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Mortality Impact of Low Annual Crop Yields in a Subsistence Farming Population of Burkina Faso under the Current and a 1.5°C Warmer Climate in 2100

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Abstract

In subsistence farming populations of sub-Saharan Africa reliant on rainfed agriculture, years of low crop yields result in poorer child nutrition and survival. Estimates of such impacts are critical for their reduction and prevention. We developed a model to quantify such health impacts, and the degree to which they are attributable to weather variations, for a subsistence farming population in the Nouna district of Burkina Faso (89,000 people in 2010). The method combines data from a new weather-crop yield model with empirical epidemiological risk functions. We quantify the child mortality impacts for 1984–2012 using observed weather data and estimate potential future burdens in 2050 and 2100 using daily weather data generated by global climate models parameterized to simulate global warming of 1.5°C above pre-industrial levels. For 1984–2012, crop yields below 90% of the period average were estimated to result in the total of 109.8 deaths per 10,000 children <5 years, or around 7,122.0 years of life lost, 72% of which are attributable to unfavourable weather conditions in the crop growing season. If all non-weather factors are assumed to remain unchanged, the mortality burden related to low crop yields would increase about twofold under 1.5°C global warming by 2100. These results emphasize the importance and value of developing strategies to protect against the effects of low crop yields and specifically the adverse impact of unfavourable weather conditions in such settings under the current and future climate.

Keywords: climate change, health, child mortality, crop yield, agriculture, vulnerable population

1. Introduction

Studies from Ethiopia, Mali, and Burkina Faso (Belesova et al., 2017a; Grace et al., 2016; Johnson and Brown, 2014; Yamano et al., 2005) suggest that low crop yields are an important risk factor for child nutrition and health in subsistence farming populations of sub-Saharan Africa, and that low crop yields in the year of birth have an adverse effect on child survival (Belesova et al., 2017b; Johnson and Brown, 2014). To date, there have been few attempts to quantify these impacts at population level.

Annual variations in crop yields may arise from range of factors, including the weather conditions during the growing season, pests and disease, changes in crop selections and management, food prices and trade. In this paper, we focus on weather variations (precipitation, temperature, solar radiation) as the principal factor of importance for a subsistence farming population dependent on rain-fed agriculture (Ray et al., 2015).

Altered weather patterns under climate change may present additional challenges for such populations (Phalkey et al., 2015). Nelson et al (2009) suggested that climate change-related impacts on yields may increase the worldwide number of underweight children by 24% by 2050, while Lloyd et al (2018, 2011) suggests a 45% increase in child stunting in West Africa by the same year through changes in crop productivity and an even further increase through changes in food prices and incomes of the poorest 20% of the population. However, these estimates are based on aggregate-scale modelling rather than direct empirical relationships between the weather, food production, nutrition, and health. A few empirical studies have analysed the association of variations in precipitation or in the Normalized Difference Vegetation Index (NDVI) with child nutrition and survival (Grace et al., 2016; Johnson and Brown, 2014; Kumar et al., 2016; Rukumnuaykit, 2003; Yamano et al., 2005), but these studies do not enable a clear interpretation of specific pathways through which these associations operate.

In this paper, we report a method of quantification that links a (local) weather-crop yield model with empirical epidemiological evidence to model the impact of low crop yields on child mortality in a subsistence farming population of sub-Saharan Africa. The Paris Agreement of the United Nations

Framework Convention on Climate Change set the aspirational target to limit the global warming to a 1.5°C increase in global temperatures above preindustrial levels (UNFCCC, 2015). Evidence on the potential climate change impacts under a scenario of meeting this target is synthesised in the special report of the Intergovernmental Panel on Climate Change (IPCC, 2018). Although the report suggested that health risks associated with food insecurity are lower under 1.5°C than 2°C global warming, the possible magnitude of such health risks under a 1.5°C warmer climate remains unclear, particularly in vulnerable populations. Here, we examine the potential effect of changes in weather patterns on crop deficits and their associated child mortality in a vulnerable subsistence farming population of Burkina Faso under climate change consistent with a 1.5°C increase in global temperatures above preindustrial levels.

2. Methods

2.1. Study population and setting

We developed a model of child mortality using data and evidence for the population of the Nouna Health and Demographic Surveillance System (HDSS) in Kossi province, North West Burkina Faso. The area of residence of this population is classified as dry orchard savannah with annual average precipitation of 796 mm over the past five decades (Diboulo et al., 2012). In 2010, the Nouna HDSS system covered a population of 89,000 from 59 villages located across a third of the area of Kossi province (Schoeps et al., 2014). This population has been followed up by the Centre de Recherche en Santé de Nouna (CRSN) since 1992 through regular surveys of demographic, socio-economic, and health data (Sankoh and Byass, 2012). The single agricultural production season in this area covers the rainy season months of June to October (Dabat et al., 2012). The population relies almost exclusively on subsistence farming based on rain-fed agriculture (Dabat et al., 2012). Irrigation has been implemented in only 210 ha (<0.03%) of the 732,800 ha of the total area of the province (Dabat et al., 2012).

2.2. Modelling methods

We developed a model with two main elements: (1) a model of weather-crop yield relationships, and (2) a model of crop yield-mortality (Figure 1):

(i) Weather-crop yield model

We developed a separate weather-crop yield model for each of the five main crops grown in Kossi province following the methods of Gornott and Wechsung (2016) adjusted to the specific local conditions.

The models were estimated with log-transformed functional form (Cobb–Douglas production function) [eq 1] (Lee et al., 2013; You et al., 2009). We applied fixed effects transformation to the endogenous variable crop yield (y) and the vector of exogenous variables (x): G weather variables $(g = 1, \dots, G)$, H economic variables ($h = 1, \dots, H$, here only acreage), and I (range 0 – 2) dummy variables $(i = 1, \dots, I)$ – used to control for extreme yield anomalies, as in Albers et al. (2017) and Blanc (2012).

[eq 1]

$$\log \ddot{y}_{jt} = \sum_{g=1}^{G} \beta_{jg} \log \ \ddot{x}_{jgt} + \sum_{h=1}^{H} \beta_{jh} \log \ \ddot{x}_{jht} + \sum_{i=1}^{I} \beta_{ji} \, x_{jit} + \log \ddot{u}_{jt}$$

$\log \ddot{y}_t = \log\left(\frac{y_t}{\bar{y}}\right)$, $\bar{y}$ as arithmetic average of y_t and respectively for x and u. The term β represents the parameters, u is the error term, t as the time-index $(t = 1, \dots, T)$ and j the crop (millet, sorghum, maize, fonio, and rice).Crop-specific yield anomalies, i.e., the ratio of the annual yield to the period average ($\ddot{y} = \left(\frac{y_t}{\bar{y}}\right)$), 1984–2012, were regressed on growing season weather parameters (Mainardi, 2011; Rowhani et al., 2011). Crop-specific relative yield estimates and acreage (ha) for Kossi province were obtained from the national Annual Agricultural Surveys of Burkina Faso, which used a consistent year by year province-level estimation approach based on the crops cut method (Direction Générale des Prévisions et des Statistiques Agricoles, 2013). The crops cut estimation method is potentially subject to bias (e.g., resulting from uneven plant density of the fields) (Fermont and Benson, 2011). We minimised the risk of such bias by using measures of relative crop yield variation from one year to another.

The growing season weather variables used in each crop model were selected from knowledge of plant physiology (Gornott and Wechsung, 2016; Schauberger et al., 2017). The variables were derived from WFDEI* data, originally available at 0.5° (approximately 50 km at the equator) spatial and daily temporal resolution (Weedon et al., 2014). We extracted the data for the area of Kossi province and derived relevant annual weather variable values by aggregating the weather data over the growing season of each crop (see Appendix A for technical details on weather variable derivation). We assumed the following crop growing seasons for the Kossi province, as informed by data from the local agricultural authority, the agricultural crop calendar of the Food and Agriculture Organisation, and the Global Yield Gap and Water Productivity Atlas: for maize and millet 1 August to 31 October, for rice 1 May to 31 October, for sorghum 15 March to 31 October, and for fonio 15 April to 15 September (Food and Agriculture Organization, 2010; Yield Gap, 2013).

The following growing season variables were tested and retained in the model if they contributed to the model goodness of fit (R^2): solar radiation, cumulative precipitation, mean vapour pressure deficit, growing degree days (optimum temperature for crop growth of 8–30°C), killing degree days (temperature >30°C), days without precipitation, dry spells longer than 5 days, and heavy precipitation events (>40 mm per day). In addition, total acreage under cultivation was included to capture inter-annual changes in agricultural management (Iizumi and Ramankutty, 2015).Further technical details on weather-crop yield models, including key assumptions of these models and validation details, are provided in Appendix A.

Using these models we determined for each year of the analysis period the weather-attributable variation in each of the five main crop types (Albers et al., 2017), and hence the contribution of weather impacts to the annual yield deficit. To extract the weather-attributable share of the yield variability we applied the equation [1], setting acreage to constant, and exponentiating the result:

[eq 2]

*WFDEI -- Water and Global Change Forcing Data Methodology Applied to the European Centre for Medium-Range Weather Forecasts Interim Re-Analysis

$$y_{jt} = \exp\left(\left(\sum_{g=1}^{G} \beta_{jg} \log\ \ddot{x}_{jgt} + \sum_{\mathrm{h}=1}^{H} \beta_{jh}\ \overline{\log \ddot{x}_{jht}}\ + \sum_{i=1}^{I} \beta_{ji}\ x_{jit}\right) + \overline{\log y_{jt}}\right)$$

(ii) Crop yield-mortality model

To estimate mortality impacts we used life tables (Miller and Hurley, 2003) constructed for the Nouna population using age- and sex-specific Nouna HDSS mortality data, 1992–2012. A previous epidemiological study provided relative risks for mortality in children under 5 years in relation to the annual crop yield deficits for the year of the child's birth (Belesova et al., 2017b). The relative risks in that study were derived as hazard ratios from Cox proportional hazard models adjusted for a range of potential confounders. The confounders were determined a priori based on existing studies and the local context, and included age, sex, season, crop yield in subsequent years of life, ethnicity, religion, mother's and father's ability to read, semi-rural *vs* rural residence, indicators of village infrastructural characteristics (presence of a market, health care facility, drilled water wells, and quality of road connection), other village-level random effects, time trend (calendar year), and the existence of an undernutrition treatment programme. The relative risks for child mortality in relation to the annual crop yield deficits for the year of the child's birth is most likely a consequence of in utero exposures to poor nutrition on the part of the mother leading up to birth, or of poor nutrition during the first year of life (Belesova et al., 2017b). Risks associated with exposure to crop deficits at subsequent years of life or exclusively in utero were not available from the existing literature for the purpose of our life table models.

The crop yield deficit was defined by a parameter we refer to as the annual Food Crop Productivity Index (FCPI) (Belesova et al., 2017b). The FCPI reflects the weighted average of the yield (kg/ha) of the five main food crops in the Nouna area (millet, sorghum, maize, fonio (a form of millet), rice) relative to their annual mean yield for the period of 1992–2012, and is expressed as a percentage of the period average. Thus, an FCPI of 80% represents a 20% deficit in overall food crop yield in Kossi province relative to the period average. Algebraically, for year i, the FCPI was calculated as follows:

[eq 3]

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

$FCPI_i$ – relative food crop yield (%) for year i

y_{ij} – yield of crop j in year i relative to its mean yield in 1992–2012

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 $j = 1, \dots, J$

The needed input data to compute the FCPI – the annual crop harvests (kg), acreage (ha), and yields (kg/ha) for each of the five food crops – were obtained from national Annual Agricultural Surveys supplied by the Agricultural Statistics Service of Burkina Faso (Direction Générale des Prévisions et des Statistiques Agricoles, 2013).

With these data, we were therefore able to derive the annual crop deficits and hence compute the relative risk for mortality of children born in the same year up to 5 years of age. The relative risk of mortality in a given year was applied to the cohort of children born in that year and to their mortality risk in each subsequent year until the age of 5 years but not at 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). Such calculations were done for years with a crop yield of 90% or lower than the period average. Years with yields greater than 90% of the period average were assumed to carry no excess risk of mortality.

The FCPI was also converted into the weight of grain per adult equivalent per year (kg/ae/year) and its food energy value (Stadlmayr et al., 2012) per adult equivalent per day (kcal/ae/day). We made this conversion using evidence from another study (Belesova et al., 2017a), where those values were available.

2.3. Quantifying the impact of crop yield deficits

Using the modelling methods outlined above, we carried out two sets of computations of the child mortality impacts associated with:

(1) The *observed* pattern of crop deficits for the period 1984–2012 and the fraction attributable to unfavourable growing season weather conditions during this period; and

(2) A ‘thought experiment’ of *projected* future crop deficits for 2050 and 2100 under a pattern of climate change consistent with a 1.5°C warming above pre-industrial levels (but assuming all other factors are held constant at baseline levels).

To examine how crop yields might vary in the *future* under climate change, we applied the regression coefficients from the crop models (calibrated on the observed weather and yield data) to weather projections data derived from two general circulation model (GCM) realizations provided by the Inter-Sectoral Impact Model Inter-comparison Project (ISI-MIP2b), an international climate-impact modelling network, for the period of 1700–2100: IPSL-CM5A-LR (Institute Pierre Simon Laplace Climate Model) and MIROC5 (Model for Interdisciplinary Research on Climate) (Frieler et al., 2016), corrected against reanalysed weather observations by the ISI-MIP. These two model realizations were chosen because they cover a wide range of the projected uncertainty in future changes in precipitation in our study region. Both model realizations project warmer future temperatures, while MIROC5 projects wetter conditions and IPSL-CM5A-LR projects dryer conditions. Our estimates do not account for future changes in any other factors than weather (e.g., agricultural management practices and adaptation, prices, socio-economic and demographic conditions etc.) to indicate the independent effect of climate change alone. The projections were summarized for 30 year periods centred on 2015 (current conditions), 2050, and 2100. The GCM realizations used in this paper correspond to a conservative assumption of a global mean temperature increase of 1.5°C above pre-industrial levels by the end of the century (Frieler et al., 2016), the aspirational target agreed at the 2015 Paris conference of the UNFCCC (UNFCCC, 2015).

Additional analyses were performed based on upper and lower bounds of the model parameters as a way of exploring the influence of parameter uncertainty on the results (Appendix B).

The study was conducted following the ethical standards of the Declaration of Helsinki and was approved by the [*name of the institution blinded for peer-review*] Observational Ethics Committee and the Comité Institutionnel d'Ethique du Centre de Recherche en Santé de Nouna.

3. Results

3.1. *Crop yield deficits and mortality impacts, 1984-2012*

Over this 29 year period, crop yields were <90% of the period average in eight years, and <80% in two years (Figure 2, Table 1). The yield deficit in years with <90% of the period average yield was equivalent to an annual average harvest deficit of 18.2 kg/ae/year (kilograms/adult equivalent/year) or 177.9 kcal/ae/day – when averaged across all 29 years of observation. The lowest annual crop yield, 65% of the period average, was observed in the year 2000. It was equivalent to a harvest deficit of 109.8 kg/ae/year or 1,073.5 kcal/ae/day in that year, which is more than a third of the recommended daily food energy intake (2,900 kcal/ae/day) for a moderately active adult male of 30–60 years of age.

The impact attributed to these crop yield deficits was estimated as 3.8 deaths or 245.6 YLL per 10,000 children under 5 years, when averaged across all 29 years of the period of observation (1984–2012) – Table 1. For the year of lowest crop yield (2000), the attributed mortality impact was equivalent to 22.9 deaths or 1,477.3 YLL per 10,000 children under 5 years.

Figure 3 shows the cumulative total of the attributed child mortality and YLL over our period of observation 1984–2012, reaching the total of 109.8 child deaths and 7,122.0 YLL per 10,000 children under 5 years. Over this period, *weather* factors during the crop-growing season were estimated to account for 72% of the crop deficit and mortality impacts (Table 1). Over the period of observation, the additional mortality from crop yields <90% of the period average represented around 1.45% (95% CI 0.29, 8.61%) of all-cause mortality in children <5 years in that period.

3.2. *Projected crop yields deficits and mortality under 1.5°C global warming*

Figure 4 shows the crop deficit simulations from the GCM models with future projections of weather data. Crop yield projections demonstrate some background variability (which is the likely reason for the difference in the direction of FCPI projections between the two GCMs around 2050 in Table 2). Despite the background variability, the outputs of both GCMs suggest progressively less favourable growing conditions by the middle and end of the 21st century, with a steeper decline projected by IPSL-CM5A-LR than MIROC5. This is mainly because of an increase in temperatures above the optimal levels for crop growth and changing precipitation variability (Figure 5). As expected, both GCMs suggest an increase in the number of days with temperatures above the optimal levels for crop growth, and decreasing precipitation by IPSL-CM5A-LR but increasing precipitation by MIROC5 by the end of the century.

The per cent of years with FCPI <90% of the baseline period average, and the corresponding mortality impacts, were estimated approximately to double from the period of 2000–2030 to the period of 2085–2115 (Table 2). Central estimates suggested that the annual average mortality impact attributed to crop yield deficits could raise between 2000–2030 and 2085–2115 from 3.8 to 5.8 child deaths and from 245.7 to 374.3 YLL per 10,000 children under 5 years, according to the IPSL-CM5A-LR climate model, or from 1.6 to 3.3 child deaths and from 102.5 to 210.0 YLL per 10,000 children under 5 years, according to the MIROC5 climate model. Further analyses suggested that there is considerable uncertainty in these estimates. Results based on the lower bound of the parameters were compatible with no effect in any of the projection time periods, while results based on the upper bound of the parameters suggested a possibility that the annual average child mortality impact of crop yield deficits might reach 99.3 child deaths and 6,388.1 YLL per 10,000 children under 5 years in the year 2100, assuming all other factors than weather remain constant (see Appendix B: Supplementary figures and tables).

4. Discussion

The evidence we present here provides, to our knowledge, the first empirically grounded estimates of the impact of low crop yields, and weather-related low crop yields, on child mortality in a subsistence farming population of sub-Saharan Africa.

The estimates reflect the evidence of an adverse effect of low crop yield in the year of birth on child survival to the age of five years. They suggest an appreciable impact of current crop yield variations and patterns of changing climate that are likely to increase those impacts even under the very conservative assumptions of 1.5°C global warming. Although based on models and data specific to the Nouna HDSS population of Kossi province, Burkina Faso, our findings are likely to be broadly indicative of the impact of low crop yields in other similar populations in the region.

Our model of health impact was based only on the mortality impacts of low yields, as the only outcome with a clearly established relationship with annual crop yield deficits. Furthermore, yield deficit in the year of birth was the only timing of exposure examined in relation to a health outcome, as relative risks for other exposure timings were not available in the literature. The relative risks used in this study were estimated by relating child survival from birth (to 5 years of age) to relative yield of the last harvest preceding or at the time of the date of birth (Belesova et al., 2017b). Hence, these relative risk estimates reflect the effect of exposures to crop yield deficits that children in the study population experienced in part in utero and in part in their first year of life. The modelling inputs available for our analyses do not allow estimating the child survival effect of exposures to crop yield deficit beyond the first year of life or of exposures that occurred exclusively in utero. Our results may not capture the full health burden of the cumulative lifetime exposure to low crop yields. Other epidemiological evidence suggests that *in utero* exposure and low crop yields in later childhood, adolescence, and adulthood may also have negative effects on health and survival (Belesova et al., 2017b). Furthermore, our estimates did not consider morbidity impacts related to undernutrition, the associated increased susceptibility to infectious diseases, compromised cognitive development and immunity, as well as compromised productivity in later life (Belesova et al., 2017b). Currently, the epidemiological evidence is too insecure to allow the development of a health impact model that integrates all these effects, but they may add appreciably to our current estimates. Furthermore, we defined the deficits in relation to the period average crop yield level, which might be sub-optimal for the nutritional needs of this population (Belesova et al., 2017a). Therefore, we interpret our estimates as representing a lower bound estimate of the actual impact of crop yield deficits on child health.

Our estimates of future impacts of low crop yields under climate change should not of course be interpreted as showing the real impact to be expected in the future. Many factors other than climate are likely to change over the course of this century (and some have already changed in the past, e.g., child mortality rate, crop yield productivity, and population size) which will have a bearing on the health and survival of the child population in subsistence farming areas of sub-Saharan Africa. Exploring whether changes in such factors have made a contribution in the past and are likely to contribute in the future to increased or decreased vulnerability of our study population was beyond the scope of our study. The purpose of our estimates was rather to indicate the likely influence of changes in weather patterns alone if all other factors are held constant. With this assumption, they suggest that climate change would have an appreciably adverse impact even using the conservative rise of 1.5°C above preindustrial levels.

Our future projections of weather parameters, crop yields, and child mortality differed depending on the GCM. Our study area is located in a region where GCM agreement on changes in precipitation is relatively low (Schewe and Levermann, 2017). MIROC5, which projects wetter conditions, suggested somewhat smaller reduction in the projected future crop yields and correspondingly smaller increase in the attributed child mortality by 2100, as compared to IPSL-CM5A-LR, which projects drier future conditions (when compared to the current levels). In climate impact assessments, it is important to cover a range of climate model outputs. The two GCMs used in our assessment reflect relatively high and low estimates in changes in temperature and precipitation (Schewe and Levermann, 2017). Despite the background variability in crop yield projections, our results suggest consistent trends of decline in future crop yield projections across both GCMs. The central estimates of our projections under both GCMs suggested an increase in the attributed child mortality by 2100 with the 1.5°C global temperature increase above preindustrial levels, as compared to the current conditions. Future research should attempt further disentangling the variability and uncertainty in yield and child mortality projections using a wider range of GCMs.

Current nationally determined contributions of all signatories of the Paris agreement would lead to a 3°C warming, unless radical emission reduction is undertaken by all countries (IPCC, 2018). The impacts are likely to be greater under other climate change scenarios projecting a greater extent of global temperature increase than 1.5°C (Blanc, 2012) and requires further investigation. In this sense, our projections of the yield deficit attributed child mortality also give a lower bound estimate of the impact of climate change on child mortality in subsistence farming populations. Our results support the urgent need to limit any further global warming to 1.5°C above the pre-industrial levels.

It was beyond the scope of this paper to consider what form such strategies or interventions might take. Determining this is a complex scientific undertaking and requires assessment of a range of factors and implementation research. However, as our weather-crop yield model shows, low crop yields are largely attributable to the variations in the weather (Blanc, 2012). Moreover, applying the model to daily weather data generated under the 1.5°C global warming target suggests that crop yields will fall over time (all other things being equal) as growing season temperatures rise and the distribution of precipitation becomes less reliable. This observation suggests that efforts targeted specifically at ameliorating the effects of weather on crop yield should be considered (e.g., use of drought resistant seeds or improved irrigation as risk reduction measures or crop insurances as risk transfer measures). Nutritional protection measures and interventions such as food and supplement distribution, conditional cash transfers, food-for-work programmes, crop insurance schemes or other support might also be appropriate (del Ninno et al., 2005).

As with any modelling study, there are uncertainties and limitations. Several of our modelling inputs, including the central exposure–response (yield–mortality) function, which was derived from a single relevant study available to date (Belesova et al., 2017b), and modelled crop yield based on assumptions detailed in Appendix A, were based on limited data leading to limitations concerning the precision of the function and modelled yield estimates. Further uncertainty concerns the precipitation trends projected by the GCMs, as explained above. Other general circulation models might have yielded somewhat different estimates of changes in weather patterns, and we deliberately did not attempt to account for the (uncertain) trends in non-climate factors, such as socio-economic development. Other studies reporting climate impact projections at the national, and global levels attempted accounting for such trends using the country-level projections of Gross Domestic Progress (GDP), population, education, and urbanisation available under the Shared Socioeconomic Pathways (SSPs) scenario framework (Riahi et al., 2017). Socio-economic and demographic scenarios are not yet available at sub-regional level of Burkina Faso and hence were beyond the scope of our analyses. Nonetheless our analyses offer valuable first insights into the magnitude of the child mortality burdens related to crop yield deficits. It is noteworthy that the full health and wellbeing burden of the cumulative lifetime exposure to low crop yields is likely to be appreciably greater than our estimated impact.

Future research on health impacts of crop yield variation in the context of weather variability should attempt to address a broader set of health outcomes and wider aspects of their temporal effects, beyond the effect of the exposure in the year of birth. To strengthen the evidence and provide conclusive policy advice, similar modelling studies are required on other settings with high prevalence of rain-fed subsistence agriculture. Such studies require further epidemiological evidence on the exposure–response function of crop yield variation and health outcomes from other settings, as well as meta-analytical estimates of this function across settings once more empirical studies are available. Furthermore, improvements in the precision of the exposure–response function and crop yield modelling, which require long time-series yield data, as well as advancements in the reduction of uncertainty associated with the general circulation models are important steps for future research.

5. Conclusion

This study contributes evidence of an appreciable impact of low crop yields on population health in the subsistence farming population of rural Burkina Faso. Much of this health impact appears to be related to the negative agricultural impact of increasing weather variability, which is likely to worsen under climate change (all other factors being equal). These results emphasize the importance and value of developing strategies to protect against the effects of low crop yields and specifically the adverse impact of unfavourable weather conditions during the growing season on crop yields in such settings.

Tables

Table 1. Crop deficits and weather-related crop deficits, and their attributed child mortality impact, 1984–2012.

	Average year*		Worst year (2000)	
	Overall	**Weather-related**	**Overall**	**Weather-related**
Deficit in food crop harvest and yield				
kg per adult equivalent/year	18.2	13.5	109.8	106.2
kcal per adult equivalent/day	177.9	131.8	1,073.5	1,038.4
% FCPI below the period average	6%	4%	35%	34%
Mortality per 10,000 children <5 years				
Child deaths (<5 years)	3.8	2.9	22.9	21.9
YLL (not discounted)	245.6	185.7	1,477.3	1,418.3

*Based on deficits in years with FCPI<90% averaged across all years of the period 1984–2012.

Table 2. Crop yield, and attributable mortality impacts under 1.5°C global warming.

	IPSL-CM5A-LR			MIROC5		
	2015 (2000–2030)	2050 (2035–2065)	2100 (2085–2115)	2015 (2000–2030)	2050 (2035–2065)	2100 (2085–2115)
No (%) years with yield (FCPI) relative to the period average of:						
<90%*	11 (37%)	7 (23%)	17 (57%)	5 (17%)	13 (43%)	11 (37%)
<80%	1 (3%)	3 (10%)	2 (7%)	0 (0%)	0 (0%)	1 (3%)
Average annual deficit in food crop harvest						
kg per adult equivalent/year	18.3	13.6	28.0	7.6	18.6	15.8
kcal per adult equivalent/day	179.1	133.4	273.9	74.8	181.9	154.4
Deaths per 10,000 children <5 years						
Average year**	3.8	2.9	5.8	1.6	3.8	3.3
Worst year	16.9	15.3	16.2	12.1	12.2	15.5
YLL per 10,000 children <5 years						
Average year**	245.7	185.0	374.3	102.5	246.9	210.0
Worst year	1,086.9	980.0	1,038.9	774.1	785.8	994.1

*Includes years with FCPI<80%.

**Based on deficits in years with FCPI<90% averaged across all years in the respective 30-year time periods.

Figures

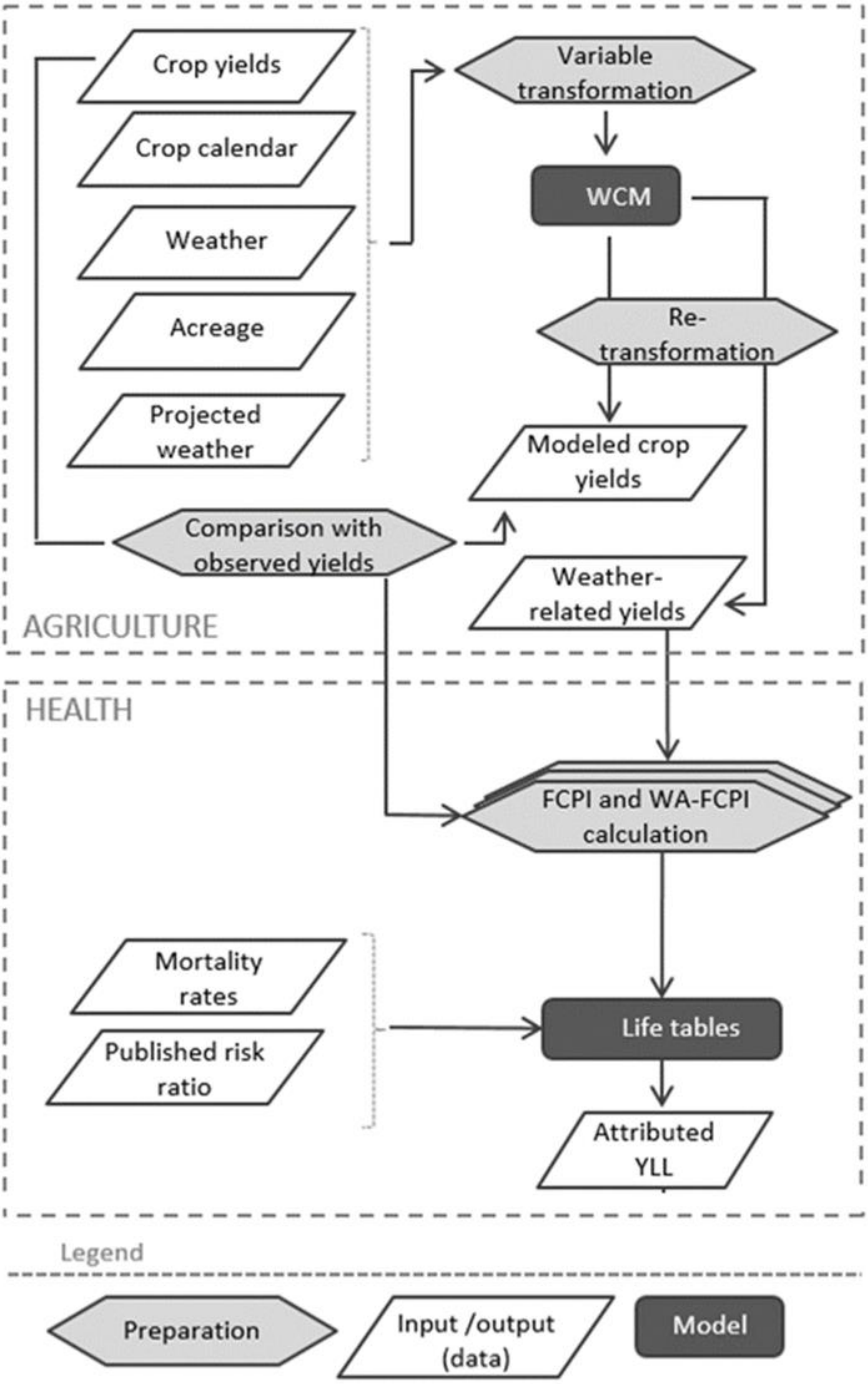

Figure 1. Flowchart of weather-agriculture-health modelling approach.

To develop estimates of child mortality attributable to low crop yields under the current and a 1.5°C warmer climate we combined agricultural models of weather effect on crop yields (components: observed crop yield and acreage data, observed and projected weather data, crop calendar) with the calculations of child mortality impact attributable to annual crop yield deficits (components: age- and sex-specific mortality rates, published risk ratio of child mortality impact of low crop yields (Belesova et al., 2017b), observed and projected crop deficits).

Abbreviations: FCPI, Food Crop Productivity Index; WCM, Weather-Crop Model, WA-FCPI, Weather-Attributed Food Crop Productivity Index; YLL, Years of Life Lost.

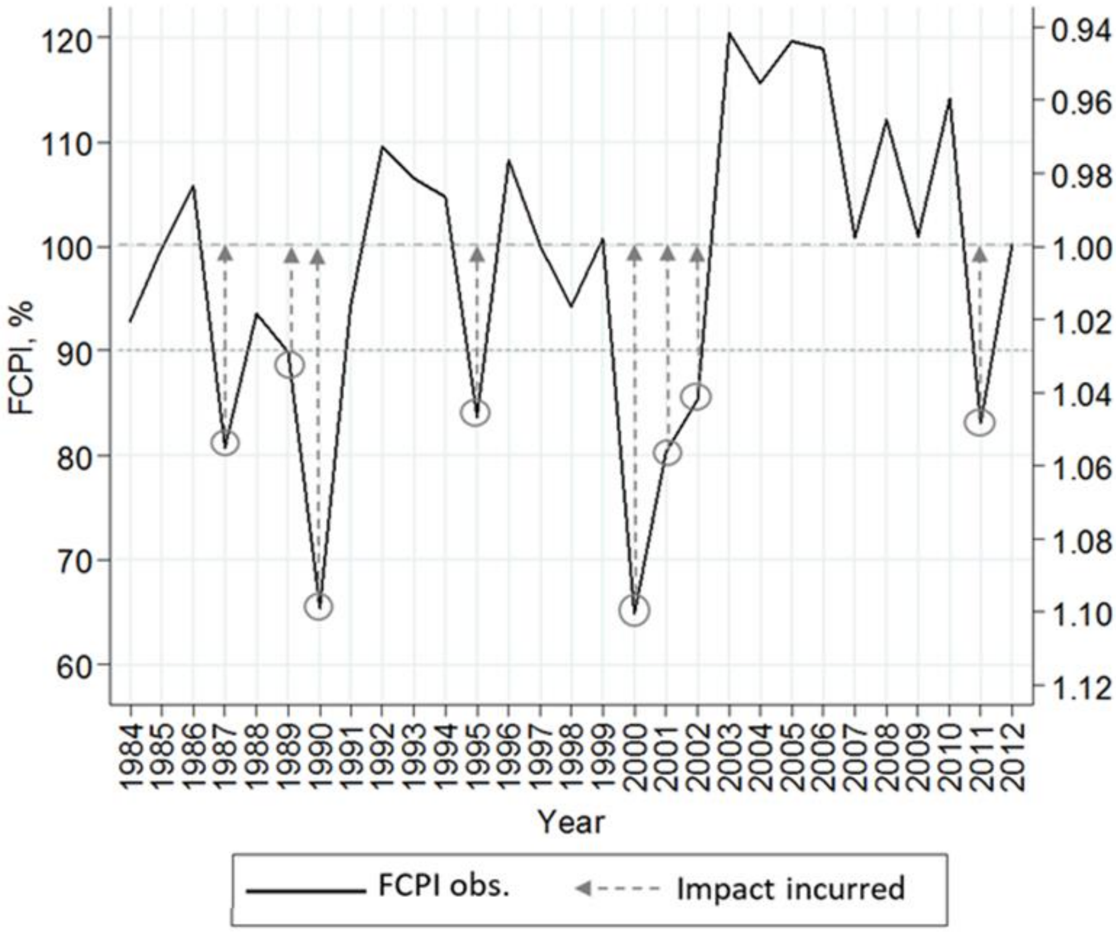

Figure 2. Time series of the Food Crop Productivity Index (FCPI) with the corresponding mortality risk ratio.

Circled markers indicate years with FCPI<90%. Arrows with dotted lines show the extent of the yield deficit below the counterfactual of 100% FCPI.

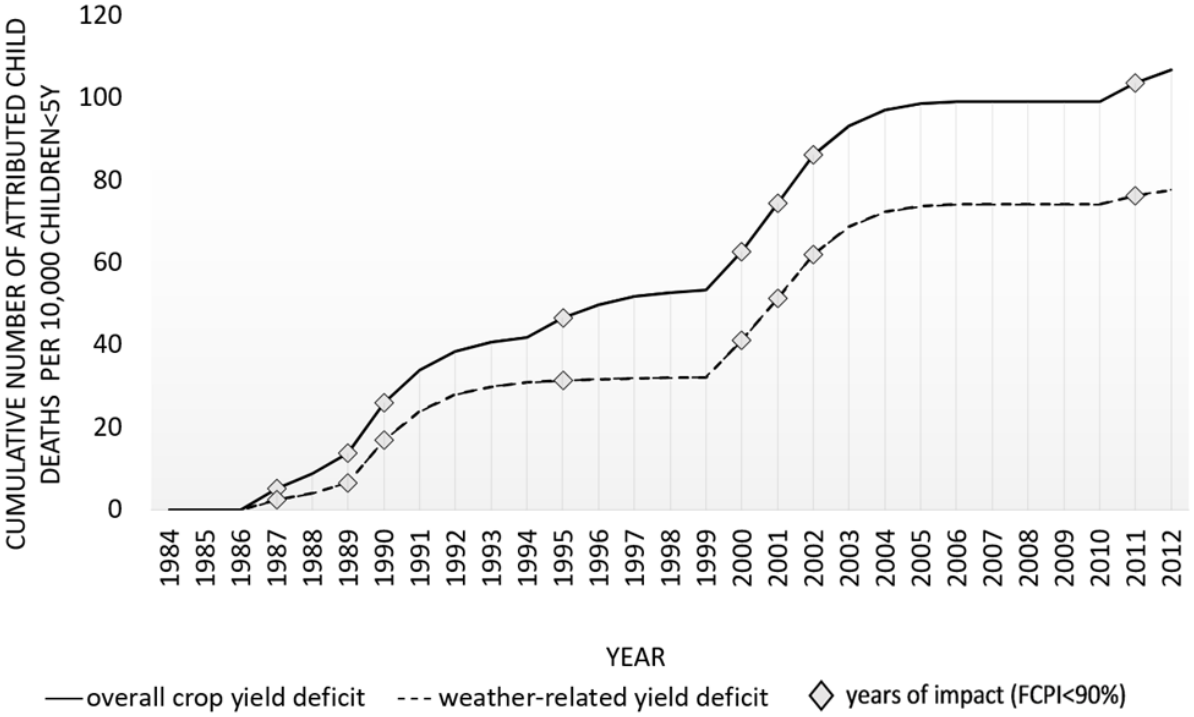

Figure 3. Cumulative health impact incurred over the period of 1984–2012 and attributed to the exposure in the year of birth to the overall and weather-attributed yield deficit in years with FCPI<90%.

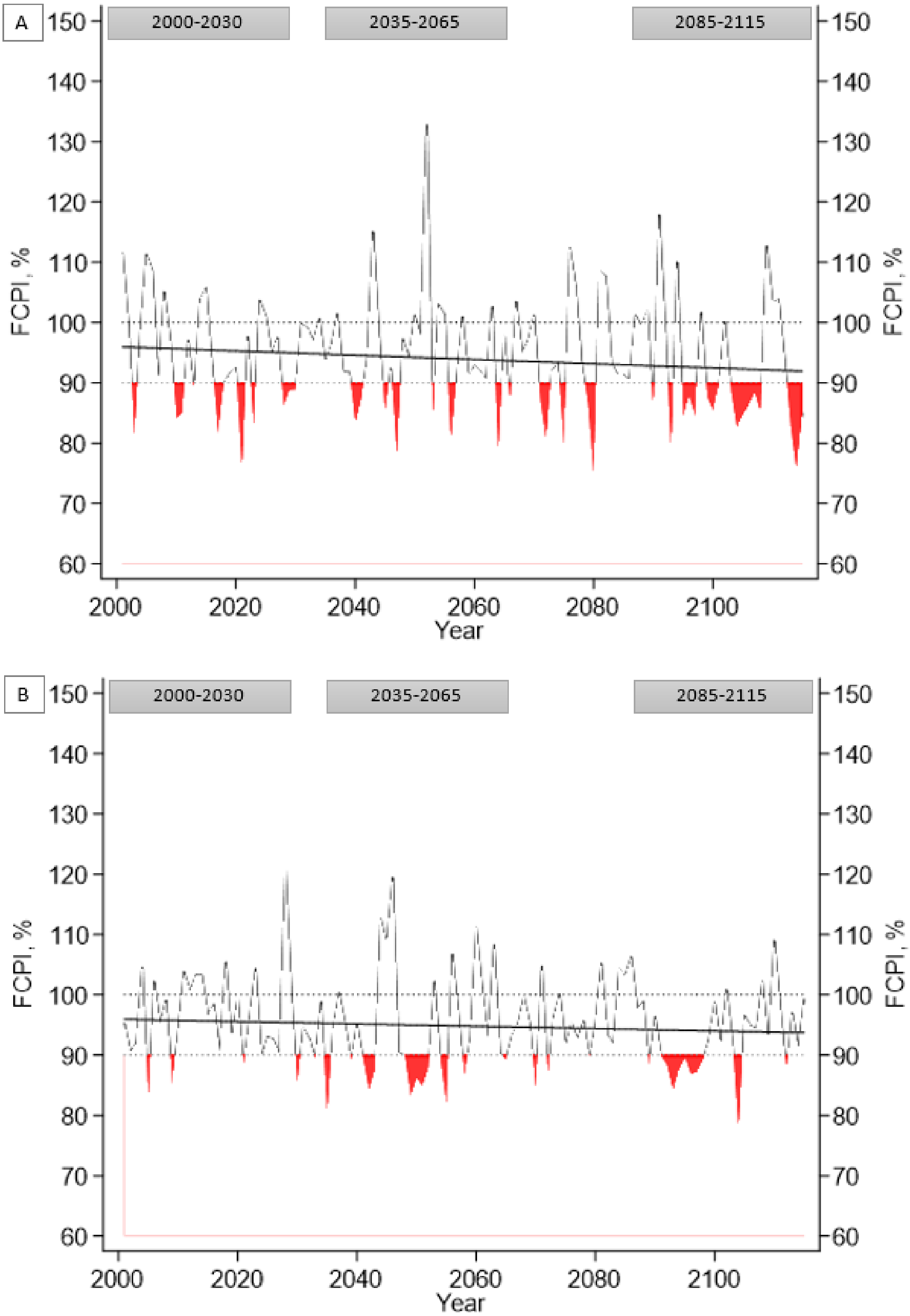

Figure 4. Food Crop Productivity Index (FCPI) projections based on climate data of each of the general circulation models separately: A – IPSL-CM5A-LR, B – MIROC5. Red colouring at the bottom of the time series indicates years when FCPI declines below 90%.

Linear trends: (1) black – trend in FCPI, suggesting -0.45 (95% CI -0.90, 0.01) and -0.20 (95% CI -0.63, 0.24) percentage point change in FCPI per decade for IPSL-CM5A-LR and MIROC5, respectively.

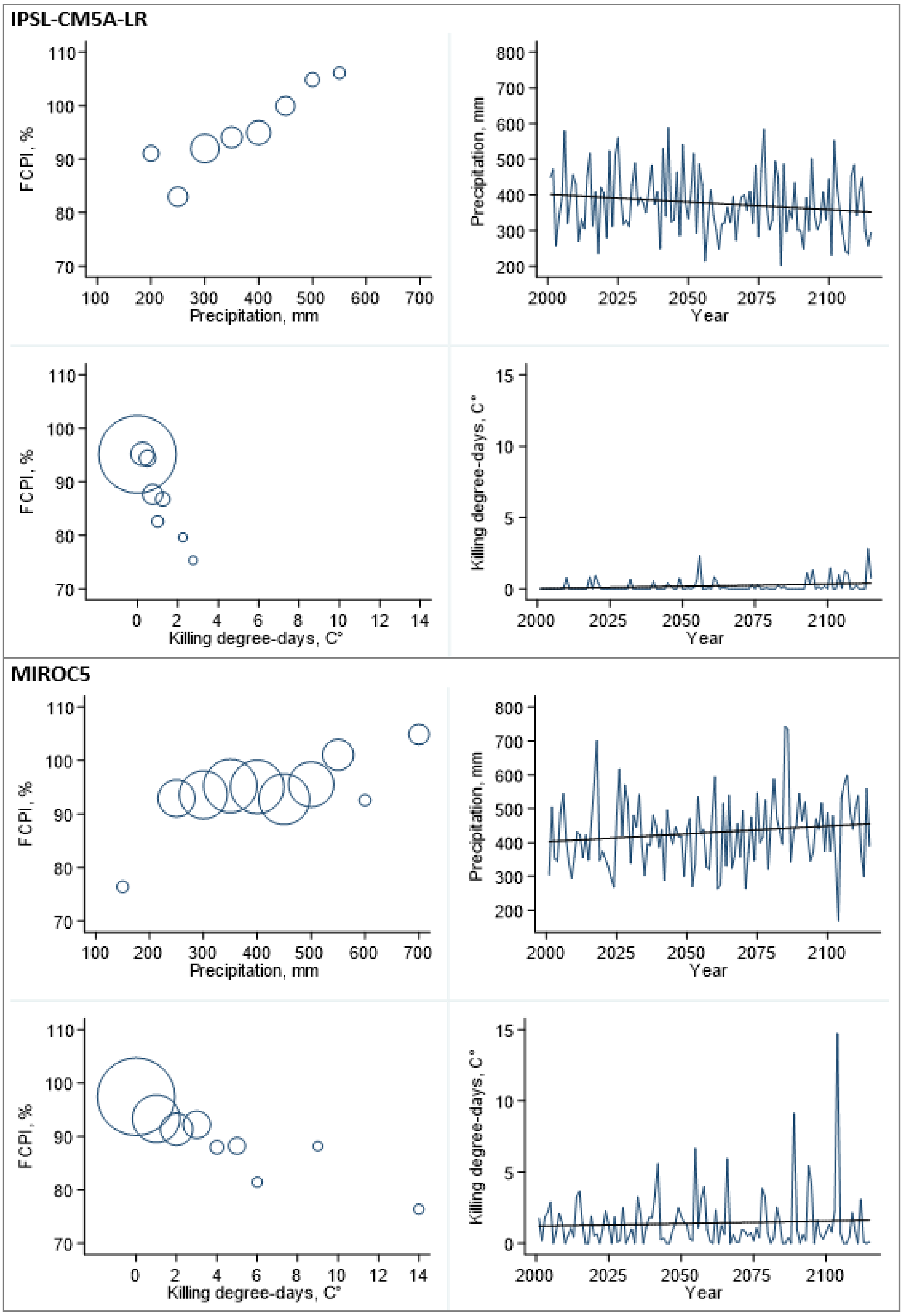

Figure 5. Future projections of selected the key weather variables explaining crop yield variability (killing degree days and precipitation over the growing season of millet – the main food crop in Nouna area) and their correlation with the Food Crop Productivity Index (FCPI), presented for each Global Circulation Model.

Linear trends: increase in killing degree days by 0.03 (95% CI 0.01, 0.06) °C per decade and a decrease in precipitation of -4.40 (95% CI -9.34, 0.54) mm, according to IPSL-CM5A-LR; increase in killing degree days by 0.04 (95% CI -0.08, 0.15) °C per decade and a decrease in precipitation of -58.81.40 (95% CI -289.59, 171.98) mm, according to MIROC5.

Appendix A: Technical details on weather-crop yield models

1. Weather variable derivation

Table A1. Weather variables used for the construction of the crop-specific statistical models.

Variable	Unit	Purpose	Calculation
solar radiation (SR)	J/cm²	to determine crop growth potential	sum over the growing season
precipitation (*PREC*)	mm	to capture deviations from the optimal plant water supply	sum over the growing season
vapour pressure deficit (*VPD*)	mm	to capture the atmospheric water demand	sum of daily vapour pressure deficit values over the growing season, as derived from the maximum ($TMP_{\max}$) and minimum temperature ($TMP_{\min}$) (DVWK, 1996, Sonntag, 1990, Roberts et al., 2013) $VPD = 6.11\left(e^{\left(\frac{17.269\,TMP_{\max}}{237.3+TMP_{\max}}\right)} - e^{\left(\frac{17.269\,TMP_{\min}}{237.3+TMP_{\min}}\right)}\right)$
growing degree days (*GDD*)	°C	to explain the (positive) influence on crop growth	sum of days with daily mean temperature falling within the range of optimal temperature for the growing season, 30–8 °C for all examined crops
killing degree days (*KDD*)	°C	to account for temperatures leading to heat stress and potentially negative impact on crop yields (Roberts et al., 2013)	cumulated temperature sum of daily mean temperature above the optimal temperature (of 30 °C) over the growing season
days without precipitation (*DWP*)	days	to capture precipitation distribution which might hamper the crop development	sum of days with no precipitation over the growing season, identified as follows: $DWP_t = \sum_{d=1}^{D} dwp_d = \begin{cases} 1, & \text{if } PREC_d = 0 \\ 0, & \text{if } PREC_d > 0 \end{cases}$ d = the day within each of the crop development periods ($d = 1, \dots, D$)
dry spells longer than 5 days (*SP5*)	days	to capture crop yield impact of the dry spells	number of days with dry spells longer than 5 days over the growing season, identified as: $SP5_t = \sum_{d=1}^{D} SP5_d = \left\{\begin{matrix} 1 & \text{if } RD_d \geq 5 \ \& \ RD_{d+1} = 0 \\ 0 & \text{if } RD_d \geq 5 \ \& \ RD_{d+1} \neq 0 \end{matrix}\right\}$ with $RD_d = \left\{\begin{matrix} RD_{d-1}+1 & \text{if } PREC_d < 0.5 \\ 0 & \text{if } PREC_d \geq 0.5 \end{matrix}\right\}$ and RD as rainy day
heavy precipitation events >40mm per day (*PE40*)	number of the events	to capture negative impact of soil erosion and nitrogen leaching	number of events over the growing season, identified as: $PE_t = \sum_{d=1}^{D} PE_d = \left\{\begin{matrix} 1 & \text{if } PREC_d \geq 20 \\ 0 & \text{if } PREC_d < 20 \end{matrix}\right\}$
acreage	ha	to capture changes in agronomic management practices and land use (Iizumi and Ramankutty, 2015) in the model	hectares of land cultivated under the respective crop type in Kossi province

2. Crop yield model assumptions

The crop models were based on the following assumptions:

(1) We assumed the relationship of weather and management impacts on crop yields to be linear

Since we use a statistical regression model with only linear exogenous variables, non-linear yield impacts were not considered, which corresponds to the approach of Schlenker & Lobell (2010). To ensure that our models did not omit such impacts, we conducted a statistical test (RESET) (Croissant and Millo, 2008).

(2) We assumed that weather variables have equal impact on yield at every stage of crop development

The magnitude of the effect of weather variation on crop yield, in terms of grain quantity and quality, differs depending on the stage of crop development during which the crop was exposed to these weather variations (Rötter and Van de Geijn, 1999). However, many statistical crop models, e.g., the models of Moore & Lobell (2014), Blanc (2012) and You et al (2009) did not divide the growing period into sub-periods to allow for differential impact of weather variables in these sub-periods and showed that weather variables aggregated over the entire growing season are able to sufficiently explain crop yield variability. We used the out of sample cross validation to corroborate robustness of our crop models (in which weather variables were aggregated over the entire growing season) for yield estimation beyond the time period of the observed yield data. The out of sample cross validation confirmed the robustness of our models.

(3) We assumed that estimated model parameters are valid for the future climate conditions of 1.5 °C warming

Estes et al (2013) and Lobell & Burke (2010) show that statistical models have high capacity to reproduce observed conditions (often better than process-based models), however, they are more limited in their ability to project in unobserved conditions. As the future climate conditions under 1.5 °C global warming may be relatively similar to the current climate conditions, we assumed that our model parameters are valid for these conditions. A comparison of the past and future climate data showed that the range of the inter-annual weather variability observed in the past included most of the variability projected under the 1.5 °C of global warming.

(4) We assumed that fixed effects transformation controls for any time-invariant effects, such as soil conditions, market access, and land tenure, which we assumed to be time-invariant

Our model captures time-invariant effects like the soil conditions or other farm-specific conditions though the fixed effects variable transformation (Wooldridge, 2013). The fixed effect transformation eliminates time-invariant effects in the data by capturing them implicitly in the statistical model. We assumed that the transformation allows controlling for such factors as investment in agricultural equipment, market access, land tenure security, and soil conditions (Brasselle et al., 2002; Lay et al., 2009). Under these assumptions, we suggest that the model parameters are not biased by these time-invariant effects (no omitted variable bias).

(5) Management impacts are reflected by crop acreage

Often, information on agronomic management is not available for many regions in sub-Saharan Africa (Müller and Robertson, 2014). Since changes in acreage are often an indicator for changes in soil quality and available labour, we used acreage to capture possible effects of such factors (Iizumi and Ramankutty, 2015; Wouterse, 2010).

3. Additional considerations in crop model validation

(1) The model goodness of fit for each crop type is shown in table A2:.

Table A2. Model goodness of fit and variables for each crop type.

Crop	R^2	Variables
Fonio	0.92	GDD, KDD, DWP, Acreage_Fonio, dummy84, dummy85
Maize	0.51	KDD, SR, VPD, SP05, Acreage_Maize
Millet	0.64	PREC, GDD, KDD, VPD, SR, SP05, PE40, Acreage_Millet, dummy00, dummy90
Rice	0.53	GDD, KDD, VPD, SR, DWP, SP05, PE40, Acreage_Rice
Sorghum	0.54	PREC, GDD, KDD, VPD, SR, DWP, Acreage_Sorghum, dummy00, dummy90

(2) The weather variables explained large parts of crop yield variability. In comparison to the full model (in parenthesis), the weather variables explained the following percentage of yield variability: 50% (51%) for maize, 86% (92%) for fonio, 63% (64%) for millet, 51% (53%) for rice, and 54% (55%) for sorghum. Although the effect of the acreage is rather small, it was retained in the model as

a measure of reducing the risk of bias. In Kossi, acreage of the respective crops shows strong inter-annual changes and long-term increase in fonio and millet by 64% (10-year averages) and 36% respectively. The maize and sorghum acreage declined by 57% and 45%. Rice acreage shows a very strong increase of +337%, but this is mostly driven by few observations in the mid-1990s and from 2008 to 2010 much above the average level. Yet, mostly the variable acreage shows no significant contribution to the explained yield variability. Despite this strong inter-annual and long-term change, we concluded that land productivity was unlikely to have changed in this period and that the farmers have not moved to less suitable land.

(3) We conduct several statistical tests to verify model robustness and validity. The statistical tests are described by Croissant & Millo (2008). The regression equation specification error test (RESET) was used to investigate whether quadratic variables are missed in the model. The RESET showed that quadratic variables were not neglected for any of the crops. The Breusch–Godfrey and Breusch–Pagan tests were applied to test against autocorrelation and heteroscedasticity. In two cases the model residuals were autocorrelated (fonio and millet), the other crops show no autocorrelation (Breusch–Godfrey test). As the time series are relatively short ($T = 28$) and the variable transformation tends to cause autocorrelation (Baltagi, 2005), we judged that this was unlikely to bias parameters in the models of fonio and millet. There appeared to be no heteroscedasticity (Breusch–Pagan test) in any of the models. The distribution of residuals was tested using the Shapiro–Wilk test, suggesting normal distribution of residuals in all models.

Appendix B: Supplementary figures and tables

Table B1 provides uncertainty estimates of the results reported in the Table 1 of the main text.

Table B1. Central and uncertainty estimates of the mortality impact of crop deficits and weather-related crop deficits over the period of 1984–2012.

Across columns and rows of the table, lower and upper bound estimates were based on different sources of uncertainty.

First and third columns (from the left): uncertainty estimates derived using the 95% confidence interval bounds (instead of the central estimate) of the risk ratio of child survival in relation to crop yield.

Second and fourth columns (from the left): uncertainty estimates derived using the 95% confidence interval bounds (instead of the central estimates) of the risk ratio of child survival in relation to crop yield and of the estimates of the weather-attributed part of crop yield variation.

	Average year*		**Worst year (2000)**	
	Overall	**Weather-related**	**Overall**	**Weather-related**
Mortality per 10,000 children <5 years				
Child deaths (<5 years)	3.8 (0.7, 24.8)	2.9 (0.2, 25.5)	22.9 (4.6, 126.4)	21.9 (1.3, 126.1)
YLL (not discounted)	245.6 (47.6, 1,591.7)	185.7 (5.5, 1,636.5)	1,477.3 (296.7, 8,169.6)	1,418.3 (84.2, 8,151.8)

*Deficits in years with FCPI<90% averaged across all years of the period 1984–2012.

Table B2 provides uncertainty estimates of the results reported in the Table 2 of the main text.

Table B2. Central and uncertainty estimates of the annual average attributable years of life lost per 10,000 children <5 years under 1.5 °C global warming for three 30-year periods centred on years 2015, 2050, and 2100.

The uncertainty estimate are based on the lower and upper bounds of the 95% confidence intervals of the model parameters, i.e., mortality risk ratio and crop yield projections.

	IPSL-CM5A-LR			**MIROC5**		
	2015 (2000–2030)	2050 (2035–2065)	2100 (2085–2115)	2015 (2000–2030)	2050 (2035–2065)	2100 (2085–2115)
Deaths per 10,000 children <5 years						
Average year*	3.8 (0, 91.2)	2.9 (0, 97.0)	5.8 (0, 99.3)	1.6 (0, 82.4)	3.8 (0, 87.1)	3.3 (0, 91.2)
Worst year	16.9 (0, 156.8)	15.3 (0, 152.4)	16.2 (0, 138.9)	12.1 (0, 129.4)	12.2 (0, 131.7)	15.5 (0, 145.9)
YLL per 10,000 children <5 years						
Average year*	245.7 (0, 5,869.2)	185.0 (0, 6,234.5)	374.3 (0, 6,388.1)	102.5 (0, 5,300.8)	246.9 (0, 5,600.0)	210.0 (0, 5,862.4)
Worst year	1,086.9 (0, 10,068.1)	980.0 (0, 9,787.7)	1,038.9 (0, 8,919.4)	774.1 (0, 8,313.3)	785.8 (0, 8,462.0)	994.1 (0, 9,369.0)

*Based on deficits in years with FCPI<90% averaged across all years in the respective 30-year time periods.

Note: the lower estimates in the projections are equal to 0 as a result of our assumption that mortality impact is incurred only in years with yield <90% of the baseline period average. The lower bound of the modelled crop yield estimates in all cases exceeded 90% FCPI, hence, not incurring mortality impact as a result of our modelling assumption that mortality impact is only incurred in years with FCPI <90%.

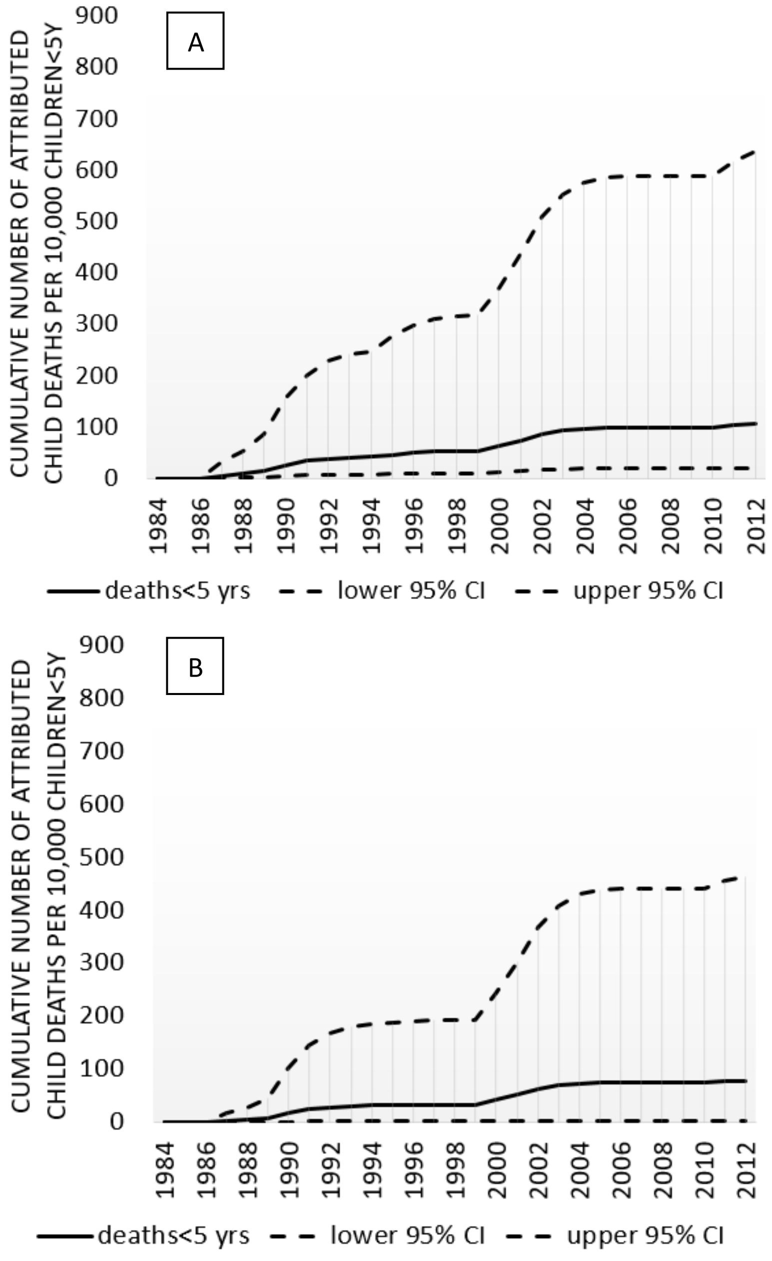

Figure B1. Cumulative mortality impact attributable to crop yield deficits in years with FCPI<90% (A) and to weather-related crop deficits (B).

Dashed lines represent uncertainty estimates based on 95% confidence intervals of the relative risk for child mortality used in the calculations (Belesova et al., 2017b).

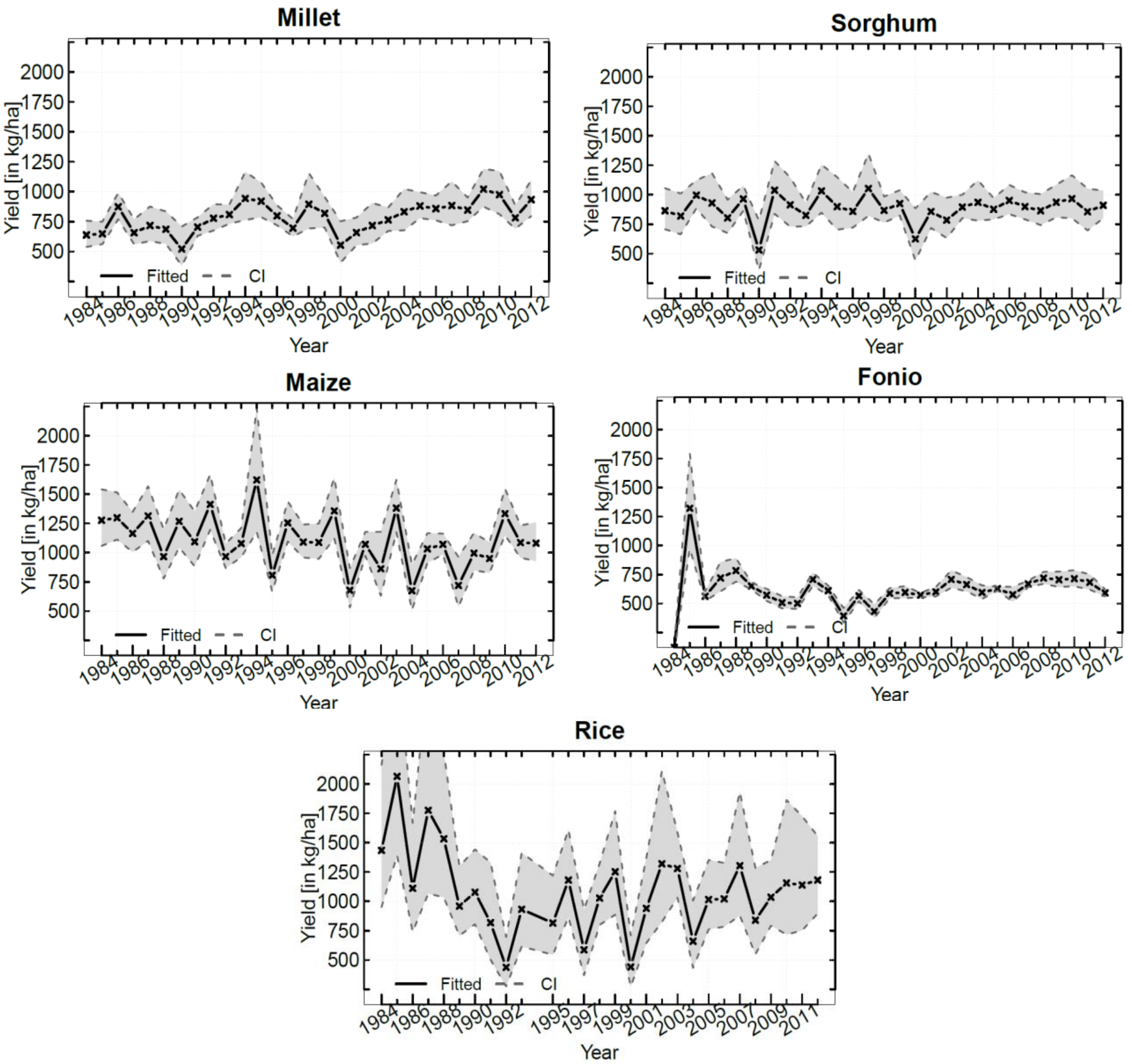

Figure B2. Estimates of weather-attributable variation in crop yields, Kossi province, Burkina Faso, 1984–2012, based on estimates of the weather–crop model. Shaded bands indicate 95% confidence intervals.

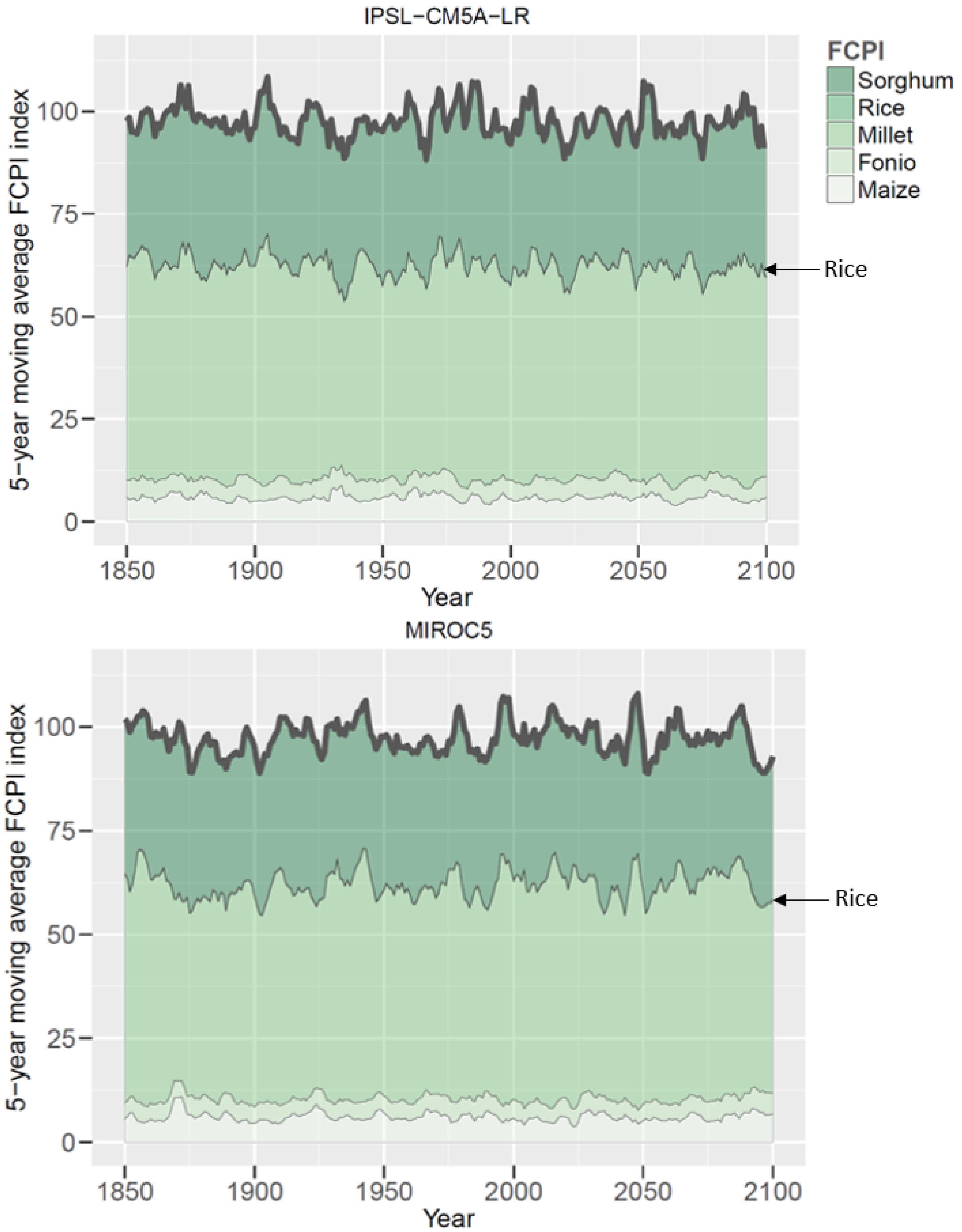

Figure B3. Crop-specific yield and Food Crop Productivity Index (FCPI) projections based on climate data of each of the general circulation models separately: A – IPSL-CM5A-LR, B – MIROC5.

References

Albers, H., Gornott, C., Hüttel, S., 2017. How do inputs and weather drive wheat yield volatility? The example of Germany. Food Policy 70, 50–61.

Baltagi, B.H., 2005. Econometric Analysis of Panel Data, Third edit. ed. John Wiley & Sons Ltd.

Belesova, K., Gasparrini, A., Sié, A., Sauerborn, R., Wilkinson, P., 2017a. Household cereal crop harvest and children's nutritional status in rural Burkina Faso. Environ. Heal. 16, 1–11.

Belesova, K., Gasparrini, A., Sié, A., Sauerborn, R., Wilkinson, P., 2017b. Annual Crop Yield Variation, Child Survival and Nutrition among Subsistence Farmers in Burkina Faso. Am. J. Epidemiol. kwx241, 15–17.

Blanc, E., 2012. The Impact of Climate Change on Crop Yields in Sub-Saharan Africa. Am. J. Clim. Chang. 01, 1–13.

Brasselle, A.S., Gaspart, F., Platteau, J.P., 2002. Land tenure security and investment incentives: puzzling evidence from Burkina Faso. J. Dev. Econ. 67, 373–418.

Castellvi, F., Perez, P.J., Stockle, C.O., Ibaiiez, M., 1997. Methods for estimating vapor pressure deficit at a regional scale depending on data availability. Agric. For. Meteorol. 87, 243–252.

Castellví, F., Perez, P.J., Villar, J.M., Rosell, J.I., 1996. Analysis of methods for estimating vapor pressure deficits and relative humidity. Agric. For. Meteorol. 82, 29–45.

Croissant, Y., Millo, G., 2008. Panel data econometrics in R: The plm package. J. Stat. Softw. 27.

Dabat, M., Zongo, I., Kiendrebeogo, R., 2012. Etude sur les relations entre marchés et sécurité alimentaire au Burkina Faso. Montpellier: CIRAD.

del Ninno, C., Dorosh, P.A., Subbarao, K., 2005. Food Aid and Food Security in the Short- and Long Run: Country Experience from Asia and sub-Saharan Africa. The World Bank Social Safety Nets Primer. [online] Available at: http://www.fao.org/fsnforum/sites/default/files/files/Have %20your%20say/Food_aid_in_Afri 427 ca_and_Asia.pdf [Accessed 14 Oct 2017]

Diboulo, E., Sié, A., Röcklov, J., Niamba, L., Ye, M., Bagagnan, C., Sauerborn, R., 2012. Weather and mortality: retrospective analysis of 10 years of data from Nouna Health and Demographic Surveillance System, Burkina Faso. Glob. Health Action 5, 1–8.

Direction Générale des Prévisions et des Statistiques Agricoles et Alimentaires (DPSAA), 2011. Resultats Definitifs de l'Enquete Permanente Agricole 2007/2008. Ouagadougou: DPSAA

Dvwk (1996) Ermittlung der Verdunstung von Land- und Wasserflächen, Bonn, Wirtschafts- und

Verlagsgesellschaft Gas und Wasser mbH.Estes, L.D., Beukes, H., Bradley, B.A., Debats, S.R., Oppenheimer, M., Ruane, A.C., Schulze, R., Tadross, M., 2013. Projected climate impacts to South African maize and wheat production in 2055: a comparison of empirical and mechanistic modeling approaches. Glob. Chang. Biol. 19, 3762–3774.

Fermont A, Benson T. Estimating yield of food crops grown by smallholder farmers: A Review in the Uganda Context. IFPRI Discussion Paper No. 01097. 2011;1–57.

Food and Agriculture Organization, 2010. Crop calendar. [online] Available at: http://www.fao.org/agriculture/seed/ cropcalendar/welcome.do [Accessed 29 March 2017]

Frieler, K., Betts, R., Burke, E., Ciais, P., Denvil, S., Deryng, D., Ebi, K., Eddy, T., Emanuel, K., Elliott, J., Galbraith, E., Gosling, S.N., Halladay, K., Hattermann, F., Hickler, T., Hinkel, J., Huber, V., Jones, C., Krysanova, V., Lange, S., Lotze-Campen, H., Mengel, M., Mouratiadou, I., Müller Schmied, H., Ostberg, S., Piontek, F., Popp, A., Reyer, C.P.O., Schewe, J., Stevanovic, M., Suzuki, T., Thonicke, K., Tian, H., Tittensor, D.P., Vautard, R., van Vliet, M., Warszawski, L., Zhao, F., 2016. Assessing the impacts of 1.5°C global warming - simulation protocol of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP2b). Geosci. Model Dev. Discuss. 1–59.

Gornott, C., Wechsung, F., 2016. Statistical regression models for assessing climate impacts on crop yields: A validation study for winter wheat and silage maize in Germany. Agric. For. Meteorol. 217, 89–100.

Grace, K., Nagle, N.N., Husak, G., 2016. Can Small-Scale Agricultural Production Improve Children's Health? Examining Stunting Vulnerability among Very Young Children in Mali, West Africa. Ann. Am. Assoc. Geogr. 4452, 1–16.

Iizumi, T., Ramankutty, N., 2015. How do weather and climate influence cropping area and intensity? Glob. Food Sec. 4, 46–50.

IPCC, 2018: Summary for Policymakers. In: Global warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty [V. Masson-Delmotte, P. Zhai, H. O. Pörtner, D. Roberts, J. Skea, P. R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J. B. R. Matthews, Y. Chen, X. Zhou, M. I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, T. Waterfield (eds.)]. World Meteorological Organization: Geneva.

Johnson, K., Brown, M.E., 2014. Environmental risk factors and child nutritional status and survival in a context of climate variability and change. Appl. Geogr. 54, 209–221.

Kumar, S., Molitor, R., Vollmer, S., 2016. Children of Drought: Rainfall Shocks and Early Child Health in Rural India. Popul. Dev. Rev. 42, 53–68.

Lay, J., Narloch, U., Mahmoud, T.O., 2009. Shocks, Structural Change, and the Patterns of Income Diversification in Burkina Faso. African Dev. Rev. 21, 36–58.

Lee, B.H., Kenkel, P., Brorsen, B.W., 2013. Pre-harvest forecasting of county wheat yield and wheat quality using weather information. Agric. For. Meteorol. 168, 26–35.

Lloyd, S.J., Bangalore, M., Chalabi, Z., Kovats, R.S., Hallegatte, S., Rozenberg, J., Valin, H., Havlík, P., 2018. A Global-Level Model of the Potential Impacts of Climate Change on Child Stunting via Income and Food Price in 2030. Environ. Health Perspect. 126, 1–15.

Lloyd, S.J., Kovats, S.R., Chalabi, Z., 2011. Climate change, crop yields, and undernutrition: Development of a model to quantify the impact of climate scenarios on child undernutrition. Environ. Health Perspect. 119, 1817–1823.

Lobell, D.B., Burke, M.B., 2010. On the use of statistical models to predict crop yield responses to climate change. Agric. For. Meteorol. 150, 1443–1452.

Mainardi, S., 2011. Cropland use, yields, and droughts: Spatial data modeling for Burkina Faso and Niger. Agric. Econ. 42, 17–33.

Miller, B.G., Hurley, J.F., 2003. Life table methods for quantitative impact assessments in chronic mortality. J. Epidemiol. Community Health 57, 200–6.

Moore, F.C., Lobell, D.B., 2014. Adaptation potential of European agriculture in response to climate change. Nat. Clim. Chang. 4, 610–614.

Müller, C., Robertson, R.D., 2014. Projecting future crop productivity for global economic modeling. Agric. Econ. 45, 37–50.

Nelson, G.C., Rosegrant, M.W., Koo, J., Robertson, R., Sulser, T., Zhu, T., Ringler, C., Msangi, S., Palazzo, A., Batka, M., Magalhaes, M., Valmonte-Santos, R., Ewing, M., Lee, D., 2009. Climate Change and Agriculture Impacts and Costs of Adaptation, Food Policy Report. Washington, D.C.

Phalkey, R.K., Aranda-Jan, C., Marx, S., Höfle, B., Sauerborn, R., 2015. Systematic review of current efforts to quantify the impacts of climate change on undernutrition. Proc. Natl. Acad. Sci. 112, E4522–E4529.

Ray, D.K., Gerber, J.S., MacDonald, G.K., West, P.C., 2015. Climate variation explains a third of global crop yield variability. Nat. Commun. 6, 1–9.

Riahi, K., van Vuuren, D.P., Kriegler, E., Edmonds, J., O'Neill, B.C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J.C., KC, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpenöder, F., Da Silva, L.A., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Strefler, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J.C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A., Tavoni, M., 2017. The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. Glob. Environ. Chang. 42, 153–168.

Roberts, M.J., Schlenker, W., Eyer, J., 2013. Agronomic Weather Measures in Econometric Models of Crop Yield with Implications for Climate Change. Am. J. Agric. Econ. 95, 236–243.

Rötter, R., Van de Geijn, S.C., 1999. Climate Change Effects on Plant Growth, Crop Yield and Livestock. Clim. Change 43, 651–681.

Rowhani, P., Lobell, D.B., Linderman, M., Ramankutty, N., 2011. Climate variability and crop production in Tanzania. Agric. For. Meteorol. 151, 449–460.

Rukumnuaykit, P., 2003. Crises and Child Health Outcomes: The Impacts of Economic and Drought /Smoke Crises on Infant Mortality and Birthweight in Indonesia. Michigan State Univ.

Sankoh, O., Byass, P., 2012. The INDEPTH network: Filling vital gaps in global epidemiology. Int. J. Epidemiol. 41, 579–588.

Schauberger, B., Gornott, C., Wechsung, F., 2017. Global evaluation of a semi-empirical model for yield anomalies and application to within-season yield forecasting. Glob. Chang. Biol., 23, 4750–4764.

Schewe, J., Levermann, A. 2017. Non-linear intensification of Sahel rainfall as a possible dynamic response to future warming, Earth Syst. Dynam., 8, 495-505.

Schlenker, W., Lobell, D.B., 2010. Robust negative impacts of climate change on African agriculture. Environ. Res. Lett. 5, 1–8.

Schlenker, W., Roberts, M.J., 2009. Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. Proc. Natl. Acad. Sci. U.S.A. 106, 15594–8.

Schoeps, A., Souares, A., Niamba, L., Diboulo, E., Kynast-Wolf, G., Müller, O., Sié, A., Becher, H., 2014. Childhood mortality and its association with household wealth in rural and semi-urban Burkina Faso. Trans. R. Soc. Trop. Med. Hyg. 108, 639–647.

Sonntag D (1990) Important new Values of the Physical Constants of 1986, Vapour Pressure Formulations based on ITS-90, and Psychrometer Formulae. Meteorologische Zeitschrift, 4, 340-344.

Stadlmayr, B., Charrondiere, U.R., Enujiugha, V.N., Bayili, R.G., Fagbohoun, E.G., Samb, B., Addy, P., Barikmo, I., Ouattara, F., Oshaug, A., Akinyele, I., George Amponsah Annor, K.B., Ene-Obong, H., Smith, I.F., Thiam, I., Burlingame, B., 2012. West African food composition table. FAO: Rome.

UNFCCC, 2015. Adoption of the Paris Agremeent: Proposal by the President Draft decision-/CP.21. UNFCCC: Paris.

Weedon, G.P., Balsamo, G., Bellouin, N., Gomes, S., Best, M.J., Viterbo, P., 2014. Data methodology applied to ERA-Interim reanalysis data. Water Resour. Res. 50, 7505–7514.

Wooldridge, J.M., 2013. Introductory Econometrics – A modern approach, 5th ed. South-Western Cengage Learning: Mason.

Wouterse, F., 2010. Migration and technical efficiency in cereal production: evidence from Burkina Faso. Agric. Econ. 41, 385–395.

Yamano, T., Alderman, H., Christiaensen, L., 2005. Child growth, shocks, and food aid in rural Ethiopia. Am. J. Agric. Econ. 87, 273–288.

Yield gap, 2013. Information from collected literature for Burkina Faso to be used for crop modelling for Burkina Faso. [online] Available at: http://www.yieldgap.org/gygamaps/pdf/Details%20on%20crop%20information%20to%20calibrate%20crop%20models%20for%20Burkina%20Faso.pdf [Accessed 14 October 2017]

You, L., Rosegrant, M.W., Wood, S., Sun, D., 2009. Impact of growing season temperature on wheat productivity in China. Agric. For. Meteorol. 149, 1009–1014.