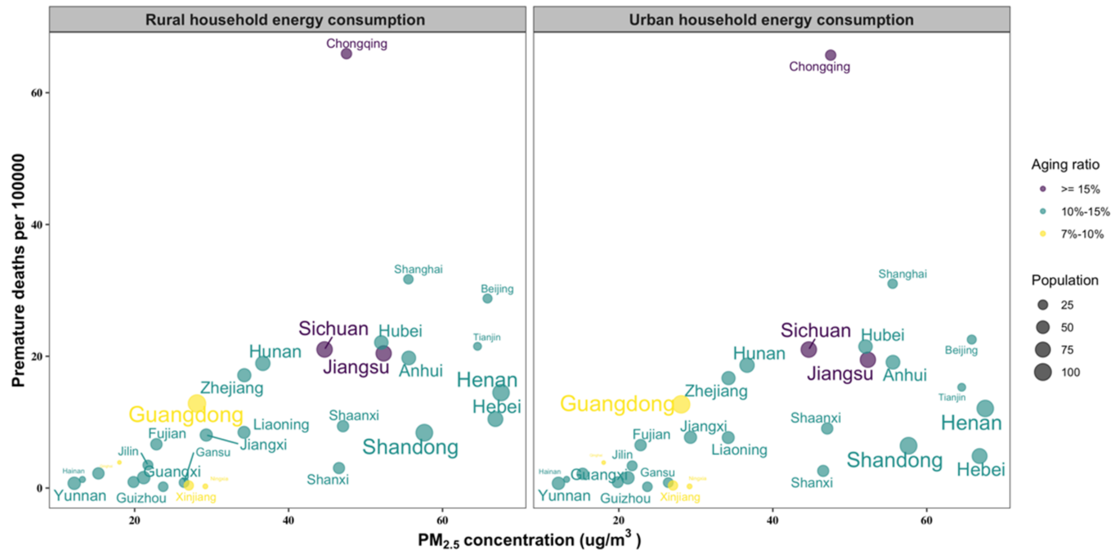

Figure 6. Provincial-level premature deaths per 100 000 people and population weighted $PM_{2.5}$ concentration by rural and urban household energy consumption in China in 2015. The colorful dots show the aging ratio of population over 65 year-old and grey dots represents the size of population (million population) in 30 provinces in China in 2015.

80 year-old accounted for over half the total household energy consumption-$PM_{2.5}$-related premature deaths (66.3%–66.5%), with the age category 25–29 year-old recording the lowest. Premature mortality is higher among the male population compared to the female population, ranging from 62.3% to 62.4% of household energy consumption $PM_{2.5}$-related premature deaths (figure 5(B)).

The number of premature deaths per 100 000 people had a positive correlation with $PM_{2.5}$ concentration, as shown in figure 6, with rural household energy consumption attributable to a larger number of premature deaths per 100 000 people compared to urban household. When the $PM_{2.5}$ concentration was less than 45 $\mu g\ m^{-3}$, premature deaths was less than 20 per 100 000. Thirteen provinces (Henan, Hebei, Beijing, Tianjin, Shandong, Anhui, Shanghai, Jiangsu, Hubei, Chongqing, Shaanxi, Shanxi and Sichuan) had $PM_{2.5}$ concentration over 45 $\mu g\ m^{-3}$, with associated premature deaths per 100 000 people, ranging from 65.9 (Chongqing) to 2.6 (Shanxi). Chongqing, Shanghai, Beijing, Hubei and Sichuan had the highest estimated premature deaths per 100 000 (figure 6).

Figure 7 shows the provincial distribution of premature deaths per 100 000 people and premature deaths per 100 000 people by age and sex- specific

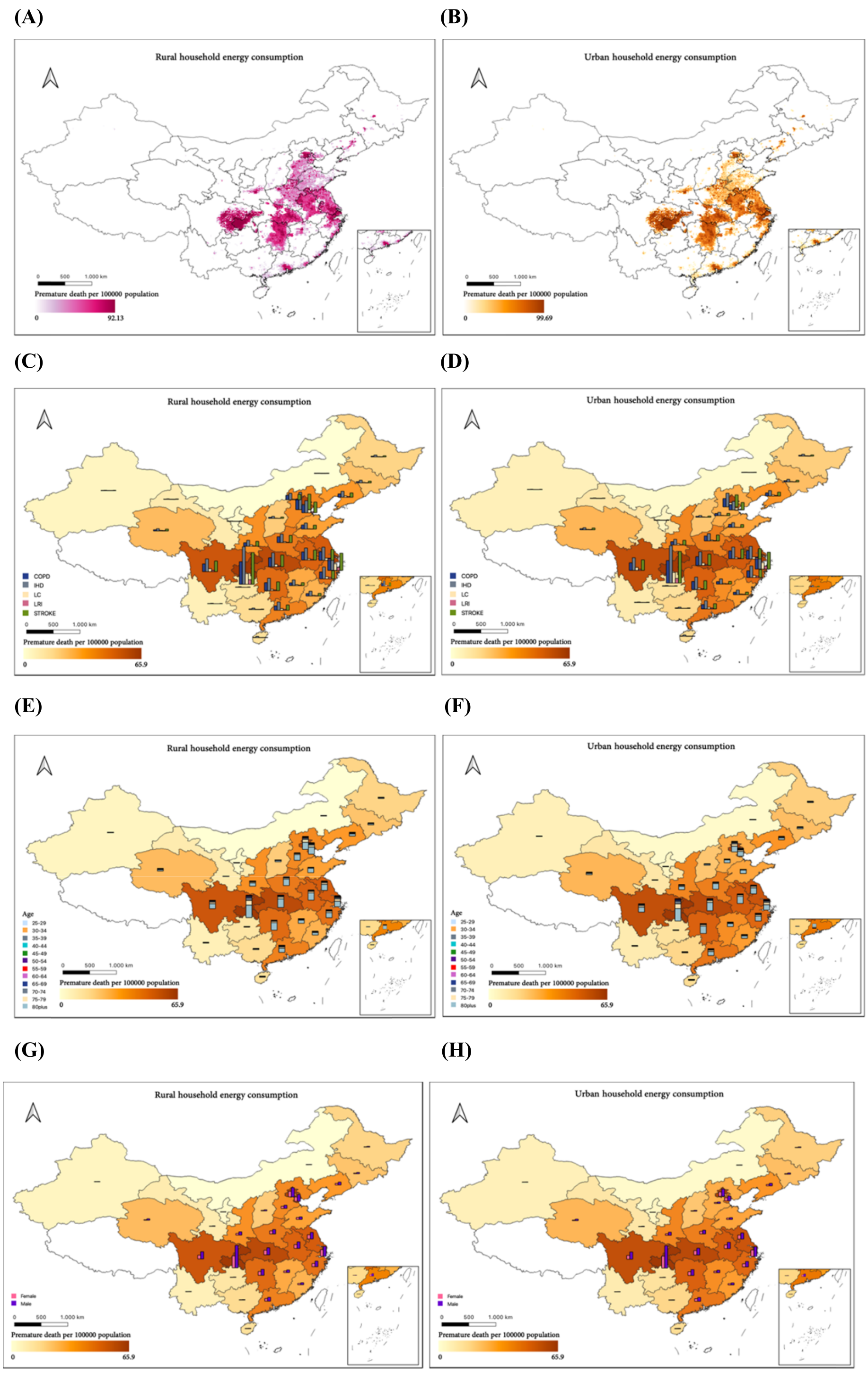

Figure 7. Maps of provincial-level estimates of premature deaths per 100 000 people by rural and urban household energy consumption in China in 2015. (A) Distribution of provincial-level estimates of premature deaths per 100 000 people by rural household energy consumption in China in 2015 at a spatial resolution of 0.1° × 0.1°. (B) Distribution of provincial-level estimates of premature deaths per 100 000 people by urban household energy consumption in China in 2015 at a spatial resolution of 0.1° × 0.1°. (C), (E) and (G) Maps of provincial-level estimates of premature deaths per 100 000 people in health endpoint-, age and sex- specific by rural household energy consumption in China in 2015. (D), (F) and (H) Maps of provincial-level estimates of premature deaths per 100 000 people in health endpoint-, age and sex- specific by urban household energy consumption in China in 2015. The values of base map shows the provincial average value of premature deaths per 100 000 people (these values are calculated from the mean of provincial values of premature deaths per 100 000 people at a spatial resolution of 0.1° × 0.1).

health endpoints by rural and urban household energy consumption. The number of premature deaths associate with rural household energy consumption per 100 000 of the population were highest in Chongqing, Shanghai, Beijing, Hubei and Tianjin (65.9, 31.7, 28.8, 22.1 and 21.5, respectively); while the number of premature deaths per 100 000 associated with urban energy consumption

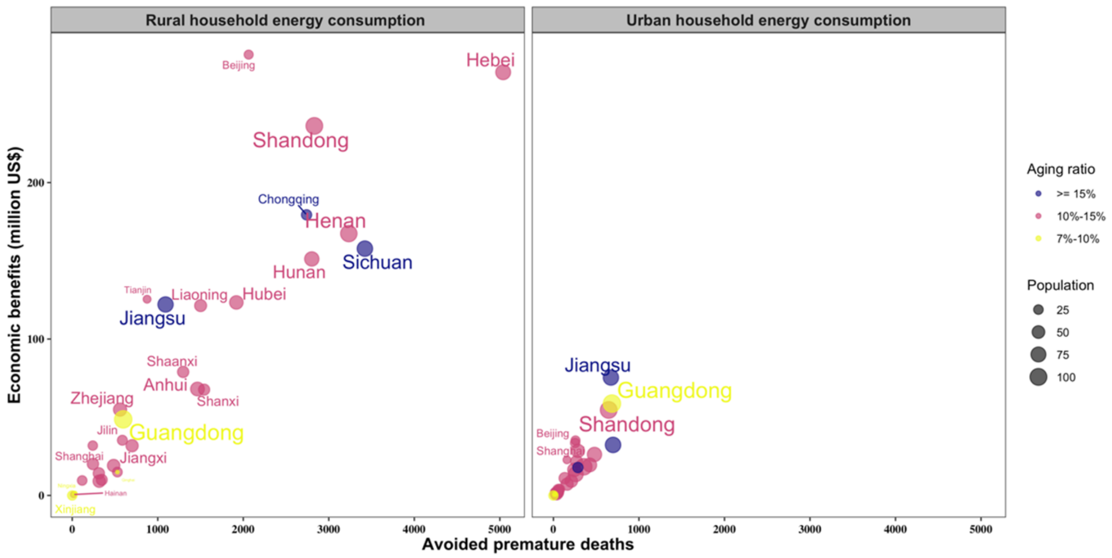

Figure 8. Provincial-level economic benefits and avoided premature deaths by rural and urban household energy consumption in China in 2015. The colorful dots show the aging ratio of population over 65 year-old and grey dots represents the size of population (million population) in 30 provinces in China in 2015.

was highest in Chongqing, Shanghai, Beijing, Hubei and Sichuan (65.7, 31, 22.5, 21.5 and 21, respectively). Although the highest levels of $PM_{2.5}$ concentration were in the Northern coastal economic zone of China, the highest numbers of premature deaths per 100 000 people were more located in the Southern area of China which include the Southern coastal, the middle reaches of the Yangtze River and Yellow River, Eastern coastal economic zones, and the Sichuan Basin area in the Southwestern economic zone. Provincial level premature deaths per 100 000 attributable to $PM_{2.5}$ pollution by age- and sex-specific health endpoint. Details of provincial health burden from household consumption can be seen in figure S5.

3.4. Avoided premature deaths and economic benefits from reduced direct coal consumption

If rural and urban households in China substituted electricity for coal and biomass, the model suggests that this could result in a significant reduction in deaths: such substitution could save 37 400 (95% CI: 31 800–41 800) deaths attributable to rural household consumption and 6900 (95% CI; 6100–7900) lives attributable to urban household consumption, meaning on average 3 lives per 100 000 people can be saved in 2015. This corresponds to 28% and 6% of the total premature deaths caused by rural and urban household consumption in 2015. Economically, such a shift would result in US$ 2.5 billion (95% CI: 2.1–2.7) economic benefits for rural households, equaling 0.09% (95% CI: 0.08%–0.1%) of GDP of the rural region of China in 2015, and it could create 522 (95% CI: 468–594) million US$ economic benefits by urban household consumption, equaling 0.006% (0.005%–0.007%) of GDP of the urban region of China in 2015. A shift to electricity by rural households would result in the largest economic benefits in Beijing (282: 252–307 US$), the highest number of deaths avoided in Hebei did (5000: 4400–5450). A shift to electricity by urban households, would witness the Jiangsu area receive the largest economic benefits (75: 65–82 US$) and Sichuan recoding the largest reduction in premature motilities (697: 696–868) (figure 8).

4. Discussion

A number of recent studies have examined the health burden attributable to $PM_{2.5}$ exposure in China (Song *et al* 2017, Li *et al* 2018, 2021, Maji *et al* 2018, Liu *et al* 2021), and shown the scale of the challenge. This study confirms the scope and scale of the challenge and focuses specifically on the direct role of household energy consumption specifically. The contribution here builds on knowledge of household energy use (Chen *et al* 2018, Zhao *et al* 2018, Yun *et al* 2020) to implement an integrated assessment approach connecting energy, emission, air pollution and health outcomes. Hence, we investigate the adverse impacts of household energy consumption by various fuel types across rural and urban areas on $PM_{2.5}$ related age- and sex-specific premature deaths at provincial levels for 2015. This provides new insights by estimating the premature death associated with each of the 15 fuel types used by households in China across different age and gender groups at the national/regional/provincial levels for China. We further apply a scenario analysis to calculate the economic benefits from switching solid fuels into electricity.

Our estimates found that in 2015, 17% of national premature deaths could be attributed to outdoor

$PM_{2.5}$ from residential energy sector. Although urban households consumed nearly 1.6 times energy than rural households, premature deaths attributable to $PM_{2.5}$ exposure from household energy was 1.1 times higher from rural household consumption compared to urban households due to rural households use of solid fuel products. Regarding urban-rural differences, these findings are consistent with a similar study by Zhao *et al* (2019) using data from 2012. However, Zhao *et al* (2019) reported higher estimates for premature deaths for rural areas compared to our study (18% vs 8.7%). Direct energy consumption was higher in 2012 than 2015, but the difference may also be underpinned by to cleaner energy sources in rural. In 2012, raw coal energy usage corresponded to 50% and 1.3% of the total energy consumption in rural and urban households, whereas in 2015, the proportion of raw coal proportion had decreased to 46% and 0.9% for respectively rural and urban households (NBSC 2016).

Analysis at the regional level incorporating differences between urban and rural areas and age-sex specific mortality rates by five health outcomes, finds that between 37.5% and 37.8% premature deaths attributable to household energy consumption were due to IHD. Importantly, the analysis found that the distribution of household energy consumption-related premature deaths is not just a product of energy consumption and outdoor $PM_{2.5}$ concentration, but also population density and demographic structure (figures S6 and S7). The population aged over 80 year-old accounts for over half the total household energy consumption-$PM_{2.5}$-related premature deaths (66.3%–66.5%), with the age category 25–29 year-old recording the lowest. Premature mortality was higher among the male population compared to the female population, ranging from 62.3% to 62.4% of household energy consumption $PM_{2.5}$-related premature deaths. Household energy consumption-related premature deaths are shown to be highest in the Southern area of China, explained by a combination of high population density and an aging population. For example, Chongqing has the highest number of premature deaths as well as premature deaths per 100 000 and this was mainly attributable to its aging population (highest among the 30 provinces, figure S7), population density (listed as 11/30) and $PM_{2.5}$ concentration (listed as 10/30).

The scenario analysis finds that if coal and biomass had been replaced with electricity in both urban and rural households, 28% (rural) and 6% (urban) premature deaths would have been avoided. Previous research by Zhao *et al* (2018) similarly found that if solid fuels by Chinese household had been replaced with clean fuels, it could have saved 33% of the $PM_{2.5}$-induced mortality in 2015. With regard to the lower estimates presented here, Zhao *et al* (2018) also calculated the avoid deaths from indoor air pollution. This is equivalent to US$ 2.5 billion (95% CI: 2.1–2.7) economic benefits for rural households and US$ 522 million (95% CI: 468–594) for urban household consumption. The estimates presented here are also lower than those by Yun *et al* (2020), who found that the residential sector contributed to 71% of the indoor $PM_{2.5}$ concentrations and 67% of $PM_{2.5}$-induced premature deaths in 2014 in China. However, once again our model may underestimate pre-mature deaths as we do not account for indoor household energy consumption.

This research suggests that households in Beijing would receive the largest economic benefits from cleaner air. However, it is important to note that the value of statistical life approach inevitably gives disproportionate weight to wealthier regions because of the innate characteristics of the method. Larger potential economic benefits of cleaner air to regions with high concentrations of wealth and income remains a significant challenge in policy and decision-making, not least in the context of just and fair decarbonization transitions (Friel *et al* 2008). This study illustrates the large positive health and economic impacts that would be obtained from a shift to cleaner energy types within households in China, particularly regarding rural households.

From a policy perspective, this analysis suggests that mitigation measures such as promoting cleaner household fuel, through the subsidization of modern stoves within rural household will have large health and economic impacts, particularly in rural China. Li *et al* (2019) found that switching from solid fuels into carbonized fuels (higher thermal efficiencies and lower pollutant emissions) can generate environmental benefits for household residents. However, the health impacts of such a switch need to be more fully explored. For example, a recent clinical trial in the USA found that cookstoves emitting lower $PM_{2.5}$ emissions still had a negative impact on cardiac health (Cole-Hunter *et al* 2021). Irrespective of measures, the role of local municipalities will be crucial for the promotion and operationalization of new technologies, especially communities in poorer areas with resources are fewer higher baseline health risks than those in richer areas (Liu *et al* 2021).

There are two major limitations in this research which can lead to further research. First, our estimates do not account for indoor household energy consumption. Indeed research by Yun *et al* (2020) found that the residential sector contributed to 71% of the indoor $PM_{2.5}$ concentrations and 67% of $PM_{2.5}$-induced premature deaths in 2014. As such this analysis is (a) a lower bound estimate of total premature deaths from direct household energy consumption and (b) likely underestimates the impact on women as they may well have higher exposure to indoor air pollution due to their longer duration indoors in residential settings, as suggested by Hashim and Boffetta (2014). Secondly, we do not consider fuel sources of power producing in our scenario analysis as electricity supplies are mostly from coal power plants in China (Hubacek *et al* 2009), hence the health co-benefits from fuel switching and decarbonizing in our research may be even more significant than portrayed.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

Contributors

C L contributed to this study concept and design, did data collection, data analysis, data interpretation, visualization and wrote the draft of the manuscript. S Z supervised research, methodology and provided revision. Z L, W N A and K M supervised the research and revision. C T, T S, H Y and J G participated in data input into models. Y L participated in visualization and data collection. All authors approved the final version.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research received funding from National Natural Science Foundation of China (71874097, 41921005 and 71904007), the GEIGC Science and Technology Project on 'Modelling Air Pollution Control and Environmental Health Perspectives under the Green and Low Carbon Transition of Global Energy System' (2900/2020-75001B) and the Fine Particle Research Initiative in East Asia Considering National Differences (FRIEND) Project through the National Research Foundation of Korea (NRF) funded by the Ministry of Science and ICT (Project No. 2020M3G1A1114622).

ORCID iDs

Chenxi Lu https://orcid.org/0000-0003-3616-7622
Shaohui Zhang https://orcid.org/0000-0003-2487-8574
W Neil Adger https://orcid.org/0000-0003-4244-2854

References

Amann M *et al* 2011 Cost-effective control of air quality and greenhouse gases in Europe: modeling and policy applications *Environ. Model. Softw.* **26** 1489–501

Amann M *et al* 2020 Reducing global air pollution: the scope for further policy interventions *Phil. Trans. R. Soc.* A **378** 20190331

Andersson H and Treich N 2011 The Value of a Statistical Life *Handbook in Transport Economics* ed Cheltenham A R, Lindsey E, Quinet E and Vickerman R (Cheltenham: Edward Elgar Publishing) 396–424

Anenberg S C *et al* 2017 Impacts and mitigation of excess diesel-related NOx emissions in 11 major vehicle markets *Nature* **545** 467–71

Archer-Nicholls S *et al* 2016 The regional impacts of cooking and heating emissions on ambient air quality and disease burden in China *Environ. Sci. Technol.* **50** 9416–23

Burnett R *et al* 2018 Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter *Proc. Natl Acad. Sci. USA* **115** 9592–7

Chafe Z A, Brauer M, Klimont Z, Van Dingenen R, Mehta S, Rao S, Riahi K, Dentener F and Smith K R 2014 Household cooking with solid fuels contributes to ambient $PM_{2.5}$ air pollution and the burden of disease *Environ. Health Perspect.* **122** 1314–20

Chen Y, Guo F, Wang J, Cai W, Wang C and Wang K 2020 Provincial and gridded population projection for China under shared socioeconomic pathways from 2010 to 2100 *Sci. Data* **7** 83

Chen Y, Shen H, Smith K R, Guan D, Chen Y, Shen G, Liu J, Cheng H, Zeng E Y and Tao S 2018 Estimating household air pollution exposures and health impacts from space heating in rural China *Environ. Int.* **119** 117–24

Clark M L, Peel J L, Balakrishnan K, Breysse P N, Chillrud S N, Naeher L P, Rodes C E, Vette A F and Balbus J M 2013 Health and household air pollution from solid fuel use: the need for improved exposure assessment *Environ. Health Perspect.* **121** 1120–8

Cole-Hunter T *et al* 2021 Short-term differences in cardiac function following controlled exposure to cookstove air pollution: the subclinical tests on volunteers exposed to smoke (STOVES) study *Environ. Int.* **146** 106254

Ding Q, Cai W, Wang C and Sanwal M 2017 The relationships between household consumption activities and energy consumption in china—an input-output analysis from the lifestyle perspective *Appl. Energy* **207** 520–32

Du W, Li X, Chen Y and Shen G 2018 Household air pollution and personal exposure to air pollutants in rural China—a review *Environ. Pollut.* **237** 625–38

Fan J-L, Liao H, Liang Q-M, Tatano H, Liu C-F and Wei Y-M 2013 Residential carbon emission evolutions in urban–rural divided China: an end-use and behavior analysis *Appl. Energy* **101** 323–32

Friel S, Marmot M M, McMichael J, Kjellstrom T and Vågerö D 2008 Global health equity and climate stabilisation: a common agenda *Lancet* **372** 1677–83

GBD 2016 Burden of disease attributable to coal coalburning and other major sources of air pollution in China *Special Report* 20 (Boston, MA: Health Effects Institute)

Hashim D and Boffetta P 2014 Occupational and environmental exposures and cancers in developing countries *Ann. Glob. Health* **80** 393–411

Hubacek K, Guan D, Barrett J and Wiedmann T 2009 Environmental implications of urbanization and lifestyle change in China: ecological and water footprints *J. Clean. Prod.* **17** 1241–8

Li J, Liu H, Lv Z, Zhao R, Deng F, Wang C, Qin A and Yang X 2018 Estimation of $PM_{2.5}$ mortality burden in China with new exposure estimation and local concentration-response function *Environ. Pollut.* **243** 1710–8

Li Q, Jiang J, Wang S, Rumchev K, Mead-Hunter R, Morawska L and Hao J 2017 Impacts of household coal and biomass combustion on indoor and ambient air quality in China: current status and implication *Sci. Total Environ.* **576** 347–61

Li Q, Qi J, Jiang J, Wu J, Duan L, Wang S and Hao J 2019 Significant reduction in air pollutant emissions from household cooking stoves by replacing raw solid fuels with their carbonized products *Sci. Total Environ.* **650** 653–60

Li Y, Liao Q, Zhao X, Tao Y, Bai Y and Peng L 2021 Premature mortality attributable to $PM_{2.5}$ pollution in China during 2008–2016: underlying causes and responses to emission reductions *Chemosphere* **263** 127925

Liu L-C, Wu G, Wang J-N and Wei Y-M 2011 China's carbon emissions from urban and rural households during 1992–2007 *J. Clean. Prod.* **19** 1754–62

Liu M, Huang Y, Jin Z, Liu X, Bi J and Jantunen M J 2017 Estimating health co-benefits of greenhouse gas reduction strategies with a simplified energy balance based model: the Suzhou City case *J. Clean. Prod.* **142** 3332–42

Liu M, Saari R K, Zhou G, Li J, Han L and Liu X 2021 Recent trends in premature mortality and health disparities attributable to ambient $PM_{2.5}$ exposure in China: 2005–2017 *Environ. Pollut.* **279** 116882

Maji K J, Ye W F, Arora M and Shiva Nagendra S M 2018 $PM_{2.5}$-related health and economic loss assessment for 338 Chinese cities *Environ. Int.* **121** 392–403

NBSC 2011 *National Statistical Yearbook 2010* (Beijing: China Statistics)

NBSC 2016 *National Statistical Yearbook 2015* (Beijing: China Statistics)

Orimo H, Ito H, Suzuki T, Araki A, Hosoi T and Sawabe M 2006 Reviewing the definition of 'elderly' *Geriatr. Gerontol. Int.* **6** 149–58

Pachauri S, Mueller A, Kemmler A and Spreng D 2004 On measuring energy poverty in Indian households *World Dev.* **32** 2083–104

Shan Y, Guan D, Zheng H, Ou J, Li Y, Meng J, Mi Z, Liu Z and Zhang Q 2018 China CO2 Carbon emission accounts 1997-2015 *Sci. Data* **5** 1–14

Song C, He J, Wu L, Jin T, Chen X, Li R, Ren P, Zhang L and Mao H 2017 Health burden attributable to ambient $PM_{2.5}$ in China *Environ. Pollut.* **223** 575–86

WHO 2010 *Definition of an Older or Elderly Person* (Geneva, Switzerland: WHO)

Wu H 2014 Carbon emission reduction in China's eight comprehensive economic zones: type division and policy suggestions

Xu X 2017 *China's Population Spatial Distribution Kilometer Grid Dataset* (Chinese Academy of Sciences)

Yin H *et al* 2021 Population ageing and deaths attributable to ambient $PM_{2.5}$ pollution: a global analysis of economic cost *Lancet Planet. Health* **5** e356–67

Yun X *et al* 2020 Residential solid fuel emissions contribute significantly to air pollution and associated health impacts in China *Sci. Adv.* **6** eaba7621

Zhang J J and Smith K R 2007 Household air pollution from coal and biomass fuels in China: measurements, health impacts, and interventions *Environ. Health Perspect.* **115** 848–55

Zhang Q *et al* 2017a Transboundary health impacts of transported global air pollution and international trade *Nature* **543** 705–9

Zhang X, Ou X, Yang X, Qi T, Nam K-M, Zhang D and Zhang X 2017b Socioeconomic burden of air pollution in China: province-level analysis based on energy economic model *Energy Econ.* **68** 478–89

Zhao B *et al* 2018 Change in household fuels dominates the decrease in $PM_{2.5}$ exposure and premature mortality in China in 2005–2015 *Proc. Natl Acad. Sci. USA* **115** 12401–6

Zhao H *et al* 2019 Inequality of household consumption and air pollution-related deaths in China *Nat. Commun.* **10** 1–9