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Use of a synthetic population to model co-benefits to air quality and health from household fuel emission mitigation policies in Kenya

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Abstract

Energy emissions mitigation policies bring co-benefits for health and opportunities to drive sustainable development for rapidly transitioning economies in sub-Saharan Africa. Developing methods of quantifying these co-benefits in differing demographic groups is an area of interest for policymakers to support resource allocation efforts. Using synthetic populations of three municipalities in Kenya, we assessed the impact of policies to promote the use of clean cooking fuels on exposure to ambient and household air pollution and associated age- and gender-specific mortality. Exposure to household $PM_{2.5}$ for a range of cooking fuel types and informal and formal housing archetypes were simulated using the building physics software, EnergyPlus. A combined household and ambient $PM_{2.5}$ exposure was calculated for each individual by weighting $PM_{2.5}$ concentrations using national demographic-specific time-activity estimates. Exposure-response functions were applied to quantify the burden of mortality for six associated health outcomes. To compare the health impacts of energy policy implementation, a two-stage policy was tested through medium and long-term transitions towards successively cleaner cooking fuels prioritising liquid petroleum gas and ethanol. The resulting difference in mortality consecutively declined through the two-stage policy transition with the greatest impact after the first transition and an incremental but smaller impact after the second. The overall difference in mortality burden averted per 100 000 population relative to the baseline scenario was largest in Kisumu (males: 39.23; females: 18.09), with smaller decreases in Mombasa (males: 5.71; females: 3.03) and Nairobi (males: 1.82; females: 1.08). A sensitivity analysis showed reductions in $PM_{2.5}$ exposure under the policy scenarios may be overestimated in the presence of fuel stacking practices, where households rely on multiple fuels and stoves. This model provides a proof-of-concept for the use of individual-level modelling methods to estimate demographic-specific health impacts from environmental exposures and quantitatively compare health co-benefits of household fuel emission mitigation policies.

1. Introduction

Recent public health crises have illustrated how the evidence-to-policy translation cycle can be enriched through cross-sectoral collaboration and a whole-of-government approach (Arora *et al* 2014, Ortenzi *et al* 2022). During the COVID-19 pandemic these integrative frameworks gained traction in the development of a coherent strategy across government ministries, departments and agencies (MDAs) to support the public health response. While the pandemic demonstrated the application of this approach to rapidly contain a global disease outbreak, a parallel process has not yet been adopted for the looming public health crisis associated with climate change.

Reasons for the lack of urgency of health policymakers to act on climate change vary but may hinge on insufficient quantitative evidence of health impacts to strengthen the case for action. Microsimulation methods have attracted particular interest to inform health policy decision-making due to the application of spatially fine scales of data and ability to generate demographic-specific disease burden estimates (Hennesey *et al* 2015). These individual-based models rely on synthetic populations generated from publicly available, highly granular data sources to replicate distributions of exposure and population characteristics with a high degree of specificity. The versatility of microsimulation models allows a range of socio-economic variables to be used to capture individual vulnerability, defined as an individual's susceptibility and adaptive capacity to an environmental exposure (IPCC 2021). Accounting for the unequal distribution of vulnerability across social groups is increasingly important in climate change mitigation and adaptation planning; identifying its drivers can refine attribution and burden estimates and enhance decision-making and resource allocation (Thomas *et al* 2019).

In sub-Saharan Africa (SSA), health disparities resulting from rapid population growth, urbanisation and industrialisation are increasingly evident. For instance, in Nairobi, the capital of Kenya, deteriorating air quality is due to combined effects of an influx of people, multi-sector emissions, and weak enforcement and control policies (Gaita *et al* 2014). Measurements of average airborne particulate matter found in the city exceed hazardous levels defined by the World Health Organization (WHO) (Egondi *et al* 2016, World Health Organisation (WHO) 2021). Contributing to this are household air pollutants, produced by combustion of solid cooking and heating fuels which disproportionately impact the urban poor, children and women (Egondi *et al* 2013). Studies have shown that children in Nairobi with exposure to $PM_{2.5}$ in high-pollution areas are at a greater risk of associated health outcomes (Egondi *et al* 2018). Traditional gender roles imply that women may be more vulnerable to household air pollution due to periods of prolonged exposure to high $PM_{2.5}$ levels during food preparation in poorly ventilated cooking areas. The burden of deaths attributable to household air pollution is estimated to be 50% higher for women than men globally (Goldemberg *et al* 2004, Dida *et al* 2022) but few estimates exist for the attributable disease burden of air pollution in Kenya, particularly for gender-specific estimates at sub-national levels. As they share sources with greenhouse gas emissions, air pollutants are a target for climate change mitigation efforts and an essential component of health policy to avert future population health impacts (Zhang *et al* 2017).

To investigate demographic trends in air pollution exposure and health vulnerability, we developed an individual-based synthetic population model of three municipalities in Kenya. Our objectives for the model were two-fold: (1) to estimate age- and gender-specific mortality attributable to spatially varying $PM_{2.5}$ concentrations and accounting for a set of social vulnerabilities; and (2) to provide a proof-of-concept model as a decision-support tool to quantify and compare the ancillary health benefits of a two-stage energy policy for climate change mitigation and sustainable development. Here, we outline work that builds on recent applications of this modelling method for climate change mitigation policies (Philips *et al* 2017, Symonds *et al* 2019) by additionally exploring the linkage of building simulation software, EnergyPlus, to estimate indoor personal $PM_{2.5}$ exposures and the influence of social determinants on health outcome disparities between genders and municipalities.

2. Method

Synthetic populations of Nairobi, Kisumu and Mombasa were generated using a combination of empirical and modelled data sets to develop distributions of demographic features, air pollution ($PM_{2.5}$) exposures, and mortality rates, each of which was subsequently sampled and systematically allocated to each synthetic individual based on their characteristics. Policy interventions were simulated by adjusting the distribution of household cooking fuels and $PM_{2.5}$ exposures in the synthetic population and calculating the corresponding change in health burden. Initial model construction was conducted on the Nairobi population as described here and below and subsequently replicated for Kisumu and Mombasa using municipal-specific data sets.

2.1. Population

A representative synthetic population of each municipality was modelled and coded in R statistical software (R Core Team 2021). The synthetic population was constructed from the 2019 Kenyan census (Kenya National Bureau of Statistics 2019) to form a database of age- and gender-matched individuals directly equivalent to the census populations of Nairobi, Kisumu and Mombasa. Individuals in the model were allocated into single-year age categories from age 0–99 years, male or female genders and into municipal sub-counties based on disaggregated census data. In Kenya, sub-counties are the smallest spatial unit available for population density estimates and together comprise 47 counties to which devolved health responsibilities are administered (Masaba *et al* 2020). Distributions of population attributes for type of housing, type of household primary fuel and indoor/outdoor time-activity data were created from sample data and proportionally allocated to the population; these are described in detail in the next sections.

2.2. Ambient $PM_{2.5}$ exposure

Air pollution was represented in the model by fine particulate matter ($PM_{2.5}$) from observation-constrained, model-derived estimates of annual average $PM_{2.5}$ concentrations at 1×1 km resolution based on previously published methods (Hammer *et al* 2020). The source contribution estimates were obtained from the ECHAM/MESSy atmospheric chemistry (EMAC) general circulation model at a spatial resolution of roughly $1.1 \times 1.1°$. Within EMAC, the monthly varying Community Emissions Data System (CEDS) anthropogenic emission inventory was used at $0.5 \times 0.5°$ resolution for primary $PM_{2.5}$ species (Hoesly *et al* 2018). Annual average $PM_{2.5}$ exposure was sampled for each individual in the model from sub-county specific distributions of gridded exposures.

2.3. Household $PM_{2.5}$ exposure

Domestic indoor $PM_{2.5}$ concentrations were modelled using the building physics tool, EnergyPlus. EnergyPlus is a whole building simulation tool which dynamically models indoor air pollution given building characteristics such as geometry, building materials, airtightness, and occupant behaviour (e.g. window opening frequencies) as inputs (US Department of Energy 2020). Two broad building archetypes were defined in Kenya's 2019 census data: informal and formal housing. For each fuel type and housing (formal/informal) scenario, $n = 100$ simulations were run to capture the underlying variation in housing characteristics that will exist across homes throughout Kenya. Given that there is a dearth of evidence regarding the physical dimensions of housing in Kenya, particularly for informal settlements which are typically self-built using salvaged materials (Janda *et al* 2019), the informal housing archetype model was constructed to be a representation of the large informal settlements found across Nairobi, with floor area inputs sampled according to a distribution informed by data from the WHO Household Multiple Emission Sources (HOMES) model for internal volumes in SSA homes (WHO 2022). Window and door configurations were varied randomly, with some units possessing one or two hollowed out window areas (without glass). Each unit had a doorframe/entrance area that was variably covered with a door material or left open. This was done to introduce variation to the modelled indoor exposure estimates in the absence of empirical data from housing surveys. For formal housing, an existing archetype developed within UCL's Institute for Environmental Design and Engineering (IEDE) based on a high-rise flat was selected to represent a housing unit in one of Nairobi's multi-storey districts. Likewise with the informal archetype, floor areas and glazing proportions for each formal housing unit were varied according to distributions. The thermal characteristics of the dwellings were modified to reflect building air change rates (ACH) seen across the literature for homes in SSA, again informed by data from the WHO HOMES model (WHO 2022) and indicative of the warmer climate of Nairobi.

Data from the Kenya 2019 census provided proportionate use estimates for seven fuel types in Nairobi, Kisumu and Mombasa (shown in table 1). Although it is common for households to use fuel stacking in which primary and secondary fuel types are used for different cooking purposes or to supplement supply limitations (Ochieng *et al* 2020), the dominant fuel is most likely to be reported in surveys and this was therefore used to keep the model parsimonious. To assess the contribution of these fuels to household concentrations of $PM_{2.5}$, distributions of $PM_{2.5}$ emission rates for each fuel were obtained from the literature. We additionally assessed the impact of using ethanol and wood pellets for household fuel, as recent research has shown that ethanol may be a viable alternative to charcoal and the popular stove, Kenyan Ceramic Jiko, may be retrofitted to burn ethanol (Chomanika *et al* 2022). Likewise, gasifier-based wood pellet stoves have been piloted in peri-urban parts of Kenya as an alternative to traditional firewood (Bailis *et al* 2020). Emission rates were primarily obtained from studies conducted in laboratory conditions provided by the WHO HOMES model (WHO 2022).

Emission rates for charcoal and firewood were derived from the Stove Emissions Inventory (Berkley Air Monitoring Group 2012) and emission rates for liquid petroleum gas (LPG) were derived from a study of 89

Table 1. Fuel type usage for Nairobi, Kisumu and Mombasa and fuel-specific $PM_{2.5}$ emission rates (mean ± standard deviation).

Fuel type	Proportion of usage (%) Nairobi	Kisumu	Mombasa	$PM_{2.5}$ emission rate $\mu g\ m^{-3}$ (mean ± SD)	Emission rate source
Firewood	0.76	44.87	4.32	43.40 ± 29.40	(Berkeley Air Monitoring Group 2012)
Charcoal	2.68	24.28	21.69	6.20 ± 4.60	(Berkeley Air Monitoring Group 2012)
Paraffin (Kerosene)	25.50	9.55	30.80	0.70 ± 0.30	(Watts *et al* 2019)
Liquid petroleum Gas (LPG)	68.18	19.69	40.70	0.20 ± 0.16	(Shen *et al* 2018)
Electricity	2.25	0.88	1.37	0.18 ± 0.82	(Hu 2012)
Ethanol (Biogas)	0.62	0.58	1.11	0.09[a]	(Chomanika *et al* 2022)
Wood pellets	0.00	0.00	0.00	3.21 ± 2.03	(Gituku *et al* 2021)
Total	100	100	100	—	—

[a] *No standard deviation was provided for ethanol fuel in* Chomanika *et al* (2022)*, thus a constant value was assumed.*

laboratory tests on five commercially available household LPG stoves (Shen *et al* 2018). There is a paucity of data on measured kerosene emission rates in both field and laboratory settings, despite the widespread use of this fuel across many low- and middle-income countries. We therefore used a value previously applied in modelling studies by authors where the resultant household concentrations broadly align with empirical data (Watts *et al* 2019). For electric stoves, a database of $PM_{2.5}$ emission rates compiled from 13 different studies was used (Hu *et al* 2012). For the two intervention fuels, ethanol $PM_{2.5}$ emission rates were taken from a study testing Kenyan Ceramic Jikos in Malawi kitchens under laboratory conditions (Chomanika *et al* 2022) and laboratory tests assessing emissions in wood pellet gasifier stoves (Gituku *et al* 2021).

A distribution of emission rates was generated for each fuel and assigned to $n = 100$ EnergyPlus models for each archetype (formal and informal) to capture the underlying uncertainty associated with this parameter. Indoor cooking was assumed to last for three hours per day at different time intervals, informed by the WHO HOMES model (WHO 2022). The emission rate for each home was assumed to be constant during appliance use but varied across different homes using the same fuel type. The $PM_{2.5}$ emission rates taken from the literature are shown in table 1, along with their source and the proportion of fuel types used in each municipality. The two dominant fuel types in use across Nairobi's housing stock are LPG and paraffin (also known as kerosene). Firewood and charcoal are minimal contributors to Nairobi's fuel landscape, unlike Mombasa, where charcoal contributes approximately one-fifth of fuel use, with a similar proportion in Kisumu. More than 60% of households in Kisumu rely principally on firewood and charcoal solid fuels (table 1).

Simulations were run for one year at hourly time steps using an EnergyPlus weather file (.epw) for Nairobi, provided by the American Society of Heating, Refrigerating and Air-conditioning Engineers (ASHRAE 2021). The annual average household $PM_{2.5}$ concentration was calculated for each EnergyPlus simulation ($n = 100$). The infiltration of outdoor-sourced air pollution within the household was also accounted for by modelling a dwelling infiltration factor (the proportion of the outdoor air pollution concentration that has infiltrated the building) in the range of 0.00–1.00. The average infiltration factor for the informal housing archetype was 0.72, compared with 0.60 for the formal archetype. This factor was then multiplied by the outdoor concentration assigned to each individual and added to the annual average air pollution from household sources, to estimate total indoor exposure from indoor-sourced cooking and outdoor infiltration.

2.4. Time-weighted exposure

A time-weighted annual average exposure from indoor and outdoor $PM_{2.5}$ was calculated for each individual using data from the 2021 Kenya Continuous Household Survey Programme (KCHSP) (KNBS 2021). Survey variables relating to economic activities and the number of hours per week spent in employment were used to calculate the percentage of hours spent outside of the home for each participant. Where the participant had indicated they were not in paid employment, estimates of time-use were drawn from the available literature for Kenya.

The percentage of time outside the home for those who indicated they were not working due to family and household responsibilities, termed homemakers (11% of the survey population, comprised entirely of females), was taken from time-activity budget data for females aged between 16–50 years old in a rural Kenyan study where domestic labour was the primary occupation (Ezzati *et al* 2000). Similarly, for those who indicated they were retired (3.9% of the survey data), time-activity budget data was taken from Ezzati *et al*

(2000) for the over 50 age group. School children were assumed to spend school hours outside of the dwelling, roughly 7.5 h per day for five days a week. Infants who were not yet enrolled in school were assumed to accompany their mother. Those who indicated they were ill or permanently disabled (<2.2% of the survey sample) were assumed to spend two hours per day outside of the dwelling, as there was no empirical data which characterised the time-activity patterns of individuals living with long-term illness in Kenya or East Africa in the literature.

The individual microdata[11] was linked with the household microdata file using a linking key available in the survey variables. The household microdata contained information pertaining to the type of dwelling occupied by each survey participant. This was used to disaggregate the time-activity patterns for individuals living in informal and formal settlements, as previous research has suggested women in Kenya's informal settlements may bear a disproportionate risk from air pollution due to variations in time-activity patterns (Ngo *et al* 2015, 2017). Individual survey weights were available in the KCHSP, allowing time-activity estimates to be scaled up to the approximately 7.1 million residents in Nairobi, Kisumu and Mombasa.

Estimates for personal $PM_{2.5}$ exposure from combined sources were calculated by weighting the household and ambient exposures using the time-activity data to generate an annual average $PM_{2.5}$ exposure per person. Household $PM_{2.5}$ concentrations were capped with a cut-off of 1000 μg m^{-3} in line with recently published empirical values of indoor concentrations in Kenya from Shupler *et al* (2024).

2.5. Health outcomes

The relative risk (RR) of mortality attributable to $PM_{2.5}$ exposure was calculated for each individual for six health outcomes, namely, ischemic heart disease (IHD), ischemic stroke (IS), chronic obstructive pulmonary disease (COPD), lower respiratory infections (LRIs), tracheal, bronchus and lung cancer (LC), and diabetes mellitus type II (DM). For all health conditions, gender- and age-disaggregated mortality rates were applied to the synthetic population using data from the Global Burden of Disease (GBD) study (Institute for Health Metrics and Evaluation 2022) for each municipality for <1 year olds, 1–4 year-olds and then at five-year intervals between age 5–95, as well as 95+ years of age.

We estimated gender- and age-dependent RRs using the GBD's meta-regression-Bayesian, regularised, trimmed (MR-BRT) exposure-response functions for $PM_{2.5}$ implemented using look-up tables applied to each individual's time-weighted $PM_{2.5}$ exposure and mortality rates. The distribution of RR was normalised by the RR at the theoretical minimum risk exposure level (TMREL) as per methods described in Ghosh *et al* (2021). For $PM_{2.5}$ exposures below the TMREL of 4.2 μg m^{-3} (selected as the median of 1000 draws), we set RR = 1. Where mortality attributable to $PM_{2.5}$ exposure is age-dependent, RR was also set to 1 for age groups below 25 years for all health conditions other than LRI (Ghosh *et al* 2021). The age-specific RRs were subsequently used to determine $PM_{2.5}$-attributable mortality using a standard population attributable fraction (PAF) equation and aggregated by age, gender and health conditions.

2.6. Cleaner cooking fuels policy scenarios

To estimate the health impacts of climate change mitigation policies, scenarios representing a two-stage transition to cleaner cooking fuels were applied to the baseline exposure model to replicate wholesale implementation of energy policies that result in $PM_{2.5}$ reductions. These scenarios were informed by national climate change ambitions for Kenya's energy sector emissions mitigation targets (National Climate Change Action Plan 2023–2027) and recent feasibility studies for use of ethanol cooking fuels (Chomanika *et al* 2022). The hypothetical policy ambitions were defined as:

1. **Baseline**: health impacts associated with existing cooking fuel distributions.
2. **Medium-term scenario**: all users of firewood switch to wood pellets and all users of charcoal and kerosene change to LPG fuel.
3. **Long-term scenario**: all LPG and wood pellets users transition to ethanol fuel.

For each municipal population, the medium-term policy was implemented by converting the distribution of synthetic individuals allocated as firewood users to wood pellet users and changing both charcoal and kerosene users to LPG, then adjusting the emissions as per table 1 and re-running the simulations. The long-term policy was implemented by building upon the medium-term ambition by converting LPG and wood pellet users to ethanol fuel using the same methods. To compare the influence of policy implementation on gender-disaggregated mortality, the difference in mortality under each scenario was calculated relative to the baseline scenario.

[11] Microdata is defined as anonymised survey information available at the unit of interest, e.g. individual people or homes.

2.6.1. Sensitivity analysis

We conducted sensitivity analyses on the proportion of informal households within each municipality. Since construction of informal households is typically unregulated, census data on the number and existence of informal households may be uncertain. We compared the census results (19%, 18%, and 7% for Nairobi, Kisumu, and Mombasa respectively) with hypothetical increases in informal housing proportions of 40% and then 60% within each municipality and re-calculated personal $PM_{2.5}$ exposures to assess the sensitivity of the simulation to input data.

We conducted an additional sensitivity analysis to assess the impacts of fuel stacking on modelled $PM_{2.5}$ reductions, given its widespread practice in Kenya. For the purpose of this analysis, we defined fuel stacking as the practice of using two different fuel types at baseline and the adoption of a cleaner primary fuel with simultaneous retention of a secondary fuel in the medium-term scenario. Data from a national survey (Table E S1, Republic of Kenya Ministry of Energy 2019) was used to inform the primary and secondary fuel choices of individuals in the Kisumu synthetic population. With limited data describing fuel stacking patterns, two assumptions were made: (1) that fuel choice patterns were identical for those in formal and informal households, and (2) that the primary fuel was used 60% of the time, with the secondary fuel used for the remaining 40% of time per each individual. The baseline and medium-term scenarios were then re-calculated to evaluate modelled personal $PM_{2.5}$ exposure for firewood users in Kisumu simulating fuel stacking with two different fuels. This demographic was targeted due to their high reliance on firewood, an unsustainable fuel associated with some of the highest $PM_{2.5}$ emissions.

3. Results

3.1. Descriptive population statistics

Age and gender distributions of the generated synthetic populations of Nairobi, Kisumu and Mombasa yielded comparable results to census data. There are slightly more females than males in Nairobi and Kisumu (females: 51%, males: 49%) but in Mombasa male gender was slightly dominant (males: 51%). The mean age in each of the three cities ranged between 23 and 24 years. Nairobi's modelled population at 4.4 M is approximately three times greater than each of Mombasa's and Kisumu's populations.

3.2. Time activity by population group

Our generated distributions of the percentage of time spent outside the home for different population groups is illustrated by the ridgeline plot in figure 1. No activity information was available for those aged 60+ living in informal housing from the KCHSP (KNBS 2021). The results show that women generally spend less time outside the home than men. Working age men spend the most time outside the dwelling. Both men and women in the over 60 age group show a bimodal distribution, due to some still being in employment while others are retired. Infants less than five years old spend the least amount of time outside the dwelling (mean = 20.3%–20.6% for males and females from formal and informal settlements). Working-age females living in informal settlements spend 21.8% versus 26.4% of their time outside the home for those in formal settlements. This is due to a higher proportion in informal settlements identifying as homemakers (14% vs 10%).

3.3. Personal $PM_{2.5}$ exposure by gender and municipality

Individual time-weighted $PM_{2.5}$ exposures were calculated by combining spatially explicit ambient and household $PM_{2.5}$ concentrations weighted by indoor and outdoor time-activity estimates at baseline and in the two policy scenarios. The log-transformed combined ambient and household annualised mean $PM_{2.5}$ exposure distributions per municipality are shown in figure 2(a)–(c). Mean personal exposures at baseline in all three municipalities exhibit a right-skewed distribution with a long tail indicating the wide range of $PM_{2.5}$ exposures experienced by individuals in the population (see table 2 for mean values).

Exposures under the medium-term scenario (transition from firewood to wood pellets and all other fuels to LPG) show a bimodal distribution for Kisumu, however for Nairobi and Mombasa and for all three municipalities in the long-term scenario (replacement of LPG cooking fuel with ethanol) the distributions approach normality on the log-scale; in the latter policy scenario this occurs around mean concentrations of 10.89 $\mu g\ m^{-3}$ (Mombasa), 15.50 $\mu g\ m^{-3}$ (Nairobi) and 19.26 $\mu g\ m^{-3}$ (Kisumu, see table 2). Mean exposures also declined under the medium-term scenario, relative to baseline, by 22%, 80%, and 61% in Nairobi, Kisumu and Mombasa, respectively. Further declines in mean exposure under the long-term scenario resulted in smaller reductions of 4% in Nairobi, 30% in Kisumu, and 10% in Mombasa (table 2). Combined mean $PM_{2.5}$ concentrations ranged from 20.51 $\mu g\ m^{-3}$ (95% CI: 14.08, 27.87, Nairobi), 30.94 $\mu g\ m^{-3}$ (95% CI: 10.17, 95.89, Mombasa) and up to 140.13 $\mu g\ m^{-3}$ (95% CI: 19.35, 471.70, Kisumu) under the baseline scenario.

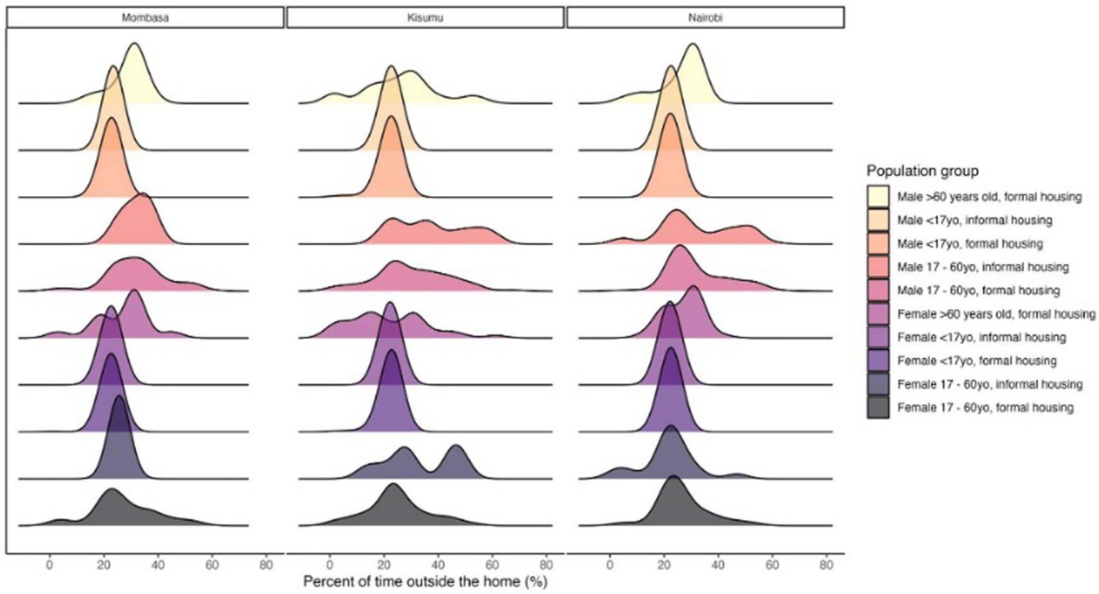

Figure 1. Percentage of time spent outside the home environment, by demographic.

Descriptive statistics for ambient and household source exposures contributing towards the combined personal $PM_{2.5}$ concentrations are shown for Mombasa in table 3. Mean and median values differ for household concentrations with higher mean values influenced by the non-normal data distribution at baseline. The mean ambient $PM_{2.5}$ concentration is lower than the mean household source exposure for both informal (ambient: 14.46 vs. household: 41.11 μg m^{-3}) and formal housing types (ambient: 14.45 vs. household: 27.29 μg m^{-3}) in contrast to median $PM_{2.5}$ values for household sources which trend lower for both dwelling types (see table 3) resulting in overall lower median personal exposure concentrations. Modelled median household $PM_{2.5}$ exposures in formal housing in Kisumu are observed to be several orders higher than ambient source exposures (household: 100.43 μg m^{-3}, ambient: 26.73 μg m^{-3}; descriptive statistics for Kisumu and Nairobi are available in supplementary materials table 1A).

Gender-disaggregated $PM_{2.5}$ exposures for individuals are illustrated in the violin plots for each municipality in figures 3(a)–(c). The wider probability density functions of personal exposures at baseline and for the medium-term scenario in Kisumu, relative to Mombasa and Nairobi, most clearly illustrate differential effects of the policies between different urban populations in Kenya. The violin plots also highlight the serial impact of the two-stage policy measures on the maximum range of exposures experienced by individuals in the population.

To compare exposure variations by housing type, disaggregated personal $PM_{2.5}$ concentrations were charted for the city of Mombasa in figure 4. Personal exposure distributions showed more variation between informal versus formal housing types, in contrast to children and adult age groups or gender.

Individuals in informal housing benefit most from the change to an improved fuel source in the medium-term scenario due to lower pre-existing usage of LPG at baseline, in comparison to those in formal housing (see table 2(A) for proportions of improved fuel source users disaggregated by housing type, supplementary materials). In the long-term scenario, the differential effect between informal and formal housing is tempered as all individuals, irrespective of household type, switch over to ethanol with minimal pre-existing usage.

3.4. Baseline health outcomes

Our estimates suggest that in Nairobi, 420 deaths are attributable to current $PM_{2.5}$ exposure, 551 in Kisumu and 111 in Mombasa, and are broadly comparable to other estimates of $PM_{2.5}$ attributable mortality in Kenya (GBD 2019). The mortality (attributable deaths) per 100 000 population was calculated to provide a comparable disease burden estimate between genders and municipalities (table 4). Baseline all-cause mortality estimates attributable to $PM_{2.5}$ exposure generated by the model are greatest in Kisumu, followed by Nairobi and Mombasa. For each health condition, mortality is consistently higher in males than in females as illustrated in table 4. All-cause mortality in men is nearly twice that of women in Mombasa (1.73:1) and Nairobi (1.83:1) and more than twice as high in Kisumu (2.34:1). The burden of disease is highest for IHD and LRIs for both genders in all municipalities, apart from Kisumu where the highest

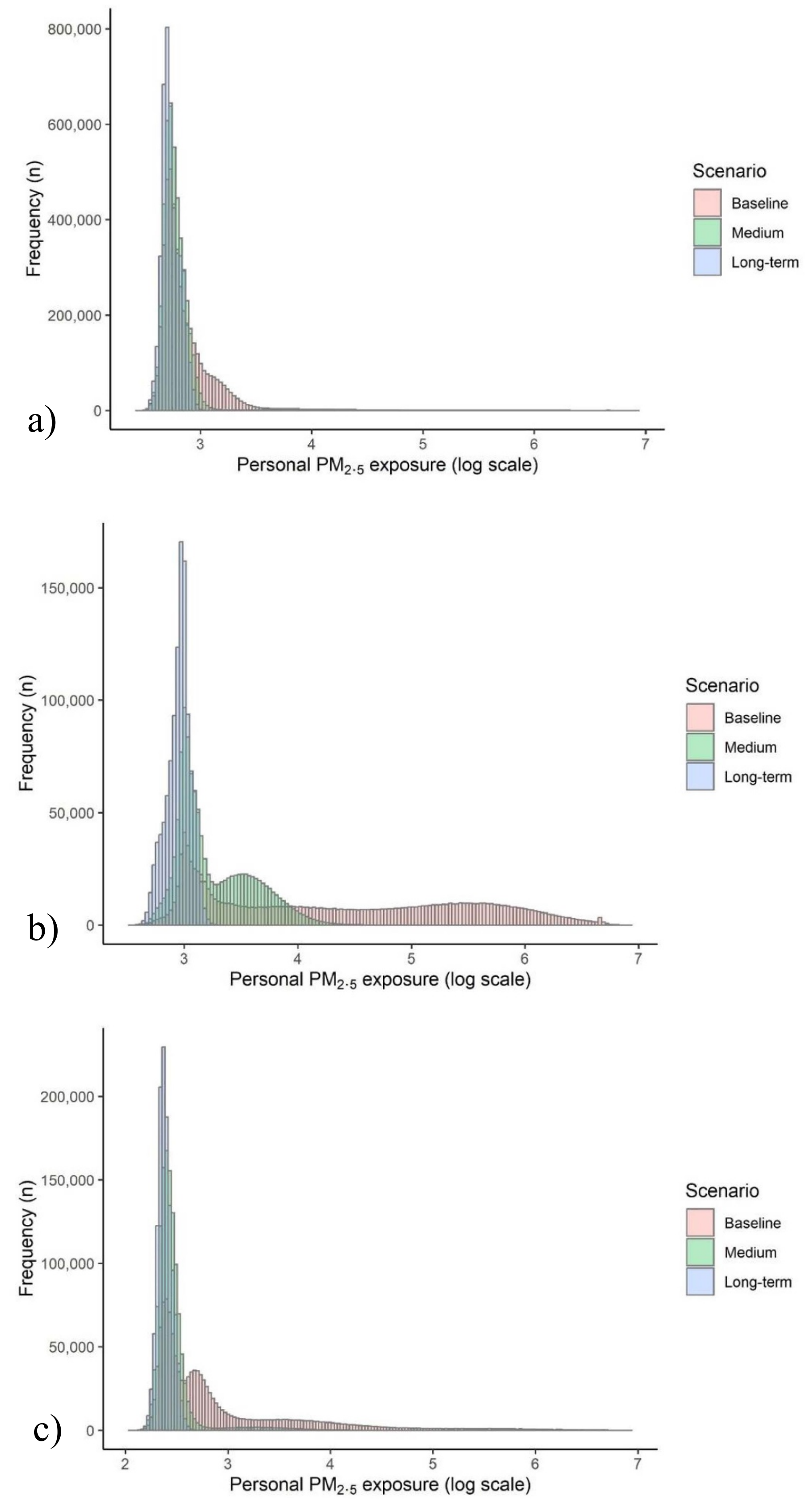

Figure 2. (a)–(c) Log-scale histograms of personal $PM_{2.5}$ exposure for (a) Nairobi, (b) Kisumu and (c) Mombasa.

(19.16) and second highest (7.68) mortality burden is for COPD in males and females, respectively. Mortality from IHD in males ranges from 4.06 in Mombasa to 18.12 in Kisumu, whereas in females, the highest mortality (5.97) is found in Kisumu where it is more than twice as high as in Nairobi (2.23) and Mombasa

Table 2. Mean exposure and 95% confidence intervals from ambient and household $PM_{2.5}$.

Policy scenario	Mean ambient and household $PM_{2.5}$ exposure $\mu g\ m^{-3}$ (95% CI)		
	Nairobi	Kisumu	Mombasa
Baseline	20.51 (14.08, 27.87)	140.13 (19.35, 471.70)	30.94 (10.17, 95.89)
Medium term	16.12 (13.98, 18.97)	27.59 (17.63, 49.08)	12.08 (9.92, 14.80)
Long term	15.50 (13.80, 17.88)	19.26 (15.68, 22.57)	10.89 (9.78, 12.30)

Table 3. Contribution of ambient, household, infiltrated household, and time-weighted combined ambient and household to $PM_{2.5}$ personal exposures, Mombasa.

Variable	Mombasa $PM_{2.5}$ exposures ($\mu g\ m^{-3}$)				
	Median	Mean	SD	Min	Max
Informal dwelling					
Ambient $PM_{2.5}$	14.38	14.46	0.62	11.76	17.80
Household source $PM_{2.5}$	11.60	41.11	105.82	0.02	1000.00
Infiltrated household source $PM_{2.5}$[a]	22.01	51.51	105.84	9.51	1012.36
Weighted ambient + household $PM_{2.5}$	19.99	41.70	78.07	10.16	882.26
Formal dwelling					
Ambient $PM_{2.5}$	14.43	14.45	0.65	11.20	18.56
Household source $PM_{2.5}$	4.66	27.29	82.57	0.00	1000.00
Infiltrated household source $PM_{2.5}$[a]	13.33	35.96	82.57	7.33	1009.98
Weighted ambient + household $PM_{2.5}$	13.64	30.16	60.89	7.63	1008.80

[a] Infiltrated household source $PM_{2.5}$ is the indoor $PM_{2.5}$ concentration from infiltrated outdoor air plus that generated from indoor sources.

(2.00). The effect of gender was most notable for LC in municipalities where mortality ratios for men relative to women are 2.6, 4.4, and 3.1 times greater in Nairobi, Kisumu, and Mombasa, respectively. Diabetes burden is also 3.1 times higher in men than in women in Kisumu.

3.5. Health outcomes under policy scenarios

The difference in mortality was calculated to describe the averted mortality per 100 000 population between the baseline and policy scenarios and to identify the clean cooking fuel policies with the greatest impact on population health. As shown in tables 5(a) and (b), the most substantial gains were made in the medium-term policy scenario in Kisumu with wholesale changeover of cooking fuels from kerosene to LPG and firewood to wood pellets resulting in a reduction in all-cause mortality of 29.88 male and 13.92 female deaths per 100 000 population. Smaller gains in all-cause mortality were found in Mombasa and Nairobi (table 5(a)). In contrast, the long-term policy scenario led to smaller reductions in mortality for all three municipalities using the baseline mortality as referent for both policy scenarios (table 5(b)). Notably, health impacts were greater for males over females for all outcomes in all municipalities for each policy implementation.

3.5.1. Sensitivity analyses

Our housing sensitivity analysis (figure 1(A), supplementary materials) confirms that baseline personal exposure estimates in all municipalities are influenced by housing type proportions, particularly in Kisumu. In contrast, results from the policy scenarios appear far less sensitive to housing type. The results from the sensitivity analysis on fuel stacking are shown in figure 2(A) (supplementary materials). Baseline exposure was overestimated in Kisumu households relying solely on firewood compared with those who practice fuel stacking with charcoal, LPG and kerosene. The modelled reduction in exposure under the medium-term policy transition was greater for households who fuel-stack with LPG and kerosene, compared to wholesale switchover to wood pellets. However, $PM_{2.5}$ exposure reductions were *lower* for households who fuel-stack with charcoal and wood pellets, as indoor emissions from charcoal are higher than those from wood pellets alone.

4. Discussion

Using a novel linkage of a synthetic population and building physics software, we tested emission mitigation policies entailing transition to sequentially cleaner household cooking fuels to quantify the reduction in

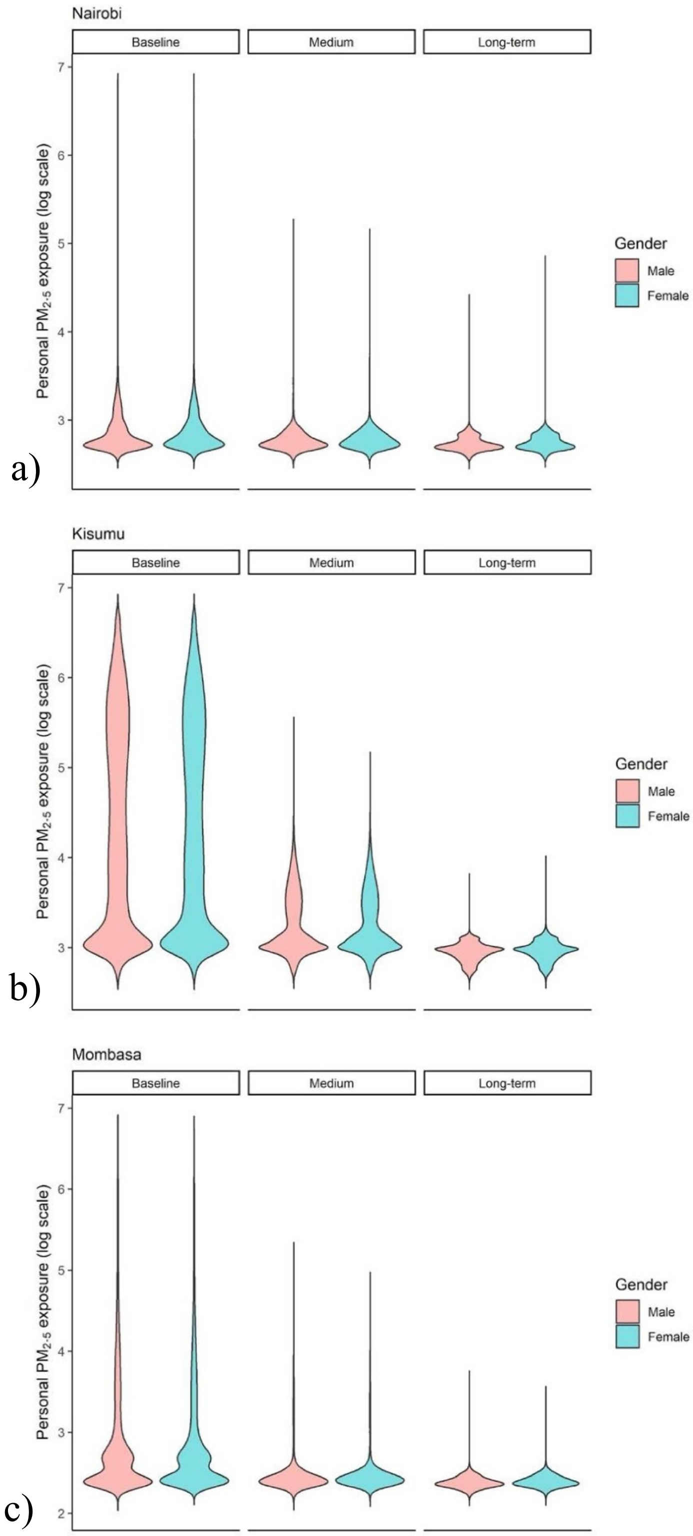

Figure 3. (a)–(c). Distribution of personal $PM_{2.5}$ exposure (log scale) by gender in (a) Nairobi, (b) Kisumu, and (c) Mombasa.

$PM_{2.5}$ exposure and estimate the health co-benefits in Kenya's three largest municipalities. Our policy scenario testing demonstrated that LPG and wood pellet replacement of dirty cooking fuels results in a more substantial reduction of $PM_{2.5}$ exposure and mortality than a more ambitious policy for a complete transition towards ethanol use, though results are sensitive to the prevalence and type of fuel-stacking across each municipality. These findings may be due to the marginal difference in emissions between LPG and ethanol fuel, as well as widespread and pre-existing use of LPG, particularly in Nairobi and Mombasa where the lowest burden of attributable mortality was estimated. Successively larger reductions in mortality

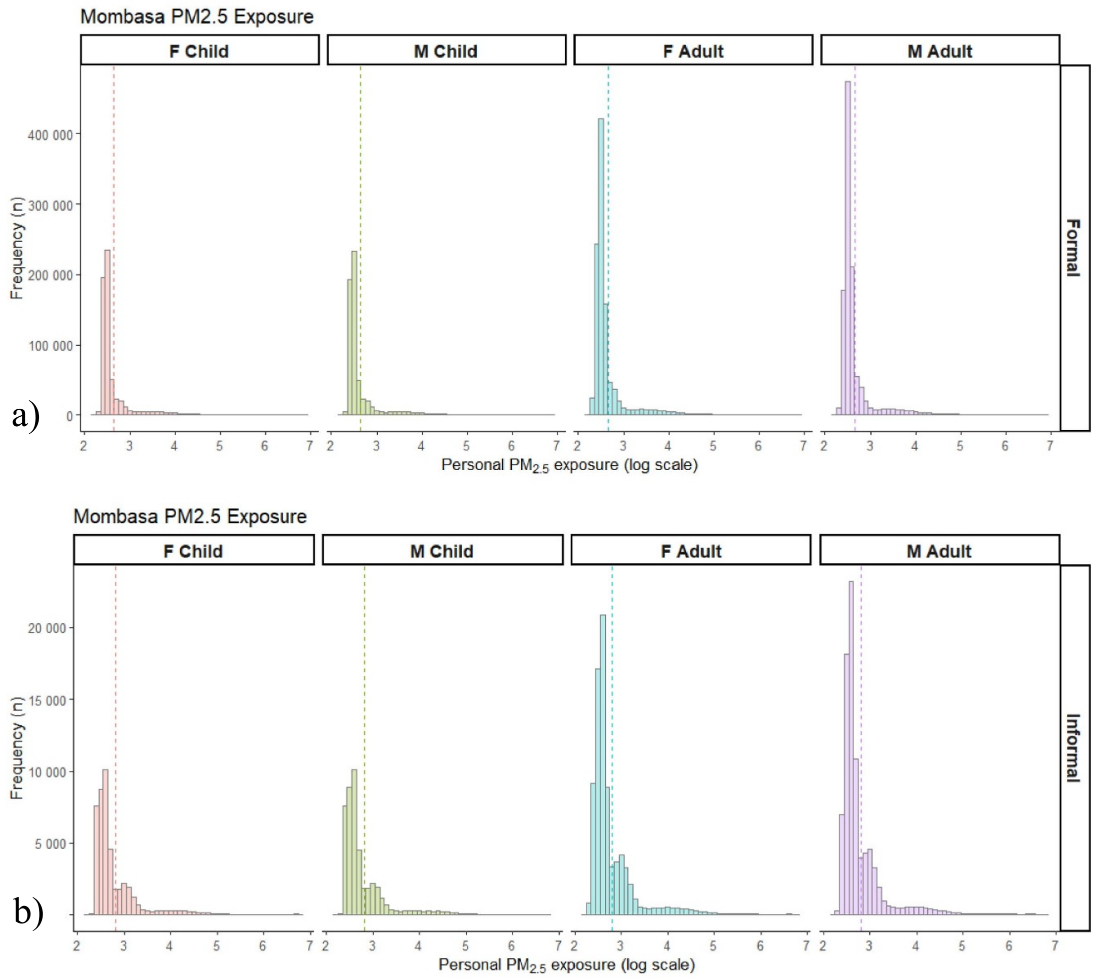

Figure 4. (a), (b): Personal $PM_{2.5}$ exposure (log-scale) histograms for Mombasa disaggregated by gender and age group under baseline for (a) formal and (b) informal housing types.

predicted in Kisumu by the two-stage policy scenario are thus explained by greater use of firewood at baseline and the cumulative effects of wood pellet followed by ethanol substitution. In addition, under each stage of policy scenario testing, the distribution of personal $PM_{2.5}$ exposures consistently narrowed around the median value. This was observed across all modelled populations with the greatest effect seen in Kisumu, where survey data suggests that high proportions of firewood are used in formal housing, resulting in exceptionally large household emissions and high $PM_{2.5}$ concentrations in comparison to those in Nairobi or Mombasa. Kisumu county has a high prevalence of rural households with high firewood usage which may influence higher rates of usage in formal households in Kisumu municipality. Nonetheless, our policy simulations suggest that individuals with the highest personal exposure will gain more benefit as cleaner cooking fuels are implemented.

Despite these findings, combined personal $PM_{2.5}$ exposures under the most ambitious policy of ethanol fuel changeover remained between two and four times higher than the WHO air quality annual exposure target of 5 μg m^{-3} in each of the three modelled municipalities (WHO 2021). The persistence of high personal exposure concentrations in spite of reductions in household source emissions indicates that action on clean cooking fuels, while highly beneficial to some individuals, is insufficient on its own and should be accompanied by mitigation strategies targeting ambient emissions. Despite the higher ambient concentrations found in other LMIC settings, these findings are supported by recent evidence from India, which suggested the benefits of cleaner cooking fuels are not sufficient alone to offset moderate to high ambient $PM_{2.5}$ concentrations (Parchure *et al* 2024).

4.1. Gendered outcomes

We illustrated differential exposures and impacts on mortality across demographic groups by reporting gender-disaggregated data and consistently found greater health risks for men than for women. These findings are not consistent with prior reports of higher health risks in women on account of increased

Table 4. Mortality per 100 000 people for six health conditions associated with $PM_{2.5}$ exposure in three Kenyan municipalities at baseline and under policy scenarios.

	Nairobi		Kisumu		Mombasa	
Cause	Male	Female	Male	Female	Male	Female
Baseline (Mortality Per 100 000)						
IHD	4.67	2.23	18.12	5.97	4.06	2.00
LRI	3.18	2.06	18.83	9.70	3.77	2.49
COPD	1.03	0.51	19.16	7.68	0.86	0.34
Stroke	0.95	0.78	4.66	3.53	1.13	1.02
Lung cancer	0.43	0.16	1.46	0.33	0.36	0.12
Diabetes	2.10	0.99	5.40	1.72	1.41	0.71
All-cause mortality	**12.37**	**6.73**	**67.64**	**28.94**	**11.59**	**6.68**
Medium term (Mortality Per 100 000)						
IHD	4.25	2.01	12.72	3.94	2.63	1.25
LRI	2.67	1.71	8.04	4.00	1.75	1.13
COPD	0.88	0.43	8.67	3.32	0.44	0.17
Stroke	0.84	0.69	2.96	2.14	0.65	0.57
Lung cancer	0.38	0.14	0.93	0.21	0.21	0.06
Diabetes	1.93	0.91	4.44	1.40	0.94	0.46
All-cause mortality	**10.96**	**5.90**	**37.76**	**15.01**	**6.61**	**3.65**
Long term (Mortality Per 100 000)						
IHD	4.11	1.94	10.10	3.00	2.39	1.12
LRI	2.55	1.62	5.56	2.70	1.50	0.97
COPD	0.85	0.41	6.22	2.31	0.39	0.15
Stroke	0.81	0.66	2.16	1.54	0.58	0.51
Lung cancer	0.37	0.14	0.69	0.15	0.18	0.06
Diabetes	1.87	0.88	3.68	1.15	0.84	0.41
All-cause mortality	**10.56**	**5.65**	**28.41**	**10.84**	**5.88**	**3.21**

Table 5. (a) and (b): Averted mortality per 100 000 population for medium-term and long-term policy scenarios relative to baseline.

(a) Medium term policy scenario (referent: baseline policy)

	Nairobi		Kisumu		Mombasa	
Cause	Male	Female	Male	Female	Male	Female
IHD	0.42	0.22	5.41	2.03	1.43	0.76
LRI	0.51	0.34	10.79	5.70	2.02	1.36
COPD	0.15	0.08	10.49	4.36	0.42	0.17
Stroke	0.11	0.09	1.70	1.39	0.48	0.45
Lung cancer	0.05	0.02	0.53	0.12	0.16	0.05
Diabetes	0.17	0.08	0.95	0.32	0.47	0.25
All-cause mortality	**1.41**	**0.84**	**29.88**	**13.92**	**4.98**	**3.03**

(b) Long term policy scenario (referent: baseline policy)

	Nairobi		Kisumu		Mombasa	
Cause	Male	Female	Male	Female	Male	Female
IHD	0.55	0.29	8.02	2.97	1.67	0.76
LRI	0.64	0.43	13.27	7.00	2.27	1.36
COPD	0.19	0.10	12.94	5.37	0.48	0.17
Stroke	0.14	0.12	2.50	1.99	0.55	0.45
Lung cancer	0.07	0.03	0.77	0.18	0.18	0.05
Diabetes	0.23	0.12	1.71	0.58	0.57	0.25
All-cause mortality	**1.82**	**1.08**	**39.23**	**18.09**	**5.71**	**3.03**

personal exposure to dirty cooking fuel emissions during traditional food preparation (Dida *et al* 2022). They may instead reflect the large differences in underlying mortality rates between women and men influenced by physiology, occupational (i.e. industrial or transport) exposures and risk-taking or lifestyle behaviours such as cigarette smoking. For instance, an analyses of cardiovascular risk factors found lower risk in women in comparison to men associated with smoking (male referent, female OR: 0.08, 95% CI: 0.06–0.11) and alcohol consumption (male referent, female OR: 0.18, 95% CI: 0.15–0.21) in Kenya, and men were more likely than women to have $\geqslant$2 cardiovascular risk factors at any age and within the 45–54-year age group, had the highest proportion altogether (51.6% vs 19.6%) (Bloomfield *et al* 2013). Importantly, these explanations for higher disease burden estimates from cardiovascular disease and stroke in men have received some scrutiny particularly in countries where cultural or social inhibitions impact health-seeking behaviours in women and result in reduced access to health facilities and underdiagnosis (Vlassoff 2007). In Kenya, gendered access to health continues to limit women's participation in health programs, even those that are subsidised, with barriers including women's primary care duties, high transport costs, negative healthcare worker attitudes, limited access to education, and limited decision-making power, amongst others (Kabia *et al* 2018, Wambalaba 2024). Misdiagnosis caused by biological differences in the presenting symptoms of cardiovascular disease may also entrench research funding allocations that focus on the male gender, in spite of recent evidence that the cardiovascular disease burden may be higher in women (Woodward 2019, Desai *et al* 2021).

4.2. Individual vulnerability

Our work also demonstrates more broadly the utility of the synthetic population approach using modelled data to capture individual vulnerability resulting from social and environmental determinants. For instance, the narrow range of ambient $PM_{2.5}$ exposures within each city provides a suitable backdrop to highlight the differential impacts of cooking fuel, dwelling type, and outdoor time activity. These measures are important modifiers of exposures that result in disproportionate vulnerability towards environmental hazards for some demographics (Thomas *et al* 2019). To that end, recent empirical evidence has indicated that determinants such as outdoor cooking and living near major roadways may outweigh the hazards of high-emitting cooking fuels (Shupler *et al* 2024), although our findings suggest that cooking fuel choice was more influential than ambient $PM_{2.5}$ concentrations, particularly in Kisumu where highly polluting fuels are widespread. Nevertheless, as cleaner fuels were implemented in our models, ambient concentrations exerted a greater proportional effect on personal exposures, likely due to high pre-existing ambient concentrations ($>$20 μg m^{-3}) and high dwelling infiltration factors (0.60 and 0.72 for the formal and informal housing archetypes, respectively). Our ambient pollution data set was also based on modelled annualised means and therefore did not exhibit the large range in variation that can occur with emissions dispersion from empirical data sets (Kinney *et al* 2011).

4.3. Strengths and limitations

Individual-level modelling methods such as microsimulation are increasingly used in health policy development to strengthen evidence-based decision-making and optimise resource allocation. However, full dynamic microsimulation can be highly complex and time consuming. In this proof-of-concept model, we demonstrate the versatility of individual-level models to evaluate policy changes for climate mitigation actions and to inform national health policy responses. We employed a novel linkage of a synthetic population, statistically indistinguishable from the real population, with a building physics tool to assess the health benefits of clean household fuel policies across three municipalities in Kenya. To our knowledge, this is the first time the impact of different structural interventions has been quantified using building physics models and the resulting changes in exposure applied to a synthetic population to assess the health benefits. This methodology allows for the impact of a range of urban policies to be quantified which would otherwise be costly and impractical with a real population and provides a proof-of-concept for low-resource settings. Nonetheless, some limitations of our model must be considered. For instance, the static nature of the current model means it is not able to account for demographic changes over time, the lag effect between policy implementation and health impact, or to account for the long-term impact of reduced household emissions on ambient $PM_{2.5}$ concentrations, the latter of which would require temporal trends data on municipal-specific sectoral emissions contributions. To this extent, availability of improved empirical source-specific data sets would benefit future iterations of the model; this may be possible soon with the newly established Air Pollution Centre of Excellence in Nairobi.

Additionally, while we acknowledge the uncertainty in the underlying data used to construct the housing stock model in Kenya, we believe that the application of building physics models to previously underserved areas in the Global South is important to bring visibility to energy issues in these communities and lead to better targeted, cost-effective interventions. These data constraints also do not prevent the use of model estimates as a tool to identify promising mitigation actions and refine short-term strategies. The overall benefit of using standardised environmental attribution methods to compare and quantify policy impacts on both emissions reduction and ancillary health outcomes provides greater consistency for policymakers, which has previously been identified as an important constraint for decision-making on climate mitigation actions (Whitmee *et al* 2024).

We also assumed that all types of $PM_{2.5}$ particles are equally hazardous to health. Although this is a simplifying assumption, our estimates of gender- and age-dependent RRs are based on the GBD study's high-quality MR-BRT exposure-response functions for $PM_{2.5}$ generated from extensive systematic review and meta-regression of the latest evidence from the global literature. We used distributions of measured household $PM_{2.5}$ emission rates to capture the underlying uncertainty associated with this parameter. Measurements carried out in a more controlled setting were sought, as emission rates measured during field studies may be biased due to the introduction of air pollution from resuspension or infiltration, but we acknowledge the values used here may be more conservative than some of the emission rates seen across the literature. Field measurements of pollutant emission rates are often orders of magnitude higher than those conducted in laboratory settings, resulting in modelled levels of household air pollution which exceed empirically measured concentrations by a significant margin (Johnson *et al* 2011, 2021). Discrepancies between field and laboratory derived emission rates may be due to variations in cooking techniques and combustion conditions, such as fuel reloading (Torkmahalleh *et al* 2017, Deng *et al* 2018).

To maintain a parsimonious model, we assumed that behavioural decisions in relation to fuel type were a single choice, with a sensitivity analysis performed to quantify the impact of this assumption on our results. In reality, households frequently choose to use or retain multiple fuel types concurrently, including both low and high emission fuels. This practice, termed fuel stacking, is driven often by the practical need for a reserve cookstove to save time or money or sometimes by cultural preference (Ochieng 2020). Our sensitivity analysis showed reductions in $PM_{2.5}$ exposure under the policy scenarios may be overestimated in the parsimonious model if fuel-stacking is omitted, though this depended on the combination of fuels used for stacking. For this reason, health impact estimates for the baseline, medium-term and particularly the long-term scenario, may be optimistic given that retention and intermittent use of high emission fuel types is conceivable even when the primary fuel used was a low emission one.

While the motivations for fuel stacking practices have been explored in the literature (Osano *et al* 2020, Okore *et al* 2022, Gill-Wiehl and Ray 2023), quantitative data on patterns of use describing the population frequency of simultaneous multi-fuel users (i.e. those who prepare different foods at the same time with different stove types) versus the frequency of people switching between fuel types based on current availability or cost (i.e. intermittent fuel changes) is scarce, especially at sub-population levels. Moreover, temporal patterns describing how regularly these practices occur and what proportion of cooking time or meals are cooked using different fuel types is extremely limited. Challenges in collating and quantifying complex behavioural decisions that drive fuel use choice, which may be variably based on cooking method preference for food preparation, time availability, or a result of unpredictable events such as fuel shortages, remain and therefore our fuel stacking analyses should be seen as illustrative only. Geolocated data on fuel stacking preferences could also be integrated into future iterations of the model if such data becomes available.

Bias in the underlying data inputs used to construct the model may also limit its applicability. We found a number of data discrepancies between the census data used to construct the synthetic population and wider estimates from the literature relating to the proportion of Kenya's population living in informal settlements. The census data indicated that 19%, 18% and 7% of Nairobi's, Kisumu's and Mombasa's population reside in informal settlements, respectively. Informal settlements are characterised by establishing tenure security through evaluation of housing structure, degree of crowding, access to water and sanitation, and land tenure (UN-HABITAT 2010). The accuracy of census data on informal settlement populations has been questioned due to perceived inconsistencies in housing tenure identification methods, however a recent remote-sensing study that mapped informal settlement populations in Nairobi reported population estimates closely aligned to census data for the capital (Ren *et al* 2020). Nonetheless, we accept that data on informal settlements in smaller cities such as Mombasa and Kisumu may be conflicting due to inconsistent definitions of informal housing used by the KNBS in comparison to UN development agencies and our sensitivity analysis to assess the effect of uncertain parameter inputs on simulation results suggests that at baseline, characterisation of household type is influential. As such, mortality estimates for these cities should be interpreted with caution (Kain *et al* 2016).

Additionally, no individuals aged over 60 living in informal settlements were included in the time-activity survey due to the high mortality burden seen across this demographic with less than 2% of the total population made up of individuals in this age group (APHRC 2018). The data scarcity characterising informal settlements in LMICs, their inhabitants and other hidden populations, such as the internally displaced, has been noted in previous work (Satterthwaite *et al* 2020, Aylett-Bullock *et al* 2022), potentially leading models to underestimate disease progression in these communities. Here, we outline a methodology able to quantify the potential health benefits of improving access to clean fuels in informal settlements by using the available data but acknowledge the uncertainty in the model due to biases in the input data. Improving data collection of underserved populations remains a priority area for epidemiological models, especially given that informal settlements are projected to increase due to urbanisation and the higher disease prevalence observed in these settings (Georganos *et al* 2020).

4.4. Implications of this work

Increasing the uptake of clean cooking fuels in Kenya could provide an opportunity for dual-purpose policy that mitigates greenhouse gas emissions while affording population health co-benefits. Kenya's rapid industrialisation and urbanisation necessitate an ambitious programme of development to control the mortality burden associated with air pollution, particularly in major cities (Health Effects Institute 2022). These ambitions have received support from the African Hub of the Sustainable Energy for All (SE4A) Initiative, which provides technical support and advocacy for members aiming to scale up electricity use and clean cooking technologies. In Kenya, the aim of full national electrification of households by 2030 appears feasible with more than 70% of households on the grid (SE4A 2024). However, this may not lead to the universal adoption of electricity as a cooking fuel due to cost implications especially for poor households given the current high cost of electricity in Kenya. In addition, there is a cost implication with the purchase of electric cooking appliances that may lock out many households. Further, achievement of a comparable aim to provide universal access to clean cooking fuels may fall short due to slower action to widen consumer access and lack of available technology such as storage solutions that would enable reliable solar energy capture for cooking (Cardoso *et al* 2023).

Nonetheless, the recent value-added-tax exemption (zero-rating) and reduction in import tariffs for ethanol suggests a path forward for clean fuel uptake through competitive pricing. This is a key factor expected to influence adoption by lower income households and accelerate scalability, particularly when set against rising prices for LPG (Osiolo *et al* 2023). In addition, the proposed electricity tariff meant to encourage e-cooking may push more households to transition to electricity (Leary *et al* 2023). Efforts to address the cost of fuel need complementary reductions in the cost of cooking appliances through, for example, tax waivers for local manufacturers. Further, investment in supply chain infrastructure for LPG and ethanol to bring them closer to consumers would open up markets in previously difficult to reach communities and encourage the uptake of these alternative fuels. Lastly, educational/awareness creation campaigns are needed to demystify clean cooking and demonstrate to diverse communities the options available to them.

Finally, the results from Kisumu may be more applicable to Kenya's majority rural population than those from Nairobi and Mombasa since traditional cookstoves and solid biomass fuels are more commonly used among rural communities and the urban poor. As the results from Kisumu show a clear benefit in averted mortality, in contrast to marginal gains in Nairobi and Mombasa from the same policy application, our proof-of-concept demonstrates the critical importance of capturing variations and inequities of exposures for distinct sub-populations. This work therefore demonstrates that the use of individual-based health impacts models can provide a simple and versatile method to account for differential demographic vulnerability and support equitable decision-making for municipal emissions mitigation strategies.

5. Conclusion

Our two-stage policy scenario yielded sequential reductions in personal $PM_{2.5}$ exposure in three Kenya cities after substitution with successively cleaner cooking fuels, however even after implementation of the most ambitious policy, estimated personal exposures remained above the WHO-recommended annual exposure target in all modelled cities. To fully realise air quality goals, strategies for concomitant reductions in sources of ambient $PM_{2.5}$ emissions, as well as other household sources such as lighting, must be considered. This model nonetheless demonstrates how construction of a synthetic population can be used as a basis to compare and contrast mitigation policies to evaluate public health benefits of emissions reduction. Our results confirm that differential benefits for individuals would occur as emissions distributions narrow after policy implementation. While some limitations remain, the ability of individual level models to identify drivers of uneven risk in particular demographic groups and the application of standardised methods for calculating health attribution to environmental hazards clearly convey the benefits of these methods to decision-making for climate mitigation. Future iterations of the model could aim to test additional energy policy aspirations informed by stakeholders or policymakers in Kenya, or simulate policies from other sectors, for example housing policy, to evaluate health benefits of multisectoral climate initiatives.

Data availability statement

The data cannot be made publicly available upon publication because the cost of preparing, depositing and hosting the data would be prohibitive within the terms of this research project. The data that support the findings of this study are available upon reasonable request from the authors.

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Authors Contributions

Ariel Brunn: Conceptualization, Formal Analysis, Data Curation, Writing—Original Draft, Writing—Review & Editing. **Lauren Ferguson**: Conceptualization, Formal Analysis, Visualization, Writing—Original Draft, Writing—Review & Editing. **Jessica Gerard**: Formal Analysis, Visualization, Data Curation, Writing—Original Draft, Writing—Review & Editing. **Kanyiva Muindi**: Methodology, Writing—Review & Editing. **Sourangsu Chowdhury**: Methodology, Data Curation, Writing—Review & Editing. **Jonathon Taylor**: Methodology, Writing—Review & Editing. **James Milner:** Conceptualization, Methodology, Formal Analysis, Writing—Review & Editing, Supervision.

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