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Article

Keywords:

Posted Date: July 16th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10019654/v1>

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Additional Declarations: There is **NO** Competing Interest.

Attributing child mortality and farmers migration to climate change through crop yield reductions in rural Burkina Faso

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Abstract

Anthropogenic climate change affects health through pathways beyond direct weather exposure, yet attribution studies largely focus on direct impacts in high-income settings and rarely capture agriculturally mediated effects. We present an attribution framework quantifying health and migration impacts of climate change-driven crop yield losses in rural Burkina Faso. Integrating factual and counterfactual climate simulations, machine-learning crop-yield models, and life tables from the Nouna Health and Demographic Surveillance System, we estimate farmer out-migration and child mortality attributable to climate-induced yield reductions. Over 1984–2016, climate change contributed to an ~8.0% yield reduction, a 1.9% increase in farmer out-migration, 2.3% more deaths among children <5 across all households, and 12.6% more child deaths in households experiencing out-migration. These results demonstrate that climate change has already produced measurable agriculturally mediated impacts on vulnerable rural populations in the Sahel, highlighting the need for effective and ambitious adaptation policies.

Climate change and weather extremes are adversely affecting food security, especially in low-income regions such as Sub-Saharan Africa^{1,2}. In turn, this affects health outcomes and shapes migration patterns in subsistence farming populations^{3–5}. Migration, when voluntary,

safe, and orderly, allows for the reduction of risks to climatic stressors and therefore, can be an adaptive strategy minimising health impacts of climate change³⁻⁶. In other circumstances, migration can be maladaptive and increase the health burden of climate change⁷, underscoring the limits of adaptation in rural communities.

Advances in counterfactual climate data and impact attribution methodologies now enable increasingly robust estimation of the contribution of climate change to observed impacts across multiple sectors⁸. Climate impact attribution considers cascading impacts of climate change in sectors like agriculture, health and others by comparing impact model outputs driven by factual versus counterfactual simulations, enabling the isolation of human-induced contributions to climatic change and their socio-environmental consequences⁹⁻¹².

Despite these methodological advances, health impact attribution to climate change remains nascent. Between 2013 and 2024, only 13 studies have rigorously quantified climate-attributable health impacts¹³. Since then, a small but growing body of attribution studies has broadened the evidence base beyond heat-mortality relationships to encompass temperature-related neonatal mortality in low- and middle-income countries and mortality attributable to wildfire-derived PM_{2.5}¹⁴⁻¹⁶. Nevertheless, the literature remains heavily concentrated on direct pathways — temperature extremes, extreme weather events, and ambient air pollution — leaving agriculturally mediated health impacts and climate-driven migration as an adaptive response substantially underexplored. Few empirical studies have quantified associations of health and migration with all-cause crop yield variability or investigated whether migration in response to crop yield reductions protects child survival^{17,18}. Owing to the greater complexity of agriculturally mediated pathways and persistent data limitations, no published studies to date have attributed health and migration impacts from crop yield fluctuations to already observed climate changes.

Sub-Saharan Africa remains a hotspot of data gaps for climate change and health research. Localised studies based on high quality longitudinal data remains the best approach for developing robust and reliable evidence on health impacts of climate change in this region. Such data are, for example, provided by Health and Demographic Surveillance Systems (HDSS) that comprise open dynamic cohorts monitoring health in defined populations over time (10,000-300,000 people, depending on the HDSS)¹⁹.

Previously, we used Nouna HDSS data to estimate the impact of weather-related annual crop yield reductions on child mortality in a subsistence farming population in Burkina Faso¹⁷.

Here, we extend our earlier modelling framework to allow for a robust attribution of indirect, agriculturally mediated health impacts to anthropogenic climate change. Additionally, we extend the framework by incorporating a new focus – on farmer out-migration as a potential response strategy – and its interaction with child mortality. Employing a machine-learning crop yield model which is making use of a trend attribution approach and a multi-model climate ensemble, we simulate yields under factual and counterfactual climates from 1984–2016 to estimate the attributable climate change impacts on agricultural production as well as on child mortality and migration, using a life table calculation framework. We also assess the interactive impacts of farmer out-migration and climate-induced child mortality, specifically whether out-migration of household members following yield reductions across the province mitigates or instead aggravates the attributable child mortality burden^{20–23}.

Results

The impact of climate change on crop yield fluctuation

To quantify the food availability status, we use the annual Food Crop Productivity Index (FCPI) based on the five main food crops in Kossi province – millet, sorghum, maize, fonio (a form of millet), and rice. The FCPI reflects the weighted average yield (kg/ha) of these crops relative to their mean yield over the period of 1984–2016²⁴. It is expressed as a percentage of the period average. The influence of anthropogenic climate change on the FCPI was examined by analysing its relationship with key agro-climatic variables using a machine learning crop yield model (see Methods). These variables are calculated from factual and counterfactual runs from six General Circulation Model (GCM)²⁵, obtained from simulation round 3b of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3b) (see SI Fig 1. for the model validation)²⁶.

Over the period 1984–2016, annual fluctuations in FCPI were primarily driven by variations in temperature and precipitation. The FCPI was negatively correlated with both median and maximum temperatures, highlighting the detrimental effects of heat on crop growth in the Kossi province (Figure 1, right column). These temperature metrics show significant increases in simulations under anthropogenic forcing (Figure 1, left column), with mean growing-season temperatures averaging about 0.8 °C higher than in the counterfactual climate (SI Table 1). In contrast, precipitation-related variables were positively associated with FCPI: higher total precipitation and maximum daily precipitation corresponded to improved crop yield, whereas a greater number of dry days was negatively correlated,

emphasizing the adverse impact of dry conditions on the region's five main food crops. Although precipitation exhibits weaker differences between factual and counterfactual simulations (both in trend and annual amounts), it remains a key determinant of year-to-year variability in FCPI.

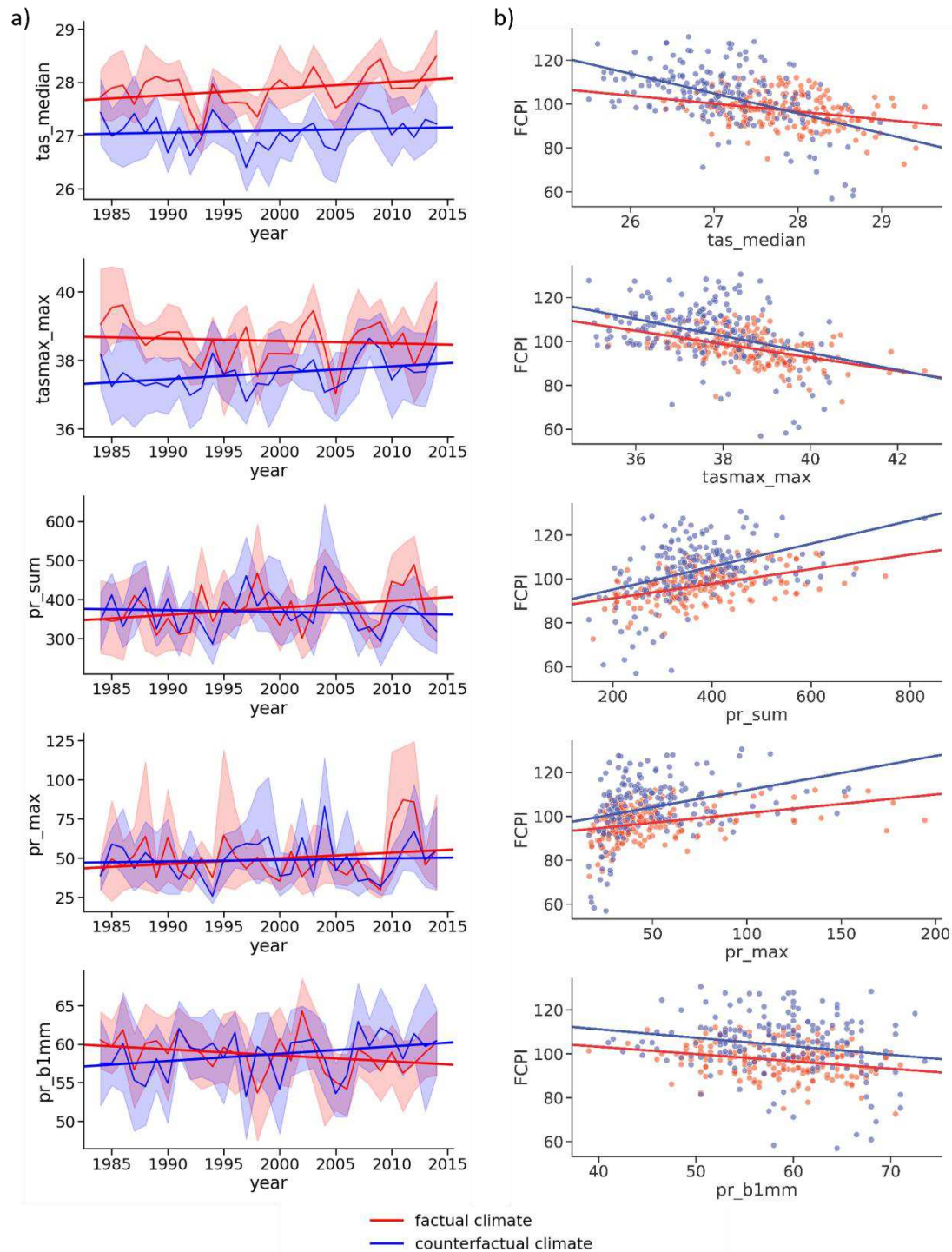


Figure 1: a) Agro-climatic variables for factual and counterfactual simulations for the growing season of millet - the main food crop in Kossi. Linear trends show an increase in median daily mean temperature (*tas_median*) by 0.01 (95% CI 0.00, 0.02) °C for factual climate and no change for counterfactual climate (95% CI -0.01, 0.02) °C; a decrease in the maximum

of daily maximum temperatures (*tasmax_max*) by -0.01 (95% CI -0.03, 0.01) °C for factual climate and an increase by 0.02 (95% CI -0.00, 0.04) °C for counterfactual climate; an increase in the precipitation sum (*pr_sum*) by 1.80 (95% CI 0.12, 3.48) mm for factual climate and a decrease by -0.43 (95% CI -2.07, 1.21) mm for counterfactual climate; an increase in the maximum daily precipitation sum (*pr_max*) by 0.36 (95% CI -0.14, 0.86) mm for factual climate and an increase by 0.10 (95% CI -0.33, 0.52) mm for counterfactual climate and a decrease in the days with precipitation amounts equal or below 1mm (*pr_b1mm*) by -0.08 (95% CI -0.17, 0.02) mm for factual climate and an increase by 0.09 (95% CI -0.01, 0.20) mm for counterfactual climate. b) Agro-climatic variables for factual and counterfactual simulations and their correlation with the Food Crop Productivity Index (FCPI); plots a) and b) are presented for the ensemble of six considered General Circulation Model from CMIP6/DAMIP and ISIMIP3b: CanESM5, CNRM-CM6-1, GFDL-ESM4, IPSL-CM6A-LR, MIROC6 and MRI-ESM2-0. SI Figure 1 shows the individual model results.

The comparison of factual and counterfactual FCPI calculated by agro-climatic variables shows that human-induced climate change reduced FCPI in Kossi between 1984 and 2016 (Figure 2): The difference in median values of the simulations indicate that FCPI would have been approximately 8.0% higher under a counterfactual climate, i.e., in the absence of human-induced climate change. This difference is statistically significant (paired t-test p-value <0.01) across all climate models.

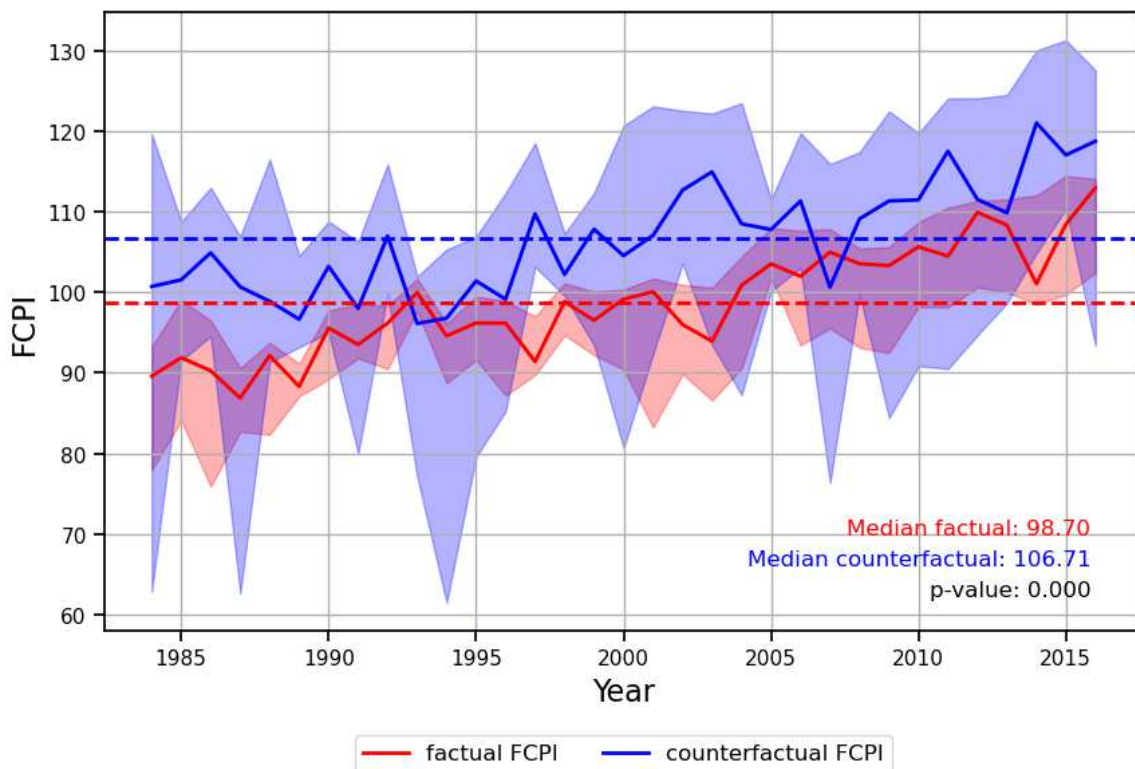


Figure 2: FCPI for factual (red) and counterfactual (blue) climate simulations from 1984 to 2016 for Kossi province, Burkina Faso. The dotted lines represent the median value over the whole period. The p-value provides the result of the paired t-test. The shaded areas show values between the 5th and 95th percentile over the six considered GCMs.

This climate-attributable difference is largely driven by the adverse effects of rising maximum temperatures on millet. Millet carries the greatest weight in the FCPI, accounting for 52% of total crop production across the five crops in Kossi (SI Table 2). Maximum temperature exhibits the highest feature importance for millet, contributing 73% to the overall reduction in prediction error (Figure 3). Across crops, indicators of climatic extremes were

more influential than variables representing mean conditions, with maximum daily precipitation showing the highest mean feature importance (33%), followed by maximum daily maximum temperature (25%) during the growing season.

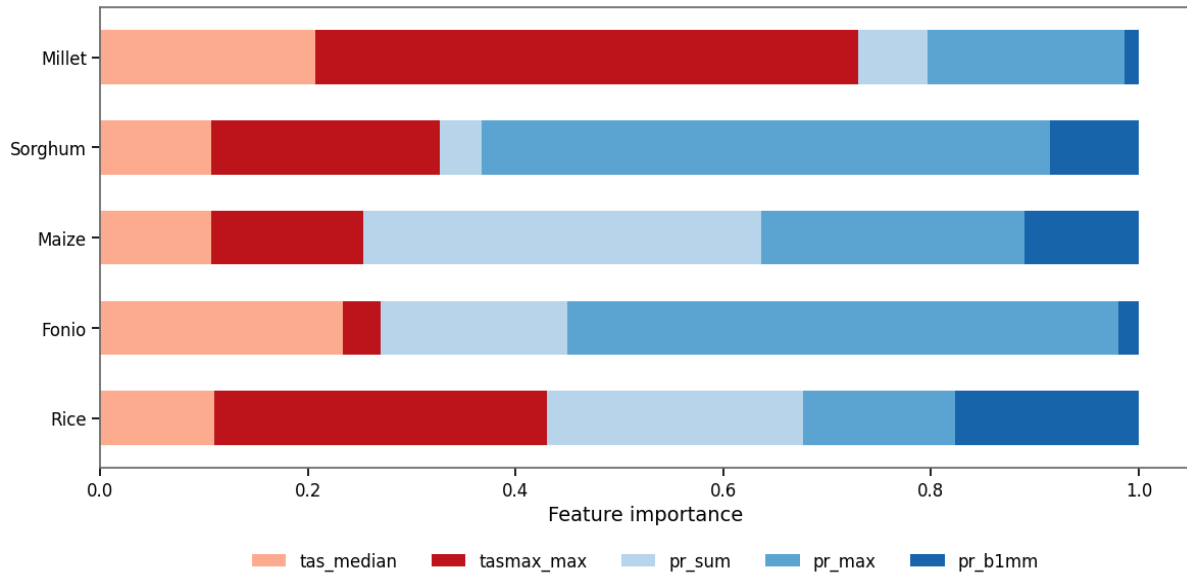


Figure 3: Feature importance for individual random forest crop yield models of the median daily mean temperature (*tas_median*), the maximum of daily maximum temperature (*tasmax_max*), the precipitation sum (*pr_sum*), the maximum daily precipitation sum (*pr_max*) and days with precipitation amounts equal or below 1mm (*pr_b1mm*) in the growing season for Kossi province in Burkina Faso. The feature importance is a relative measure of how much each feature helps improve the random forest model.

Attributable child mortality and migration impacts

Prior studies in the Nouna HDSS area have documented associations between child mortality, farmers' out-migration, and FCPI (Figure 4)^{27,28}. For child mortality, these associations represent the proportional increase in risk from birth to age five, reflecting estimates derived from Cox proportional hazards models. For migration, the associations capture risk over the full lifetime, as estimated using Prentice–Williams–Peterson models.

We extended this analysis by stratifying the relative risk of child mortality according to whether any farmers in the children's households migrated for work outside of the Nouna HDSS area. For this analysis we focussed on the period after a harvest season with provincial FCPI below the period average level (see the Methods for further details). The results indicate a substantially higher risk (hazard ratio) of child mortality in households with farmers' out-migration, while no significant association was observed in households without out-migration (Figure 4; SI Table 3).

We used these hazard ratios to derive empirical impact—exposure functions, which we transferred into life table calculation frameworks of child mortality and migration impacts and integrated into climate change attribution frameworks.

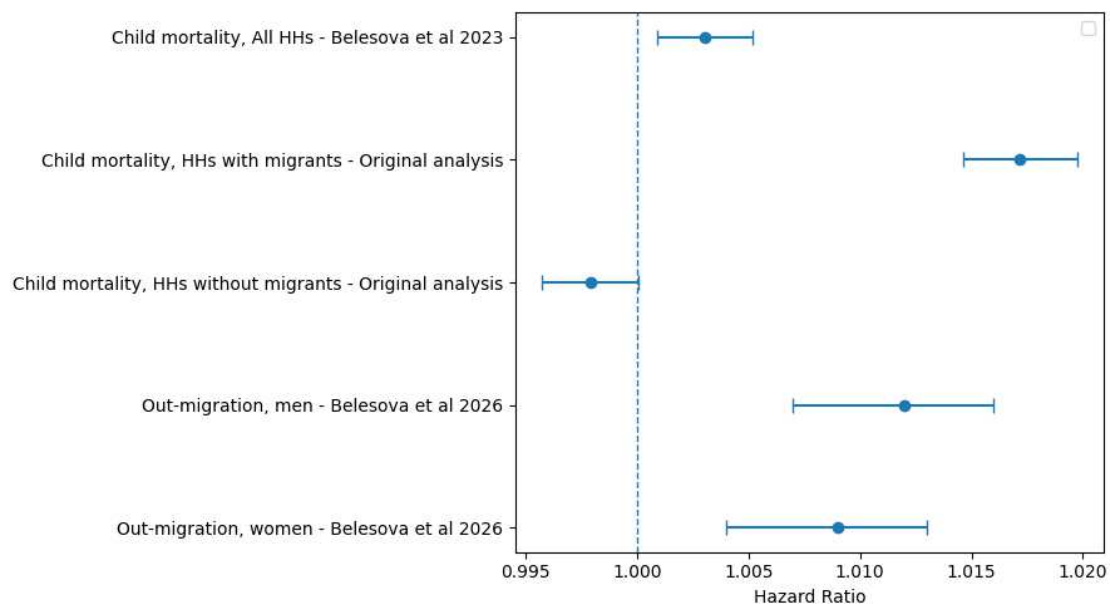


Figure 4: Hazard ratios of child mortality and farmer out-migration associated with 1% decrease in FCPI, based on past studies and original analyses^{27,28}.

Panel A of Figure 5 presents the burdens associated with a single year of exposure to the period-average difference between factual and counterfactual yield over the period of 1984–2016: child deaths subsequently occurring up to age five and the corresponding years of life lost (YLL), and farmer out-migration occurring over the remaining life course. The figure reflects the shares of these burdens occurring independently of anthropogenic climate change and the share attributable to already observed climate change. Attribution is based on the period-average difference (8.0%) between factual and counterfactual FCPI, derived as a period mean of the annual GCM ensemble medians.

In a year with average crop yields — based on data from 1984 to 2016 — approximately 120 out of every 6,479 out-migration events per 10,000 farmers could be attributed to human-caused (anthropogenic) climate change. This corresponds to a Population-Attributable Fraction (PAF) of 1.9%. Similarly, of 397 deaths per 10,000 children under five years of age, 9 were attributable to climate change. This corresponded to 592 out of 26,418 YLL per 10,000 children. These estimates translate into the PAF of 2.3% for child deaths and YLL.

In a year with average crop yields based on data from the same period, baseline child mortality was generally lower in households with the out-migration compared to households

without the migration and to the overall population (133 vs 920 and 397 deaths per 10,000 children under five, respectively). However, the climate change-attributable fraction of child mortality was observed only in households with out-migration and was nearly twice as high as in the overall population (15 vs 9 deaths per 10,000 children <5 years). In households with out-migration, the PAF was 12.6%.

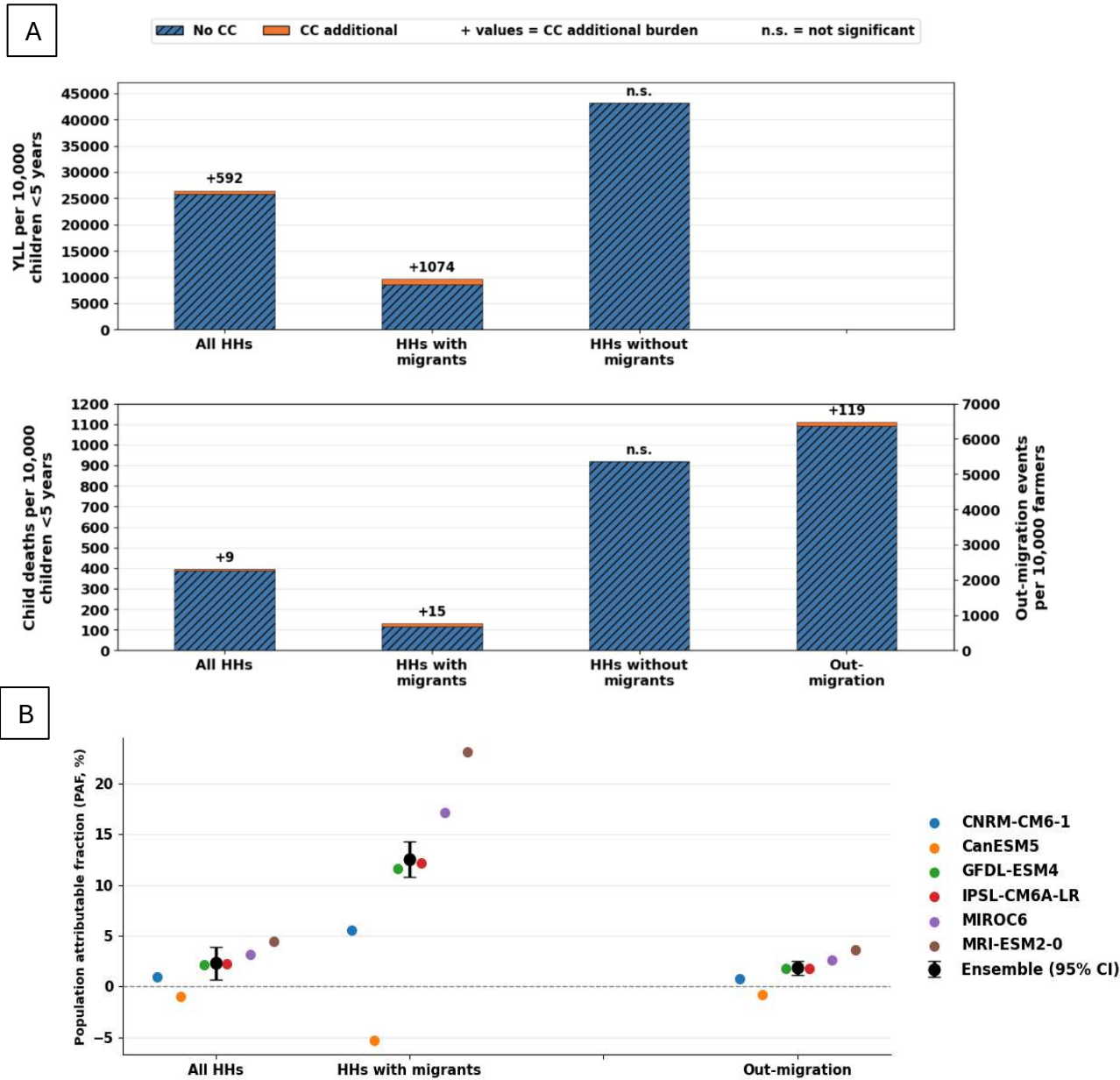


Figure 5: The burden of child deaths and years of life lost (YLL) per 10,000 children under 5 years of age — broken down by all households, households with farmer out-migration, and households without farmer out-migration — alongside farmer out-migration events per 10,000 farmers, in an average year (based on data from 1984 to 2016). Panel A shows the baseline burden in the absence of anthropogenic (human-caused) climate change, together with the additional climate-attributable burden; the “+” values indicate the absolute increase in outcomes attributable to climate change. Panel B shows the corresponding population-attributable fractions (PAFs).

In Panel A, the attributable burdens are shown for the ensemble summary of General Circulation Models (GCMs). In Panel B, results are presented for both each individual GCM and the ensemble summary. The confidence interval for the ensemble PAF reflects only the uncertainty in the hazard ratio used to calculate the attributable burden, and does not capture the uncertainty arising from the GCM ensemble.

GCM: General Circulation Model; HH: household; FCPI: Food Crop Productivity Index; n.s.: not significant; YLL: Years of Life Lost.

Panel A of Figure 5 presents PAFs estimated separately for each individual GCM and for the ensemble summary. For all models except one (CanESM5, which did not show a statistically significant difference between factual and counterfactual scenarios, $p = 0.302$; SI Figure 3), the central estimates indicated adverse impacts attributable to anthropogenic climate change, including reduced crop yields, increased farmers' out-migration, and higher child mortality.

SI Figure 4 shows the cumulative progression of the attributable child mortality farmer out-migration incurred over the study period. The attribution is based on annual difference between factual and counterfactual FCPI, based on the ensemble summary. The cumulative attributable impact of climate-change-driven yield reductions incurred over 1984-2016 amount to 2,013 out-migration events per 10,000 farmers, 283 child deaths and 4,721 YLL per 10,000 children <5 years of age in all households. In households with the out-migration the corresponding numbers are 446 child deaths and 7,348 YLL per 10,000 children <5 years.

Discussion

We attribute agriculturally mediated child mortality, farmer out-migration, and their interactions in Kossi Province, Burkina Faso, showing that anthropogenic climate change is already undermining food security, child survival, and migration in rural Burkina Faso. Using bias-adjusted climate simulations with factual and counterfactual historical data from six state-of-the-art general circulation models (GCMs), along with empirically calibrated machine learning-based crop models and a life table framework based on epidemiological exposure-response functions, we show that substantial fractions of child mortality and farmer out-migration over the last three decades are attributable to human-induced climate change.

By tracing the full chain from human-induced climate signals to agricultural production, health, and migration outcomes, this study makes a novel contribution to the field. Notably, mortality and migration are interconnected, as child mortality is higher in households that have experienced out-migration — indicating that these are not independent events. To our knowledge, these are the first published empirical estimates of climate-attributed child mortality and farmer out-migration mediated by crop yield deficits.

We estimate that anthropogenic climate change reduced the FCPI in Kossi by approximately 8.0% over the period 1984–2016, relative to a counterfactual climate without human-induced climate change. This is consistent with previously reported climate-attributed yield losses in

West Africa of 10.9–17.7% for millet and 5.9–15.0% for sorghum during 2000–2009²⁹. The effects of anthropogenic climate change are particularly evident in the rise in growing-season temperatures, with mean temperatures being 0.8 °C higher in the factual climate than in the counterfactual over 1984–2016. This is broadly consistent with regional temperature increases of ~1 °C reported across West Africa during 2000–2009²⁹.

The crop yield model identified weather-related factors particularly influential on crop growth in Kossi. Weather extremes had higher explanatory power than average conditions, consistent with a previous study in Burkina Faso³⁰. Millet – the dominant crop in the region, accounting for 52% of total production across the five crops considered – exhibited greater sensitivity to temperature-related than to precipitation-related factors, consistent with its well-documented drought tolerance³¹. For other crops, precipitation-related factors were more prominent, reflecting Burkina Faso’s strong reliance on rainfed agriculture³². The substantial influence of weather on the FCPI is further supported by the close agreement between observed and modelled FCPI ($R^2 = 0.71$) using only five agro-climatic variables. Residual yield deficits likely reflect non-weather-related factors such as agronomic management, influence of pests and diseases, political, economic or social influences.

Our results provide quantitative evidence that anthropogenic climate change has already influenced rural mobility via its impacts on agricultural productivity. We estimate that climate change increased farmer out-migration by ~2% annually between 1984 and 2016, equivalent to 2,013 additional out-migration events per 10,000 farmers over the study period. Consistent with evidence linking climatic shocks and declining productivity to migration in rain-fed agrarian regions^{33–35}, these findings show that climate-driven crop production stress is already contributing to rural mobility.

These estimates are consistent with regional projections. The Intergovernmental Panel on Climate Change synthesizes studies estimating 17–40 million internal migrants in Sub-Saharan Africa by 2050 under lower warming, rising to 56–86 million under higher warming pathways³⁶. Similarly, the World Bank Groundswell project projects up to 86 million internal climate migrants by mid-century under adverse scenarios³⁷. While these projections include multiple drivers, our historical estimates identify a key mechanism: sustained declines in agricultural productivity can increase rural out-migration, suggesting observed responses may represent early stages of long-term demographic change in response to climate pressures.

We further estimate that climate change, acting through crop-yield reductions, increased mortality among children under five by 2.3% per year between 1984 and 2016, equivalent to 283 additional deaths per 10,000 children over the study period. These findings align with evidence linking climate variability and agricultural productivity to child health via food insecurity, reduced income, and elevated disease risk in low-income agrarian settings^{24,27,38–40}. The World Health Organization projects that climate-driven undernutrition will substantially increase child deaths in Sub-Saharan Africa in coming decades⁴¹. While prior attribution studies emphasize direct heat effects on mortality^{42,43}, our results identify an agriculturally mediated pathway through which anthropogenic climate change may already be affecting child survival. Although the annual attributable fraction is modest, the cumulative burden suggests that continuous climate pressures on agriculture may erode gains in child survival over time.

Notably, the climate-attributable mortality burden was concentrated in households experiencing farmer out-migration following low-yield harvests across the province. Despite lower baseline mortality, attributable child mortality in migrant households was nearly twice that of the overall population, while none was observed in non-migrant households. Given the strong link between yield reductions and migration in the Nouna HDSS area⁴⁴, this suggests migration under climate-driven crop yield losses may not be an effective response strategy. Instead, it may represent maladaptation, consistent with frameworks showing constrained migration can redistribute and amplify household risk^{45–48}. Yield loss-driven migration may heighten vulnerability by reducing labour and caregiving capacity during stress periods. The sharp rise in climate-attributable mortality in migrant households during low-yield years indicates that climate-driven mobility in this setting may amplify, rather than buffer, climatic risk^{46–49}.

Our attribution results show that anthropogenic climate change in Burkina Faso is already driving measurable losses in agricultural production, elevated child mortality, and farmer out-migration. Future projections indicate further warming of 0.5–2 °C coupled with declining precipitation and maize yields of up to 20% under SSP2-4.5 by 2075³². This will likely exacerbate impacts on health and migration.

These findings highlight the urgency of integrated mitigation and adaptation strategies. Policies should prioritise two complementary approaches. First, building in situ resilience through climate-resilient crops, improved soil and water management, and livelihood

diversification, health interventions, nutrition-sensitive programs for pregnant women and young children, shock-responsive social protection and appropriate financing mechanisms, early warning systems and contingency planning linked to rapid food and health responses^{50–52}. Second, supporting planned migration by ensuring access to social protection, health services, and education^{53,54}.

Our study has several uncertainties and limitations. Several modelling inputs were based on limited data, including the exposure—response (yield—mortality and yield—migration) functions originating from single studies and crop yield data resolution and reliability issues that are common in Sub Saharan Africa^{27,44,55} – may have limited model performance and precision. For example, the historical crop yield data were only available at the provincial level — an area slightly larger than the HDSS population catchment — which required us to assume that all households were uniformly exposed to annual crop yield reductions and exposure only varied across years. Child mortality estimates also omit (pre-)conceptional exposures — due to unavailable baseline pregnancy data in the Nouna HDSS. These estimates are a partial representation of the full burden of health impact driven by crop yield deficits also because they omit morbidity, cognitive, immunological, and productivity impacts due to insufficient epidemiological evidence²⁴. Furthermore, in our modelling we did not account for: (1) changes in the CO₂ concentration and possible positive effect of CO₂ fertilization on crop yield^{56,57}, (2) non-climatic factors, such as socio-economic development and crop management. Finally, as a machine learning–based model, the crop yield model identifies statistical associations but does not support causal inference.

Future work should extend attribution analyses to encompass morbidity, child development, and longer-term impacts on human capital and productivity. To better inform targeted adaptation strategies, future studies should move toward causal analyses of the mechanisms linking agro-climatic conditions, crop yields, and downstream health and migration responses, for example through the integration of econometric methods and process-based crop models. Progress will also depend on improved precision of exposure—response functions and yield models, requiring longer and higher-quality yield time series and continued reductions in uncertainty in general circulation model outputs. To strengthen the evidence base and support robust policy guidance, comparable attribution studies are needed in other regions dominated by rain-fed subsistence agriculture, alongside additional epidemiological evidence to enable cross-context synthesis and meta-analysis. Finally, extending this modelling framework to future climate projections under alternative climatic

forcing and socio-economic pathways will be essential for anticipating evolving risks and informing proactive adaptation planning.

Methods

Study population and setting

For this study, we focussed on the population of the Nouna Health and Demographic Surveillance System (HDSS) in Kossi province of Burkina Faso. It has been surveyed by the Centre de Recherche en Santé de Nouna (CRSN) since 1992 recording all vital events (migration, births, deaths), selected health, socio-economic and demographic parameters⁵⁸. In 2022, the Nouna HDSS population reached the size of 125,000 people. The setting where this population resides is characterised as a dry orchard savannah with annual average precipitation of 796 mm⁵⁹. This is almost exclusively a subsistence farming population reliant on rain-fed agriculture and a single agricultural harvest per year⁶⁰.

Modelling methods

We developed a framework based on inter-linked models of three relationships: (1) weather—crop yield, (2) crop yield—migration, and (3) crop yield—mortality (Figure 6):

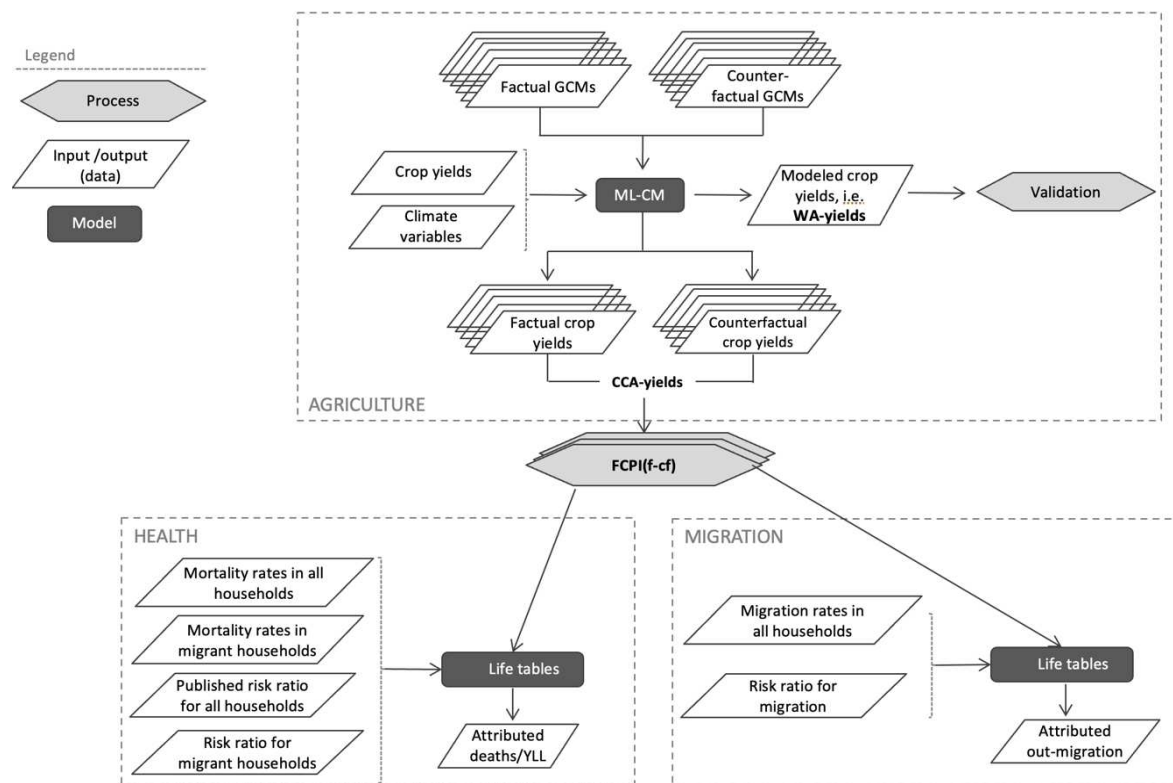


Figure 6. Flowchart of weather-agriculture-migration-health modelling framework. To develop estimates of child mortality and out-migration attributable to crop yield deficits, we combined weather-driven agricultural crop model

output with the calculations of out-migration and child mortality impact attributable to annual crop yield deficits.
 Abbreviations: FCPI: Food Crop Productivity Index; FCPI(f-cf): difference between factual and counterfactual FCPI;
 WCM: Weather-Crop Model; YLL: Years of Life Lost.

(i) Weather-crop yield model

We developed machine-learning models linking crop yield to agro-climatic variables during each crop's growing season, following the approaches of Laudien *et al*³⁰, Romanovska *et al*⁶¹ and Schauburger *et al*⁶². As yield data for the Nouna HDSS area specifically are not available, we used the highest-resolution data available – provincial-level data for Kossi. For each of the five main food crops cultivated in Kossi – millet, sorghum, maize, fonio and rice, we applied the random forest algorithm⁶³ and trained the model on past yield and observational and re-analysis climate data spanning from 1984 to 2016⁶³.

We obtained crop yield data from national Annual Agricultural Surveys, where crop yield was measured using a crop cut method with a sampling strategy representative at the province level, supplied by the Agricultural Statistics Service of Burkina Faso (Direction Générale des Prévisions et des Statistiques Agricoles, 2013). Training data included daily rainfall from the CHIRPS (Climate Hazards group Infrared Precipitation with Stations) dataset ($0.05^\circ \times 0.05^\circ$ resolution⁶⁴) and daily mean, maximum, and minimum temperatures from ERA5 ($0.25^\circ \times 0.25^\circ$ resolution⁶⁵).

Five agro-climatic variables, selected based on plant physiology and known influence on crop growth, were used to capture average conditions, extremes, and intra-seasonal variability. Variables were calculated specifically for each crop's growing season following¹⁷. To ensure comparability across crops and climate models, a fixed set of variables was applied: median daily mean temperature (tas_median) and total precipitation (pr_sum) for average conditions; maximum daily temperature (tasmax_max) and maximum daily precipitation (pr_max) for extreme conditions; and the number of days with precipitation ≤ 1 mm (pr_b1mm) to capture dry spells. These variables are commonly used in statistical weather–yield models across Sub-Saharan Africa^{30,55,66}. Descriptive statistics can be found in SI Table 1. The variables were calculated at the grid level and then aggregated to the administrative boundaries of Kossi province. To remove long-term trends associated with changes in crop management or technological development, yield time series were linearly detrended prior to model input. Climate variables were similarly detrended to ensure consistent pre-processing between the observational yield and observational and reanalysis climate data. Detrending and

standardizing of the observed, factual, and counterfactual climate variables were based on observed trends, means, and standard deviations following Romanovska *et al*⁶¹.

For each crop, an individual random forest model was trained with the following hyperparameters: 300 trees, maximum tree depth of 1–2, a minimum of 2 samples per leaf, and 5-fold cross-validation applied to the training set only.

We employed leave-one-year-out cross-validation. The dataset was divided into sections corresponding to each available year. The model was iteratively trained on all but one section (training set) and tested on the remaining year (test set). This process was repeated until every year had served as the test set once. Model performance was then assessed as the average score across all test sections⁶⁷. This approach is widely used for robust evaluation of machine learning models, particularly when datasets are small⁶⁸.

(ii) Food Crop Productivity Index – the link between crop yield and health/migration models

To reflect annual yield variation across the five crop types, we calculated the annual Food Crop Productivity Index (FCPI)²⁴. The FCPI reflects the weighted average of the yield (kg/ha) of the five main food crops in Kossi – millet, sorghum, maize, fonio (a form of millet), and rice – relative to their mean yield over the period of 1994–2016, and is expressed as a percentage of the period average. Thus, an FCPI of 70% represents a 30% deficit in overall food crop yield relative to the period average.

Algebraically, for year *i*, the FCPI was calculated as follows:

[eq 1]

$$FCPI_i = \sum_{j=1}^J y_{ij} * w_{ij}$$

FCPI_{*i*} – relative food crop yield (%) for year *i*

y_{ij} – yield of crop *j* in year *i* relative to its mean yield in 1994–2016

w_{ij} – harvest of crop *j* in year *i* as a proportion of the total harvest across the five food crops

j – identifier of each food crop (millet, sorghum, maize, fonio, rice) with *j*=1,..., *J*

(iii) Climate impact attribution to quantify human-induced crop yield and FCPI deficits

To derive the FCPI fraction that is attributable to anthropogenic climate change, we applied the weather-crop model parameters (calibrated on the observed climate and yield data) to past factual and counterfactual climate simulations derived from six General Circulation Model (GCM) realizations participating in the Coupled Model Intercomparison Project Phase 6 (CMIP6) and the Detection and Attribution Model Intercomparison Project (DAMIP) at a resolution of $0.25^\circ \times 0.25^\circ$: CanESM5, CNRM-CM6-1, GFDL-ESM4, IPSL-CM6A-LR, MIROC6, MRI-ESM2-0²⁵. The data were sourced from simulation round 3b of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3b), which provides a consistent, cross-sectoral climate impact dataset across scales and scenarios²⁶. The ISIMIP3b climate data are bias-adjusted using W5E5 v2.0⁶⁴. As these simulations are only available until 2014, we extend the analysis to 2016 using SSP3-7.0 as the closest substitute for SSP2-4.5²⁵, as SSP2-4.5 is not available in ISIMIP3b. SSP3-7.0 represents a mid-to-upper range emissions scenario within CMIP6. Over the short period immediately following 2014, differences between SSPs remain small; therefore, the choice of scenario has a negligible influence on the near-term climate signal.

We use the historical (hist) simulations as factual scenarios and the historical natural-only (hist-nat) simulations as counterfactual scenarios. We follow a trend attribution approach, i.e. we attribute the evolution of FCPI over time and do not focus on single impact events, which would be covered in a climate event attribution analysis¹⁰. To determine the fraction of FCPI attributable to past anthropogenic climate change, we first derived factual and counterfactual yields of individual crops, and then FCPI values for each of the GCMs. Differences between factual and counterfactual FCPI were then calculated for each GCM to represent the fraction of FCPI attributable to climate change. We tested whether the differences in FCPI are significant with a paired t-test.

For our main impact estimates on farmer migration and child mortality, we used the median value of the climate change attributable FCPI variation from the ensemble of GCMs. To represent the GCM-related uncertainty, we present the impact estimates for individual GCMs in Figure 5, Panel A.

(iv) Crop yield-migration and mortality modelling

To estimate the impact of annual differences between the factual and counterfactual FCPI on farmer out-migration and child mortality, we used a life table calculation framework⁶⁹, which

we developed for the Nouna population using age- and sex-specific Nouna HDSS migration data, 1994–2016, and relative risks from relevant prior epidemiological analyses.

1) Relative risks of farmers' out-migration in relation to annual crop yield were derived from a previous study⁴⁴. In that study, risks were estimated as hazard ratios for out-migration associated with the preceding year's FCPI using Prentice–Williams–Peterson regression models. Models adjusted for individual and village-level confounders identified a priori based on the local context and previous literature, including age, ethnicity, religion, literacy, and village characteristics (rural versus semi-rural setting, presence of a school, market, healthcare facility, drilled well, and road quality), as well as village-level random effects and calendar year. Effect modification was assessed by sex, household wealth, agricultural occupation, and migration order. For the life-table analysis, we derived sex-specific hazard ratios for farmers' first out-migration events by pooling estimates across household wealth strata, which were not examined in this study. We focused on farmers because yield–migration associations were strongest in this occupational group and represent the most direct pathway linking crop productivity to migration. First migrations were analysed to avoid bias arising from incomplete identification of return migrants. Estimates were calculated in Stata version 17 (StataCorp LLC, College Station, Texas).

2) The relative risk of child mortality in relation to annual crop yield was obtained from Belesova *et al*²⁷. In that study, hazard ratios were estimated using Cox proportional hazards models linking province level FCPI to household mortality, adjusting for confounders identified a priori based on prior research and local context. These included age, sex, season, ethnicity, religion, parental literacy, rural versus semi-rural residence, village infrastructure (presence of a market, health facility, drilled well and road quality), village-level random effects, calendar year and the presence of an undernutrition treatment programme. Hazard ratios were reported for several early-life exposure windows. Associations were strongest (and identical) for exposures during the first 1,000 days from conception and the first two years after birth, with no evidence of effects from exposures after age two. Because baseline mortality rates required for life-table modelling were unavailable for the in-utero period in the Nouna HDSS, we used hazard ratios for exposure from birth to two years of age.

3) To examine whether the child mortality impacts of crop-yield reductions differ between households with and without farmer migration, we extended the analyses of Belesova *et al*²⁷ by **stratifying the relative risk of child mortality by migration status** in the child's household. Specifically, we adapted the Cox proportional hazards model used in that study for the exposure window from birth to two years of age by including an interaction term between the FCPI and an indicator of out-migration among household members engaged in farming. The migration indicator identified households in which a farming household member out-migrated to work, farm or pasture outside the HDSS area during the child's observation period, defined as the interval between birth (start of exposure) and exit from the cohort through death, out-migration or censoring at five years of age. This temporal restriction focuses on migration events occurring during the period of exposure to provincial annual yield variability. The interaction analysis indicated a significant association between crop-yield reductions and child mortality only among children in households experiencing migration (SI Table 3). We therefore estimated impacts for this subgroup using separate life-table models that combined the estimated hazard ratios for crop-yield reductions with baseline mortality rates in households experiencing migration by members engaged in farming. Analyses were conducted in Stata version 17.

Using the lifetable calculation framework, we linked the annual differences between the factual and counterfactual FCPI values with baseline farmer out-migration and child mortality rates and the relative risk for out-migration of farmers and for child mortality in the year following each harvest. The relative risk of out-migration in a given year was applied to farmers in that year and each subsequent year until their exit from the cohort due to death, out-migration or loss to follow up. Applying this relative risk to the life table gave a calculation of the change in number of out-migration events by farmers. The relative risk of child death in a given year was applied to children in that year and in each subsequent year until the age of 5 years but not older ages. Applying this relative risk to the life table gave a calculation of the change in number of child deaths and years of life lost (YLL).

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