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Global estimation of exposure to fine particulate matter ($PM_{2.5}$) from household air pollution[☆]

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A R T I C L E I N F O

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A B S T R A C T

Background: Exposure to household air pollution (HAP) from cooking with dirty fuels is a leading health risk factor within Asia, Africa and Central/South America. The concentration of particulate matter of diameter ≤ 2.5 μm ($PM_{2.5}$) is an important metric to evaluate HAP risk, however epidemiological studies have demonstrated significant variation in HAP-$PM_{2.5}$ concentrations at household, community and country levels. To quantify the global risk due to HAP exposure, novel estimation methods are needed, as financial and resource constraints render it difficult to monitor exposures in all relevant areas.

Methods: A Bayesian, hierarchical HAP-$PM_{2.5}$ global exposure model was developed using kitchen and female HAP-$PM_{2.5}$ exposure data available in peer-reviewed studies from an updated World Health Organization Global HAP database. Cooking environment characteristics were selected using leave-one-out cross validation to predict quantitative HAP-$PM_{2.5}$ measurements from 44 studies. Twenty-four hour HAP-$PM_{2.5}$ kitchen concentrations and male, female and child exposures were estimated for 106 countries in Asia, Africa and Latin America.

Results: A model incorporating fuel/stove type (traditional wood, improved biomass, coal, dung and gas/electric), urban/rural location, wet/dry season and socio-demographic index resulted in a Bayesian R^2 of 0.57. Relative to rural kitchens using gas or electricity, the mean global 24-hour HAP-$PM_{2.5}$ concentrations were 290 μg/m^3 higher (range of regional averages: 110, 880) for traditional stoves, 150 μg/m^3 higher (range of regional averages: 50, 290) for improved biomass stoves, 850 μg/m^3 higher (range of regional averages: 310, 2600) for animal dung stoves, and 220 μg/m^3 higher (range of regional averages: 80, 650) for coal stoves. The modeled global average female/kitchen exposure ratio was 0.40. Average modeled female exposures from cooking with traditional wood stoves were 160 μg/m^3 in rural households and 170 μg/m^3 in urban households. Average male and child rural area exposures from traditional wood stoves were 120 μg/m^3 and 140 μg/m^3, respectively; average urban area exposures were identical to average rural exposures among both sub-groups.

Conclusions: A Bayesian modeling approach was used to generate unique HAP-$PM_{2.5}$ kitchen concentrations and personal exposure estimates for all countries, including those with little to no available quantitative HAP-$PM_{2.5}$ exposure data. The global exposure model incorporating type of fuel-stove combinations can add specificity and reduce exposure misclassification to enable an improved global HAP risk assessment.

1. Introduction

Household air pollution (HAP) from cooking with polluting ('dirty') fuels, including coal, kerosene, and biomass (wood, charcoal, crop residue and animal dung) is a global environmental health problem, affecting approximately 2.45 billion people (Health Effects Institute, 2018). Poor and rural communities in low- and middle-income countries (LMICs) in Asia, Africa and Central/South America are disproportionately affected by the risk associated with cooking with such dirty fuels.

HAP exposure has been epidemiologically linked to several adverse clinical outcomes, including respiratory infections in children (Bates

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et al., 2013; Ezzati and Kammen, 2001; Smith et al., 2011; Upadhyay et al., 2015), chronic diseases in adults (Alexander et al., 2014; Kumar et al., 2014; Kurmi et al., 2013; Siddharthan et al., 2018), lung cancer (Kurmi et al., 2012), cataracts (Pokhrel, 2004), adverse pregnancy outcomes (Alexander et al., 2018; Amegah et al., 2014; Thompson et al., 2011) and, more recently, high blood pressure (Alexander et al., 2017; Arku et al., 2017, 2018; Baumgartner et al., 2014; Baumgartner et al., 2011b; Burroughs Pena et al., 2015; Clark et al., 2013; Norris et al., 2016) and cardiovascular diseases (CVD) such as ischemic heart disease and stroke (Yu et al., 2018). In their 2016 study, the Global Burden of Disease (GBD) attributed 2.6 million deaths annually to HAP, making it the 2nd highest environmental risk factor globally and the 10th overall for global disease burden (Gakidou et al., 2017).

Since its initiation in 1990, the GBD now involves annual comparative risk assessments, describing the extent and distribution of ill health globally by age, gender, and disease for various risk factors (Murray et al., 2012). The first iteration to include HAP as a major risk factor was in 2000 (Lim et al., 2013; Murray et al., 2012). Using data on household cooking fuel types from National Censuses and demographic and health surveys, the GBD conducted sex-specific meta-analyses of HAP epidemiological studies to provide male and female relative risks of developing a particular disease based on a binary indicator of whether a household used dirty or clean (gas and electric) fuels (Smith, 2000). The estimated relative risk for a particular disease was combined with the proportion of the population in each country that cooked with dirty fuels to determine global morbidity and mortality due to HAP on an absolute scale.

While this approach provided country-specific estimates of the burden of disease due to HAP exposure for males and females, it did not account for heterogeneity in HAP across various geographies, fuel and stove types. Since its first inclusion as a GBD risk factor, dozens of quantitative HAP studies have been conducted, including personal (male, female and/or child) and cooking area (kitchen) measurements. Measurement studies have consistently shown that HAP concentrations vary by various factors across different global regions (Carter et al., 2016; Gurley et al., 2013; Jin et al., 2005; Massey et al., 2012; Ni et al., 2016). Thus, applying a single exposure measure to all males or females that are exposed to HAP worldwide can misclassify levels of disease risk. Almost two decades later, over 200 studies with quantitative HAP exposure and concentration measurements have been conducted, with fine particulate matter ($PM_{2.5}$) concentration being the most commonly measured metric to characterize HAP exposures (WHO, 2012).

The collection of $PM_{2.5}$ measurements in studies of HAP (referred to as HAP-$PM_{2.5}$) has enabled more precise exposure assignment in risk assessments. Specifically, exposure-response functions linking levels of HAP-$PM_{2.5}$ exposures with disease-specific relative risks are compared to a low exposure counterfactual $PM_{2.5}$ concentration (Burnett et al., 2014). To account for a lack of HAP-epidemiologic evidence for a number of specific diseases, integrated exposure-response (IER) curves aggregate risk estimates from available epidemiological data from other sources of $PM_{2.5}$ exposures, namely ambient air pollution, active smoking and second hand smoke (Pope et al., 2009; Pope et al., 2011; Smith and Peel, 2010). Application of such exposure response functions requires estimates of HAP-$PM_{2.5}$ exposures.

Determining a unique HAP-$PM_{2.5}$ exposure for individuals in each community where dirty fuel use (DFU) is common would require extensive HAP-$PM_{2.5}$ monitoring, which is logistically and financially prohibitive. An alternative method has been to model HAP-$PM_{2.5}$ exposures in relation to potential determinants of exposure that are collected in large national surveys (Balakrishnan et al., 2013; Baumgartner et al., 2011a, 2011b; Dasgupta et al., 2006; Gurley et al., 2013). Aside from the type of fuel and stove used for cooking, other known determinants include cooking area factors such as the presence of kitchen area ventilation, quantity of fuel, fuel moisture content, season and time spent near the cooking area and demographic factors like age and gender (Baumgartner et al., 2011a, 2011b; Bruce et al., 2013; Clark et al., 2010; Hosgood et al., 2011; Jin et al., 2005; McCracken et al., 2009). Further, urban and rural personal $PM_{2.5}$ exposures of individuals using the same fuels within the same country can vary greatly due to other factors, including ambient levels of air pollution (Li et al., 2017; Smith, 2000). Detailed qualitative characteristics of the study population and cooking environment are increasingly documented in quantitative HAP-$PM_{2.5}$ exposure assessment studies, and information on several of these determinants is readily available in national surveys.

In attempt to improve upon their initial approach, the GBD 2010 study applied modeled exposure estimates developed for India to the global population (Lim et al., 2013). All households using solid fuels were assigned the same kitchen concentration (450 μg/m^3). Median measured kitchen-to-personal exposure ratios (0.742 for women, 0.450 for men and 0.628 for children), based on the WHO Global HAP database (WHO, 2012), were applied to the single kitchen concentration to estimate exposures (Balakrishnan et al., 2013; Smith et al., 2014). These exposures were then applied to outcome-specific exposure-response curves to estimate disease burden attributable to HAP. In the GBD 2015 (Forouzanfar et al., 2015) and 2016 (Gakidou et al., 2017) studies, descriptive data obtained from the WHO database on averaging period (cooking or non-cooking period and > 24 hour or < 24 hour period) and monitoring location (kitchen or living area) were used as predictors to generate region-specific (2015) or country-specific (2016) HAP-$PM_{2.5}$ exposures. The 2016 model estimated a substantially lower global mean HAP-$PM_{2.5}$ concentration of 189 μg/m^3, compared to 450 μg/m^3 in 2010.

While these models have all predicted identical exposures regardless of fuel-stove type, we sought to refine the previous approaches by developing a global HAP-$PM_{2.5}$ exposure model which differentiated between fuel-stove types. Our study incorporated additional published exposure data, and utilized Bayesian modeling techniques. The Bayesian approach allowed us to account for unequal geographic representation of quantitative HAP-$PM_{2.5}$ monitoring data across LMICs affected by HAP, as information was shared between areas with little or no HAP-$PM_{2.5}$ measurements and areas with several data. With the use of exchangeable priors, we were able to assign valid HAP-$PM_{2.5}$ exposures to regions with less HAP-$PM_{2.5}$ exposure data and more accurately characterize the uncertainty of the predicted exposures in regions with sparse exposure data. Our goal was to incorporate heterogeneity in measured HAP-$PM_{2.5}$ concentrations within a global model to better characterize risks among the diverse target populations for more accurate estimation of the global disease burden attributable to HAP exposure.

2. Methods

2.1. Data source

The *WHO Global HAP Database* (referred to from this point forward as 'database') contains quantitative HAP-$PM_{2.5}$ concentration and exposure data from published, peer-reviewed studies. Details are described in the publication: "Global Household Air Pollution Measurements Database: Particulate Matter and Carbon Monoxide Household and Personal Exposure Measurements from Peer-Reviewed Literature" in *Data in Brief Journal* and on the World Health Organization website: http://www.who.int/airpollution/data/hap-measurements/en/ (WHO, 2012). The database is a compilation of studies of quantitative HAP measurements with detailed information on the type of PM measurement obtained in the study (e.g. fuel and stove types), size fraction ($PM_{2.5}$, PM_{10}, etc.), sampling method (gravimetric, light scattering), monitor location (personal, kitchen area, living room, etc.), averaging time (24 h, 8 h, etc.), the sample population (e.g. sample size, sex), and study environment where the air monitoring was conducted (e.g. cooking fuels and types of stoves used, kitchen location, housing material, ventilation, rural-urban location, season and altitude). The updated database contains approximately 1100 quantitative

HAP measurements from 196 studies in 53 countries. Of these, 410 quantitative measurements of HAP-$PM_{2.5}$ were from 90 peer-reviewed studies.

2.2. Outcome variable definition: HAP-$PM_{2.5}$ concentration

Summary HAP-$PM_{2.5}$ measures reported in published studies include arithmetic mean (reported for 73% of measurements in database), geometric mean (25%) or median (1%) values. To preserve the sample size of the analysis, $PM_{2.5}$ arithmetic mean, geometric mean and medians values were grouped together to form the outcome variable. Sensitivity analysis was conducted to quantify the impact of restricting analysis to studies that only reported arithmetic means (see Supplemental Information (SI)). All $PM_{2.5}$ measurements were log-transformed to meet assumptions of normality. In all analyses, log-$PM_{2.5}$ concentrations were weighted by the number of measurements (N = 2–490; median = 17) that contributed to the reported $PM_{2.5}$ average to account for variations in the sample size of different studies.

In assessing HAP-$PM_{2.5}$ kitchen concentrations and personal exposures, we excluded non-kitchen area measurements (e.g. living area) due to low sample size. Similarly, as the majority (80%) of personal exposure measurements were collected among females, personal exposure modeling was conducted for females only; models for male and child HAP-$PM_{2.5}$ exposures could not converge due to small sample sizes. Therefore, we estimated male and child exposures by combining modeled female exposures with male:female and child:female ratios averaged across seven peer-reviewed studies (the same studies as used in GBD 2015 and GBD 2016 to derive personal exposure levels) (SI Table S7). A sensitivity analysis was conducted to compare predicted male and child exposures using female:male and female:child ratios with that of exposures reported in the seven studies (SI Table S7). In accordance with the GBD study and several other studies in the literature, all results referring to children represent those aged ≤5 years old.

Measurements of HAP-$PM_{2.5}$ obtained over a period < 24 h were eliminated to avoid biases introduced by sampling only during cooking events. The potential change in the modeling results when excluding studies with < 24 hour sampling duration was tested in sensitivity analyses (see SI Table S10). The final analytic sample included 192 data points (140 kitchen; 52 female) from 44 studies (see SI Table S1 for full list of studies included in the analysis) from 13 countries (Fig. 1, with detailed breakdown by country in SI Table S2).

2.3. Main explanatory variable definition: stove & fuel types

Five stove-fuel types were used in modeling (Fig. 2) with kerosene (N = 7 measurements), charcoal (2) and crop residue fuels (2) excluded due to a low number of $PM_{2.5}$ measurements tied solely to these fuels. While there has been much research on different measurements of $PM_{2.5}$ from various types of improved cookstoves (ICS) in lab settings, measurement studies, and in the context of intervention studies, a limited sample of ICS measurements in the WHO database called for aggregating all ICS varieties together. Similarly, gas and electric stoves were grouped together, as studies in the database aggregated $PM_{2.5}$ measurements from these two types of stoves.

Approximately 15% of $PM_{2.5}$ concentrations in the final analytic sample were reported in studies as a composite average of two or more stove/fuel types. To retain these composite concentrations in the analysis and to preserve the sample size, the concentrations were equally split (1/n, where n was the total number of stove/fuel types comprising the 24-hour average $PM_{2.5}$ concentration) across the coefficients of the stove/fuel types. A sensitivity analysis was conducted with the 15% of composite measurements excluded to determine potential effects on model predictability.

Two data points of composite $PM_{2.5}$ concentrations consisting of gas stoves and dirty fuels were excluded due to potentially large discrepancies in $PM_{2.5}$ concentrations between these two fuel groupings. Further, as studies aggregated summary measures by different strata (e.g. across all fuels in the winter/summer vs. each individual fuel across each season), duplicate values that featured the same measurements aggregated in a different manner were eliminated to ensure independence.

2.4. Other predictor variable definitions

In addition to fuel-stove combinations only those descriptive variables (urban/rural binary indicator, season and geographic location) with a low (< 5%) degree of missing values were considered for inclusion in models. Of the 21 regions defined by the GBD, HAP studies were conducted in only six (Fig. 1). Although not available directly in the database, the country-level sociodemographic index (SDI, score from 0 to 1) was available for every country from 1970 to 2016 and considered as a potential predictor (Global Burden of Disease Collaborative Network, 2017). While SDI values for study countries in the modeling ranged from 0.2 to 0.8, SDI was left skewed, with two-

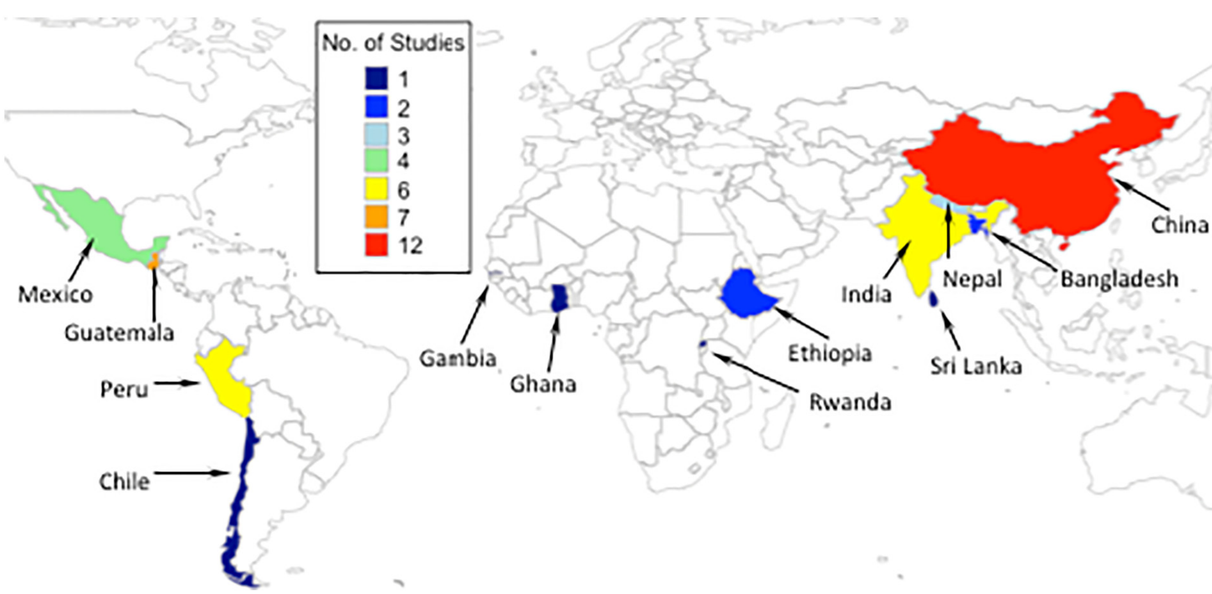

Fig. 1. Numbers of studies per country from the thirteen countries with studies included in the analysis.

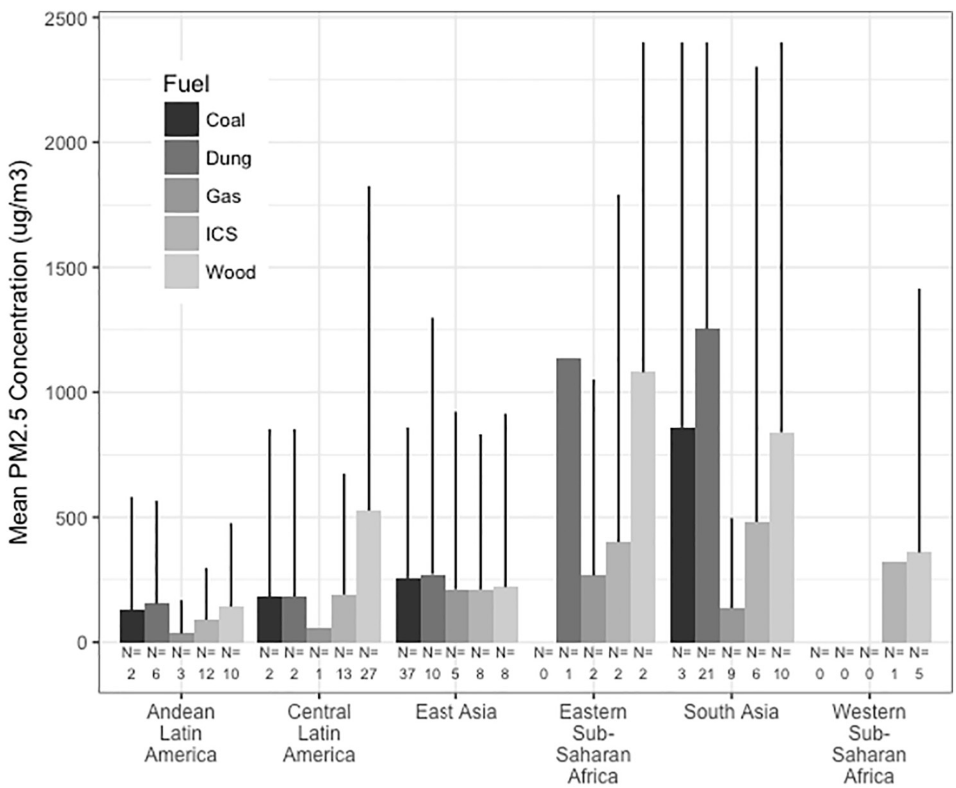

Fig. 2. Unweighted mean (95% CI) measured 24-hour HAP-$PM_{2.5}$ kitchen concentrations among rural areas in each GBD region.
Notes: 95% confidence intervals corresponding to wood fuel in Eastern Sub-Saharan Africa and coal, dung and wood fuels in South Asia were scaled down to fit into figure. No HAP-$PM_{2.5}$ data were available for coal fuel in Eastern Sub-Saharan Africa or coal, dung and gas fuels in Western Sub-Saharan Africa. Lower 95% confidence intervals crossed zero for all regions.

thirds of values falling in the range of 0.5 to 0.8. Values in the lower range (0.2 to 0.4) belonged to Sub-Saharan African countries. SDI values were matched to the year the HAP study was conducted in a particular country, thereby enabling HAP-$PM_{2.5}$ concentrations to be estimated at the country-level.

Season was a dichotomous variable of winter (dry) or summer (wet) season. Season was obtained either from publications explicitly mentioning the season of measurements, or inferred based on the study dates of data collection reported in the publication. To obtain an annual average HAP-$PM_{2.5}$ concentration, a time-weighted average of the two modeled seasonal concentrations was used. For simplicity, all analyses presented in this paper assumed each country/region had equal wet and dry seasons. Therefore, two season-specific concentrations were obtained from the model for each country/region of interest and averaged to generate the average annual concentration.

To ensure an adequate sample size for analysis, female and kitchen HAP-$PM_{2.5}$ measurements were combined in the same model by including a female/kitchen indicator variable. Female:kitchen exposure ratios were generated by exponentiating the fixed effect coefficient of the female/kitchen indicator variable; the regional random effects were added to generate region-specific exposure ratios.

2.5. Bayesian analysis

All statistical analyses were conducted in R version 3.4.4 (R Core Team, 2017). Bayesian hierarchical modeling was implemented using the *brms* package in R (Bürkner, 2017). The *brms* package uses the Stan language on the back-end and applies the No-U-Turn Sampler (Hoffman and Gelman, 2014) for parameter estimation, which is an extension of the Hamiltonian Monte Carlo algorithm and a form of Markov Chain Monte Carlo sampling.

Bayesian hierarchical models were built using main effects as well as random effects at the GBD region level. As the final analytic sample included data from 13 countries and six GBD regions, random effects were not considered at both the country and region level in any of the hierarchical models. All models were run with two chains and model convergence was monitored via visual inspection of the chains as well as each fixed parameter achieving an effective sample size of at least 20,000. The 95% credible intervals (CIs) around the posterior means were obtained by exponentiating and applying the model coefficients to the corresponding posterior samples and extracting the 0.025 and 0.975 quantiles.

Model validation, via leave-one-out cross validation, was performed using an approximation technique called Pareto smoothed important sampling. The 'loo' package (Vehtari et al., 2016) in R provided the leave-one-out information criterion (LOOIC). The model with the lowest LOOIC was selected.

Once the final fixed-effect only model was chosen, fixed effects with the highest posterior standard deviations were considered for inclusion as random effects. Final inclusion as a random effect was evaluated by the same criteria as fixed effects, in addition to model convergence. All fixed effects parameters were fit with noninformative flat priors and random effects were fit with half Student-t priors with 3 degrees of freedom (*brms* package default); this prior can lead to better model convergence, while also being relatively weakly informative (Bürkner, 2017).

2.6. Exchangeable priors

In GBD regions in which no HAP studies were available in the database but where cooking with dirty fuels is still common, exchangeable priors were used to assign HAP-$PM_{2.5}$ values at the grand mean of the posterior estimates (no regional effect) (Bernardo and Smith, 1994). With the grand mean assigned to certain GBD regions, the most recent (2016) country-specific SDI values were applied to allow for differences in national-level socioeconomic standing within these regions to impact modeled HAP-$PM_{2.5}$ concentrations. With the additional GBD regions added, a total of 106 countries were included in the final analysis.

2.7. Case study: applying the model results to fuel usage survey data in India

To demonstrate model application, state-level average 24-hour

Table 1
Season-weighted (50/50 wet/dry season), mean (95% CI) HAP-$PM_{2.5}$ kitchen, female, male and child exposure concentrations obtained from the model for each GBD region (rural areas only).

GBD region	Fuel type	Average kitchen HAP-$PM_{2.5}$ concentration	Average female HAP-$PM_{2.5}$ concentration	Average male HAP-$PM_{2.5}$ concentration	Average child HAP-$PM_{2.5}$ concentration
Andean Latin America	Gas/electric	38 (35, 40)	28 (25, 30)	20 (18, 22)	24 (22, 26)
	Traditional wood	143 (134, 150)	105 (97, 112)	76 (70, 81)	92 (84, 97)
	Improved cookstove	87 (80, 92)	64 (59, 68)	46 (42, 49)	56 (51, 59)
	Animal dung	347 (317, 372)	256 (229, 279)	184 (165, 201)	223 (199, 243)
	Coal	115 (102, 128)	85 (74, 96)	61 (53, 69)	74 (64, 84)
Central Latin America	Gas/electric	145 (133, 155)	50 (46, 54)	36 (33, 39)	44 (40, 47)
	Traditional wood	552 (521, 573)	192 (181, 199)	138 (130, 143)	167 (157, 173)
	Improved cookstove	262 (245, 273)	91 (85, 95)	65 (61, 68)	79 (74, 83)
	Animal dung	1339 (1214, 1448)	465 (423, 501)	335 (305, 361)	405 (368, 436)
	Coal	446 (390, 498)	155 (136, 172)	112 (98, 124)	135 (118, 150)
East Asia	Gas/electric	44 (40, 47)	24 (23, 26)	18 (17, 19)	21 (20, 23)
	Traditional wood	168 (157, 176)	93 (88, 96)	67 (63, 69)	81 (77, 84)
	Improved cookstove	247 (235, 255)	137 (130, 141)	99 (94, 102)	119 (113, 123)
	Animal dung	408 (368, 443)	226 (205, 243)	162 (148, 175)	196 (178, 211)
	Coal	136 (120, 150)	75 (66, 84)	54 (48, 60)	65 (57, 73)
Eastern Sub-Saharan Africa	Gas/electric	312 (269, 353)	102 (34, 314)	73 (24, 226)	89 (30, 273)
	Traditional wood	1187 (781, 1402)	388 (115, 1122)	279 (83, 808)	337 (100, 976)
	Improved cookstove	602 (496, 896)	197 (72, 697)	142 (52, 502)	171 (63, 606)
	Animal dung	2878 (2458, 3278)	940 (313, 2933)	677 (225, 2112)	818 (272, 2552)
	Coal	958 (807, 1109)	313 (105, 972)	225 (76, 700)	272 (91, 846)
South Asia	Gas/electric	247 (228, 261)	72 (58, 88)	52 (42, 63)	63 (50, 77)
	Traditional wood	939 (878, 981)	274 (221, 331)	197 (159, 238)	238 (192, 288)
	Improved cookstove	450 (402, 493)	131 (105, 160)	95 (76, 115)	114 (91, 139)
	Animal dung	2277 (2098, 2413)	665 (532, 809)	479 (383, 582)	578 (463, 704)
	Coal	758 (667, 840)	221 (175, 273)	159 (126, 197)	193 (152, 238)
Western Sub-Saharan Africa	Gas/electric	119 (39, 354)	40 (13, 117)	29 (9, 84)	35 (11, 102)
	Traditional wood	453 (147, 1343)	153 (50, 445)	110 (36, 320)	133 (44, 387)
	Improved cookstove	291 (95, 847)	98 (32, 284)	71 (23, 204)	85 (28, 247)
	Animal dung	1099 (358, 3234)	371 (122, 1073)	267 (88, 773)	322 (106, 934)
	Coal	366 (117, 1062)	123 (40, 358)	89 (29, 258)	107 (35, 311)
All Other Regions (global average)	Gas/electric	104 (39, 273)	42 (16, 114)	30 (12, 82)	37 (14, 99)
	Traditional wood	395 (148, 1039)	161 (61, 431)	116 (44, 310)	140 (53, 375)
	Improved cookstove	251 (94, 686)	102 (37, 292)	74 (27, 210)	89 (32, 254)
	Animal dung	958 (359, 2520)	391 (148, 1047)	281 (107, 754)	340 (129, 911)
	Coal	319 (119, 838)	130 (49, 348)	94 (35, 250)	114 (43, 302)

Note: 'All Other Regions' contains the grand mean of the model obtained from use of exchangeable priors. All other regions not listed in this table will have the same predicted concentrations from the model as SE Asia. All mean HAP-$PM_{2.5}$ values are centered at median SDI of each region.

HAP-$PM_{2.5}$ kitchen concentrations were estimated for India. The average 24-hour kitchen concentration for each fuel type was evaluated using SDI available at the State-level (Dandona et al., 2017). The percent of households using each cooking fuel type for urban and rural areas in the 29 Indian States were extracted using the *National Family Health Survey 2015* (NFHS 2015) (http://rchiips.org/NFHS/NFHS-4Report.shtml).

The NFHS 2015 contained more fuel-stove combinations (12) than were available in the model (5). In order to include the entire population of India in the model application, the twelve stove-fuel types available in the NFHS 2015 were re-categorized into one of the five fuel types available in the model deemed most appropriate in terms of expected exposure levels: (1) Gas: electricity, LPG/natural gas, biogas; (2) Traditional wood: wood- open fire, wood-chullah; (3) ICS: wood-stove; (4) Dung: dung cakes, agricultural crop waste, straws/shrubs/grass; (5) Coal: Coal/lignite, charcoal, kerosene. A State-level 24-hour average kitchen concentration was generated by weighting the fuel-specific kitchen HAP-$PM_{2.5}$ concentrations by the respective State percentage of fuel usage reported in the NFHS 2015.

3. Results

A total of thirteen countries contributed measurements used in the modeling. China (12 studies), Guatemala (7), India (6) and Peru (6) each contributed more than five studies, with the remaining nine countries providing 4 or fewer studies (Fig. 1).

There were clear differences in HAP-$PM_{2.5}$ measured concentrations between regions for the same fuel-stove combinations, and within regions for different fuel-stove combinations (Fig. 2). In general, concentrations were highest for use of dung or wood and higher in eastern Sub-Saharan Africa and South Asia compared to other regions.

3.1. Model selection

The best model fit, according to LOOIC, was achieved when including all available predictors. This model obtained a Bayesian R^2 of 0.57 (Gelman et al., 2017). Table S6 (SI) lists all evaluated models and their corresponding LOOIC value. All fuel/stove-specific coefficients were statistically evident (i.e. the 95% credible interval excludes the null value) (Table S3 in SI). SDI was negatively associated with the outcome, and summer (wet) season also had a statistically evident negative effect on concentrations, controlling for stove type and urban/

rural location. While urban/rural location was not significant in the model, an enhanced model fit and large spatial variation in the relative differences between urban and rural area concentrations necessitated its inclusion. The final model was:

$$\log(PM_{2.5})_{ij}|weights(Population) = B_0 + B_j + B_1(Traditional\ Wood)_{ij} + B_2(Dung)_{ij} + B_{3j}(ICS)_{ij} + B_4(Coal)_{ij} + B_5(Wet\ Season)_{ij} + B_{6j}(Rural)_{ij} + B_{7j}(Female\ Exp)_{ij} + B_8(SDI)_{ij} + e_{ij}$$

$\log(PM_{2.5})_{ij}$ is natural logarithm of mean 48-hour $PM_{2.5}$ concentration of ith study in region j, β_0 is overall intercept, B_j is random intercept for region j and e_{ij} is leftover error. '*Population*' is the number of measurements corresponding to the averaged $\log(PM_{2.5})$ value. '*Traditional Wood*', '*ICS*', '*Dung*' and '*Coal*' indicate a traditional open fire stove, improved biomass cookstove, animal dung fueled or coal fueled stove, respectively. '*Wet Season*' indicates if the measurement was obtained during the wet (summer) season or dry (winter) season. '*Rural*' indicates if the measurement was taken in a rural or urban setting. '*Female Exp*' indicates if the measurement was a female exposure measurement or a kitchen measurement. '*Rural*', '*Female Exp*' and '*ICS*' had region-specific random effects attributed to them.

3.2. Kitchen concentrations

All types of dirty fuel/stove combinations, including ICS, generated significantly higher $PM_{2.5}$ kitchen concentrations compared to gas/electric stoves (fixed and random effect coefficients from the model are shown in Table S3 in SI). The global average HAP-$PM_{2.5}$ kitchen concentrations (in rural areas) for each fuel type ranged from 104 μg/m^3 (95% CI: 39, 273) for gas/electric stoves to 958 μg/m^3 (95% CI: 359, 2520) for animal dung. Estimated GBD region-specific HAP-$PM_{2.5}$ kitchen concentrations, obtained by centering SDI at the median value of each region, are shown in Table 1.

Between rural households within some of the most populous countries, there was substantial variation in HAP-$PM_{2.5}$ kitchen concentrations among gas/electric and traditional wood stoves. For example gas/electric and wood levels were 42 μg/m^3 and 162 μg/m^3 in China, 207 μg/m^3 and 787 μg/m^3 in India, 111 μg/m^3 and 423 μg/m^3 in Nigeria and 228 μg/m^3 and 867 μg/m^3 in Pakistan, respectively. Maps depicting the average HAP-$PM_{2.5}$ kitchen concentration in all countries for each fuel type are shown in Fig. 3 (numerical country-level HAP-$PM_{2.5}$ concentrations shown in Table S4 in SI).

Controlling for stove-fuel type, SDI and seasonality, the main effect of living in a rural household on HAP-$PM_{2.5}$ concentrations, relative to that of urban households, was slightly negative. However, the model generally predicted rural areas in most regions as having greater levels of HAP-$PM_{2.5}$ concentrations than urban areas when factoring in the regional random effects. The negative main effect tied to rural areas was mainly driven by a strong negative association in East Asia (Table S3), which may be largely due to high ambient air pollution levels in urban areas of China. On average, the model estimated rural households in China using gas or electric stoves as having an average HAP-$PM_{2.5}$ kitchen concentration of 42 μg/m^3 compared to 88 μg/m^3 in urban areas in China. Conversely, rural households using gas/electric fuels in India had an average HAP-$PM_{2.5}$ kitchen concentration of 207 μg/m^3, which is higher than the average estimated concentration of 161 μg/m^3 among urban households.

3.3. Personal concentrations

Modeled global average HAP-$PM_{2.5}$ female exposure concentrations (in rural areas) ranged from 42 μg/m^3 (95% CI: 16, 114) for gas/electric stoves to 391 μg/m^3 (95% CI: 148, 1047) for animal dung. Female exposures obtained directly from the model were multiplied by a female/male and female/child exposure ratio of 0.72 and 0.87, respectively, obtained using a sample size weighted average from seven studies with male, female and child personal HAP-$PM_{2.5}$ monitoring. The resulting HAP-$PM_{2.5}$ exposures for males and children (Table 1) were comparable to those found in the literature (SI Table S7).

The global average female/kitchen exposure ratio from the model was approximately 0.40 (95% CI: 0.22, 0.73). Female:kitchen exposure ratios were approximately 0.3 for most regions, with higher ratios being East Asia (0.55) and Andean Latin America (0.74) (Table 2).

3.4. Estimated state-level kitchen concentrations for India

Applying the model exposure coefficients to State-level fuel usage data from the India National Family and Health Survey 2015 (see Tables S8A and S8B in SI for rural and urban fuel usage data, respectively) and weighting by the proportion of urban and rural populations in each State, resulted in a skewed right distribution with a median 24-hour kitchen concentration in India of 524 μg/m^3 (mean: 600 μg/m^3). This estimate for 2015 was somewhat higher than the national 24-hour mean kitchen concentration of 450 μg/m^3 estimated previously for 2005 (Balakrishnan et al., 2013). The skewed distribution can be attributed two northern States (Bihar and Uttar Pradesh) having an average 24-hour kitchen concentration > 1000 μg/m^3 due to a high proportion of the population living in rural areas and reporting heavy animal dung cooking fuel usage on NFHS 2015.

A updated map of modeled 24-hour HAP-$PM_{2.5}$ kitchen concentrations by State was generated for India (Fig. 4 (left)), for comparison to the previous Indian State-level exposure map (Fig. 4 (right)) (Balakrishnan et al., 2013). All calculated State-level HAP-$PM_{2.5}$ kitchen concentrations are available in SI. Mean female, male and child exposures in India were 299 μg/m^3, 215 μg/m^3 and 260 μg/m^3, respectively, which are comparable to the exposures of 337 μg/m^3, 204 μg/m^3 and 285 μg/m^3, respectively, reported by Balakrishnan et al., especially once the different time periods are considered.

4. Discussion

By leveraging an increased sample size of published HAP exposure studies in the WHO Global HAP Database, a global HAP-$PM_{2.5}$ exposure model was developed with capabilities to assign seasonal, fuel-specific HAP-$PM_{2.5}$ kitchen concentrations and female, male and child exposures for rural and urban settings within each country. This model adds specificity compared to previous global HAP exposure models, which were based on data from the State-level model in India by Balakrishnan et al. (used in GBD 2010) or assigned a single HAP-$PM_{2.5}$ exposure to men, women and children in each country (GBD 2016) or GBD super region (GBD 2015) irrespective of fuel type.

The increased specificity of this model was facilitated via a larger dataset of HAP-$PM_{2.5}$ studies with larger geographical variation (Fig. 1) and the use of Bayesian modeling. Combining Bayesian modeling techniques (exchangeable priors) with available quantitative HAP-$PM_{2.5}$ data enabled exposures to be estimated in regions where DFU is prevalent but where quantitative HAP studies weren't available. Future HAP studies that are conducted in regions with currently sparse quantitative HAP exposure assessment (e.g. Sub-Saharan Africa), will allow the uncertainty around the model estimates to decrease (Fig. 1). For example, several current monitoring campaigns, such as the Prospective Urban and Rural Epidemiology (PURE)-AIR study (Arku et al., 2017, 2018) and the Household Air Pollution Investigation Network (HAPIN) (Rosenthal et al., 2018), include data collection in African countries, which could help improve future global HAP-$PM_{2.5}$ exposure modeling.

The observed differences in measurement levels, improved model fit (LOOIC) (Table S6) and statistical significance of the individual fuel/stove fixed effects within the model supports the importance of specific type of fuel used for cooking as a determinant of HAP-$PM_{2.5}$ levels. Similarly, SDI was negatively associated with HAP-$PM_{2.5}$ concentrations and its addition to the model also improved model fit. This

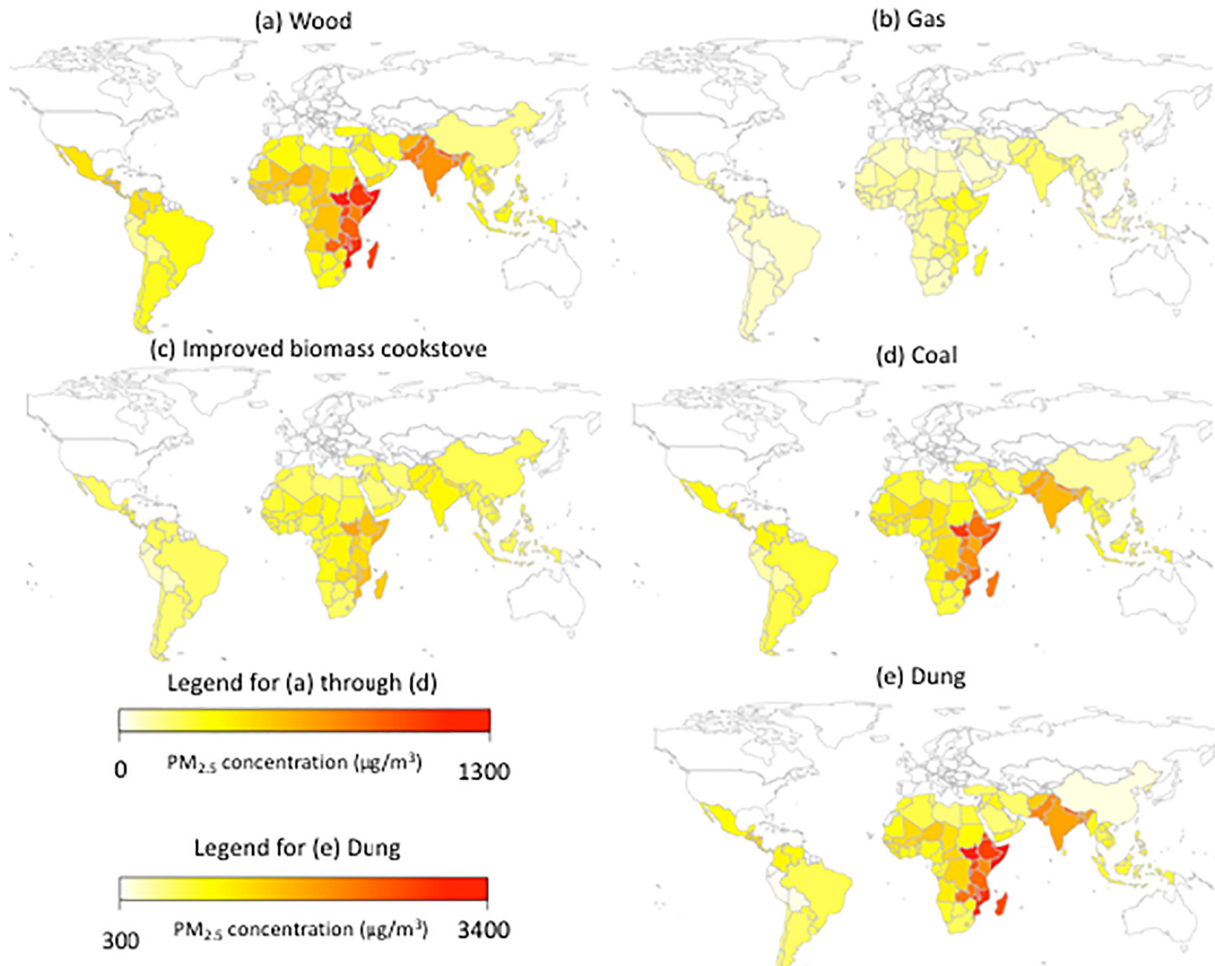

Fig. 3. Season-weighted (50/50 wet/dry season), mean 24-hour HAP-$PM_{2.5}$ kitchen concentrations in rural areas of each country using (a) traditional wood stoves (b) gas/electric stoves (c) improved biomass cookstoves (d) coal stoves and (e) dung stoves.

Table 2
Female/kitchen exposure ratios by GBD region.

GBD region	Average female/kitchen exposure ratio
Andean Latin America	0.74
Central Latin America	0.35
East Asia	0.55
Eastern Sub-Saharan Africa	0.33
South Asia	0.33
Western Sub-Saharan Africa	0.34
Global average	0.40

emphasizes the important role of sociodemographic factors and variations between countries in exposures and the overall need for country-specific exposure estimates.

Increased reporting of other cooking area factors (e.g. kitchen type, level of ventilation, fuel moisture content, average cooking time) in published papers related to HAP studies, and additional monitoring in communities commonly using less common cooking fuels (e.g. kerosene and crop residue) will increase the number of predictors and variety of fuel types available for modeling purposes, which can further enhance the exposure landscape when estimating the relative contribution of each cooking environment factor to HAP-$PM_{2.5}$ concentrations.

To demonstrate the application of the model, we used State-level urban and rural fuel usage data from the Indian National Family and Health Survey 2015 to provide an alternate and updated set of estimates of Indian State-level kitchen concentrations first reported by Balakrishnan et al. (Fig. 4). The updated estimates depict larger variability in average 24-hour HAP-$PM_{2.5}$ kitchen concentrations at State-level in India compared to the previous results, driven by the ability to account for State-level differences in the proportion of each type of DFU.

Similar model application can be followed for other countries where DFU is common, by linking the model coefficients to fuel usage data that is publicly accessible in national demographic and health surveys (https://www.dhsprogram.com/data/available-datasets.cfm). When applying the model at a country-level, the weighted contribution of seasonal HAP-$PM_{2.5}$ concentrations may need to be altered to more accurately reflect location-specific seasonal patterns (i.e. not 50/50 wet/dry season).

While the new model leverages available data and adds specificity by describing variations by fuel/stove types between countries, further improvements are possible. For example, the regional variation in urban and rural HAP-$PM_{2.5}$ exposures among the same fuel type in the same region suggests that geographical factors, like ambient air pollution levels, impact exposures. A lack of control for ambient air pollution levels in the model may be responsible for the strong negative association seen between HAP-$PM_{2.5}$ concentrations and rural areas in East Asia (Table S3), due to high ambient air pollution levels in urban areas of China. Because greater than one-third of measurements in the database were from China, any differences between rural and urban HAP exposures in GBD regions outside of East Asia may have been attenuated, which, in turn may have inflated estimated HAP-$PM_{2.5}$ concentrations in rural areas. To parse out the excess health risk posed by

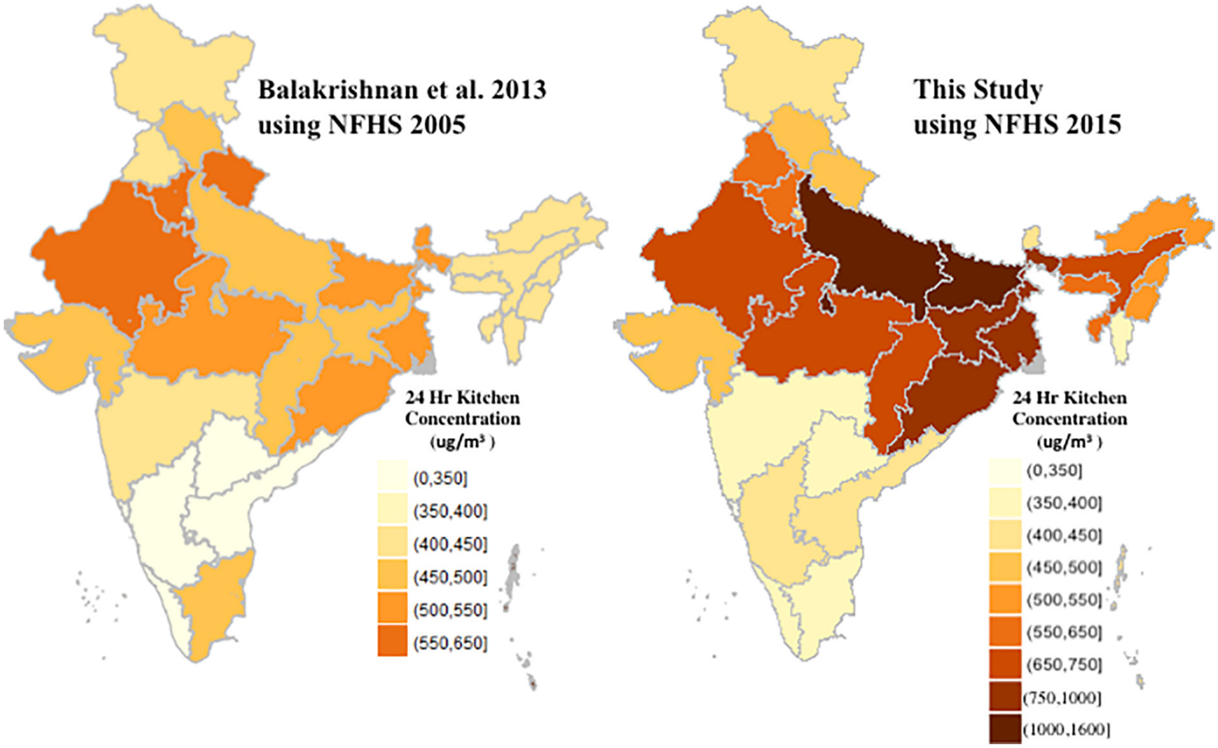

Fig. 4. (left) Map of urban/rural weighted State-level HAP-$PM_{2.5}$ kitchen concentrations in India from Balakrishnan et al. (2013) using National Family and Health Survey (NFHS) 2005 data on fuel usage and a linear regression model (plotted with permission from the authors). (right) Map of urban/rural weighted State-level HAP-$PM_{2.5}$ kitchen concentrations in India when applying the Bayesian model to NFHS 2015 data.

HAP, location-specific ambient $PM_{2.5}$ levels can be applied to the values predicted from the model to help adjust the HAP-$PM_{2.5}$ concentrations accordingly.

Additionally, fuel types included in the model were not comprehensive; limited exposure measurements from kerosene, charcoal and crop residue fuels in the database prevented their inclusion in modeling and may impact model application in specific countries where such fuels are common. The sample size-weighted average HAP-$PM_{2.5}$ kitchen concentration and personal exposure of kerosene from the limited measurements from India and Ethiopia was 259 μg/m³ (SD: 149) and 117 μg/m³ (SD: 47), respectively. While these concentrations were lower than the modeled average of all other dirty fuels, kerosene is still considered a dirty liquid fuel due to other harmful health effects that may not be accurately characterized by $PM_{2.5}$ exposures, including poisoning and burns (Lam et al., 2012). Average 24-hour HAP-$PM_{2.5}$ kitchen measurements available in the database from crop residue and charcoal fueled stoves had a large range of 1380–1920 μg/m³ and 120–870 μg/m³, respectively.

The contribution of heating fuels to HAP exposure was not directly accounted for in modeling as heating measurements were not routinely collected as part of HAP exposure assessment among the studies currently available in the database. For a crude estimate of the contribution of heating to HAP-$PM_{2.5}$ concentrations in a given country, the predicted summer (wet season) HAP-$PM_{2.5}$ concentration could be subtracted from the corresponding winter (dry season) HAP-$PM_{2.5}$ concentration (SI Table S5).

More generally, the exposure model was focused on HAP-$PM_{2.5}$ exposures in relationship to the primary cooking fuel type, given the absence of multiple fuel types in the database; however, in reality, stove stacking is a very common phenomenon (Ruiz-Mercado and Masera, 2015). HAP research has shown the complexity of a household's decision when choosing cooking fuels and stoves, which often involves multiple choices for fuel used in one or more different stoves (Heltberg, 2004; Ruiz-Mercado et al., 2011). As data describing both primary and secondary/tertiary fuels become available, future models may consider additional fuel type combinations where primary fuel types are further categorized according to secondary fuel types.

Further, while the analysis only considered primary fuel/stove type as a predictor of stove usage, nearly one-fifth of HAP-$PM_{2.5}$ measurements reported in publications were summarized over a mix of two or more primary fuel/stove types. While these composite measurements may have introduced bias to the primary fuel-specific coefficients, a sensitivity analysis revealed that including the composite measurements in the modeling improved the predictive power (Table S10 in SI). To minimize this issue, it is important that future published studies contain reported HAP-$PM_{2.5}$ stratified by each unique, fuel/stove combination.

The highest HAP-$PM_{2.5}$ kitchen concentrations were estimated for animal dung fuel, followed by traditional wood stoves, with coal having the lowest levels. Improved biomass cookstoves had the largest regional variation in HAP-$PM_{2.5}$ kitchen concentrations of any stove/fuel combination in the model. This variation may reflect the wide variety of ICS available on the market, varying levels of ICS adoption (Lewis and Pattanayak, 2012; Malla and Timilsina, 2014; Ruiz-Mercado et al., 2011; Stanistreet et al., 2014) and stove stacking (Ruiz-Mercado and Masera, 2015). Based on global average model estimates, switching from a traditional wood to an improved biomass cookstove would marginally reduce HAP-$PM_{2.5}$ kitchen concentrations by an average of approximately 150 μg/m³ (395 to 251 μg/m³), while switching from a traditional wood stove to a gas stove would reduce HAP-$PM_{2.5}$ kitchen concentrations by nearly twice that amount (395 μg/m³ to 104 μg/m³) (Table 1).

Incorporating cooking environmental factors, such as the specific fuel and stove type, to an exposure model can better capture the heterogeneous nature of HAP. In turn, applying national or sub-national household energy survey data to an enhanced HAP-$PM_{2.5}$ exposure model can add needed specificity to future global HAP-$PM_{2.5}$ exposure assessments and allow for a more accurate estimation global disease burden attributable to HAP.

It is critical for global health stakeholders to evaluate the global health impact of HAP exposure relative to other prominent global health risk factors. The most recent iteration of the GBD in 2016 ranked HAP exposure as the second highest environmental risk factor for global health burden and the 10th overall (Gakidou et al., 2017). The use of the updated exposure model can lead to more accurate assessment of disease burden and potentially impact the ranking of HAP and therefore its prioritization on global and national health agendas.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2018.08.026.

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