Macro-level indicators of household and ambient air pollution mortality risk: global evidence

Social Science & Medicine 391 (2026) 118921

Contents lists available at ScienceDirect

Social Science & Medicine

journal homepage: www.elsevier.com/locate/socscimed

Macro-level indicators of household and ambient air pollution mortality risk: Global evidence

Scott Mark Romeo Mahadeo [a], Avidesh Seenath [b,*]

[a] Department of Economics, University of Reading, UK
[b] Environmental Change Institute, University of Oxford, UK

ARTICLE INFO

Keywords:
Air pollution
Clean fuels
Energy
Gender
Health
Mortality
Rural

ABSTRACT

Household and ambient air pollution (HAAP), a major global health risk, is linked to a lower quality of life and is responsible for over six million premature deaths globally each year. We investigate country-level socioeconomic, environmental, energy, and health determinants of HAAP mortality rates, using regression analyses and global mapping of predicted probabilities of high HAAP mortality risk. While related studies are predominantly country-specific based on micro-level factors, our study provides global evidence from 150 countries based on a broad range of macro-level indicators. Our findings reveal that greater rural access to clean cooking fuels and technology and increased healthcare expenditures are critical for reducing HAAP deaths, whereas rurality and energy deprivation significantly increase such mortality risks. While advanced economies demonstrate clear resilience to HAAP mortality risks, emerging and developing economies are disproportionately vulnerable. Contrary to related literature, our analyses also reveal that males are more at risk of HAAP mortality than females. We further contextualise our global evidence with previous country-specific case studies on HAAP risks. Our research helps to appraise the progress towards achieving the United Nations Sustainable Development Goals 3, 5, and 7, addressing their associated targets and indicators, providing guidance for policymakers to strengthen efforts to reduce HAAP mortality and improve living conditions globally.

1. Introduction

Air pollution, both household (indoor) and ambient (outdoor), is a significant global environmental health risk that is linked to a lower quality of life and premature death. Associated health risks include cardiovascular disease, lung cancer, chronic obstructive pulmonary disease, and pneumonia (see Ronzi et al., 2019 and references therein), among other afflictions like asthma, tuberculosis, low birth weight, and eye diseases (see Jin et al., 2006 and references therein). Recent global estimates of annual mortality related to household air pollution range from 1.6 to 2.5 million (Dhital et al., 2022; Jewitt et al., 2022), while mortality in response to ambient fine particulate matter ($PM_{2.5}$)[1] air pollution is over 4.1 million (Wang et al., 2023). Annually, the joint mortality attributed to both household and ambient air pollution (HAAP) is about 6.7 million (World Health Organization, 2024[2]). Importantly, both household and ambient pollution are intimately connected. Globally, household air pollution from inefficient fuel use significantly increases ambient air pollution and premature mortality, necessitating an urgent need for coordinated HAAP mitigation efforts (Chowdhury et al., 2023). However, these issues and the associated health implications disproportionately affect developing countries (Das et al., 2021), rural populations (Jin et al., 2006), and women and children (Talevi et al., 2022).

Despite the extensive recognition of household air pollution risks, largely because of case studies on vulnerable villages (see, for e.g., Cundale et al., 2017; García-Frapolli et al., 2010), attempts to connect country-level factors to air pollution mortality rates remain underexplored on a global scale, with much of the existing evidence confined to village-level or single-country studies. These studies provide valuable detail on household practices and local vulnerabilities, but they do not reveal the consistent structural conditions that shape mortality across nations. As a result, the literature lacks a systematic cross-country perspective on which socioeconomic, environmental, and health system factors most reliably predict HAAP deaths. Addressing this gap is

* Corresponding author.
E-mail address: avidesh.seenath@eci.ox.ac.uk (A. Seenath).

[1] Fine inhalable particle matter in the air, with diameters less than or equal to 2.5 micrometres.
[2] See https://www.who.int/news-room/fact-sheets (accessed in June 2025).

https://doi.org/10.1016/j.socscimed.2025.118921
Received 23 June 2025; Received in revised form 11 December 2025; Accepted 29 December 2025
Available online 31 December 2025
0277-9536/

crucial not only for advancing academic knowledge but also for providing a stronger evidence base to support international and regional responses, including the monitoring of progress toward key Sustainable Development Goals (SDGs). We, therefore, aim to offer a worldwide perspective on the socioeconomic and environmental indicators that are linked to HAAP mortality risk. In doing so, we provide global insights into the common and consistent macro-level determinants of HAAP mortality rates, highlighting countries where greater policy efforts and interventions are needed to improve living conditions. Thus, our research aligns closely with the United Nations SDG 3 – *to ensure healthy lives and promote well-being for all*. In particular, our study relates to target 3.9 – part of which aims to substantially reduce the number of deaths and illnesses from air pollution and contamination by 2030 – and specifically to target 3.9.1, which tracks mortality rates attributed to HAAP.[3]

There is a wealth of cross-disciplinary literature in development, energy, environment, and health that focus on clean fuels and technologies for cooking to address HAAP-related health risks, where increased access to such resources mitigates these risks and a lack thereof worsens it. Around 40 % of the world's population use traditional methods, based on biomass energy (particularly fuelwood and charcoal), for cooking (Adrianzén, 2013; Das et al., 2021; Jewitt et al., 2022; Mekonnen et al., 2022). Such traditional cooking methods are linked to the more than 2.5 million premature deaths related to household air pollution annually, which predominantly occurs in low- and middle-income countries (Ronzi et al., 2019). Inefficient cooking also contributes to several environmental issues – air pollution, forest biomass loss, deforestation, local biodiversity and ecosystem loss, and CO_2 emissions (Alem and Demeke, 2020; Mekonnen et al., 2022). Access to clean fuels and technologies for cooking remains a significant and urgent issue. This is highlighted by the United Nations SDG indicator 7.1.2, which measures the proportion of the population that rely primarily on clean fuels and technology. Indeed, indicator 7.1.2 serves as an important metric for assessing progress toward achieving target 7.1 – *universal access to affordable, reliable, and modern energy services by 2030* – under SDG 7 on sustainable and modern energy for all.[4]

Related to both cooking and HAAP mortality risk is the broader issue of access to electricity. The use of biomass energy for heating poses similar health risks to inefficient cooking methods in rural areas (see Jin et al., 2006). Both heating and cooking with solid fuels are characteristics of energy poverty, which increases overall HAAP mortality risk. The significant time spent indoors and devoted to basic household energy needs disproportionately affects women and children (Li et al., 2017), who often take on the responsibility of these tasks. Reducing this burden can promote increased schooling for children (Lee, 2013), and greater workforce participation and income generation for women (Ssennono et al., 2021). For these reasons, energy poverty is inextricably linked to the United Nations SDG 5 – *achieve gender equality and empower all women and girls*. In our context, this link is a recurring theme, as the literature repeatedly reports that women and children face heightened health risks from indoor air pollution (see, e.g., Beyene and Koch, 2013; Kanagawa and Nakata, 2007).

Additionally, the rural-urban divide of a population is another key factor to consider when assessing HAAP mortality risk, but this is complicated. On one hand, rural households are often linked to *household* air pollution risks compared to urban households because of limited clean energy access and a greater reliance on traditional and inefficient methods of heating and cooking (see, e.g., Mestl et al., 2007). On the other hand, rural areas generally have lower *ambient* air pollution because of less industrial activity and vehicular emissions than densely populated urban areas (Castells-Quintana et al., 2021). Yet, rural populations tend to have less access to quality health care, education, and employment opportunities than urban populations, which can worsen the health impacts of air pollution, regardless of whether the source of exposure is indoor or outdoor.

Hence, given the preceding context, we examine how country-level indicators such as access to clean cooking fuels and technology, access to electricity, rurality, education, employment, solid CO_2 emissions, and health care expenditure affect HAAP mortality risk. Our cross-sectional analysis covers total (male + female), male, and female HAAP mortality rate samples for 150 countries across 2016 and 2019 datasets. Our results are based on linear and logit regressions. For the latter, we apply a clustering algorithm to classify HAAP mortality rates into relatively high and low risk countries. We use these discrete states of the world to then estimate binary logit models that provide novel insights on whether the selected macro-level indicators can accurately predict countries with a high HAAP mortality risk.

Our main findings suggest that rural access to clean fuels and technology for cooking is critically important for reducing HAAP deaths, and advanced economies are resilient to high premature HAAP deaths in contrast to emerging and developing economies. Moreover, HAAP mortality risks are jointly well-predicted by the set of macro-level indicators considered, rurality significantly increases this risk, and health care prioritisation can substantially reduce high HAAP deaths. A further notable result, which we explore in detail, is that we do not observe higher female mortality from HAAP at the country level. Instead, our descriptive statistics and spatial maps – developed based on the ability to predict a high HAAP mortality rate using the macro-level indicators – imply that males in fact face greater risk of HAAP mortality. Collectively, as outlined above, our study resonates with important United Nations SDGs (3, 5, and 7), targets (3.9 and 7.1), and indicators (3.9.1 and 7.1.2), which have a 2030 deadline. Hence, our research and associated findings are timely, as it can support policymakers in appraising the national and international efforts made to address these interrelated SDGs.

In the following sections, we begin by outlining our methods (Section 2) and data (Section 3). We then present our results, including regression analyses and spatial maps showing predicted probabilities of a high HAAP mortality risk based on macro-level indicators (Section 4). Finally, we conclude with a summary of our key findings, policy implications, and directions for future research (Section 5).

2. Methods

As a point of departure, we use simple linear ordinary least squares (OLS) regression models to estimate the effects of macro-level determinants on HAAP mortality rates as below:

$$\begin{aligned} HAAP_{i,\bar{t},k} = \beta_0 + \beta_1 RCCA_{i,\bar{t},\bar{k}} + \beta_2 REA_{i,\bar{t},\bar{k}} + \beta_3 LFPR_{i,\bar{t},k} + \beta_4 RPP_{i,\bar{t},\bar{k}} \\ + \beta_5 PSE_{i,\bar{t},k} + \beta_6 SFE_{i,\bar{t},\bar{k}} + \beta_7 HCE_{i,\bar{t},\bar{k}} + \varepsilon_{i,\bar{t},k} \end{aligned} \quad \text{Eq. 1}$$

where $HAAP_{i,\bar{t},k}$ is household ambient and air pollution mortality rate for a given country (i), time ($\bar{t}$ = 2016 or 2019), and sample (k = total, male, or female), and is a function of several explanatory variables whose importance are discussed in Section 1 above. In all cases, the regressions are estimated separately for 2016 and 2019 (hence, $\bar{t}$), so that each year is treated as an independent cross-sectional regression model rather than pooled or averaged. As there are only two years of data and countries are not consistent across both years, panel techniques such as fixed or random effects are not employed, as these require longer time series, consistent across observations (i.e., countries - i). The explanatory variables considered are: rural clean cooking access (*RCCA*); rural electricity access (*REA*); labour force participation rate (*LFPR*); rural population percent (*RPP*); primary school enrolment (*PSE*); solid CO_2 fuel emissions (*SFE*); and health care expenditure (*HCE*). Finally, β_0 is the regression constant, $\beta_1, \ldots, \beta_7$ are the estimated coefficients of the explanatory variables, and ε_i is the stochastic error term. As total (male

[3] See https://sdgs.un.org/goals/goal3#targets_and_indicators.

[4] See https://sdgs.un.org/goals/goal7#targets_and_indicators.

+ female combined) and gender-specific data (separate male and female data) are available for three variables – the dependent (*HAAP*) and two independent (*LFPR* and *PSE*) variables – k varies in each regression model according to the sample (total [male + female combined], male, or female) for these variables. All remaining regressors are not gender-specific and are, therefore, denoted as $\bar{k}$ to show that they are consistent across samples (total [male + female], male, and female) in a given year (2016 or 2019). Thus, there are six OLS regressions in all: a separate model for total (male + female combined), male, and female samples, for the 2016 and 2019 datasets.

We conduct a series of diagnostic tests to ensure the reliability and validity of our estimated OLS regressions models. In particular, we assess model adequacy using the F-test to evaluate the joint significance of the explanatory variables, and we use the coefficient of determination (R^2) to assess explanatory power. We check model specification with the Ramsey regression equation specification error tests (*RESET*), which indicates the omission of non-linear functional forms in the regression specification, and we assess multicollinearity using variance inflation factors (VIF). Concerning the latter, we check that VIF values fall below the conventional threshold of 5, where $5 < VIF < 10$ indicate moderate correlation among regressors and $VIF > 10$ indicate high collinearity. As cross-country data often exhibit heteroskedasticity, we estimate all regressions with robust standard errors. Although residuals are unlikely to be perfectly normal in large heterogeneous samples, these robust estimators ensure valid inference even when normality is violated. Together, these diagnostic procedures allow us to confirm that our empirical models are appropriately specified, and that the estimated relationships are statistically sound and theoretically meaningful. We report the detailed results of these diagnostics in Section 4.2.

To complement our OLS regression analysis, we assess whether the macro-level indicators are factors that predict if a country will have a high or low HAAP mortality rate. This is in line with global health practices that often distinguishes “priority” high-risk countries from “the rest of the world”. Although the HAAP mortality rate is continuous, several policy frameworks rely on threshold-based categorisations to identify priority countries. For example, WHO burden-of-disease assessments and SDG-related monitoring practices routinely differentiate between “high burden” and “non-high burden” countries to guide programme implementation decisions, target technical assistance, and support resource mobilisation. If countries in the upper tail of the mortality distribution experience a clearly elevated public health risk profile, this implies that the determinants of belonging to this group are particularly relevant for policy. The binary split adopted here, therefore, reflects a substantive policy distinction: whether a country falls into the highest-mortality segment of the global distribution. This structure enables regression models to identify the macro-level factors associated with being a high-burden country, which can directly support health intervention policies.

As such, within each sample (total, male, and female) for the two datasets (2016 and 2019), we classify the world into relatively *high* and *low* HAAP mortality rates, using a non-hierarchical k-means clustering algorithm. The clustering is based on Euclidean distance as the measure of similarity/dissimilarity that maximises between cluster variance and minimises within cluster variance of the high and low HAAP mortality rate groupings. The choice of the clusters reflects our focus on distinguishing countries facing relatively higher HAAP mortality from those with comparatively lower rates. The clustering algorithm suggests three clusters (a very high, a high, and a low HAAP mortality cluster) in all three samples (total, male, and female) across both datasets (2016 and 2019). The two higher HAAP mortality clusters are then merged into one cluster, as we aim for a maximum of two final clusters (high and low mortality) that would yield the closest approximation to an equidivision in each sample. A near-balanced dichotomy of the dependent variable increases the statistical power of the binary logit model estimation, providing more precise coefficients, narrower confidence intervals, and a higher chance of detecting real effects. In doing so, we avoid the consequence of highly unbalanced samples, with small observations in one group, where coefficient estimates for predictors become unstable or biased. Importantly, HAAP mortality rates alone are used for clustering, while the explanatory variables (i.e., the macro-level indicators) are introduced only in the logit regressions, ensuring no overlap between the clustering step and predictor variables. With these binary classifications, we use maximum likelihood estimation to run the following logit regression model:

$$Pr\left(HAAP_{i,\bar{t},k}=1\right)=F\left(\beta_0+\beta_1 RCCA_{i,\bar{t},\bar{k}}+\beta_2 REA_{i,\bar{t},\bar{k}}+\beta_3 LFPR_{i,\bar{t},k}+\beta_4 RPP_{i,\bar{t},\bar{k}}+\beta_5 PSE_{i,\bar{t},k}+\beta_6 SFE_{i,\bar{t},\bar{k}}+\beta_7 HCE_{i,\bar{t},\bar{k}}\right)=F(x'\beta)=\frac{e^{(x'\beta)}}{1+e^{(x'\beta)}} \quad \text{Eq. 2}$$

such that $Pr\left(HAAP_{i,\bar{t},k}=1\right)$ is the probability that the HAAP mortality rate for a given country is high in a given year (either 2016 or 2019) and sample (either total [male + female], male, or female). Therefore, $Pr\left(HAAP_{i,\bar{t},k}=0\right)$ implies that the HAAP mortality rate is low for a given country. F is a non-linear function that bounds $(x'\beta)$ between 0 and 1, where x represents the regressors, the β_s are their corresponding estimates, and e is the exponential function. As such, there are six binary logit regressions in all, which can be seen as complements to the six OLS regression models: a separate binary logit model for total (male + female combined), male, and female samples, for the 2016 and 2019 datasets.

For the binary logit models, we also evaluate model fit using the Wald chi-square test for joint model significance and the McFadden's pseudo-R^2 to measure the improvement the regressors add to the model over a constant-only specification. We assess predictive accuracy with the correctly classified rate and the area under the receiver operating characteristic (ROC) curve, both of which capture the binary logit model's ability to distinguish between high and low HAAP mortality outcomes. As with the OLS models, we employ robust standard errors to account for potential heteroskedasticity and other distributional irregularities. We also report the detailed results of the logit model diagnostics in Section 4.2, alongside the OLS model diagnostics.

Although our OLS and logit models employ heteroskedasticity robust standard errors, an acknowledged limitation is that cross-country datasets may exhibit spatial correlation, particularly among geographically or economically proximate countries. Such correlation can lead to downward-biased standard errors if it is not addressed. Spatially robust variance estimators, such as Conley (1999)'s standard errors or related spatial heteroskedasticity and autocorrelation consistent (HAC) approaches, provide a way to account for this dependence in cross-sectional settings. However, implementing spatial HAC adjustments was not feasible in the present study because our data consist of two independent cross-sectional years, the composition of countries is not identical across these years, and globally consistent spatial-economic distance information is not available for all variables in our analysis.

Despite this limitation, our results remain robust for several reasons. *First*, all models are estimated with heteroskedasticity robust standard errors. *Second*, we make use of two separate data years, which act as a natural sensitivity check for each other. *Third*, the main findings are highly consistent across linear OLS and nonlinear logit models, and they also hold in the subsample of emerging and developing economies. We explicitly acknowledge the absence of spatially correlated standard errors as a limitation in the study, and we note that future research could extend our analysis by incorporating spatial HAC estimators when appropriate spatial-distance data become available.

Additionally, for a visual spatial analysis, we map the probability of high HAAP mortality, predicted from the binary logit regression

Table 1
Data abbreviations, definitions, and sources.

Variable	Definition	Source
HAAP	HAAP mortality rate, age-standardised (per 100,000 population)	World Health Organisation: www.who.int/data/gho/data/
	⇒Male HAAP mortality rate, age-standardised (per 100,000 male population)	
	⇒Female HAAP mortality rate, age-standardised (per 100,000 female population)	
RCCA	Rural access to clean fuels and technologies for cooking (% of rural population)	World Bank: https://data.worldbank.org/
RAE	Rural access to electricity (% of rural population)	
RPP	Rural population (% of total population)	
PSE	Primary school enrolment (% gross)	
	⇒Male primary school enrolment (% gross)	
	⇒Female primary school enrolment (% gross)	
SFE	CO2 emissions from solid fuel consumption (% of total)	
HCE	Current health expenditure (% of GDP)	
LFPR	Total labour force participation rate (% of total population ages 15+) (modelled ILO estimate)	International Labour Organisation: https://ilostat.ilo.org/data/
	⇒Male labour force participation rate (% of male population ages 15+) (modelled ILO estimate)	
	⇒Female labour force participation rate (% of female population ages 15+) (modelled ILO estimate)	

Notes – acronyms in the "Variable" column correspond to those listed in Eqs. (1) and (2). Refer to the main text for further information. Main organisational websites are cited in the "Source" column, as individual dataset URLs may change. Exact datasets used in the production of this manuscript are provided in the supplementary material for replicators. Links to the data sources for each of the series can be found by following the hyperlinks in the "Definition" column – these datasets were retrieved in July and August 2024.

specified in Eq. (2), for the 150 countries considered across the 2016 and 2019 datasets. To do this, we use ArcGIS Pro to populate the attribute table of the *World Administrative Boundaries – Countries and Territories* shapefile available from opendatasoft[5] with these predicted probabilities. For our mapping campaign in ArcGIS Pro, we use a graduated orange symbology, with lighter (darker) shades implying that the macro-level indicators jointly predict that the probability of a country being classified into the relatively high HAAP mortality rate cluster is low (high), i.e., $\leq$0.50 ($>$0.50). Our maps also provide a spatial visualisation of high HAAP mortality probabilities, based on macro-level indicators, on a global scale. Additionally, they further highlight vulnerability patterns, to support more targeted policy responses in high-risk countries and regions.

3. Data

Table 6 lists the 150 countries included in our analyses, and the associated data used for estimating our regression models in Eqs. (1)–(2) are defined in Table 1. In particular, as Table 2 shows, the 2016 regressions include 142 countries, while the 2019 regressions include 131 countries in the total sample and 130 in the gender-specific samples. Each 2016 model includes seven regressors, while each 2019 model includes six regressors because data on CO_2 emissions from solid fuel consumption are not available for that year. All data used are open access: we obtain data on *HAAP* from the World Health Organisation (WHO), *RCCA*, *RAE*, *RPP*, *PSE*, *SFE*, and *HCE* from the World Bank, and *LFPR* from the International Labour Organisation (ILO). We focus on the years 2016 and 2019, as these have the most recent and most complete global datasets on HAAP mortality rates and explanatory variables, providing consistent cross-country coverage within each of these years.

The set of explanatory variables used are theoretically comprehensive (see Section 1), yet parsimonious in preventing multicollinearity issues of duplicated information content. For instance, the natural logarithms of per capita real GDP, current health care expenditure, and CO_2 emissions are strongly correlated with rural access to clean fuels and technologies for cooking as a percent of the rural population ($\rho > 0.8$). Hence, including them in a regression model would create multicollinearity. As no suitable proxy exists for rural access to clean fuels and technologies for cooking as a percent of the rural population in models estimating HAAP mortality rates, this variable is retained. Alternative series for per capita health care expenditure and CO_2 emissions are health care expenditure as a percent of GDP and CO_2 emissions from solid fuel consumption as a percent of total fuel consumption, respectively. Both series are weakly correlated with rural access to clean fuels and technologies for cooking ($\rho < 0.4$). In the case of CO_2 emissions from solid fuel consumption, this series is arguably a more fit-for-purpose indicator in the context of HAAP mortality from the discussions established in Section 1 of this paper. As it is reasonable to assume that any measure of the national income will be correlated with rural access to clean fuels and technologies for cooking, we do not seek an alternative measure of national income. Instead, we argue that income effects are plausibly captured through other covariates – i.e., rural population size and access to clean cooking technology, fuels, and electricity.

The countries selected represent those with consistent data available for the explanatory variables considered. By consistent data, we mean comparable, complete, and regularly reported observations across countries and years, allowing reliable cross-country analysis. Countries were included only if complete data for all explanatory variables were available for at least one of the two analysis years (2016 or 2019). For example, gross primary school enrolment data are used as a metric of national education, as it is more widely available for most countries than any alternative education indicator provided in the World Bank database. This same logic applies for the modelled International Labour Organisation (ILO) estimates for labour force participation rate as a percent of total population data. The final sample of 150 countries spans all major regions and income levels, with the only exclusions being countries lacking full reporting on one or more variables. Below, we describe the *prima facie* insights the summary statistics imply about global HAAP mortality rates and its determinants.

From Table 2, 2016 and 2019 recorded a global average HAAP death rate of 89 and 87 in every 100,000 people, respectively. Global North countries generally record the world's lowest HAAP related deaths, with Australia, Canada, Finland, Iceland, Norway, and Sweden, recording total HAAP mortality rates of less than 10 per 100,000 people in 2016 and 2019. Unsurprisingly, Global South countries record the world's highest HAAP mortality rates, with countries such as Afghanistan, Benin, Cameroon, Guinea, Niger, Sierra Leone, and Togo recording death rates of more than 200 per 100,000 people in 2016 and 2019.

Additionally, Table 3 reports the number of countries assigned to each cluster. In 2016, the high-mortality cluster contains 55 countries, compared with 87 in the low-mortality cluster. In 2019, the high-mortality cluster contains 56 countries, with 75 countries in the low-mortality group. These counts confirm that the binary classifications

[5] See: https://public.opendatasoft.com/explore/dataset/world-administrative-boundaries/export/.

Table 2
Descriptive statistics for total (male + female), male, and female HAAP mortality rates and macro-level indicators, in the 2016 and 2019 datasets, across the countries included in our OLS linear regression model (Table 4).

	Summary statistics									
	2016 dataset					*2019 dataset*				
	Obs.	Mean	S.D.	Min.	Max.	Obs.	Mean	S.D.	Min.	Max.
HAAP mortality rate	**142**	**89**	**74**	**7**	**324**	**131**	**87**	**75**	**7**	**288**
Rural clean cooking access	142	60	42	0	100	131	66	40	0	100
Rural electricity access	142	78	33	2	100	131	84	29	2	100
Labour force participation rate	142	62	10	32	88	131	62	10	32	87
Rural population percent	142	42	24	0	88	131	39	23	0	87
School enrolment (primary)	142	103	11	69	145	131	104	11	66	145
Solid fuel CO_2 emissions	142	17	24	0	122	131	–	–	–	–
Health expenditure (% of GDP)	142	6	3	2	17	131	7	3	2	17
HAAP male mortality rate	**142**	**101**	**77**	**9**	**314**	**130**	**103**	**88**	**9**	**352**
Male labour force participation rate	142	72	9	47	96	130	71	9	46	96
Male school enrolment (primary)	142	105	12	67	143	130	104	12	71	143
HAAP female mortality rate	**142**	**79**	**73**	**5**	**333**	**130**	**73**	**67**	**5**	**265**
Female labour force participation rate	142	51	13	15	82	130	52	13	14	83
Female school enrolment (primary)	142	102	12	66	146	130	103	12	62	147

Notes – where the following abbreviations and acronyms apply: Obs. = observations, which refer to the number of countries included in the sample; S.D. = standard deviation; Min. = minimum; Max. = maximum; HAAP = household and ambient air pollution. There are no solid fuel CO_2 emissions data available for 2019. For further details about the data, refer to Table 1.

used in logit models are sufficiently populated in each group to support stable estimations. Moreover, as Table 3 illustrates, when clustering HAAP related deaths into relatively high (*2016*: averaging 170 per 100,000 people; *2019*: averaging 160 per 100,000 people) and low (*2016*: averaging 39 per 100,000 people; *2019*: averaging 33 per 100,000 people) rates, countries in the former versus the latter cluster are characterised by larger rural populations (*2016*: 61 % versus 30 %; *2019*: 56 % versus 27 %) and greater rural energy deprivation in terms of: (a) average rural population with access to clean fuels and technologies (*2016*: 17 % versus 87 %; *2019*: 30 % versus 93 %); and (b) average rural population with access to electricity (*2016*: 47 % versus 97 %; *2019*: 64 % versus 99 %).

Considering variables such as the labour force participation rate, primary school enrolment, solid CO_2 emissions, and health care expenditure as a proportion of GDP, differences between the high and low mortality clusters appear comparatively less pronounced.

Interestingly, from examining gender-specific data, we observe that for males, the HAAP mortality rates per 100,000 people are substantially higher than for females in both 2016 and 2019 (Table 2), for countries in our samples: in 2016, the mean HAAP mortality rate among males are 101 deaths per 100,000 of the population, compared with 79 per 100,000 among females; and by 2019, these averages are 103 and 73, respectively. Such gender disparities are plausibly linked to the various initiatives around the world that have been implemented to reduce indoor air pollution related risks among women and children (see Frempong et al., 2021; Krishnapriya et al., 2021 and references therein), but it equally highlights the need to ramp up efforts to reduce male and total (male + female) HAAP mortality rates. Additionally, in both 2016 and 2019, while there are marginal differences between primary school enrolment for males and females, the global average female labour force participation rate is considerably lower than for males.

4. Results and discussion

We first present and evaluate our results from the six OLS regression models based on Eq. (1) for the total (male + female), male, and female samples in the 2016 and 2019 datasets. We then progress to do the same for our six binary logit regression results based on Eq. (2). Next, we evaluate routine model diagnostics for the OLS and binary logit regression models. Subsequently, we contextualise our findings from the spatial mapping of predicted probabilities of a relatively high mortality risk, based on our selection of macro-level indicators, with the existing literature on country-specific studies. Finally, we provide some sensitivity tests using OLS regressions based on a subsample that include only emerging and developing economies, as well as a binary logit regression that use terciles as an alternative to the models based on cluster analysis classifications.

4.1. OLS and binary logit regression estimates

Our OLS regression results in Table 4 show that a 1 % increase in the rural population's access to clean fuels and technology for cooking reduces HAAP mortality rates, with coefficients ranging from −0.832 (female, 2016) to −1.463 (male, 2019). This range of findings are all highly statistically significant ($p < 0.01$) and consistent across the total, male, and female samples, for both 2016 and 2019 datasets. Such evidence at the global scale validates the efforts of the United Nations Global Alliance for Clean Cookstoves in the 2010s, which aimed to provide 100 million clean cookstoves by 2020, to alleviate indoor air pollution health risks (Cundale et al., 2017). We also find that a 1 % increase in the labour force participation rates is statistically significant in decreasing HAAP mortality in the 2016 dataset, with coefficients of −1.146 in the total ($p < 0.01$), −0.947 in the male ($p < 0.05$), and −0.894 in the female ($p < 0.01$) samples; while having a larger rural population is strongly statistically significant ($p < 0.01$) in increasing HAAP death rates in all samples in the 2019 dataset.[6] Considering the former finding, participation in the labour force implicitly implies less time in the household and exposure to indoor pollution related to traditional cooking, as well as the potentially higher household income from working that can increase the ability to afford cleaner cookstoves resulting in less HAAP-related deaths. A plausible explanation for the latter finding is that rural populations are more likely to use traditional fuels and means of cooking (see, e.g., Mestl et al., 2007) or have less access opportunities to quality healthcare than urbanised areas (see, e. g., Gilthorpe and Wilson, 2003), contributing to a rise in HAAP mortality. Additionally, a 1 % increase in the population with access to rural electricity also reduces HAAP mortality in the total (male + female combined) and female samples, in the 2016 dataset, with coefficients of −0.667 for the total sample and −0.853 for females ($p < 0.01$, in both cases), while the effect was smaller and not significant for males. This supports the perspective that improved rural electrification enables households to move away from polluting energy sources like biomass

[6] In 2016, a larger rural population also increased HAAP death rates for the male sample with a weak statistical significance.

Table 3
Descriptive statistics of macro-level indicators under *high* and *low* HAAP mortality rate clusters, for total (male + female), male, and female samples, in the 2016 and 2019 datasets, across the sample of countries included in our binary logit regression model (Table 5).

	Summary statistics									
	2016 dataset					*2019 dataset*				
	Obs.	Mean	S.D.	Min.	Max.	Obs.	Mean	S.D.	Min.	Max.
HAAP *high* mortality rate	**55**	**170**	**54**	**99**	**324**	**56**	**160**	**58**	**78**	**288**
Rural clean cooking access	55	17	26	0	100	56	30	34	0	100
Rural electricity access	55	47	35	2	100	56	64	36	2	100
Labour force participation rate	55	62	11	32	84	56	63	12	32	87
Rural population percent	55	61	18	0	88	56	56	19	1	87
School enrolment (primary)	55	104	17	69	145	56	105	15	66	145
Solid fuel CO_2 emissions	55	17	28	0	122	–	–	–	–	–
Health expenditure (% of GDP)	55	5	3	2	17	56	5	2	2	15
HAAP *low* mortality rate	**87**	**39**	**23**	**7**	**87**	**75**	**33**	**21**	**7**	**77**
Rural clean cooking access	87	87	24	4	100	75	93	13	38	100
Rural electricity access	87	97	9	42	100	75	99	4	80	100
Labour force participation rate	87	61	8	39	88	75	61	8	39	82
Rural population percent	87	30	19	0	82	75	27	18	0	81
School enrolment (primary)	87	103	6	79	125	75	103	7	82	126
Solid fuel CO_2 emissions	87	17	21	0	94	–	–	–	–	–
Health expenditure (% of GDP)	87	7	3	3	17	75	8	3	2	17
HAAP *high* male mortality rate	**80**	**154**	**63**	**69**	**314**	**62**	**179**	**70**	**87**	**352**
Rural clean cooking access	80	33	36	0	100	62	35	37	0	100
Rural electricity access	80	62	37	2	100	62	68	36	2	100
Male labour force participation rate	80	72	9	47	88	62	71	10	46	89
Rural population percent	80	55	19	0	88	62	54	19	10	87
Male school enrolment (primary)	80	105	14	67	143	62	106	15	71	143
Solid fuel CO_2 emissions	80	18	27	0	122	–	–	–	–	–
Health expenditure (% of GDP)	80	6	2	2	17	62	5	2	2	15
HAAP *low* male mortality rate	**62**	**34**	**17**	**9**	**65**	**68**	**35**	**20**	**9**	**80**
Rural clean cooking access	62	95	15	9	100	68	94	12	38	100
Rural electricity access	62	98	6	62	100	68	99	3	83	100
Male labour force participation rate	62	71	8	58	96	68	71	8	58	96
Rural population percent	62	24	17	0	81	68	25	18	0	81
Male school enrolment (primary)	62	104	7	79	123	68	103	7	82	124
Solid fuel CO_2 emissions	62	16	18	0	92	–	–	–	–	–
Health expenditure (% of GDP)	62	8	3	3	17	68	8	3	2	17
HAAP *high* female mortality rate	**53**	**160**	**56**	**85**	**333**	**55**	**138**	**53**	**65**	**265**
Rural clean cooking access	53	16	26	0	100	55	29	34	0	100
Rural electricity access	53	46	35	2	100	55	65	36	2	100
Female labour force participation rate	53	53	16	18	82	55	54	16	16	83
Rural population percent	53	61	18	0	88	55	56	19	1	87
Female school enrolment (primary)	53	101	18	66	146	55	104	16	62	147
Solid fuel CO_2 emissions	53	18	28	0	122	–	–	–	–	–
Health expenditure (% of GDP)	53	5	3	2	17	55	5	2	2	15
HAAP *low* female mortality rate	**89**	**31**	**20**	**5**	**75**	**75**	**26**	**17**	**5**	**63**
Rural clean cooking access	89	86	25	4	100	75	93	13	38	100
Rural electricity access	89	97	9	42	100	75	98	9	23	100
Female labour force participation rate	89	50	12	15	73	75	51	11	14	71
Rural population percent	89	30	19	0	82	75	27	18	0	81
Female school enrolment (primary)	89	103	6	78	126	75	103	7	81	129
Solid fuel CO_2 emissions	89	17	21	0	94	–	–	–	–	–
Health expenditure (% of GDP)	89	7	3	3	17	75	8	3	2	17

Notes – where the following abbreviations and acronyms apply: Obs. = observations, which refer to the number of countries included in the sample; S.D. = standard deviation; Min. = minimum; Max. = maximum; HAAP = household and ambient air pollution. There are no solid fuel CO_2 emissions data available for 2019. For further details about the data, refer to Table 1.

and kerosene, reducing exposure to harmful indoor air pollutants, particularly among women who are more likely to be involved in household cooking (Li et al., 2017), thus lowering female HAAP mortality. Finally, we find that higher healthcare expenditure is weakly statistically significant ($p < 0.10$) in reducing male HAAP mortality rate in 2016, with a coefficient of −3.696, indicating that a 1 % increase in investment in healthcare may contribute to better diagnosis, treatment, and prevention of air pollution deaths among men.

Overall, we observe some discrepancies in the OLS estimates between the 2016 and 2019 datasets. We attribute these differences to the following: first, the two datasets are independent cross-sections, not a panel, and the composition of countries differs between 2016 and 2019, which will naturally contribute to variations in coefficient significance. Moreover, recalling the descriptive statistics in Table 2, some average global conditions improved between 2016 and 2019, which could lead to a reduction in statistical significance for specific variables observed in Table 5. For instance, the percent of the rural population with access to electricity increased from 78 % to 84 % between the 2016 and 2019 datasets. Yet, despite these expected differences between datasets, the percent of the rural population with access to clean cooking fuels and technology remains a strong and consistent predictor across both years.

Based on five of our six binary logit regression results in Table 5, we find that, with the exception of the female sample in the 2016 dataset, rural access to clean cooking fuel and technology is again a statistically significant indicator of a high HAAP mortality risk status. For instance, odds ratios ranging between 0.988 and 0.923 across samples and years imply that for every 1 % increase in the rural population's access to clean cooking resources, the odds of a country being in the high HAAP mortality group fall between 1.2 % ([1-0.988]*100) and 7.7 % ([1-0.923]*100), respectively. In particular, the effects of rural access to clean

Table 4
HAAP mortality rate OLS robust regression outputs for total (male + female), male, and female samples, in the 2016 and 2019 datasets.

	2016 dataset			*2019 dataset*		
	Total	Male	Female	Total	Male	Female
Macro-level predictors coefficients						
Rural clean cooking access	−0.948***	−1.090***	−0.832***	−1.287***	−1.463***	−1.097***
Rural electricity access	−0.667***	−0.406	−0.853***	−0.166	−0.139	−0.288
Labour force participation rate	−1.146***	−0.947**	−0.894***	−0.093	−0.065	−0.430
Rural population percent	0.249	0.346*	0.236	0.597***	0.731***	0.511***
School enrolment (*primary*)	−0.435	−0.258	−0.529	−0.043	0.216	−0.210
Solid fuel CO_2 emissions	0.086	0.138	0.091	–	–	–
Health expenditure *(% of GDP)*	−2.369	−3.696*	−0.618	−1.546	−2.204	−0.595
Model fit and diagnostics						
Sample size	142	142	142	131	130	130
F-value (*joint model significance test*)	52.72***	50.25***	51.54***	79.76***	72.84***	91.98***
R^2 (*goodness-of-fit measure*)	0.769	0.750	0.772	0.782	0.766	0.782
Ramsey RESET (*omitted variables test*)	1.460	1.300	0.570	1.810	1.870	1.210
Mean VIF (*multicollinearity measure*)	2.180	2.160	2.220	1.950	1.980	1.990

Notes – these estimates relate to the OLS regression model specified in Eq. (1). ***, **, and * represent the 1 % (strong: $p < 0.01$), 5 % (moderate: $0.01 < p < 0.05$), and 10 % (weak: $0.05 < p < 0.10$) conventional levels of statistical significance, respectively. There are no solid fuel CO_2 emissions data available for 2019. A list of countries included in the models are provided in Table 6. For details about the data, see Table 1 and the main text.

Table 5
HAAP high mortality rate robust binary logit regression outputs for total (male + female), male, and female samples, in 2016 and 2019 datasets. HAAP high mortality is defined using cluster analysis.

	2016 dataset			*2019 dataset*		
	Total	Male	Female	Total	Male	Female
Macro-level predictors odds ratios						
Rural clean cooking access	0.974**	0.938***	0.988	0.931***	0.923***	0.924***
Rural electricity access	0.950**	0.992	0.922***	1.000	1.001	1.029
Labour force participation rate	0.949	0.940	0.948**	0.991	0.909*	0.990
Rural population percent	1.029	1.039**	1.039	1.040*	1.038*	1.044*
School enrolment (*primary*)	0.999	0.960	0.998	0.991	0.927*	1.016
Solid fuel CO_2 emissions	1.017	1.003	1.029**	–	–	–
Health expenditure *(% of GDP)*	0.718**	0.633***	0.677***	0.590***	0.707**	0.654***
Model fit and diagnostics						
Sample size	142	142	142	131	130	130
Wald χ^2 (*joint model significance test*)	39.16***	31.22***	42.85***	48.27***	56.54***	52.52***
Pseudo R^2 (*goodness-of-fit measure*)	0.653	0.620	0.686	0.672	0.620	0.659
Correctly classified rate	90.14 %	90.85 %	90.85 %	90.84 %	87.69 %	88.46 %
Area under ROC curve	0.961	0.953	0.971	0.967	0.953	0.965

Notes – these estimates relate to the binary logit regression model specified in Eq. (2), using cluster analysis on HAAP mortality for the total, male, and female samples in 2016 and 2019. For all other details, see notes on Table 4.

cooking are largest and strongly significant (where all $p < 0.01$) in the 2019 samples, such that a 1 % increase in rural access reduces the probability that a country is classified in the high HAAP mortality cluster by 6.9 % ([1-0.931]*100) in the total sample, by 7.7 % ([1-0.923]*100) in the male sample, and 7.6 % ([1-0.924]*100) in the female sample. For 2016, rural access to clean cooking resources is moderately significant (where $p < 0.05$) for the total sample, decreasing the probability of being in the high HAAP mortality cluster by 2.6 % ([1-0.974]*100); strongly significant (where $p < 0.01$) in the male sample, decreasing the probability of being in the high HAAP mortality cluster by 6.2 % ([1-0.938]*100); but not significant for the female sample ([1-0.988]*100 = 1.2 %). Instead, for the female sample in the 2016 dataset, other important macro-level predictors include: (i) the proportion of the population with rural access to electricity – the odds of being classified as a high HAAP mortality country decreases by 7.8 % ([1-0.922]*100, where $p < 0.01$) when there is a 1 % increase in rural electricity access; (ii) female labour force participation rate – where greater participation reduces the odds of being classified in the high HAAP mortality grouping by 5.2 % ([1-0.948]*100, where $p < 0.05$); and (iii) CO_2 emissions from solid fuel consumption, where a higher portion of solid fuel emissions as a percent of total fuel consumption increases the odds of a country being characterised by high HAAP related deaths by 2.9 % ([1.029-1]*100, where $p < 0.05$). This latter finding resonates with a wide body of literature on the elevated health risk that the combustion of biomass poses for women (see, e.g., Gwenzi et al., 2015; Srinivasan and Carattini, 2020). For males, the 2019 dataset shows that a 1 % increase in their participation in the labour force and their gross primary school enrolment rate reduce their odds of a high HAAP mortality rate by 9.1 % ([1-0.909]*100) and 7.3 % ([1-0.927]*100), respectively, with weak statistical significance in both instances ($0.05 < p < 0.10$). Moreover, the odds of a relatively higher HAAP mortality rate status increase in countries with relatively higher rural populations. In 2019, these effects are weakly significant ($p < 0.10$) across all samples, where a 1 % rise in the rural population increases the odds of being in the high HAAP mortality cluster by 4 % ([1.040-1]*100) in the total (male + female) sample, by 3.8 % ([1.038-1]*100) in the male sample, and by 4.4 % ([1.044-1]*100) in the female sample; while for males in 2016, a 1 % increase in the rural population leads to a 3.9 % ([1.039-1]*100) increase in being in the high HAAP mortality cluster, with moderate statistical significance ($0.01 < p < 0.05$). Importantly, an increase in current healthcare expenditure as a percent of GDP is statistically significant in reducing the odds of being in the high HAAP mortality cluster across all of our six binary logit regression models. For example, across both 2016 and 2019 datasets and samples (total, male, and female), the

Table 6
The 150 countries included in our OLS and binary logit regression models across total (male + female), male, and female samples for the 2016 and 2019 datasets.

Country	2016			2019			Country	2016			2019			Country	2016			2019		
	T	M	F	T	M	F		T	M	F	T	M	F		T	M	F	T	M	F
Afghanistan	H	H	H	H	H	H	Germany	L	L	L	L	L	L	Pakistan	H	H	H	H	H	H
Albania	L	H	L	X	X	X	Ghana	H	H	H	H	H	H	Panama	L	L	L	X	X	X
Algeria	L	L	L	L	L	L	Greece	L	L	L	L	L	L	PNG	H	H	H	X	X	X
Argentina	L	L	L	L	L	L	Guatemala	L	H	L	H	H	H	Peru	L	H	L	L	L	L
Armenia	L	H	L	L	H	L	Guinea	H	H	H	H	H	H	Philippines	H	H	H	H	H	H
Australia	L	L	L	L	L	L	Hungary	L	L	L	L	L	L	Poland	X	X	X	L	L	L
Austria	L	L	L	L	L	L	Iceland	L	L	L	L	L	L	Portugal	L	L	L	L	L	L
Azerbaijan	L	H	L	H	H	H	India	H	H	H	H	H	H	Qatar	L	L	L	H	L	H
Bahrain	L	L	L	L	L	L	Indonesia	H	H	H	H	X	X	Romania	L	H	L	L	H	L
Barbados	L	L	L	L	L	L	Iran	L	L	L	L	L	L	Russia	L	L	L	L	H	L
Belarus	L	H	L	L	H	L	Ireland	L	L	L	L	L	L	Rwanda	H	H	H	H	H	H
Belgium	L	L	L	L	L	L	Israel	L	L	L	L	L	L	Samoa	L	H	L	H	H	H
Belize	L	L	L	L	L	L	Italy	X	X	X	L	L	L	STP	H	H	H	X	X	X
Benin	H	H	H	H	H	H	Japan	L	L	L	L	L	L	Saudi Arabia	L	H	L	X	X	X
Bhutan	H	H	H	H	H	H	Jordan	L	L	L	L	L	L	Senegal	H	H	H	H	H	H
Bolivia	L	H	L	L	L	H	Kazakhstan	L	H	L	H	H	H	Serbia	L	H	L	L	H	L
Brazil	L	L	L	L	L	L	Kenya	L	H	L	H	H	H	Sierra Leone	H	H	H	H	H	H
Brunei	L	L	L	L	L	L	Korea	L	L	L	L	L	L	Singapore	L	L	L	L	L	L
Burundi	H	H	H	H	H	H	Kuwait	H	H	H	L	L	L	Slovak Republic	L	L	L	L	L	L
Cabo Verde	H	H	H	H	H	H	Kyrgyz Rep.	H	H	H	H	H	H	Slovenia	L	L	L	L	L	L
Cambodia	H	H	H	H	H	H	Lao PDR	H	H	H	H	H	H	Solomon Isl.	H	H	H	H	H	H
Cameroon	H	H	H	H	H	H	Latvia	L	L	L	L	L	L	South Africa	L	H	L	L	H	L
Canada	L	L	L	L	L	L	Lesotho	H	H	H	H	H	H	Spain	L	L	L	L	L	L
CAF	H	H	H	X	X	X	Liberia	H	H	H	X	X	X	Sri Lanka	L	H	L	H	H	H
Chad	H	H	H	X	X	X	Lithuania	L	L	L	L	L	L	St. Lucia	L	L	L	L	L	L
Chile	L	L	L	L	L	L	Luxembourg	L	L	L	L	L	L	St. VCT	L	L	L	L	L	L
China	H	H	H	H	H	H	Madagascar	X	X	X	H	H	H	Sudan	H	H	H	X	X	X
Colombia	L	L	L	L	L	L	Malawi	H	H	H	H	H	H	Suriname	L	H	L	L	L	L
Comoros	H	H	H	X	X	X	Malaysia	L	L	L	L	H	L	Sweden	L	L	L	L	L	L
Costa Rica	L	L	L	L	L	L	Maldives	L	L	L	L	L	L	Switzerland	L	L	L	L	L	L
Cote d'Ivoire	H	H	H	H	H	H	Mali	H	H	H	X	X	X	Tajikistan	H	H	H	X	X	X
Croatia	L	L	L	L	L	L	Malta	L	L	L	L	L	L	Tanzania	H	H	H	H	H	H
Cuba	L	L	L	L	L	L	Mauritius	L	L	L	L	L	L	Thailand	L	H	L	L	L	L
Cyprus	L	L	L	L	L	L	Mexico	L	L	L	L	L	L	Timor-Leste	H	H	H	H	H	H
Czechia	L	L	L	L	L	L	Moldova	L	H	L	L	H	L	Togo	H	H	H	H	H	H
Denmark	L	L	L	L	L	L	Mongolia	H	H	H	H	H	H	Tonga	X	X	X	L	L	L
Djibouti	H	H	H	H	H	H	Montenegro	L	H	L	H	H	H	Tunisia	L	H	L	X	X	X
Dominican Rep.	L	L	L	L	L	L	Morocco	L	L	L	L	L	L	Turkiye	L	H	L	L	L	L
Ecuador	L	L	L	L	L	L	Mozambique	H	H	H	H	H	H	Turkmenistan	X	X	X	H	H	H
Egypt	H	H	H	H	H	H	Myanmar	H	H	H	X	X	X	Uganda	H	H	H	X	X	X
Eritrea	H	H	H	H	H	H	Namibia	H	H	H	H	H	H	UAE	L	L	L	L	L	L
Estonia	L	L	L	L	L	L	Nepal	H	H	H	X	X	X	United Kingdom	L	L	L	L	L	L
Eswatini	H	H	H	H	H	H	Netherlands	L	L	L	L	L	L	United States	L	L	L	L	L	L
Ethiopia	H	H	H	H	H	H	New Zealand	L	L	L	L	L	L	Uruguay	L	L	L	L	L	L
Fiji	H	H	L	H	H	H	Nicaragua	L	L	L	H	H	H	Uzbekistan	L	H	L	H	H	H
Finland	L	L	L	L	L	L	Niger	H	H	H	H	H	H	Vanuatu	H	H	H	H	H	H
Gambia	H	H	H	X	X	X	Nigeria	H	H	H	H	H	H	Venezuela	L	L	L	X	X	X
France	X	X	X	L	L	L	N. Macedonia	X	X	X	H	H	H	Vietnam	L	H	L	H	H	H
Gabon	X	X	X	H	H	L	Norway	L	L	L	L	L	L	Zambia	H	H	H	X	X	X
Georgia	H	H	L	H	H	H	Oman	L	L	L	H	H	H	Zimbabwe	H	H	H	H	H	H

Notes – the countries included in the OLS and logit regression models for the dataset of the same year are identical within the total (T); male (M); and female (F) samples. Between these samples (T, M, and F) for a given year, there is only one omission – in 2019, for both male and female samples, Indonesia is excluded because of missing data. The following additional abbreviations and acronyms apply: H (L) is the high (low) household and ambient air pollution (HAAP) mortality rate group, sorted using a -means cluster analysis algorithm based on Euclidean distance; and X implies a country is omitted due to missing data. Additionally, Isl. = Islands; N. = North; Rep. = Republic; United Arab Emirates = UAE. The following ISO alpha-3 country codes are adopted for the Central African Republic (CAF); Papua New Guinea (PNG); Sao Tome and Principe (STP); and Saint Vincent and the Grenadines (St. VCT). Korea refers to the Republic of Korea (South Korea). Country names highlighted in dark (light) green are Advanced Economies (Emerging and Developing Economies), classified by the IMF World Economic Outlook (available at https://www.imf.org/en/Publications/WEO/weo-database/2023/April/groups-and-aggregates). Cuba is unclassified because it is not an IMF member country. For details on the graduated orange colour palette used in the individual cells, refer to the legends and notes in Figs. 1 – 2.

odds ratios indicate that a 1 % rise in healthcare expenditure as a percent of GDP reduces the probability of a country being in the high HAAP mortality cluster with values ranging between 28.2 % ([1-0.718]*100) and 41.0 % ([1-0.590]*100), respectively, with high ($p < 0.01$) or moderate ($p < 0.05$) statistical significance across the six binary logit regressions.

4.2. Model diagnostics

In evaluating the overall fit of the six estimated OLS regression

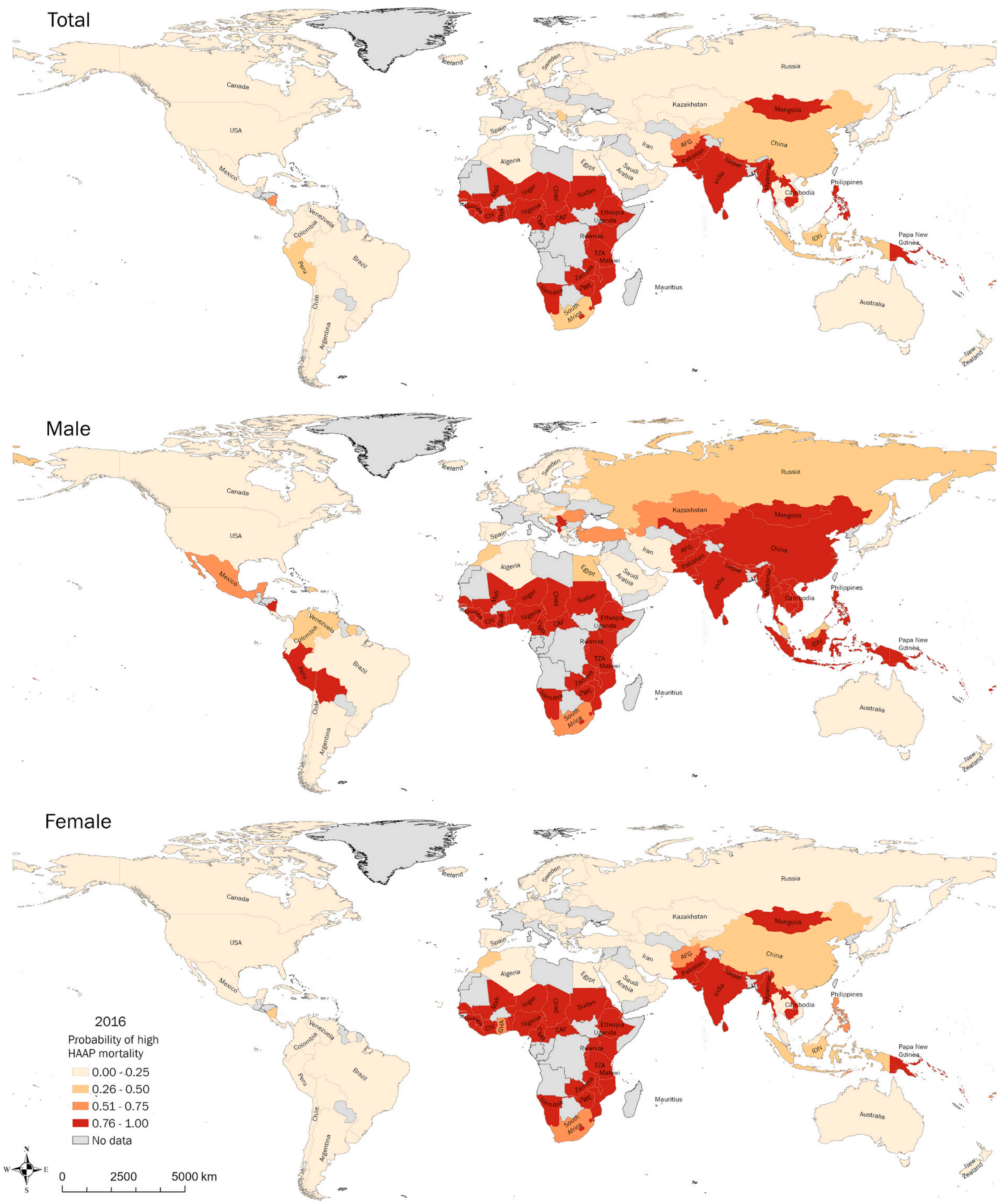

Fig. 1. Global map of predicted high HAAP mortality risk probabilities in 2016, based on our binary logit regression (Eq. (2)). Lighter (darker) shades imply that the macro-level indicators underpinning our logit regression (Table 5) jointly predict that the probability of a country falling in the relatively high HAAP mortality rate cluster is low (high), i.e., less than or equal to 0.50 (more than 0.50). For further details, refer to the map's legend, Table 6, and the main text. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

models in Table 4, the *F*-values suggest that jointly, the macro-level predictors are strongly statistically significant in explaining HAAP mortality rates ($p < 0.01$, for all OLS regressions). Moreover, the R^2 values range from 0.75 to 0.78, showing that more than 75 % of the changes in HAAP mortality rates can be predicted by the variations in the selected macro-level indicators. Additionally, the functional form of the OLS regression model is appropriately specified, as implied by the non-significance of the estimates in the Ramsey *RESET* results at any conventional levels of statistical significance. Thus, there are no omitted non-linear forms of explanatory variables in these regressions. Furthermore, values of $VIF < 5$ suggest that multicollinearity is not an issue in our models. Finally, all our regressions employ robust standard errors as a routine control for the presence of heteroskedasticity.

For our six binary logit regression models, the bottom panel in Table 5 show that the joint model significance tests suggest the macro-level predictors are collectively highly statistically significant ($p < 0.01$, for all logit regressions). In addition, McFadden's pseudo R^2 values are greater than 0.62 for all regressions, suggesting that the

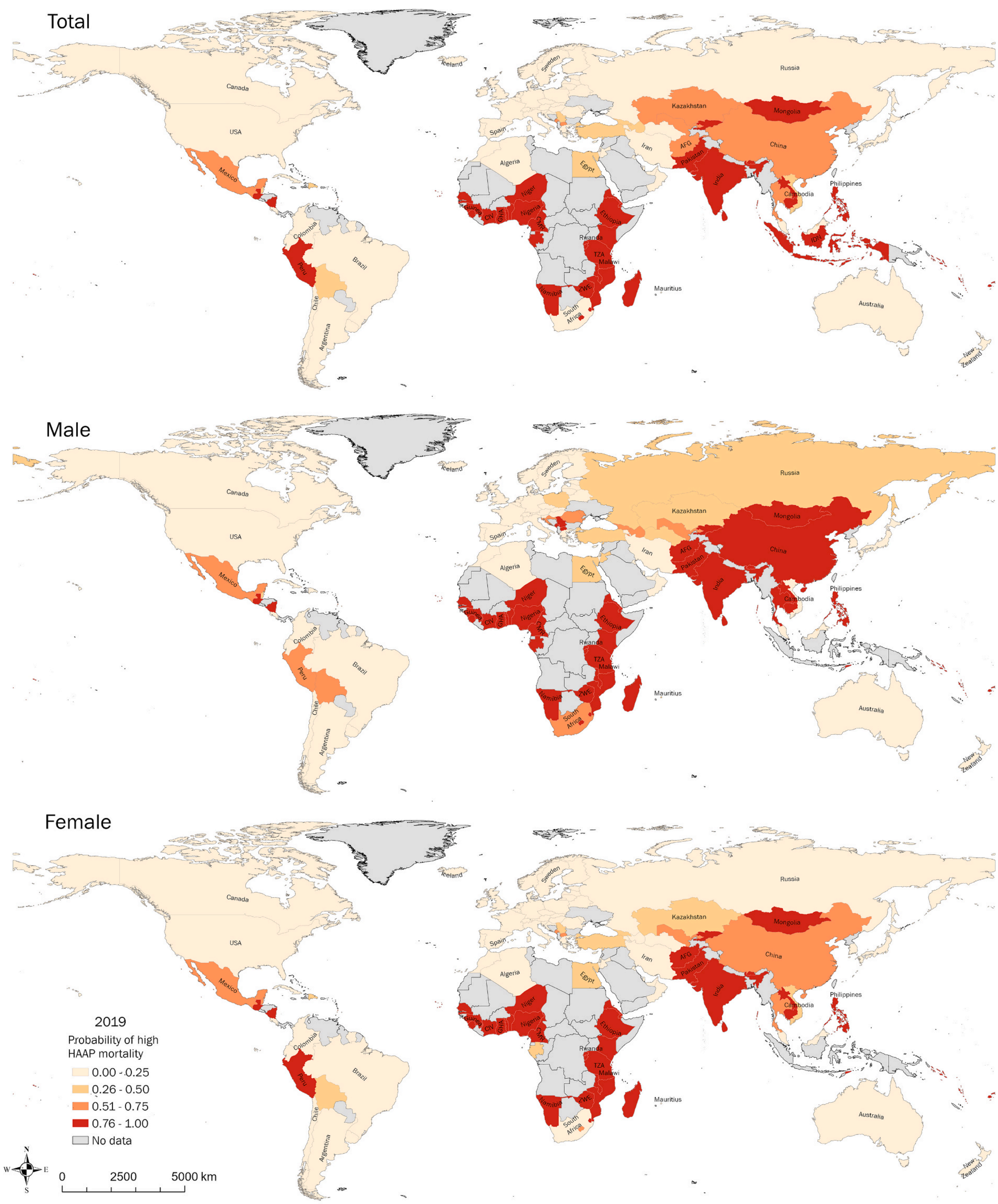

Fig. 2. Global map of predicted high HAAP mortality risk probabilities in 2019, based on our binary logistic regression (Eq. (2)), underpinned by the macro-level indicators in Table 5. For further details, refer to the notes in Fig. 1.

macro-level predictors perform very well in explaining the discrete high and low HAAP mortality outcomes of the binary logit model against a model with only a constant. The correctly classified rate also explains that the models predict the majority of the high and low HAAP mortality rate countries correctly, with values ranging between 88 – 91%. Similarly, the areas under the ROC curves exceed 0.95 in all six binary logit regressions, implying that, for a given country, there is a greater than 95% chance that the selected macro-level indicators will correctly classify a high HAAP mortality rate country as having a high (rather than a low) HAAP mortality rate. Once again, similar to the OLS regression models, robust standard errors are used as a routine control for heteroskedasticity in the logit models.

4.3. Global mapping of predicted probabilities for high HAAP mortality rates

Our global maps of predicted high HAAP mortality risk probabilities illustrate that the macro-level indicators show this environmental health problem affects the Global South more severely than the Global North, across both 2016 and 2019 datasets (Figs. 1–2). In particular, our maps show that it is the Sub-Saharan African and Asian countries in our sample that are at an elevated risk of high HAAP mortality rates. In fact, using the IMF World Economic Outlook dichotomous classification, we see a clear divide on HAAP resilience in Table 6: advanced economies (dark green) are generally resilient to high HAAP mortality risk while emerging and developing economies (light green) are more vulnerable. The only exception here is the 2019 male sample in Croatia (an advanced economy). Table 6 further reveals that the categorical probabilities of high HAAP death rates predicted by our selected macro-level indicators (represented by darker orange shades) conform with the non-hierarchical clustering of the world into high (H) and low (L) mortality countries. This echoes the high McFadden indices (Pseudo R^2; > 0.62), correctly classified rates ($> 87\%$), and areas of the ROC curves (> 0.95) of our six binary logit regression models (reported in Section 4.2 and the bottom panel of Table 5).

It is, therefore, understandable that much of the case studies in the literature have devoted special critical attention to the environmental, health, and development issues that HAAP poses to rural areas in Global South countries. Hence, we frame our results for several of the Global South countries in our samples, which are classified with a relatively high HAAP mortality rate by the clustering algorithm and the selected macro-level predictors, with the findings from these case studies. For example, Krishnapriya et al. (2021) investigate how improved cookstove adoption across six countries – Ethiopia, Zambia, Rwanda, Myanmar, Nepal, and Cambodia – affects time use and labour supply, particularly examining gender-disaggregated impacts using household survey data. They found that, by reducing time spent cooking and exposure to indoor air pollution, especially for women, improved cookstoves can contribute to better health outcomes and increased productivity. Indeed, their analysis is consistent with our regression results on the importance of rural clean cooking technology and fuel access in reducing HAAP mortality.

Focusing on the Sub-Saharan countries with a high HAAP mortality risk, based on both our cluster analysis and macro-level predictors, provide important country-level context for this region. In Chilumba in Malawi, Cundale et al. (2017) found that clean cookstoves are not widely perceived as a "health intervention". From a cooking and pneumonia randomised control trial, they also reveal that cookstoves have no significant impact on pneumonia reduction in children under five. Additionally, Ronzi et al. (2019)'s study on the advancement and uptake of clean cooking in South-West Cameroon revealed that affordability, accessibility, and safety concerns are key barriers to adopting liquefied petroleum gas for cooking, while community-driven approaches like photovoice can help engage stakeholders and identify solutions for advancing equitable access to clean cooking fuels. Harrell et al. (2016) compared alternative methods for measuring cookstove use in rural Mbarara households in Uganda, and found that using multiple monitoring strategies can more accurately audit carbon offsets, which is critical for ensuring that improved cookstove programmes effectively reduce harmful indoor air pollution and improve public health outcomes. The findings of these studies on Sub-Saharan Africa echo the importance of the macro-level patterns identified in our analysis, particularly the role of limited rural access to clean cooking fuels and electricity in driving high HAAP mortality rates, reinforcing the structural vulnerabilities of this region.

Examining studies undertaken for South Asian countries classified with a relatively high HAAP mortality rate from the cluster analysis and macro-level predictors in our sample, the subsequent country-specific evidence is useful for painting a similar picture. Jewitt et al. (2022) highlight that reducing household air pollution requires not only improved cookstove adoption but sustained use in the Majhi Feda Nepalese village, facilitated by behavioural change strategies and kitchen reconfigurations, to achieve lasting respiratory health benefits. Using a nationally representative survey and satellite $PM_{2.5}$ data from Bangladesh, Kurata et al. (2020) found that household air pollution is linked to greater respiratory illness in girls while prenatal ambient pollution increases stunting in boys, highlighting the need for targeted interventions. Additionally, Jeuland et al. (2015) employed both revealed and stated preference analyses among rural households in the north Indian states of Uttar Pradesh and Uttarakhand, to assess demand for improved cookstove features. They suggested that a persistent preference for traditional stoves, unless substantial reductions in smoke and fuel consumption are achieved, hinders the uptake of cleaner technologies and consequently deter potential health improvements from reduced household air pollution. Again, these South Asian studies align with our regression results and spatial mapping, which reveal that countries with low rural access to clean cooking fuels and high rural populations are consistently predicted to have elevated HAAP mortality risk, highlighting the need for both infrastructural and behavioural interventions.

Penultimately, we further contextualise our analysis in terms of the recent (2025) World Bank report, on '*Accelerating Access to Clean Air for a Livable Planet*'.[7] Indeed, the two analyses complement each other – while the World Bank report examines forward-looking scenario modelling to project reductions in $PM_{2.5}$ exposure by 2040 and advocates for a suite of decarbonisation and air-quality management policies to unlock substantial co-benefits, our study provides empirical evidence from 150 countries that highlights how specific macro-level factors (such as access to clean cooking fuels, rural electrification, and healthcare expenditure) critically influence HAAP mortality rates. Our granular analysis supports the World Bank report's broader recommendations by emphasising the socioeconomic, gendered, and rural/urban disparities which influence health outcomes that align with achieving key United Nations SDGs (3, 5, and 7).

Finally, an important consolidated result illustrated by our preliminary data analysis (Section 3) and global spatial mapping (Figs. 1 and 2, and Table 6) is that males are more at risk of premature HAAP related death than females. For example, in 2016, the average male HAAP mortality rate across countries was 101 deaths per 100,000 compared to 79 deaths per 100,000 for females; while, in 2019, the averages were 103 and 73, respectively (Table 2). Moreover, visual inspections of the global spatial maps in Fig. 1 (2016) and 2 (2019) show higher predicted probabilities of a high HAAP mortality classification for males (compared to females) based on the macro-level indicators. Such findings diverge from conventional assumptions in the related literature previously mentioned, which typically emphasises the disproportionate burden of indoor air pollution on women and children because of

[7] World Bank. Accelerating Access to Clean Air for a Livable Planet (English). Washington, D.C.: World Bank Group. http://documents.worldbank.org/curated/en/099032625132535486 (accessed in June 2025).

household cooking roles. However, by considering both sources (household and ambient) of pollution mortality at the national level, a more complex gendered exposure pattern emerges. In emerging and developing economies, men are generally disproportionately employed in manual occupations that involve heightened exposure to ambient air pollution from transportation, construction, or manufacturing (Pan et al., 2023). Men also have higher rates of tobacco use,[8] compounding their respiratory risk. Studies further suggest that men underutilise preventive healthcare services (Baker, 2024), making them less inclined to seek timely medical treatment for air pollution-related symptoms. Therefore, biological and behavioural vulnerabilities may intersect with occupational exposure in ways that elevate male mortality risk despite women's reportedly greater time spent indoors. Thus, using gender-disaggregated HAAP mortality data to inform targeted interventions remains a key priority, alongside the need to avoid one-size-fits-all policy assumptions that dominate the discourse on health risks in rural villages of the Global South.

4.4. Sensitivity tests

Although the 2016 and 2019 datasets serve as sensitivity for each other in terms of data, and the OLS (linear) and binary logit (non-linear) regressions serve as sensitivity in terms of models, a natural extension is to determine the consistency of our findings in Table 4 with a subsample of Global South countries. To this end, we use the IMF World Economic Outlook classification adopted in Table 6 (see table notes), which sorts the countries in our sample into "Advanced Economies" and "Emerging and Developing Economies", to develop a further sensitivity exercise. Given that our main findings suggest advanced economies demonstrate a clear resilience to HAAP mortality risks, and that emerging and developing economies (EDEs) are disproportionately vulnerable, we rerun the OLS regression on the sample of EDEs and compare the findings with the full sample.

In 2016 datasets, in the EDEs subsample, there are 108 countries in the total (male + female), male, and female groups (compared to 142 countries in the full sample) while, in 2019 EDEs subsample, there are 95 countries in the total (male + female), and 94 in the male and female groups (compared to 131 in the total [male + female] and 130 in male and female groups in the full sample). The results of the EDEs subsample regressions are provided in Table 7. These additional results show that, in a subsample of countries that consist of EDEs only, there is a general consistency in the sign, size, and statistical significance of rural access to clean cooking fuels and technology in both 2016 and 2019 datasets. For example, a 1 % increase in access to clean cooking tools in rural populations significantly reduces HAAP mortality rates ($p < 0.01$) in all six regressions. We also observed that, once again, rural electricity access and labour force participation rates are both important factors in reducing HAAP mortality in the 2016 dataset ($p < 0.01$ in the total [male + female] and male groups, and $p < 0.05$ in the female group). Furthermore, the composition of the total population that is rural is significant in increasing HAAP mortality rates in the 2019 dataset ($p < 0.05$). As with the main OLS results (Table 4), the EDEs subsample (Table 7) also show some differences in significance between the 2016 and 2019 estimates. These variations reflect the fact that the two datasets are independent cross-sections with partly different country compositions and evolving macro-level conditions across years, which naturally affect coefficient precision in smaller subsamples. Yet, once again, the percentage of the rural population with access to clean cooking methods remains a stable and influential predictor in both years, reinforcing the robustness of our central findings.

Model diagnostic tests are also satisfied. For instance, the variables included in the regression models are jointly significant ($p < 0.01$, for the *F*-values of all six regressions), goodness-of-fit measures are marginally lower than the full sample to reflect the smaller sample size (now in the high 0.60s compared to high 0.70s in the full sample), and the mean VIFs are still all < 5 which indicates that multicollinearity is non-consequential in the EDEs subsample regression models. While some of the Ramsey *RESET* results ($p < 0.05$ in four of the subsample regressions, $p < 0.01$ in one of the subsamples, and p not significant in another) indicate that alternative functional forms of the explanatory variables might better represent the data, we do not explore these additional specifications to keep the subsample results comparable with the main results, for the sake of brevity, and because this can be a consequence of the smaller sample size of the EDEs subsample.

We also check whether our findings from the six binary logit regressions (Table 5), which decompose HAAP mortality rates into high and low categorisation with a non-hierarchical k-means clustering algorithm based on Euclidean distance, is robust to an alternative classification method. For this purpose, we compare the top tercile of the HAAP mortality rate countries with the rest of that sample (i.e., the middle + bottom terciles), within each sample (total, male, and female), for each dataset (2016 and 2019). Using this alternative binary classification, we re-estimate the logit regressions and present the results in Table 8. These sensitivity results are broadly consistent with the cluster analysis-based estimates reported in Table 5. In both classifications, rural access to clean cooking fuels remains a strong, stable, and statistically significant predictor of lower HAAP mortality risk across nearly all samples and years. Similarly, rural population share and solid-fuel CO_2 emissions (where available) continue to be positively associated with high mortality risk, while higher healthcare expenditure consistently reduces the likelihood of belonging to the high-risk group.

Some differences in statistical significance emerge between the two classification approaches (cluster analysis and tercile distribution), particularly for labour force participation, rural electricity access, and primary school enrolment in certain samples. These discrepancies arise because the tercile-based approach imposes a mechanically fixed cutoff that does not necessarily reflect the natural separation in the underlying mortality distribution, whereas the clustering algorithm produces groupings that maximise within-group similarity and between-group separation. The resulting differences in group composition and balance affect the precision of estimated coefficients. Nevertheless, the overarching patterns remain stable: the macro-level determinants that are statistically significant and directionally consistent in the cluster-based models behave similarly in the tercile-based models. These findings strengthen confidence in the robustness of our conclusions regarding the key predictors of high HAAP mortality risk.

5. Conclusion

We provide a novel global perspective on the macro-level determinants of HAAP mortality risk, by integrating evidence from 150 countries across recent datasets. We demonstrate that access to clean cooking fuels and technology, rural electrification, and healthcare expenditure are critical factors in reducing premature deaths from HAAP. In contrast, we find that larger rural populations and inefficient energy practices serve as significant risk factors. Importantly, our analyses reveal that males face higher HAAP mortality risks than females, with global average differences of 22 (in 2016) and 30 (in 2019) excess deaths for males per 100,000 people, drawing attention to gender-specific dynamics that require further examination and gender-targeted policy interventions.

Our work makes two important contributions. *First*, we contribute to the literature by moving beyond localised case studies to offer comprehensive global evidence linking socioeconomic and environmental indicators with HAAP mortality. Our OLS and binary logit regression analyses, alongside our spatial mapping, highlight the robustness of these macro-level determinants. *Second*, our research provides a breath of analysis that span the areas of health, energy, labour, environment, and education, which are all important dimensions

[8] See: https://ourworldindata.org/who-smokes-more-men-or-women.

Table 7

HAAP mortality rate OLS robust regression outputs in the *Emerging and Developing Economies* subsample for total (male + female), male, and female samples, in the 2016 and 2019 datasets.

	2016 EDE dataset			*2019 EDE dataset*		
	Total	Male	Female	Total	Male	Female
Macro-level predictors coefficients						
Rural clean cooking access	−0.840***	−0.939***	−0.773***	−1.173***	−1.345***	−1.007***
Rural electricity access	−0.727***	−0.502**	−0.872***	−0.229	−0.212	−0.322
Labour force participation rate	−1.112***	−1.203**	−0.827***	−0.020	−0.268	−0.320
Rural population percent	0.196	0.225	0.220	0.561**	0.672**	0.497**
School enrolment (*primary*)	−0.525	−0.358	−0.604*	−0.138	0.100	−0.294
Solid fuel CO_2 emissions	0.170	0.247*	0.147	–	–	–
Health expenditure *(% of GDP)*	−1.054	−1.982	0.291	0.614	0.259	1.055
Model fit and diagnostics						
Sample size	108	108	108	95	94	94
F-value (*joint model significance test*)	31.37***	27.75***	34.38***	37.10***	36.39***	41.75***
R^2 (*goodness-of-fit measure*)	0.689	0.665	0.698	0.696	0.673	0.698
Ramsey RESET (*omitted variables test*)	2.790**	2.74**	1.14	3.29**	2.86**	4.18***
Mean VIF (*multicollinearity measure*)	1.94	1.91	1.98	1.71	1.71	1.75

Notes – the results of these regressions are based on a subsample which includes all countries listed in light green in Table 6. This corresponds to all countries in our sample that are classified as Emerging and Developing Economies in the IMF World Economic Outlook (see notes on Table 6 for further details). For all other details, see notes on Table 4.

Table 8

HAAP high mortality rate robust binary logit regression outputs for total (male + female), male, and female samples, in 2016 and 2019 datasets. HAAP high mortality is defined using the top mortality tercile.

	2016 dataset			*2019 dataset*		
	Total	Male	Female	Total	Male	Female
Macro-level predictors odds ratios						
Rural clean cooking access	0.959**	0.941***	0.978	0.961***	0.956***	0.956***
Rural electricity access	0.939***	0.990	0.901***	0.983	0.987	0.985
Labour force participation rate	0.897**	0.941	0.930**	0.994	0.979	0.999
Rural population percent	1.043*	1.024	1.068**	1.055***	1.064***	1.035*
School enrolment (*primary*)	1.008	0.949*	1.012	1.010	1.000	0.982
Solid fuel CO_2 emissions	1.046***	1.018	1.038***	–	–	–
Health expenditure *(% of GDP)*	0.684***	0.847	0.726*	0.808*	0.832	0.768**
Model fit and diagnostics						
Sample size	142	142	142	131	130	130
Wald χ^2 (*joint model significance test*)	42.60***	48.78***	29.76***	56.60***	65.20***	52.93***
Pseudo R^2 (*goodness-of-fit measure*)	0.770	0.652	0.822	0.637	0.666	0.624
Correctly classified rate	95.07 %	91.55 %	96.48 %	91.60 %	91.54 %	91.54 %
Area under ROC curve	0.986	0.966	0.992	0.959	0.968	0.952

Notes – these estimates relate to the binary logit regression model specified in Eq. (2), using the top tercile of HAAP mortality for the total, male, and female samples, in 2016 and 2019. For all other details, see notes on Table 4.

in understanding HAAP mortality risks. Such perspectives are directly relevant to governmental and international initiatives aimed at realising several United Nations Sustainable Development Goals, namely SDG 3 (good health and well-being), SDG 5 (gender equality), and SDG 7 (affordable and clean energy). In doing so, our study helps to close a clear gap in the literature. Earlier work has mostly focused on villages or single countries, but here we provide the bigger picture across 150 nations. This broader perspective not only enhances academic understanding but also provides international agencies and governments with further evidence to design interventions and monitor progress toward critical SDGs.

From a policy perspective, our findings point to the need for a reorientation of policy strategies toward integrated, sector-spanning solutions. Clean cooking initiatives, for example, should be prioritised in countries with low rural access to clean cooking fuels. Programs such as India's Pradhan Mantri Ujjwala Yojana 2.0,[9] which distributed subsidised liquefied petroleum gas connections to poor rural households, offer a promising blueprint. However, expanding access must be accompanied by sustained affordability, user training, and behavioural reinforcement to prevent a fallback to traditional (inefficient) cooking fuels. Similarly, rural electrification efforts must go beyond infrastructure provision to ensure reliability, affordability, and end-use connectivity. Decentralised energy solutions, such as solar photovoltaic mini-grids (Baldi et al., 2022), may offer faster and more inclusive gains in hard-to-reach areas. Healthcare systems must also be strengthened to better diagnose and manage pollution-related illnesses, especially in rural zones where under-resourced clinics may be common. Our findings also support gender-sensitive policy design. For example, promoting women's labour force participation could have indirect health benefits by reducing time spent in polluting household environments. Education and awareness campaigns can further empower households to adopt cleaner practices. Regionally targeted interventions also seem essential from our findings: in Sub-Saharan Africa, for example, efforts should focus on improving affordability, accessibility, and community engagement to enhance clean fuel access and adoption; while in South Asia, scaling sustained behaviour-change strategies, stove use monitoring, and targeted health interventions is key to reducing household air pollution.

Building on the above, future research should further examine regional disparities and the underlying reasons for higher male mortality rates, to rollout new intervention strategies that address gender-specific vulnerabilities and lower overall HAAP mortality rates. These are the imperative next steps to take in achieving sustainable development and

[9] See https://pmuy.gov.in/about.html.

improving public health resilience in the Global South.

CRediT authorship contribution statement

Scott Mark Romeo Mahadeo: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Avidesh Seenath:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Data curation.

Ethics statement

We do not require ethics approval as our study relies primarily on secondary, publicly available, and anonymised data sources (World Health Organization, World Bank, and International Labour Organization). It does not involve human participants, animals, or any form of primary data collection.

Declaration of competing interest

We declare that there are no known competing financial interests or personal relationships that could have appeared to influence the work in our paper.

Acknowledgments

Earlier versions of this paper were presented as an invited talk in the Masaryk University Economics Seminar series in 2025; at the 2025 European Geosciences Union General Assembly special session on "atmospheric science for action: linking air quality, climate, health, equity, and policy"; and as an invited lecture at the University of Oxford's Environmental *Change* Institute in 2024. We thank, without liability, the audiences at these events, as well as the comments received from the anonymous reviewers, for their helpful feedback.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2025.118921.

Data availability

We provide a copy of our results replication files as supplementary materials. No primary data were used in this study. We provide the links to all open-access data accessed in this study.

References

Adrianzén, M.A., 2013. Improved cooking stoves and firewood consumption: Quasi-experimental evidence from the northern Peruvian andes. Ecol. Econ. 89, 135–143.
Alem, Y., Demeke, E., 2020. The persistence of energy poverty: a dynamic probit analysis. Energy Econ. 90.
Baker, P., 2024. Missing persons? Men's use of primary care services. Trends in Urology & Men's Health 15, 2–5.
Baldi, D., Moner-Girona, M., Fumagalli, E., Fahl, F., 2022. Planning sustainable electricity solutions for refugee settlements in Sub-Saharan africa. Nat. Energy 7, 369–379.
Beyene, A.D., Koch, S.F., 2013. Clean fuel-saving technology adoption in urban Ethiopia. Energy Econ. 36, 605–613.
Castells-Quintana, D., Dienesch, E., Krause, M., 2021. Air pollution in an urban world: a global view on density, cities and emissions. Ecol. Econ. 189.
Chowdhury, S., Pillarisetti, A., Oberholzer, A., Jetter, J., Mitchell, J., Cappuccilli, E., Aamaas, B., Aunan, K., Pozzer, A., Alexander, D., 2023. A global review of the state of the evidence of household air pollution's contribution to ambient fine particulate matter and their related health impacts. Environ. Int. 173, 107835.
Conley, T.G., 1999. Gmm estimation with cross sectional dependence. J. Econom. 92, 1–45.
Cundale, K., Thomas, R., Malava, J.K., Havens, D., Mortimer, K., Conteh, L., 2017. A health intervention or a kitchen appliance? Household costs and benefits of a cleaner burning biomass-fuelled cookstove in Malawi. Soc. Sci. Med. 183, 1–10.
Das, D.K., Islam, M.S., Dutta, C.B., Hassan, M.M., Hossen, S.S., 2021. Is there any demand for improved cooking stoves? Evidence from Bangladesh. J. Environ. Manag. 298, 113412.
Dhital, S., Rupakheti, D., Rupakheti, M., Yin, X., Liu, Y., Mafiana, J.J., Alareqi, M.M., Mohamednour, H., Zhang, B., 2022. A scientometric analysis of indoor air pollution research during 1990-2019. J. Environ. Manag. 320, 115736.
Frempong, R.B., Orkoh, E., Kofinti, R.E., 2021. Household's use of cooking gas and children's learning outcomes in rural Ghana. Energy Econ. 103.
García-Frapolli, E., Schilmann, A., Berrueta, V.M., Riojas-Rodríguez, H., Edwards, R.D., Johnson, M., Guevara-Sanginés, A., Armendariz, C., Masera, O., 2010. Beyond fuelwood savings: valuing the economic benefits of introducing improved biomass cookstoves in the Purépecha region of Mexico. Ecol. Econ. 69, 2598–2605.
Gilthorpe, M.S., Wilson, R.C., 2003. Rural/urban differences in the association between deprivation and healthcare utilisation. Soc. Sci. Med. 57, 2055–2063.
Gwenzi, W., Chaukura, N., Mukome, F.N.D., Machado, S., Nyamasoka, B., 2015. Biochar production and applications in Sub-Saharan Africa: opportunities, constraints, risks and uncertainties. J. Environ. Manag. 150, 250–261.
Harrell, S., Beltramo, T., Blalock, G., Kyayesimira, J., Levine, D.I., Simons, A.M., 2016. What is a "meal"? Comparative methods of auditing carbon offset compliance for fuel-efficient cookstoves. Ecol. Econ. 128, 8–16.
Jeuland, M.A., Bhojvaid, V., Kar, A., Lewis, J.J., Patange, O., Pattanayak, S.K., Ramanathan, N., Rehman, I.H., Tan Soo, J.S., Ramanathan, V., 2015. Preferences for improved cook stoves: evidence from rural villages in North India. Energy Econ. 52, 287–298.
Jewitt, S., Smallman-Raynor, M., K, C.B., Robinson, B., Adhikari, P., Evans, C., Karmacharya, B.M., Bolton, C.E., Hall, I.P., 2022. Domesticating cleaner cookstoves for improved respiratory health: using approaches from the sanitation sector to explore the adoption and sustained use of improved cooking technologies in Nepal. Soc. Sci. Med. 308, 115201.
Jin, Y., Ma, X., Chen, X., Cheng, Y., Baris, E., Ezzati, M., China Rural, E., Health Research, G., 2006. Exposure to indoor air pollution from household energy use in rural China: the interactions of technology, behavior, and knowledge in health risk management. Soc. Sci. Med. 62, 3161–3176.
Kanagawa, M., Nakata, T., 2007. Analysis of the energy access improvement and its socio-economic impacts in rural areas of developing countries. Ecol. Econ. 62, 319–329.
Krishnapriya, P.P., Chandrasekaran, M., Jeuland, M., Pattanayak, S.K., 2021. Do improved cookstoves save time and improve gender outcomes? Evidence from six developing countries. Energy Econ. 102.
Kurata, M., Takahashi, K., Hibiki, A., 2020. Gender differences in associations of household and ambient air pollution with child health: evidence from household and satellite-based data in Bangladesh. World Dev. 128.
Lee, L.Y.-T., 2013. Household energy mix in Uganda. Energy Econ. 39, 252–261.
Li, Q., Jiang, J., Wang, S., Rumchev, K., Mead-Hunter, R., Morawska, L., Hao, J., 2017. Impacts of household coal and biomass combustion on indoor and ambient air quality in China: current status and implication. Sci. Total Environ. 576, 347–361.
Mekonnen, A., Beyene, A., Bluffstone, R., Gebreegziabher, Z., Martinsson, P., Toman, M., Vieider, F., 2022. Do improved biomass cookstoves reduce fuelwood consumption and carbon emissions? Evidence from a field experiment in rural Ethiopia. Ecol. Econ. 198.
Mestl, H.E., Aunan, K., Seip, H.M., Wang, S., Zhao, Y., Zhang, D., 2007. Urban and rural exposure to indoor air pollution from domestic biomass and coal burning across China. Sci. Total Environ. 377, 12–26.
Pan, X., Hong, F., Li, S., Wu, J., Xu, H., Yang, S., Chen, K., Baima, K., Nima, Q., Meng, Q., Xia, J., Xu, J., Guo, B., Lin, H., Xie, L., Zhang, J., Zhao, X., China Multi-Ethnic Cohort Collaborative, G, 2023. Long-term exposure to ambient pm(2.5) constituents is associated with dyslipidemia in Chinese adults. Ecotoxicol. Environ. Saf. 263, 115384.
Ronzi, S., Puzzolo, E., Hyseni, L., Higgerson, J., Stanistreet, D., Hugo, M.N.B., Bruce, N., Pope, D., 2019. Using photovoice methods as a community-based participatory research tool to advance uptake of clean cooking and improve health: the lpg adoption in Cameroon evaluation studies. Soc. Sci. Med. 228, 30–40.
Srinivasan, S., Carattini, S., 2020. Adding fuel to fire? Social spillovers in the adoption of lpg in India. Ecol. Econ. 167.
Ssennono, V.F., Ntayi, J.M., Buyinza, F., Wasswa, F., Aarakit, S.M., Mukiza, C.N., 2021. Energy poverty in Uganda: evidence from a multidimensional approach. Energy Econ. 101.
Talevi, M., Pattanayak, S.K., Das, I., Lewis, J.J., Singha, A.K., 2022. Speaking from experience: preferences for cooking with biogas in rural India. Energy Econ. 107.
Wang, P., Liu, D., Mukherjee, A., Agrawal, M., Zhang, H., Agathokleous, E., Qiao, X., Xu, X., Chen, Y., Wu, T., Zhu, M., Saikawa, E., Agrawal, S.B., Feng, Z., 2023. Air pollution governance in China and India: Comparison and implications. Environ. Sci. Pol. 142, 112–120.
World Health Organization, 2024. See. https://www.who.int/news-room/fact-sheets (accessed in June 2025).