



## RESEARCH ARTICLE

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## Key Points:

- We use a sensitivity analysis to highlight inputs contributing to uncertainty in mortality, finding key contributors vary by region
- In Asia and Latin America, mortality estimates are most sensitive to uncertainty in population using solid fuel and health response function
- We develop a new estimate of mortality attributable to SFU due to the joint exposure from household and ambient PM<sub>2.5</sub> pollution

## Supporting Information:

- Supporting Information S1
- Data Set S1
- Data Set S2
- Data Set S3

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## Quantifying the Contribution to Uncertainty in Mortality Attributed to Household, Ambient, and Joint Exposure to PM<sub>2.5</sub> From Residential Solid Fuel Use

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**Abstract** While there have been substantial efforts to quantify the health burden of exposure to PM<sub>2.5</sub> from solid fuel use (SFU), the sensitivity of mortality estimates to uncertainties in input parameters has not been quantified. Moreover, previous studies separate mortality from household and ambient air pollution. In this study, we develop a new estimate of mortality attributable to SFU due to the joint exposure from household and ambient PM<sub>2.5</sub> pollution and perform a variance-based sensitivity analysis on mortality attributable to SFU. In the joint exposure calculation, we estimate 2.81 (95% confidence interval: 2.48–3.28) million premature deaths in 2015 attributed to PM<sub>2.5</sub> from SFU, which is 580,000 (18%) fewer deaths than would be calculated by summing separate household and ambient mortality calculations. Regarding the sources of uncertainties in these estimates, in China, India, and Latin America, we find that 53–56% of the uncertainty in mortality attributable to SFU is due to uncertainty in the percent of the population using solid fuels and 42–50% from the concentration-response function. In sub-Saharan Africa, baseline mortality rate (72%) and the concentration-response function (33%) dominate the uncertainty space. Conversely, the sum of the variance contributed by ambient and household PM<sub>2.5</sub> exposure ranges between 15 and 38% across all regions (the percentages do not sum to 100% as some uncertainty is shared between parameters). Our findings suggest that future studies should focus on more precise quantification of solid fuel use and the concentration-response relationship to PM<sub>2.5</sub>, as well as mortality rates in Africa.

### 1. Introduction

Close to 40% of the world's population relies on combustion of solid fuels for residential cooking and heating (Bonjour et al., 2013). Incomplete combustion of these fuels emits substantial amounts of particulate matter (PM) that are harmful to human health (Brook et al., 2010; Naeher et al., 2007). While solid fuel use (SFU) as a source of household energy is concentrated in developing regions of the world, high-income countries also burn biomass as a heating fuel (Rogalsky et al., 2014). Research over the past several decades consistently suggests that the health burden from exposure to air pollutants from SFU is likely to be substantial (e.g., Forouzanfar et al., 2016; Smith et al., 2014; World Health Organization, 2014).

Exposure to PM with aerodynamic diameters less than 2.5 μm (PM<sub>2.5</sub>) has been linked to an increased risk of mortality from cardiovascular and respiratory diseases. The Global Burden of Disease 2015 report (GBD2015) estimates that 2.85 (95% confidence interval (CI): 2.18–3.59) million deaths in the year 2015 were due to exposure to household air pollution from SFU (Forouzanfar et al., 2016). The GBD2015 ranks exposure to household air pollution from SFU among the leading risk factors contributing to premature mortality, globally (Forouzanfar et al., 2016). Using similar methods as GBD2015 but with different input data, the World Health Organization (WHO) estimates 4.3 million deaths from household air pollution from SFU in the year 2012 (WHO, 2014). In addition, SFU has the potential to degrade ambient (i.e., outdoor) air quality. Estimates of mortality due to exposure to ambient PM<sub>2.5</sub> from SFU typically range from 0.3 to 0.5 million (Butt et al., 2016; Chafe et al., 2014; Lacey et al., 2017). However, to our knowledge, no work has yet tried to estimate premature mortality associated with SFU by an approach that jointly considers ambient and household exposures. Rather, estimates rely on separate calculations for household (indoor) air pollution and ambient air pollution (e.g., Anenberg et al., 2017; Forouzanfar et al., 2016; Smith et al., 2014).

Estimates of mortality from exposure to PM<sub>2.5</sub> from SFU (including exposure to household and/or ambient air pollution from this source) rely on input data sources including country-level baseline mortality rates, PM<sub>2.5</sub> exposure levels, the magnitude and shape of concentration-response functions, and the number of people exposed to a specific concentration. Each of these data sources contains an uncertainty range reflecting the degree of confidence of the estimate in a given region. As a result of the various sources of uncertainties in the input parameters, there is a large variance in estimates of mortality attributable to exposure to PM<sub>2.5</sub> from SFU. To reduce the variance in estimated mortality, recent effort has focused on reducing uncertainty in the input parameters that contribute the most to the uncertainty in mortality. However, no studies, to our knowledge, have investigated the sensitivity of mortality estimates to these input parameters.

In this work, we perform a variance-based sensitivity analysis to quantify the contribution of uncertainty in mortality attributable to SFU to each of the following input parameters: baseline mortality rates, household and ambient PM<sub>2.5</sub> exposure concentrations, concentration-response functions, and population exposed to household and ambient PM<sub>2.5</sub> from SFU. A variance-based sensitivity analysis provides a framework to apportion uncertainty in model output (in this case mortality) to sources of uncertainty from model input (Saltelli et al., 2007). This approach involves calculating mortality tens of thousands of times based on random draws from the input parameter distributions. The end result of this analysis is a percent contribution of each input term to the overall variance (the quantified uncertainty) in the mortality estimate. This allows for selection of parameters that can be prioritized to reduce uncertainty in mortality estimates. This approach has been used for other environmental applications, recently for particulate matter in the context of cloud condensation nuclei and radiative forcing (Carslaw et al., 2013; Lee et al., 2013) and simulated acetone budget (Brewer et al., 2017). A limitation of this approach is that we do not test the sensitivity to the major assumptions and uncertainties from GBD2015 that are not quantifiable (e.g., equal toxicity of PM<sub>2.5</sub> regardless of source or composition, lack of direct evidence of mortality caused by cardiovascular disease from household air pollution, and application of a single exposure-response function across diverse populations).

The objectives of this study are to evaluate the sensitivity of mortality estimates attributable to SFU to the five aforementioned data input sources with quantified uncertainty bounds. In addition, we present a new calculation to quantify the joint effect of exposure to household and ambient PM<sub>2.5</sub> pollution. In section 2.1, we describe the input parameters used in mortality estimates. In section 2.2, we describe the calculation of mortality from household, ambient, and the joint exposure to PM<sub>2.5</sub>. In section 2.3, we describe the variance-based sensitivity analysis. In section 3.1, we compare the mortality attributed to PM<sub>2.5</sub> exposure from SFU in the joint exposure calculation to the mortality attributed to PM<sub>2.5</sub> exposure from SFU through separate calculations for household and ambient exposures. We present the results of the sensitivity analysis in section 3.2 and share our conclusions in section 4.

## 2. Methods

### 2.1. Uncertain Parameters and Data Sources

We briefly describe the nomenclature, uncertain input parameters, and relevant citations here. In sections 2.2 and 2.3, we present how these data are used in estimating mortality from SFU and the resulting sensitivity analysis.

#### 1. Nomenclature:

*H-SFU*: This refers to household PM<sub>2.5</sub> pollution from solid fuel use. The H-SFU mortality calculation uses similar assumptions and methods as the GBD “household air pollution” calculation.

*A-SFU*: This refers to ambient PM<sub>2.5</sub> pollution from solid fuel use. The A-SFU mortality calculation uses similar assumptions and methods as the GBD “ambient air pollution” calculation.

*J-SFU*: This refers to the joint effect of ambient and household PM<sub>2.5</sub> pollution from solid fuel use. The J-SFU mortality calculation is a new estimate of mortality described in this study.

#### 2. Uncertain factors:

*Baseline mortality rates (BMR)*: Reported country-level and age-specific mortality rates for ischemic heart disease (IHD), stroke, lower respiratory infections (LRI), chronic obstructive pulmonary disease (COPD), and lung cancer (LC). Baseline mortality rates were compiled for GBD2015 and include published 95% confidence intervals (<http://ghdx.healthdata.org/gbd-results-tool>).

*Concentration-response functions (CRF):* Functions relating  $PM_{2.5}$  exposure to a relative risk of mortality from IHD, stroke, LRI, COPD, and LC. Age-specific adjustments are included for IHD and stroke. The concentration-response functions are based on the integrated exposure-response function of Burnett et al. (2014) with updates as described in Cohen et al. (2017). The integrated exposure-response function published in Cohen et al. (2017) includes 1,000 sets of coefficients fit to the health data.

*$PM_{Amb}$ :* Ambient  $PM_{2.5}$  exposure concentration from all sources (available from <https://www.stateofglobalair.org/>) presented as an annual, population-weighted mean at the country level. Mean  $PM_{2.5}$  and 95% confidence levels (also country level) about the mean are included in Cohen et al. (2017) and based on methods described in Shaddick et al. (2017). Following the assumptions in Cohen et al. (2017), the ambient  $PM_{2.5}$  concentrations are assumed to represent exposure.

*$\%PM_{A-SFU}$ :* Percent of the  $PM_{Amb}$  originating from SFU emissions. Mean, country-level  $PM_{2.5}$  concentrations with and without residential emissions are simulated with the GEOS-Chem chemical-transport model (Bey et al., 2001) for this work (described in the supporting information). Ninety-five percent confidence intervals are estimated as a factor of 2 about the mean, following uncertainty estimates in the emission inventory described in Bond et al. (2007).

*$\%SFU$ :* The percent of a country's population using solid fuels (coal, wood, charcoal, dung, and agricultural residues). Estimates of household SFU (and 95% confidence levels) are based on Bonjour et al. (2013) and updated in Forouzanfar et al. (2016). Upcoming iterations of the GBD assume low (<5%) solid fuel use in high-income countries.

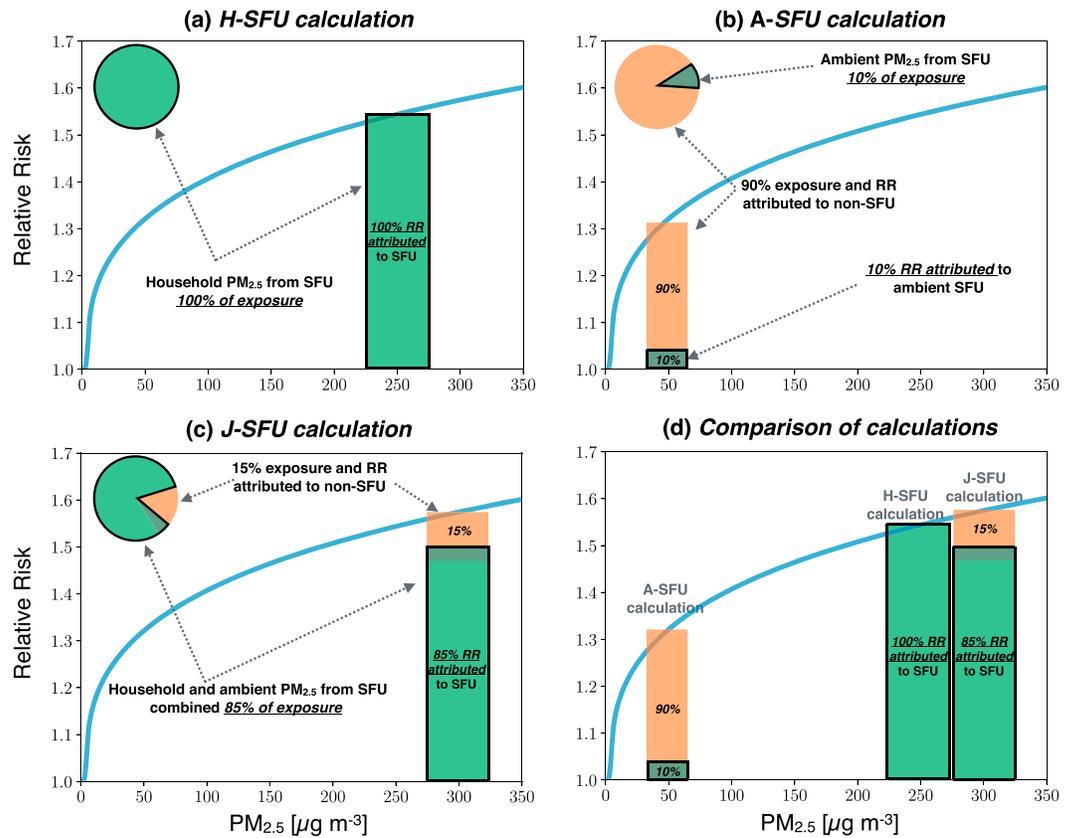
*$PM_{H-SFU}$ :* Twenty-four hour average household exposure to  $PM_{2.5}$  originating from SFU. The household  $PM_{2.5}$  exposure concentrations are taken from GBD2015. These exposure concentrations are based on the ratio of indoor  $PM_{2.5}$  concentrations and personal exposures measured in India from Balakrishnan et al. (2013) with added exposure studies across several countries and a mixed effect model to estimate region specific concentrations as described in World Bank (2016) and Forouzanfar et al. (2016). Exposure concentrations are reported at the regional level. Uncertainty intervals are taken from 95% confidence levels of indoor kitchen concentrations from Balakrishnan et al. (2013), resulting in a factor of 1.4 in both directions about the central estimate. In this study, we average exposure concentrations across reported values for men, women, and children. Household exposure to  $PM_{2.5}$  from solid fuel use is assumed to be zero in high-income countries. Quantifying the variability in this parameter is an open area of research and the sensitivity analysis results are likely sensitive to the assume confidence bounds.

The input parameters listed here, with the exception of the concentration-response functions, are published reporting mean or median values with 95% confidence intervals. We assume the underlying uncertainty is lognormally distributed and discuss calculating the parameters that describe the lognormal distribution in the supporting information. Also in the supporting information, we present results assuming a uniform distribution, and we find that this assumption does not greatly impact our conclusions. For the concentration-response functions, we interpolate between the 1,000 sets of coefficients to include a smooth distribution of relative risk at each  $PM_{2.5}$  concentration. In addition, there are separate uncertainty distributions for each of the five disease outcomes for baseline mortality rate and the concentration-response functions. We treat each disease outcome as a separate uncertain parameter.

Counting five unique baseline mortality rate parameters, five unique concentration-response function parameters, three measures of  $PM_{2.5}$  exposure, and the parameter estimating the percent of a country's population using solid fuels, we consider 14 uncertain parameters. In addition, there are a number of major uncertainties and assumptions that are made in  $PM_{2.5}$  mortality calculations that cannot be quantified. We follow the major assumptions inherent in the GBD concentration-response functions, including a globally applicable function and equal toxicity regardless of PM source. The implications of these assumptions are discussed below.

## 2.2. Calculation of Premature Mortality From Solid Fuel Use

We estimate mortality from SFU under three different  $PM_{2.5}$  exposure scenarios. To help explain the implications of the different assumptions, we include a schematic illustrating the differing approaches to calculating



**Figure 1.** Schematic showing the calculation of relative risk (RR) from SFU and ambient sources in (a) the H-SFU calculation, (b) A-SFU calculation, and (c) the J-SFU calculation for a given disease (IHD) and population group (65–70 year olds). To apportion mortality attributed to exposure to PM<sub>2.5</sub> from a specific source (in this case SFU), we assume the total health risk from exposure to PM<sub>2.5</sub> from all sources scales proportionally with the percent of exposure from only SFU (following the discussions in GBD MAPS Working Group, 2017). The benefit of this method is that the apportionment of health risk does not depend on the order of the source contribution to exposure. In the H-SFU calculation (Figure 1a), the GBD Comparative Risk Assessment assumes 100% of the PM<sub>2.5</sub> exposure concentration (in this example 250 μg m<sup>-3</sup>) is from SFU, and thus, 100% of the health risk is apportioned to SFU. In the A-SFU calculation (Figure 1b), the total PM<sub>2.5</sub> exposure concentration is composed of emissions from SFU and non-SFU sources. In this example, the total PM<sub>2.5</sub> exposure concentration is 50 μg m<sup>-3</sup>, of which 10% (or 5 μg m<sup>-3</sup>) is from SFU. Using the proportionality assumption, we thus assume that 10% of the health risk is apportioned to SFU and the remaining 90% from non-SFU sources. For the J-SFU calculation (Figure 1c), we assume that the total PM<sub>2.5</sub> exposure concentration (300 μg m<sup>-3</sup>) is the sum of PM<sub>2.5</sub> concentrations associated with household SFU (250 μg m<sup>-3</sup>), ambient SFU (5 μg m<sup>-3</sup>), and all other ambient sources (45 μg m<sup>-3</sup>). As SFU sources account for 85% of the total PM<sub>2.5</sub> exposure in this example (255 μg m<sup>-3</sup> divided by 300 μg m<sup>-3</sup>), we apportion 85% of the health risk to SFU. (d) Comparison of the attributed relative risk (RR) using the three calculation approaches. In the J-SFU calculation, the total PM<sub>2.5</sub> exposure concentration is higher than in the H-SFU calculation; however, a lower percent of the total exposure is associated with SFU. As this concentration-response function is sublinear in this range and assuming PM<sub>2.5</sub> source-specific mortality scales proportionally with exposure concentration, less of the health risk is thus apportioned to SFU.

PM<sub>2.5</sub> exposure and associated health response (Figure 1). Figure 1 contains a representative concentration-response function (IHD age group 65–70) with PM<sub>2.5</sub> exposure concentration on the x axis and relative risk of disease on the y axis. For this schematic, we use relative risk as a proxy for health burden. The green bars represent PM<sub>2.5</sub> or relative risk associated with SFU, while the orange bars represent all other PM<sub>2.5</sub> sources.

*Mortality calculation for exposure to household PM<sub>2.5</sub> pollution from SFU.* We calculate deaths attributable to exposure to household PM<sub>2.5</sub> pollution from SFU (H-SFU) for the year 2015 following the methods and assumptions in GBD2015 for the “household air pollution” calculation (Forouzanfar et al., 2016; Smith et al., 2014). For a given country, health outcome, and age group, the number of premature deaths from H-SFU can be described as

$$M_{H-SFU} = P \times BMR \times \%SFU \times \frac{RR(PM_{H-SFU}) - 1}{RR(PM_{H-SFU})}$$

where  $M_{H-SFU}$  is the premature mortality from household solid fuel use,  $P$  is the country-level population,  $RR$  is the relative risk, and the other parameters are as described in section 2.1. The relative risk quantifies the increased risk of mortality due to exposure to the given  $PM_{2.5}$  concentration. The relationship between relative risk and exposure is given by the concentration-response function (or the CRF parameter defined in the previous section). The H-SFU calculation assumes the total  $PM_{2.5}$  exposure for the SFU population originates from H-SFU (with negligible impacts from other  $PM_{2.5}$  sources). This assumption is qualitatively described in Figure 1a. In this example, the  $PM_{2.5}$  exposure is  $250 \mu\text{g m}^{-3}$  (approximately the median value for India) resulting in a relative risk of 1.5. Since the H-SFU calculation assumes all of the  $PM_{2.5}$  exposure is from H-SFU, all of the relative risk (or health burden) is attributed to SFU. Following the definitions of GBD2015, the H-SFU calculation does not include household exposure to wood heating in high-income countries (for instance, %SFU is assumed to be zero in Canada).

*Mortality calculation for the contribution of SFU to exposure to ambient  $PM_{2.5}$  pollution.* The number of deaths from A-SFU, for a given country, health outcome, and age group, can be described by

$$M_{A-SFU} = P \times BMR \times \frac{RR(PM_{Amb}) - 1}{RR(PM_{Amb})} \times \%PM_{A-SFU}$$

In the calculation of mortality from A-SFU, we assume the total  $PM_{2.5}$  exposure for the entire population is characterized by  $PM_{Amb}$ ; however, only a fraction of this exposure originates from SFU. To estimate mortality associated with ambient exposure to  $PM_{2.5}$  from SFU emissions only ( $M_{A-SFU}$ ), we assume the mortality attributed to exposure to  $PM_{2.5}$  from all sources scales proportionally with the fraction of  $PM_{2.5}$  from SFU emissions to the total ambient  $PM_{2.5}$  concentration (following the discussion in Global Burden of Disease (GBD) Major Air Pollution Sources (MAPS) Working Group, 2017). This proportionality assumption yields a different estimate of mortality than subtracting the estimated number of deaths with and without  $PM_{2.5}$  from SFU (e.g., Kodros et al., 2016). The proportionality assumption is qualitatively described in Figure 1b. In this example, the total  $PM_{2.5}$  exposure is  $50 \mu\text{g m}^{-3}$ . Of this concentration, approximately 10% of the  $PM_{2.5}$  concentration ( $5 \mu\text{g m}^{-3}$ ) is apportioned to emissions of SFU, while the remaining 90% is apportioned to emissions of other sources. As a result, only 10% of the relative risk is attributed to SFU. In this study, % $PM_{A-SFU}$  includes emissions of SFU from residential heating in high-income countries in addition to residential cooking and heating emissions in all other countries.

*Mortality calculation for joint exposure to household and ambient  $PM_{2.5}$  pollution from SFU.* To further investigate mortality from SFU, we present a new estimate of the joint effect of exposure to household and ambient  $PM_{2.5}$  from SFU. This calculation is not included in GBD2015. We estimate the number of deaths from J-SFU for a given country, health outcome, and age group by

$$M_{J-SFU} = P \times BMR \times \%SFU \times \frac{RR(PM_{H-SFU} + PM_{Amb}) - 1}{RR(PM_{H-SFU} + PM_{Amb})} \times \frac{PM_{H-SFU} + PM_{Amb} \times \%PM_{A-SFU}}{PM_{H-SFU} + PM_{Amb}} + P \times BMR \times (1 - \%SFU) \times \frac{RR(PM_{Amb}) - 1}{RR(PM_{Amb})} \times \%PM_{A-SFU}$$

In the J-SFU calculation, we assume that the population using solid fuels ( $P \times \%SFU$ ) is exposed to both  $PM_{H-SFU}$  and  $PM_{Amb}$ . This is a result of two assumptions. First,  $PM_{H-SFU}$  is defined, following the definition in Forouzanfar et al. (2016), as the exposure concentration only to  $PM_{2.5}$  originating from household solid fuel use. Second, we assume that ambient  $PM_{2.5}$  concentration also exists indoors (for instance, in the absence of any local emissions from household solid fuel the household  $PM_{2.5}$  concentration would equal  $PM_{Amb}$ ). In contrast to the H-SFU calculation, we do not assume that all of this exposure (and thus all of the health risk) originates from SFU. Similar to the A-SFU calculation, we assume that the mortality attributed to exposure to  $PM_{2.5}$  from all sources scales proportionally with the fraction of  $PM_{2.5}$  originating from just SFU emissions. This assumption is depicted qualitatively in Figure 1c. In this figure, the total  $PM_{2.5}$  exposure for the population using solid fuels is  $300 \mu\text{g m}^{-3}$ . This is a sum of  $PM_{H-SFU}$  (assumed to be only from SFU) along with  $PM_{Amb}$  (of which only % $PM_{A-SFU}$  is from SFU and the rest from other sources). In this example,  $PM_{H-SFU}$  is  $250 \mu\text{g m}^{-3}$ ,

$PM_{Amb}$  is  $50 \mu\text{g m}^{-3}$ , and  $\%PM_{A-SFU}$  is 10% (or  $5 \mu\text{g m}^{-3}$ ). This results in 85% of the total  $PM_{2.5}$  exposure apportioned to SFU ( $255 \mu\text{g m}^{-3}$  divided by  $300 \mu\text{g m}^{-3}$ ). Using the proportionality assumption for source-specific mortality, only 85% of the relative risk is assumed to be from SFU. The remaining population not using solid fuels (described by  $1 - \%SFU$ ) is still exposed to ambient  $PM_{2.5}$  as in the A-SFU calculation. We acknowledge that we follow the same assumption as in Burnett et al. (2014), Smith et al. (2014), and Forouzanfar et al. (2016) that health risk from exposure to ambient and household  $PM_{2.5}$  pollution is estimated using a single (integrated) exposure-response curve.

### 2.3. Variance-Based Sensitivity Analysis

We use the Fourier amplitude sensitivity test (FAST; Saltelli et al., 1999) to attribute the fraction of total variance in mortality from SFU to each uncertain input parameter. The FAST algorithm selects sets of input parameters across the uncertainty space to develop the output distribution. FAST then apportions the variance in the output distribution to the contribution by each input parameter. The result of this analysis is to quantify the *main effect index* and *total effect index* for each parameter. Following the descriptions in Saltelli et al. (2010), the main effect (or first-order or additive effect) of a parameter describes the expected reduction in output variance if that parameter alone were held fixed (e.g., what is the expected reduction of uncertainty in our mortality calculation if the concentration-response function were perfectly known?). The total effect index of a parameter includes the main effect index plus the variance contributed by interactions of that parameter with all other parameters. The total effect thus describes the expected remaining variance if all other parameters were held fixed (e.g., what is the expected amount of remaining uncertainty in our mortality calculation if all parameters except the concentration-response function were perfectly known?). In the absence of interactions between parameters, the main effect index would equal the total effect index.

We perform a variance-based sensitivity analysis on the H-SFU, A-SFU, and J-SFU mortality calculations separately. For each calculation, the number of random draws is set to be equal to the number of uncertain parameters times 10,000. As discussed in section 2.1, we assume that the underlying uncertainty follows a lognormal distribution for each parameter except for the concentration-response function, where the uncertainty space follows the interpolation of the 1,000 parameter fits. In the supporting information, we test an underlying uniform distribution and find this does not greatly impact our results. In the case of baseline mortality rate and concentration-response function, each disease is treated as a separate uncertain parameter; however, age group is not treated as an independent parameter. Instead, we assume a z score to apply across all age groups. Mortality calculations and the resulting sensitivity analysis are done at the country level.

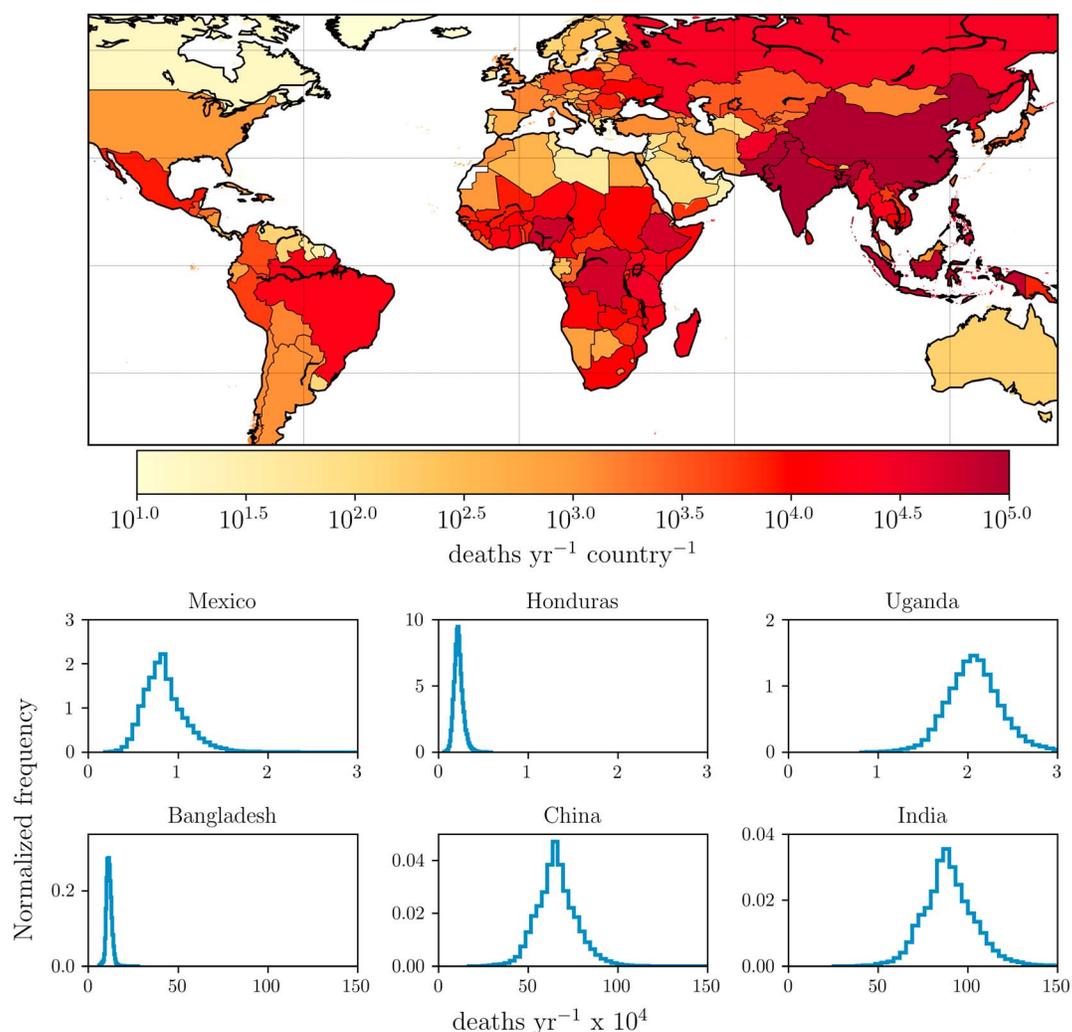
## 3. Results and Discussion

### 3.1. Country-Level Mortality Attributed to Solid Fuel Use

#### 3.1.1. Premature Mortality From H-SFU and A-SFU

We estimate 2.76 (95% CI: 2.37–3.31) million deaths from H-SFU and 0.66 million (95% CI: 0.52–1.0 million) deaths from A-SFU in 2015. The deaths attributable to A-SFU represent approximately 17% of the total mortality burden attributed to exposure to ambient  $PM_{2.5}$  from all sources. The countries with the largest mortality from H-SFU are India (0.86 million; 95% CI: 0.58–1.26 million), China (0.63 million; 95% CI: 0.43–0.92 million), Bangladesh (0.12 million; 95% CI: 0.09–0.15 million), and Pakistan (0.11 million; 95% CI: 0.08–0.16 million). The countries with the largest mortality from A-SFU are India (0.29 million; 95% CI: 0.14–0.60 million), China (0.14 million 95% CI: 0.07–0.30 million), Bangladesh (0.04 million; 95% CI: 0.02–0.08 million), and Pakistan (0.02 million 95% CI: 0.01–0.04 million). The mortality attributable to A-SFU in these countries represents 30%, 14%, 38%, and 18%, respectively, of mortality attributable to ambient exposure to  $PM_{2.5}$  from all sources. Mortality estimates for each calculation and for all countries are included in the supporting information.

Our estimate of mortality from H-SFU is slightly less than the estimate of 2.85 (95% CI: 2.18–3.59) million from GBD2015 household air pollution (“HAP”) calculation for several possible reasons. First, estimates of the percent of the population using solid fuel have been updated slightly since GBD2015 (to assume no household solid fuel use exposure in high income countries). Second, due to data limitations, we do not separate exposure by gender. Third, due to computational limitations, we do all calculations at the country level. Finally, in this calculation we assume that the uncertain parameters follow a lognormal distribution. A different



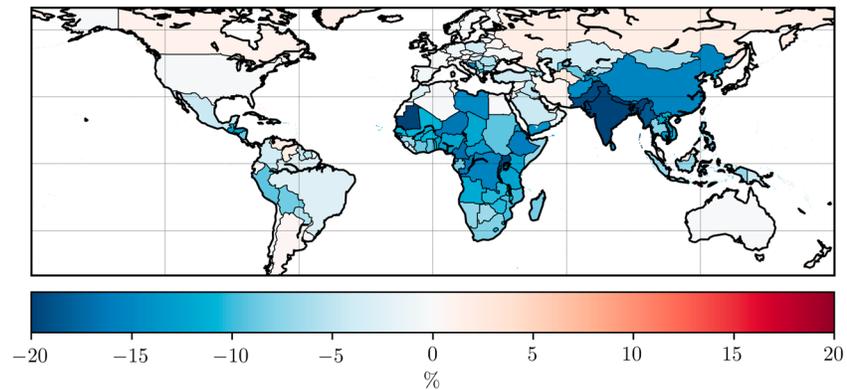
**Figure 2.** Annual mortalities by country due to the joint effect from indoor and outdoor exposure to PM<sub>2.5</sub> in 2015. Map colors represent the median of each country's mortality distribution; the normalized probability distributions of six representative countries are also shown. The mortality distributions are different for each country, reflecting differences in model uncertainties for each country's input data.

assumption of underlying mortality distribution may impact the uncertainty range. Despite this, we note that our calculation of mortality from H-SFU are within 3% of the household air pollution calculation from GBD2015 and thus we do not plot them here. Similarly, our estimates of mortality in the A-SFU calculation for India and China compare well with estimates made by the GBD Major Air Pollution Sources working group (GBD MAPS Working Group, 2017).

### 3.1.2. Premature Mortality From J-SFU

Figure 2 presents a map of the median estimated mortality in 2015 from J-SFU along with normalized probability distributions of six representative countries. The mortality distributions are different for each country, reflecting differences in uncertainties in input data sources. Our sensitivity analysis (section 3.2) further investigates the factors contributing to variance in these mortality distributions. We estimate 2.81 (95% CI: 2.48–3.28) million premature deaths from J-SFU, with the largest contributing countries similar to the ranking for H-SFU (India, China, Pakistan, and Bangladesh).

Globally, we estimate 0.58 million fewer deaths in the J-SFU calculation than would result from summing of our H-SFU and A-SFU calculations. When considering only the population using solid fuels, the J-SFU calculation predicts 0.26 million fewer deaths than in the H-SFU calculation. The reason for the fewer deaths in the population using solid fuels for the J-SFU calculation is qualitatively depicted in Figure 1d. In the H-SFU



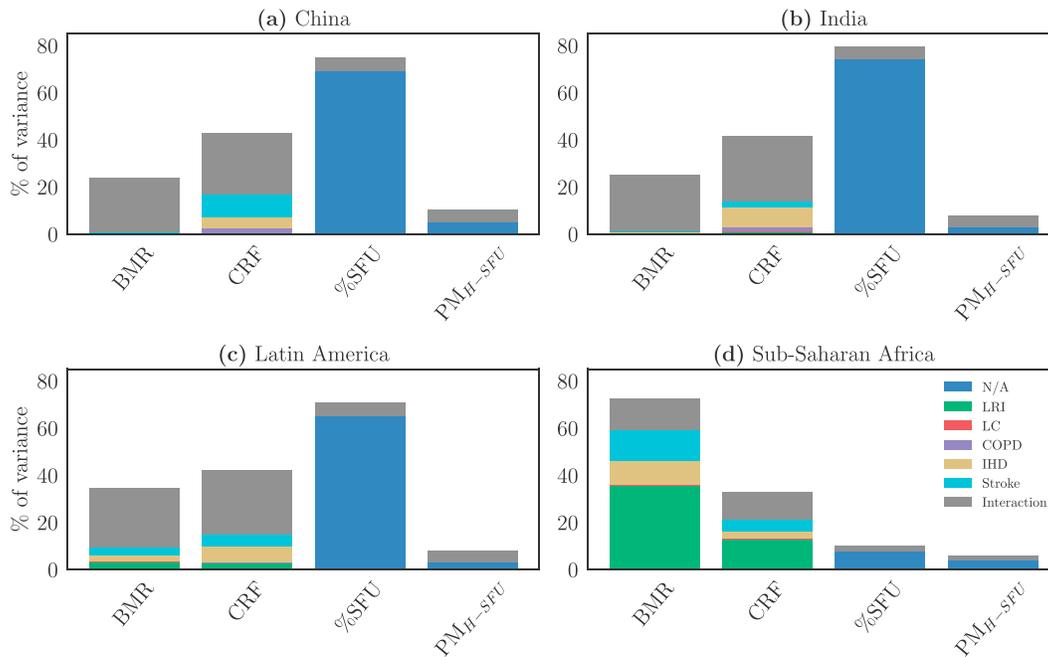
**Figure 3.** Percent difference in estimated country-level mortalities in 2015 using J-SFU relative to mortalities determined using the sum of the H-SFU and A-SFU calculations.

calculation, we assume that all of the  $PM_{2.5}$  exposure ( $PM_{H-SFU}$ ), and thus all the increased health risk, is from SFU emissions. In the J-SFU calculation, we assume that the  $PM_{2.5}$  exposure for the same population (i.e., solid fuel users) is the sum of  $PM_{H-SFU}$  and  $PM_{Amb}$ . This increases the exposure concentration (in the example in Figure 1d from  $250 \mu g m^{-3}$  to  $300 \mu g m^{-3}$ , which is roughly representative of India and China) and thus the relative risk; however, as  $PM_{Amb}$  includes non-SFU sources, we only attribute a fraction of the relative risk to SFU (in this example approximately 85%). As the concentration-response function is sublinear in this range for IHD and stroke, the increase in relative risk does not scale proportionately to the increase in  $PM_{2.5}$  exposure, resulting in lower SFU-attributable health risk for the population using solid fuels in the J-SFU approach than in the H-SFU approach. In the J-SFU calculation, we also account for exposure to ambient  $PM_{2.5}$  from SFU ( $\%PM_{A-SFU}$ ) in the population not using solid fuels, calculated as  $(1 - \%SFU)$ .

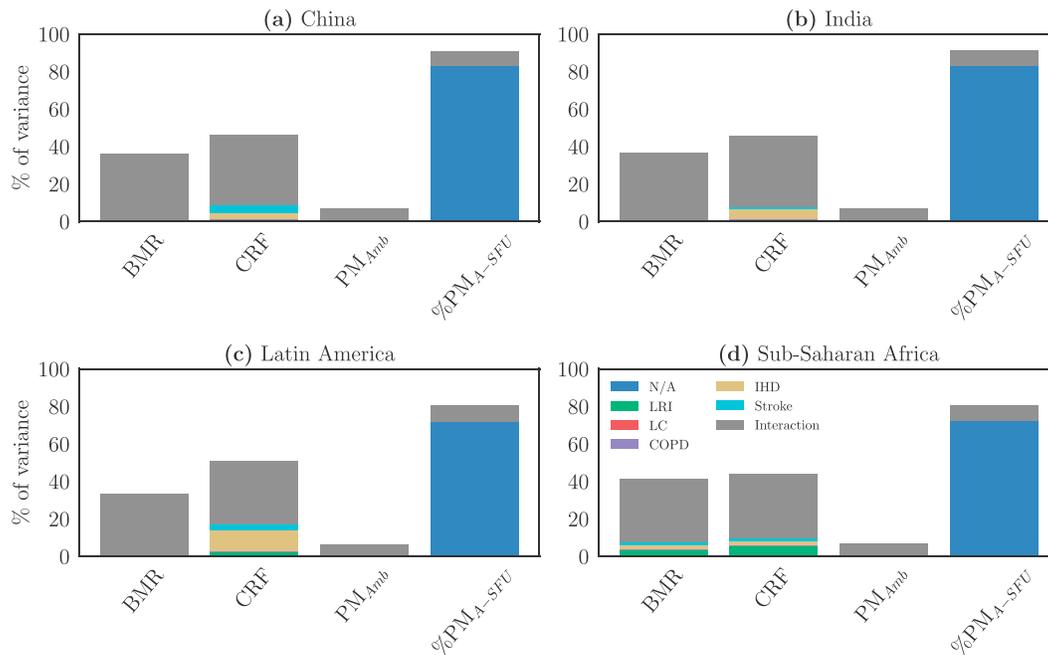
Shown in Figure 3 are the percent difference in mortality calculated with the J-SFU and sum of the H-SFU and A-SFU calculations. It is not recommended to add deaths from H-SFU and A-SFU exposure, as this does not account for a nonlinear health response to exposure; however, we show this difference to demonstrate the impact of considering joint exposure to ambient and household  $PM_{2.5}$ , as in the J-SFU calculation. Since the high-income countries only have mortality attributed to A-SFU, the difference between mortality estimates using the J-SFU calculation and the sum of independent mortality estimates from H-SFU and A-SFU is negligible (it is nonzero due to the stochastic sampling of input parameters). For most countries, we estimate fewer deaths using our J-SFU calculation than would be estimated by summing mortality estimates from the independent H-SFU and A-SFU calculations. This is because the J-SFU calculation no longer attributes all of the household exposure to SFU. Countries in South Asia and sub-Saharan Africa where a substantial (i.e., greater than ~50%) of the population uses solid fuels are more impacted by the change in assumptions regarding exposure (Figure 1d) and thus show a larger reduction in mortality attributed to SFU. In India and Pakistan, a large percent of the population using solid fuels combined with a substantial concentration of  $PM_{2.5}$  from non-SFU sources results in a greater than 20% reduction in mortality in the J-SFU calculation. In sub-Saharan Africa, smaller absolute concentrations of ambient  $PM_{2.5}$  from non-SFU sources limits this reduction in mortality to between 7 and 15% despite greater than 90% of the population using solid fuels in many countries in this region.

### 3.2. Sensitivity Analysis

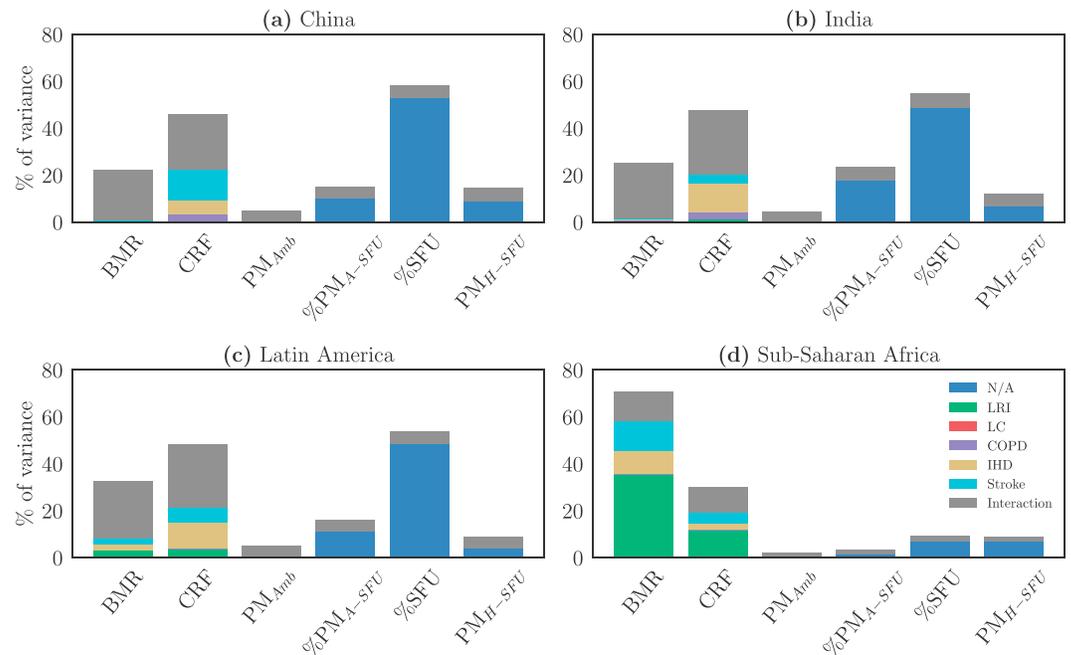
The results of the variance-based sensitivity analysis for (a) China, (b) India, (c) Latin America, and (d) sub-Saharan Africa are presented in Figures 4–6 for the H-SFU, A-SFU, and J-SFU mortality calculations, respectively. These representative regions are selected due to their high rates of solid fuel use (notably sub-Saharan Africa) and high estimated air pollution-related mortality (notably India and China). The bar plots for Latin America and sub-Saharan Africa are averages over the sensitivity indices of each country in the region weighted by that country's SFU mortality. The y axis quantifies the percent of the variance in the mortality distribution in each country/region contributed by each input parameter outlined on the x axis. As discussed in section 2.3, we present the main effect and total effect indices for each parameter. The



**Figure 4.** Contribution to variance in mortality attributed to H-SFU by each parameter for (a) China and (b) India as well as regional averages weighted by cookstove mortalities for countries in (c) Latin America and (d) Sub-Saharan Africa. Acronyms on the x axis are as defined in section 2.1 (BMR: baseline mortality rate, CRF: concentration-response function, % SFU: percent of the population using solid fuel, and PM<sub>H-SFU</sub>: exposure to PM<sub>2.5</sub> from household solid fuel use). Acronyms in the legend refer to LRI: lower respiratory infection, LC: lung cancer, COPD: chronic obstructive pulmonary disease, IHD: ischemic heart disease, Stroke: ischemic and hemorrhagic stroke, and N/A: not applicable (referring to input parameters that do not depend on disease).



**Figure 5.** Contribution to overall variance in mortality attributable to A-SFU by each parameter for (a) China and (b) India as well as regional averages weighted by cookstove mortalities for countries in (c) Latin America and (d) Sub-Saharan Africa. Acronyms are as defined in section 2.1 (BMR: baseline mortality rate, CRF: concentration-response function, PM<sub>Amb</sub>: Exposure to ambient PM<sub>2.5</sub> from all sources, and %PM<sub>A-SFU</sub>: exposure to ambient PM<sub>2.5</sub> from solid fuel use). Acronyms in the legend refer to LRI: lower respiratory infection, LC: lung cancer, COPD: chronic obstructive pulmonary disease, IHD: ischemic heart disease, and Stroke: ischemic and hemorrhagic stroke.



**Figure 6.** Contribution to overall variance by each parameter to the uncertainty in the joint effect mortality calculation in (a) China and (b) India as well as regional averages weighted by cookstove mortalities for countries in (c) Latin America and (d) Sub-Saharan Africa. Acronyms are as defined in section 2.1 (BMR: baseline mortality rate, CRF: concentration-response function,  $PM_{Amb}$ : Exposure to ambient  $PM_{2.5}$  from all sources,  $\%PM_{A-SFU}$ : exposure to ambient  $PM_{2.5}$  from solid fuel use,  $\%SFU$ : percent of the population using solid fuel, and  $PM_{H-SFU}$ : exposure to  $PM_{2.5}$  from household solid fuel use). Acronyms in the legend refer to LRI: lower respiratory infection, LC: lung cancer, COPD: chronic obstructive pulmonary disease, IHD: ischemic heart disease, Stroke: ischemic and hemorrhagic stroke.

total effect index is represented by the total height of the bar with the interaction term represented in grey. The nongrey portion of the bar represents the main effect index. The contributed variance for baseline mortality rate and concentration-response function are separated by disease outcome (represented by the different colors), while the remaining parameters are not dependent on disease. Sensitivity analysis results for all countries are provided in the supporting information.

### 3.2.1. Sensitivity Analysis for the H-SFU Calculation

Shown in Figure 4 are the H-SFU sensitivity analysis results. Considering only the main effect index, the percent of the population using solid fuels ( $\%SFU$ ) dominates the uncertainty in H-SFU mortality (contributing greater than 70%) in China, India, and Latin America. This implies that learning this parameter precisely would reduce the variance in the H-SFU mortality distribution in these regions by approximately 70%. In terms of absolute numbers, the variance in mortality would be reduced by 0.44, 0.63, 0.03 million deaths in China, India, and Latin America, respectively. Conversely, in sub-Saharan Africa, the percent of the population using solid fuels contributes only 8% to the variance (or 0.04 million deaths). In sub-Saharan Africa, the percent of the population using solid fuels in many countries is greater than 90% with a small relative uncertainty. The small relative uncertainty in this parameter is reflected in the small contribution to variance in the H-SFU mortality distribution in this region. Baseline mortality rate contributes the most uncertainty in sub-Saharan Africa (close to 70%), specifically from lower respiratory infections. The large contribution to overall variance from lower respiratory infections is caused by the combined impact of their large contribution to H-SFU mortality and a large relative uncertainty range on this contribution, as opposed to lung cancer, which also has a large uncertainty range but contributes only a small number of deaths to H-SFU.

The main effect index combined with the interaction term (represented by the grey bars in Figure 4) yields the total effect index (the percent of the variance we would expect to remain if all other parameters were known). The total effect for the four parameters sums to 125–154% across these four regions, indicating a fair amount of interaction between terms. The high degree of interaction shared between baseline mortality rate, concentration-response function, and  $PM_{H-SFU}$  is likely a result of the FAST sampling algorithm selecting extreme values (in the upper and lower 10th percentiles).

In all four regions,  $PM_{H-SFU}$  contributes only a minor amount to the total variance. This is in part due to the relatively flat response of the concentration-response function for IHD and stroke at high  $PM_{2.5}$  concentrations. While there are large uncertainties in estimates of  $PM_{H-SFU}$ , the relative risk changes by a small amount relative to the large uncertainties present in the concentration-response function. Thus, in the  $PM_{2.5}$  concentration range typical of household solid fuel use, the uncertainty in the concentration-response function dominates over uncertainty in  $PM_{2.5}$ ; however, we note that some of the uncertainty in the concentration-response function is shared with  $PM_{H-SFU}$  (indicated by the grey portion of the  $PM_{H-SFU}$  bar).

### 3.2.2. Sensitivity Analysis for the A-SFU Calculation

Figure 5 presents the sensitivity analysis results for the A-SFU mortality calculation. In all regions, the total effect index for  $\%PM_{A-SFU}$  dominates the variance in A-SFU mortality (approximately 80%), reflecting the large uncertainty bounds on this parameter (section 2.1). This implies that if all other parameters except  $\%PM_{A-SFU}$  were known, an uncertainty range of 0.13, 0.26, 0.01, 0.03 million deaths would remain in China, India, Latin America, and Africa. A majority of the uncertainty in  $\%PM_{A-SFU}$  comes from the main effect index. In contrast,  $PM_{Amb}$  contributes less than 9% of the variance, with most of this contribution resulting from the interaction term. The difference in the contribution to variance from the two  $PM_{2.5}$  parameters can be attributed to two main factors. First, the relative uncertainty ranges for  $PM_{Amb}$  and  $\%PM_{A-SFU}$  are very different. Satellite retrievals and surface observations provide constraints on the uncertainty range for  $PM_{Amb}$ . Conversely, the uncertainty range for  $\%PM_{A-SFU}$  (estimated here as a factor of 2 about the mean) is a result of estimates of uncertainty from emission factors (e.g., Johnson et al., 2008, 2011) and fuel use (e.g., Fernandes et al., 2007) and are much wider than for  $PM_{Amb}$ . Second,  $PM_{Amb}$  is the exposure concentration included in the concentration-response function. The concentration-response function for IHD and stroke is sublinear, so the changes in relative risk due to different selections of  $PM_{Amb}$  are dampened in regions with high  $PM_{Amb}$ . Similar to the H-SFU calculation, there are large interaction terms shared between baseline mortality rate, concentration-response function, and  $PM_{Amb}$  that are likely caused by sampling from extreme values in the uncertainty distribution.

### 3.2.3. Sensitivity Analysis for the J-SFU Calculation

The sensitivity analysis results for the J-SFU calculation are presented in Figure 6. In the four representative regions, the relative order of parameters in the variance contributions in the J-SFU calculation closely follow the H-SFU calculation. This is because most of the mortality in the J-SFU calculation come from the population using solid fuels, and so the results are more similar to the results for H-SFU. Conversely, in countries where a very low percent of the population uses solid fuels and the mortality burden is primarily from A-SFU (such as in Canada or Algeria), the variance contributions in the J-SFU calculation follow the A-SFU calculation. In China, India, and Latin America, the largest contributions to the variance (in the total effect index) come from the percent of the population using solid fuels (53–56% or 0.03–0.49 million deaths) followed by concentration-response function (42–50% or 0.03–0.42 million deaths). In sub-Saharan Africa, baseline mortality rate (72%) and concentration-response function (33%) dominate the uncertainty space. While  $\%PM_{A-SFU}$  dominates the variance in all four regions in the A-SFU calculation, this term contributes only a small amount of variance in the J-SFU calculation (15–23% in China, India, and Latin America, but less than 5% in sub-Saharan Africa). As A-SFU has only a minor contribution to the total mortality in J-SFU calculation, this parameter contributes a much smaller amount of the variance in the J-SFU calculation compared to the A-SFU calculation. In all four regions, the three  $PM_{2.5}$  concentrations ( $PM_{Amb}$ ,  $\%PM_{A-SFU}$ , and  $PM_{H-SFU}$ ) combined account for 15–38% of the variance in the total effect index; however, some of the interaction term in concentration-response function is shared between the  $PM_{2.5}$  terms. With the exception of sub-Saharan Africa, most of the variance in mortality apportioned to the three  $PM_{2.5}$  parameters comes from the percent of ambient  $PM_{2.5}$  originating from SFU rather than the total ambient and household concentrations themselves. In sub-Saharan Africa,  $PM_{H-SFU}$  is the most important  $PM_{2.5}$  factor due to the very high percent of the population using solid fuels. The low contribution of  $PM_{2.5}$  concentrations to the mortality uncertainty suggests that much of the uncertainty in mortality estimates are from the health inputs (baseline mortality rate and concentration-response function) and percent of the population using solid fuels as opposed to the  $PM_{2.5}$  exposure. In the SI, we present results truncating the uncertainty distributions at the 95% CI. This reduces the summed total effect to 118–130% across all four regions. Sampling from a uniform distribution (which also truncates at the 95% CI), as opposed to a lognormal distribution, reduces the interaction term to 108–110% (see supporting information). The nonlinear interactions between the various input terms increase when sampling from the tails of the uncertainty distributions.

### 3.2.4. Limitations of This Work

We acknowledge a number of limitations in the sensitivity analysis in this study. In addition to the factors with quantifiable uncertainty ranges described above, there are several major assumptions in which a specific quantified confidence range cannot be applied due to limitations in our current knowledge. Mortality estimates from SFU have required applying and extrapolating epidemiological evidence from studies of outdoor air pollution conducted in high-income countries (mainly the United States and Europe) along with studies of secondhand smoke exposure and tobacco smoke exposure to developing countries with typically higher exposure concentrations (Burnett et al., 2014); whether this extrapolation holds between countries is unclear. In addition, we assume an equal toxicity of different chemical composition of  $PM_{2.5}$  (Burnett et al., 2014). Further, while there is limited emerging evidence of links between measures of cardiovascular health with household air pollution (e.g., Agarwal et al., 2017; Mitter et al., 2016), direct evidence of exposure to household air pollution contributing to increased risk of mortality through cardiovascular diseases was not included in the Burnett et al. (2014) concentration-response function (though evidence of cigarette smoking and of ambient air pollution contributing to this health outcome was included). The sensitivity analysis presented here describes the apportioned uncertainty in mortality from input parameters with quantified uncertainty ranges, and thus, additional uncertainty in mortality should be considered from the major assumptions of the concentration-response function in addition to what is considered here. For instance, IHD and stroke contribute substantially to uncertainty in mortality due to exposure to household air pollution in all regions; however, there is additional uncertainty beyond what we quantified here for parameters related to IHD and stroke because of the lack of direct evidence relating exposure to household air pollution and cardiovascular disease outcomes (i.e., events such as stroke). An additional limitation is that the sensitivity analysis used here is itself sensitive to the uncertainty range provided for each data input source. For example, measurements of personal  $PM_{2.5}$  exposure are limited, and several studies (e.g., Baumgartner et al., 2011; Ni et al., 2016) report personal exposures with a different uncertainty distribution including portions of the distribution outside the published range used in this study. To test this limitation, we increased the 95% uncertainty levels for the  $PM_{H-SFU}$  parameter from a factor of 1.4 to 2 in both directions around the central estimate. In the H-SFU calculation, this increased the percent contribution in the total effect index of the parameter from 6–10% to 15–20% (across the four regions). Despite these limitations, the sensitivity analysis in this study provides valuable information on the sources of uncertainty in mortality calculations attributed to SFU.

## 4. Conclusions

The large health burden attributed to SFU has motivated interventions aimed at replacing traditional cookstoves with cleaner-burning fuels and combustion devices (e.g., M. L. Clark et al., 2010, 2013; Mortimer et al., 2016; Piedrahita et al., 2016; Ruiz-Mercado et al., 2011; S. Clark et al., 2017); however, there are large uncertainties in the number of deaths attributed to exposure to  $PM_{2.5}$  from SFU. These uncertainties originate from uncertain input parameters as well as the contribution of health risk from other ambient  $PM_{2.5}$  sources. There is currently no framework to estimate mortality from SFU while accounting for  $PM_{2.5}$  from other sources. In this study, we estimate 2.81 (95% CI: 2.48–3.28) million deaths in 2015 from the joint exposure to household and ambient  $PM_{2.5}$  from SFU using the J-SFU calculation. This estimate has 580,000 (18%) fewer deaths than the sum of the H-SFU and A-SFU calculations, and 260,000 fewer deaths among the population using solid fuel in the J-SFU calculation than in the H-SFU calculation alone. This indicates that treating household and ambient pollution as independent risk factors leads to overestimates of mortality attributed to SFU, particularly in regions with high ambient  $PM_{2.5}$  concentrations. Health and epidemiology studies taking place in areas (such as periurban areas) with high  $PM_{2.5}$  concentrations from sources other than SFU may expect a smaller health response due to decreases in  $PM_{2.5}$  from SFU.

We performed a variance-based sensitivity analysis on each mortality calculation to apportion the variance in mortality attributed to SFU to each uncertain input parameter. In the H-SFU calculation, the percent of the population using solid fuels and the concentration-response function contribute the most uncertainty in SFU mortality except in regions where greater than 90% of the population uses solid fuels and the uncertainty range is small. The  $PM_{2.5}$  exposure estimates contribute a relatively small amount of uncertainty in mortality because the range of exposures associated with household solid fuel use extends across a flatter part of the

concentration-response function for dominant causes of death (IHD and stroke). While the percent of the population using solid fuels has a smaller relative uncertainty than the  $PM_{2.5}$  exposure, it contributes a much larger percent of the uncertainty in mortality. We note that the results of this study do not rank input parameters by their precision but rather by how the uncertainty in each input parameter affects the uncertainty in model output.

In the A-SFU calculation, the contribution of SFU emissions to ambient  $PM_{2.5}$  concentration dominates the uncertainty space. This is a result of large uncertainties in SFU emission inventories, which are a result of the combination of uncertainties in emission factors and fuel use. This is also a reflection of the difficulty of atmospheric models to attribute the fraction of ambient  $PM_{2.5}$  to a specific source (even though the total ambient  $PM_{2.5}$  can be constrained with surface observations and satellite retrievals).

The sensitivity analysis on our J-SFU calculation reflects a combination of the contributed uncertainty in mortality from the H-SFU calculation and the A-SFU calculation. In the J-SFU calculation, a majority of the total deaths occur in the population using solid fuels (and are thus exposed to higher indoor concentrations). As a result, the sensitivity analysis results are more similar to the results from the H-SFU calculation. In China, India, and Latin America, the parameters that contribute the most uncertainty to mortality attributed to  $PM_{2.5}$  exposure from SFU are the percent of the population using solid fuels (53–56%) and the concentration-response function (42–50%). The three  $PM_{2.5}$  exposure concentrations contribute between 15 and 38% of the variance in mortality distributions. Our findings suggest that future research focused on constraining the health response of exposure to  $PM_{2.5}$  and estimates of solid fuel use could measurably reduce uncertainty in premature mortality estimates associated with solid fuel use. Improving solid fuel use estimates would reduce uncertainty in both the H-SFU calculation (where the leading contribution to mortality is from the population using solid fuels) and the A-SFU calculation (where the large uncertainties in ambient  $PM_{2.5}$  from SFU emissions are linked to uncertainty in solid fuel use). In sub-Saharan Africa, where the percent of the population using solid fuels is relatively well constrained, our results suggest that future work should focus on reducing the uncertainty in baseline mortality rates.

It is important to note that while our sensitivity analysis shows a relatively small contribution from  $PM_{2.5}$  exposure to uncertainty in J-SFU mortality estimates, this by no means implies that  $PM_{2.5}$  exposure is unimportant for estimating premature mortality from SFU. Fundamentally, there must be exposure to  $PM_{2.5}$  from SFU in order to have mortality from  $PM_{2.5}$  attributable to SFU. This analysis only estimates the contribution to variance in SFU mortality. It is not meant to indicate which factors contribute the most to the estimated magnitude of mortality from SFU. As such, our results do not indicate that reducing exposure to  $PM_{2.5}$  from SFU would not have a health benefit; we mean to suggest that the uncertainty in the magnitude of the health benefit is largely from uncertainties in the population using solid fuels and the concentration-response function. Additionally, improving concentration-response functions (one of the largest contributors to uncertainty identified here) necessitates accurate measurements of  $PM_{2.5}$  exposure in the epidemiological studies used to generate the concentration-response functions.

The estimated health burden attributed to SFU is substantial both in terms of mortality, disability adjusted life years, years of life lost, and willingness to pay losses (Cohen et al., 2017; WHO, 2014; World Bank, 2016). Future studies may seek to quantify uncertainty in mortality from SFU in different years or with different data inputs (such as those compiled by the World Health Organization). To gain a better understanding of the expected benefits of SFU interventions, future research should also focus on more accurate and precise estimates of populations using solid fuels, exposure-response relationships, and mortality rates in sub-Saharan Africa.

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