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Quantifying national household air pollution (HAP) exposure to $PM_{2.5}$ in rural and urban areas

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Abstract. According to WHO (World Health Organization), in 2020, 14% of people in global urban areas relied on polluting solid fuels and technologies, compared with 52% of the rural population. The health impacts of such inequality are massive. It was estimated that 3.2 million premature deaths per year (2020), particularly in low-income and middle-income countries due to household air pollution (HAP). Several studies provide estimates of the exposure to fine particulate matter ($PM_{2.5}$) from household air pollution (HAP-$PM_{2.5}$) for users of different fuel/cookstove types in rural and urban areas. However, hardly any studies estimate the population-weighted exposure to HAP-$PM_{2.5}$ at the global scale. A Bayesian hierarchical model was developed to estimate $PM_{2.5}$ exposure coefficients and their uncertainties for an annual average of HAP-$PM_{2.5}$ personal exposure. The predicted HAP-$PM_{2.5}$ exposure at the user level was used to estimate the national-level exposure for the population living in urban and rural areas. The results suggest that switching from polluting solid fuels (biomass, charcoal, coal) to cleaner fuels (gas and electricity) for heating and cooking can potentially reduce the national-level HAP-$PM_{2.5}$ personal exposure on average by 53%. However, there exists a significant disparity between rural and urban areas, partly reflecting inequality in energy access. More specifically, switching from polluting solid fuels for heating and cooking to cleaner fuels can reduce the personal exposure to HAP-$PM_{2.5}$ in rural areas by 54% and in urban areas by 38%. The study indicates that increased access to clean fuels and improved stove interventions are needed to achieve the goals of universal energy access and equality between urban and rural areas.

Keywords: Household air pollution; Bayesian hierarchical modelling; $PM_{2.5}$; Personal exposure

1. Introduction

Several studies provide estimates of the exposure to fine particulate matter ($PM_{2.5}$) from household air pollution (HAP-$PM_{2.5}$) in rural and urban areas of different countries/regions for different fuel types (dirty fuels such as biomass, coal, charcoal) and stove technologies [1-3]. However, hardly any studies quantify the population-weighted exposure to HAP-$PM_{2.5}$ in urban and rural areas at the global scale. Quantifying the $PM_{2.5}$ population-weighted exposure from solid dirty fuels and cleaner fuels can be challenging. This is partly due to the lack of HAP-$PM_{2.5}$ monitoring data for model training as well as (i) insufficient information on the fuels and stoves used for cooking, and heating monitoring location (kitchen, living room), (ii) building material, (iii) ventilation, (iv) time spent near the cooking area, (v) socio-demographic factors (such as age, gender, education) and (vi) income level of households. Additionally, there have been no studies that include the effects of climate and ambient air pollution on the HAP-$PM_{2.5}$ exposure of individuals. This is important since urban and rural HAP-$PM_{2.5}$ exposure of individuals using the same fuels and the same stove technologies within a given country can vary partly depending on the climate as well as ambient levels of air pollution. Ambient levels also affect the household air pollution through the infiltration of outdoor air into houses. Studies show using polluting fuels and inefficient technologies for cooking and heating results in various adverse effects on health, as well as on the environment, and the climate (e.g., increasing emissions of greenhouse gases and black carbon) [4-7].

The current study aims to estimate the national-level (after weighed by population) exposure to HAP-$PM_{2.5}$ for 62 countries across the world. Using sample data of personal exposure from an updated World Health Organization Global HAP database (Shupler et al., 2018), a Bayesian hierarchical $PM_{2.5}$ exposure model was developed to estimate the user-level household exposure to $PM_{2.5}$ (from both outdoor and indoor sources) across global countries for users of different fuel types (dirty fuels: biomass, charcoal, coal; cleaner fuels: gas, electricity) and different stove technologies (traditional and improved) in rural and urban areas separately. The national-level annual averages of HAP-$PM_{2.5}$ exposures for urban and rural areas in these countries were then calculated.

2. Data and method

2.1 Data

We extend the updated World Health Organization (WHO) HAP database [2, 8] from including 196 peer-reviewed studies (192 sample data points from 13 developing countries between 1996 and 2018) to the present database, which includes 282 studies (249 sample data points from 19 countries between 1996 and 2021). Figure 1 shows the sample data of $PM_{2.5}$ personal exposures for primary dirty fuels (biomass, charcoal, coal) and clean fuels (gas and electricity) for urban and rural locations classified based on the Human Development Index. The stove technology is classified as traditional (unvented - no chimney in the kitchen/heating area) and improved cookstove (vented and mentioned explicitly in the studies of collected sample data). To predict $PM_{2.5}$ personal exposure, we collected and pre-processed the data for countries with unknown personal exposure. The following data are used for the prediction: (i) Fuel Use and stove types [9-10]; (ii) Ambient $PM_{2.5}$ concentrations for rural and urban areas [11]; (iii) Heating degree days for rural and urban areas [12], (iv) GNI classification from World Bank [13], (v) Education index which is a component of the Human Development Index (HDI) [13].

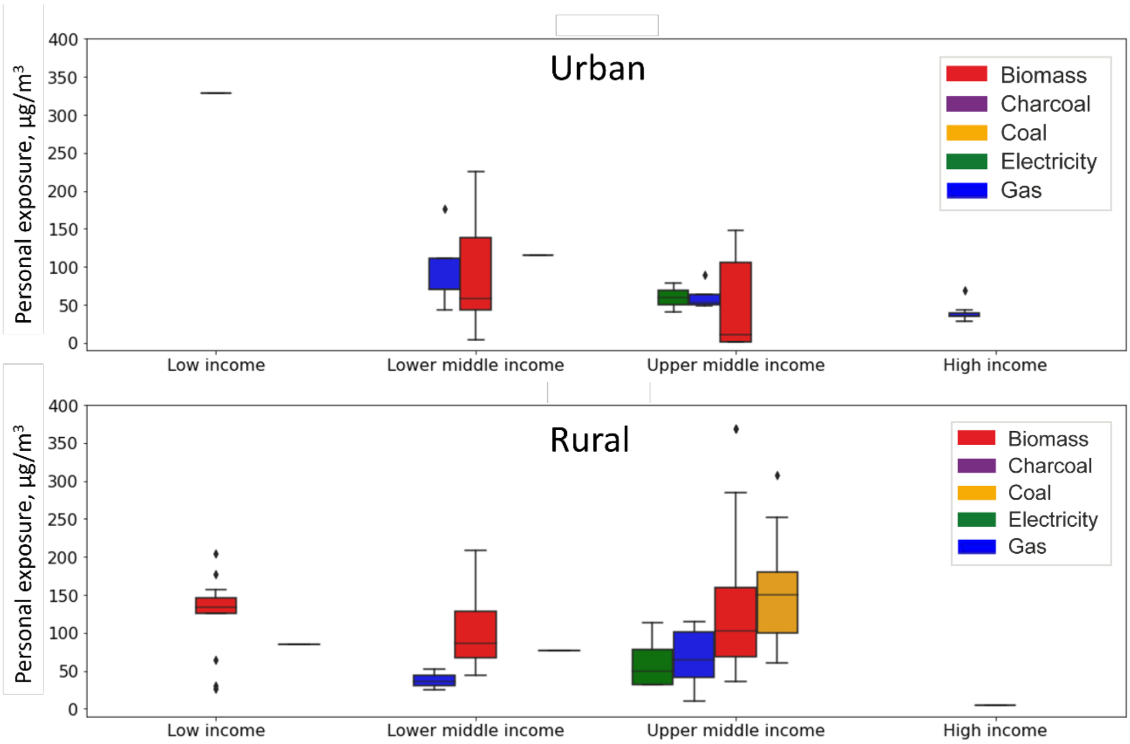

Figure 1. Sample data, primarily from developing countries, for HAP-$PM_{2.5}$ personal exposure for primary fuel use in households classified based on the Human Development Index (HDI) which is a measure of economic development and welfare

2.2. A Bayesian hierarchical model

A Bayesian hierarchical model was developed to estimate $PM_{2.5}$ exposure coefficients and their uncertainties for an annual average of HAP-$PM_{2.5}$ personal exposures. Using Bayesian hierarchical modelling allowed us to consider the influences of the clustered data (i.e., households are nested in countries, which are nested in regions) as well as the interactions between them. This helps the model to borrow the strength from other areas across the entire study countries as well as from the neighbouring countries within the regions, particularly when the data is dispersed (Figure 1). Model variables were selected from the sample data, which include region, country, location of households (urban and rural), primary fuel types (biomass, charcoal, coal, gas, and electricity), stove technologies (traditional and improved stoves), country education index, Gross National Income per capita (GNI), and season (winter and summer). Also, ambient air pollution ($PM_{2.5}$) and Heating Degree Days (HDD) as a proxy for climate-related heating demand, for urban and rural areas, are used in the predictive Bayesian model to obtain a more realistic estimation of the HAP-$PM_{2.5}$ exposures coefficients.

Bayesian hierarchical models were implemented using the 'brms' package in R [14]. Bayesian log-linear regression models were then built using fixed effects as well as random effects at both Country and WHO regions to be consistent with the multiple-nested data structure. We set a weakly informative prior over the fixed-effect slope coefficients, that is, a normal distribution with 0 mean and standard deviation of 10 [15,16]. We use the weakly informative prior as it is simple to implement in any standard Bayesian model. It does help to stabilize posteriors and regularize parameter estimates, thus, reduce the error rates [16]. To sample posterior distributions for parameter estimation, we apply the No-U-Turn Sampler (NUTS), an extension to Hamiltonian Monte Carlo (HMC), which is a Markov chain Monte Carlo (MCMC) algorithm using Stan language in the 'brms' package. To assess the model performance, we apply Leave-One-Out (LOO) Cross-Validation to approximate the ELPD (posterior predictive performance criterion) using Pareto smoothed important sampling technique [17]. Three metrics for model diagnostics are used to verify whether the chosen model is suitable. This includes (i) Posterior Predictive Check (PPC), using visual inspection, to verify whether simulated data distribution resembles the true data distribution, (ii) the Bayesian R^2, (iii) visualising the distribution of the posterior residuals to ensure the assumption of normally distributed residual is fulfilled. The personal exposure results are obtained with 95% credible intervals around the posterior means by applying the model coefficients to the corresponding posterior samples. The hierarchical model for personal exposure incorporating the above variables resulted in a Bayesian R^2 of 0.67 (standard error: 0.007; Q2.5 (lower quartile) = 0.65; Q97.5 (upper quartile) = 0.68) for personal exposure (μg/m^3).

2.3. National-level estimation

The estimated HAP-$PM_{2.5}$ exposures represent the value for typical users of each fuel type (biomass, charcoal, coal, electricity, gas), stove technology (improved, traditional), and separately for those who live in urban or rural areas. To estimate exposures at the national level (weighted by population) for clean and dirty fuels, three different weighted averages are used: (i) The proportion of people using each fuel type in each country obtained from WHO for the year 2020 [8]; (ii) The proportion of people using each stove type (traditional, improved); (iii) The proportion of people living in urban and rural areas

3. Results

The Baysian model performance is assessed using Leave-One-Out (LOO) Cross-Validation and the model with the lowest LOO-ELPD is remained as the best model. Three methods mentioned above (PPC, visual inspection, and the Baysian R^2) are applied to verify the suitability of the model. The developed Bayesian model which generates HAP-$PM_{2.5}$ personal exposure coefficients and their uncertainties (confidence intervals) can be used to predict HAP-$PM_{2.5}$ personal exposure for countries with no available exposure data (62 countries). Our results show biomass and gas have the highest and lowest personal exposure level, respectively. The estimated annual average HAP-$PM_{2.5}$ personal exposure for users of biomass with traditional stoves in rural areas is 184 μg/m^3 [95% CI 166-202] compared with urban areas with an average of 125 μg/m^3 [95% CI 111-138]. For improved stoves, the average for users of biomass in rural areas is 139 μg/m^3 [95% CI 126-151] compared with 90 μg/ m^3 [95% CI 78-102] in urban areas. For cleaner fuels, the annual average HAP-$PM_{2.5}$ personal exposures for users of gas is estimated at 71 μg/m^3 [95% CI 67-75] in rural areas and 48 μg/m^3 [95% CI 45-52] in urban areas.

Using three weighted averages described above, the exposures at the national level for clean and dirty fuels were estimated. The national-level HAP-$PM_{2.5}$ results show there is a large difference in the exposure level of polluting solid fuels and clean fuels between urban and rural areas. The estimated HAP-PM2.5 personal exposures of 62 countries show that the use of polluting solid fuels for cooking and heating in 2020 led to a national-level annual average exposure of 151 μg/m^3 [95% CI 133-169], with rural households having an average of 171 μg/m^3 [95% CI 153-189] and urban households an average of 92 μg/m^3 [95% CI 77-106]. The use of clean fuels, for all the estimated countries, gives rise to a national-level average exposure of 69 μg/m^3 [95% CI 62-76], with rural households having an average of 76 μg/m^3 [95% CI 69-83] and urban households an average of 49 μg/m^3 [95% CI 46-53].

Figure 2 shows the urban, rural, and national-level annual weighted averages for HAP-PM2.5 personal exposures of polluting solid fuels (biomass, coal, charcoal) and clean fuels (gas, electricity) classified for 5 WHO regions. SEAR has the highest level of HAP-$PM_{2.5}$ exposure for both polluting solid fuels and clean fuels in rural and urban areas.

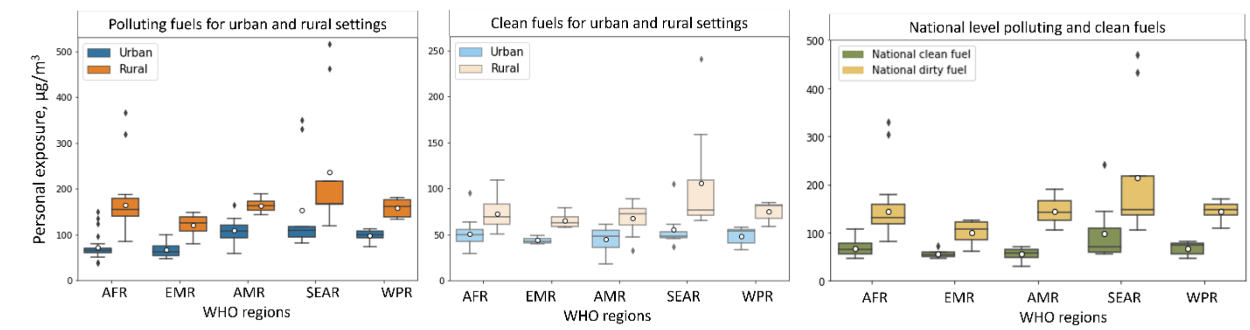

Figure 2. The urban, rural, and national-level annual weighted averages, medians, quartiles, and outliers for HAP-$PM_{2.5}$ personal exposures of polluting solid fuels (biomass, coal, charcoal) and clean fuels (gas, electricity) classified for 5 WHO regions. AFR (African Region), AMR (Region of the Americas), SEAR (South-East Asian Region), WPR (Western Pacific Region), and Eastern Mediterranean Region (EMR).

4. Conclusion and future work

The study provides very useful information as to the variation of population-weighted $PM_{2.5}$ exposure from users of different fuel and stove types and urban/rural areas for different countries. However, several limitations need to be resolved in the future extension of this study. Household air pollution estimation at the global level is complex and impacted by several different factors including housing characteristics (e.g., ventilation rate, kitchen location, window settings, roof materials) which are not typically captured in all the monitored data. Updating the sample data with information on these and related factors should greatly improve future predictions. Another challenge related to the measured/monitored data, more specifically, is the concerns as follows: a rather limited number of households monitored in each study; diverse monitoring technology to collect the data; and different measurement periods as well as different analytic methods for data processing in each study. Nevertheless, using Bayesian predictive models developed in this study allows us to explore a wide range of population weighted $PM_{2.5}$ exposures for different urban and rural areas. The HAP-$PM_{2.5}$ exposure provides useful information to estimate the associated health burden across urban and rural areas. The present study is the first to quantify the national-level personal exposure (weighted by population) to HAP for people living in urban and rural areas. The results suggest that switching from polluting solid fuels (biomass, charcoal, and coal) to cleaner fuels (gas and electricity) for heating and cooking can potentially reduce the national-level HAP-$PM_{2.5}$ personal exposure on average by 53% (rural areas reduced by 54% and urban areas reduced by 38%). The results show that there is a significant difference in HAP-$PM_{2.5}$ personal exposure between rural and urban areas, highlighting the inequality in clean energy access. In addition, the study indicates that increased access to clean fuels and improved stove interventions are needed to achieve the goals of universal energy access and equality between urban and rural areas.

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