Modelling the relation between climate change and undernutrition at the global-level: the use of multiple perspectives to gain new insights

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Declaration

'I, Simon John Lloyd, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis'

[redacted]

Date: 25th April, 2020

'In my view every economic fact, whether or not it is of such a nature as to be expressed in numbers, stands in relation as cause and effect to many other facts; and since it never happens that all of them can be expressed in numbers, the applications of exact mathematical methods to those which can is nearly always a waste of time, while in the large majority of cases it is positively misleading.'

Alfred Marshall (1901), quoted in Milanovic (2016)[1]

'A man with one watch always knows the time. A man with two watches is never sure.'

Segal's Law, quoted in Kline (2016)[2]

'Complexity is not a condition to be tamed, but a lesson to be learned.'

James Bridle (2018)[3]

*'Therefore we attempt to treat the same problem with several alternative models …
Hence our truth is the intersection of independent lies.'*

Levins (1966)[4]

[1] MILANOVIC, B. 2016. Global Inequality: A New Approach for the Age of Globalization, Cambridge (Mass), Belknap.
[2] KLINE, R. B. 2011. Principles and Practice of Structural Equation Modelling, New York, Guildford Press.
[3] BRIDLE, J. 2018. New Dark Age: Technology and the End of the Future, London, Verso.
[4] LEVINS, R. 1966. The Strategy of Model Building in Population Biology. American Scientist, 54, 421-431.

Abstract

Global-level models have consistently found that climate change will increase the risk of hunger. The climate-undernutrition relation is complex, and choices must be made about what is brought into focus, with these choices drawing attention to particular causes and solutions. A critical overview of the literature showed, however, that all previous models had adopted one general conceptualisation: less or lower quality food means more hunger. This leaves much unexplored.

The central idea of this thesis is that when faced with complex health problems, a fuller understanding may be gained by developing multiple models, each adopting a different perspective. The thesis aims to develop a series of global-level climate-undernutrition models, with the insights from one model guiding the development of the next. These models are presented as four research papers.

Papers 1 and 2 adopt a 'crop productivity' perspective to quantify stunting. The results suggest that future socioeconomic conditions will play a larger in role in shaping stunting than climate change. Thus, Paper 3 places food production in the background and asks how climate change may impact on stunting via its impacts on two socioeconomic factors: incomes and food price. The results imply that slowly rising food prices lead to decent farm incomes, which may reduce the risk climate change poses to nutrition in rural areas. Producer-consumer farmers, however, were not directly represented. Given this, Paper 4 assesses the health-related implications for rural populations of producer-consumer households practising different styles of farming in the global food system under climate change. The results suggest that how farming is done – whether more entrepreneurial- or peasant-like – will impact on future nutrition and the conditions that support rural health.

Collectively, the research papers demonstrate the utility of a multiple model-approach to complexity, and the benefits of drawing on a range of theories when building models.

Acknowledgements

This thesis took a rather long time to complete and may never have materialized without the enduring (exceedingly tolerant? brave?) support of a number of people.

At LSHTM…

> Zaid Chalabi encouraged me to pursue my ideas from day one. He did so by engaging both academically and – equally importantly - with kindness and generosity. I could not have had a finer mentor. This work has concluded but I hope our friendship will continue.
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> Paul Wilkinson very kindly allowed me to clear my work schedule so I could dedicate a block of continuous time to finish things off.

… and from further afield…

> Richard Levins, although I was not fortunate enough to have met him, echoes throughout this thesis. After I encountered his ideas, nothing appeared the same. The Truth is Whole.

… and from closer to home.

> Ines. What can I say? Il mare si è fermato[5]. Thankyou for everything. And likewise, to my wonderful children, Teresa-Teresa and Mr Andres (whom I won't have to grumpily kick out of the 'office' anymore (well, at least as often)).
>
> And of course, I mustn't forget my mother: thanks Mum!

[5] Bollani, not Parente.

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List of abbreviations

ABM: Agent-Based Model

DALYs: Disability Adjusted Life Years

DAtUs: Disability-adjust life Years Attributable to Underweight

FAO: Food and Agricultural Organization

GDPpc: Gross Domestic Product per capita

GLOBIOM: Global Biosphere Management Model

IFPRI: International Food Policy Research Institute

IIASA: International Institute for Applied Systems Analysis

MDGs: Millennium Development Goals

NERC: Natural Environment Research Council (UK)

QUEST-GSI: Quantifying and Understanding the Earth System – Global Scale Impacts

SDGs: Sustainable Development Goals

SSPs: Shared Socioeconomic Pathways

SRES: Special Report on Emissions Scenarios

WHO: World Health Organization

Chapter 1. Introduction

Despite decades of efforts to reduce and eliminate it, hunger still affects an estimated 820 million people (FAO et al., 2019) and undernutrition remains a major cause of morbidity and mortality in children (GBD 2017 SDG Collaborators, 2018). Climate change is expected to further hinder progress even if the most ambitious targets of the Paris Agreement to limit climate change are met (Ebi et al., 2018). Developing an understanding of how the mutually conditioning processes associated with climate change (as well as actions to mitigate and adapt to it) and development (whether "sustainable" or not) will shape future undernutrition poses considerable challenges, not least because the causes of undernutrition itself are complex (Scanlan, 2003, Smith and Haddad, 2015), as is the relation between climate change and undernutrition (Myers et al., 2017).

In this thesis, I develop a series of new models that look at the potential impacts of climate change on hunger and undernutrition under given development scenarios, with the findings and questions raised by each model guiding the development of the next model.

Given the complexity of the climate-undernutrition relation, when building – as well as assessing output from - climate-undernutrition models, questions arise not just about *"what we (already) know"* about future undernutrition under climate change, but also about *"how we know what we know"*. The former question has been comprehensively reviewed by others on a number of occasions (e.g. Parry et al., 2009, Wheeler and von Braun, 2013, Smith et al., 2014), and a summary of what is known is given in the next section of this chapter. *"How we know"* – that is, how have the relations between climate change and undernutrition been represented in models, along with the implications of this – has been less explicitly explored: this is the focus of the critical literature overview in Chapter 2.

The key specific finding of the literature overview is that perspectives that view poverty and inequality as the root causes of undernutrition have been largely omitted. A more general implication arising from the overview is that, in order to gain new insights into complex health problems, it is useful – if not necessary – to develop multiple models, each viewing the problem from a different perspective (Levins, 1966). Both the specific finding and the general implication are reflected in the thesis aims and objectives, which are given in Chapter 3.

Following this, Chapters 4, 5 and 6 describe newly developed climate-undernutrition models that address some previously omitted perspectives. The model in Chapter 4 (which is included in the above literature overview[6]) focusses on a more health-relevant final outcome (child stunting) than the preceding literature; the model in Chapter 5 takes a poverty perspective; and, the model in Chapter 6 centres on the development trajectories of subsistence farming. Each of the models described has been published or prepared for submission as a research paper.

Finally, the concluding chapter (Chapter 7) draws the research papers together to summarize how they collectively broaden our understanding of the climate change-undernutrition problem, thus illustrating the utility of the general principle of approaching complexity with a set of models based on different abstractions. I also briefly discuss possible directions for future research and the limitations of thesis.

Of note, the scope of the thesis has been limited to global-level models[7]. This is because, firstly, the scientific community (that is, funders and research groups) has been, and remains, interested in climate-undernutrition research conducted at this level. Secondly, the food system is becoming increasing globalised (Weis, 2007, Cleveland, 2014), and this is being actively promoted by various institutions (e.g. World Bank, 2007)). Thirdly, while national- and local-level studies (recently reviewed by Phalkey et al (2015)) may attempt to capture the particularities of a given place and time, global-level dynamics – which partly shape within-country conditions – are of interest in their own right (e.g. Mazoyer and Roudart, 2006). For instance, global food trade – at least in its current form – appears to be both decreasing and increasing the risk of undernutrition for different population groups (McMichael, 2012, Moore Lappe and Collins, 2015). Additionally, the 2007-08 food price crisis showed clearly how global-level processes may combine to impact on population groups in multiple countries simultaneously, with hunger-associated riots occurring in around 30 countries (Holt-Gimenez and Patel, 2009). Thus, the global-level is not simply a "blurry" version of something better viewed more locally: processes operating all levels are of consequence (Krieger, 2011, Levins and Lewontin, 1985).

The next section provides a brief general discussion of *what we know* about undernutrition and how climate change may impact on it.

[6] Over the time period during which I have worked on this thesis, the relevant climate-undernutrition literature has expanded; thus, the first model I developed (described in Chapter 4) is now part of the established literature and was thus included in the literature overview.

[7] I use "global-level" to refer to models that focus on multiple countries in multiple regions and represent (at some point in the model) global-level processes (e.g. global food trade; global food price transmission), rather than models that necessarily focus on all or most countries.

Undernutrition and climate change: an overview

The literature on undernutrition is extremely large and diverse, and the literature on climate change and undernutrition continues to grow. The following is intended to give a brief overview of current knowledge[8].

Undernutrition

Hunger and undernutrition have been the focus of global attention for decades – from the eradication (within a decade) pledges following the food crisis in the 1970s (Holt-Gimenez and Patel, 2009), to the reduction goals of the Millennium Development Goals (MDGs) (Pogge, 2010), and back to eradication (by 2030) goals under the Sustainable Development Goals (SDGs) (United Nations, 2017) – but progress has been mixed and slow in many locations (Rieff, 2016). Stunting (a measure of undernutrition based on height-for-age), for instance, affects an estimated 149 million children aged under five, 55% of who live in Asia and 39% in Africa (UNICEF et al., 2019). Since the year 2000, there have been large disparities in prevalence reduction, both across- and within-regions. For example: Latin America and the Caribbean saw a drop from 16.7% to 9%; South Asia from 49.7% to 32.7%; and, Africa from 38% to 30% (with the number of stunted children actually rising from 50.3 million to 58.8 million) (UNICEF et al., 2019).

There is an important distinction between the metrics commonly used to quantify the prevalence of hunger and undernutrition. As well as shaping the apparent magnitude of the problem, the choice of metric influences the causes of the problem that are brought into focus. And this in turn may influence the types of actions taken to solve the problem. "Undernourishment", or synonymously "being at risk of hunger"[9], is a theoretically-based, modelled estimate (all undernourishment estimates are modelled, even those for the present) of the distribution of calories in a national population, that was developed by the Food and Agricultural Organization (FAO) (FAO, 2003). The "proportion undernourished" is defined as the proportion of a population "whose dietary energy consumption is continuously below a minimum dietary energy requirement for maintaining a healthy life and carrying out light physical activity with an acceptable minimum body-weight for attained-height". That is, undernourishment has one essential cause: a lack of food; specifically, calorie intake. Thus, key solutions involve increasing the quantity of food produced and ensuring improved access.

[8] Climate-health impact models have also examined other nutrition-related outcomes, such as non-communicable diseases (e.g. Springmann et al., 2016) and sustainable diets (e.g. Willett et al., 2019). Such outcomes are beyond the scope of the thesis.
[9] This term was typically used in early climate change-nutrition assessments (e.g. Parry and Rosenzweig, 1993).

In contrast, “undernutrition” refers to a physical state that may be measured using anthropometric indices, including stunting and underweight (low weight-for-age) (WHO, 2017). Aside from the advantage of being measured in real populations rather than modelled, undernutrition has two characteristics that render it preferable to undernourishment when assessing population health.

Firstly, undernutrition has complex causation, with a lack of food (i.e. undernourishment) being just one - and often not the most important – cause. For instance, Smith and Haddad (2015) found that between 1970 and 2012, 67% of the reduction in stunting was due to improvements in women’s education, gender equality, and access to adequate water and sanitation services. Further, causes operate at multiple levels (UNICEF, 1990, World Bank, 2008), ranging from:

- individual: e.g. lack of energy and nutrient intake (Black et al., 2008), repeated episodes of diarrhoeal disease (Checkley et al., 2008), sub-clinical gut inflammation Guerrant et al., 2013))
- local: e.g. rainfall patterns (Jankowska et al., 2011, Grace et al., 2012)
- national: e.g. proportion of women with access to education (Smith and Haddad, 2000), per capita national income (Vollmer et al., 2014), civil conflict (Jenkins and Scanlan, 2001)); to,
- global: e.g. foreign direct investment (Wimberley and Bello, 1992), position in the World-System[10] (Kick et al., 2011), global food prices (Mazoyer and Roudart, 2006).

That is, undernutrition draws attention to a wide range of (changing) non-food causes that strongly influence its prevalence and trajectory.

Secondly, undernutrition may be directly linked to concrete health impacts. For instance, stunting is estimated to contribute to 45% of child deaths (Black et al., 2013); it increases morbidity for diseases including diarrhoeal disease and pneumonia (Prendergast and Humphrey, 2014); and, in the long term it increases the risk of reduced neurodevelopmental and cognitive function (manifesting as reduced learning and earning capacity) as well as chronic disease (Victora et al., 2008, de Onis and Branca, 2016). In contrast to undernourishment, the potentially major health implications of undernutrition for both individuals and populations are clearly evident.

In sum, in many – but not all – settings, and despite ongoing efforts, undernutrition has proved difficult to reduce (relative to aspirations), which is partly because it has complex multi-level causation that reaches beyond food availability and access, and it remains a major cause of ill health and death.

[10] World-Systems Analysis looks at between-country relations as (partial) explanations for within-county processes (Wallerstein, 2004).

Climate and weather have always been associated with undernutrition, but anthropogenic climate change – in combination with a changing food system – is likely to bring new patterns of risk.

Climate change and undernutrition

Climate change is expected to impact on undernutrition via multiple routes (Figure 1). Some key pathways shown in the figure include:

> Greenhouse gas emissions cause changes in weather, climate and the wider environment (e.g. temperature and rainfall patterns; extreme weather events; ocean temperature and acidity) – *which will impact on* – crops, animals, and ocean life - *which may lead to* – changed quantity and quality of food produced – *and may also* – reduce agricultural labour capacity (due to increased heat stress) and alter patterns of infectious diseases (such as diarrhoeal disease) – *which collectively may* – impact on each of the four dimensions of food security (quantity and quality of food; access to food; stability of food supply; and, ability of individuals to utilize (i.e. gain benefits from) food intake) (FAO, 2017c).

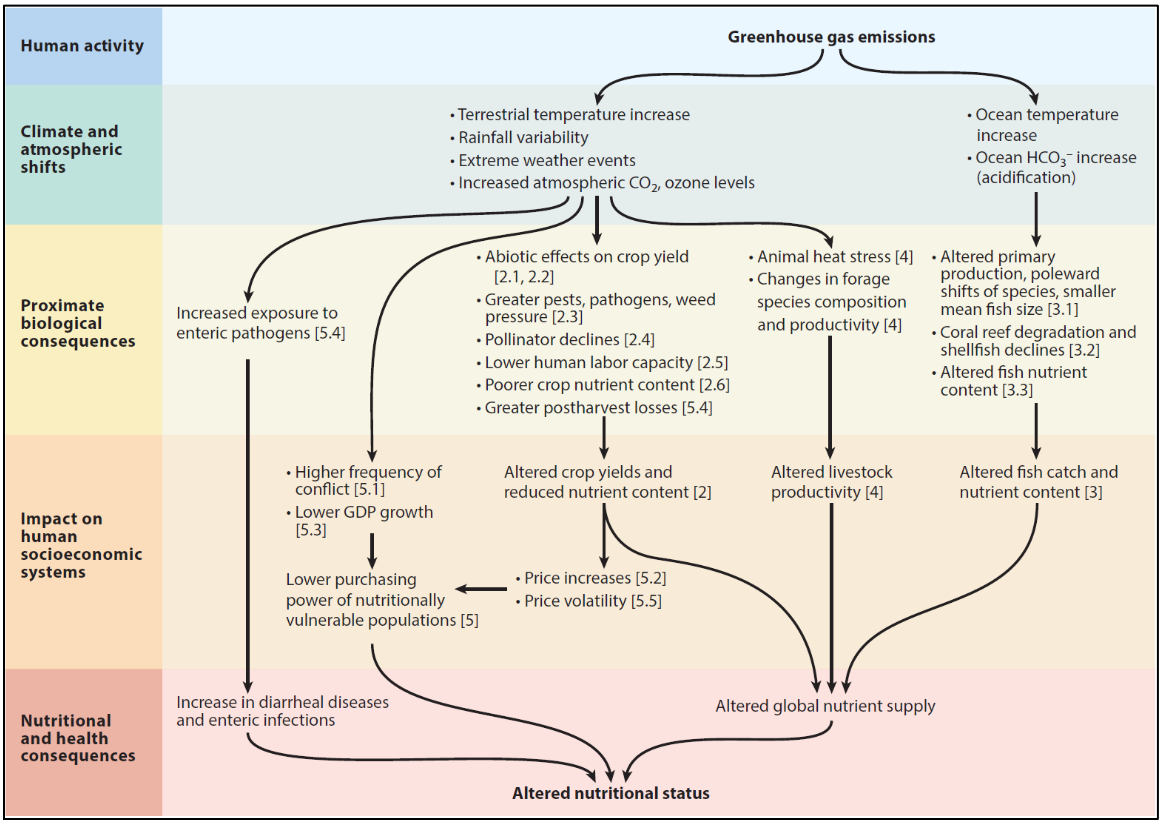

Figure 1 Pathways from climate change to undernutrition
Source: Myers et al. (2017) [Licensed under a Creative Commons Attribution-ShareAlike 4.0 (CC-BY-SA) International License]

To date, modelling of the potential impacts of climate change on undernutrition have tended to trace pathways associated with crop (and by extrapolation, food more generally) productivity; climate change impacts on agricultural labour and infectious disease, for instance, have been treated as separate outcomes using independent models (e.g. Hales et al., 2014).

Global-level modelling studies have consistently found that the impacts of climate change on food availability are likely to increase the risk of poor nutrition (compared to futures without climate change), with the magnitude of the impact estimates varying with the particular model used and the future scenarios considered (for reviews, see: Myers et al., 2017, Parry et al., 2009, Schmidhuber and Tubiello, 2007, Smith et al., 2014, Wheeler and von Braun, 2013). Indicative examples suggest the "risk of hunger" (i.e. proportion undernourished) may increase (relative to a future without climate change) by 5 to 25% globally by 2080 (Schmidhuber and Tubiello, 2007), and that regionally, stunting may increase (relatively) by 23% in parts of Africa and 62% in South Asia by 2050 (Lloyd et al., 2011). Further, changes in food quality may increase the risk of dietary deficiencies (Medek et al., 2017, Myers et al., 2015). For instance, Myers et al. (2015) estimated that by 2050, climate change may put an additional 140 million people at risk of zinc deficiency, with the greatest number of affected people being in Africa and South Asia.

The Paris Agreement (United Nations, 2015) aims to limit average global warming to 2^{o}C, or preferably to 1.5^{o}C, and recent work has attempted to estimate levels of poor nutrition under these conditions (Ebi et al., 2018). While noting limitations in the methods employed, it was estimated that at 1.5^{o}C of warming the global undernourished population would be 530 to 550 million compared to 540 to 590 million at 2^{o}C. Uncertainty is wide, but taking a worst case-perspective suggests that the additional 0.5^{o}C of warming may place around 40 million more people at risk.

Overall, climate change may impact on undernutrition through various paths, and, a number of global-level modelling studies suggest that climate change - even at "low levels" – will place significantly more people at risk. A key question arising from this is: given the complexity of the climate-undernutrition relation, which aspects of this have been focussed upon when developing our understanding? i.e. *How do we know what know?* This is addressed in Chapter 2.

Chapter 2. Critical overview of the literature: How we know what we know about the potential impacts of climate change on undernutrition at the global-level

Introduction

As discussed in Chapter 1, both the causation of undernutrition and the relation between climate change and undernutrition are complex. Consequently, no single model of the potential impacts of climate change on undernutrition will be able to capture the whole of this relation. The implication is, that when developing such models, *choices* about which pathways are brought into focus must be made, although these choices may be made implicitly or by necessity due to data and/or knowledge limitations.

In recent years, an increasing number of papers have made the case for introducing mathematical modelling methods[11] into population health that are better able to deal complexity (e.g. Hammond and Dubé, 2012, El-Sayed and Galea, 2017, Maglio and Mabry, 2011, Mellor et al., 2016). These approaches represent a potential advance, as they allow – for example – system feedbacks to be represented and emergent properties to be examined. However, what is generally omitted from discussions is that these methods do not alleviate the need to make choices about how a system is represented. In fact, arguably, given the flexibility of the methods and the sensitivity of model behaviour to its specification (Puccia and Levins, 1985), these methods may make these choices even more important.

The upshot is, regardless of the technical method adopted, abstraction cannot be avoided (e.g. Levins, 2006). It is always necessary "to simplify … models in a way that preserves the essential features of the problem" (Levins, 1966). Crucially, these essential features are not fixed: they are a function of (amongst other things) the particular question of interest (Hedström, 2005), what is already known (Levins, 1966), and the theory of the causation being employed (Krieger, 2011). Further, such choices are not merely academic considerations; they may have real world consequences, as they draw attention to particular causes of, and solutions to, the health outcome of interest (for relevant discussions, see: Scanlan, 2003, Buttel, 2000, Le Heron, 2013, Levins, 1966, Krieger, 2011, Krieger, 2013).

[11] For example, systems dynamics modelling and agent-based modelling.

Given this, the underlying theme of the critical literature overview is abstraction choice, which is addressed by considering: *how we know what we know about climate change and undernutrition at the global-level*. That is, it examines the choices that have been made about where to focus when modelling the causes of undernutrition and how climate change may impact on it[12].

Methods

I adopted a three-stage process. Firstly, I identified global-level modelling studies that include estimates of the impacts of climate change on an undernutrition-related outcome (e.g. undernourishment or "proportion at risk of hunger"[13], underweight, stunting[14], dietary deficiency[15]). This was an iterative process carried out over the course of the PhD, with literature being identified as part of the development of each of the component papers. To do this, I drew on existing comprehensive reviews (Parry et al., 2009, Smith et al., 2014, Wheeler and von Braun, 2013, Schmidhuber and Tubiello, 2007, Myers et al., 2017), personal communications with other groups working in this area, and informal searches of standard databases (e.g. Medline, Scopus). The time period covered by the literature extends from 1994 (the year of the earliest paper that was identified) to the year 2017 (which was prior to the submission of Research Paper 3 (Chapter 5) to a journal[16])[17].

In the second stage (at each step in the iterative process), I evaluated the identified papers from the perspective of the underlying conceptualisation of the relation between climate change and undernutrition rather than in terms of their specific findings. This was done at a relatively high level of abstraction. For example, if a suite of crop models were employed as part of an overall model, the specific crops modelled or the particular crop model used would not be considered relevant from the perspective of this review[18]; what would be considered important is that (i) that crop models were

[12] In addition to this literature overview, Chapter 1 provides a brief summary of the literature and refers to a number of reviews by other authors, and, each of the papers in Chapters 4, 5, and 6 include brief literature reviews.

[13] These first two outcomes are used synonymously in the literature reviewed and are modelled using a method developed by the FAO (2017a); also see Chapter 1.

[14] These second two concepts are anthropometric measures of nutrition status. "Underweight" is low weight-for-age, "stunting" is low height-for-age (WHO, 2017); also see Chapter 1.

[15] For example, deficiency of a micro- or macronutrient.

[16] Note that Research Papers 1 and 2 were published during the period covered by the literature overview.

[17] Since this literature overview was carried out, additional global-level climate-undernutrition papers have been published (e.g. Beach et al., 2019, Fujimori et al., 2019, Nelson et al., 2018, Zhu et al., 2018). While there have been ongoing methodological advances (e.g. Smith and Myers, 2018) the essence of the underlying conceptualisations have remained the same and the conclusions of this overview are unaffected.

[18] This is not intended to suggest that these details are not relevant when interpreting the findings of a paper; only that they are not relevant when developing an abstract conceptual understanding of the approach employed in a paper.

included in the conceptualisation, and (ii) the way in which these were ultimately linked to human health.

In the third stage, I grouped the papers by the general types of conceptualisation employed.

The findings of the above are presented in the results section. In the discussion section, I consider the implications the adopted conceptualisations have for the development of our understanding of the climate-undernutrition relation.

Results

I identified 19 papers published over the past two and a half decades (Table 1). The primary purpose of many of these papers was not to estimate impacts on human health (see article titles in Table 1). However, in all these papers undernourishment or undernutrition estimates were made as part of the modelling process, and the purpose of this review is to assess these papers from a population health perspective rather than the perspective of central interest to the paper's authors.

When the underlying conceptualisations used in the papers are considered, it is seen that in all papers the route from climate to undernutrition is via *the impacts of climate change on food production*. This is represented in two general ways – as changes in food quantity, or, food quality - and the papers have been grouped accordingly. The food quantity group comprises 16 papers (the first published in 1994), where quantity is represented as national-level calorie availability. The food quality group is comprised of 3 papers (the first published in 2015), where quality is represented as micronutrients (zinc), macronutrients (protein), or food groups (e.g. fruit and vegetables) (Table 1). In both groups of papers, populations at risk of hunger or undernutrition are represented as consumers confronted with a climate change-impacted food supply.

Models centred on quantity of food produced

All the papers in this group are based on the same underlying general conceptualisation of how climate change will impact on undernutrition, which may be represented by a chain of linked component models (Figure 2, Panel A). The starting point is climate models (providing, for example, temperature and rainfall data for future worlds) which are used to drive a suite of crops models (generally comprised of some combination of wheat, maize, soy, rice, and groundnut). The resulting climate-associated changes in crop production are then extrapolated to estimate climate-associated changes in all food production.

Table 1 Global-level climate-undernutrition modelling studies that include a health-related outcome, grouped by whether they focus on food quantity of food quality [a]

Author/year	Title	Health-related outcome
Models based on food quantity (calorie availability)		
Rosenzweig and Parry (1994)	Potential impact of climate change on world food supply	Undernourishment[b]
Parry et al. (1999)	Climate change and world food security: A new assessment	Undernourishment
Parry et al. (2004)	Effects of climate change on global food production under SRES emissions and socio-economic scenarios	Undernourishment
McMichael et al. (2004)	Global Climate, *In*: *Comparative Quantification of Health Risks: Global and Regional Burden of Disease due to Selected Major Risk Factors*	Undernourishment
Fischer et al. (2005)	Socio-economic and climate change impacts on agriculture: an integrated assessment, 1990-2080.	Undernourishment
Tubiello and Fischer (2007)	Reducing climate change impacts on agriculture: Global and regional effects of mitigation	Undernourishment
Nelson et al. (2009)	Climate change: Impact on agriculture and costs of adaptation	Underweight
Nelson et al. (2010)	Food security, farming, and climate change to 2050	Underweight
Lloyd et al. (2011)	Climate change, crop yields, and undernutrition: Development of a model to quantify the impact of climate scenarios on child undernutrition	Stunting
Lloyd et al. (2014)	Undernutrition. *In: Quantitative risk assessment of the effects of climate change on selected causes of death, 2030s and 2050s.*	Stunting, stunting-attributable mortality
Ishida et al. (2014)	Global-scale projection and its sensitivity analysis of the health burden attributable to childhood undernutrition under the latest scenario framework for climate change research	DALYs[c] attributable to underweight
Hasegawa et al. (2014)	Climate change impact and adaptation assessment on food consumption utilizing a new scenario framework	Undernourishment
Hasegawa et al. (2015a)	Consequence of climate mitigation on the risk of hunger	Undernourishment
Hasegawa et al. (2015b)	Scenarios for the risk of hunger in the twenty-first century using shared socioeconomic pathways	Undernourishment
Hasegawa et al. (2016)	Economic implications of climate change impacts on human health through undernourishment	Undernourishment and DALYs attributable to underweight
Dawson et al. (2016)	Modelling impacts of climate change on global food security.	Undernourishment
Models based on food quality (micro- and macronutrients, food groups)		
Myers et al. (2015)	Effect of increased concentrations of atmospheric carbon dioxide on the global threat of zinc deficiency: a modelling study.	Zinc deficiency
Springmann et al. (2016)	Global and regional health effects of future food production under climate change: a modelling study	Mortality due to underweight, overweight/obesity, and changed diet
Medek et al. (2017)	Estimated effects of future atmospheric CO_2 concentrations on protein intake and the risk of protein deficiency by country and region	Protein deficiency

[a] The papers highlighted in grey are Research Papers 1 and 2 (Chapter 4) in this thesis.

[b] Undernourishment is often referred to as "being at risk of hunger".

[c] "DALYs" is Disability-Adjusted Life Years

Next, this (along with other factors) drives a global food trade model[19], which re-distributes food commodities between countries and then estimates post-trade national-level calorie availability. The food trade model then connects to an undernourishment model, in which calorie availability is used to estimate the expected proportion of a national population that is undernourished.

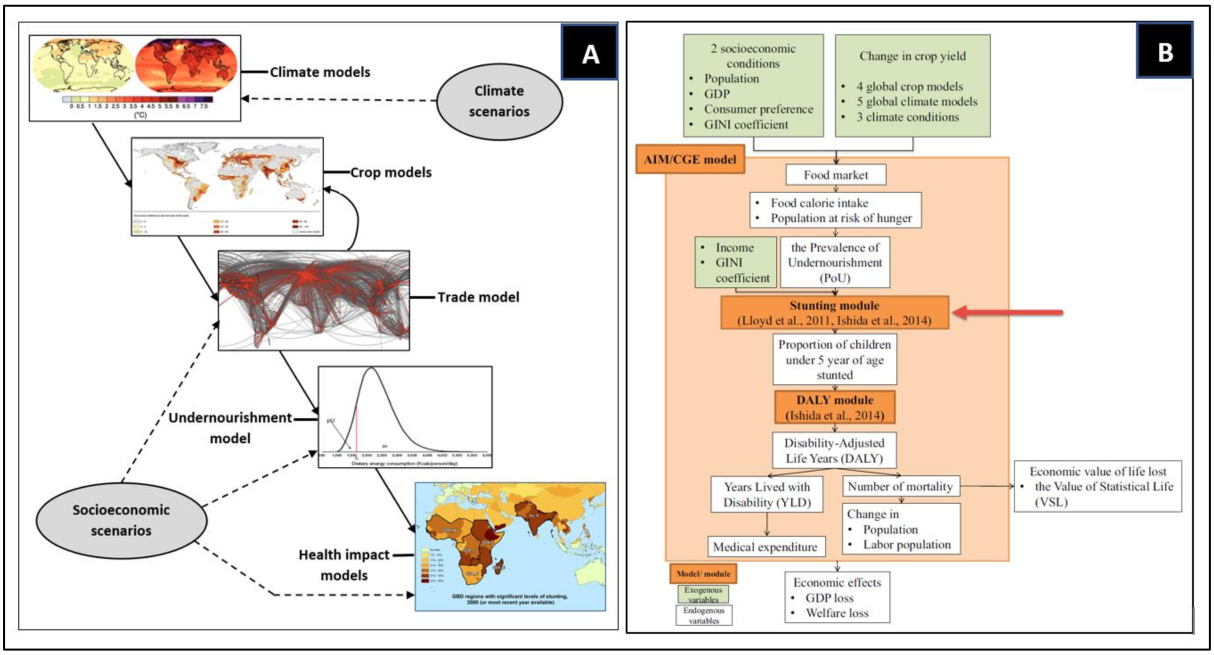

Figure 2 Panel A: The chain of component models (shown as boxes) underlying global-level climate-undernutrition models centred on the quantity of food produced, with future scenarios shown as ovals. Panel B: Example of the further extension of the chain on models, with the first model built for this thesis (Chapter 4) indicated by the red arrow.
Panel B Source: Hasegawa et al. (2016) [Licensed under a Creative Commons Attribution 4.0 International Licence]

Undernourishment was the human health-related outcome of models pre-dating the commencement of this thesis (in 2010). As discussed in Chapter 1, undernourishment is a theoretically-based outcome that, as it is essentially driven by calorie availability estimates (Svedberg, 2000, Klasen, 2006), does not account for how changing socioeconomic conditions may influence future nutrition [20]. Given this, in the first model built for this thesis (Chapter 4), I extended the chain of models to add a health impact model to estimate child stunting (Lloyd et al., 2011) as this better reflects the combined effects of climate and socioeconomic conditions in future worlds, and can be more concretely connected to

[19] The food trade model also represents additional economic processes which then feedback to influence production decisions; e.g. shifts in land allocated to crop production.
[20] Strictly speaking, this is not entirely true: the undernourishment model attempts to account for within-country inequalities in food distribution, but it has been found that this has much smaller influence on changes in estimated levels of undernourishment than calorie availability (Svedberg, 2000, Klasen, 2006). Additionally, the FAO have recently updated their method which may increase the influence of non-calorie factors (FAO, 2014), but to my knowledge the original method is employed in existing climate-undernutrition models.

health outcomes[21,22]. Following this, the stunting model was extended to estimate child mortality (Lloyd et al., 2014) (also described in Chapter 4).

Since then, the above stunting model has itself been incorporated into the chain of models, with other groups further extending the chain to estimate more detailed health-related outcomes such as Disability-Adjusted Life Years (DALYs) as well as their economic implications (e.g. Ishida et al., 2014, Hasegawa et al., 2016) (Figure 2, Panel B).

The general approach utilised in the food quantity-centred models has three additional features relevant to health modelling. First, health impact models sit at the end of the chain of models. This means that they (i.e. the health impact models) necessarily inherit the assumptions made in the upstream models. What may be reasonable assumptions given the concerns and disciplinary conventions of modellers working upstream may prevent health modellers from considering particular processes. For instance, from an economist's perspective and for a given application, it may be considered reasonable to assume "perfect markets" in a trade model. This assumption would then be passed along the chain. From a health perspective, however, the potential role of imperfect food markets or externalities (e.g. arising from agricultural subsidies that favour large scale farms) in generating undernutrition risk in certain groups may be of central interest (Moore Lappe and Collins, 2015, Rossett, 2006). This issue is not necessarily a problem in itself (assumptions must be made), but it curtails the range of what health modellers may investigate[23].

The second feature is the way future scenarios are used in the chain of models. Climate scenarios (which are represented as greenhouse gas emissions or radiative forcing (Moss et al., 2010)) enter via the climate models, and socioeconomic scenarios (e.g. demographics and incomes) enter via the trade, undernourishment, and health impact models (Figure 2, Panel A). In this approach, while the climate and socioeconomic scenarios are usually paired in plausible combinations, climate does not directly impact on the socioeconomic scenario input data (although some recent models include indirect feedback (e.g. Hasegawa et al., 2016)). It is expected, however, that climate change will affect human health, including nutrition, via its impacts on socioeconomic conditions including – for example

[21] See Chapter 1.

[22] Around the same time, a group at the International Food Policy Research Institute (IFRPI) (Nelson et al., 2009, Nelson et al., 2010) similarly extended the chain by estimating child underweight. However, their underweight model was limited by the fact that scenario-specific data were not available to drive it. Additionally, the upstream component models represent average changes in food supply over the long term: the implications of this for nutrition are better captured by stunting than underweight. For a brief discussion, see Lloyd et al. (2011) in Chapter 4.

[23] At the same time, perspectives taken and assumptions made in upstream models may enable health modellers to explore new issues.

– poverty and incomes (Hallegatte et al., 2016). These routes are not represented in the papers included in the overview.

Thirdly, as noted above, over time, the general strategy employed to increase our understanding of the potential impacts of climate change on undernutrition has been to lengthen the chain of models (Figure 2, Panel B). In doing this, the component models have been improved and future scenarios have evolved, but this group of models has arguably – at least in essence – been asking the same question each time (albeit attempting to answer it more precisely and/or focussing on particular sub-questions) rather than interrogating the problem from new angles. I return to this issue in the discussion.

Models centred on quality of food produced

This group of papers represent a recent development in climate-nutrition modelling. The focus has shifted to how climate change-associated[24] changes in the quality of food (zinc or protein content) or dietary composition (e.g. fruit and vegetable consumption) may impact on undernutrition (due to dietary deficiencies) or non-communicable diseases.

Viewed in terms of conceptualisation, two approaches have been used. In the first approach, Springman et al (2016) (who focus on agriculturally-mediated dietary changes) begin with the initial part of the chain of models used in the "food quantity" papers, running from the climate to the trade model (Figure 3, Panel A)[25]. At this point, a new dietary component model is linked to the trade model. Rather than only considering calorie availability, the dietary component model assesses the availability of a wider range of food groups and nutrients. This is then connected to a new set of health sub-models which estimates how changed dietary quality may impact on various health outcomes.

While this is an important innovation, for the purposes of this review the approach may be seen as a branching of the existing chain of models. The pathway from climate to undernutrition remains centred on changed food production, albeit with more detailed representation of food available to consumers.

[24] Here, climate change may be represented directly as changed weather conditions, or indirectly as changed atmospheric carbon dioxide.
[25] The climate-crop-trade modelling was done by the same group that provided input data for a number of the 'food quantity' papers (Lloyd et al., 2011, Lloyd et al., 2014, Nelson et al., 2009, Nelson et al., 2010).

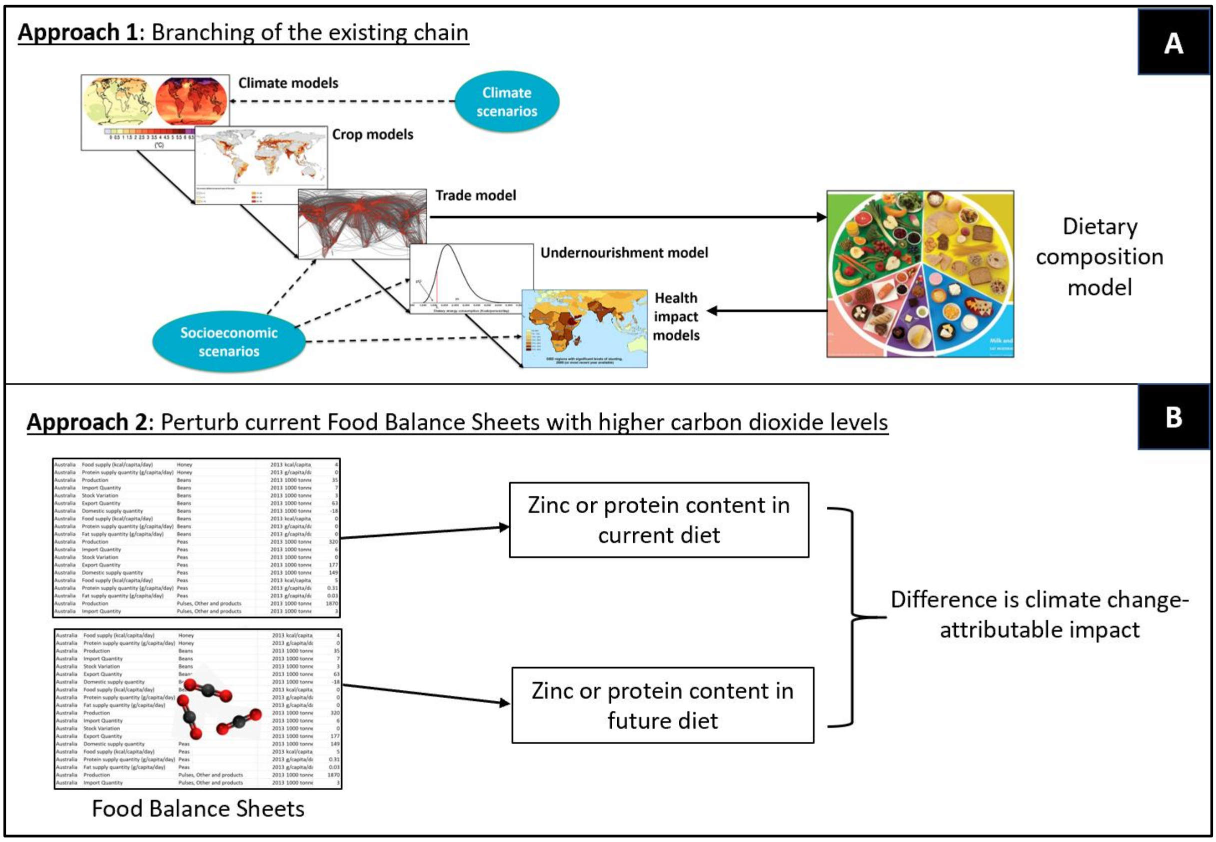

Figure 3 Underlying conceptualisations employed in papers focussed on changes in food quality, where Approach 1 (Panel A) is a branching of the chain of models used in the food quantity papers (Figure 2, Panel A) and Approach 2 (Panel B) is a based on FAO Food Balance Sheets.

The second approach was used by Myers et al (2015) to look at zinc deficiency and Medek at al (2017) to look at protein deficiency (Figure 3, Panel B). The starting point is Food Balance Sheets for the present (produced by the FAO (2017b)), which give detailed country-level estimates of per capita availability of standard groups of food commodities. A series of calculations are used to estimate the total zinc or protein content of the available food, and the expected distribution of these nutrients across national populations is then modelled. This provides an estimate of dietary quality in the present.

As well as causing climate change, rising atmospheric carbon dioxide levels are expected to reduce the zinc and protein content (along with other nutrients) of food. To simulate future diets under climate change, current Food Balance Sheets are “exposed” to higher levels of carbon dioxide and the changes in nutrient content are estimated. These reduced nutrient levels are distributed across national populations to estimate future dietary quality. Climate change-attributable changes in dietary quality are calculated as the difference between the former and latter estimates. This also represents an important innovation; however, the essence of the conceptualisation remains centred on changes in food production.

Discussion

The above papers have led to ongoing advances in our knowledge of the potential impacts of climate change on future undernutrition. The purpose of this overview, however, is not to critique individual papers and their findings, but rather to identify patterns and trends in the perspectives and conceptualisations used in literature. In these terms, the central perspective taken in all papers (i.e. both those focussed on food quantity and food quality) are variants of:

Climate change-associated changes in food production

– represented as either food quantity or quality –

will impact on the food supply available to consumers,

and this will influence the risk of future undernutrition[26].

While acknowledging the oversimplification, this may be boiled down to the following theory of hunger or undernutrition:

Less or lower quality food means more undernutrition.

Intuitively, this may suggest that existing models have focussed exactly on the most pressing issues: millions of people are already hungry, global population is growing rapidly, and climate change threatens our ability to produce food. A lack of food appears to be the central concern, and this suggests increased production is paramount.

At present, however, despite the persistence of undernutrition, there is currently enough food produced “to make us all chubby”, even after accounting for food used for animal feed and biofuels as well as waste (Moore Lappé, 2013). Historically there has been a shift from “hunger amidst scarcity” to “hunger amidst abundance” (Araghi, 2000). This suggests that, over time, the dominant causes of hunger have shifted. Given the large role played by socioeconomic factors in shaping undernutrition, and that socioeconomic conditions are changing rapidly, this possibility is plausible. Of course, in the future, the threat of genuine scarcity may return, but this does not obviate the need to better understand other processes that are shaping undernutrition and how climate change may impact on them.

The above raises the question: alongside examining the role of the quantity and/or quality of food produced as a cause of future undernutrition, which other perspectives could be usefully explored? One way of approaching this question is via theory.

[26] With Springman et al (2016) also considering obesity and non-communicable diseases.

There are many theories of hunger and undernutrition (e.g. Mazoyer, 2001, Moore Lappe and Collins, 2015, Rieff, 2016, Devereux, 1993, Fogel, 2004). A useful way to approach these is to use a general typology of macro-theories[27] of hunger developed by Buttel (2000)[28], in which theories are grouped along two dimensions (Table 2). The first dimension reflects the importance given to food production. Theories may be "productionist" – that is, the production of insufficient quantities of food is seen as the main cause of hunger - or "non-productionist" – which, while recognising that the quantity of food produced is important, do not see this as the central issue. The second dimension reflects the importance given to population. "Neo-Malthusian" theories see population growth as a key cause of undernutrition, whereas as "non-Malthusian" theories see population as important but not central. This gives a typology of four groups of theories.

Table 2 A typology of macro-theories of hunger and undernutrition, classified along dimensions relating to (i) the importance given to the quantity of food produced (vertical), and (ii) the importance given to population growth (horizontal).

Assumptions about the importance of increased food production	**Assumptions about the importance of population growth**	
	Non-Malthusian	**Malthusian**
Productionist	<u>Modernisation</u> Hunger is caused by a lack of modernisation and technology Solution: "Development"	<u>Productionist Neo-Malthusian</u> Hunger is caused by food production falling behind population growth Solution: Agricultural research and development
Non-productionist	<u>Political Economy</u> Hunger is caused by social inequality and poverty produced both globally and locally Solution: Address root causes of inequality and poverty (i.e. tends to look at factors internal to society)	<u>Ecological Neo-Malthusian</u> Hunger is caused by population growth and environmental degradation Solution: Live within the limits of the Earth (i.e. tends to look at factors external to society)

Based on Buttel (2000), Table 2.

Critically, as shown in the table, each theory potentially acts as a guide to practical action by suggesting particular types of solutions to undernutrition. These range from general development (akin to modernisation theories of development (Payne and Phillips, 2010)) to science (i.e. agricultural research and development) to recognising the "limits to growth" (i.e. factors largely, but not entirely, external to society) to addressing poverty and inequality (i.e. factors largely internal to society).

In this conceptualisation, particular theories aren't seen as "right" or "wrong", and there is some empirical evidence to support each of them. Rather, each theory is seen as a lens through which to view different aspects of complex (and changing) reality. Further, the groups of theories are not

[27] Buttel notes these macro-theories (or 'families of theories') attempt to focus on the general dynamics of hunger, but in doing so gloss over a number of important factors including war, disasters, and gender relations. For the purposes of this overview, however, these macro-theories are sufficient to identify the broad perspectives taken in previous climate-undernutrition modelling.
[28] Of note, Buttel examined theories of hunger in general; not theories in light of the potential threat to nutrition posed by climate change.

intended to be rigidly distinct, and in practice the central theory underlying a given model may partially incorporate elements of other theories (I return to this below).

To identify gaps in the climate-undernutrition modelling literature, the papers included in the overview may be assessed in relation to the typology. It is clear that all the papers have adopted "productionist" perspectives, with particular papers tending more towards "modernisation" or "neo-Malthusian" perspectives depending on their specific assumptions (e.g. for the former, as Gross Domestic Product per capital (GDPpc) rises the risk of undernutrition may be assumed to fall (e.g. Lloyd et al., 2011); in the latter, models may attempt to account for improvements in agricultural technology (e.g. Hasegawa et al., 2015b)). Additionally, elements of ecological limits appear in that, for example, assumptions regarding soil degradation may be included (e.g. Nelson et al., 2010).

Perspectives that view poverty and inequality as the major causes of undernutrition, however, have not been represented in the modelling literature. Given that, as noted above, (i) there is currently sufficient food to feed the global population (Moore Lappé, 2013), (ii) poverty and hunger tend to occur together (Pogge, 2010)[29], and (iii) climate change is expected to impact on patterns of incomes and poverty (Hallegatte and Rozenberg, 2017), this appears to be a crucial omission. Two models in this thesis (Chapters 5 and 6) attempt to begin to fill this gap.

A more general suggestion also arises from the above. Table 2 shows the wide range of processes that are associated with undernutrition. Arguably, no single model will be able to capture them all simultaneously. This is because of the inherent limits of the technical methods (regardless of how sophisticated) that a model may employ. Further, even if a given model were able to capture all the major processes (or at least, those that a particular modelling group thought were the most important), the causes of undernutrition are contested, as are the types of solutions that are considered to be viable: thus, different models (and modelling strategies) would be required to give representation to these differing ideological standpoints. For instance, Buttel (2000) argues that "productionist neo-Malthusian" perspectives tend to be widely accepted because the solution they point to is increased production (i.e. a technological solution). In contrast, "ecological neo-Malthusian" perspectives are less palatable to many as they suggest solutions lie in deeper social changes such as the need to constrain expansion and consumption. In sum, this suggests that, in order to gain a broad range of new insights into complex health problems such as undernutrition, it is useful – if not necessary – to develop multiple models, each viewing the problem from a different perspective.

[29] In some conceptualisations, poverty is defined by hunger (Ravallion, 1992).

Conclusions

Over the past 25 years, 19 papers (including those in Chapter 4 of this thesis) have modelled the potential impacts of climate change on undernourishment or undernutrition at the global-level. Assessing the papers in terms of their underlying conceptualisations shows that all papers rest on variants of how climate change will impact on food supply (in terms of quantity or quality) and how this in turn may impact the nutritional status of populations of consumers. This captures an important but limited range of the possible conceptualisations of the climate-undernutrition relation, and predominately draws attention to increasing food production. One potentially crucial but omitted perspective suggests the root causes of undernutrition lie in patterns of poverty and inequality: the models developed in Chapters 5 and 6 adopt different standpoints within this general perspective.

The overview has also raised the wide range of processes that generate undernutrition and argues that no single model can simultaneously represent them all, partly because of the contestation over the causes of undernutrition and its solutions. Given this, the concluding chapter (Chapter 7) summarizes how the findings of the models developed for this thesis collectively illustrate the utility of approaching complexity with a set of models based on different abstractions.

In the following chapter (Chapter 3), I outline the aims and objectives of this thesis.

Chapter 3. Aims, objectives, and chapter structure

The previous chapters have established that: (i) the causation of undernutrition, as well as the relation between climate change and undernutrition, are complex and contested, and may be viewed through various theoretical lenses, and (ii) previous global-level modelling - at least prior to the publication of Research Paper 3 (Chapter 5) - has consistently focussed on how climate-associated[30] changes in food production (as quantity and/or quality) may affect food supplies available to consumers. Taken together, this means significant knowledge gaps exist.

A central tenet of this thesis is that when faced with complex health issues such as undernutrition, to gain a fuller understanding, it is useful (if not necessary) to develop multiple models, each based on different conceptualisations or theories. Further, it follows that new insights gained from one model can act as a guide to the questions addressed in a subsequent model: that is, model building can be seen as an ongoing process (Levins, 1966, Levins, 1993). Relatedly, Nancy Krieger and George Davey Smith (2016) have argued that "robust causal inference" should "comprise a complex narrative … from diverse perspectives … produced by myriad methods".

Drawing on these ideas, the overall **aim** of the proposed PhD is:

> *To develop - and illustrate the benefits of developing - multiple global-level undernutrition models, each adopting a different perspective and making different assumptions, and each providing different but complementary insights into how climate change may impact on future undernutrition and health.*

This aim will be met via the following **objectives,** with the chapter addressing the objective shown in square brackets:

1. Develop a critical overview of the global-level climate-undernutrition literature in order to identify:
    i. how the climate-undernutrition relation has been conceptualised, and
    ii. some omitted but potentially important conceptualisations [Chapter 2].
2. Develop and run three new global-level climate-undernutrition models, viewing the relation from the perspectives of:
    i. changed crop productivity [Chapter 4],
    ii. low income populations and relative food prices [Chapter 5], and

[30] Including both the direct effects of climate change and impacts associated with raised atmospheric carbon dioxide.

iii. the development trajectories of different styles of farming[31] in the global food system [Chapter 6].

3. Summarize the ways in which the insights from the new models broaden our understanding of the climate change-undernutrition problem, and thus illustrate the utility of approaching complexity with a set of models based on different abstractions [Chapter 7].

The chapter structure of the thesis is shown in Figure 4. Running diagonally through the figure, the grey boxes joined by the solid arrows show the chapters. The underlying logic which links the chapters is shown by the paths marked with the curved dashed arrows: that is, this shows how the key insights of one chapter lead to the question addressed in the next chapter. The aim of the thesis is shown in the grey box in the top right.

[31] 'Styles of farming' refers to, for instance, how food is produced and the way farmers relate to markets, with a key distinction being between peasant and entrepreneurial farming (van der Ploeg, 2018).

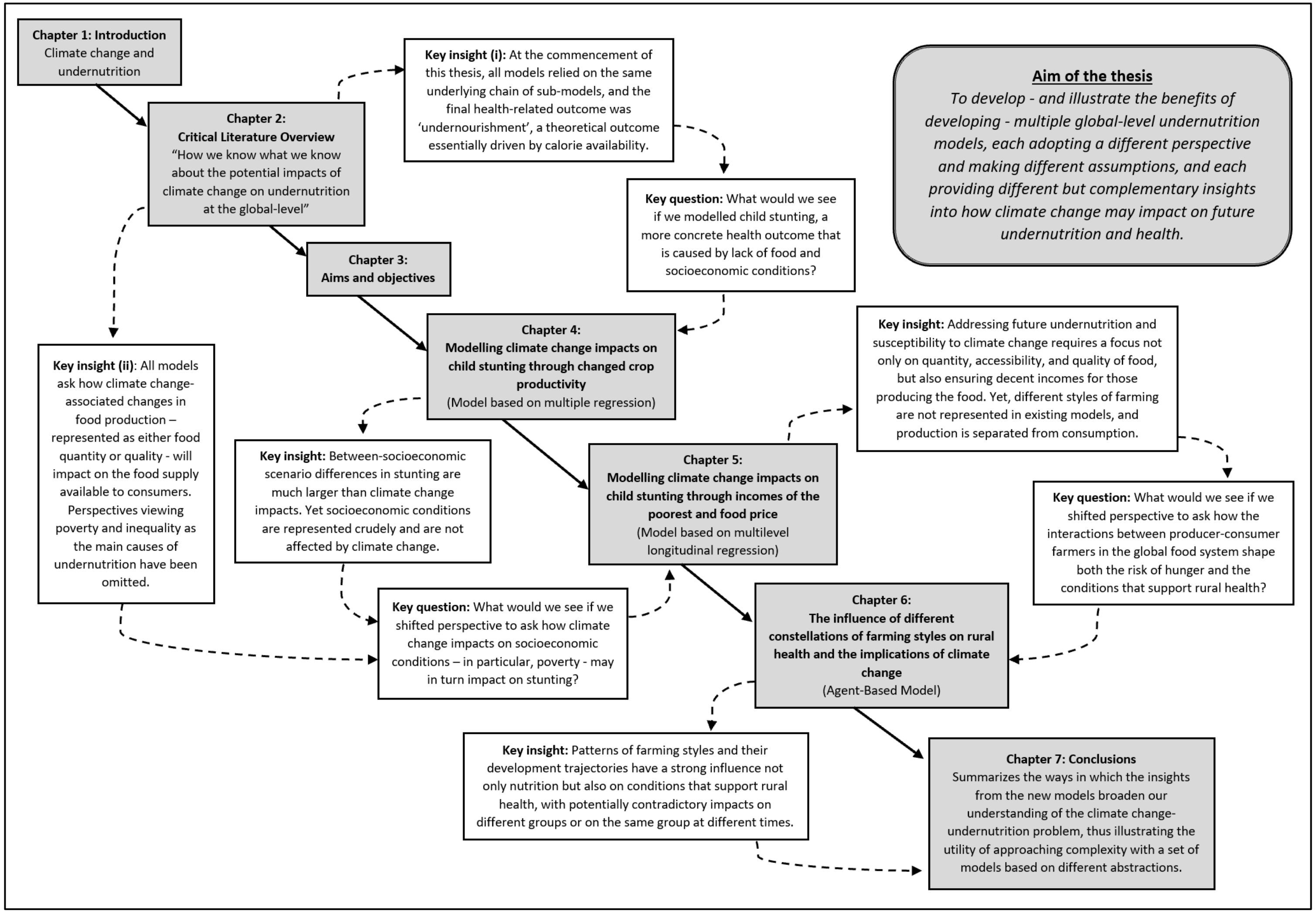

Figure 4 Chapter structure, with the chapters shown in the diagonally running grey boxes joined by solid arrows, and the logic linking the chapters shown by the paths marked by dotted curved arrows.

This PhD contains sections written specifically for the thesis (Chapters 1, 2, 3, and 7), as well as published papers (Chapters 4 and 5). Chapter 6 is an extended version of a paper in preparation for submission to a journal.

Chapter 4. Modelling climate change impacts on child stunting through changed crop productivity

Background

This chapter is composed of two research papers. It focusses on the development and application of a statistically-based model (multiple regression) that assesses how climate change-associated changes in crop productivity may impact on future child stunting and mortality.

Research Paper 1 (Lloyd et al., 2011) was developed as part of the NERC (Natural Environment Research Council, UK) funded multidisciplinary QUEST-GSI project[32], with additional model inputs provided by the International Food Policy Research Institute (IFPRI). The paper describes the development of the model and provides estimates of climate change-attributable moderate and severe stunting in children aged <5, in South Asia and Sub-Saharan Africa, under moderate to high climate change, for one socioeconomic scenario, for the year 2050.

Research Paper 2 (Lloyd et al., 2014) was part of a World Health Organization (WHO) report on the potential health impacts of climate change (Hales et al., 2014). For this report, the model developed in Research Paper 1 was extended to estimate stunting-attributable child mortality. The paper describes the model and makes estimates of climate change-attributable moderate and severe stunting in children <5, as well associated child mortality, in 12 world regions, under moderate climate change, under three socioeconomic scenarios, for the 2030s and 2050s. As this paper was a chapter of a report, relevant associated chapters and the reference list are provided in the accompanying appendix (“Research Paper 2: Supplemental Material”) rather than in the chapter itself.

[32] QUEST: Quantifying and Understanding the Earth System; GSI: Global-Scale Impacts.

Research Paper 1: Climate Change, Crop Yields, and Undernutrition: Development of a Model to Quantify the Impact of Climate Scenarios on Child Undernutrition

For accompanying supplemental material, see the appendix “Research Paper 1: Supplemental Material”.

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Please note that a cover sheet must be completed <u>for each</u> research paper included within a thesis.

SECTION A – Student Details

Student ID Number	246266	**Title**	Mr
First Name(s)	Simon John		
Surname/Family Name	Lloyd		
Thesis Title	Modelling the relation between climate change and undernutrition at the global-level: the use of multiple perspectives to gain new insights		
Primary Supervisor	Ben Armstrong		

If the Research Paper has previously been published please complete Section B, if not please move to Section C.

SECTION B – Paper already published

Where was the work published?	Environmental Health Perspectives		
When was the work published?	15 Aug 2011		
If the work was published prior to registration for your research degree, give a brief rationale for its inclusion	N/A		
Have you retained the copyright for the work?*	**Yes**	Was the work subject to academic peer review?	**Yes**

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SECTION C – Prepared for publication, but not yet published

Where is the work intended to be published?	
Please list the paper's authors in the intended authorship order:	

Stage of publication	Choose an item.

SECTION D – Multi-authored work

For multi-authored work, give full details of your role in the research included in the paper and in the preparation of the paper. (Attach a further sheet if necessary)	This paper was developed as part of the NERC funded QUEST project, which modelled the impacts of climate change on various sectors. For the food production and nutrition-related work, a multidisciplinary team (crop modelling, geography, health) was involved in the initial discussions of approaches to modelling. For the included paper: I designed the model, assembled the data, conducted the analysis, ran the model, and wrote the first draft of the paper. Sari Kovats and Zaid Chalabi provided advice throughout and co-authored the paper.

SECTION E

Student Signature	[redacted]
Date	6 Nov, 2019

Supervisor Signature	[redacted]
Date	6 Nov 2019

Climate Change, Crop Yields, and Undernutrition: Development of a Model to Quantify the Impact of Climate Scenarios on Child Undernutrition

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Background: Global climate change is anticipated to reduce future cereal yields and threaten food security, thus potentially increasing the risk of undernutrition. The causation of undernutrition is complex, and there is a need to develop models that better quantify the potential impacts of climate change on population health.

Objectives: We developed a model for estimating future undernutrition that accounts for food and nonfood (socioeconomic) causes and can be linked to available regional scenario data. We estimated child stunting attributable to climate change in five regions in South Asia and sub-Saharan Africa (SSA) in 2050.

Methods: We used current national food availability and undernutrition data to parameterize and validate a global model, using a process-driven approach based on estimations of the physiological relationship between a lack of food and stunting. We estimated stunting in 2050 using published modeled national calorie availability under two climate scenarios and a reference scenario (no climate change).

Results: We estimated that climate change will lead to a relative increase in moderate stunting of 1–29% in 2050 compared with a future without climate change. Climate change will have a greater impact on rates of severe stunting, which we estimated will increase by 23% (central SSA) to 62% (South Asia).

Conclusions: Climate change is likely to impair future efforts to reduce child malnutrition in South Asia and SSA, even when economic growth is taken into account. Our model suggests that to reduce and prevent future undernutrition, it is necessary to both increase food access and improve socioeconomic conditions, as well as reduce greenhouse gas emissions.

Key words: cereal crops, climate change, Monte Carlo simulation, quantitative model, undernourishment, undernutrition. *Environ Health Perspect* 119:1817–1823 (2011). http://dx.doi.org/10.1289/ehp.1003311 [Online 15 August 2011]

Hunger and undernutrition are pervasive, thought to be worsening in absolute terms, and are major contributors to global ill health [Black et al. 2008; Food and Agricultural Organization of the United Nations (FAO) 2009]. More than one billion people are undernourished (FAO 2009), and about a third of the burden of disease in children < 5 years of age is attributable to undernutrition (Black et al. 2008). Economic growth is anticipated by many to reduce future undernutrition (Smith and Haddad 2002), although recent observations do not support this assumption (Subramanyam et al. 2011).

Global food security depends on a range of factors (Schmidhuber and Tubiello 2007), with cereal production playing a major role (Parry et al. 2009). Data suggest that global per capita cereal production plateaued during the 1980s and has since declined (Magdoff and Tokar 2010), despite production increases in some regions (FAO 2011). Further, with economic growth, dietary preferences tend toward greater meat consumption, placing greater demands on cereal production to provide animal feed (Msangi and Rosegrant 2011).

Concern is growing that efforts to reduce undernutrition in the coming decades may be threatened by global climate change (Nelson et al. 2010; Parry et al. 2009; Schmidhuber and Tubiello 2007). Scientific assessments indicate that warming will have an overall negative impact on major cereal yields in low-latitude areas, although yields may increase in some high-latitude areas (Easterling et al. 2007). Climate change could place an additional 5–170 million people "at risk of hunger" by the 2080s (Parry et al. 1999, 2004; Rosenzweig and Parry 1994). Food security is now one of the leading concerns associated with anthropogenic climate change (Parry et al. 2009).

A number of terms are used to describe hunger and undernutrition. "Undernourishment" is not a health outcome per se; it is a theoretical model-based estimate of access to calories developed by the FAO and is defined as the proportion of people "whose dietary energy consumption is continuously below a minimum dietary energy requirement for maintaining a healthy life and carrying out light physical activity with an acceptable minimum body-weight for attained-height" (FAO 2010). That is, it has one final cause: a lack of food. "At risk of hunger" is synonymous with undernourishment.

"Undernutrition" refers to a physical state and is measured using (among other things) anthropometric indices such as stunting (height-for-age) and underweight (weight-for-age) [World Health Organization (WHO) 2010]. A lack of food—that is, undernourishment—is one of the many causes of undernutrition, which also include poor water and sanitation provision, low levels of women's education, repeated episodes of infectious diseases, and low birth weight [United Nations Children's Fund (UNICEF 1990); for more details on causes, see Black et al. 2008; UNICEF 1990]. Checkley et al. (2008), for example, estimated that 25% [95% confidence interval (CI): 8, 38%] of irreversible stunting at 24 months of age could be attributed to having had five or more episodes of diarrhea. Although it can be argued that undernutrition itself is not a health outcome, undernutrition can be directly linked to increased risk of death and poor health (Black et al. 2008). Additionally, child undernutrition has long-term consequences for the health and earning potential of adults (Victora et al. 2008).

To quantify future health burdens, it is preferable to model undernutrition (which refers to a physical state and accounts for complex causation) rather than undernourishment (which is a theoretical concept). They are often poorly correlated (Klasen 2006; Svedberg 2002) and this suggests that undernourishment is a poor proxy for undernutrition. The WHO concluded that (using a number of simplifying assumptions) undernutrition represented a significant proportion of the total burden of disease estimated to be attributable to climate change in 2000 (McMichael et al. 2004). Only one group has provided more recent quantitative estimates of future undernutrition attributable to climate change. Nelson et al. (2009) reported that, for two climate scenarios, climate change may increase underweight in children < 5 years of age by around

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Supplemental Material is available online (http://dx.doi.org/10.1289/ehp.1003311).

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The authors declare they have no actual or potential competing financial interests.

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20% by 2050. Underweight was estimated using an equation developed by Smith and Haddad (2000), which is driven by per capita calorie availability and socioeconomic indicators: the ratio of female to male life expectancy, female enrollment in secondary education, and access to improved water supply. Future per capita calorie availability was estimated by modeling crop yield and global food trade. All other nonclimate factors were assumed to stay constant over time (i.e., unchanged from baseline values). These assumptions are likely to have led to an overestimate of the future burden attributable to climate change because this approach assumes that living conditions in countries will improve little over the next 40 years. This is not consistent with historical trends; between 1970 and 1995, 43% of the reduction in child underweight has been attributed to improved female education, compared with 26% for increased food availability and 19% from improved water access (Smith and Haddad 2000).

More recently, the same group produced updated estimates for a broader range of scenarios using a similar strategy (Nelson et al. 2010). Based on expert opinion, the socioeconomic variables driving the underweight model were varied with time but were considered constant across three socioeconomic scenarios broadly representing pessimistic, business-as-usual, and optimistic economic growth.

Despite the importance of socioeconomic influences on health, the data currently available for climate impact studies are largely limited to population and gross domestic product (GDP) projections that were created for estimating future greenhouse gas emission concentrations. At present, any modeling efforts must work within these constraints. However, attention is now being focused on creating a wider range of plausible socioeconomic scenarios for climate impact assessments (Moss et al. 2010).

We developed a parsimonious model for estimating future undernutrition attributable to global climate change, specifically due to its impacts on crop productivity. We then estimated the future impact of climate scenarios on undernutrition in children for five world regions in Africa and Asia in 2050 using previously published estimates of climate change–attributable changes in calorie availability from Nelson et al. (2009). [The more recent estimates (Nelson et al. 2010) are not included in our assessment because they were released after the completion of our project.]

Materials and Methods

We first describe the development and fitting of a model for estimating the prevalence of stunting. Second, we outline the process of estimating the proportion undernourished (PoU) using per capita calorie availability estimates from Nelson et al. (2009). Finally, we discuss the simulation process for estimating future undernutrition attributable to global climate change.

Model development. Our outcome of interest is stunting in children < 5 years of age, because this best captures the impact of conditions over the long term (Black et al. 2008). Children are considered moderately stunted if they are > 2 SDs below the mean expected height-for-age and severely stunted if > 3 SDs below the mean (de Onis and Blossner 2003).

Scenario data are limited essentially to future food availability and per capita GDP, and many causes of stunting cannot be explicitly modeled. We considered stunting to have two main causes, which we refer to as "food causes" and "nonfood causes." Food causes are represented as PoU, which accounts for climate change effects on calorie availability (via changes in crop productivity) and food access. [Stunting has food causes other than calories, e.g., micronutrient deficiencies (Black et al. 2008), but these are not represented in PoU, nor are they modeled in climate-crop models.] Nonfood causes are represented as a "black box cluster" of socioeconomic factors acting at various levels and represent the wide range of social and demographic causes of stunting, such as low female literacy and poor health care access (Frongillo et al. 1997). Nonfood causes are modeled using per capita GDP and the Gini coefficient for income distribution to generate a "development score," as described below.

The conceptual model is represented by two general equations:

$$y_{ijk} = \alpha_k + \beta_k x_{ij} + \gamma_k w_{ij} + \theta_k x_{ij} w_{ij} \qquad [1]$$

for every i, j; $k = 2, 3$,

$$y_{ij1} = 1 - y_{ij2} - y_{ij3} \qquad [2]$$

for every i, j; $k = 1$,

where y_{ijk} is the proportion of children < 5 years of age stunted in country i, in region j, at level k, where k is 1 if no/mild stunting, 2 if moderate stunting, or 3 if severe stunting; x_{ij} is food causes of stunting, represented by the PoU in country i, in region j; and w_{ij} is nonfood causes of stunting, represented by the "development score" (defined below) in country i, in region j. The parameters α_k, β_k, γ_k, and θ_k are to be determined: β_k is the physiological relation between undernourishment and stunting (details given below), γ_k relates the development score to stunting, θ_k relates the interaction between undernourishment and the development score to stunting, and α_k is the regression constant.

Equation 1 is a bilinear model because it is a linear function of the independent variables (x_{ij} and w_{ij}) and their product ($x_{ij}w_{ij}$). After estimating moderate (y_{ij2}) and severe (y_{ij3}) stunting, we estimated the proportion not or mildly stunted (y_{ij1}) as described in Equation 2.

The "development score" is an indicator of the nonfood causes of stunting. It is driven by country-level projections of future per capita GDP and the baseline (i.e., most recent estimate available) Gini coefficient (because no projections were available). The development score is scaled from 0 to 1; it equals 0 when socioeconomic conditions are optimal (in terms of avoiding undernutrition) and all undernutrition is attributable to food causes, and it equals 1 when nonfood causes are at their current (baseline) global maximum [for additional information on development score calculations, see Supplemental Material, Annex 1 (http://dx.doi.org/10.1289/ehp.1003311)].

To parameterize the equations, we assembled a global data set obtaining country-level undernourishment estimates from the FAO (FAO 2010), per capita GDP and Gini data from the World Bank Development Indicators (WBDI) database (World Bank 2010), and stunting data from the WHO's Global Database on Child Growth and Malnutrition (WHO 2010).

Stunting data were matched to undernourishment data to within a 1-year period. Per capita GDP and Gini coefficient estimates were matched as closely as possible to the stunting data year. The data set covered the period 1988–2008 and contained 186 records with complete data. Countries were included in the data set more than once if they had data for multiple years.

Fitting the model. We decided, *a priori*, to use a process-driven (theory-based) rather than a standard data-driven (statistical) approach to develop and parameterize the model equations. The purpose of the model is to describe plausible futures, so we designed it to be driven as much as possible by relationships that will be stable over time.

Of the two model variables, we assumed that food causes have a more stable relationship with stunting than do nonfood causes because food causes are physiologically related to stunting, and it is reasonable to assume that this relationship will hold over the next 50 years. In contrast, we assumed that nonfood causes—which we modeled using per capita GDP and the Gini coefficient—do not necessarily have a stable relationship with stunting because the relationship is mediated, at least partly, by social and political factors that may change over time. Therefore, when fitting our model, we first quantified the relationship between stunting and food causes and then considered socioeconomic factors.

We assumed that if someone had insufficient food, and nonfood causes of stunting were absent (i.e., socioeconomic conditions were optimal in terms of avoiding undernutrition), there would be a predictable risk of stunting;

that is, we assumed the relationship between food intake and stunting is physiologically determined and holds globally. This assumption is supported by ample evidence that, at least until 6 years of age, all adequately nourished and optimally cared for children will have similar, predictable growth rates (WHO 2006). In addition to this food intake–related burden, if socioeconomic conditions are poor, there is an additional risk of stunting from nonfood causes and their interaction with food causes, for example, high rates of diarrhea associated with inadequate sanitation. We do not consider it probable that a country will lack sufficient food but otherwise have "optimal" socioeconomic conditions; our conception is theoretical.

Using the data set, we estimated the predictable but unknown physiologically based relationship between undernourishment and stunting at level k (β_k) as

$$\beta_k = \min_{i,j} \{y_{ijk}/x_{ij};\ i = 1\ldots, j = 1\ldots\}. \quad [3]$$

(The operator $min_{i,j}\{\cdot\}$ means the minimum of the argument in $\{\cdot\}$.) This minimum proportion was obtained by finding the minimum value of the ratio of y_{ijk} to x_{ij} among all the countries in all regions, where, as defined above, y_{ijk} represents the proportion stunted < 5 years of age in country i, in region j, and stunting level k; and x_{ij} represents the proportion of the population undernourished in county i, in region j. Because it is unlikely that all stunting in a country is caused by food causes alone, our estimate of β_k will be an overestimate of the purely physiological relationship between food and stunting. In practice, because the minimum observed value may be too low because of data errors, we chose to use the 5th percentile of the distribution of y_{ijk}/x_{ij} as the best estimate of β_k and used the 1st and 10th percentiles as the boundaries of its plausible range (see "Estimating future stunting," below).

Once the above relationship was found, one-fifth of the data set (37 records) was randomly selected and reserved for model validation; the remainder (149 records) was used to parameterize the equations. (To obtain the best possible estimate, and considering that our method of estimation provides a rough approximation, we used the entire data set to estimate β_k.)

We parameterized the equations in a stepwise manner. In the first step, we used β_k to attribute a proportion of stunting to food causes in all countries in the parameterization data set:

$$r_{ijk} = \beta_k x_{ij} \quad [4]$$
for every i, j, k,

where r_{ijk} is the proportion of stunting attributable to food causes in country i, in region j, at level k.

In the second step, we attributed the remaining proportion of stunting to nonfood causes and the interaction between food and nonfood causes:

$$s_{ijk} = y_{ijk} - r_{ijk} \quad [5]$$
for every i, j, k,

where s_{ijk} is the proportion of stunting attributable to nonfood causes and the interaction between food and nonfood causes in country i, in region j, at level k. We then used linear methods to estimate the parameters (α_k, γ_k, θ_k) of the bilinear model:

$$s_{ijk} = \alpha_k + \gamma_k w_{ij} + \theta_k x_{ij} w_{ij} \quad [6]$$
for every i, j, k.

The model was validated by comparing levels of stunting predicted by the model to observed stunting in the reserved portion of the data set (37 records).

For α_k, γ_k, and θ_k we used the standard errors of the estimates to describe the plausible range of their true values. We carried out our analysis with Stata (version 11; StataCorp, College Station, TX, USA).

Estimating future population undernourished. The model required estimates of future PoU with and without climate change. Calculation of PoU requires data for *a*) the coefficient of variation for within-population calorie distribution, *b*) the average minimum calorie requirements to avoid undernourishment in the population, and *c*) per capita calorie availability (FAO 2003). Because projection data for *a*) and *b*) are not available, we assumed they remain at baseline levels. For *c*), we used estimates made by Nelson et al. (2009) for futures with and without climate change. The future without climate change (reference scenario) was represented with the 1950–2000 climate. The two climate change scenarios were derived from two climate models [the National Centre for Atmospheric Research (NCAR) model and the Commonwealth Scientific and Industrial Research Organisation (CSIRO) model] forced by a medium-high emissions scenario [the Intergovernmental Panel on Climate Change A2 scenario from the Special Report on Emissions Scenarios; see Nakicenovic and Swart (2000)]. The two climate scenarios were used to address uncertainty in the climate system; the NCAR model is warmer and wetter than the CSIRO model. The global average increases in maximum temperature and precipitation over land by 2050 were 1.9°C and 10%, and 1.2°C and 2% for the NCAR and CSIRO scenarios, respectively. For details of the assumptions in the crop modeling (e.g., carbon dioxide fertilization, irrigation, and adaptation responses), extrapolations to other food groups, and the trade model, see Nelson et al. (2009). For additional information on PoU estimation, see Supplemental Material, Annex 2 (http://dx.doi.org/10.1289/ehp.1003311).

Estimating future stunting. The principal input to our simulation model was future country-level PoU derived from Nelson et al. (2009). We ensured within-scenario consistency by using the same GDP (G. Nelson, International Food Policy Research Institute, personal communication) and population projections [United Nations medium variant, 2006 revision (United Nations 2007)] used in the calorie availability projections. Our estimates of the Gini coefficient were the most recent estimates available from the WBDI (World Bank 2010).

To account for parameter uncertainty, we used a standard Monte Carlo approach. Each of α_k, γ_k, and θ_k were assumed to be normally distributed about their point estimates as defined by their respective standard errors. β_k was assumed to be uniformly distributed between the 1st and 10th percentiles of the distribution of y_{ijk}/x_{ij}. This method produced probability density functions (PDFs) of future stunting.

We aimed to base each PDF on 100,000 estimates. We selected the first 100,000 estimates that were > 0 and < 1. By rejecting low and high estimates, we potentially introduced an upward or downward bias; to assess this, we quantified the proportion of rejected results [see Supplemental Material, Table 1 (http://dx.doi.org/10.1289/ehp.1003311)].

Final estimates were produced at the regional level for South Asia and four regions in sub-Saharan Africa [SSA; central, east, south, and west; see Supplemental Material, Table 2 (http://dx.doi.org/10.1289/ehp.1003311)]. We aggregated stunting from the country to regional level using population weighting. We ran the simulation using MATLAB (version 2009b; MathWorks, Natick, MA, USA).

Results

Model development and parameters. Table 1 summarizes the data set used to parameterize our model. The correlation coefficients between stunting and PoU were 0.16 and 0.19 for moderate and severe stunting, respectively. For univariate analysis of stunting and the development score, R^2 was 0.40 for moderate stunting and 0.45 for severe stunting; when PoU was added to these models, R^2 was unchanged. That is, using a data-driven approach, including PoU as an explanatory variable would not improve the model fit to estimate stunting in the present compared with using the development score alone. This supported our approach using a theory-based model that accounts for both food access and socioeconomic conditions.

The model parameter estimates are shown in Table 2. The β parameter is an estimate of the assumed physiological relationship between a lack of food and stunting. Thus, the central estimate of $\beta = 0.35$ for moderate stunting suggests that for every 1% of the population who are undernourished, on average 0.35% of children < 5 years of age will be moderately stunted. Using the validation data set, the predicted and observed values are well correlated, with correlation coefficients of 0.78, 0.66, and 0.80 for no/mild, moderate, and severe stunting, respectively [for scatterplots, see Supplemental Material, Figure 1 (http://dx.doi.org/10.1289/ehp.1003311)].

Estimates of future proportions undernourished. The proportions of regional populations projected to be undernourished in 2050 are shown in Table 3. Countries for which complete data were not available were excluded [see Supplemental Material, Table 2 (http://dx.doi.org/10.1289/ehp.1003311)]. The estimates suggest that climate change will increase PoU compared with a future without climate change, and also that climate change and population growth will increase it to above current levels in all regions.

Projections of stunting in 2050. We estimate that climate change will increase stunting in all regions (Table 3), with severe stunting increasing by 30–50%. The estimated relative change in stunting was smaller than the estimated relative change in undernourishment. Figure 1 shows the uncertainty in the stunting estimates as histograms of probabilistic outcomes derived from the Monte Carlo simulation.

We compared our stunting estimates with underweight estimates made by Nelson et al. (2009) (Table 4). The results are not directly comparable, but we have assumed that the ratio of underweight to stunting at baseline remains constant in the future. The final column shows this ratio as a regional, population-weighted average calculated using the most recent estimates of underweight and stunting (FAO 2010).

Discussion

We have developed the first global model to estimate the impact of climate change on future stunting—a more relevant outcome measure for human population health than "population at risk of hunger" (i.e., undernourishment) or underweight. Additionally, our model distinguishes moderate from severe stunting, which bring substantially different health risks (Black et al. 2008). Based on our conservative assumptions, the model suggests that climate change will have significant effects on future undernutrition, even when the beneficial effects of economic growth are taken into account. This is particularly so for severe stunting, with a 62% increase in South Asia and a 55% increase in east and south SSA. The health implications of this are large: according to Black et al.

Table 1. Summary of the data used to parameterize the model.

Region	No. observations	Children stunted[a] (%) Moderate	Severe	Undernourished[a] (%)	Per capita GDP[a] (2000 US$)	Gini[a,b]
Global	149	19 (3–30)	16 (1–36)	24 (5–70)	897 (81–5,513)	0.45 (0.17–0.74)
Caribbean	9	8 (3–14)	4 (1–8)	12 (5–27)	2,398 (942–3,688)	0.47 (0.4–0.53)
Central America	12	19 (13–27)	12 (4–29)	19 (5–52)	2,051 (633–5,513)	0.53 (0.49–0.58)
South Asia	8	26 (22–30)	26 (2–35)	22 (16–26)	364 (207–589)	0.38 (0.3–0.47)
Southeast Asia	12	22 (11–27)	18 (3–33)	21 (9–41)	729 (232–1,958)	0.4 (0.33–0.44)
SSA						
Central	5	21 (16–26)	24 (15–35)	49 (21–76)	309 (81–578)	0.51 (0.44–0.61)
East	23	24 (14–29)	23 (12–34)	36 (15–62)	286 (110–757)	0.43 (0.3–0.6)
South	8	30 (19–23)	14 (9–30)	29 (14–46)	1,298 (415–2,599)	0.60 (0.5–0.74)
West	35	20 (13–25)	19 (7–30)	24 (8–51)	315 (138–684)	0.43 (0.36–0.53)
Other regions	37	16 (6–23)	16 (6–23)	18 (5–58)	1,249 (206–3,975)	0.43 (0.17–0.62)

Data are shown globally (for all those countries for which data were available) and for regions defined for the Global Burden of Disease Study (Harvard University et al. 2009).
[a]Values are regional means (minimum–maximum); numbers are based on records from between 1991 and 2008. [b]The Gini coefficient ranges from 0, where there is perfect income equality, to 1, where all income goes to one person.

Table 2. Central estimates and plausible ranges of model parameters.

Level of stunting	β_k	α_k	γ_k	θ_k
Moderate ($k = 2$)	0.35 (0.20–0.44)	0.025 ± 0.013	0.26 ± 0.028	–0.43 ± 0.041
Severe ($k = 3$)	0.18 (0.11–0.28)	–0.052 ± 0.021	0.34 ± 0.044	–0.18 ± 0.064

β_k is the physiological relation between undernourishment and stunting [5th percentile (1st–10th percentile)]; α_k is the regression constant, γ_k relates the development score to stunting, and θ_k relates the interaction between undernourishment and the development score to stunting (regression estimate ± SE).

Table 3. Estimates of undernourishment and stunting at baseline (present) and in 2050 with and without climate change (CC).

Region	Percent undernourished[a] Baseline	2050 No CC	2050 NCAR	2050 CSIRO	Percent relative increase in PoU under climate change[b]	Stunting level	Percent stunted (mean ± SD) of the PDFs[a,c] Baseline	2050 No CC	2050 NCAR	2050 CSIRO	Percent relative increase in stunting under climate change[d]
South Asia	22	15	30	29	97	Moderate	23	11.2 ± 1.8	14.6 ± 2.6	14.3 ± 2.5	29
						Severe	19	2.9 ± 1.2	4.8 ± 1.7	4.6 ± 1.6	61
SSA											
Central	65	53	81	80	52	Moderate	20	19.9 ± 4.7	20.1 ± 5.7	20.1 ± 5.7	1
						Severe	20	16.8 ± 5.6	22.1 ± 6.1	22.0 ± 6.1	31
East	35	24	52	52	116	Moderate	22	19.3 ± 2.9	21.1 ± 4.6	21.1 ± 4.5	9
						Severe	18	9.7 ± 1.9	15.0 ± 2.3	15.0 ± 2.3	55
South	32	33	60	60	82	Moderate	16	17.1 ± 3.0	21.0 ± 4.8	21.0 ± 4.8	23
						Severe	12	8.8 ± 3.3	13.6 ± 4.0	13.6 ± 4.0	55
West	15	12	29	29	142	Moderate	17	17.0 ± 2.2	18.6 ± 2.9	18.5 ± 2.9	9
						Severe	16	6.8 ± 1.6	9.3 ± 1.8	9.2 ± 1.8	36

[a]Baseline undernourishment and stunting data are from FAO (2010) and are calculated as population-weighted averages using the most recent data available; countries without data are excluded. "No CC" is the reference scenario (i.e. future without climate change); "NCAR" and "CSIRO" are futures under climate change scenarios based on the NCAR and CSIRO models respectively. [b]Compared with a future with no climate change; estimate based on average estimates from NCAR and CSIRO. For example, for South Asia the calculation was:

$$\left(\frac{\frac{30+29}{2}}{15} - 1\right) \times 100 = 97.$$

[c]Empirically derived PDF, derived from the Monte Carlo simulations. [d]Compared with a future with no climate change; estimate based on average of the mean of the estimates from NCAR and CSIRO. For example, for moderate stunting in South Asia the calculation was:

$$\left(\frac{\frac{14.6+14.3}{2}}{11.2} - 1\right) \times 100 = 29.$$

(2008), moderate stunting increases the risk of all-cause death 1.6 times (95% CI: 1.3, 2.2) and severe stunting increases the risk 4.1 times (95% CI: 2.6, 6.4).

Comparing our results with those of Nelson et al. (2009) should be done cautiously because the outcome measures are different. Our estimates for stunting are lower than estimates from Nelson et al. (2009) for underweight in both South Asia and SSA (Table 4). Our estimates for SSA are closer but still lower. It is likely these differences are largely explained by how the models account for socioeconomic conditions. Nelson et al. (2009) estimated underweight using a complex model that accounted for many socioeconomic factors, but because of a lack of data, all the factors (except for food access) were held at baseline levels. Our stunting equation represents socioeconomics more simply but is able to account for expected changes over the next 40 years. World Bank projections suggest that in South Asia, GDP will increase nine times between 2005 and 2050—an absolute increase of about $7,000 billion (year 2000 US$); in SSA the figures are five times and $1,700 billion. Hence, allowing for these changes results in lower future stunting estimates, with a greater reduction in South Asia.

Model approximations and assumptions. We used a theory-based rather than statistically based approach to modeling. Although we accept that a statistical approach would

Table 4. Model estimates of numbers of children affected by undernutrition in 2050: underweight and stunting.

Region	Outcome	Millions of children affected by undernutrition in 2050			Additional millions of children affected by undernutrition with climate change		Baseline ratio of underweight to stunting[a]
		No CC	NCAR	CSIRO	No CC	NCAR	
South Asia	Underweight[b]	52	59	59	7	7	1.1
	Stunting[c]	20	27	26	7	6	
SSA	Underweight[b]	42	52	52	10	10	0.7
	Stunting[c]	45	54	54	9	9	

[a]Calculated as [(moderate + severe underweight)/(moderate + severe stunting)] using data for the present (FAO 2010) and as a regional, population-weighted average. [b]Underweight estimates for 2050 are from Nelson et al. (2009). [c]Stunting estimates are the sum of the numbers moderately and severely stunted, based on the mean estimates of the empirically derived PDFs.

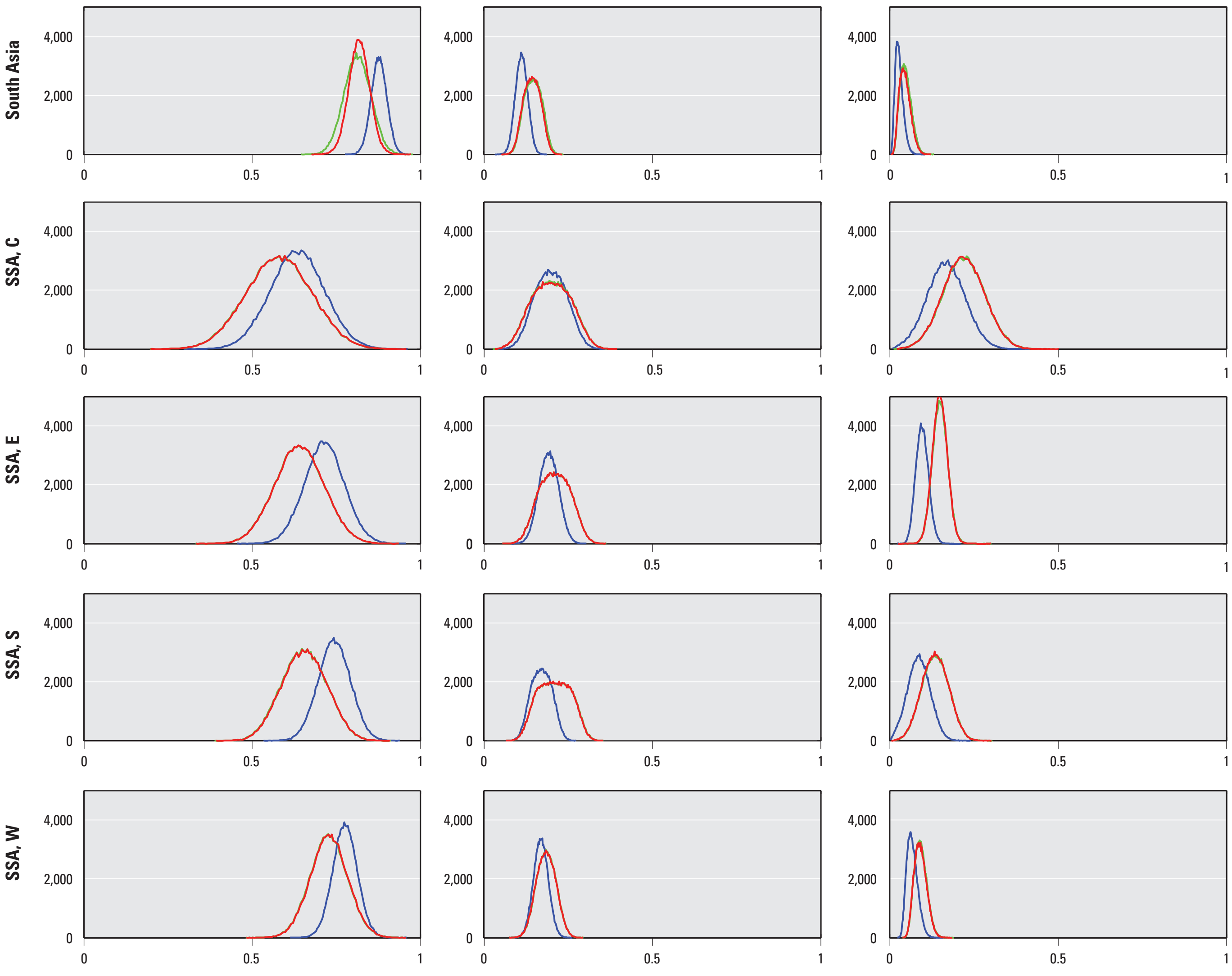

Figure 1. Histograms proportional to the PDFs for the proportion estimated to be stunted in 2050, by region: SSA, C (central); SSA, E (east); SSA, S (south); SSA, W (west). Histograms were derived from 100,000 Monte Carlo runs. The *x*-axes are proportion stunted at a given level; the *y*-axes are number of estimates. The curves are blue for no climate change, green for NCAR, and red for CSIRO. There is large overlap of the NCAR and CSIRO curves.

be sound if our aim were to estimate current stunting, our aim was to estimate future stunting. Thus, we developed a model that was driven as much as possible by a relationship that can reasonably be expected to remain constant over time. We assumed that the physiological relationship between stunting and undernourishment will remain constant and approximated this relationship in the first step. After this, because the relationship between stunting and GDP (which is mediated by, among other things, political and social conditions) may vary significantly over time, we fitted the development score and interaction term as a second step.

We made several key approximations in constructing the model. The first approximation was to fit a separate bilinear regression model to two of the stunting levels and then use these to estimate no/mild stunting. Although a more rigorous approach would fit the three regression models simultaneously while ensuring that the proportions (for each country) are positive and always add up to unity, this could lead to an imbalance in the goodness of model fit of one level at the expense of another. The second approximation was to treat the food causes and the product of the food causes and nonfood causes as two independent variables in the least squares fit. This, of course, would introduce errors because the variables are correlated. Nevertheless, the approximation was validated against a data set different from that on which it was based. The third approximation concerns the approach we adopted for the probabilistic (Monte Carlo) simulations. Simulated values that were either < 0 or > 1 were discarded. This could introduce bias, and we quantified this potential. No estimates were rejected for being > 1, meaning there is no risk of downward biasing. For estimates < 0, no moderate stunting estimates were rejected, but severe stunting estimates were rejected in all regions [see Supplemental Material, Table 1 (http://dx.doi.org/10.1289/ehp.1003311)], meaning there is some potential for upward bias. Because more estimates were rejected in the "no climate change" future compared with the "climate change" future, this may have reduced the apparent impact of climate change on severe stunting.

The fourth approximation was the estimate of the physiological relationship between stunting and a lack of food (as represented by undernourishment). We ran our model assuming that a uniform distribution of values between the 1st and 10th percentile of the ratio of stunting to undernourishment adequately represented the true value. In support of our estimates, our parameters suggest that about 60% of stunting could not be directly attributed to a lack of food; this is in line with previous estimates that around 40–60% of undernutrition could be attributed to environmental conditions (predominantly a lack of water and sanitation) (Pruss-Ustun and Corvalan 2006).

Although a more elaborate approach could have been used, inevitably there is always a trade-off between model complexity and ease of model use. We have tilted more toward model simplicity but at the same time quantified the errors induced by the approximations, as far as possible.

We made estimates of future undernourishment from projected calorie availability. In doing so we assumed that both within-country food distribution and average minimum calorie requirement remained at baseline levels. In support of these assumptions, we note that FAO estimates of within-country food distribution are based on extrapolations of infrequently collected data from relatively few countries and are restricted to lie between values representing a given maximum and minimum equity of distribution (based on estimated requirements). Varying values within this range has been found to have little impact on PoU in countries with low calorie availability (FAO 1996; Svedberg 2002). Considering minimum calorie requirements, the estimated mean change in requirements across all countries was just 0.1% per year over the period 1990–1992 to 2004–2006 (FAO 2010). Further, according to FAO data (FAO 2010), the average minimum calorie requirements are increasing in most low-income countries and are higher (and increasing) in middle-income countries. This means our estimate may be conservative. Finally, Svedberg (2002) estimated that over a 20-year period, 88% of the change in regional undernourishment was explained by changes in per capita calorie availability.

We assumed that, once per capita GDP reached $10,000 (2000 US$; with an associated Gini coefficient of 0.38), socioeconomic conditions no longer contributed to stunting. We tested the sensitivity of the model to this assumption by rerunning it without this assumption. This made a negligible difference to estimates (data not shown).

Finally, a limitation of the overall modeling strategy is that climate change is assumed to enter the system only through its impact on crop production. First, this allows only a partial consideration of future food security: food availability and, to a degree, access are modeled, but stability and utilization are not (for a discussion, see Schmidhuber and Tubiello 2007). Second, climate change is likely to affect undernutrition by a variety of routes, including plant diseases, extreme drought events, infectious disease, labor productivity, water availability, and overall impact on GDP. So far, these aspects have not been accounted for, and we recommend that future assessments (of all health impacts, not just undernutrition) attempt to account for the multiple effects of climate change.

Model behavior. We examined model behavior over the range of plausible input variable values. When either undernourishment or the development score are high (a high development score indicates poor socioeconomic conditions), moderate stunting decreases. However, this is accompanied by increases in severe stunting, providing that undernourishment is not too high [for the model's equations surface plots, see Supplemental Material, Figure 2 (http://dx.doi.org/10.1289/ehp.1003311)]. As with any model, output for input variable values falling outside the range within which the model was fitted should be interpreted with caution. In the data used to parameterize the equations, the maximum value for undernourishment was 76% (Table 1), and the surface plots suggest that above this value, stunting estimates may be invalid. In our future estimates, only undernourishment in central SSA under climate change exceeded this (80% and 81%; Table 3); although these PoU estimates are only just outside the fitting range, the resulting stunting estimates should be interpreted cautiously.

The model's equations suggest that, as either food access or general socioeconomic conditions worsen, severe stunting increases more rapidly than moderate stunting; that is, more children shift from moderate to severe stunting than shift from no/mild stunting to moderate stunting. It is likely that this behavior is partly because the model assumes that, regardless of conditions, the distribution of access to food remains constant. This assumption is a property of the FAO undernourishment model (FAO 2003) and of our development score (i.e., the Gini coefficient is assumed to remain constant at baseline levels). We believe that allowing distributions to vary should be considered in future work.

The θ parameters have negative values. This was unexpected but, when considered in the context of the full equation and in terms of observed model behavior, the model equations predicted stunting changes as expected. Thus, if either food or nonfood causes are high and those causes are then reduced, the impact on stunting is greater than if both food and nonfood causes are high and only one variable is lowered. This suggests, as expected, that to best deal with stunting it is necessary to address both food and nonfood causes.

Dealing with uncertainty. It is axiomatic that there are uncertainties in any risk assessment model. In this assessment, we have addressed parametric uncertainty in the stunting model through the use of Monte Carlo simulations. Structural uncertainty will be addressed in future work by exploring nonlinear interactions. It was not possible to assess the uncertainty in the upstream models (e.g., climate models, crop models, trade model) that drive our model (i.e., the input uncertainties associated with x_{ij}

and w_{ij}) because we lacked the necessary information. Future assessments should use a wide range of climate and socioeconomic scenarios in order to capture the uncertainty of future emission pathways and the world in which the climate impacts will occur.

Conclusions

Previous studies have shown that climate change is likely to have negative effects on future hunger and undernutrition (Nelson et al. 2009, 2010; Parry et al. 1999, 2004; Rosenzweig and Parry 1994), and our results are consistent with these. This reinforces the evidence base for action to be taken to reduce carbon emissions and the impacts of the climate change to which we are already committed. Additionally, our model suggests that to reduce and prevent future undernutrition, it is necessary to both increase food access and improve socioeconomic conditions.

Quantifying the size of the impact presents difficulties. Our work illustrates the importance of the outcome considered—for example, undernourishment versus stunting, and moderate stunting versus severe stunting. These outcomes have different implications for adaptation and decision making (e.g., whether adaptation policies should focus only on food supplies or consider water and sanitation provision) and different implications for health (e.g., severe stunting is a much greater health threat than is moderate stunting). Further, future socioeconomic conditions must be considered; this involves both developing new data sets and designing models that recognize data constraints. Above all, because none of the above issues will be easily overcome, modeling efforts should explicitly describe their assumptions and limitations.

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Erratum: Climate Change, Crop Yields, and Undernutrition: Development of a Model to Quantify the Impact of Climate Scenarios on Child Undernutrition

Lloyd SJ, Kovats RS, Chalabi Z. 2011. Environ Health Perspect 119(12):1817–1823; http://dx.doi.org/10.1289/ehp.1003311
Published online 15 August 2011

Table 2 originally contained two incorrect values. In column 3 (α_k), –0.052 ± 0.021 has been corrected to 0.025 ± 0.013, and –0.013 ± 0.014 has been corrected to –0.052 ± 0.021. The HTML and PDF versions of the article reflect these changes. The results in the article were calculated using the correct values for the parameter estimates and remain unchanged.

The authors regret the errors.

Research Paper 2: Quantitative risk assessment of the effects of climate change on selected causes of death, 2030s and 2050s – Chapter 7 Undernutrition

For accompanying supplemental material - including the reference list - see the appendix "Research Paper 2: Supplemental Material".

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Student ID Number	246266	**Title**	Mr
First Name(s)	Simon John		
Surname/Family Name	Lloyd		
Thesis Title	Modelling the relation between climate change and undernutrition at the global-level: the use of multiple perspectives to gain new insights		
Primary Supervisor	Ben Armstrong		

If the Research Paper has previously been published please complete Section B, if not please move to Section C.

SECTION B – Paper already published

Where was the work published?	Chapter 7 of "Quantiative risk assessment of the effects of climate changes on selected causes of death, 2030s and 2050s", published by the World Health Organization.		
When was the work published?	2014		
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For multi-authored work, give full details of your role in the research included in the paper and in the preparation of the paper. (Attach a further sheet if necessary)	This chapter was part of the WHO commissioned report, "Quantitive risk assessment of the effects of climate change on selected causes of death, 2030s and 2050s". I was an editor of the report. The approach to modelling taken in the overall report was developed in discussions with a team of health experts. "Chapter 7: Undernutrition" is based on an extension of the undernutrition model published in Environmental Health Perspective in 2011. I developed the model extension, assembled the required data, ran the model, and wrote the first draft of the chapter. Sari Kovats and Zaid Chalabi provided advice throughout and co-authored the chapter.

SECTION E

Student Signature	[redacted]
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Undernutrition

7

Simon Lloyd, Sari Kovats, Zaid Chalabi

7.1 Background

Hunger and undernutrition are major contributors to the global burden of disease and are the leading risk factors for death and morbidity in children aged under 5 years (IHME, 2013).

Around 1 billion people are thought to have insufficient food to meet their needs (FAO, 2009). In children aged under 5 years, 45% of deaths (3.1 million deaths) were attributed to undernutrition in 2011 (Black et al 2013). The reduction of hunger and undernutrition is one of the Millennium Development Goals, but although progress has been made, reductions lag behind aspirations, particularly following the food price and financial crises in 2008–2009 (UN, 2010). Box 7.1 defines the key terms used in this assessment.

Box 7.1 Definitions used in this assessment

Undernourishment, modelled using the FAO (2003) method, is defined as having a “dietary energy consumption [that] is continuously below a minimum dietary energy requirement for maintaining a healthy life and carrying out a light physical activity with an acceptable minimum body-weight for attained-height” (FAO, 2010). Undernourishment has one final cause: a lack of calories.

Undernutrition is conventionally measured using anthropometrics such as stunting (height for age) and underweight (weight for age) (WHO, 2010). It has multiple causes, of which lack of food is one. In this assessment, since we are looking at long-term average conditions such as average crop productivity, we focus on stunting, which best reflects these conditions (Black et al., 2008) and use the terms undernutrition and stunting synonymously.

The causes of undernutrition are complex, extending beyond food availability to include factors such as poverty, access to services (such as adequate water and sanitation), social conditions (such as women’s access to education) and underlying population health (such as prevalence of diarrhoeal disease) (UNICEF, 1990). For example, Checkley and colleagues (2008) found that a quarter of irreversible stunting in young children could be attributed to having had five or more episodes of diarrhoea. Smith & Haddad (2000) attributed 43% of the reduction in child underweight between 1970 and 1995 to greater access of women to education, 26% of the reduction to greater food access, and 19% of the reduction to improved water and sanitation.

Climate change is expected to have significant impacts on cereal production, particularly at low latitudes. Crop models have been used to estimate changes in yield under a range of climate scenarios. The 4th IPCC assessment report concluded that although moderate warming may benefit crop yields in mid- to high-latitude regions, it is likely that there will be decreases in yields in seasonally dry and low-latitude regions (Meehl et al., 2007).

Methods for estimating the impacts of reduced average food yields on human health and welfare are complex, linking various models (such as crop, food trade and health) and using a range of metrics to estimate health impacts. Initial models were based on a threshold level of per capita calorie availability that meets an average individual's calorie estimated minimum requirements (FAO, 2003). Populations below the threshold were considered at risk of hunger. Thus, studies have estimated an additional 5 million to 170 million people may be at risk of hunger by the 2080s (Parry et al., 2004; Schmidhuber & Tubiello, 2007). More recent modelling efforts have quantified more direct outcome measures. For example, Nelson and colleagues (2009) estimated that under a medium-high emissions scenario (SRES A2), global reductions in crop productivity could increase the proportion of underweight children by around 20% in 2050.

Future climate change may also affect crop productivity through a range of mechanisms that are not included within current crop yield modelling, including increases in extreme weather events (such as droughts and heavy rainfall – although some climate variability is incorporated in some models), spatially remote conditions that influence local conditions (such as rainfall higher in a river catchment), sea-level rise (such as loss of crop land from inundation or salinization), changes in demand for water, and increases in pests and diseases (Gornall et al., 2010). Furthermore, climate change is likely to affect undernutrition through routes other than crop productivity. Livelihoods may be lost if formerly productive land ceases to be productive and poverty may increase. Infectious diseases such as diarrhoeal disease (see Chapter 4) and malaria (see Chapter 5) may become more prevalent. These factors, which may be anticipated to increase the risk of future undernutrition, are not accounted for in existing models.

Food security is defined as the "situation that exists when all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and health life" (FAO, 2011) and is commonly considered along the dimensions of availability, access, stability and utility (Schmidhuber & Tubiello, 2007). Existing health impact modelling covers the dimensions of food availability (such as crop productivity) and access (such as global distribution via trade), but it does cover not stability (such as losses due to extreme weather) or utility (such as absorption of nutrients compromised in a child with chronic diarrhoea) or how these factors are affected via routes other than food production. For more details, see Schmidhuber & Tubiello (2007).

7.2 Assessment method: linking crop, trade and health impact models

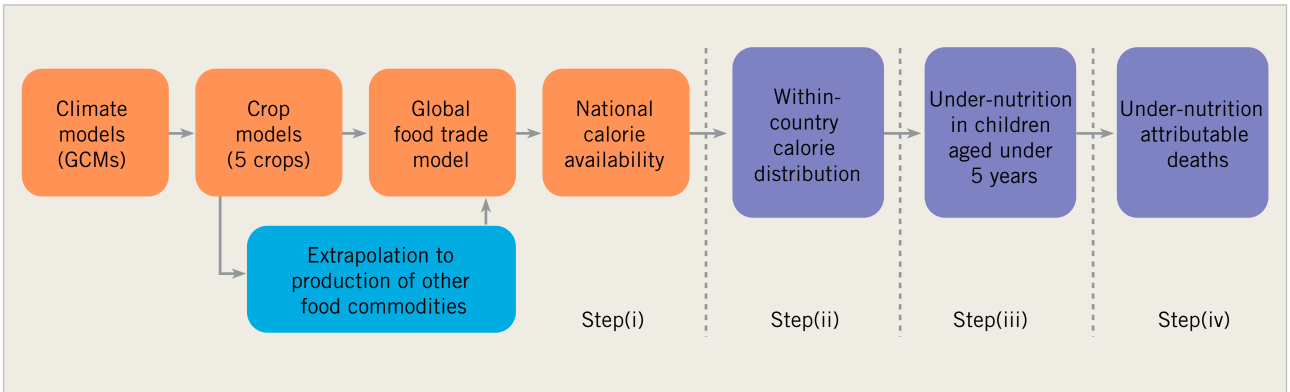
The connections between climate change and undernutrition are many and complex. We used the output from a chain of models shown in Figure 7.1. We used the following steps to estimate climate change-attributable burden of undernutrition:

1. Future post-global food trade national calorie availability estimates for 2030 and 2050 with and without climate change were obtained from the dataset accompanying the report of Nelson and colleagues (2010).
2. Within-country food distribution estimates, represented as the proportion of population undernourished, were generated using the method of the Food and Agriculture Organization of the United Nations (FAO, 2003).
3. Estimates of regional-level child stunting were generated from national proportion of population undernourished values and projections of GDP per capita, using an undernutrition model (Lloyd et al., 2011).
4. Estimates of all-cause mortality attributable to child stunting were made using the methods of the WHO Burden of Disease Assessment, with population-attributable fractions. This used our stunting estimates, estimates of relative risk of mortality in stunted children from Black and colleagues (2008), and mortality projections (see Chapter 8).

7.2.1 Step 1: national calorie availability estimates

Nelson and colleagues (2010) estimated national calorie availability in future worlds with climate entering the model via crop productivity. Estimates were calculated in the absence of climate change and under two climate change scenarios (MIROC and CSIRO) driven by A1 emissions, for three socioeconomic futures (see Section 7.3). Future cereal production under particular scenarios was estimated using the Decision Support System for Agrotechnology Transfer (DSSAT) crop models for rice, wheat, maize, soy and groundnut (Jones et al., 2003). Crop production was assessed for average weather conditions and did not include extreme weather or other events such as potential pest invasions.

Figure 7.1 Schematic illustration of the modelled pathway from climate change to child undernutrition and its consequences



Changes in other food commodities were estimated by extrapolating from the five modelled crops (Nelson et al., 2010). Of note, using data from WHO (2010) and FAO (2010), we found that in the 34 countries that together account for 90% of all stunting, on average about 50% of calories come from wheat, rice, maize or soy, and the contribution of animal products to calorie intake is about 10% (unpublished results). Thus, the crop yield changes that were explicitly modelled in this assessment account for a significant portion of calorie intake in countries with the highest rates of undernutrition.

To estimate global food distribution, the food production estimates were used to drive the IMPACT model (Rosegrant et al., 2008), which in turn partially drives future crop production. IMPACT analyses 32 crop and livestock commodities in 281 world regions, covering all land surface except for Antarctica. Production and demand are linked via global trade; crop production is determined by factors including prices, area expansion, irrigation and water availability, and demand is based on food, feed, biofuels and other uses. In a globalized world, the trade model component is essential to estimate future food availability, as countries will either grow or import food. The assumptions about economic growth are therefore important, as this will determine whether or not a country can afford to purchase food in the model.

The final output was future national-level per capita calorie availability in 2030 and 2050, under two climate scenarios and without climate change, for each of the three socioeconomic scenarios. We used this as the basis for our undernutrition estimates.

The calorie availability data did not cover all countries and the spatial aggregations did not directly match the 21 world regions used in this assessment; therefore, we made estimates for 12 world regions (Box 7.2). Two of these regions are aggregated: tropical Latin America and Andean Latin America were combined into mid Latin America, and some countries from the Caribbean region where included in central Latin America.

Box 7.2 Countries[a] included in our regional projections based on output from the IMPACT model

Asia, central: Armenia, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Mongolia, Tajikistan, Turkmenistan, Uzbekistan

Asia, east: China, Democratic People's Republic of Korea

Asia, south: Afghanistan, Bangladesh, Bhutan, India, Nepal, Pakistan

Asia, southeast: Cambodia, Indonesia, Lao People's Democratic Republic, Malaysia, Myanmar, Philippines, Sri Lanka, Thailand, Viet Nam

Latin America, central: Belize,[b] Colombia, Costa Rica, El Salvador, French Guiana,[b] Guatemala, Guyana,[b] Honduras, Mexico, Nicaragua, Panama, Suriname,[b] Venezuela (Bolivarian Republic of)

Latin America, mid: Bolivia (Plurinational State of),[c] Brazil,[d] Ecuador,[c] Paraguay,[d] Peru[c]

Latin America, south: Argentina, Chile, Uruguay

North Africa and the Middle East: Algeria, Bahrain, Egypt, Iran (Islamic Republic of), Jordan, Kuwait, Lebanon, Libyan Arab Jamahiriya, Morocco, Oman, Qatar, Saudi Arabia, Syrian Arab Republic, Tunisia, Turkey, United Arab Emirates

Sub-Saharan Africa, central: Angola, Central African Republic, Congo, Democratic Republic of the Congo, Equatorial Guinea, Gabon

Sub-Saharan Africa, eastern: Burundi, Djibouti, Eritrea, Ethiopia, Kenya, Madagascar, Malawi, Mozambique, Rwanda, Somalia, Sudan, Uganda, United Republic of Tanzania, Zambia

Sub-Saharan Africa, southern: Botswana, Lesotho, Namibia, South Africa, Swaziland, Zimbabwe

Sub-Saharan Africa, western: Benin, Burkina Faso, Cameroon, Chad, Cote d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone, Togo

[a] The list in this box has not been changed from the original study and does not comply with WHO style for country references

[b] Countries from the Caribbean region included in Latin America, central

[c] Countries from Latin America, Andean

[d] Countries from Latin America, tropical

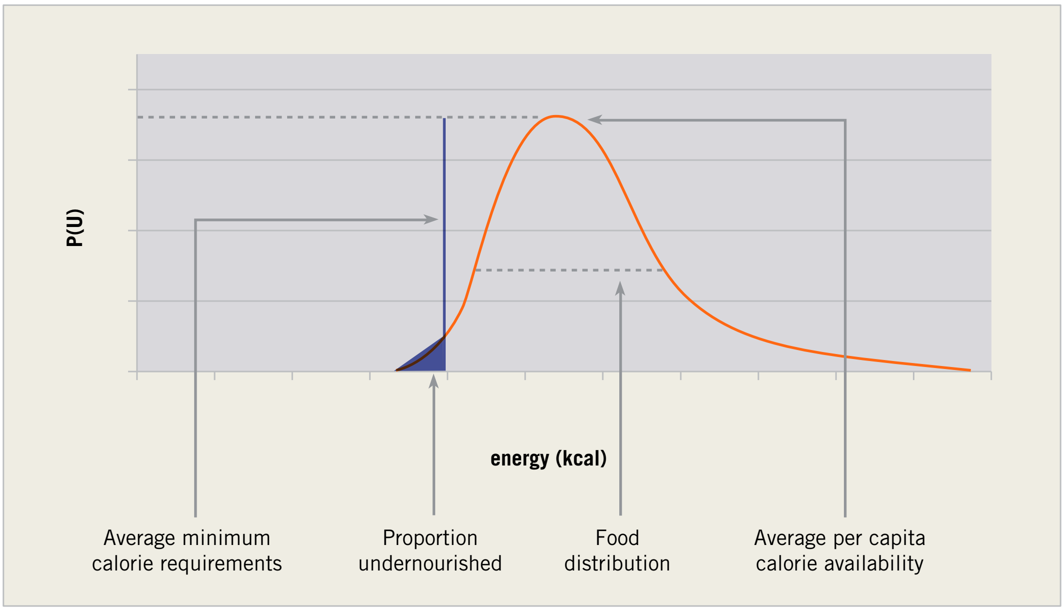
For full details of the methods and assumptions underlying the calorie availability estimates, see the original paper by Nelson and colleagues (2010).

7.2.2 Step 2: within-country food distribution estimates

We used national calorie availability estimates from Step 1 to estimate the proportion of the population expected to be undernourished in each scenario combination using the FAO (2003) method. The method assumes that within a country, food distribution is described by a right-skewed log-normal distribution. The peak of the curve is determined by average calorie availability (calories/capita), the spread is determined by a measure of inequality of food distribution (similar to the commonly used Gini coefficient for income distribution), and the cut-off point for being undernourished is based on estimated average minimum calorie needs for a given population. The proportion undernourished is the area under the curve up to the minimum requirements cut-off point (Figure 7.2). For a full explanation of the method, see the original FAO (2003) document.

To use this method, in addition to national calorie available data, we required data on the within-country food distribution and the average minimum calorie requirement to avoid undernourishment. As projection data were not available for either of these, we obtained baseline (current) FAO data and assumed the values would remain constant in the future. We believe this approach is reasonable. For within-country food distribution, even at baseline, FAO country-level estimates are based on extrapolations of infrequently collected data from relatively few countries and are restricted to values between 0.2 and 0.35 (this is a convention of the FAO (2003) method). Variation within this range has been found to have little impact on changes in undernourishment in countries with low calorie availability (FAO, 1996; Svedberg, 2002). For average minimum calorie requirements across all countries, the mean change was 0.1% per year over the period 1990–1992 to 2004–2006 (FAO, 2010). Furthermore, Svedberg (2002) found that over a 20-year period, 88% of the change in regional undernourishment was explained by changes in per capita calorie availability.

Figure 7.2 FAO method for estimating the proportion of a population that is undernourished[a]



[a] *x*-axis is energy intake; *y*-axis is proportion of population with that energy intake

7.2.3 Step 3: estimates of child stunting

We used a model that we had previously developed to estimate future stunting attributable to global climate change (Lloyd et al., 2011). The model considers stunting to have two broad causes: a lack of food (food causes), which is represented as proportion of population undernourished, and non-food causes, which are a cluster of socioeconomic factors modelled using GDP per capita and the Gini coefficient for income distribution. The model also includes the interaction of food and non-food causes; for instance, a given intake of food will have different impacts on nutrition, depending on the presence and severity of diarrhoeal disease. See the original paper by Lloyd and colleagues (2011) for more details on the modelling method.

For model inputs, we used national-level estimates of the proportion of population undernourished derived from Step 2, national population and national GDP per capita projections (Nelson et al., 2010), and the current Gini coefficient for income distributions (World Bank, 2010a). (Projections for the Gini coefficient were not available. We used the most recent estimates available and assumed they remained constant in the future.)

The model output is the proportion of children moderately and severely stunted, as defined by the WHO (2006) child growth standards. A child is considered to be moderately stunted if they are more than two standard deviations below the mean expected height for age, and severely stunted if they are more than three standard deviations below the mean expected height for age.

To account for parameter uncertainty in the undernutrition model, stunting was estimated as probability density functions using a Monte Carlo simulation. We ran the simulation

100 000 times (each using a randomly selected combination of parameter values) for each scenario combination to obtain estimated distributions of the proportion stunted. We then combined the distributions for the two climate scenarios[2] to obtain a single distribution of proportion stunted under climate change for each scenario combination.

For each distribution of proportion stunted, we used the mean to represent our best estimate and represent the uncertainty interval as mean ± 1 standard deviation. We estimated stunting attributable to climate change by subtracting the mean estimate without climate change from the mean estimate with climate change, and combined their variances to estimate uncertainty,[3] reported as mean ± 1 standard deviation.

The undernutrition model has three underlying assumptions of relevance to our stunting estimates. First, the model estimates stunting specifically in children aged under 5 years, but the proportion undernourished is estimated for the entire population. As a result, estimates made with the model implicitly assume that, in all populations, the age distribution of undernourishment remains constant over time.

Second, the model is partly driven by an estimate of the physiological relationship between stunting and undernourishment; it is assumed that this estimate is representative of the true relationship and that it will be constant over the 50-year period included in this assessment. In terms of representativeness, the estimate is an approximation made for modelling purposes, and it gave a good fit between predicted and observed stunting in the model validation. Of note, the estimate suggests that about 60% of stunting could not be attributed directly to a lack of food, which is consistent with a previous estimate that around 40–60% of undernutrition could be attributed to environmental conditions (Pruss-Ustun & Corvalan, 2006).

Third, the undernutrition model accounts for socioeconomic conditions using an indicator based on GDP per capita and the Gini coefficient for income distribution (the "development score"). We assume that the Gini coefficient remains at baseline levels, although it may change significantly over the next 50 years. Also, in using the development score, we effectively assumed that the current relationship between GDP and socioeconomic conditions (such as access to adequate water supplies, health-care provision and education) will hold in the future. As this relationship is determined by many factors that may change, such as those shaped by politics and cultural norms, the relationship may change over the assessment period.

Due to a lack of data, we were unable to quantify the implications of the above assumptions.

---

2 We combined the distributions of proportion stunted for the MIROC and CSIRO scenarios based on their means and variances using the formulae $mean_{combined} = \frac{mean_{MIROC}+mean_{CSIRO}}{2}$ and $variance_{combined} = \frac{variance_{MIROC} + variance_{CSIRO}}{4}$

3 To estimate climate change-attributable proportion of stunting, we used the formulae $mean_{attributable} = mean_{with\ climate\ change} - mean_{without\ climate\ change}$ and $variance_{attributable} = variance_{with\ climate\ change} + variance_{without\ climate\ change}$

7.2.4 Step 4: estimates of all-cause mortality attributable to stunting

We combined our estimates of the future proportion of children who are moderately and severely stunted with odds ratios for all-cause mortality associated with each level of stunting from Black and colleagues (2008) to estimate population-attributable fractions of deaths due to stunting. The odds ratios were estimated using data from eight low-income countries considered to be broadly representative of all low-income countries and were adjusted for confounding due to socioeconomic factors (Table 7.1). For more details, see the paper by Black and colleagues (2008).

Table 7.1 Odds ratio for all-cause mortality associated with moderate and severe stunting

Cause	Moderate stunting[a]	Severe stunting[a]
All causes	1.6 (1.3 to 2.2)	4.1 (2.6 to 6.4)

a Odds ratios shown as central estimates with 95% confidence intervals in brackets
Source: Black et al. (2008)

Following the method of Black and colleagues (2008), we assumed that the odds ratios were a reasonable first-order approximation of the equivalent relative risks. We estimated population-attributable fractions using

$$PAF = \frac{\sum_{i=1}^{n}[P_i(RR_i - 1)]}{\sum_{i=1}^{n}[P_i(RR_i - 1)] + 1} \qquad [7.1]$$

where PAF is the population-attributable fraction; P_i is the proportion affected by the exposure of interest at level i; RR_i is the relative risk for a given outcome when exposed at level i; and i is a level exposure, where there are n levels of exposure, with $1 \le i \le n$.

Specifically in our use, $i = 1$ for moderate stunting and $i = 2$ for severe stunting; P_i is the proportion stunted at level i; and RR_i is the relative risk of all-cause mortality associated with stunting at level i (compared with being not stunted).

When estimating the population-attributable fractions, we accounted for uncertainty in the proportion stunted and the mortality odds ratios as follows: for the proportion stunted, using our regional-level mean estimates and standard deviations generated in Step 3, we ran a standard Monte Carlo simulation to estimate 100 000 plausible values of the true proportion stunted at each level in each region. Similarly, for the odds ratios, using the central estimates and 95% confidence intervals, we estimated 100 000 plausible estimates of the true odds ratio.[4] Thus, we estimated population-attributable fractions for each region with and without climate change as distributions (probability density functions), based on 100 000 plausible estimates. The climate change-attributable population-attributable fractions were

[4] The odds ratios in Table 7.1 were estimated in the log scale and then transformed to the natural scale. Therefore, the confidence intervals are asymmetrical about the means. Thus, we logged the odds ratios and confidence intervals and then calculated the averages of the upper and lower confidence intervals. We estimated the standard deviation for use in the Monte Carlo simulation. After running the simulation, we exponentiated the results.

estimated by subtracting the vectors of population-attributable fraction estimates without climate change from the vectors of population-attributable fraction estimates with climate change.

To estimate the number of deaths due to stunting in each scenario, we applied the population-attributable fractions directly to the projections of the all-cause mortality in children aged under 5 years (see Chapter 8 for discussion of mortality projections). We obtained probability density functions of stunting-attributable deaths for each region and used the mean as our best estimate and one standard deviation to describe the uncertainty interval.

7.3 Scenario data

As this chapter was dependent on input data produced outside this project (national-level calorie availability estimates), it uses a different set of scenarios from the other chapters.

7.3.1 Observed climate data

The current climate was represented using the WorldClim current conditions dataset, which represents the period 1950–2000 and provides monthly averages for minimum and maximum temperature and precipitation (Hijmans et al., 2005). The data were generated by interpolating average monthly data for weather stations to a 1 km^2 grid. For details of how the data were used to drive the crop models, see the paper by Nelson and colleagues (2010).

7.3.2 Climate scenarios

Two climate scenarios were used to drive the DSSAT model, both forced by the A1b emissions scenario:

- CSIRO model: by 2050, the mean change in annual average minimum and maximum temperatures is 1.6°C and 1.4°C, respectively, with a 0.7% increase in average annual precipitation.
- MIROC model: by 2050, the mean change in annual average minimum and maximum temperatures is 3.0°C and 2.8°C change, respectively, with a 4.7% increase in average annual precipitation.

7.3.3 GDP and population projections

The estimates of calorie availability from Step 1 (Nelson et al., 2010) were made under three socioeconomic scenarios intended to represent pessimistic, baseline (business as usual) and optimistic futures (Table 7.2). We note that these scenarios are quantitatively different from those used elsewhere in the CCRA project (see Chapter 8).

Of particular note, as seen in Table 7.2, the GDP data used in this chapter were in a different metric from the GDP data used in other chapters (market exchange rate versus purchasing power parity); thus, the data are not directly comparable. In general, purchasing power parity may better reflect conditions within a given country. The estimates tend to be of

Table 7.2 Socioeconomic scenarios subsequently used to estimate future national calories availability, showing global totals of GDP per capita and population for 2050[a] and socioeconomic scenarios used in the other chapters of the CCRA

Scenario	GDP			Population		
	Nelson et al. (2010)		CCRA	Nelson et al. (2010)		CCRA
	Source	Global GDP per capita, 2050[b]	Global GDP per capita, 2050[c]	Source	Global population, 2050[d]	Global population, 2050[d]
Pessimistic/ low growth	Low scenario from Millennium Ecosystem Assessment,[e] with growth rates used in base	8779	9191	UN high variant, 2008 revision	10 99	9130
Baseline/ base case	Based on rates from World Bank EACC study,[f] updated for sub-Saharan Africa and south Asia	17 23	29 84	UN medium variant, 2008 revision	9906	9130
Optimistic/ high growth	High scenario from Millennium Ecosystem Assessment,[e] with growth rates used in base	23 60	44 94	UN low variant, 2008 revision	7913	9130

a Based on Tables 1.1 and 1.3 in Nelson et al. (2010)
b GDP per capita in constant US$ 2000 as market exchange rate
c GDP per capita in 2005 international dollars as purchasing power parity
d Population totals in millions
e Millennium Ecosystem Assessment (2005)
f Margulis et al. (2010)

greater magnitude as they reflect the relative cost of living within a particular country, which tends to be lower in low-income compared with high-income countries. In contrast, market exchange rates may better reflect relative currency values, critical to global food trade, which is of major importance to estimates in this chapter. We assume that the purchasing power parity and market exchange rate data are roughly equivalent in each of the three socioeconomic scenarios; it is not, however, possible to test this assumption. The assumption is stronger for the baseline/base case and optimistic/high growth cases: in both studies, GDP continues to grow over the century. For the pessimistic/low growth scenarios, growth continues over the century in the purchasing power parity estimates (pessimistic scenario), but with the market exchange rate data used in other chapters (low growth scenario), GDP growth tapers towards zero and ceases to grow in any country after 2015.

As we have assumed equivalence between Nelson and colleagues' (2010) and the CCRA scenarios, for consistency with other chapters, we refer to our estimates as being for low growth, base case and high growth scenarios.

For population, the CCRA uses a common population projection for all three socioeconomic scenarios, while Nelson and colleagues use different projections for each scenario. In the optimistic and baseline scenarios, Nelson and colleagues use a higher population than the CCRA (for high growth and base case) (see Table 7.2). Compared with using a lower population estimate (as in the CCRA), the use of the higher populations could have two opposing effects within the calorie availability model: having more people to feed may mean more people are undernourished (that is, the proportion of population undernourished would be higher than if the population were lower); but having more people to feed may lead to greater demand and thus production, resulting in increased food availability. The degree to which one effect is offset by the other is unknown; when scaling the results to be consistent with the CCRA population (see below), we assume the offset is complete – in effect, we assume that the proportion of population undernourished is independent of population (providing population total or growth is not excessively high) and that any additional risk of hunger due to a higher population is balanced by the accompanying decrease in risk due to increased demand-driven production). The same argument applies to the lower population (compared with the CCRA) in Nelson and colleagues' pessimistic scenario.

7.3.4 Scaling output for consistency with other health outcomes in the global assessment

It is important that all outcomes in this climate change assessment are based on a consistent set of assumptions about future worlds (particularly for economic growth and population growth). However, the future calorie estimates used in this chapter were based on a different set of scenarios. To bring our results in line with other chapter estimates as far as possible, we used the following strategies and assumptions:

- We estimated national-level stunting using data for the countries shown in Box 7.2, based on the population scenarios used by Nelson and colleagues (2010). This ensured within-model consistency between the calorie estimates and the undernutrition estimates.
- We aggregated the national-level stunting estimates to estimate the proportion stunted at regional level, using the regional definitions shown in Box 7.2. As noted in Step 1, these regional definitions do not match the regional definitions used in the other chapters of this assessment; in particular, due to missing data, fewer countries are included in the regions in Box 7.2. Hence, we assumed that our regional estimates of proportion stunted were representative of regional stunting when all countries in the region are included (that is, based on the world regions).
- To estimate the number stunted or number of deaths, we used population totals consistent with the CCRA population. This ensured comparability between estimates of number stunted and number of deaths in this chapter, and numbers estimated in other chapters of this assessment. We note that this assumes that the calorie availability estimates (which underlie the stunting estimates) are relatively independent of total population (that is, the two effects outlined above balance each other).

7.4 Results

Climate change is expected to cause a significant increase in the number of children with severe stunting, regardless of the socioeconomic scenario considered (Figure 7.3). In the base case, in a future without climate change, we estimate there will be 142.4 million

Figure 7.3 Additional number[a] of children aged under 5 years stunted due to climate change in 2030 and 2050 in the 12 study regions under low growth (L), base case (B) and high growth (H) socioeconomic scenarios

[a] Bars show additional number of children stunted due to climate change as a mean of the probability density function for the combined climate change scenario estimates minus the mean of the probability density function for the estimates without climate change

(uncertainty interval 139.8 million to 144.6 million) moderately stunted children and 58.2 million (uncertainty interval 56.3 million to 59.9 million) severely stunted children in 2030. The corresponding figures for 2050 are 101.9 million (uncertainty interval 100.1 million to 103.4 million) for moderate stunted children and 31.5 million (uncertainty interval 30.5 million to 32.5 million) for severely stunted children. We estimate that climate change will result in an additional 3.6 million (uncertainty interval 2.9 million to 4.4 million) moderately stunted children and 3.9 million (uncertainty interval 3.5 million to 4.4 million) severely stunted children by 2030; in total, this is 7.5 million (uncertainty interval 6.7 million to 8.4 million) additional stunted children. In 2050, additional severe stunting is estimated to remain at 3.9 million (uncertainty interval 3.6 million to 4.1 million), but moderate stunting is expect to rise to 6.2 million (uncertainty interval 5.4 million to 7.0 million), giving a total of 10.1 million (uncertainty interval 9.2 million to 11.0 million) additional stunted children.

Under the low growth scenario, without climate change we estimate that in 2030 there will be 162.3 million (uncertainty interval 159.5 million to 165.1 million) moderately stunted children and 73.6 million (uncertainty interval 71.7 million to 75.9 million) severely stunted children. For 2050, the corresponding estimates are 213.5 million (uncertainty interval 210.2 million to 216.4 million) and 112.6 million (uncertainty interval 109.6 million to 115.7 million), respectively. Our estimates suggest climate change will lead to a large increase in severe stunting. Climate change is projected to increase moderate stunting by 3.3 million (uncertainty interval 2.4 million to 4.1 million) by 2030, but then reduce it by 4.9 million (uncertainty interval 5.9 million to 3.9 million) (compared with a future without climate change). This apparent benefit, however, is offset as severe stunting is expected to increase by 5.2 million (uncertainty interval 4.5 million to 5.9 million) by 2030 and 8.2 million (uncertainty interval 6.9 million to 9.5 million) by 2050. Total climate change-attributable stunting is expected to be 8.5 million (uncertainty interval 7.4 million to 9.5 million) in 2030 and 3.3 million (uncertainty interval 1.6 million to 4.9 million) in 2050.

For the high growth scenario without climate change, moderate and severe stunting in 2030 are estimated to be 123.1 million (uncertainty interval 121 million to 125.1 million) and 43.5 million (uncertainty interval 42.1 million to 45.2 million), respectively. In 2050 our estimates are 70.1 million (uncertainty interval 68.8 million to 71.6 million) for moderate stunting and 14.3 million (uncertainty interval 13.5 million to 15.2 million) for severe stunting. Climate change is expected to increase moderate stunting by 3.3 million (uncertainty interval 2.7 million to 4.0 million) in 2030, and 3.8 million (uncertainty interval 3.3 million to 4.3 million) by 2050. Severe stunting is estimated to increase by 3.1 million (uncertainty interval 2.7 million to 3.6 million) and 1.4 million (uncertainty interval 1.3 million to 1.6 million) in 2030 and 2050, respectively. Total stunting is expected to increase by 6.5 million (uncertainty interval 5.7 million to 7.2 million) in 2030 and 5.2 million (uncertainty interval 4.7 million to 5.7 million) in 2050.

Figure 7.4 shows additional severe stunting attributable to climate change in the sub-Saharan African regions, which are, along with south Asia, expected to be the most affected[5] by climate change (in terms of stunting). Table 7.3 shows the estimated number of children with stunting attributable to climate change in sub-Saharan Africa and south Asia.

Table 7.3 Estimated number[a] of children aged under 5 years with climate change-attributable stunting in 2030 and 2050 in sub-Saharan Africa[b] and south Asia

Region	Climate change–attributable stunting (millions of children aged < 5 years)						
	Stunting level	Base case		Low growth		High growth	
		2030	2050	2030	2050	2030	2050
Sub-Saharan Africa	Moderate	0.8 (0.4 to 1.1)	1.8 (1.6 to 2.1)	0.4 (–0.06 to 0.8)	–2.6 (–3.0 to –2.1)	0.7 (0.4 to 1.1)	1.2 (1.0 to 1.4)
	Severe	2.3 (2.0 to 2.6)	2.4 (2.2 to 2.5)	2.9 (2.6 to 3.2)	3.9 (3.5 to 4.3)	1.9 (1.7 to 2.2)	1.1 (9.7 to 1.2)
Asia, south	Moderate	1.1 (0.6 to 1.6)	1.8 (1.6 to 2.1)	1.1 (0.6 to 1.6)	–1.5 (–2.1 to –0.9)	1.1 (0.8 to 1.5)	1.3 (1.1 to 1.5)
	Severe	0.9 (0.6 to 1.3)	0.9 (0.8 to 1.0)	1.4 (0.9 to 1.9)	2.1 (1.2 to 3.1)	0.6 (3.5 to 0.9)	0.2 (0.1 to 0.3)

a Numbers are mean estimate (millions of children aged under 5 years) with uncertainty interval (mean ± 1 standard deviation) in brackets

b Sub-Saharan Africa is the sum of estimates for central, eastern, southern and western sub-Saharan Africa. The mean estimate is the sum of the mean estimates from each region; the uncertainty interval is based on the uncertainty interval in each region (and was calculated by summing the variances in each region)

5 With the exception of southern sub-Saharan Africa, which has lower rates of stunting than the other regions in sub-Saharan Africa.

Figure 7.4 Number[a] of children with severe stunting, with and without climate change (CC), in 2030 and 2050 in four African regions under (a) base case, (b) low growth and (c) high growth scenarios

SSA,C – sub-Saharan Africa, central;
SSA,E – sub-Saharan Africa, eastern;
SSA,S – sub-Saharan Africa, southern;
SSA,W – sub-Saharan Africa, western

[a] Note y-axis scale is different for each graph; bars show number of children severely stunted as mean of the probability density function for the estimates without climate change and the mean additional number stunted with climate change based on the probability density function of the combined climate change scenario estimates

7.5 Regional estimates of children with stunting due to climate change

Table 7.4 gives regional estimates of the number of children with stunting due to climate change in 2030 and 2050.

Table 7.4 Percentage of children aged under 5 years estimated to be moderately or severely stunted in 2030 and 2050, with and without climate change, for (a) base case, (b) low growth and (c) high growth scenarios[a]

(a) Base case

Region	Stunting level	2030			2050		
		No climate change	With climate change	Climate change-attributable	No climate change	With climate change	Climate change-attributable
Asia, central	Moderate	11.9 (11.7 to 12.1)	13.1 (13.0 to 13.3)	1.2 (1.0 to 1.5)	7.9 (7.8 to 8.0)	9.9 (9.8 to 10.0)	2.0 (1.8 to 2.1)
	Severe	3.4 (3.3 to 3.5)	4.1 (4.1 to 4.2)	0.8 (0.6 to 0.9)	1.3 (1.2 to 1.3)	2.1 (2.0 to 2.1)	0.8 (0.7 to 0.9)
Asia, east	Moderate	9.0 (8.8 to 9.2)	9.6 (9.5 to 9.8)	0.6 (0.5 to 0.8)	4.1 (4.0 to 4.2)	5.1 (5.0 to 5.2)	1.1 (0.9 to 1.2)
	Severe	1.9 (1.8 to 2.0)	2.1 (2.0 to 2.2)	0.2 (0.0 to 0.4)	0.2 (0.2 to 0.3)	0.4 (0.3 to 0.4)	0.1 (0.1 to 0.2)
Asia, south	Moderate	13.7 (13.5 to 13.9)	14.4 (14.3 to 14.6)	0.7 (0.5 to 1.0)	8.1 (8.0 to 8.2)	9.4 (9.2 to 9.5)	1.3 (1.1 to 1.4)
	Severe	4.4 (4.2 to 4.6)	5.0 (4.9 to 5.1)	0.6 (0.4 to 0.8)	1.5 (1.5 to 1.6)	2.1 (2.1 to 2.2)	0.6 (0.5 to 0.7)
Asia, south-east	Moderate	10.8 (10.6 to 10.9)	11.7 (11.5 to 11.8)	0.9 (0.7 to 1.1)	6.7 (6.6 to 6.8)	8.3 (8.2 to 8.4)	1.6 (1.4 to 1.7)
	Severe	2.8 (2.7 to 2.9)	3.3 (3.2 to 3.3)	0.5 (0.4 to 0.6)	1.1 (1.0 to 1.1)	1.6 (1.5 to 1.6)	0.5 (0.4 to 0.6)
Latin America, central and Caribbean	Moderate	9.7 (9.5 to 9.8)	10.8 (10.6 to 10.9)	1.1 (0.9 to 1.3)	6.1 (6.0 to 6.1)	7.8 (7.7 to 7.9)	1.7 (1.6 to 1.9)
	Severe	2.1 (2.0 to 2.2)	2.5 (2.4 to 2.5)	0.4 (0.3 to 0.5)	0.6 (0.5 to 0.6)	1.1 (1.0 to 1.1)	0.5 (0.4 to 0.6)

[Continues]

[Continued]

Region	Stunting level	2030			2050		
		No climate change	With climate change	Climate change-attributable	No climate change	With climate change	Climate change-attributable
Latin America, mid	Moderate	7.0 (6.9 to 7.1)	7.8 (7.7 to 7.9)	0.8 (0.7 to 1.0)	5.2 (5.1 to 5.3)	6.4 (6.3 to 6.5)	1.2 (1.1 to 1.3)
	Severe	1.0 (1.0 to 1.1)	1.3 (1.3 to 1.3)	0.3 (0.2 to 0.3)	0.4 (0.4 to 0.4)	0.7 (0.7 to 0.8)	0.3 (0.3 to 0.4)
Latin America, south	Moderate	3.2 (3.1 to 3.3)	3.5 (3.4 to 3.6)	0.3 (0.2 to 0.5)	2.9 (2.8 to 3.0)	3.3 (3.3 to 3.4)	0.4 (0.3 to 0.5)
	Severe	0.0 (0.0 to 0.1)	0.1 (0.0 to 0.1)	0.0 (0.0 to 0.0)	0.0 (0.0 to 0.0)	0.0 (0.0 to 0.1)	0.0 (0.0 to 0.0)
North Africa/Middle East	Moderate	8.4 (8.3 to 8.5)	9.0 (8.9 to 9.1)	0.6 (0.5 to 0.8)	5.3 (5.2 to 5.4)	6.1 (6.0 to 6.2)	0.8 (0.7 to 0.9)
	Severe	1.6 (1.5 to 1.6)	1.8 (1.7 to 1.8)	0.2 (0.1 to 0.3)	0.5 (0.5 to 0.5)	0.7 (0.6 to 0.7)	0.2 (0.1 to 0.2)
Sub-Saharan Africa, central	Moderate	19.7 (19.2 to 20.1)	19.7 (19.3 to 20.1)	0.0 (–0.5 to 0.6)	18.2 (17.8 to 18.5)	19.1 (18.8 to 19.5)	1.0 (0.5 to 1.5)
	Severe	17.3 (16.7 to 17.8)	19.4 (19.0 to 19.8)	2.1 (1.5 to 2.8)	12.3 (11.9 to 12.8)	15.4 (15.1 to 15.8)	3.1 (2.5 to 3.6)
Sub-Saharan Africa, eastern	Moderate	19.8 (19.5 to 20.1)	20.3 (20.1 to 20.6)	0.5 (0.1 to 0.9)	15.6 (15.4 to 15.8)	17.0 (16.9 to 17.2)	1.4 (1.2 to 1.7)
	Severe	10.8 (10.6 to 10.9)	12.5 (12.4 to 12.6)	1.8 (1.5 to 2.0)	5.8 (5.7 to 5.9)	7.5 (7.4 to 7.6)	1.8 (1.6 to 1.9)
Sub-Saharan Africa, southern	Moderate	11.6 (11.4 to 11.8)	12.4 (12.2 to 12.6)	0.8 (0.5 to 1.1)	8.4 (8.2 to 8.5)	9.7 (9.5 to 9.8)	1.3 (1.1 to 1.5)
	Severe	5.8 (5.6 to 5.9)	6.6 (6.5 to 6.7)	0.8 (0.6 to 1.0)	3.7 (3.6 to 3.8)	4.6 (4.5 to 4.7)	0.9 (0.7 to 1.1)
Sub-Saharan Africa, western	Moderate	17.6 (17.3 to 17.8)	18.1 (17.9 to 18.3)	0.5 (0.2 to 0.8)	13.4 (13.2 to 13.6)	14.1 (14.0 to 14.3)	0.8 (0.5 to 1.0)
	Severe	7.1 (6.9 to 7.3)	8.0 (7.9 to 8.1)	0.9 (0.6 to 1.1)	4.1 (4.0 to 4.2)	4.7 (4.6 to 4.8)	0.6 (0.4 to 0.7)

[Continues]

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(b) Low growth

Region	Stunting level	2030			2050		
		No climate change	With climate change	Climate change-attributable	No climate change	With climate change	Climate change-attributable
Asia, central	Moderate	13.6 (13.4 to 13.8)	14.8 (14.6 to 14.9)	1.2 (0.9 to 1.5)	26.7 (26.4 to 27.0)	25.6 (25.4 to 25.9)	–1.1 (–1.5 to –0.6)
	Severe	4.2 (4.1 to 4.3)	5.1 (5.0 to 5.2)	0.9 (0.8 to 1.1)	14.1 (13.7 to 14.4)	15.6 (15.4 to 15.9)	1.5 (1.1 to 2.0)
Asia, east	Moderate	12.0 (11.8 to 12.2)	12.7 (12.6 to 12.8)	0.7 (0.5 to 0.9)	26.9 (26.5 to 27.2)	26.1 (25.8 to 26.3)	–0.8 (–1.2 to –0.4)
	Severe	3.2 (3.0 to 3.4)	3.6 (3.4 to 3.7)	0.4 (0.1 to 0.7)	13.8 (13.1 to 14.5)	15.0 (14.4 to 15.5)	1.1 (0.2 to 2.0)
Asia, south	Moderate	16.4 (16.2 to 16.6)	17.1 (16.9 to 17.3)	0.7 (0.4 to 1.0)	26.0 (25.7 to 26.4	25.0 (24.7 to 25.2)	–1.0 (–1.4 to –0.6)
	Severe	6.4 (6.2 to 6.7)	7.3 (7.1 to 7.5)	0.9 (0.6 to 1.2)	15.1 (14.5 to 15.6)	16.6 (16.2 to 16.9)	1.5 (0.8 to 2.1)
Asia, south-east	Moderate	12.6 (12.4 to 12.8)	13.5 (13.3 to 13.6)	0.9 (0.7 to 1.1)	23.3 (22.9 to 23.6)	22.5 (22.3 to 23.7)	–0.7 (–1.1 to 0.4)
	Severe	3.9 (3.8 to 4.0)	4.5 (4.4 to 4.5)	0.6 (0.5 to 0.7)	12.9 (12.6 to 13.2)	14.3 (14.0 to 14.5)	1.4 (1.0 to 1.28)
Latin America, central and Caribbean	Moderate	10.0 (9.9 to 10.2)	11.1 (10.9 to 11.2)	1.0 (0.8 to 1.2)	15.0 (14.8 to 15.1)	15.6 (15.5 to 15.8)	0.7 (0.5 to 0.9)
	Severe	2.3 (2.2 to 2.4)	2.7 (2.6 to 2.8)	0.4 (0.3 to 0.5)	6.4 (6.1 to 6.6)	7.1 (6.9 to 7.3)	0.8 (0.5 to 1.0)
Latin America, mid	Moderate	8.8 (8.6 to 8.9)	9.6 (9.4 to 9.7)	0.8 (0.6 to 1.0)	11.5 (11.3 to 11.6)	11.9 (11.8 to 12.0)	0.4 (0.2 –0.6)
	Severe	1.7 (1.7 to 1.8)	2.1 (2.0 to 2.1)	0.3 (0.2 to 0.4)	4.3 (4.1 to 4.4)	4.8 (4.7 to 4.9)	0.5 (0.3 to 0.7)

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Region	Stunting level	2030			2050		
		No climate change	With climate change	Climate change-attributable	No climate change	With climate change	Climate change-attributable
Latin America, south	Moderate	3.3 (3.2 to 3.4)	3.7 (3.6 to 3.7)	0.4 (0.3 to 0.5)	3.2 (3.1 to 3.3)	3.8 (3.7 to 3.8)	0.6 (0.5 to 0.7)
	Severe	0.0 (0.0 to 0.1)	0.1 (0.1 to 0.1)	0.0 (0.0 to 0.1)	0.0 (0.0 to 0.1)	0.1 (0.1 to 0.1)	0.0 (0.0 to 0.1)
North Africa/Middle East	Moderate	10.5 (10.3 to 10.6)	11.2 (11.0 to 11.3)	0.7 (0.5 to 0.9)	25.6 (25.3 to 25.9)	25.5 (25.3 to 25.7)	–0.2 (–0.5 to 0.2)
	Severe	2.4 (2.3 to 2.4)	2.7 (2.6 to 2.7)	0.3 (0.2 to 0.4)	11.3 (11.1 to 11.6)	12.0 (11.8 to 12.2)	0.7 (0.3 to 1.0)
Sub-Saharan Africa, central	Moderate	19.8 (19.3 to 20.3)	19.8 (19.4 to 20.1)	0.0 (–0.6 to 0.5)	22.0 (21.5 to 22.4)	20.3 (19.9 to 20.7)	–1.6 (–2.3 to –1.1)
	Severe	17.6 (17.1 to 18.2)	19.8 (19.4 to 20.2)	2.2 (1.5 to 2.8)	21.5 (20.8 to 22.1)	24.2 (23.8 to 24.7)	2.8 (2.0 to 3.5)
Sub-Saharan Africa, eastern	Moderate	21.0 (20.6 to 21.4)	21.2 (20.9 to 21.5)	0.2 (–0.3 to 0.7)	24.8 (24.4 to 25.2)	23.1 (22.8 to 23.3)	–1.7 (–2.2 to –1.3)
	Severe	14.2 (14.0 to 14.4)	16.1 (16.0 to 16.3)	1.9 (1.7 to 2.2)	16.9 (16.6 to 17.1)	19.5 (19.3 to 19.7)	2.7 (2.3 to 3.0)
Sub-Saharan Africa, southern	Moderate	14.1 (13.9 to 14.4)	15.0 (14.8 to 15.2)	0.9 (0.6 to 1.3)	25.2 (24.8 to 25.4)	23.9 (23.7 to 24.1)	–1.2 (–1.6 to –0.9)
	Severe	6.9 (6.7 to 7.1)	7.8 (7.6 to 7.9)	0.9 (0.6 to 1.1)	16.5 (16.0 to 17.0)	18.4 (18.0 to 18.7)	1.9 (1.3 to 2.5)
Sub-Saharan Africa, western	Moderate	20.2 (19.9 to 20.5)	20.5 (20.3 to 20.7)	0.3 (–0.1 to 0.7)	26.2 (25.8 to 26.5)	24.9 (24.6 to 25.1)	–1.3 (–1.7 to –0.9)
	Severe	10.8 (10.6 to 11.1)	12.4 (12.2 to 12.5)	1.5 (1.2 to 1.8)	14.8 (14.5 to 15.1)	16.7 (16.5 to 17.0)	1.9 (1.5 to 2.3)

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(c) High growth

Region	Stunting level	2030			2050		
		No climate change	With climate change	Climate change-attributable	No climate change	With climate change	Climate change-attributable
Asia, central	Moderate	9.3 (9.1 to 9.4)	10.4 (10.2 to 10.5)	1.1 (0.9 to 1.3)	3.5 (3.5 to 3.6)	4.4 (4.4 to 4.5)	0.9 (0.8 to 1.0)
	Severe	1.9 (1.8 to 1.9)	2.4 (2.3 to 2.4)	0.5 (0.4 to 0.6)	0.1 (0.0 to 0.1)	0.2 (0.2 to 0.2)	0.1 (0.1 to 0.1)
Asia, east	Moderate	6.7 (6.6 to 6.8)	7.2 (7.1 to 7.3)	0.5 (0.4 to 0.7)	3.2 (3.0 to 3.3)	3.7 (3.6 to 3.8)	0.6 (0.4 to 0.7)
	Severe	0.8 (0.7 to 0.9)	1.1 (1.0 to 1.1)	0.3 (0.2 to 0.4)	0.0 (0.1 to 0.1)	0.1 (0.0 to 0.1)	0.0 (0.0 to 0.1)
Asia, south	Moderate	12.3 (12.1 to 12.5)	13.0 (12.9 to 13.1)	0.7 (0.5 to 0.9)	5.1 (5.0 to 5.2)	6.0 (5.9 to 6.1)	0.9 (0.8 to 1.0)
	Severe	3.3 (3.1 to 3.4)	3.7 (3.6 to 3.8)	0.4 (0.2 to 0.6)	0.4 (0.3 to 0.4)	0.5 (0.5 to 0.5)	0.2 (0.1 to 0.2)
Asia, south-east	Moderate	7.4 (7.2 to 7.5)	8.1 (8.0 to 8.2)	0.7 (0.6 to 0.8)	3.6 (3.6 to 3.7)	4.4 (4.3 to 4.4)	0.8 (0.7 to 0.8)
	Severe	1.1 (1.1 to 1.2)	1.4 (1.4 to 1.5)	0.3 (0.2 to 0.4)	0.1 (0.1 to 0.1)	0.2 (0.2 to 0.2)	0.1 (0.1 to 0.1)
Latin America, central and Caribbean	Moderate	7.0 (6.9 to 7.1)	7.9 (7.8 to 8.0)	1.0 (0.8 to 1.1)	3.5 (3.4 to 3.6)	4.4 (4.3 to 4.4)	0.9 (0.8 to 1.0)
	Severe	1.0 (0.9 to 1.0)	1.2 (1.2 to 1.3)	0.2 (0.2 to 0.3)	0.0 (0.0 to 0.1)	0.1 (0.1 to 0.1)	0.1 (0.0 to 0.1)
Latin America, mid	Moderate	5.9 (5.8 to 6.0)	6.6 (6.5 to 6.7)	0.7 (0.6 to 0.8)	3.3 (3.2 to 3.4)	3.9 (3.9 to 4.0)	0.6 (0.5 to 0.7)
	Severe	0.6 (0.6 to 0.7)	0.8 (0.7 to 0.8)	0.2 (0.1 to 0.2)	0.0 (0.0 to 0.1)	0.1 (0.1 to 0.1)	0.0 (0.0 to 0.1)

[Continues]

[Continued]

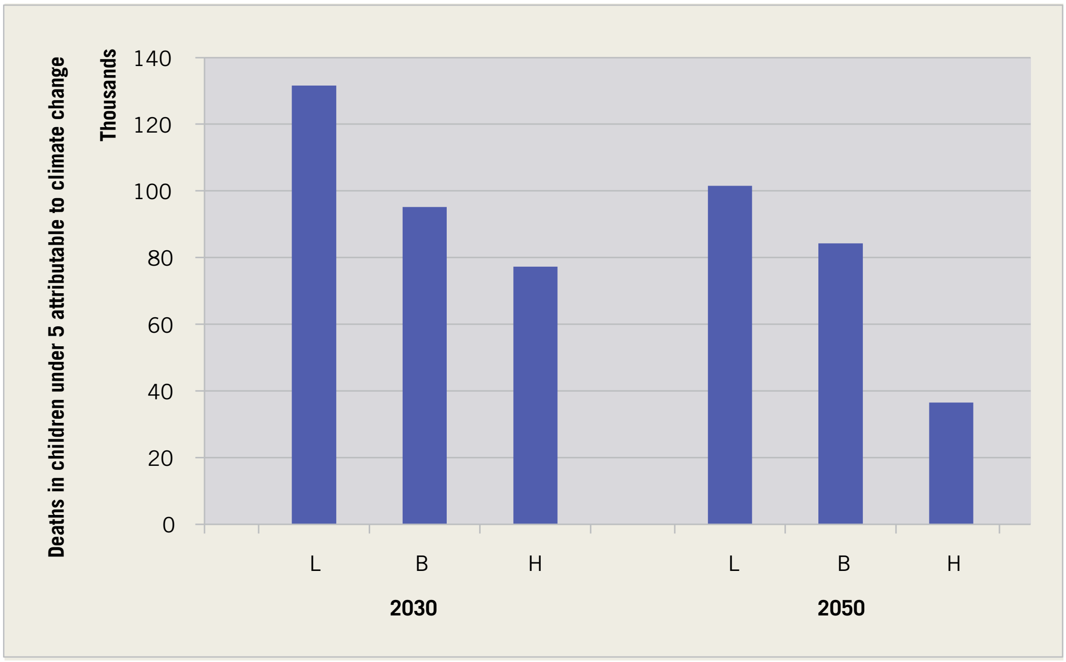
Region	Stunting level	2030			2050		
		No climate change	With climate change	Climate change-attributable	No climate change	With climate change	Climate change-attributable
Latin America, south	Moderate	3.1 (3.1 to 3.2)	3.5 (3.4 to 3.6)	0.3 (0.2 to 0.5)	2.8 (2.7 to 2.9)	3.0 (3.0 to 3.1)	0.3 (0.1 to 0.4)
	Severe	0.0 (0.0 to 0.1)	0.1 (0.0 to 0.1)	0.0 (0.0 to 0.0)	0.0 (0.0 to 0.0)	0.0 (0.0 to 0.0)	0.0 (0.0 to 0.0)
North Africa/Middle East	Moderate	8.0 (7.9 to 8.1)	8.5 (8.5 to 8.6)	0.6 (0.4 to 0.7)	3.4 (3.3 to 3.4)	3.7 (3.7 to 3.7)	0.4 (0.3 to 0.4)
	Severe	1.4 (1.4 to 1.7)	1.6 (1.5 to 1.6)	0.1 (0.1 to 0.2)	0.1 (0.0 to 0.1)	0.1 (0.1 to 0.1)	0.0 (0.0 to 0.0)
Sub-Saharan Africa, central	Moderate	20.1 (19.6 to 20.5)	20.4 (20.0 to 20.7)	0.3 (–0.2 to 0.9)	15.6 (15.4 to 15.9)	16.9 (16.7 to 17.2)	1.3 (1.0 to 1.7)
	Severe	14.7 (14.2 to 15.2)	17.1 (16.7 to 17.5)	2.4 (1.8 to 3.0)	7.8 (7.5 to 8.2)	10.8 (10.5 to 11.1)	2.9 (2.5 to 3.4)
Sub-Saharan Africa, eastern	Moderate	19.2 (18.9 to 19.5)	19.7 (19.5 to 20.0)	0.5 (0.1 to 0.9)	11.8 (11.6 to 12.0)	12.8 (12.6 to 12.9)	1.0 (0.8 to 1.2)
	Severe	9.9 (9.7 to 10.1)	11.5 (11.3 to 11.6)	1.5 (1.3 to 1.8)	3.1 (3.0 to 3.2)	3.7 (3.6 to 3.7)	0.6 (0.5 to 0.7)
Sub-Saharan Africa, southern	Moderate	8.4 (8.3 to 8.6)	9.2 (9.1 to 9.3)	0.8 (0.6 to 1.0)	4.7 (4.6 to 4.8)	5.4 (5.3 to 5.5)	0.7 (0.6 to 0.8)
	Severe	3.3 (3.2 to 3.3)	4.0 (3.9 to 4.1)	0.7 (0.5 to 0.8)	0.6 (0.5 to 0.6)	0.8 (0.8 to 0.8)	0.2 (0.2 to 0.3)
Sub-Saharan Africa, western	Moderate	15.7 (15.5 to 15.9)	16.1 (16.0 to 16.3)	0.4 (0.1 to 0.6)	9.6 (9.5 to 9.8)	9.9 (9.8 to 10.0)	0.3 (0.1 to 0.5)
	Severe	5.5 (5.4 to 5.7)	6.0 (5.9 to 6.1)	0.5 (0.3 to 0.6)	2.1 (2.0 to 2.2)	2.2 (2.1 to 2.3)	0.1 (0.0 to 0.2)

a All numbers are percentages as a mean of the probability density function and uncertainty interval (in brackets), defined as mean ± 1 standard deviation

7.6 Mortality due to climate change-attributable undernutrition

Climate change is estimated to increase mortality due to undernutrition, compared with a world without climate change (Figure 7.5).

Figure 7.5 Estimated additional deaths in children aged under 5 years attributable to climate change in 2030 and 2050, in the 12 study regions, under low growth (L), base case (B) and high growth (H) scenarios[a]



[a] Bars show additional numbers of deaths in children attributable to climate change as mean of the probability density function for the combined climate change scenario estimates minus the mean of the probability density function for the estimates without climate change

There are important differences in mortality impacts, depending on the economic growth scenario. In the base case, we estimate there will be an additional 95 175 (uncertainty interval −3586 to 193 937) deaths in 2030 and 84 695 (uncertainty interval 29 815 to 139 576) deaths in 2050. The corresponding numbers for the low growth scenario are 131 634 (uncertainty interval −11 273 to 274 541) deaths in 2030 and 101 484 (uncertainty interval −32 326 to 235 294) deaths in 2050; and for the high growth scenario 77 205 (uncertainty interval −12 491 to 166 900) deaths in 2030 and 36 524 (uncertainty interval 2518 to 70 530) deaths in 2050.

The regional distribution of mortality is shown in Table 7.5.

Table 7.5 Estimated number of deaths in children aged under 5 years attributable to moderate and severe stunting in 2030 and 2050, with and without climate change for (a) base case, (b) low growth and (c) high growth scenarios[a]

(a) Base case

Region	2030			2050		
	No climate change	With climate change	Climate change-attributable	No climate change	With climate change	Climate change-attributable
Asia, central	3149 (2328 to 3970)	3622 (2820 to 4423)	473 (–215 to 1161)	846 (589 to 1102)	1160 (873 to 1446)	314 (66 to 563)
Asia, east	15 734 (9711 to 21 756)	16 888 (11 606 to 22 171)	1155 (–5313 to 7622)	2363 (1345 to 3381)	3063 (1957 to 4169)	700 (–427 to 1828)
Asia, south	240 492 (174 541 to 306 443)	261 185 (201 266 to 321 103)	20 692 (–39 019 to 80 404)	66 908 (47 388 to 86 428)	83 438 (62 739 to 104 137)	16 530 (–1582 to 34 642)
Asia, south-east	29 989 (22 349 to 37 629)	33 337 (25 917 to 40 756)	3348 (–2635 to 9331)	9562 (6762 to 12 362)	12 611 (9566 to 15 656)	3049 (605 to 5494)
Latin America, central and Caribbean	6526 (4634 to 8418)	7385 (5584 to 9185)	859 (–837 to 2554)	1657 (1085 to 2230)	2363 (1689 to 3037)	706 (100 to 1311)
Latin America, mid	2700 (1856 to 3544)	3145 (2311 to 3979)	445 (–327 to 1218)	937 (599 to 1275)	1267 (895 to 1638)	330 (–6 to 665)
Latin America, south	154 (86 to 221)	168 (104 to 231)	14 (–49 to 76)	89 (49 to 129)	100 (61 to 138)	11 (–27 to 49)
North Africa/Middle East	17 151 (12 515 to 21 788)	18 769 (14 275 to 23 262)	1617 (–2030 to 5264)	5693 (3818 to 7568)	6860 (4926 to 8794)	1167 (–480 to 2813)
Sub-Saharan Africa, central	212 737 (165 285 to 260 189)	227 121 (186 129 to 268 113)	14 385 (–27 448 to 56 217)	131 831 (98 655 to 165 007)	150 104 (121 101 to 179 106)	18 273 (–12 372 to 48 918)
Sub-Saharan Africa, eastern	332 128 (269 769 to 394 487)	360 127 (298 601 to 421 654)	27 999 (–8701 to 64 699)	152 953 (120 400 to 185 507)	179 433 (145 544 to 213 322)	26 480 (4936 to 48 024)
Sub-Saharan Africa, southern	12 779 (9476 to 16 082)	14 024 (10 970 to 17 077)	1245 (–1505 to 3994)	5632 (3957 to 7306)	6663 (5064 to 8262)	1032 (–516 to 2580)
Sub-Saharan Africa, western	324 418 (252 177 to 396 659)	347 362 (279 731 to 414 993)	22 944 (–31 728 to 77 616)	176 163 (132 115 to 220 211)	192 267 (150 862 to 233 673)	16 105 (–19 500 to 51 709)

[Continues]

[Continued]

(b) Low growth

Region	2030			2050		
	No climate change	With climate change	Climate change-attributable	No climate change	With climate change	Climate change-attributable
Asia, central	4569 (3457 to 5682)	5188 (4094 to 6283)	619 (–268 to 1507)	5522 (4480 to 6563)	5775 (4813 to 6737)	253 (–522 to 1029)
Asia, east	33 309 (20 895 to 45 722)	35 996 (25 248 to 46 744)	2687 (–10 707 to 16 082)	63 415 (45 215 to 81 614)	66 312 (51 584 to 81 040)	2897 (–16 284 to 22 079)
Asia, south	403 558 (294 010 to 513 105)	437 660 (340 635 to 534 684)	34 102 (–68 345 to 136 548)	490 521 (381 807 to 599 235)	513 270 (419 341 to 607 200)	22 749 (–76 357 to 121 856)
Asia, south-east	45 141 (34 172 to 56 110)	49 726 (39 100 to 60 351)	4585 (–3841 to 13 010)	68 288 (54 671 to 81 906)	71 700 (59 132 to 84 268)	3412 (–7033 to 13 857)
Latin America, central and Caribbean	7814 (5592 to 10 036)	8799 (6682 to 10 916)	985 (–992 to 2962)	9060 (6605 to 11 515)	9773 (7611 to 11 936)	713 (–1528 to 2954)
Latin America, mid	4413 (3027 to 5800)	4976 (3698 to 6255)	563 (–732 to 18 58)	5003 (3677 to 6330)	5379 (4158 to 6600)	376 (–755 to 1506)
Latin America, south	186 (105 to 267)	207 (129 to 284)	21 (–54 to 95)	136 (76 to 196)	163 (102 to 223)	26 (–31 to 83)
North Africa/Middle East	27 155 (20 276 to 34 034)	29 493 (22 860 to 36 125)	2338 (–2827 to 7503)	57 523 (46 658 to 68 387)	59 111 (49 054 to 69 168)	1588 (–5840 to 9016)
Sub-Saharan Africa, central	260 373 (203 148 to 317 597))	277 273 (227 695 to 326 851)	16 901 (–33 191 to 66 993)	232 162 (185 407 to 278 918)	245 642 (204 704 to 286 580)	13 480 (–26 491 to 53 451)
Sub-Saharan Africa, eastern	474 650 (391 172 to 558 129)	506 556 (424 377 to 588 735)	31 906 (–14 849 to 78 660)	449 793 (375 099 to 524 487)	477 993 (405 041 to 550 944)	28 200 (–13 843 to 70 244)
Sub-Saharan Africa, southern	17 047 (13 000 to 21 095)	18 506 (14 720 to 22 292)	1458 (–1746 to 4663)	21 210 (16 827 to 25 593)	22 300 (18 445 to 26 155)	1089 (–2645 to 4824)
Sub-Saharan Africa, western	486 798 (388 603 to 584 993)	522 268 (429 362 to 615 174)	35 470 (–34 802 to 105 742)	518 904 (425 297 to 612 511)	545 604 (457 297 to 633 611)	26 700 (–37 825 to 91 235)

[Continues]

[Continued]

(c) High growth

Region	2030			2050		
	No climate change	With climate change	Climate change-attributable	No climate change	With climate change	Climate change-attributable
Asia, central	1977 (1404 to 2550)	2325 (1763 to 2888)	348 (–163 to 859)	204 (128 to 281)	270 (178 to 361)	65 (–5 to 136)
Asia, east	8709 (4933 to 12 485)	9916 (6426 to 13 405)	1207 (–3031 to 5444)	1281 (640 to 1923)	1484 (879 to 2088)	202 (–460 to 865)
Asia, south	193 269 (134 936 to 251 603)	209 274 (157 373 to 261 175)	16 005 (–39 902 to 71 912)	30 312 (19 489 to 41 136)	36 847 (25 141 to 48 553)	6535 (–4076 to 17 145)
Asia, south-east	14 139 (10 010 to 18 268)	16 325 (12 273 to 20 377)	2186 (–1240 to 5611)	2590 (1653 to 3527)	3237 (2190 to 4283)	646 (–141 to 1434)
Latin America, central and Caribbean	3177 (2147 to 4207)	3714 (2699 to 4730)	537 (–432 to 1506)	545 (331 to 759)	687 (443 to 930)	141 (–58 to 341)
Latin America, mid	1647 (1098 to 2197)	1906 (1362 to 2450)	259 (–243 to 760)	362 (209 to 516)	421 (267 to 576)	59 (–83 to 201)
Latin America, south	119 (67 to 172)	130 (80 to 179)	11 (–38 to 59)	58 (31 to 85)	62 (37 to 87)	4 (–21 to 29)
North Africa/ Middle East	14 837 (10 723 to 18 951)	15 995 (12 075 to 19 914)	1158 (–2135 to 4451)	2295 (1460 to 3129)	2518 (1658 to 3379)	224 (–394 to 842)
Sub-Saharan Africa, central	188 709 (144 726 to 232 691)	205 167 (167 101 to 243 233)	16 458 (–22 983 to 55 900)	71 966 (50 263 to 93 668)	87 345 (68 203 to 106 488)	15 379 (–6274 to 37 033)
Sub-Saharan Africa, eastern	307 504 (248 677 to 366 330)	332 996 (275 109 to 390 883)	25 492 (–9248 to 60 233)	85 365 (64 811 to 105 919)	95 226 (74 838 to 115 614)	9861 (–5158 to 24 881)
Sub-Saharan Africa, southern	6668 (4697 to 8639)	7650 (5800 to 9499)	982 (–826 to 2790)	907 (573 to 1241)	1117 (775 to 1460)	210 (–140 to 560)
Sub-Saharan Africa, western	246 894 (188 621 to 305 167)	259 457 (205 791 to 313 124)	12 563 (–33 392 to 58 518)	75 617 (53 967 to 97 267)	78 813 (59 431 to 98 196)	3196 (–15 451 to 21 844)

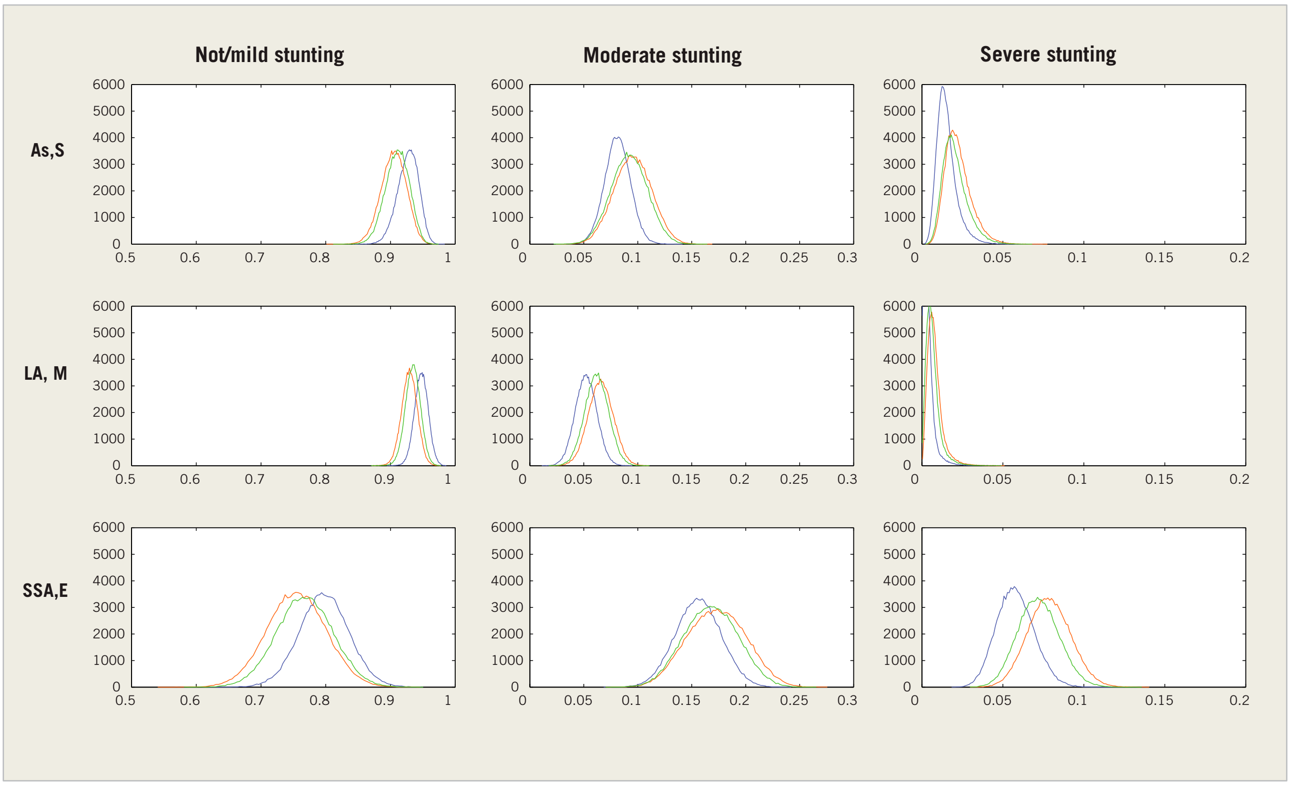
a All numbers are absolute number of deaths as mean of the probability density function and uncertainty interval in brackets defined as mean ± 1 standard deviation

7.7 Uncertainty

7.7.1 Parameter uncertainty in the health model

To account for parameter uncertainty in stunting model, we used a standard Monte Carlo approach (see also Lloyd et al., 2011). Each parameter was assumed to be distributed either normally or uniformly about its point estimate (for details, see Lloyd et al., 2011). Figure 7.6 shows the histograms proportional to the probability density functions of future stunting for selected regions in the base case.

Figure 7.6 Histograms proportional to probability density functions for the proportion of children estimated to be stunted in 2050 under the base case scenario, for selected regions[a]



As,S – Asia, south; LA,M – Latin America, mid; SSA,E – sub-Saharan Africa, eastern

[a] Histograms were derived from 100 000 Monte Carlo runs. The *x*-axes show proportion of children stunted at a given level. Note that the *x*-axis scale runs from 0.5 to 1 in column 1, from 0 to 0.3 in column 2, and from 0 to 0.2 in column 3. The *y*-axes show number of estimates. The curves are blue for no climate change, red for MIROC and green for CSIRO

7.7.2 Uncertainty in stunting-attributable death

To estimate stunting-attributable deaths, we required data on the proportion of children stunted and the relative risk of death in moderate and severe stunting (relative to not stunted). For the stunting data, we used the probability density functions for stunting with and without climate change. For the relative risk estimates, we used the odds ratios shown in Table 7.1. Using the mean and standard deviations of the probability density functions for stunting and odds ratios, we estimated the population-attributable fractions using a standard Monte Carlo simulation (100 000 runs).

It was not possible to assess the uncertainty in the upstream models (such as climate, crop and trade models) that drive our model as we lacked the necessary information. This assessment has included two climate scenarios and three health futures.

The large uncertainty is a natural consequence of propagating uncertainties in a chain of models. More important than presenting uncertainty is taking into account the uncertainty of making robust decisions, such as in terms of prioritizing interventions to reduce the impact of climate change on health. This can be done using decision-analytical methods. Calculating uncertainty is a necessary first step to support policy-makers making robust decisions under uncertainty.

7.8 Discussion

Previous studies have shown that climate change is likely to increase future hunger and undernutrition (Rosenzweig & Parry, 1994; Parry et al. 1999, 2004; Nelson et al., 2009, 2010). A previous assessment using the same undernutrition model but under different climate and socioeconomic scenarios estimated that moderate stunting in sub-Saharan Africa and south Asia would increase by 1–29% by 2050, with increases of 23–62% in severe stunting (Lloyd et al., 2011). At the time of writing, no other studies have estimated future mortality attributable to undernutrition as a result of climate change, and therefore a direct comparison cannot be attempted.

According to this assessment, regardless of the future socioeconomic scenario considered, climate change will result in millions more children being stunted. In the base case scenario, our mean estimate suggests an additional 7.5 million children will be stunted by 2030, increasing to an additional 10.1 million by 2050. In the low growth scenario, moderate stunting is estimated to be 4.9 million (mean estimate) lower by 2050 in a future with climate change (compared with a future without climate change), but severe stunting is expected to increase by 8.2 million (mean estimate). This poses a major health risk: moderate stunting has an all-cause mortality odds ratio (compared with not being stunted) of 1.6; the odds ratio for severe stunting is 4.1 (Black et al., 2008). Furthermore, severe stunting brings a higher risk of morbidity (Black et al., 2008) and has a greater impact on future potential, such as education and earning potential (Victora et al., 2008).

In the high growth scenario, climate change is expected to increase severe stunting by 3.1 million in 2030 and 1.4 million in 2050 (mean estimates). This is despite the considerable income growth in this scenario, which (due to assumed accompanying lowering of the non-food risks of stunting such as those related to physical infrastructure and education) lowers the risk of stunting. This scenario assumes that high income growth can be achieved without increasing climate change (that is, the amount of climate change in this scenario is the same as in the base and optimistic scenarios); in other words, it is optimistic in terms of the development of green technology.

Geographically, the areas expected to be most affected (in terms of numbers of children stunted) by climate change are sub-Saharan Africa (with the exception of southern sub-Saharan Africa) and south Asia. That these regions are also expected to have a generally high burden of disease magnifies the likely impacts of stunting, which acts synergistically with many infectious diseases and increases the risk of some chronic diseases (Black et al., 2008; Victora et al., 2008).

In terms of the proportion of children stunted, regardless of the presence or absence of climate change, economic growth is expected to reduce child stunting. Over time, the proportion of children stunted drops considerably in the high growth scenario; it drops less so, but still considerably, in the base case scenario. In contrast, in the low growth scenario, the proportion of children stunted increases over time. Despite the potential benefits of economic growth, climate change leads to an increase in the proportion stunted in all scenarios.

These results may appear to suggest that high economic growth (as in the high growth scenario) is the optimal pathway to reduce stunting; in our results, stunting in the base case scenario without climate change exceeds stunting in the high growth case with climate change. We caution against such an interpretation for the following reasons. First, the high growth scenario assumes that additional economic growth brings no increase in climate change; this is highly unlikely. In reality, unless there is a rapid advance in the availability and use of green technology, the likely increase in emissions and accompanying climate change will have negative impacts on food production that are not accounted for in this assessment. Second, the undernutrition model we used assumes that the relationship between national income and stunting risk remains constant over time at baseline levels. This relationship has been estimated at a time (currently) when there are vast inequalities between and within countries, and there are many initiatives aimed at improving the situation. These initiatives, from the standpoint of the undernutrition model, aim to change the relationship between national income and stunting risk; that is, although one possible path to reducing stunting is to maximize national income (which may have unforeseen or unconsidered consequences that offset the expected benefits, such as greater climate change), another possible path is to reduce inequalities and improve living conditions.

We estimate that in the base case scenario, climate change-attributable stunting will result in about 95 000 extra child deaths in 2030 and 80 000 extra child deaths in 2050 (mean estimates). This finding is not insignificant, but it is lower than may have been anticipated given that we estimate climate change will result in millions more stunted children in all three socioeconomic scenarios. We believe our estimates should be considered very conservative for the following two reasons. First, the burden of disease projections assume that with time and development, there is a shift away from communicable diseases and towards noncommunicable diseases. The population projections assume the population of children aged under 5 years is declining in all but three countries included in our analysis, despite growth in total population. Considered together, this means over time there are fewer communicable disease deaths in fewer children; this shrinking group is the particular group at risk of stunting associated mortality. Furthermore, stunting in childhood has been associated with a greater risk of noncommunicable diseases and lower economic productivity in adulthood (Victora et al., 2008); this is not accounted for in our model. It is reasonable to expect that an increase in stunting of the magnitude we estimate would lead to an increase in rates of (and death rates due to) noncommunicable disease and reduce national income.

Second, our modelling does not include the impact of shocks; it considers stunting due only to expected average conditions. Climate shocks may occur in the form of acute food production decreases due to extensive and prolonged droughts, or increased food price instability leading to rapid price increases. Relevant shocks need not be related directly to food access; for example, there may be an epidemic of diarrhoea associated with changed temperature regimes. In the face of such shocks, stunting can be considered as a cause of vulnerability: if an already stunted child has a sudden decrease in food access, or a sudden increase in disease risk, then the risk of further morbidity or mortality is considerably higher than in non-stunted children. At the population level, if there are large numbers of already stunted children, then it will be considerably more difficult for a nation to cope with shocks.

Contribution of Research Papers 1 & 2 and new questions raised

The model developed for Research Papers 1 and 2 represented an advance in that it estimated a more health-relevant outcome (child stunting, split into moderate and severe stunting) than previous assessments (Lloyd et al., 2011), and attempted to explicitly account for the influence of socioeconomic development. The latter was done by aggregating the causes of stunting into food- and non-food-causes. Overall, the findings of the model showed that as climate change increased and socioeconomic conditions worsened, child stunting – in particular, severe stunting, which is considerably more lethal than moderate stunting (Black et al., 2008) - increased.

Subsequently, the stunting model has been incorporated into models developed by other groups (e.g. Ishida et al., 2014, Hasegawa et al., 2016). This involved two sequential innovations. Firstly, Ishida et al. (2014) developed a statistically-based model that transformed the output of the stunting model into estimates of 'Disability-adjusted Life Years Attributable to Underweight' (DAtUs). They then estimated DAtU's globally and for world regions under various climate and socioeconomic scenarios. In their approach, the authors effectively lengthened the existing chain of models that represented the pathway from climate change to undernutrition-related outcomes (Figure 1, panel A in Chapter 2 of this thesis, and, Figure 1 in Ishida et al. (2014)). That is, they added the DAtU model to the end of the chain.

Secondly, Hasegawa et al. (2016) developed new models with transformed the output of the DAtU model initially into Disability Adjusted Life Years (DALYs) for various health outcomes, and then used these outputs to estimate economic measures (e.g. medical expenditures, value of lives lost). Impact estimates were made for various world regions and globally under combinations of climate and socioeconomic scenarios. An advance in this approach was the incorporation of feedbacks: (i) from medical expenditure to income, and (ii) from mortality to labour availability. From a health perspective, however, the model essentially represented a further lengthening of the chain of models (see Figure 1, panel B in Chapter 2 of this thesis (which is a reproduction of Figure 1 in Hasegawa et al. (2016)), notwithstanding feedbacks which indirectly influence stunting estimates in subsequent years (via effects on GDPpc and aggregate food production).

Both of the above were important innovations which advanced existing knowledge. In doing so, however, they continued to view the climate-undernutrition relation from the same perspective as previous models, asking: *how climate change-associated changes in food production will impact on food supply available to consumers and how this will influence the risk of undernutrition.* Further, existing structural features were retained: (i) the downstream health component models inherit the assumptions of the upstream component models, including that production and consumption (and thus, producers and consumers) can be considered separately, and, (ii) climate does not directly impact on scenario-specific socioeconomic conditions (albeit Hasegawa et al. (2016) allow for some indirect effects of climate on GDPpc and population via its impacts on stunting).

The results generated by the model in Chapter 2, as well as in the successor models described above (Hasegawa et al., 2016, Ishida et al., 2014), raise new questions. Research Paper 2 found that the differences in stunting between socioeconomic scenarios were considerably larger than climate change-attributable stunting (Figure 5; also see Figure 7.4 in Research Paper 2). Ishida et al. (2014) and Hasegawa et al. (2016) found likewise. That is, all these results suggest that socioeconomic development (blue bars in Figure 5) has a much greater influence on the magnitude of estimated child stunting than climate change (orange bars in Figure 5) (Lloyd and Hales, 2019). Yet, when estimating undernutrition in all these models, socioeconomic conditions are represented crudely, essentially as national-level GDPpc. Further, although it is expected that climate change will impact on socioeconomic conditions (Hallegatte and Rozenberg, 2017), these models only account for climate impacts on crop production.

Given this, the questions arising are, *what would we see if a model attempted to (i) better represent aspects of development?, and (ii) account for the direct impacts of climate change on development rather than only on crop production?* A first step in this direction was taken in Research Paper 3.

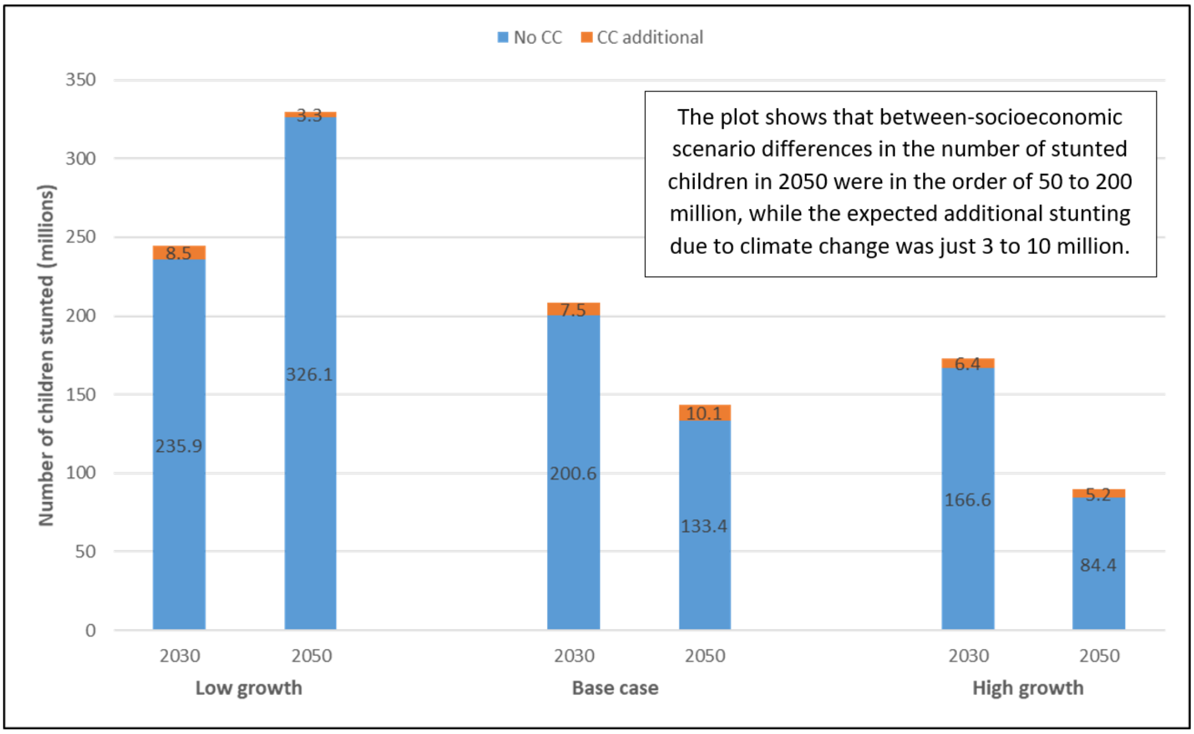


Figure 5 Estimates of number of children stunted in futures with and without climate change, in 2030 and 2050, under moderate to high emissions, for three socioeconomic scenarios. Impacts without climate change are shown in blue; additional impacts with climate change are shown in orange; in the legend, "CC" stands for "climate change". The emissions scenario was SRES (Special Report on Emissions Scenarios) A1b (Nakicenovic and Swart, 2000). Each pair of bars represents a given socioeconomic scenario in the 2030s (left bar) and 2050s (right bar); the socioeconomic scenarios are "low growth", "base case", and "high growth", which assume low, moderate, and high economic growth, respectively (for details, see "Research Paper 2: Supplemental Material").

Based on results from Lloyd et al (2014).

Chapter 5. Modelling climate change impacts on child stunting through incomes of the poorest and food price

Background

This chapter is composed of a research paper (Lloyd et al., 2018) that was originally commissioned by the World Bank as part of the "Shock Waves" report on climate change and poverty (Hallegatte et al., 2016). It describes the development of a statistically-based (multilevel longitudinal regression) health model that estimates the impacts of climate change on child stunting in rural and urban areas through its effects on incomes and food prices. The poverty modelling was carried out by the World Bank (Hallegatte and Rozenberg, 2017) and the food price modelling was carried out by IIASA (International Institute for Applied Systems Analysis) using GLOBIOM (Global Biosphere Management Model) (Havlík et al., 2014, Havlík et al., 2015). Stunting estimates are given for the year 2030 under low and high climate change, and under "poverty" and "prosperity" socioeconomic scenarios.

Research Paper 3: A Global-Level Model of the Potential Impact of Climate Change on Child Stunting via Income and Food Price in 2030

For accompanying supplemental material, see the appendix "Research Paper 3: Supplemental Material".

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First Name(s)	Simon John		
Surname/Family Name	Lloyd		
Thesis Title	Modelling the relation between climate change and undernutrition at the global-level: the use of multiple perspectives to gain new insights		
Primary Supervisor	Ben Armstrong		

If the Research Paper has previously been published please complete Section B, if not please move to Section C.

SECTION B – Paper already published

Where was the work published?	Environmental Health Perspectives		
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SECTION D – Multi-authored work

For multi-authored work, give full details of your role in the research included in the paper and in the preparation of the paper. (Attach a further sheet if necessary)	This work was commissioned by the World Bank as part of the Shock Waves report, which looked at the impacts of climate change on poverty. For the included paper: I designed the model, assembled the data, conducted the analysis, ran the model, and wrote the first draft of the paper. Mook Bangalore advised on data availability and assembled data for various variables. Zaid Chalabli, Sari Kovats, and Stephane Hallegatte provided advice on the form of the model. All co-authors contributed to writing the paper.

SECTION E

Student Signature	[redacted]
Date	6 Nov, 2019

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Date	6 Nov 2019

A Section 508–conformant HTML version of this article
is available at https://doi.org/10.1289/EHP2916.

A Global-Level Model of the Potential Impacts of Climate Change on Child Stunting via Income and Food Price in 2030

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Background: In 2016, 23% of children (155 million) aged <5 were stunted. Global-level modeling has consistently found climate change impacts on food production are likely to impair progress on reducing undernutrition.

Objectives: We adopt a new perspective, assessing how climate change may affect child stunting via its impacts on two interacting socioeconomic drivers: incomes of the poorest 20% of populations (due to climate impacts on crop production, health, labor productivity, and disasters) and food prices.

Methods: We developed a statistical model to project moderate and severe stunting in children aged <5 at the national level in 2030 under low and high climate change scenarios combined with poverty and prosperity scenarios in 44 countries.

Results: We estimated that in the absence of climate change, 110 million children aged <5 would be stunted in 2030 under the poverty scenario in comparison with 83 million under the prosperity scenario. Estimates of climate change–attributable stunting ranged from 570,000 under the prosperity/low climate change scenario to >1 million under the poverty/high climate change scenario. The projected impact of climate change on stunting was greater in rural vs. urban areas under both socioeconomic scenarios. In countries with lower incomes and relatively high food prices, we projected that rising prices would tend to increase stunting, whereas in countries with higher incomes and relatively low food prices, rising prices would tend to decrease stunting. These findings suggest that food prices that provide decent incomes to farmers alongside high employment with living wages will reduce undernutrition and vulnerability to climate change.

Conclusions: Shifting the focus from food production to interactions between incomes and food price provides new insights. Futures that protect health should consider not just availability, accessibility, and quality of food, but also the incomes generated by those producing the food. https://doi.org/10.1289/EHP2916

Introduction

Despite being a focus of health and global development policy for decades, and notwithstanding significant progress in many countries, child undernutrition remains a major contributor to the global burden of disease (GBD). An estimated 23% (155 million) of children aged <5 were stunted (low height-for-age) in 2016 (UNICEF et al. 2017), which has major health implications. In comparison with not being stunted, moderate stunting has an all-cause mortality odds ratio (OR) of 1.6; for severe stunting, it increases to 4.1 (Black et al. 2008). Morbidity risk increases for diseases, including pneumonia and diarrheal disease (Prendergast and Humphrey 2014). In the longer term, a reduction in neurodevelopmental and cognitive function may lead to reduced learning and earning capacity, and the risk of chronic disease is increased (de Onis and Branca 2016; Victora et al. 2008).

Global-level modeling studies have consistently found that climate change is likely to impair progress on reducing undernutrition (e.g., Hasegawa et al. 2015; Ishida et al. 2014; Nelson et al. 2010). For instance, Lloyd et al. (2011) found that that high climate change may result in a relative increase in severe stunting of 23% in Sub-Saharan Africa and 62% in South Asia in the 2050s. In such global-level studies, the mechanism via which climate change affects undernutrition is through changed crop productivity, which affects post-trade national calorie availability. Projected calorie availability is combined with fixed (i.e., not affected by climate change) scenario-specific socioeconomic variables, such as population size and per capita Gross Domestic Product (GDPpc), to estimate undernutrition. These fixed socioeconomic variables have a major influence: A consistent finding is that the differences in undernutrition between plausible socioeconomic futures is considerably larger than that between plausible climate change futures (e.g., Lloyd et al. 2014; Schmidhuber and Tubiello 2007).

This finding raises three related issues. First, given the complexity of the causation of undernutrition, the large influence of socioeconomic conditions is expected. For example, Smith and Haddad (2015) found that between 1970 and 2012, 67% of the reduction in stunting was due to improvements in women's education, gender equality, and access to adequate water and sanitation services. Rayner and Lang (2012) state that measures of height (including stunting) are "less an indicator of nutritional status and more a comment on the 'nutrition-environment interaction,'" where "environment" refers to context rather than just the natural environment. That is, at the population level, stunting is about more than food. Second, as well as affecting food production, climate change may affect undernutrition via socioeconomic routes. For instance, recent work shows that climate change may affect the income of the poorest population groups disproportionately (Hallegatte et al. 2016), and this impact may in turn influence undernutrition risk. Third, interactions between routes from climate to undernutrition may mean the combined impacts are not simply additive and are

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thus not easily predictable. However, to our knowledge, no previous global-level climate–undernutrition models have considered impacts operating through routes other than food production or more than one climate entry point at a time.

In this paper, we take a first step toward examining how climate change entering through two interacting socioeconomic drivers—incomes of the poorest 20% of a country and food price—may affect child stunting at the national level and in rural and urban areas. Both drivers may significantly influence undernutrition. Climate change may influence incomes via its impacts on crop production, health, labor productivity, and disasters (Hallegatte and Rozenberg 2017). In turn, low income and poverty manifest in a constellation of forms, including lack of access to water and sanitation, essential medicines, education, and adequate shelter and food; these forms combine to increase the risk of undernutrition (Pogge 2010). Food prices have a more complex relation to undernutrition: As well as directly influencing ability to purchase food, prices may influence incomes and wages. For instance, sustained high prices may increase risks for low-income net food consumers while reducing the risk for net food producers (Hertel 2016; Ivanic and Martin 2008). Thus, interactions between food price and incomes, and how they are each affected by climate change, may have unexpected aggregate effects.

To investigate this, we used multilevel statistical modeling to develop a global-level model that could be driven by projection data provided by "poverty" and "food price" models. We then projected moderate and severe stunting in children aged <5 at the national level and in rural and urban areas in 2030 under low and high climate change scenarios combined with poverty and prosperity socioeconomic scenarios.

Methods

In this section, we describe: *a*) the historical data and indicators used when fitting the stunting model, *b*) the forms of the equations and the process of fitting the stunting model, and *c*) the poverty and food-price models and the scenario-specific projection data used to make the estimates of future stunting. For the latter, a full set of projection data was available only out to 2030, and this limited the temporal horizon of our stunting estimates.

Historical Data and Indicator Development

Stunting data for children <5 y of age were from the Global Database on Child Growth and Malnutrition, which is based on survey data using consistent growth standards to identify moderate stunting (height-for-age Z-scores of −3 to −2) and severe stunting (height-for-age Z-scores <−3) (WHO 2017). Data for individual countries during a given year were available for moderate stunting and severe stunting, both at the national level and separately for rural and urban areas in each country. Individual countries were included in our analysis if they met three criteria. First, data were available on the prevalence of moderate and severe stunting from surveys performed on at least three occasions from 1990 onward. Second, they had sufficient data to derive estimates of food prices at the national level and of incomes of the poorest 20% of the population in rural and urban areas, respectively, for the majority of the years with stunting data. Third, these estimates of food price and incomes of the poorest populations could also be calculated for future years using output from poverty and food price models (described below.)

To develop an indicator of rural and urban incomes for each country, we obtained historical data on the average GDPpc of the population in the lowest 20% of the income distribution in each country (*GDPpc20*), in Purchasing Power Parity 2005 dollars (PPP$2005) (World Bank 2017) for each year with stunting data (matched as closely as possible, within a maximum of 5 y). Next, we used the ratio of rural to urban income or consumption to derive area-level income indicators for the rural and urban populations in the lowest 20% of the income distribution ($inc20^R_{ij}$ and $inc20^U_{ij}$, respectively) for each country *j* on occasion *i* when stunting was measured:

$$inc20^{(R)}_{ij} = GDPpc20_{ij} \times \left(\frac{income^{(R)}_{ij}}{income^{(R)}_{ij} + income^{(U)}_{ij}} \right) \quad \text{and}$$

$$inc20^{(U)}_{ij} = GDPpc20_{ij} \times \left(\frac{income^{(U)}_{ij}}{income^{(R)}_{ij} + income^{(U)}_{ij}} \right) \tag{1}$$

where $GDPpc20_{ij}$ is the national-level average GDPpc of the lowest 20% of the population of country *j* on occasion *i* (in PPP$ 2005) ["i" is a sequential index of measurement occasion; this is used because it corresponds to indexing commonly used in longitudinal multilevel models (see below)], and $income^{(R)}_{ij}$ and $income^{(U)}_{ij}$ represent the average values for income or consumption in rural and urban areas of country *j* during year *i*. This metric can be derived using data on either income or consumption, as long as the same units are used for rural and urban areas in each country and year. The indicator does not give an estimate of actual income; rather, it provides a measure of the size of rural and urban incomes that is comparable over time and across countries. An increase in the income indicator for a given rural or urban area indicates an increase in the average income of the population in the lowest 20% of the income distribution for the area.

There are two key assumptions in this indicator. First, projection data from the poverty model are for agricultural and nonagricultural incomes. We assumed these corresponded to rural and urban areas, respectively, because stunting data and historical income data were split rural–urban. Second, historical data for rural and urban incomes of the bottom 20% were not available; we thus assume that average incomes are roughly proportional to incomes of the bottom 20%.

In addition, we derived the ratio of the rural-to-urban income indicator for country *j* on occasion *i* as:

$$D_{ij} = \frac{inc20^{(R)}_{ij}}{inc20^{(U)}_{ij}} \tag{2}$$

We next developed an indicator of the affordability of food for the poorest 20% of the population in a given country. The model used to project future food prices (described below) estimated within-country changes in average national-level food prices relative to the year 2000 with the effects of inflation removed, such that the projected value is set to 1 for the year 2000 in all countries, and a 10% increase in price in a given country and year would result in an indicator = 1.1. We produced equivalent historical price data by dividing the national-level Consumer Price Index (CPI) for food ($fCPI_{ij}$) by the general CPI ($gCPI_{ij}$) (both set to 100 for the year 2000) (ILO 2017) to get an indicator of change in "real" food prices for country *j* on occasion *i*. Next, to develop an indicator of food price relative to incomes of the population in lowest 20% of the income distribution that is comparable across countries, we multiplied this by the domestic food price index (DFPI, an indicator of average food price in a given country relative to other countries) for county *j* in the year 2000 (FAO 2017b) and then divided it by $GDPpc20_{ij}/460$, in which "460" represents an annual income of $1.25 PPP2005, equal to the World Bank poverty line (Chen and Ravallion 2008). The full equation for the food price indicator ($price_{ij}$) is:

$$price_{ij} = \frac{\left(\frac{fCPI_{ij}}{gCPI_{ij}}\right) \times DFPI_j}{\left(\frac{GDPpc20_{ij}}{460}\right)} \tag{3}$$

Due to a lack of data, we could not derive separate indicators for rural and urban areas; hence, price_{ij} is a national-level indicator of average prices across rural and urban areas in each country on each occasion relative to incomes in the lowest 20% of the income distribution. Additionally, a lack of data meant we were unable to account for differing expenditure patterns in low-income populations; in effect, it is assumed that expenditure patterns are similar in this population group in the study countries. As the food-price indicator increases, food becomes less affordable (on average) for the poorest part of the population. If data required to derive price_{ij} for a specific year were missing, we interpolated or extrapolated the existing series or used data from the country's nearest neighbor to derive a value.

Forms of the Model Equations and Model Fitting

As we had a mix of national-level and area-level predictors, we used a two-stage approach, first modeling national-level moderate or severe stunting longitudinally, and then modeling area-level (i.e., rural and urban) moderate or severe stunting as a function of national-level stunting. We used random-effects models to account for unmeasured influences on stunting, and to allow us to make general inferences for all countries at risk of stunting, rather than limiting inferences only to the countries used to fit the model.

In the first stage, we used "growth-curve" modeling (Rabe-Hesketh and Skrondal 2012; Steele 2014) to estimate national-level trajectories of moderate stunting and severe stunting, using longitudinal national-level predictors while allowing for autocorrelation, and to assess time-varying and fixed predictors and unexplained differences (Rabe-Hesketh and Skrondal 2012). We used separate binomial logistic regression models (with the number stunted being calculated using prevalence and sample size from the survey data for stunting) to derive estimates for the prevalence of moderate stunting or severe stunting, respectively.

We initially fit "null" growth-curve models that included random effects and year only. The approach provides a formal test of whether a multilevel model gives a better fit than an equivalent single-level model and provides an initial assessment of stunting trajectories in recent decades. Following this we fit "full" models containing the predictor variables for each outcome.

Separate first-stage models for the log odds of moderate or severe stunting vs. no stunting (respectively) at the national level for each country j on occasion i for degree of stunting k ($Y_{ijk}^{(N)}$) (where the superscript N refers to national level) had the following form:

$$log\left(\frac{Y_{ijk}^{(N)}}{1-Y_{ijk}^{(N)}}\right) = \beta_{0jk}^{(N)} + \beta_{1jk}^{(N)}(t_{ij}) + \beta_{2k}^{(N)}(G_{ij}) + \beta_{3k}^{(N)}(P_{ij}) + \beta_{4k}^{(N)}(G_{ij} \times P_{ij}) + \mathbf{B}\cdot\mathbf{R} \tag{4}$$

$$\beta_{0jk}^{(N)} = \beta_{0k}^{(N)} + u_{0jk}^{(N)} \tag{5}$$

$$\beta_{1jk}^{(N)} = \beta_{1k}^{(N)} + u_{1jk}^{(N)} \tag{6}$$

where t_{ij} is the year of measurement of stunting, centered on the year 2010; G_{ij} is $\log(GDPpc20_{ij})$; P_{ij} is mean centered log ($price_{ij}$); $\mathbf{R}$ is a column vector of 11 indicator variables for GBD regions (as a contextual variable) (IHME 2015), and $\mathbf{B}$ is the corresponding row vector of fixed parameters for each region. The subscript k is degree of stunting (0 for moderate, and 1 for severe). The coefficients $\beta_{2k}^{(N)}$, $\beta_{3k}^{(N)}$, and $\beta_{4k}^{(N)}$ are fixed global parameters; $\beta_{0jk}^{(N)}$ and $\beta_{1jk}^{(N)}$ are country-specific parameters. The random effects, representing unmeasured time-invariant country-specific effects, capture (given the covariates) country-level differences, where $u_{0j}^{(N)}$ is the random intercept, and $u_{1j}^{(N)}$ is the random slope for year. The u terms are assumed to be normally distributed with a mean of zero and collectively follow a multivariate normal distribution with a mean of zero and a specified covariance (Steele 2014):

$$\begin{pmatrix} u_{0jk}^{(N)} \\ u_{1jk}^{(N)} \end{pmatrix} \sim N(0,\Omega_u) \text{ where } \Omega_u = \begin{pmatrix} \sigma_{u_0}^2 & \\ \sigma_{u_0u_1} & \sigma_{u_1}^2 \end{pmatrix} \tag{7}$$

where σ_{u0k}^2 is the variance of $u_{0jk}^{(N)}$, σ_{u1k}^2 is the variance of $u_{1jk}^{(N)}$, and σ_{u0u1} is the covariance of $u_{0jk}^{(N)}$ and $u_{1jk}^{(N)}$.

In the second stage, we used multilevel binomial logistic regression and area-level variables to estimate the log odds of moderate stunting or severe stunting in rural areas and urban areas, respectively ($Y_{ijk}^{(A)}$), where the superscript A refers to rural or urban area, as a function of national-level stunting:

$$log\left(\frac{Y_{ijk}^{(A)}}{1-Y_{ijk}^{(A)}}\right) = \gamma_{0jk}^{(A)} + \gamma_{1jk}^{(A)}\left(Y_{ijk}^{(N)}\right) + \gamma_{2k}^{(A)}\left(I_{ij}^{(A)}\right) + \gamma_{3k}^{(A)}\left(Y_{ijk}^{(N)} \times I_{ij}^{(A)}\right) + \gamma_{4k}^{(A)}(D_{ij}) + \gamma_{5k}^{(A)}\left(I_{ij}^{(A)} \times D_{ij}\right) \tag{8}$$

$$\gamma_{0jk}^{(A)} = \gamma_{0k}^{(A)} + w_{0jk}^{(A)} \tag{9}$$

$$\gamma_{1jk}^{(A)} = \gamma_{1k}^{(A)} + w_{1jk}^{(A)} \tag{10}$$

$Y_{ijk}^{(N)}$ is national-level stunting on occasion i in country j of degree k (i.e., moderate or severe); $I_{ij}^{(A)}$ represents area-level income as $\log(inc20_{ij}^{(R)})$ or $\log(inc20_{ij}^{(U)})$ (from Equation 1) centered just below its historical minimum; and D_{ij} represents rural–urban inequalities (from Equation 2). The coefficients $\gamma_{2k}^{(A)}$, $\gamma_{3k}^{(A)}$, $\gamma_{4k}^{(A)}$, and $\gamma_{5k}^{(A)}$ are fixed area-level global parameters; $\gamma_{0jk}^{(A)}$ and $\gamma_{1jk}^{(A)}$ are country-specific area-level parameters. The random effects $w_{0jk}^{(A)}$ and $w_{1jk}^{(A)}$ capture unmeasured time-invariant country-specific area effects (country-specific random intercepts and random slopes, respectively) for national-level stunting, which are assumed to be normally distributed (as in Equation 7).

When making projections of rural and urban stunting, to ensure consistency with the national-level projections, we proportionally rescaled the rural and urban estimates for moderate and severe stunting so that they summed to the national-level estimates.

All equations were fitted in Stata 13.0 (StataCorp LLC) using the "meqrlogit" command, which fits random-effects models for binomial responses using QR decomposition.

Upstream Models and Scenario-specific Projection Data

Two streams of modeled scenario-specific projection data were used to drive the stunting model. The first, for incomes, was from a "poverty model" (Hallegatte and Rozenberg 2017), which is a microsimulation model based on household surveys from 92 countries, thus representing individual households from across the income spectrum. The second, for food prices, was from the Global Biosphere Management Model (GLOBIOM) (Havlík et al. 2014; Havlík et al. 2015) (Figure 1). Both models were initially driven by standard climate and socioeconomic scenarios. Climate data were from five General Circulation Models (GCMs) under two emissions scenarios (Representative Concentration Pathways (RCPs) (Moss et al. 2010)). RCP 2.6 represents a low emissions future and RCP8.5 represents a high emissions future. Socioeconomic data were from two Shared Socioeconomic Pathways (SSPs) (O'Neill et al. 2017). SSP4 represents a world of rapid population growth, low economic growth, and high inequalities. SSP5 is scenario with low population growth, high economic growth, and large environmental pressures.

For the poverty model, based on the above scenarios, a set of tailored scenarios were developed to account for both socioeconomic and climate uncertainties in 2030. Firstly, socioeconomic futures were developed. A total of 300 subscenarios for each SSP were generated to capture the various ways that the macrolevel conditions specified in the SSPs may be reached by 2030. This included differences in factors such as: *a*) structural change, as share of labor force in each sector (i.e., agriculture, manufacturing, services) by skill level (i.e., low, high) and participation rates; *b*) productivity growth of skilled and unskilled labor and in each sector; *c*) demographic change, and *d*) policies (e.g., pensions and social transfers). The scenarios based on SSP4 represent "poverty" futures, with a global stability in the fraction of people living in poverty. Those based on SSP5 represent "prosperity" futures, which are broadly consistent with the achievement of the Sustainable Development Goals (SDGs) (United Nations 2018).

Following this, climate was introduced into the model: first, as a counterfactual future without climate change and then as low- and high-impact climate change scenarios. Because the magnitude of climate change in 2030 is only minimally affected by future emissions and climate policies, the difference between the low- and high-impact scenarios is related to the magnitude of expected impacts, rather than emissions. Impacts in a set of sectors were assessed across all the initial climate scenarios. These sectors included: *a*) food prices and food production (as impacts of food price on households' available income, and changes in farmers' incomes); *b*) health and labor productivity (stunting, as lost income over a lifetime; malaria and diarrheal disease, as treatment costs and days of work lost; *c*) labor productivity losses, as proportion of labor time lost; and, *d*) disasters, as income losses due to exposure to cyclones, storm surge, floods, and drought). The smallest impacts were taken to represent "low climate change" and the highest to represent "high climate change."

Of note, when accounting for uncertainty on how high food prices translate into higher revenues and for the difference between landowners and laborers, different assumptions were made in the poverty and prosperity scenarios: in the prosperity scenario, a 1% increase in food price translates into a 1% increase in farmers' income; in the poverty scenario, a larger fraction of the gain is captured by landowners at the expense of laborers, and a 1% increase in food price translates into a 0.5% increase in farmers' income.

Finally, the three climate-change scenarios (no change, low, and high) were combined with the two sets of socioeconomic scenarios to give six sets of climate-socioeconomic scenarios under which the poverty model was run. The data outputs from the poverty model used to drive the stunting model were national-level average GDPpc of the lowest 20% of the population ($GDPpc20_{ij}$) and average incomes in rural and urban areas ($income^R_{ij}$ and $income^U_{ij}$, respectively), as well as population (split into agricultural and nonagricultural for all ages and children <15). (See the original paper for a full description of the poverty model (Hallegatte and Rozenberg 2017)).

For food prices, GLOBIOM accounted for (among other things) future changes in crop productivity and global food trade, and estimated relative changes in national-level food prices based on results from Havlík et al. (2015). This provided data for the national-level deflated food CPI (i.e., $fCPI_{ij}/gCPI_{ij}$). Following the method used for poverty model, we used the lowest prices in 2030 under SSP4 and SSP5 from any RCP-GCM combination for "low climate change" in the "poverty" and "prosperity" scenarios, respectively; similarly, we used the highest prices for "high climate change." Prices in futures without climate change were used for the "no climate change" scenarios.

Additionally, SSP-specific population projections for children <5 y of age were taken from the Wittgenstein Centre for Demography and Global Human Capital (2017). The poverty model provided population data for children <15 y in agricultural and nonagricultural families; we assumed that the agricultural-to-nonagricultural ratio in children <5 y of age was the same as that for children <15 y of age. Further we assumed that agricultural populations lived in rural areas, and nonagricultural families lived in urban areas.

In the stunting model, we combine the above projection data to estimate patterns of undernutrition in children <5 y of age given climate change–impacted incomes and food prices under the climate and socioeconomic scenarios developed for the poverty model.

Two issues arise in relation to the stunting model input data. First, food-price estimates from GLOBIOM are one of the inputs into the poverty model. That is, food prices influence incomes. Second, in the poverty model, stunting affects incomes. However, as stunting-related income losses are seen in adults who were stunted when children—i.e., 10 to 20 y previously—we assume this is independent of stunted children <5 y of age in the time period of interest (Figure 1). Combining these issues, we assume that following the initial impacts of food prices and adult stunting on income (along with impacts on income due to other factors), children <5 y old are "exposed" to particular levels of income and food prices relative to income, which together influence their risk of stunting: this risk is quantified by the stunting model.

Results

Historical Data Holdings

We began with a dataset for all countries with stunting data from 1990 onwards (WHO 2017). We then dropped observations where stunting data were not split into moderate and severe (15 observations) and countries with measurements on less than three occasions (39 countries). We then obtained income and price data to match the stunting data.

The final dataset was unbalanced (the number and years of observation differed by country). It included 3–6 (mean = 4) observations from 49 countries (Table 1) for a total of 194 country-year observations. Countries from 12 of the 21 GBD regions (IHME 2015) were included (Table 1, Table S1). We did not include countries from high-income regions (Asia Pacific, High Income; Australasia; Europe, Western; Latin America, Southern; North America, High Income), where the prevalence of child stunting is very low, nor did we include data from any countries in four of the low- and middle-income GBD regions, specifically: Europe, Eastern; Latin America, Tropical; Oceania; Sub-Saharan Africa, Central.

For the national-level stunting data in the final dataset, moderate stunting ranged from 2.9% (The Former Yugoslav Republic of Macedonia in 2011) to 32.8% (Nepal in 1998), with a mean of 18.6% and a median of 19.5%. Severe stunting ranged from 1.3% (Jamaica in 1999) to 34.6% (India in 1993), with a mean of 14.6% and a median of 13.4%. For the data underlying the income indicator (Equation 1), 82 estimates were based on consumption (i.e., household spending) and 112 on income (i.e., household total income). A total of 29% of observations were matched to the same year as the stunting estimate, an additional 46% within 2 y, and the remaining 25% within 5 y. For the data underlying the food price indicator (Equation 2), 17% of values for the food CPI ($fCPI_{ij}$) and

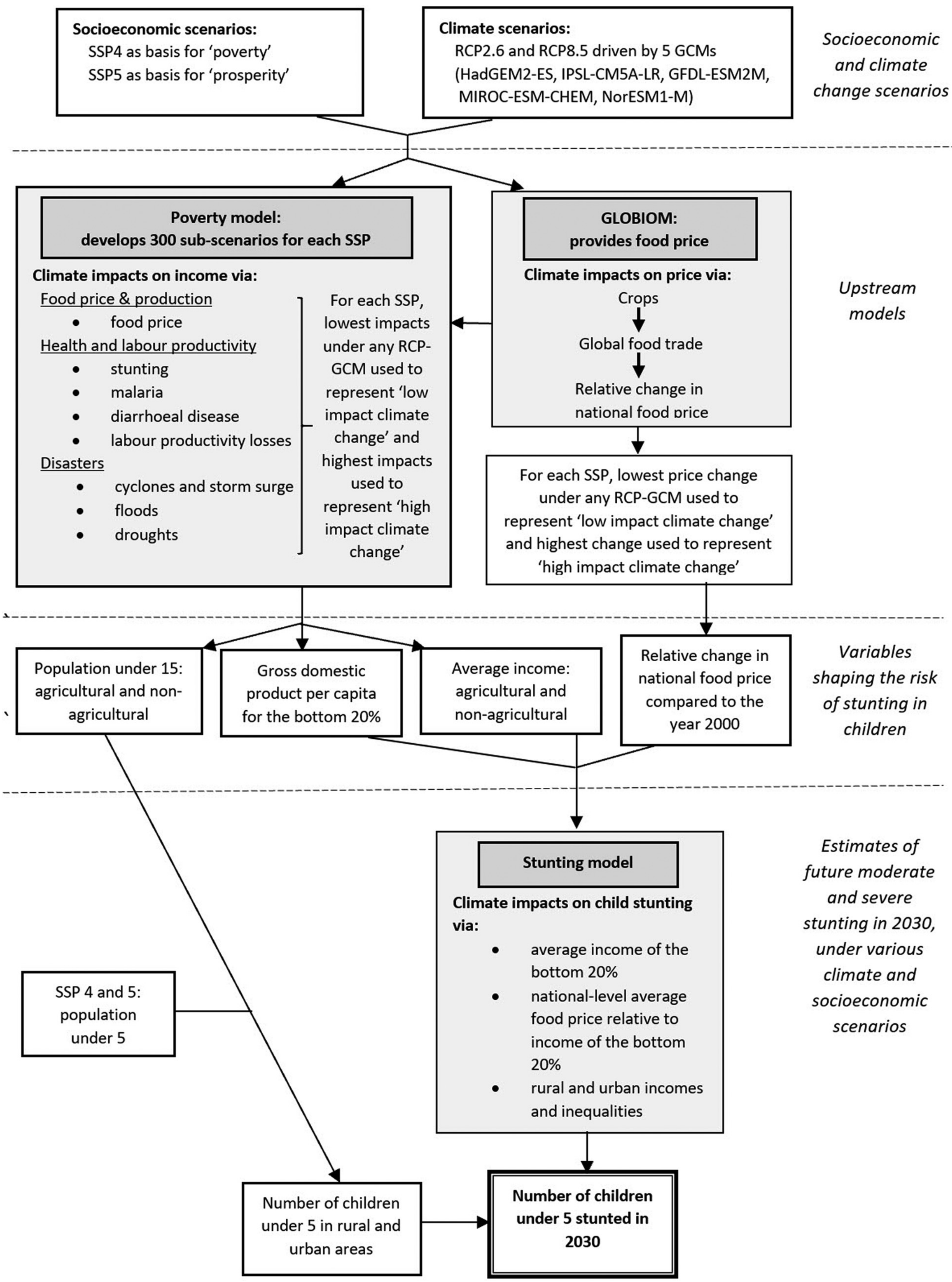


Figure 1. Conceptual diagram of the relations among climate and socioeconomic projection data, upstream models, and the stunting model. Abbreviations: SSP, Shared Socioeconomic Pathways; RCP, Representative Concentration Pathways; GCM, General Circulation Model; GLOBIOM, Global Biosphere Management Model. In the "Upstream models" food price is one of the drivers of the impacts of climate change on income (shown by the link between GLOBIOM and the poverty model), and, stunting is one of the drivers of income loss in the poverty model (due to income losses in adults who were stunted as children 10 to 20 y previously). It is assumed that "agricultural" corresponds to rural populations and "nonagricultural" to urban populations and that the proportions of children <5 y of age in rural and urban areas were the same as the estimated proportions of children <15 y of age in agricultural and nonagricultural families outputted from the poverty model.

Table 1. Estimated parameters for national-level models of moderate and severe stunting (odds ratios and 95% confidence intervals (CI) for fixed parameters; coefficients and standard errors for random variables).

	Moderate		Severe	
Parameters[a]	Null model	Full model	Null model	Full model
Fixed part				
Year	0.986 (0.980, 0.992)	0.99 (0.984, 0.996)	0.962 (0.953, 0.972)	0.97 (0.96, 0.98)
log(GDP per capita of the bottom 20%)		0.912 (0.851, 0.977)		0.6 (0.553, 0.652)
log(food price indicator)		0.814 (0.727, 0.911)		1.229 (1.072, 1.409)
Interaction of GDP and food price terms		1.03 (1.011, 1.05)		0.928 (0.907, 0.949)
Constant	0.193 (0.164, 0.227)	0.346 (0.215, 0.557)	0.109 (0.086, 0.138)	3.192 (1.729, 5.894)
Region:				
Asia, Central		1 (reference)		1 (reference)
Asia, East		0.531 (0.327, 0.862)		0.308 (0.12, 0.795)
Asia, South		1.693 (1.341, 2.138)		2.227 (1.318, 3.762)
Asia, South East		1.325 (1.065, 1.648)		1.29 (0.796, 2.091)
Caribbean		0.357 (0.253, 0.505)		0.183 (0.087, 0.385)
Europe, Central		0.501 (0.382, 0.659)		0.512 (0.298, 0.88)
Latin America, Andean		1.33 (0.981, 1.804)		0.752 (0.374, 1.509)
Latin America, Central		1.057 (0.856, 1.306)		0.6 (0.371, 0.968)
North Africa and Middle East		0.785 (0.571, 1.079)		0.592 (0.294, 1.192)
Sub-Saharan Africa, Eastern		1.569 (1.284, 1.916)		1.605 (1.043, 2.47)
Sub-Saharan Africa, Southern		1.405 (1.075, 1.835)		1.076 (0.598, 1.936)
Sub-Saharan Africa, West		1.093 (0.995, 1.201)		1.147 (1.03, 1.278)
Random part				
Variance in country-specific intercepts	0.332 (0.0699)	0.046 (0.0122)	0.702 (.147)	0.2706 (0.0597)
Variance in country-specific slopes	0.0004 (0.0001)	0.0004 (0.0001)	.0012 (0.0003)	0.0013 (0.0003)
Covariance of intercepts and slopes	0.00853 (0.0024)	0.0016 (0.001)	0.01 (0.0048)	0.0086 (0.0034)

Note: Countries included are Albania, Armenia, Bangladesh, Bolivia, Bosnia & Herzegovina, Burkina Faso, Cambodia, Cameroon, China, Columbia, Cote d'Ivoire, Dominican Republic, Egypt, El Salvador, Ghana, Guatemala, Honduras, India, Indonesia, Jamaica, Kenya, Kyrgyzstan, Lao PDR, Lesotho, Madagascar, Malawi, Mauritania, Mexico, Mongolia, Mozambique, Namibia, Nepal, Nicaragua, Niger, Pakistan, Peru, Romania, Rwanda, Senegal, Sierra Leone, Sri Lanka, Swaziland, Tajikistan, Tanzania, TFYR of Macedonia, Turkey, Uzbekistan, Vietnam, Zambia.

[a]The corresponding symbols used in Equations 4 to 6 are "Year": $\beta^{(N)}_{1k}$, "log(GDP per capita of the bottom 20%)": $\beta^{(N)}_{2k}$, "log(food price indicator)": $\beta^{(N)}_{3k}$, "Interaction of GDP and food price terms": $\beta^{(N)}_{4k}$, "Constant": $\beta^{(N)}_{0k}$, "Region": vector B, "Variance in country-specific intercepts": var($\beta^{(N)}_{0jk}$), "Variance in country-specific slopes": var($\beta^{(N)}_{1jk}$), "Covariance of intercepts and slopes": cov($\beta^{(N)}_{0jk}$, $\beta^{(N)}_{1jk}$).

16% for general CPI ($gCPI_{ij}$) were interpolated or extrapolated, and 5% of estimates for both were from nearest-neighbor countries. Screening for outliers showed that the food CPI (which was set equal to 100 in the year 2000) in Angola was 251 in the year 2001 and 2,618 in the year 2007. This apparent rapid rise to an extreme level (the next-highest estimate in the dataset is 422) appears, if assumed to be correct, to represent an outlier case in the dataset so all observations were dropped. (Note that Angola is not included in the summary data above.)

For full country-year level details of the data described above, see Excel Table S1.

Model Fitting

We first fit national-level models (Equation 4) for moderate and severe stunting, initially as null growth curve models (i.e., with random effects but no predictors other than year) and then as full models (i.e., including all predictors) (Table 1). Null models for both moderate and severe stunting had a good fit and better explained stunting trajectories than equivalent single-level models (i.e., the same models without random effects) (Likelihood ratio tests: $p < 0.0001$). That is, as expected, there are substantial between-country differences in stunting prevalence in the year 2010 as well as in trajectories of stunting over time. Using the random parts of the null models, we estimated 95% coverage intervals (the range over which 95% of country-specific values would be expected to lie) for percent stunted in 2010 (based on $\beta^{(N)}_{0jk}$) and absolute change in percent stunted from 2000 to 2010 (based on $\beta^{(N)}_{1jk}$). This involved conversion between log odds, odds ratios, and predicted probabilities, and using the standard formula for 95% coverage intervals (Rabe-Hesketh and Skrondal 2012) (See Appendix S1 for a full explanation of the calculations). For moderate stunting, predicted prevalence in 2010 across all countries (as mean (fifth centile, 95th centile)) was 16% (6% to 37%). For severe stunting, prevalence in 2010 was predicted to be 10% (2% to 36%). The estimated absolute change in percent stunting over the decade from 2000 to 2010 was −2.0% (−8.8% to 3.3%) for moderate, and −4.0% (−14.1% to 2.3%) for severe stunting (positive numbers indicate stunting increased). Additionally, the covariances for the random intercept and slope [covariance($\beta_{0jk}^{(N)}$, $\beta_{1jk}^{(N)}$); 0.00853 and 0.01 for moderate and severe stunting, respectively] indicate that when the random intercept for stunting in the year 2010 increases, the slope for year also tends to increase (i.e., the rate of decline of stunting decreases). This suggests that, in general, countries with more stunting in 2010 experienced slower rates of decline, and this relationship is stronger for severe stunting than for moderate stunting. (The correlation between the estimated random effects for slope ($u_{1jk}^{(N)}$) and intercept ($u_{0jk}^{(N)}$) is 0.37 for moderate stunting and 0.50 for severe stunting.) In line with this, between-country variance in stunting [calculated as: variance$(\beta_{0jk}^{(N)}) + 2\,[\text{covariance}(\beta_{0jk}^{(N)}, \beta_{1jk}^{(N)}) \times t_{ij}] + \text{variance}(\beta_{1jk}^{(N)}) \times t_{ij}^2$ (Rabe-Hesketh and Skrondal 2012; Steele 2014)] has been increasing with time (i.e., as all variance terms are positive, the value of the previous equation becomes more positive as time increases); that is, although stunting has generally been declining, some countries are being left behind. If it is assumed that the countries included in the analysis represent a random sample of all countries at risk of stunting, the above ranges and patterns may be interpreted as reflecting those seen globally.

Both full models for moderate and severe stunting had better fits than their counterpart null models (Likelihood ratio tests: $p < 0.0001$). After adding the main predictors to the model (i.e., G_{ij}, P_{ij}, $G_{ij} \times P_{ij}$), adding the contextual region variable had little influence of the predictor coefficients but the intercept random variance [var($\beta_{0jk}^{(N)}$)] decreased from 0.2716 to 0.046 (i.e., more than quartered) and from 0.6856 to 0.2706 (i.e., more than halved) in the moderate and severe stunting models, respectively. This suggests unexplained between-country differences tend to cluster by region, with stronger clustering for moderate than severe stunting.

We checked the model for multicollinearity of the main predictors (the income and food-price indicators) as well as year and concluded it was unlikely to influence model predictions. First, when adding predictors to the models, there were no large increases in standard errors, and these remained small (i.e., the 95% confidence intervals of the odds did not cross one) in the final equations (Table 1) (Goldberger 1991). Second, to assess this more formally, we used a two-step approach suggested by Hill and Adkins (2003). In step one, Variance Inflations Factors (VIFs) are used to check for the presence of multicollinearity. A commonly used rule of thumb is that values greater than 10 suggest "serious" multicollinearity. VIFs for the main predictors (excluding interaction terms) were all less than 10 [1.1, 8.7, 8.9, for year, the log of the food-price indicator (P_{ij}), and the log of *GDP20pc* (G_{ij}), respectively]. As may be expected, however, the addition of the interaction terms resulted in large VIFs (1.1, 61.7, 8.9, 54.6, for year, the log of food-price indicator (P_{ij}), the log of *GDP20c* (G_{ij}), and the price–income interaction ($P_{ij} \times G_{ij}$), respectively). In step two, we derived signal-to-noise ratios (log(odds)/SE) for each predictor to assess whether multicollinearity is likely to bias model coefficients. If the ratios are judged to be sufficiently high, multicollinearity is not likely to bias estimates (Hill and Adkins 2003). For instance, a ratio $>|1.96|$ would indicate that the 95% confidence interval would not cross the null (Kirkwood and Sterne 2003). Signal-to-noise ratios were within acceptable levels. For instance, for moderate stunting, these were −2.6, −3.6, and 3.1 for the log of *GDP20pc* (G_{ij}), the log of the food-price indicator (P_{ij}), and their interaction, respectively (Table S2). Third, in situations where multicollinearity is judged to be potentially harmful, parameters for individual coefficients may be biased (making it difficult to separate the effects of individual predictors), whereas predictions made by the model as a whole tend to remain reliable (Goldberger 1991; Hill and Adkins 2003). In our results, we do not attempt to separate the effects of income on stunting from those of price; in fact, we argue they are inseparable. All our results are based on predictions made by the model as a whole. In sum, although multicollinearity appears to be present due to the inclusion of the interaction term, it is unlikely to affect the predictions made by the model.

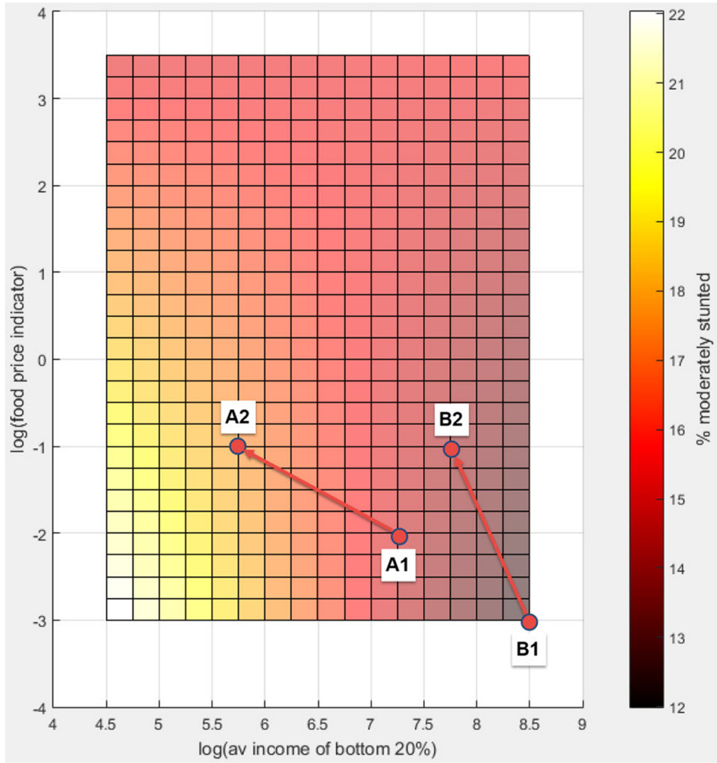
To illustrate the change in stunting when income and food price change together, we plot estimated percent stunted for average countries (i.e., random effects equal 0) in the reference region, with year held constant at 2010, over a slightly larger range of GDP20pc and the food-price indicator seen in the historical data (Figure 2). Both moderate and severe stunting are at their predicted maximums (~22% and 32%, respectively) when average income and food price relative to income are at their lowest levels. This corresponds to an average income level well below the \$1.25 per day poverty line. At this income, stunting declines as relative food prices rise. However, at this income, even at the highest relative prices in the plots, moderate and severe stunting remain high (~15% and 20% respectively). The lowest level of moderate stunting (~12%) is seen when incomes are highest (~10 times the poverty line) and relative prices are lowest. In contrast, the lowest level of severe stunting (~1%) is seen when incomes are highest but relative prices are highest; this is also when total stunting (moderate plus severe) is at its lowest.

The vectors in the plots in Figure 2 give a hypothetical example of the possible impacts of climate change on stunting if incomes were to fall and prices were to rise. In the movement from A1 to A2, as income falls and the price indicators rises, moderate stunting increases from 15% to 18% and severe stunting increases from 13% to 21%; total stunting rises by 11%. In contrast, at a higher income, when going from B1 to B2, moderate stunting increases from 12% to 14%, but severe stunting falls from 13% to 8%; total stunting decreases by 4%. This shows there is an important interaction between these two routes from climate to stunting.

Due to the limited availability of historical data we were unable to validate the model using independent data. However, based on the data used to fit the models, the correlation between observed and predicted stunting was high ($r = 0.98$, for both models) and within-countries trajectories appeared to be well reproduced. Model diagnostics also suggested the models fit well (Figures S1 and S2).

We next fit the within-country models for distributing national-level stunting between rural and urban areas (Table 2). We fit models with the full set of predictors of interest, and then used backwards stepwise regression to remove nonsignificant predictors (i.e., with 95% confidence intervals that included the null). Again, no independent data were available to validate the models, but correlations between observed and predicted stunting were consistently high (between 0.97 and 0.99) (Figure S3). Likelihood ratio tests suggest the multilevel models have a better fit than equivalent single level models. However, model residuals for the random effects for all models (moderate and severe stunting, rural and urban) show that the 95% confidence intervals are wide and frequently include zero. Further, residual plots for predicted stunting show that the pattern of errors differs by level of stunting and tend to be greatest at lower prevalences (Figures S4 and S5). This suggests that national-level stunting projections made using the equations, particularly when prevalence is low, should be interpreted cautiously. We assessed the model for multicollinearity using the same procedure we employed for Equation 5 and again found it was not likely to affect model predictions. (We note that standard errors were wide for the inequalities predictor in the rural severe

A



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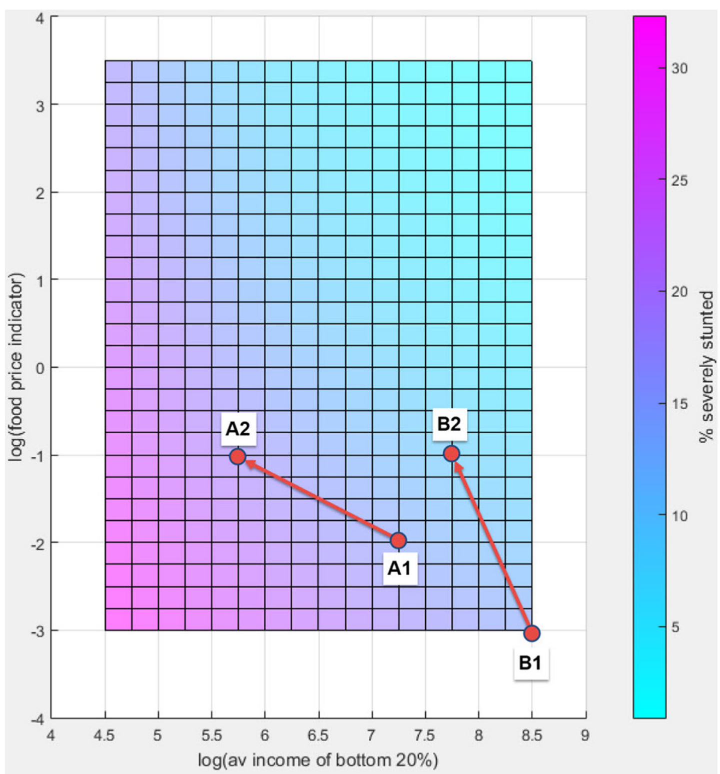

Figure 2. Plots for the full national-level (I) moderate and (II) severe stunting models showing the predicted prevalence of stunting as a function of log of the average income of the bottom 20% of the income distribution and the log of the food-price indicator, in average countries (i.e., random effects equal 0) in the reference region in the year 2010. Note that the z-axis scale differs for the moderate and severe stunting plots. Ranges of the average income and food-price indicator axes are slightly larger than those in the historical data. Note that because the food-price indicator represents price relative to income, it is partly a function of income; that is, the x- and y-axes are not independent. The vectors show examples of how the combined effects of a fall in income and a rise in price relative to income (i.e., moving from A1 to A2, and, from B1 to B2) can lead to either an increase or decrease in stunting. See the model fitting subsection of the results section for details.

Table 2. Estimated parameters for the area-level models of moderate and severe stunting (odds ratios an 95% CI for fixed parameters; coefficients and standard error for random variables).

Parameters[a]	Rural		Urban	
	Moderate	Severe	Moderate	Severe
Fixed part:				
National-level stunting	1.026	1.069	1.071	1.044
	(1.014, 1.039)	(1.051, 1.087)	(1.062, 1.08)	(1.017, 1.073)
log(income indicator)	0.744	0.873	0.861	0.878
	(0.682, 0.813)	(0.786, 0.97)	(0.776, 0.954)	(0.77, 1.001)
Interaction of national-level stunting and income indicator terms	1.015	1.011		1.017
	(1.011, 1.019)	(1.007, 1.015)		(1.01, 1.025)
Rural-urban inequalities	0.9	0.992	0.865	
	(0.845, 0.959)	(0.845, 1.164)	(0.68, 1.101)	
Interaction of income indicator and inequalities terms		0.934	1.131	
		(0.861, 1.013)	(1.007, 1.27)	
Constant	0.179	0.09	0.066	0.041
	(0.136, 0.237)	(0.07, 0.116)	(0.049, 0.089)	(0.026, 0.066)
Random part:				
Variance in intercepts	0.0803	0.152	0.2722	0.3936
	(0.0295)	(0.0389)	(0.0843)	(0.094)
Variance in slopes	0.0001	0.0015	0.0005	0.0014
	(0.0001)	(0.0005)	(0.0002)	(0.0004)
Covariance of intercepts and slopes	−0.003	−0.0134	−0.0114	−0.0219
	(0.0012)	(0.0043)	(0.0038)	(0.0057)

[a]The corresponding symbols used in Equation 8 to 10 are "National-level stunting": $\gamma^{(A)}_{1k}$, "log(income indicator)": $\gamma^{(A)}_{2k}$. "Interaction of national-level stunting and income indicator terms": $\gamma^{(A)}_{3k}$, "Rural-urban inequalities": $\gamma^{(A)}_{4k}$, "Interaction of income indicator and inequalities terms": $\gamma^{(A)}_{5k}$, "Constant": $\gamma^{(A)}_{0k}$, "Variance in intercepts": var($\gamma^{(A)}_{0jk}$), "Variance in slopes": var($\gamma^{(A)}_{1jk}$), "Covariance of intercepts and slopes": cov($\gamma^{(A)}_{0jk}$, $\gamma^{(A)}_{1jk}$).

and urban moderate models; however, these were included in the model as the standard errors for their interaction terms were small.) (Table S3).

Estimates of Future Stunting

Projection data to drive the stunting model were available for 44 of the 49 countries used to fit the model. Figure 3 shows the aggregated estimates of the number of children <5 y of age stunted in the study countries in 2030 under the six scenarios (as means and 5th and 95th centiles across the 300 socioeconomic subscenarios). The plot suggests, first, within any socioeconomic scenario, the impact of climate change in 2030 is relatively small (although not negligible, as discussed ahead). This finding is consistent with previous work (e.g., Lloyd et al. 2014). Second, projected differences between the two socioeconomic scenarios are large, with mean estimates of 110 million stunted children in the poverty scenario and 83 million in the prosperity scenario. Third, however, within-socioeconomic scenario uncertainty in the magnitude of the estimates is large: Estimates of total stunting range from 80 to 140 million in the poverty scenario, and from 57 to 108 million in the prosperity scenario. That is, although there is generally less stunting in the prosperity scenario, allowing for uncertainties shows there is significant across-socioeconomic scenario overlap.

Table 3 shows aggregated climate change–attributable stunting by scenario. These indicate, first, in all scenarios, that there is more stunting in 2030 in futures with climate change than without. Across the scenarios, mean climate-change attributable stunting is estimated to be between 570,000 (prosperity/low climate change) and 1 million (poverty/high climate change). Second, in the poverty scenarios, a large proportion of climate change–attributable stunting is severe, whereas under the prosperity scenarios, the moderate/severe balance tends to be more even. For example, under poverty/high climate change, the mean estimate of the ratio of moderate to severe climate change–attributable stunting is 0.39, whereas under prosperity/high climate change it is 0.95. Third, in both socioeconomic scenarios, as climate change increases, rural areas bear a greater proportion of the burden than urban areas, but less so in the prosperity than in the poverty scenarios. For the mean estimates, the ratio of climate change–attributable number of people stunted in rural versus urban areas rises from 1.06 to 1.22 under poverty, and from 1.05 to 1.12 under prosperity. Fourth, within-socioeconomic scenario uncertainty matters considerably more under poverty/high climate change than in other scenarios, with a difference of 550,000 stunted between the 5th and 95th centiles, mostly due to differences in severe stunting. In general, this within-socioeconomic scenario uncertainty in how macro conditions specified by the SSPs are met matters more for severe than moderate stunting in all scenarios.

Finally, aggregate results conceal underlying patterns in country-level climate change–attributable stunting. We developed a typology based on whether high climate change is expected to increase or decrease the mean estimates of country-level total stunting relative to low climate change in the poverty and prosperity scenarios (Table 4). The typology is intended to indicate general tendencies in stunting patterns in groups of countries sharing similar characteristics rather than rigidly separate countries and expectations regarding stunting based on statistical criteria. Type I includes 64% of countries (28 of 44) in which high climate change is expected to bring more stunting than low climate change in both socioeconomic scenarios. In 36% of countries, however, there was less climate change–attributable stunting under the high than under the low climate change scenario. In type II countries (11), this occurred in both the poverty and prosperity scenarios; in type III countries (5), this was only in the poverty scenario; and in type IV countries (2), this was only in the prosperity scenario.

Table 4 shows the patterns of incomes and food prices as countries move from low to high climate change, by country type. In type I countries, under low climate change, average incomes of the bottom 20% are relatively low (2 to 2.5 times the poverty line) and the food-price indicator (which indicates food prices relative to income) is relatively high. Under both poverty and prosperity scenarios, high climate change reduces incomes by a relative amount that is fairly typical across all study countries ($\sim 4\%$) but increases in the food-price indicator are relatively high. The combination of low incomes and large increases in price results in increased stunting as climate change increases under both socioeconomic scenarios. In type II countries under low climate change, incomes are relatively high (4 to 5 times the poverty line), and the food-price indicator is

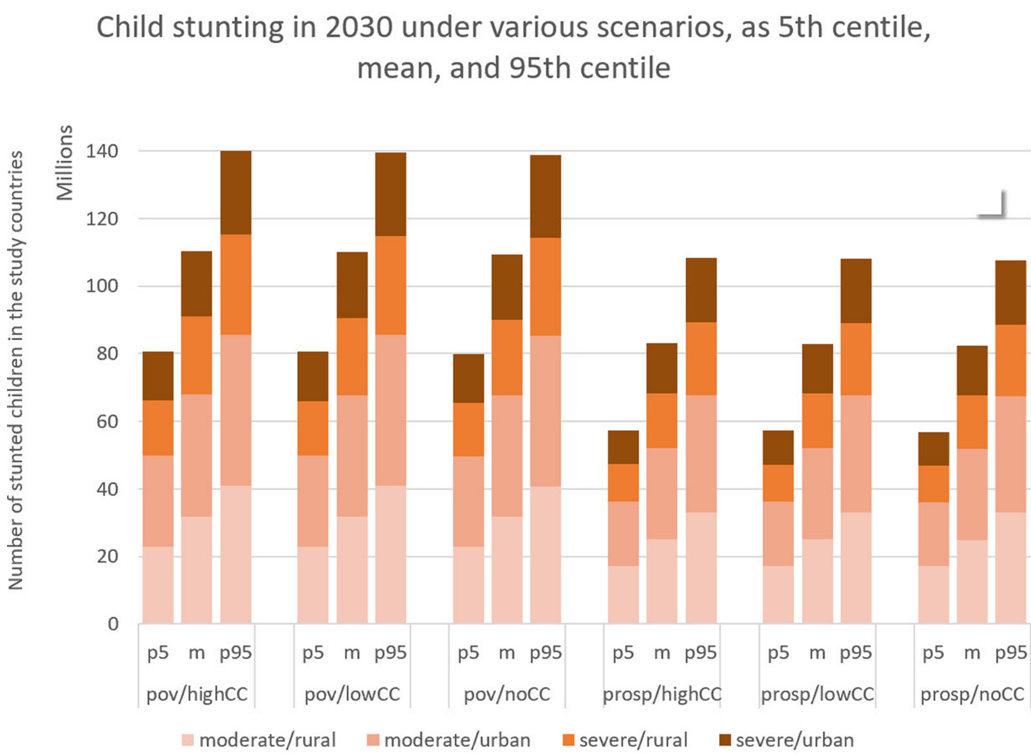

Figure 3. Projected numbers of stunted children (age <5 years) in the 49 study countries in 2030 under combined socioeconomic (poverty or prosperity) and climate change scenarios (high climate change or low climate change), according to the degree of stunting (moderate or severe) and rural or urban area. Values shown for each socioeconomic/climate change combination represent the distribution of estimates for 300 subscenarios for poverty and property projections, respectively. Abbreviations: p5, 5th percentile; m, mean; p95, 95th percentile; pov, poverty scenario; prosp, prosperity scenario; CC, climate change.

relatively low. High climate change brings typical (relative) drops in incomes, but increases in the food-price indicator are relatively small. This combination of higher average incomes and rising relative prices leads to decreases in stunting as climate change increases under both socioeconomic scenarios.

In type III countries under low climate change, incomes (3 times the poverty line) and relative prices are at an intermediate level (Table 4). High climate change brings typical relative decreases in income in both socioeconomic scenarios. In the poverty scenario, the rise in relative price is relatively high, and—at these intermediate incomes—the combination of income loss and high price increases reduces overall stunting as climate change increases. In the prosperity scenarios, the rise in relative price is relatively small and does not appear to offset the loss of income, resulting in an increase in stunting as climate change increases. Thus, type III countries appear to be at incomes where the overall effects of increases in relative food prices tend to be either harmful or beneficial.

Table 3. Estimated numbers of children (means, 5th and 95th percentiles) with climate change–attributable stunting in 2030 according to socioeconomic and climate change scenarios in the 49 study countries.

	Stunting Severity			Rural vs. Urban Areas			
Scenario	Moderate	Severe	Moderate: Severe[a]	Rural	Urban	Rural: Urban[b]	Total stunted
Poverty / high climate change							
5th centile	269,800	489,100	0.55	409,700	349,200	1.17	758,900
Mean	288,400	736,500	0.39	563,300	461,700	1.22	1,025,000
95th centile	323,200	981,300	0.33	773,400	531,100	1.46	1,304,600
Poverty / low climate change							
5th centile	181,600	432,100	0.42	328,900	284,700	1.16	613,600
Mean	199,200	569,300	0.35	396,100	372,400	1.06	768,500
95th centile	225,000	650,000	0.35	468,400	406,600	1.15	875,000
Prosperity / high climate change							
5th centile	306,100	246,700	1.24	277,700	275,000	1.01	552,800
Mean	348,400	366,700	0.95	377,700	337,400	1.12	715,100
95th centile	385,900	493,500	0.78	490,600	388,800	1.26	879,500
Prosperity / low climate change							
5th centile	207,000	256,100	0.81	232,100	231,000	1.00	463,100
Mean	222,300	347,600	0.64	291,800	278,100	1.05	569,900
95th centile	231,400	395,800	0.58	330,200	297,100	1.11	627,200

Note: Estimated numbers of children with climate change–attributable stunting are calculated for each combined scenarios as the number with stunting under high or low climate change vs. no climate change with the socioeconomic scenario (poverty or prosperity) held constant. Study countries are listed below Table 1. Values for the 5th and 95th percentiles represent distributions over the 300 subscenarios for each socioeconomic scenario (i.e., poverty or prosperity).
[a]Ratio of the projected numbers of children with moderate vs. severe stunting due to climate change.
[b]Ratio of the projected numbers of children with stunting due to climate change (regardless of severity) in rural vs. urban areas.

Table 4. Projected average income of the bottom 20%, deflated food-price index, and food-price indicator for countries grouped by the pattern of the estimated impact of high vs. low climate change on stunting under socioeconomic scenarios of poverty and prosperity.

	Low climate change			High climate change			Relative difference between high vs. low climate change		
Country type	GDP20pc mean (range)	Deflated fCPI mean (range)	log(Food price indicator) mean (range)	GDP20pc mean (range)	Deflated fCPI mean (range)	log(Food price indicator) mean (range)	GDP20pc	Deflated fCPI	log(Food price indicator)
Type I[a]									
Poverty	869 (161 to 2157)	116 (91 to 171)	0.2 (−1.86 to 2.25)	832 (149 to 2094)	122 (94 to 182)	0.3 (−1.82 to 2.36)	−4%	5%	50%
Prosperity	1142 (255 to 2867)	105 (90 to 137)	−0.24 (−1.95 to 1.69)	1101 (243 to 2799)	108 (95 to 139)	−0.17 (−1.91 to 1.64)	−4%	3%	29%
Type II[b]									
Poverty	1839 (244 to 4957)	111 (96 to 129)	−0.42 (−2.18 to 1.41)	1764 (226 to 4792)	119 (98 to 149)	−0.31 (−2.12 to 1.67)	−4%	7%	26%
Prosperity	2174 (481 to 5327)	104 (96 to 117)	−0.79 (−2.24 to 0.64)	2082 (459 to 5065)	110 (99 to 125)	−0.69 (−2.17 to 0.67)	−4%	6%	13%
Type III[c]									
Poverty	1262 (380 to 1938)	102 (88 to 120)	−0.37 (−1.92 to 1.06)	1211 (364 to 1867)	110 (93 to 135)	−0.25 (−1.83 to 1.22)	−4%	8%	32%
Prosperity	1603 (697 to 2207)	97 (90 to 106)	−0.76 (−2.07 to 0.38)	1531 (676 to 2101)	102 (94 to 113)	−0.68 (−2.00 to 0.44)	−4%	5%	11%
Type IV[d]									
Poverty	703 (601 to 805)	123 (118 to 128)	0.09 (−0.58 to 0.75)	649 (556 to 742)	134 (131 to 138)	0.25 (−0.42 to 0.93)	−8%	9%	178%
Prosperity	1045 (916 to 1174)	108 (107 to 109)	−0.43 (−1.12 to 0.26)	999 (878 to 1119)	115 (113 to 117)	−0.32 (−1.01 to 0.27)	−4%	6%	26%

Note: *GDPpc20*: per capita Gross Domestic Product of the bottom 20% in PPP 2005 (~$460 is on the World Bank poverty line of $1.25 per day); Deflated *fCPI* = national food consumer price index/national general consumer price index, an indication of the difference in within-country average food prices for 2030 relative to the year 2000 (i.e., it equals 1 in the year 2000; a value of 1.1, for example, indicates a 10% rise in price); log(Food price indicator): mean-centered natural log of the food price indicator ($price_{ij}$) (Equation 3), higher values indicate that food is less affordable for the poorest part of the population.

[a]Type I countries: Stunting increases more with high climate change than low climate change under both poverty and prosperity scenarios (Bangladesh, Bolivia, Cambodia, Cameroon, Cote d'Ivoire, Dominican Republic, El Salvador, Ghana, Honduras, India, Jamaica, Kenya, Madagascar, Malawi, Mexico, Mongolia, Mozambique, Nicaragua, Pakistan, Peru, Romania, Rwanda, Sierra Leone, Sri Lanka, Swaziland, Tanzania, Vietnam, Zambia).

[b]Type II countries: Stunting increases more with low climate change than high climate change under both poverty and prosperity scenarios (Albania, Bosnia and Herzegovina, Burkina Faso, Egypt, Guatemala, Indonesia, Lao PDR, Niger, TFYR of Macedonia).

[c]Type III countries: Stunting increases more with low climate change than high climate change under poverty scenarios, but not under prosperity scenarios (China, Kyrgyzstan, Nepal, Senegal, Tajikistan).

[d]Type IV countries: Stunting increases more with low climate change than high climate change under prosperity scenarios, but not under poverty scenarios (Mauritania, Namibia).

There are just two type IV countries, so interpretation should be cautious (Table 4). Under low climate change, these countries have the lowest average income (1.5 to 2 times the poverty line) and high relative prices. In the poverty scenario, as climate change increases, both the average decrease in incomes and increase in relative prices are at their highest. Together, these factors increase stunting. In the prosperity scenario, climate change brings typical reductions in incomes and a much lower increase in price; in this case, stunting is reduced.

In sum, this research suggests that when average incomes of the poorest are low and food prices are relatively high, losses of income and further increases in price tend to increase stunting at the national level. When incomes are higher and prices relative to income are relatively low (note: this does not suggest absolute food prices are low), losses of income may be offset by price increases, and overall stunting tends to decrease. This is presumably due to gains made by low-income food producers and perhaps by nonskilled wage earners. At intermediate incomes (i.e., around 3 times the poverty line) and relative prices, the overall impact of higher relative prices tends to change from increasing stunting to decreasing stunting as incomes of poorest rise further.

Discussion

To our knowledge, we have developed the first global-level model for estimating future climate change–attributable stunting in which climate change acts through two interacting socioeconomic drivers: incomes of the bottom 20% of a population and food price relative to incomes. Previous global-level undernutrition models have focused on changed food production and calorie availability in fixed socioeconomic conditions (e.g., Lloyd et al. 2011; Nelson et al. 2010). Such models provide insights into a key influence on future undernutrition while placing other influences in the background. Previous work has also suggested that socioeconomic conditions play a major role in shaping future undernutrition (e.g., Lloyd et al. 2014; Schmidhuber and Tubiello 2007): our model attempts to offer new insights by focusing on two of these conditions while placing other influences in the background. Incomes of the poorest groups and food prices are likely to play a central role in shaping future undernutrition (Mazoyer and Roudart 2006; Pogge 2010). In rural areas, smallholder farms (i.e., farms <2 hectares) are "home to about two billion people, including half the world's undernourished people and the majority of people living in absolute poverty" (IFAD 2011). The urban poor are also at high risk of undernutrition and to the impacts of price and financial shocks (Ruel et al. 2010).

Our null model suggests that the historical rate of decline in stunting has generally been slow, even during the period in which hunger was a focus of the Millennium Development Goals (United Nations 2017). The average absolute annual decline over the period 2000 to 2010 was estimated to be 0.2% for moderate stunting and 0.4% for severe stunting, although larger declines were seen in some countries (5th centiles of 0.88% for moderate and 1.41% for severe). This estimate is similar to previous estimates (Rieff 2016). Additionally, between-country differences widened as the biggest improvements tended to be in countries with lower levels of stunting. This widening suggests child stunting is likely to remain a major contributor to the global burden of disease in the coming decades, even without the additional threats posed by climate change. In the full model, when incomes and relative food price were added, we found that their interaction was critical: In some instances, a decline in income and increase in relative prices increased stunting, whereas in others they reduced it (Figure 2).

Adding regions to the model led to large reductions in unexplained between-country differences, with a much larger reduction in the moderate than in the severe stunting model. This addition suggests that, although moderate and severe stunting are distinguished using a quantitative scale, there may be qualitative differences in their causes: Moderate stunting may tend to be influenced more by regional structural factors operating both within and between countries, whereas severe stunting may tend to be more influenced by within-country processes (for example, civil conflict). Given that severe stunting brings considerably worse morbidity and mortality risks than moderate stunting does (Black et al. 2008; Victora et al. 2008), further investigation of this aspect in future work may provide useful insights.

Consistent with previous work (Lloyd et al. 2014), our projections suggest that climate change will have a relatively small—but not insignificant—impact on stunting in 2030, whereas estimated between-socioeconomic scenario differences are large. Mean estimates of child stunting in the study countries in the poverty and prosperity scenarios are 110 million and 83 million, respectively (Figure 3). Of note, the wide variation in these estimates across the 300 subscenarios for each SSP (which differed by demographic characteristics, economic policies, the distribution and participation of labor, productivity growth by sector, and labor skill levels), suggests that the particular mechanisms that produce poverty or prosperity futures could have substantial influences on patterns of health.

Our projections suggest that, in aggregate, stunting will increase as climate change increases, with larger impacts under the poverty scenario: We estimate that >1 million additional children would be stunted under poverty/high climate change, in comparison with 570,00 under prosperity/low climate change (Table 3). Further, our estimates suggests that severe stunting would account for a greater proportion of climate change–attributable stunting under the poverty scenarios than in the prosperity scenarios, and that the potential impact of climate change on stunting would be greater in rural areas in comparison with urban areas under both socioeconomic scenarios (Table 3). Previous analyses have suggested that the impact of rising food prices on poverty is, in general, greater in urban areas than in rural areas (Hertel et al. 2010; Ivanic and Martin 2008). These results, however, are not directly comparable to our findings. First, the causal pathways and outcome differ: Our model looks at the combined impacts of changes in food prices and incomes of the poorest populations on child stunting, rather than how food prices may affect the number of people below a fixed poverty line. Second, the poverty model driving the stunting model assesses how climate change may affect incomes via multiple routes rather than through food prices alone (Figure 1). Third, our estimates are based on scenario-specific projections of future socioeconomic conditions, whereas Hertel et al. (2010) hold future socioeconomic conditions constant at present level and Ivanic and Martin (2008) analyze historical data. Although this different approach may explain the differences in the results, below we briefly discuss further differences in the modeling approaches and how the stunting model may be improved by drawing on this food price–poverty literature.

We developed a typology based on country-level changes in stunting in response to increasing climate change (Table 4). In type I countries, incomes of the poorest are relatively low and relative prices tend to be high; in this situation, our projections suggest that increasing climate change is likely to increase stunting. In type II countries, incomes are higher and relative prices are lower; there, increasing climate change is likely to decrease stunting. Type III countries have intermediate incomes and relative food prices, and in these cases, increasing climate change might increase or decrease stunting. That is, type III countries appear to be at income levels where they may transition to type I countries if incomes of the poorest fall, or to type II countries if incomes of the poorest rise.

These patterns suggest that the impact of climate change will be an increase in aggregate country-level stunting for countries in which average incomes of the poorest are low and food is generally less affordable, even though rising food prices may benefit some population subgroups. However, when incomes of the poorest are higher, sustained higher food prices (relative to incomes) tend to lower country-level stunting (although some groups may be harmed). This suggests that it is not continually falling food prices that will eliminate undernutrition (see also: Hertel 2016); rather, food prices that provide a decent income to farmers alongside high levels of employment with wages that adequately cover the costs of living is required (among other things) (Holt-Giménez and Patel 2009; Mazoyer and Roudart 2006; Weis 2007). In sum, the reduction and then elimination of poverty and inequality are required. If these conditions were generally met, our estimates suggest that—at least out to the 2030s—the potential harms of climate change on stunting via the pathways considered would be significantly reduced. We stress that this does not suggest that climate change may improve population health if incomes increase. Rather, it suggests that higher incomes combined with "fair" food prices may reduce stunting and vulnerability to the impacts of climate change.

Our model has a number of limitations. The first relates to data availability. For the historical stunting data, we found 49 countries with at least three observations covering rural and urban areas and split as moderate and severe since 1990 (WHO 2017) (Table S1). We used random-effects modeling which, by assuming these countries represent a random sample of all countries at risk of stunting, allows us to make general statements about all affected countries. However, although the data covered many countries at greatest risk of stunting (including 18 in Sub-Saharan Africa and 9 in South and Southeast Asia), and countries with a wide range of stunting (2.9% to 32.8% for moderate stunting; 1.3% to 34.6% for severe stunting), we cannot rule out the potential for bias. Further, we included data for China, a country whose size and particular patterns of development can have a large influence on global-level trends of various factors. For instance, an estimated one third of global farms are in China (Lowder et al. 2016), and the inclusion or exclusion of China from global trends in poverty reduction can reverse trajectories (Pogge 2010). Given this, we assessed the potential influence of China on our model by excluding it and found only very small changes in the parameters for the main predictors. Despite these limitations, model diagnostics for the national-level model show the random effects and residuals follow the expected distributions (Figure S2), suggesting that general inferences may be both reasonable and useful.

For the predictor variables, finding data that matched the available projections for incomes and prices, and that were comparable across countries and over time, was difficult. Consequently, it was necessary to develop indicators using available data. However, as the income indicator was split by area but the price indicator was at the national level, we took a two stage-approach to modeling, first modeling the national level longitudinally and then modeling stunting by area (i.e., rural and urban). Of note, we did not model area as a distinct level as it not a random sample of area categories; rather it is a dichotomous fixed category within a country.

Second, we modeled moderate and severe stunting using independent equations. This separation is unable to capture the dynamics of changes in nutritional status and within-country migration. For example, a severely stunted child in a rural area may leave this category by becoming moderately stunted or well nourished, or by dying; additionally, the child's family may migrate to an urban area, thus reducing rural stunting but increasing urban stunting. Given the available data, it was not possible to include these dynamics in our model.

Third, again due to limited data availability, we were not able to formally validate the model. The national-level equations appear to have a reasonably good fit and show strong correlations between observed and predicted stunting; however, the diagnostics for the area-level models show the fit is not as good (Figures S3 and S4). This was further evident when rescaling rural and urban moderate and severe stunting projections so they summed to the national-level projections. For the poverty/high climate change scenarios, for example, the ratio of estimated rural and urban moderate stunting to estimated national-level stunting had a median of 1.02, meaning the magnitude of rescaling was small. The 95th centile was 1.15, requiring modest rescaling. However, the 5th centile was 0.63, which necessitated significant rescaling. For severe stunting, the ratio had a median of 0.95, 5th centile of 0.28, and 95th centile of 1.35. That is, significant rescaling was often required. Thus, the projected patterns of rural and urban stunting should be interpreted with some caution. This does not, however, affect the national-level projections, which are the basis of our core findings.

Fourth, due to the limits of the projection data, our stunting estimates do not go beyond 2030. Further into the future, it would be expected that increasing climate change would have greater impacts on poverty and food prices due to, for example, increased crop productivity losses, labor losses, infectious diseases, and disasters (Smith et al. 2014). Our findings suggest that moderate price increases in the context of reasonable incomes may bring aggregate reductions in stunting. However, increased climate change beyond 2030 may drive incomes of the poorest to low levels and food prices steeply upwards, in turn bringing increased child stunting. This possibility suggests the importance of near-term changes that increase incomes and protect the livelihoods of the poorest (in both rural and urban areas), alongside actions to improve the resilience of food crops to climate change.

A related issue is that our model assumes that an adequate food supply is available. This is arguably reasonable for the 2030s as estimates suggest there is currently sufficient food to adequately feed about 1.5 times the current population (Moore Lappé 2013), meaning we have historically moved from "hunger amidst scarcity" to "hunger amidst abundance" (Araghi 2000). However, further into the future, increasing climate change and growing populations may make food production an increasingly important cause of stunting (e.g., Lloyd et al. 2011; Nelson et al. 2010). If our model were to be used to make projections beyond 2030, it may need to be modified to include food availability (and perhaps food quality).

Fifth, our model is driven by income projections that consider shifts between general labor sectors (Hallegatte and Rozenberg 2017), represented as agricultural and nonagricultural incomes (taken to represent rural and urban incomes, respectively) in our model. However, previous studies looking at how food prices affect poverty have shown the importance of more detailed patterns of income sources, as well as ratios of net buyers to net consumers of food, in shaping the aggregate impacts of food prices on poverty (Hertel et al. 2010; Hertel 2016; Ivanic and Martin 2008). These impacts of food prices on poverty would be expected to influence patterns of undernutrition. Future undernutrition models could attempt to represent this explicitly, perhaps by closer integration with the poverty model. However, obtaining the required historical and projection data from a large number of countries is likely to be difficult. (For example, Hertel et al. (2010) included 15 countries and Ivanic and Martin (2008) included 9 countries.)

Sixth, despite the complexity of the causation of undernutrition, we include explicit predictors related only to incomes and food prices in our model. However, as our aim is to represent the total effects of incomes and food prices on stunting, we follow the general logic outlined by Biggs et al. (2010). Although other factors, such as education and access to water and sanitation, affect stunting, they are also likely to be strongly influenced by incomes. This influence means that: *a*) if such factors were added to a regression model, they would absorb some of the effects of income on stunting; and *b*) such factors are likely to be highly collinear with income and may cause model fitting problems. Thus, by including just income and price, we attempt to capture their full effects regardless of the specific causal pathway from the predictors to the outcomes.

Conclusions

Previous global-level models have shown that climate change–attributable changes in food production and distribution may affect undernutrition and have highlighted the importance of socioeconomic conditions. Our model shifts the focus to how climate change may affect two key socioeconomic drivers—incomes of the poorest and food price—and assesses how their interaction may influence stunting in the 2030s. The patterns in our aggregate results suggest that stunting will increase as climate change increases, with a greater proportion of the burden falling on rural areas, and larger increases in severe stunting in comparison with moderate stunting in the poverty scenarios.

The disaggregated country-level patterns offer a different insight: In situations when incomes of the poorest are relatively high, modest and sustained increases in food prices relative to incomes may reduce overall stunting. This finding suggests, along with ensuring that adequate quantities of food are produced in the future, a key means of reducing the impacts of climate change on stunting may be—rather than seeking ever-lower food prices—to ensure food prices are high enough to sustain farming households and that decent work with adequate incomes is available for all. Views on how this, particularly the former, might be best achieved are contested (e.g., FAO 2017a; McIntyre et al. 2009; Patel 2009), but the results of our model suggest that agricultural futures that protect health must consider not just availability, accessibility (e.g., Hasegawa et al. 2016; Lloyd et al. 2011), and quality of food (Myers et al. 2015), but also the incomes generated by those producing the food. This aspect is perhaps particularly urgent as, counterintuitively, food producers currently comprise around half of the world's undernourished people (IFAD 2011).

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Contribution of Research Paper 3 and new questions raised

The model developed for Research Paper 3 adopted a novel perspective on the climate-nutrition relation. Previously, climate-nutrition modelling had focused on how climate change impacts on crop productivity may impact on food quantity and quality, and how this in turn may impact on nutrition (see Chapter 2). The model in this chapter shifted the perspective to ask how climate change may affect child stunting through its impacts on two interacting socioeconomic drivers: incomes of the poorest 20% of a population and food price. Additionally, the model split the impact estimates into rural and urban areas.

In aggregate, the results showed that futures in which incomes of the poorest remain low and in which climate change is allowed to worsen would have significantly more child stunting in the near-term (i.e. in 2030) than futures in which incomes of the poorest rise and climate change is partly mitigated. Additionally, in the former situation, the degree of stunting would tend to be worse (i.e. there would be more severe stunting), and a greater proportion of the burden would fall on rural areas.

Arguably, the patterns in the results based on a typology of countries (see Table 4 in Research Paper 3) were the most interesting findings. These showed that when incomes of the poorest were low and prices (relative to income) rose fairly abruptly, stunting tended to increase (as would be expected). In contrast, when incomes of the poorest were higher, gradual rises in relative price tended to reduce stunting. Drawing on theory and previous empirical work, we argued that the underlying mechanism may be that sustained higher prices raised both farm incomes and rural wages, thus reducing the risk of both undernutrition and the risk that climate change posed to nutritional status.

When formulating our conclusions, we partly drew on some relevant papers from the agricultural economics literature (Hertel, 2016, Hertel et al., 2010, Ivanic and Martin, 2008). On the one hand, our work reached the same general conclusion as this literature; on the other, our framing of the research question – and thus our methodological approach - differed.

In terms of the general conclusions, in contrast to the tendency in the literature to assume that higher food prices lead to lower food security (Hertel, 2016), higher food prices are likely to have mixed effects and may result in improved nutrition in many groups. Our work suggested that in the context of incomes that aren't too low (i.e. above the poverty line, but still poor), slowly rising food prices appear to reduce stunting and vulnerability to climate change. In line with this, Hertel (2016), for instance, cites literature (i) from Bangladesh that found that rural wage increases associated with sustained raised food prices appeared to increase the well-being in many households (Ravallion, 1990, World Bank, 2013), and, a multi-country statistical study that found higher food prices tended to reduce poverty, most likely due to their influence on the prices of agricultural supplies and rural wages (Headey, 2014).

At the same time, however, the framing of the research question differed. In our model we asked, *how does a given combination of food price and average income amongst the poorest, at a given time and in a given country, impact on child stunting?* Incomes were influenced by a range of processes other than food price (including health care costs, labour productivity losses, and disasters), and populations were split dichotomously into rural and urban. In contrast, Hertel et al. (2010) and Ivanic and Martin (2008), for instance, asked, *how do changes in food prices impact on poverty in households given their sources of income?* In this framing, incomes (and thus poverty rates) are influenced only by changes in food price: this is a simpler pathway than that considered in our model. However, households - specifically their means of income generation – are represented in a more sophisticated way than in our work, providing a better understanding of the pattern of impacts. Further, these differences in simplifications and complexities had implications for the scope of viable impact estimates in terms of spatial and temporal and resolution. Our model looked at 44 countries under future socioeconomic scenarios out to 2030; Hertel et al. (2010) also assessed impacts in 2030 but in just 15 countries and under the assumption of unchanging socioeconomic conditions (other than food price and household income patterns); Ivanic and Martin (2008) looked at historical data in 9 countries.

In line with the theme of this thesis, the upshot of the above is that – given the complexity of the relation between food price, incomes, poverty, and nutrition – trade offs are inevitable when making abstractions (and, given a researcher's objectives, choices are often shaped by data limitations). Thus the adoption of multiple perspectives should be seen as a useful for strategy for deepening our understanding of a problem and for guiding the development of ongoing empirical analyses and models. Both Research Paper 3 and the agricultural economics papers draw the same general conclusion, but the details of the findings differ. I would argue that the key question arising from this is not, *which of the approaches is right (or at least better)?*, but rather, *how can the work be synthesised to guide future work?*

In sum, the Research Paper 3 (along with the supportive evidence from the agricultural economics literature discussed above) suggests that as well as ensuring an adequate quantity, accessibility, and quality of food for consumers, a key means of reducing the impacts of climate change on stunting appears to be ensuring food prices are high enough to sustain those producing the food; i.e. producer-consumer peasant farmers.

Producer-consumer farmers, however, were not explicitly represented in the health model described in this chapter. Further, in previous climate-nutrition work based on the chain of models shown in Chapter 2, Figure 2, Panel A, production and consumption are separated by design. This is despite the fact that smallholder producer-consumer farmers comprise an estimated two fifths of the global population, the majority of those living in extreme poverty, and more than half of the world's undernourished (IFAD, 2011). Further, it has been argued that this same group could play a key role in both mitigating climate change and providing sufficient food to feed growing populations, although the particular way farming could or ought to be done is contested (HLPE, 2019).

This raises the question: *what would we see if we shifted perspective to ask how interactions between producer-consumer farmers in the global food system shape both the risk of hunger and the conditions that support rural health?* A first attempt to address this question was made in Research Paper 4.

Chapter 6. The influence of different constellations of styles of farming on rural health and the implications of climate change

Background

This chapter is composed a research paper that is being prepared for submission to a journal. It describes the development of an Agent-Based Model (ABM) that focuses on producer-consumer farmers practicing different styles of farming in the global food system, and assesses how their interactions shape hunger and other health-supporting conditions, under various climate, agricultural policy, global price transmission, and farming style preference scenarios. This work was not funded.

Research Paper 4: Climate change and hunger through the lens of farming styles and rural health: insights from an agent-based model

For accompanying supplemental material, see the appendix "Research Paper 4: Supplemental Material". In the appendix, the model is described using an ODD+D (Overview, Design Concepts and Details plus Decision-Making) (Müller et al., 2013), which is a widely adopted format for giving complete and consistently organized descriptions of ABMs.

RESEARCH PAPER COVER SHEET

Please note that a cover sheet must be completed for each research paper included within a thesis.

SECTION A – Student Details

Student ID Number	246266	**Title**	Mr
First Name(s)	Simon John		
Surname/Family Name	Lloyd		
Thesis Title	Modelling the relation between climate change and undernutrition at the global-level: the use of multiple perspectives to gain new insights		
Primary Supervisor	Ben Armstrong		

If the Research Paper has previously been published please complete Section B, if not please move to Section C.

SECTION B – Paper already published

Where was the work published?			
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Where is the work intended to be published?	Undecided at time of thesis submission. Considering Environmental Health Perspectives, PLoS ONE, Global Environomental Change.
Please list the paper's authors in the intended authorship order:	Simon Lloyd, Zaid Chalabi

Stage of publication	**Not yet submitted**

SECTION D – Multi-authored work

For multi-authored work, give full details of your role in the research included in the paper and in the preparation of the paper. (Attach a further sheet if necessary)	This work was unfunded and was prepared specifically for the thesis. I conceptualized, designed, and coded the model; assembled the underlying literature; designed, ran, and interpretted the simulations; and, wrote the first draft of the paper. Zaid Chalabi provided advice on various aspects of the model throughout, and provided advice and suggestions as the final text was developed.

SECTION E

Student Signature	[redacted]
Date	November 7, 2019

Supervisor Signature	[redacted]
Date	Nov 7 2019

Climate change and hunger through the lens of farming styles and rural health: insights from an agent-based model

Abstract

Undernutrition is a major contributor to the global-burden of disease, and global-level models suggest that climate change-mediated reductions in food quantity and quality will negatively affect it. These models, however, capture just some of the processes that will shape future nutrition.

We adopt a novel standpoint, developing an agent-based model in which producer-consumer smallholders practice different styles of farming in the global food system. The model represents a hypothetical rural community in which 'orphan' (i.e. subsistence) farmers may develop by adopting a farming style that is either highly market-dependent ('entrepreneurial') or more autonomous ('peasant' agroecology). We take a first look at the question: how might farm development trajectories - under various climate, policy, price transmission, and farming style-preference scenarios - impact on hunger and health-related conditions (incomes, work, inequality, 'real land productivity') in rural areas?

Simulations without climate change or agricultural policy found that style preference patterns influence production, food price, and incomes, and there were trade-offs between them. For instance, entrepreneurial-oriented futures had the highest production and lowest prices but were simultaneously those in which farms tended towards crisis. Simulations with climate change and agricultural policy found that peasant-orientated agroecology futures had the highest production, prices equal to or lower than those under entrepreneurial-oriented futures, and better supported rural health. There were, however, contradictory effects on nutrition, with benefits and harms for different groups.

Collectively the findings suggest that when attempting to understand how climate change may impact on future nutrition and health, patterns of farming styles - along with the fates of the households that practice them – matter. These issues, including the potential role of peasant farming, have been neglected in previous climate-nutrition modelling but go to the heart of current debates on the future of farming: thus, they should be given more prominence in future work.

Introduction

Hunger and undernutrition are major contributors to the global burden of disease and have proven difficult to eliminate despite long being the focus of global programmes [1-3]. For instance, current estimates suggest 820 million people are undernourished (insufficient calorie intake) and 149 million children aged under 5 are stunted (low height-for-age) [4]. Part of the reason for this seeming intractability is the complexity of its causation, involving factors and processes operating at the individual- and population-level in multiple spheres, ranging from infectious diseases [5], to education [6], to civil conflict [7], to foreign direct investment [8]. While climate and weather have always played a role in hunger, ongoing climate change is increasing this complexity and is likely to further impede actions to eradicate it [9].

Global-level climate-undernutrition models have repeatedly found that population undernourishment, child undernutrition (e.g. stunting), and dietary quality will be negatively affected by climate change-mediated changes in food production [e.g. 10,11-20]. Ultimately, whether or not an individual is poorly nourished is determined by the quantity and quality of food they can access, as well as whether they are affected by infectious diseases that compromise nutrient absorption [21,22], and this is reflected in both the method and theory underlying extant climate-nutrition models [10-20]. Methodologically (and put in general terms), climate impacts on crop production are assessed in order to estimate changes in food quantity and quality, and this is in turn used to assess expected dietary changes in consumers. Socioeconomic conditions associated with nutritional status (for example, water, sanitation, and female access to education [6]) are also typically accounted for as modifying factors, albeit usually crudely represented as exogenously specified (i.e. not modelled or affected by climate change) Gross Domestic Product per capita (GDPpc). In terms of theory (which is often implicit), these approaches tend to see the dominant cause of poor nutrition as food scarcity (in terms of quantity or quality), which may arise from an absolute lack of food or its unaffordability. This is a crucial perspective given expected population growth and the threat climate change poses to food production.

The complexity of undernutrition suggests, however, that previous climate-undernutrition modelling captures just some of the processes that are likely to shape future nutrition. In fact, despite the persistence of undernutrition, there is currently more than enough food produced globally to feed everyone [23]. No single model could be expected to represent all the important processes but it would be useful to develop models that adopt perspectives in addition to that of total food production. Illustrating this, recent modelling found that ensuring decent incomes for farmers may be a key means of reducing future undernutrition and vulnerability to climate change, although farming households were not directly represented in the model [24].

In this paper, we describe a model that takes a novel perspective on the climate-undernutrition relation. We developed our perspective based on the following. Firstly, ‘half the world’s undernourished people and the majority of people living in absolute poverty’ are found amongst the 2 billion producer-consumers living on smallholder farms [25]. At the same time, it has been argued this same group could hold the key to feeding populations healthily, mitigating climate change (and other environmental damages), and providing decent rural livelihoods [26-28]. Yet, producer-consumers are not explicitly included in existing global-level climate-undernutrition models which separate production and consumption by design.

Secondly, when representing production, existing climate-undernutrition models allow for between-farm quantitative differences (e.g. farm size, input use) but do not qualitatively distinguish ‘farming styles’ [29]. Literature on both historical [29] and future farming [28], however, has highlighted non-trivial distinctions in terms of on-farm practices (e.g. preferences for labour-capital balances), goals (e.g. profit, autonomy), and farm connections to the ‘rest-of-the-world’ (e.g. relations with input and food markets). It may be expected that such differences – and particularly the pattern of uptake of different farming styles - will influence population health under future climate change. To our knowledge, however, this has not been examined in a model.

In this paper, we develop an agent-based model (ABM) in which the agents are producer-consumer smallholders practicing different styles of farming in the global food system. We use the model to take a first look at the question: *how might farm development trajectories - under various climate, policy, price transmission, and farming style-preference scenarios - impact on hunger and health-related conditions in rural areas?* That is, in contrast to previous work that traces a pathway from climate change to hunger, we begin by assessing how patterns of farming styles may impact on rural health (in the absence of climate change), and then assess how climate change may modify this relation. Our model is a ‘proof of concept’ model, set in a hypothetical farming community.

This paper has three main purposes: (i) to familiarize the climate-health community (and other interested groups) with the concept of ‘styles of farming’, particularly in terms of inseparable ideas about who is farming (‘peasants’ vs ‘entrepreneurs’ [29,30]) and how they are farming (agroecology vs reliance on purchased inputs [26,31]); (ii) to use patterns in the model outputs to draw attention to the role different farming futures may play in shaping population health via both food- and non-food-related processes, and the implications of climate change; and (iii) stimulate debate about the importance of these largely neglected (at least in climate-health modelling) issues and spur the development of more detailed models.

The next section gives an overview of the ABM. Following this, results from a set of simulation experiments conducted under various scenarios are presented and discussed. We finish with some concluding remarks on the implications for future research.

Methods

ABMs are simulation models which represent agents, their goal-orientated decisions, the actions they take, and their interactions with other agents and the environment (understood in broad terms) [32]. They track how micro-level actions unfold over time to give rise to macro-level patterns. While ABMs have been used to study population health [e.g. 33] and agricultural systems [e.g. 34], to our knowledge they have not been previously used to assess the potential impacts of climate change on health.

Existing global-level climate undernutrition models typically link together a chain of component models. In this approach, the health component model is generally driven by macro-to-macro statistical correlations (e.g. the correlation between 'total quantity of food' and 'proportion at risk of stunting'), and the crop production component model generally assumes homogeneity of farmer goals [e.g. 10,11-17,35]. That is, health component model operates entirely at an aggregate level, where the latter (partly) arises from homogenous farming-related behaviours at a lower level. We argue this is a critical limitation given the contested nature of how farming futures could or should look [28,36]; what happens at the micro-level matters for population health.

ABMs overcome these limitations. In our case, ABM allows an assessment of how changing patterns of heterogenous behaviour in agents at the micro-level - i.e. farmers practicing different styles of farming - interact to give rise to macro-level conditions – for instance, aggregate food price - which in turn (via feedback), along with other structural conditions (such as climate, agricultural policy), influence micro-level behaviour, giving rise to farm development trajectories and patterns of health-related conditions [cf. 30,37]. Our model, however, introduces a new set of limitations (see

‘Discussion’). Thus, our approach should be seen as offering insights that are complimentary to previous work, as well as providing guidance on the development of future models.

Overview of the model and simulations

Our ABM represents a hypothetical world in which a population of peasant producer-consumer farming households practicing ‘orphan’ farming (i.e. subsistence farming) on one hectare plots may develop by adopting a farming style which is either dependent on purchased inputs (‘entrepreneurial’ farming) or that is driven by enhancing and utilizing on-farm ecological processes (‘agroecology’) [29,38,39] (Fig 1). This occurs under scenarios which vary by (i) the proportion of farmers preferring a given style of farming, (ii) the style favoured by agricultural policy, (iii) the degree of influence of global food prices on local prices (as an indicator of globalization of the food system), and (iv) the severity of climate change. Simulations are run in annual time steps for 50 years and, amongst other things, five health-supporting outcomes from different spheres are assessed: basic nutrition (biological); farm incomes and labour (economic); income inequality (social); and, ‘real land productivity’ (a measure of farming intensity; environmental). Fig 1 shows a schematic of the model.

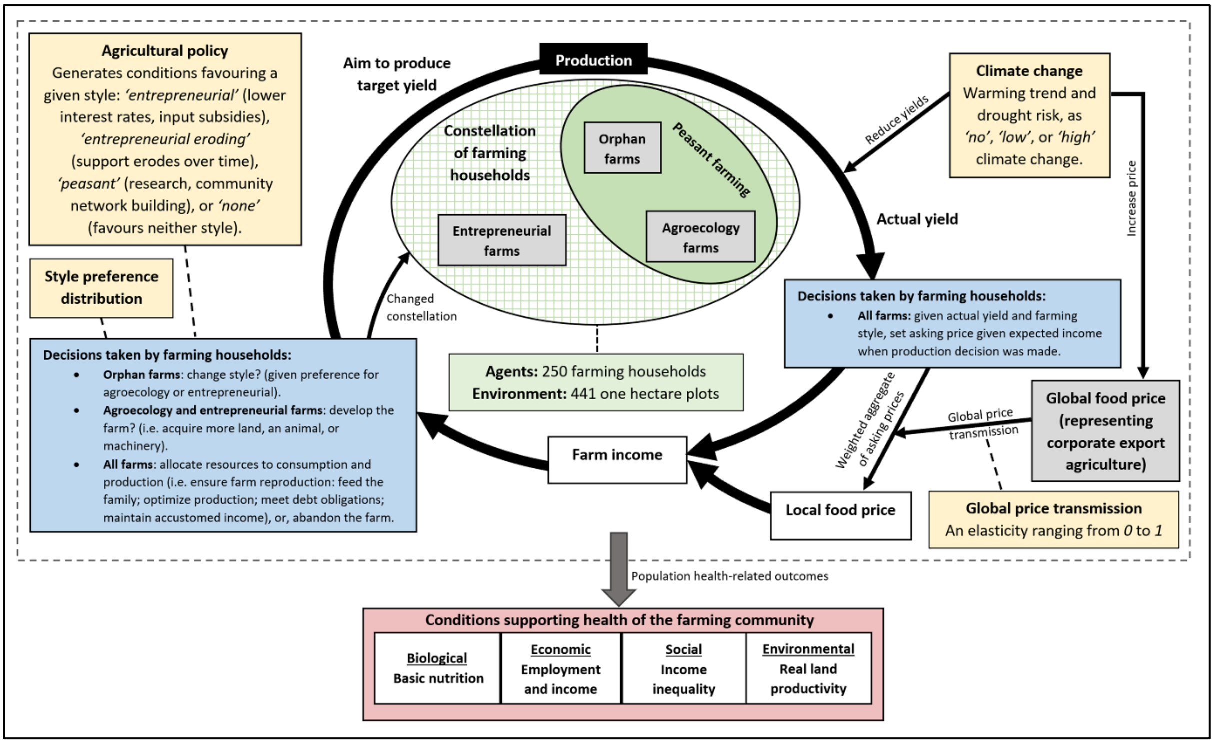

Fig 1. Schematic diagram of the agent-based model. The central cycle (thick black arrows) represents the farm production process, with each cycle occurring over one year (i.e. one timestep). Agents (farming households plus an a-spatial mega-agent representing corporate agriculture) and the environment (1ha plots) are shown in grey and green. Agent decisions are shown in blue. Scenario options are shown in orange. Health-related outcomes are shown in red. See text for further details.

We developed our agent types based on the work of van der Ploeg [29,30,36], and for theoretical consistency we drew on the same body of work to model their economic behaviours. While there are well developed approaches to agricultural household modelling which explicitly represent producer-consumers [40], we did not utilise these methods as their assumptions (e.g. all households are profit maximizers) are inconsistent with the van der Ploeg typology. We further describe our approach ahead (see 'Model process') and return to agricultural household modelling in the 'Discussion' section (see 'Model limitations').

Tables 1 and 2 describe the key model variables and parameters. In general, we parameterized the model using approximations based on the literature. For instance, we derived approximate rates of temperature rise in our climate change scenarios based on averages in the Representative Concentration Pathways (RCPs; these are the scenarios currently used in climate change impact assessments) [41]; we estimated yield loss per degree of warming based on existing quantifications [42,43]; we used 'rules of thumb' for productivity and consumption in subsistence farming (Mazoyer and Roudart, 2006)); and, we estimated annual yield increments in peasant agriculture based on qualitive knowledge (van der Ploeg, 2013)). We took this approach because: (i) it allowed for simplicity and transparency; (ii) the model represents a hypothetical rural area; (iii) quantitative estimates for some parameters were not available; and, (iv) patterns in the results rather than quantifications are of central interest (We discuss this further in the ‘Model limitations’ section of the ‘Discussion’).

Table 1. Key environment and agent factors, their initial values, and how they change over time[a].

Factor (units)	Function or effect	Initial value	Change over time	Notes
Landscape				
'Local area' (ha)	Grid of 1ha plots.	441 1ha plots.	No change.	A 21 by 21 grid of arable plots.
Plot max productivity (kg/year)	Each plot has a maximum productivity under orphan agriculture (i.e. in which no non-labour farm inputs are used).	Randomly set for each plot: 1000kg/year $\pm$20% (uniform distribution). [Based on [38]]	Slow rise on optimized peasant farms. 'Peasant' policy: orphan 1.5%/year, Agroecology 3% per year; other policies: Orphan 1%/year, Agroecology 1.5%/year. Max productivity = max productivity for entrepreneurial farmers. [Based on [30]]	'Optimized' in terms of production; assumed that if farmer unable to optimize, then also unable to gain production increases. Assumes no land degradation under any style.
Plot agroecology yield multiple (scalar)	Max productivity of a plot is raised by a given multiple after transitioning to agroecology.	Randomly set for each plot: mean=4, SD=1.5 (normal distribution, restricted to values between 2 and 7). [Based on [39,44,45]]	No change.	Productivity rises slowly during the transition phase, with the full yield multiple being achieved after the agroecology transition period.
Agroecology transition period (years)	Number of years to transition a plot to agroecology.	3 years. [Based on [39]]	No change.	Transition achieved via labour intensification.
Agents				
Farming households (number)	Farming households, each of four people, practicing a particular style of farming. Using manual tools, each household can farm one hectare.	250; each randomly assigned a 1ha plot; all practicing orphan agriculture; preference to develop via a particular style distributed according to scenario.	Households change to preferred style if they have access to sufficient resources, or, abandon farming if nutrition falls below 50% of a basic diet.	Initially ~40% of plots are unoccupied. Approximates conditions in lower income countries. [38,46,47]
Family basic diet (kg of cereal/year)	Quantity of cereal equivalents providing a basic diet to a family for one year.	700kg/year (equiv. to ~2200kcal/person/day). [Based on [38]]	No change. Households abandon their farm if they are unable to obtain 50% of a basic diet.	Household members do not age over time.
Labour diet (kcal/day)	Worker calorie intake/day to allow a given amount of labour power.	5100kcal/day for max production on 1ha; diminishing returns as intake increases to this level. [Based on [48,49]]	Acquiring working animals or a small tractor allows a worker to farm more than 1ha (Table 2). Labour input requirements double under agroecology.	For orphan agriculture, max production on 1ha with manual tools requires 150 ten hour labour days/year. [Based on [48]]
Agroecology labour multiple (scalar)	Increase in labour requirements for maximum production in agroecology.	2 (i.e. for max production, required labour time doubles). [Based on [39]]	No change.	'Necessary input' requirements rise proportionally with labour (see Table 2).
Climate				
Warming trend and yield losses (degrees/year, and, % loss/degree of warming)	Yields decline as warming increases, with lower losses for agroecology. (For effects on global food price, see Table 2.)	Warming = 0. Yield loss = 4%/degree of warming [Based on [42,43]]; losses reduced by 10% under agroecology. [Based on [39]]	Linear rise in warming. High CC: 2 degrees/50 years; Low CC: 1 degree/50 years; No CC: no warming. [Based on [50]]	An approximation guided by average warming under the Representative Concentration Pathways [41]. Agroecology loss reductions are an approximation.
Drought risk and yield losses (annual risk, and, % loss/event)	Proportion of yield lost if a drought occurs; lower losses under agroecology. (For effects of global food price, see Table 2.)	Drought risk = 5%/year Drought yield losses are - High CC: av. 15%, up to 30%; Low CC: av. 10%, up to 25%; No CC: av. 7.5%, up to 20%. Losses reduced by 20% under agroecology. [Based on [39]]	Linear increase in risk – High CC: doubles after 50 years; Low CC: 1.5 times after 50 years; No CC: no change. Yield losses are fixed over time.	Drought losses are contingent on multiple processes meaning no generally applicable quantification available. Plausible approximations used, including for agroecology.

av., average; CC, climate change; ha, hectare; SD, standard deviation.

[a] Note that model parameters are approximations derived from the literature. See text and the ODD+D (S1 Appendix) for further details.

Table 2. Prices for key factors, their initial values, and how they change over time[a].

Factor (units)	Function or effect	Initial value	Change over time	Notes
Food price				
Local food price (cents/kg)	Food price faced by farming households.	40c/kg (Given input prices (see below), this places the average farmer close to the threshold for development.)	Calculated as the production-weighted average of farmer asking prices, adjusted for global price given price transmission.	Farm gate and consumer prices assumed to be the same.
Global food price (cents/kg)	Represents price arising from global corporate agriculture: influences trend in local price via global price transmission (Figure 1).	40c/kg	General tendency to fall (most rapidly under 'no climate change' and most slowly under 'high climate change' (due to warming)) & oscillate. Drought causes price increases, with the greatest increases under 'high climate change' (See text for details).	The simulations aim to assess the impact of the tendency for global prices to fall and oscillate on smallholder farming. [Based on [38]]
Inputs				
Labour: low skilled wage ($)	Cost of a full-time farm worker (Labour time may be purchased in fractions given target yield).	Price = 180% of the cost of a basic diet for a family of four. [e.g. [51]]	Same formula (based on average local price over last 5 years), but with an additional rise of 2% per year [Based on [52]].	Peasants do not cost labour. Over time, food costs represent a smaller proportion of people's income.
Purchased inputs: necessary inputs ($)	'Necessary inputs' represent expenditure required to enable production. Assumed to be scalable given target production.	Necessary inputs for max production: price/ha = 15% of a low skilled wage. [Based on [53,54]]	Under agroecology, necessary inputs for maximum production double (i.e. in proportion to increased labour requirements (Table 1)).	Necessary inputs include clothing, tool repair, building maintenance, etc [38].
Purchased inputs: fertilizer ($/kg)	Increases productivity of a plot up to 10 times [38], with diminishing returns as quantity used increases to max.	Price of 1kg = local food price/kg X 10. Max productivity at 500kg [e.g. [55-57]]. Under 'Entre' and 'entre eroding' policy: 50% subsidy.	Same formula, but price rises 1%/year. Under 'Entre eroding', subsidy falls by 1%/year.	'Fertilizer' assumed to represent all non-necessary purchased inputs (e.g. pesticides, seeds). Thus, the fertilizer:food price ratio accounts for this.
Working (i.e. draught) animals ($)	Allows one worker to farm up to 5ha (cf. manual tools, which allow 1ha to be farmed).	Price = 30 years of net income (i.e. after feeding the family) of average orphan ag farm. [Based on [38]]	Same formula, based on average local food price over the last five years.	Working animals allow workers to farm a greater area but do not increase plot productivity.
Small tractor ($)	Allows one worker to farm up to 16 hectares (cf. manual tools, which allow 1ha to be farmed).	Price = 150 years of net income (i.e. after feeding the family) of average orphan agriculture farm. [Based on [38,48]]	Same formula, based on average local food price over the last five years.	Tractors allow workers to farm a greater area but do not increase plot productivity.
Land price ($/ha)	Farmers may expand by purchasing unused adjacent plots.	Price/ha = the cost of 30 tonnes of cereal (Equivalent to the value of 30 years of average max production of orphan agriculture)	Same formula, based on average local food price over the last five years.	Price chosen as this roughly represents the gross value produced on the land over the working life of an orphan farmer.
Credit				
Annual interest rates (%)	Interest rates on loans for fertilizer (short-term), animals and tractors (mid-term), and land (long-term) [29].	Short-term (1 year): 20%, mid-term (3 to 6 years): 15%, long-term (8 years): 10%. Rates halved under 'Entre' and 'Entre eroding' policy.	Fixed, except under 'Entre eroding' policy where rates increase linearly over time, returning to their full values after 50 years.	Peasant farmers do not use credit. Rates based on [58-61].

ha, hectare

[a] Note that model parameters are approximations derived from the literature. See text and the ODD+D (S1 Appendix) for further details.

We ran two sets of simulation experiments and conducted a sensitivity analysis. Previous climate-undernutrition modelling has assessed how climate impacts on food production may in turn impact on health; our simulations develop an alternative perspective in two stages. First, the 'Style preference and globalization' runs assess how different combinations of style preferences and global price transmission influence farm development trajectories – in terms of total food production, food price, and farm incomes - in the absence of climate change or specific agricultural policies. Second, the 'Climate change and agricultural policy' runs look at how climate change and agricultural policy may modify these development trajectories, and how these may in turn shape the conditions that support (or undermine) the health of rural communities. Following this we ran a sensitivity analysis to assess how assumptions about maximum productivity and climate-related losses of agroecology and entrepreneurial farming influence model outputs for total food production and food price.

Below, we provide further detail on the ABM and then describe our scenarios and simulation experiments. Full details of the model are given in the accompanying ODD+D (Overview, Design Concepts and Details plus Decision-Making) [62] (S1 Appendix). The latter is a widely adopted format for giving a complete and consistently organized description of ABMs. The model was implemented in Netlogo 6.0.1 [63].

Model details

This section describes the following: the rural landscape, the agents, how climate change is represented, some key model processes, and the main outcomes assessed.

Rural landscape

The landscape is a 21 by 21 grid (441 cells) of 1ha arable plots, which represents the 'local area' occupied by the hypothetical rural community. Each plot is randomly assigned a maximum productive potential of between 800kg and 1200kg of cereal equivalents/year (see below for how these quantities relate to dietary intake requirements) (Based on [38]). Additionally, each plot is randomly assigned a yield multiple that may be achieved under agroecology following a transition period of three years (Table 1).

Agents

The agents are farming households comprised of four people (Table 1), and farms produce a generic crop measured in cereal equivalents [38]. Households may be 'peasant' or 'non-peasant' and are represented by three types of agent defined by their style of farming (Figure 1). Two styles represent peasant farming: 'orphan' and 'agroecology'. The third style, which is non-peasant, is 'entrepreneurial'.

The distinctions between peasant and (non-peasant) entrepreneurial farming are derived from empirically-based categories developed by van der Ploeg [29] (We note that van der Ploeg does not claim a rigid distinction between entrepreneurial and peasant farming exists in the real world. Rather, the 'peasant condition' is an ongoing process that develops in response to changing contextual conditions, and which may express more or less 'peasantness'. For the purposes of the model, however, we assume entrepreneurial and peasant farming are distinct categories). In essence, entrepreneurial farming predominately relies upon purchased farm inputs (e.g. fertilizers) and wage labour, often using credit to obtain these, and develops via capital intensification. This means the logic driving production decisions is largely shaped by off-farm processes, such as price ratios (determining the margin) and technology (determining scale); thus, the market acts as an ordering principle, and the goals of entrepreneurial farming are to maximise returns-on-investment and expand (market share and/or farm size) [29].

Peasants farming differs in that a major goal is to deepen autonomy. This is achieved by largely relying on on-farm produced inputs, avoiding credit, and maximising returns-to-labour, with development being via labour and knowledge intensification. Thus, farmers attempt to shape the production process such that it guarantees the next year of production without recourse to the market. In this sense, autonomy means reduced market dependence. This does not imply peasants isolate themselves from markets; rather, markets are used as an outlet for surplus production [29].

Another key difference between peasant and entrepreneurial farming is that peasants only use family labour and do not consider labour costs when optimizing production [30]; instead, they must provide a labour diet adequate for the required labour power (Table 1). In contrast, entrepreneurial farmers employ labour, paying a wage (Table 2) and costing labour in optimization decisions, including when a labourer is a family member [30].

The first style of peasant farming is orphan agriculture. Following Mazoyer and Roudart [38], this is defined as farming with manual tools (e.g. a hoe) and very limited input use (e.g. fertilizers), meaning that one worker labouring at full capacity can farm 1 hectare to produce an average of 1000kg of cereal equivalents per year. Of this, 700kg provides a family of four a basic diet

(~2200kcal/person/day), and full capacity labour requires an additional (i.e. additional to a basic diet) 2900kcal/labour-day, which is equivalent to ~110kg of cereal/year (Table 1). Thus, limited production potential relative to needs renders orphan livelihoods precarious.

The second style of peasant farming is agroecology. In the ABM, during an agroecology transition period of three years, orphan farmers intensify the productive potential of their land (and thus deepen their autonomy) to gain an average yield multiple of four (e.g. an initial maximum yield of 1000kg/ha would be increased to 4000kg/ha) (Table 1). This is achieved by developing and modifying on-farm ecological processes, generally via labour intensification (Table 1) and learning via community networks (Note that these ecological processes and networks are not explicitly represented in the ABM) [26,39].

Additionally, as peasant farming (both agroecology and orphan agriculture) is labour and knowledge intensive, slow ongoing gains in maximum productivity per hectare may also be achieved by fine-tuning farming practices (Table 1) [30].

As well as agents representing farming households, an a-spatial (i.e. not located in the landscape) mega-agent represents ‘corporate agriculture’, which is large-scale agriculture with a profit-making goal [29]. Over recent decades, various processes - including productivity increases and subsidies - have led corporate agriculture to be associated with a general tendency for global food prices to fall, and it has been argued that this has caused poverty and untenability of livelihoods for many smallholders (i.e. both peasant and entrepreneurial farmers) [23,38,64,65]. Additionally, global prices tend to oscillate, with troughs potentially forcing the worst-off farmers permanently out of farming [38]. Given this, rather than representing corporate agriculture explicitly as farms, the model represents it implicitly as a price trend that tends to fall but oscillate (Fig 1, Table 2; further details ahead).

In sum, the ABM represents peasant and non-peasant farming households (agents), practicing one of three styles of farming (orphan, agroecology, entrepreneurial; i.e. the agent types)), in a local area comprised of 441 one hectare plots (landscape), who collectively form a constellation of farming households that operate in a global context in which prices associated with corporate agriculture (a-spatial mega-agent) tend to fall but oscillate. The context of farming is also shaped by climate change.

Climate change

There are multiple pathways from climate change to nutrition [66], and different agricultures in different parts of the world are expected to face varying degrees and forms of change in weather and climate [67]. In the ABM, however, as we aim to look at patterns in the results rather than quantify outcomes, we incorporate climate using a simple approach. We consider three climate change scenarios ('no', 'low', and 'high'), with each of the warming scenarios being associated with a linear increase in temperature (equivalent to 1^{o}C and 2^{o}C of warming over 50 years in the low and high scenarios, respectively) and a rise in drought risk, with the same changes experienced on all plots of land (Table 1).

Climate affects farmers in the local area as well as global food price (i.e. corporate agriculture). For farmers in the local area, climate change is expressed as yield losses. As temperature rises, yields decline on all plots. If a drought occurs, yield losses vary randomly (around an average loss) by farm. Agroecology farms face lower temperature-related and drought losses as the diverse on-farm ecology confers greater resilience [39] (Table 1). For global food price, temperature rise and droughts lead to price increases (Fig 1, Table 2).

Model processes

Each time step represents one year during which a set of processes associated with production occur sequentially (Fig 1). At the start of each time step, farms have a potential income given what they produced in the previous time step and the local food price, and (possibly) savings. Following this orphan farmers decide whether to convert to their preferred style. Those who prefer agroecology will begin conversion if their savings are sufficient to cover the additional inputs required during the labour-intensive transition period (i.e. additional labour diet and necessary inputs). The use of savings means they will not be dependent on credit. Those who prefer entrepreneurial style will convert if their income (after feeding the family) plus their savings will cover a low skilled wage, which is assumed to make them eligible for credit (e.g. to purchase fertilizer).

Following this, agroecology and entrepreneurial farmers decide whether to expand their farm, by acquiring land, working animals or small tractors (Table 2). Agroecology farmers will gradually acquire up to two lots of working animals and 10ha of land as this is manageable using family labour. They will only acquire new land or animals if all their existing plots have been transitioned to agroecology (thus, the maximum rate of expansion is 1ha every 3 years) and if all costs can be met using savings. Entrepreneurial farmers will acquire land, working animals or tractors if their income and savings cover at least half the cost, using credit to cover the balance (Table 2, main text). They may acquire 1ha of land per year. When acquiring land, all farmers choose the plot with the highest productive potential that is contiguous with their farm.

Next farmers allocate resources to consumption and production. Each farmer estimates their expected food price in the coming year, based on current price, the price change over the previous five years, style-specific considerations, and some random variation (representing unmodelled factors that may affect expectations). Farmers then find their target level of production using standard economic methods [68,69], but with the following style-specific modifications (See Appendix S1 for additional details, including Figures B and C which show decision-type trees for resource allocation).

Peasant farmers initially aim to maximise returns-to-labour, which is equivalent to optimizing without costing labour [30]. However, if income at this level of production would not meet their autonomy-related goal of increasing value added per labour object (i.e. increase net income per hectare), they will attempt to produce at a higher level. If necessary, households ration resources between consumption and production, and if they are unable to provide themselves with at least 50% of a basic diet they will either sell assets (if owned) or abandon the farm.

Entrepreneurial farmers first assess whether their income plus savings is sufficient to meet their current debt obligations and provide at least 50% of a basic diet for the family. If not, they sell assets (if owned) or abandon the farm. Following this, they find optimal production by maximising returns-on-investment [30]. If, however, either (i) the farm would run at a loss at this level of production, they will sell assets (if owned) and re-optimize or abandon the farm, or (ii) farm income at this level of production would not meet their expansion-related goals, they will attempt to increase production, again selling assets if necessary.

All farmers then attempt to produce their target yield, with actual yield being determined by climate effects and random variation (Figure 1). The model accounts for expected annual increases in temperature and drought risk; calculates expected yield losses due to warming; and, assesses whether a local drought occurs (given drought risk) and, if so, the expected average yield losses (Table 1). Actual yield for each farming household is then calculated given climate change-associated losses and random variation (of $\pm$ 15% to account for unmodelled factors).

Given their actual yield, each farming household now calculates their asking price. In doing so, both peasant and entrepreneurial farmers seek to maintain their respective autonomy- and expansion-related goals. An initial aggregate local price is then calculated by combining the asking prices of each household to give a production-weighted average. Finally, this initial local price is adjusted for global price (see below) according to scenario-specific global price transmission (an elasticity) (Figure 1); for example, if global food price had risen by 5% and global price transmission were 0.5, then local food price would be increased by 2.5%.

Global food price is set such that it has a tendency to fall and oscillate, but will rise in response to a drought. The average rate of price decline is determined by the climate scenario: 1.5%/year, 1.25%/year and 1%/year under 'no', 'low' and 'high' climate change, respectively (The actual change in each time step is randomly determined and includes the possibility of a price rise). This tendency is combined with an oscillator function has an amplitude of 1.5 cents and period of 10 years (These parameters were chosen subjectively by observing price behaviour while varying their values). Finally, the model assesses whether there is a drought that affects global prices. If a drought occurs, price is adjusted upwards by a random amount dependent on the climate change scenario (5% to 7.5%, 7.5% to 12.5%, and 10% to 17.5%, under no, low, and high climate change, respectively).

Local food price and farm production are then combined to estimate the incomes of each farming household, the next time step begins, and the model processes are repeated. Each simulation is run for 50 years (i.e. time steps).

<u>Outcomes assessed</u>

The following outcomes are tracked by the model and presented in the results. 'Local food price' is the price faced by farming households (farm-gate and consumer prices are assumed to be equal), calculated as described above. 'Total food production' is the total physical product of the entire farming community, expressed in tonnes of cereal equivalents. 'Income slope' is the average change in income over the previous ten years (i.e. slope as $ per year) for farmers practicing each style; that is, it indicates whether incomes are rising, stable, or falling, and the magnitude of the change. 'Converted farms' is the number of orphan farmers who have converted to their preferred style. 'Abandoned farms' is the number of households who left farming as they cannot provide themselves with 50% of a basic diet or meet their debt obligations.

Five health-related outcomes (i.e. that support the health of the farming community) are also tracked. 'Orphan nutrition' is the average proportion of a basic diet (in calories; Table 1) available for remaining orphan households. 'Labour' is the sum of full-time equivalent workers (including both workers on peasant farms and wage earners) on farms in the community. 'Income Gini' is a measure of income inequality amongst farming households in the community, and 'mean net farm income' is the average net income across all farming households in the community.

The fifth outcome is 'real land productivity' which is a measure of farming intensity based on value added during the farming process; that is, it removes the contribution of inputs that were produced elsewhere (e.g. purchased fertilizers) [29,53]. The latter were produced in environmental spaces other than the farm, and during the farming process their value is – in effect - transferred into final yield (rather than created on the farm). Thus, real land productivity is more environmentally-sensitive than conventional measures of intensity.

It is represented as net income per hectare adjusted for the proportion of value that was added on the farm ('endogeneity'), calculated [based on 53] as:

$$real\ land\ productivity\ [\$/ha] = \frac{farm\ net\ income\ [\$]}{farm\ size\ \ [ha]} \times endogeneity \tag{1}$$

$$endogeneity = \frac{value\ added\ on\ the\ farm\ [\$]}{value\ of\ total\ farm\ production\ [\$]}$$

$$= \frac{value\ of\ total\ farm\ production - (purchased\ inputs\ excluding\ labour)\ [\$]}{value\ of\ total\ farm\ production\ [\$]} \tag{2}$$

Scenarios, experiments, and sensitivity analysis

Model set-up: scenario settings and initialization

Prior to initialization, a scenario is chosen by the model user, which is a combination of four factors (Fig 1). First, 'Farming style preference distribution' is the proportion of orphan farming households who prefer to develop via agroecology (rather than entrepreneurial style). Second, 'Global price transmission' is the degree to which global food prices influence local food prices. This is an elasticity that specifies the percent change in local price given a 1% change in global price [70]. Third, 'Climate change' may be set to 'no', 'low' or 'high' (Table 1).

Fourth, 'Agricultural policy' specifies which farming style is favoured and has four options (see Table 3, ahead). 'Entrepreneurial' policy favours entrepreneurial farming by lowering interest rates and fertilizer prices (Table 2). 'Entrepreneurial eroding' is initialized in the same way but interest rates and fertilizer prices rise linearly to their unsubsidized levels after 50 years (Table 2). 'Peasant' policy favours orphan agriculture and agroecology by supporting research and fostering community networks, which is represented in the model by a rise in the rate of annual maximum yield increase (Table 1). 'None' means policy does not favour any style.

The model is initialized by placing each of 250 peasant households practicing orphan agriculture on randomly selected 1ha plots in the local area of 441 plots (Table 1). At initialization, it is assumed that all households have achieved their maximum yield and have no savings. Each household is randomly assigned a (fixed) preference for whether they will aim to develop by remaining peasants and adopting agroecology style, or, by adopting (non-peasant) entrepreneurial style, with the preference distribution being user-selected (Figure 1). Additionally, households are randomly assigned preferences for how they save money and whether they favour production or family nutrition when rationing.

Local and global food prices are set, then prices for productive commodities (e.g. labour, fertilizer, land) are set based on food price (Table 2). That is, productive commodity prices are linked to food price, but many of these links change over time (Table 2) as, for example, it is assumed that food prices represent a decreasing share of wages. Of note, initial prices are intentionally set at levels such that the average orphan farmer is close to an income that would allow them to develop their farm. The temperature anomaly (i.e. warming) is set to 0 and drought risk is set at 5% per year for both the local area and corporate agriculture (i.e. global food price) (Table 1).

<u>Simulation experiments</u>

We conducted two sets of simulation experiments. The 'Style preference and globalization' simulations were run without climate change (i.e. 'no' climate change) or specific agriculture policies (i.e. 'none' policy) for various combinations of proportion preferring agroecology and global price transmission. The purpose was to assess how the latter two factors influence farm development trajectories in terms of local food price, total food production, and the income trajectories of farmers practicing each style.

The second set – the 'Climate change and agricultural policy' runs – then look at how climate change and four agricultural policy scenarios (Table 3) modify farm development trajectories, and how this may in turn shape both patterns of hunger and conditions that support the health of the farming community.

Table 3. Agricultural policy scenarios and associated settings for proportion preferring agroecology and global price transmission.

Agricultural policy		Prop preferring agroecology	Global price transmission
Policy name	**Policy actions**		
Entrepreneurial	Lower interest rates and fertilizer subsidies (see Table 2).	0.25	0.75
Entrepreneurial eroding	As for entrepreneurial except interest rates and subsidies linearly increase and return to baseline level after 50 years (see Table 2)	0.25	0.75
Peasant	Support for research as well as development of community networks, represented by increased rate of yield increases (see Table 1).	0.75	0.25
None	No actions supporting any farming style.	0.5	0.5

The four agricultural policy scenarios are intended to approximate the following: (i) 'entrepreneurial' represents worlds favouring capital intensive farming that is highly dependent on and integrated into globalized markets (e.g. some farms practicing 'sustainable intensification' have these characteristics [28]); (ii) 'entrepreneurial eroding' recognises that the development trajectory of entrepreneurial farming is at least partly dependent on conditions external to farms and assesses the consequences if these conditions are not maintained over the long term [cf. 29]; (iii) 'peasant' represents worlds in which on-farm ecological processes are enhanced via labour intensification in order to develop both production and farmer autonomy, with agroecology being a key farming practice for achieving this [39]; and, (iv) 'none' represents a world where entrepreneurial and peasant farming co-existence but there is no explicit policy support for either.

For both sets of simulation experiments the ABM was run 250 times (which was judged – based on observation of outputs and across-run standard deviations - to be sufficient to capture typical model behaviour) for each combination of factors and the results for each output are shown as their across-run mean values.

<u>Sensitivity analysis</u>

In the 'Climate change and agricultural policy' simulations, the differences in the outcomes for peasant- and entrepreneurial-centred futures are of key interest. The model has many parameters, and naturally we cannot evaluate the sensitivity of the model outputs to all of them. However, two aspects of the model parameterization may have a strong influence on these results. Firstly, agroecology to entrepreneurial yield ratios. In the simulation experiments, it is assumed that (i) transitioned agroecology farms may initially produce up to an average of 4 tonnes per ha (SD = 1.5) and that this may slowly increase up to a maximum 10 tonnes per ha, and, (ii) entrepreneurial farming may produce up to an average of 10 tonnes per ha (Table 1). That is, the average agroecology to entrepreneurial yield ratio is initially 2:5 and may increase over time to 1:1. Secondly, it is assumed that climate change-related losses for agroecology are lower than entrepreneurial losses: 10% lower for warming-related losses and 20% lower for drought-related losses (Table 1).

We conducted a sensitivity analysis to assess the influence of these assumptions on two key outcomes: total food production and local food price. Under the 'entrepreneurial' and 'peasant' policy scenarios (Table 3), we re-ran the model under the following conditions: (i) fixed agroecology to entrepreneurial yield ratios of 1:4, 1:2, 3:4, and 1:1, with no increases in agroecology yield over time, and (ii) warming- and drought-related yield losses for agroecology compared to entrepreneurial of 10% lower, equal, and 10% higher.

Results

Style preference and globalization runs

These simulations assess how patterns of farming styles influence food production. More specifically, they assess how farm development trajectories – in terms of production, price, and incomes - are influenced by patterns of farming style preference and global price transmission, in the absence of climate change and particular agricultural policies. Fig 2 shows total food production and local food price (y-axes) under various combinations of global price transmission (x-axes) and proportion preferring agroecology (line colour) at 25 and 50 years.

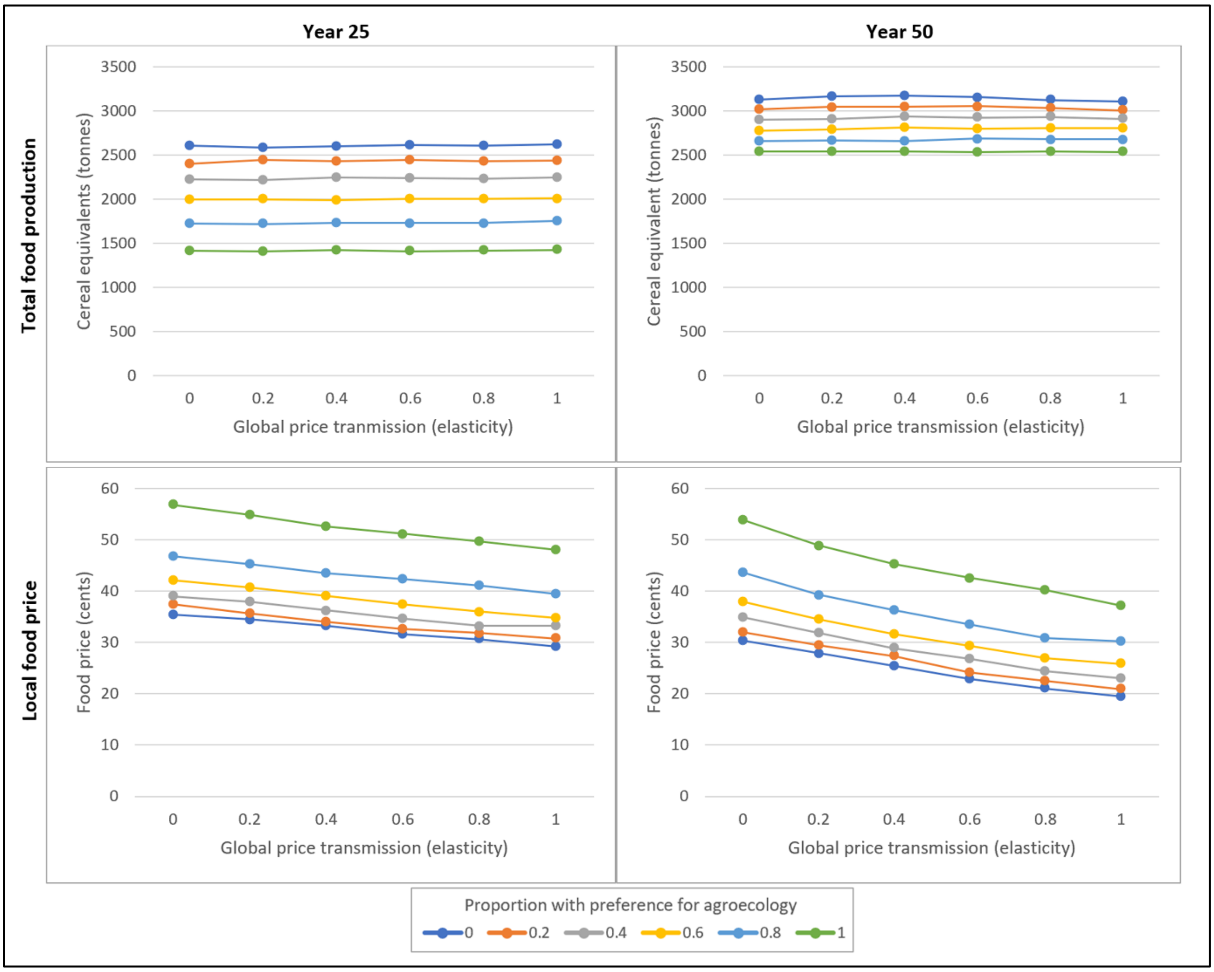

Fig 2. Total food production and local food price in the absence of climate change and agricultural policies. The plots show total food production (top two plots) and local food price (bottom two plots) (y-axes) under combinations of global price transmission (x-axes) and proportion preferring agroecology (line colour) after 25 (left plots) and 50 years (right plots), in the absence of climate change or specific agricultural policies. For the y-axes, total food production and local food price are shown as the mean result across 250 runs under each combination of factors. For the x-axes, global price transmission is an elasticity such that a value of 0.6, for example, means that a 1% rise in global food price would cause a 0.6% rise in local food price. For the line colours, a value of 0.2, for example, means that 20% of orphan farmers prefer to develop via agroecology and 80% via entrepreneurial farming.

The proportion preferring agroecology had a strong effect on total production (i.e. production summed across all farms) at 25 years (Fig 2, upper left panel), with production in runs where 80% preferred agroecology being 25% lower than when 80% preferred an entrepreneurial style. This gap declined by year 50, with production in the former being 10% lower than in latter (Fig 2, upper right panel). Global price transmission tended to have little effect on total food production.

Local prices tended to be lower at 50 years compared to 25 years (Fig 2, bottom row). Prices were lower when global price transmission increased, with the latter effect being stronger at 50 years compared to 25 years. An increase in the proportion preferring agroecology increased prices at both 25 and 50 years. Compared to the start price (i.e. at year 0) of 40c per kg, prices tended to be lower at both 25 and 50 years under most sets of conditions, except when a very high proportion preferred agroecology and/or when price transmission was very low.

Fig 3 shows the rate of change of farm net incomes (averaged over the previous 10 years) in $ per year, by farming style (i.e. as average change across all farmers practicing a given style) (y-axes), under various combinations of global price transmission (x-axes) and proportion preferring agroecology (line colour), at 25 and 50 years. For reference, the average orphan household would have a net income of about $80 per year after providing a basic family diet plus a labour diet if local food price were 40c per kg (i.e. the food price at year 0).

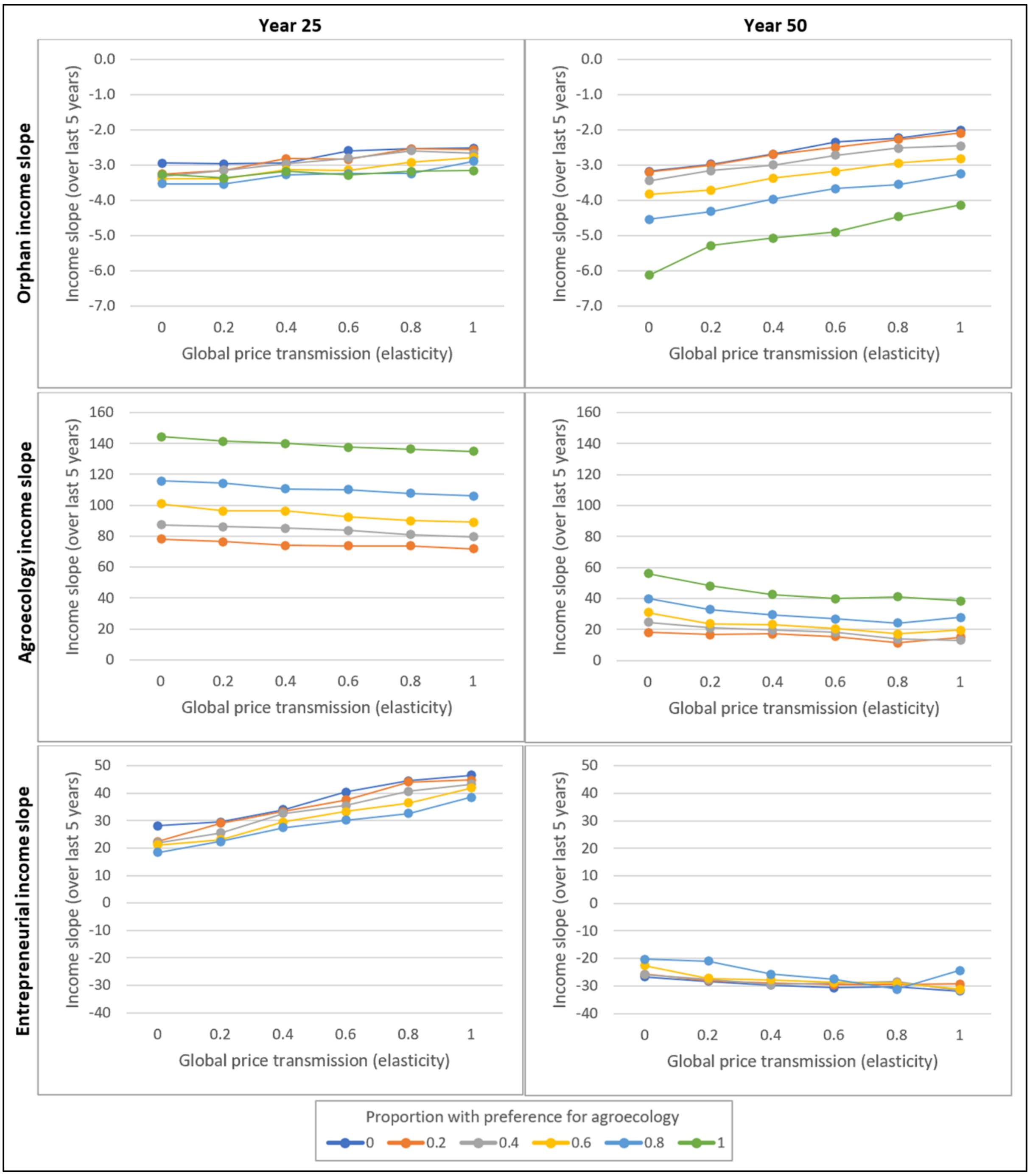

Fig 3. Income slopes by farming style in the absence of climate change and agricultural policies. The plots show income slopes for orphan, agroecology, and entrepreneurial farms (top to bottom plots, respectively) (y-axes; scale differs for each style) under combinations of global price transmission (x-axes) and proportion preferring agroecology (line colour) after 25 (left plots) and 50 years (right plots), in the absence of climate change or specific agricultural policies. For the y-axes, the income slopes are the gradient (units = $ per year) of mean farm net income by farming style over the previous ten years, shown as the mean result across 250 runs under each combination of factors. For the x-axes, global price transmission is an elasticity such that a value of 0.6, for example, means that a 1% rise in global food price would cause a 0.6% rise in local food price. For the line colours,

a value of 0.2, for example, means that 20% of orphan farmers prefer to develop via agroecology and 80% via entrepreneurial farming.

Net incomes for orphan agriculture tended to be falling slowly at both 25 and 50 years (Fig 3, top row). At 25 years, the fall in income tended to increase slightly as the proportion preferring agroecology increased, and to decrease slightly as global price transmission increased. This pattern strengthened at 50 years. For farmers practicing agroecology, net incomes tended to be increasing rapidly at 25 years, with this increase slowing at 50 years (Fig 3, middle row). Increasing price transmission tended to slow growth slightly, and increasing the proportion preferring agroecology tend to increase growth, with the latter effect being stronger at 25 years than at 50 years.

For entrepreneurial agriculture, incomes tended to be rising at 25 years, although at a slower rate than for agroecology farmers (Fig 3, lower left panel). Increasing transmission increased growth, and increasing the proportion preferring agroecology decreased it, albeit both effects were reasonably small. At 50 years, these tendencies had reversed: incomes were falling; transmission tended to steepen the fall; and, an increasing in the proportion preferring agroecology slowed the fall (Fig 3, lower right panel). These latter two effects, however, were very small.

Climate change and agricultural policy runs

The second set of simulations has two parts. Firstly, we assessed how farm development trajectories are modified by climate change and agricultural policy scenarios, where the latter are a combination of an agricultural policy plus related settings for the proportion preferring agroecology and global price transmission (Table 3). Secondly, we assessed how these farm development trajectories impact on hunger and a set of conditions that support health in the rural community.

Fig 4 shows time-series plots (covering 50 years; x-axes) for farm development trajectories, as total food production (i.e. summed across all farms), local food price, the number of farmers who have converted to their preferred style, and the number of abandoned farms. Results are shown as the mean result over 250 runs (y-axes) for each policy scenario (coloured lines).

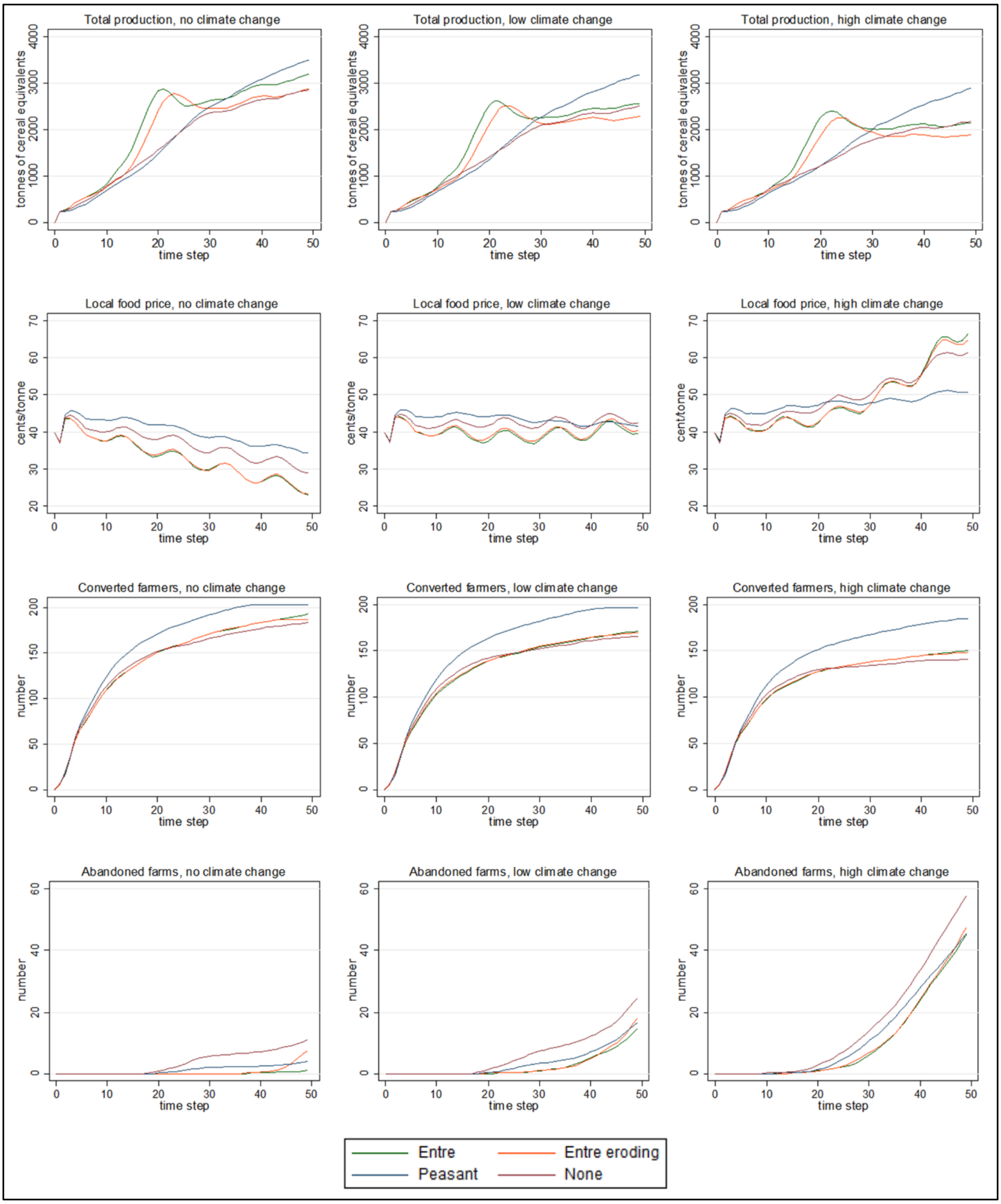

Fig 4. Total food production, local food price, and converted and abandoned farms, under the agricultural policy and climate scenarios. The plots show time-series for total food production, local food price, and the number of converted and abandoned farms (top to bottom plots, respectively) under the four agricultural policy scenarios, for no, low, and high climate change (left to right plots, respectively). For the y-axes, all results are shown as the mean value across 250 runs. For the coloured lines, the four scenarios are: (i) 'Entre' in which agricultural policy favour entrepreneurial farming, 25% of farmers prefer agroecology, and global price transmission is 0.75; (ii) 'Entre eroding' is as for 'Entre' except policy support erodes over time; (iii) 'Peasant' in which policy favours peasant farming, 75% of farmers prefer agroecology, and global price transmission is 0.25;

and, (iv) 'None' in which policy favours neither farming style, 50% prefer agroecology, and global price transmission is 0.5 (Table 3).

In futures without climate change, total production (Fig 4, top row) rises rapidly for the first 20 years under both entrepreneurial scenarios. It then falls for a short period before again beginning to slowly rise (with production gains slower under 'entrepreneurial eroding' than 'entrepreneurial'). In contrast, production rises slowly but steadily under the 'peasant' scenario, with production beginning to exceed that under 'entrepreneurial' after about 35 years. This pattern is similar under low and high climate change, but the final gap between 'peasant' and other scenarios increases as climate change worsens.

Local food price (Fig 4, second row) is falling under all policy scenarios in worlds without climate change, and is highest under the 'peasant' scenario. Under low climate change, prices tend to be fairly stable over time, and are similar under all policy scenarios after 50 years. Under high climate change, prices initially rise slowly and then begin to rise rapidly under all but the 'peasant' scenario after about 30 years.

The number of converted farmers (i.e. households who have been able to move from orphan farming to their preferred style) (Fig 4, third row) grows fastest under the 'peasant' scenario, with the gap between the latter and other scenarios growing across the no, low, and high climate scenarios, respectively. The number of abandoned farms (i.e. households who were unable to provide themselves with at least 50% of a basic diet or meet their debt obligations) (Fig 4, bottom row) increases with climate change (i.e. across the no, low, and high scenarios, respectively). Numbers are highest under the 'none' policy scenario, followed by the 'peasant' scenario (although by 50 years the numbers under 'entrepreneurial eroding' have exceeded those under the 'peasant' scenario).

Fig 5 shows time-series plots (covering 50 years; x-axes) for five health-related outcomes that arise from the farm development trajectories: nutrition in orphan households, labour, income inequality, net farm income, and 'real land productivity', as the mean result over 250 runs (y-axes) for each policy scenario (coloured lines).

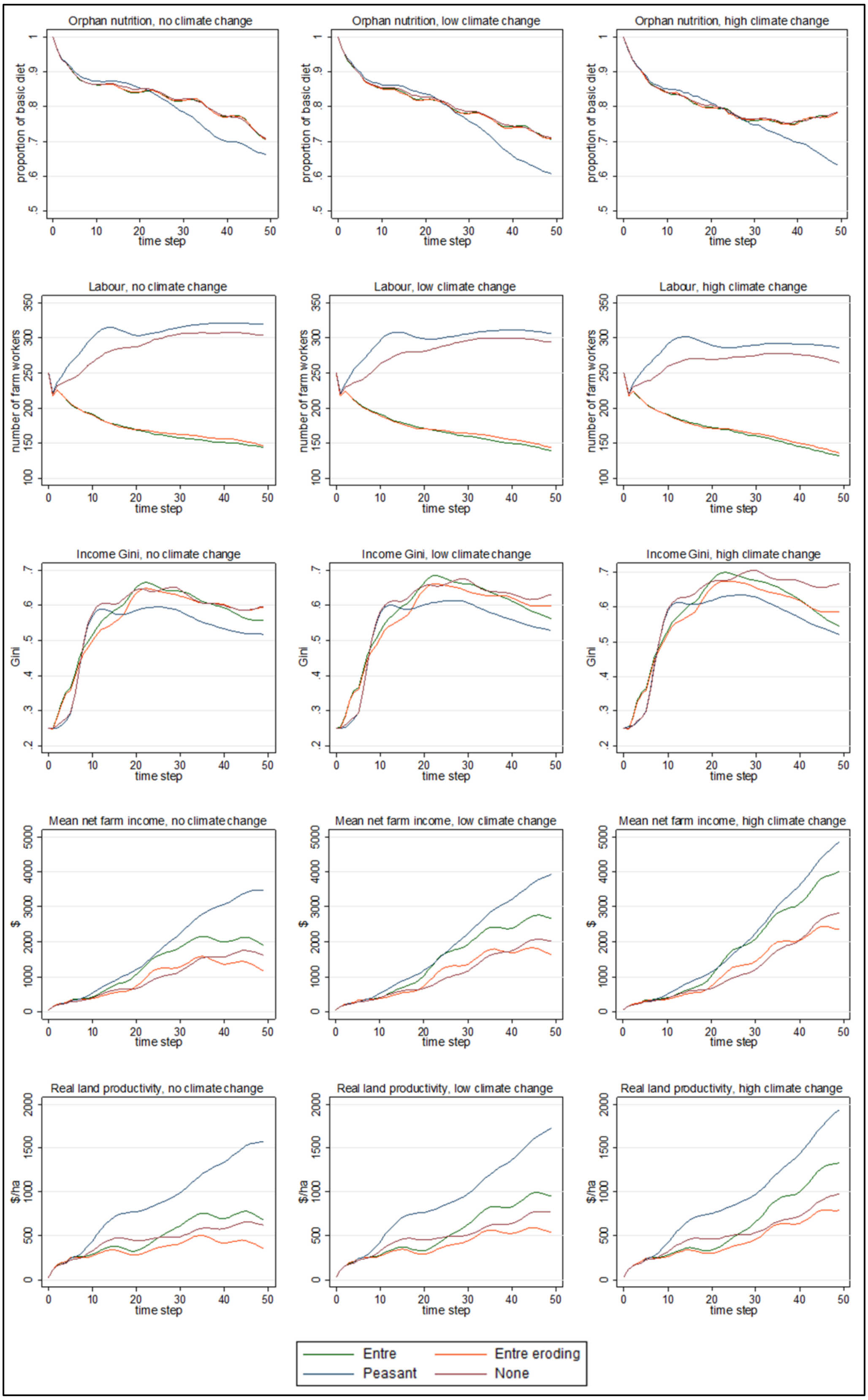

Fig 5. Nutrition, labour, income inequality, net farm income, and real land productivity under the agricultural policy and climate scenarios. The plots show time-series for nutrition in orphan farming households, labour, income inequality, net farm income, and real land productivity (top to bottom plots, respectively) under the four policy scenarios, for no, low and high climate change (left to right plots, respectively). For the y-axes, all results

are shown as the mean value across 250 runs. For the coloured lines, the four scenarios are: (i) ‘Entre’ in which agricultural policy favour entrepreneurial farming, 25% of farmers prefer agroecology, and global price transmission is 0.75; (ii) ‘Entre eroding’ is as for ‘Entre’ except policy support erodes over time; (iii) ‘Peasant’ in which policy favours peasant farming, 75% of farmers prefer agroecology, and global price transmission is 0.25; and, (iv) ‘None’ in which policy favours neither farming style, 50% prefer agroecology, and global price transmission is 0.5 (Table 3). The outcomes are as follows - ‘Orphan nutrition’: the average proportion of a basic diet being consumed in orphan farming households; ‘Labour’: the total number of full-time equivalent workers across all farming households; ‘Income Gini’: income inequality, where a higher value means greater inequality; ‘Mean net farm income’: average net farm income across all households over the previous five years;. ‘Real land productivity’: an indicator of farming intensity after removing the contribution of purchased inputs to Gross Value Product.

Orphan nutrition, which is the mean proportion of a basic diet consumed in the remaining orphan households (Fig 5, top row), is consistently lowest in the ‘peasant’ policy scenario, with the gap between the latter and the other policy scenarios widening across the no, low, and high climate change scenarios, respectively. Households that remain in orphan agriculture have had their development blocked (i.e. they are unable to convert to their preferred style); how this and other farm development processes (based on the results in Fig 4) impact on nutrition after 25 and 50 years is shown in Table 4.

Table 4. Farm development processes and their implications for nutrition, under the agricultural policy and climate scenarios at 25 and 50 years.

		Farm development process and indicator of nutrition							
		Blocked development: Mean proportion of a basic diet[a] consumed in orphan households (% of initial households in brackets)[b]		**Abandonment:** % of initial households abandoning as unable to provide ≥50% of a basic diet[a,c]		**Realised development:** % of initial households with at least a basic diet[a,d]		**Raised total production:** Total number of households potentially fed a basic diet[a,e]	
Policy scenario	**Climate scenario**	**25 years**	**50 years**	**25 years**	**50 years**	**25 years**	**50 years**	**25 years**	**50 years**
Entre	**No**	0.83 (36%)	0.70 (22%)	0%	0%	65%	77%	3,606	4,559
	Low	0.80 (41%)	0.71 (26%)	0%	6%	59%	68%	3,350	3,659
	High	0.78 (46%)	0.78 (22%)	1%	18%	53%	60%	3,173	3,059
Entre eroding	**No**	0.84 (36%)	0.71 (22%)	0%	3%	64%	75%	3,829	4,111
	Low	0.80 (41%)	0.71 (25%)	0%	7%	59%	68%	3,530	3,260
	High	0.78 (46%)	0.78 (22%)	1%	19%	54%	60%	3,213	2,694
Peasant	**No**	0.82 (26%)	0.66 (17%)	0%	2%	73%	81%	2,914	5000
	Low	0.80 (30%)	0.61 (14%)	1%	6%	70%	78%	2,664	4,553
	High	0.78 (34%)	0.63 (8%)	2%	18%	64%	74%	2,333	4,124
None	**No**	0.84 (35%)	0.71 (22%)	1%	4%	64%	74%	2,891	4,087
	Low	0.81 (39%)	0.72 (24%)	2%	10%	59%	66%	2,559	3,586
	High	0.78 (44%)	0.78 (21%)	3%	23%	53%	56%	2,181	3,106

[a] A basic diet for the farming household (assumed to be comprised of four people) requires 700kg of cereal equivalents; 200kg of cereal equivalents provides 2200 kcal/day for a year [38].
[b] The numbers show the mean proportion of a basic diet consumed across all remaining orphan households (For the corresponding time-series, see top row in Fig 5); the numbers in brackets are the percent of initial households that remain in orphan agriculture.
[c] These results are based on the number of abandoned farms (see bottom row in Fig 4 for the corresponding time-series) as part of the criteria for abandonment is the inability to provide the family with at least 50% of a basic diet (Table 1).
[d] These results are based on the number of farmers who have converted to their preferred style (agroecology or entrepreneurial) (see third row in Fig 4 for the corresponding time-series) as the results indicate that all these households are able to provide a basic family diet (results not shown).
[e] These results are based on total production (i.e. across all farms; see top row in Fig 4 for the corresponding time-series), calculated as total production divided by 700kg.

The 'blocked development' columns are based on the orphan nutrition results reported in Fig 5 (top row) but also show the percent of initial farmers who are still practicing orphan agriculture. The results show the average fraction of a basic diet being consumed by orphan (i.e. subsistence) farmers is lowest under 'peasant' policy; however, the percent of farmers remaining in orphan agriculture is also lowest under this policy. The 'abandonment' column shows the percent of farmers who have abandoned their land as they have access to <50% of a basic diet: that is, this group have left farming as they were faced with starvation. Abandonment due to starvation rises when moving from no to low to high climate change, and is highest under the 'none' policy.

The 'realised development' columns show the percent of initial farmers who have been able to convert to their preferred style (agroecology or entrepreneurial). The model results indicate that these households are consistently able to meet basic dietary requirements (results not shown); thus, these numbers show the percent of initial households with at least basic nutrition. The numbers are highest under the 'peasant' policy, and decline when moving from no to low to high climate change. Finally, the 'raised total production' columns show how many households could be fed a basic diet given the total production across all farms. Numbers are highest under the entrepreneurial scenarios at 25 years, but at 50 years are highest under the 'peasant' scenario and – for low and high climate change – lowest under 'entrepreneurial eroding'.

These same farm development processes also generate a wider set of conditions that support (or undermine) the health of the rural community. Labour, as the number of full-time equivalent farm workers across all farms (Fig 5, second row), rises rapidly under the 'peasant' scenario before plateauing, with a similar trajectory under the 'none' policy scenario. In contrast, labour continually falls under the two entrepreneurial scenarios. Climate change reduces labour in all policy scenarios. Income inequality, as the Gini coefficient (Fig 5, third row), initially rises rapidly then slowly declines under all policy and climate scenarios. Inequality tends to be the highest in the 'none' policy, under which it increases when moving from no to low to high climate change. In the 'peasant' scenario, both peak inequality and inequality at 50 years are the lowest (compared to other policy scenarios).

Average net farm incomes (Fig 5, fourth row) rise steadily under all policy scenarios under no climate change. After about 25 years, incomes under the 'peasant' scenario begin rising faster than those under the other policy scenarios, and are the highest at 50 years (at this time they are lowest under 'entrepreneurial eroding'). Similar patterns are seen under low and high climate change, but incomes are higher (as prices as higher; Fig 4, second row). Patterns for 'real land productivity' (Fig 5, bottom row) are similar to those for net farm incomes, but gaps between the 'peasant' scenario and the other policy scenarios are wider.

Sensitivity analysis

We tested how changing the assumptions about the maximum production and climate sensitivity of agroecology and entrepreneurial farming influenced total food production and local food price under the 'entrepreneurial' and 'peasant' policy scenarios (Fig 6).

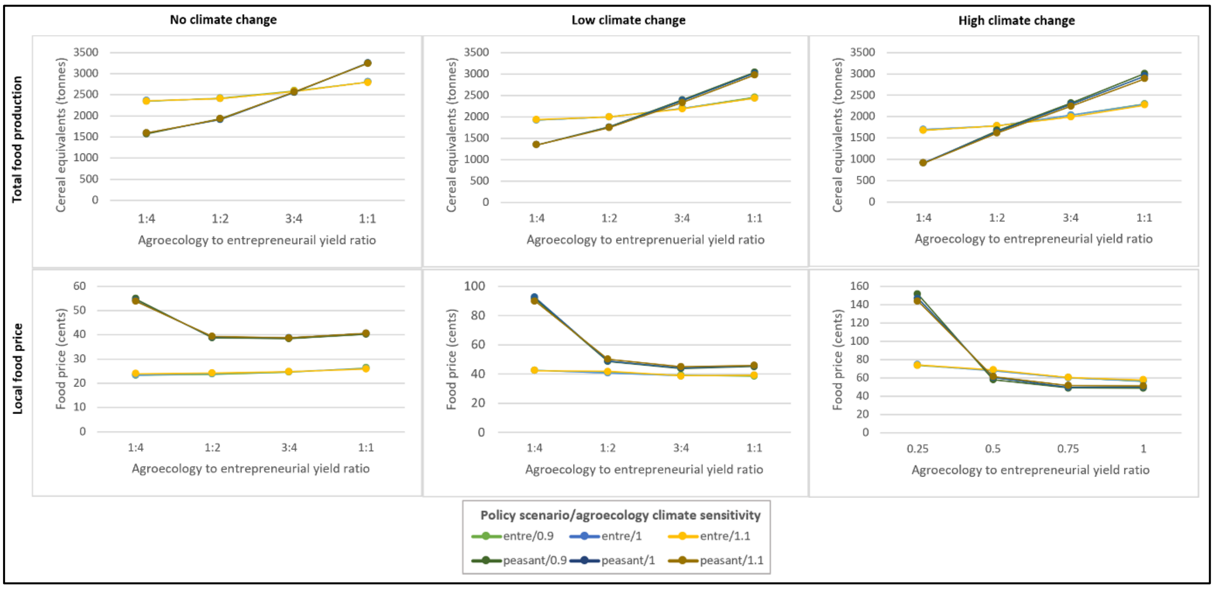

Fig 6. Total food production and local food price at year 50: sensitivity analysis. The plots show total food production (top row) and local food price (bottom row) (y-axes) after 50 years, under no, low, and high climate change (left to right plots, respectively), under different yield ratio assumptions (x-axes), for the peasant and entrepreneurial policy scenarios with different climate sensitivity assumptions (line colour). For the y-axes, values are shown as the mean result across 250 runs under each combination of factors (Note that the y-axis scale for local food price differs in each plot). For the x-axes, the numbers show the ratio of agroecology to entrepreneurial maximum production (e.g. 1:4 means maximum production for agroecology is 25% that of entrepreneurial farming). For the coloured lines, 'entre' and 'peasant' refer to the entrepreneurial and peasant scenarios, respectively, and, the numbers refer to agroecology climate sensitivity relative to entrepreneurial farming, where: 0.9 means agroecology losses are 10% lower, 1 means losses are equal, and 1.1 means agroecology losses are 10% higher.

After 50 years in futures without climate change, food production is 50% higher in the 'entrepreneurial' compared to the 'peasant' scenario when the agroecology to entrepreneurial yield ratio is 1:4 (Fig 6, upper left panel). The gap closes to 25% when the yield is ratio of 1:2, and production is equal when the ratio is 3:4. At a ratio of 1:1, total production in the peasant scenario is 15% higher than in the entrepreneurial scenario.

In futures with climate change, food production under the peasant scenario rises relative to that under the entrepreneurial scenario, with the climate sensitivity assumptions having only a small effect (Figure 6, coloured lines). When the yield ratio is 1:2, production under the peasant scenario is 14% and 8% lower than in the entrepreneurial scenario under low and high climate change, respectively (Fig 6, upper middle and right panels, respectively). When the yield ratio is 3:4, production in the peasant scenario is 7% and 11% higher than in the entrepreneurial scenario under low and high climate change, respectively. The latter figures rise to 20% and 22%, respectively, when the yield ratio is 1:1.

For local food price, in futures without climate change, prices are 35% higher under the peasant scenario relative to the entrepreneurial scenario for all yield ratios except 1:4, where prices are 55% higher (Fig 6, lower left panel). In futures with climate change, prices under the peasant scenario remain considerably higher than in the entrepreneurial scenario when the yield ratio is 1:4. For the remaining yield ratios, peasant scenario prices are 15% to 20% higher than entrepreneurial prices under low climate change. Under high climate change, peasant scenario prices are 10% to 20% lower than those in the entrepreneurial scenario.

Discussion

In this paper we have presented the first (at least to our knowledge) ABM that focusses on climate change, hunger, and health. The flexibility of this approach allowed us to include previously neglected processes in order to view climate-nutrition relation from a novel standpoint.

Previous climate-nutrition modelling essentially traces a pathway from climate change to nutrition amongst consumers, via changes in quantity and quality of food produced, where socioeconomic factors are seen as modifiers of these linkages [e.g. 12,14,17] (Fig 7, Panel A). Our model adopts an alternative standpoint, beginning with processes that shape both wealth and poverty - as well as both good nutrition and hunger - amongst subsistence farmers, and then assessing how climate change may influence these. Farm development trajectories are at the centre of the model, and these arise from the confluence of three underlying processes: 'industrialisation', in which farming increasingly depends on purchased inputs (i.e. entrepreneurial farming increases); 're-peasantization', in which peasant farming is strengthened via, for example, greater autonomy (i.e. agroecology farming increases); and 'deactivation', in which land is taken out of production (i.e. farms are abandoned) [29]. The resulting farm development trajectories manifest as changing constellations of households practicing different styles of farming, and these in turn give rise not only to patterns of nutrition but to a set of conditions that support the health of the rural community as well as vulnerability to climate change (Fig 7, Panel B). In sum, we aimed to gain new insights by shifting the standpoint of the model from that of the pathway between climate change and hunger to one based on farming styles and rural health.

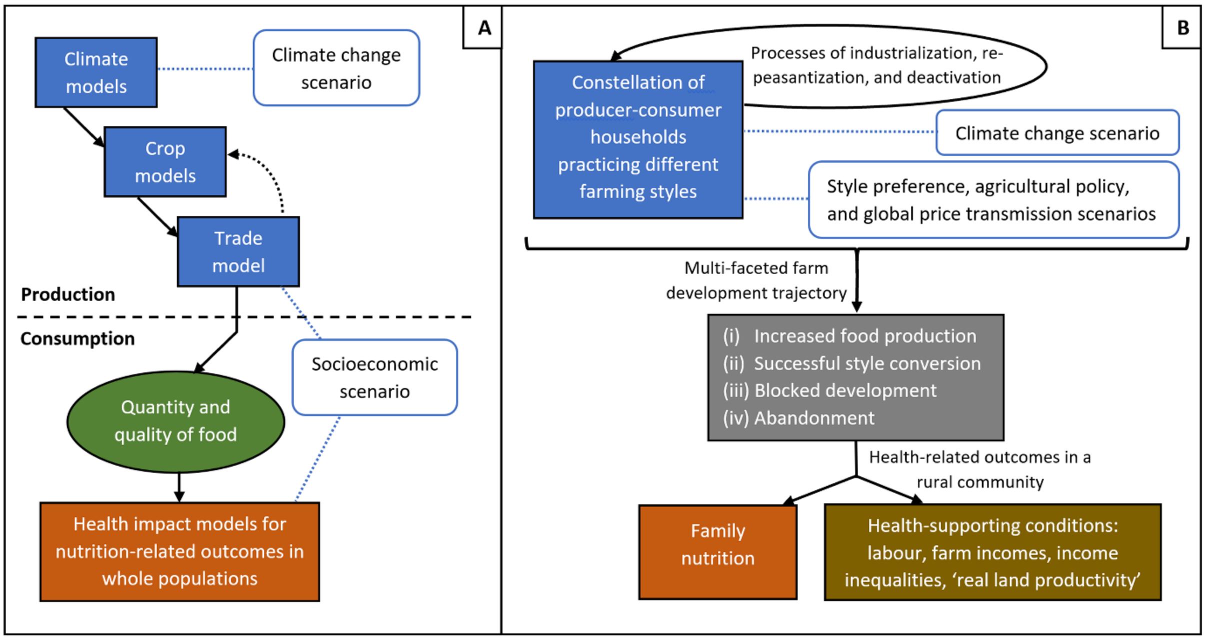

Fig 7. Alternative climate-undernutrition model structures based on different standpoints. Panel A shows the general structure underlying previous global-level climate-undernutrition models, which link together a series of component models. A pathway is traced from climate, to crops, to trade, to nutrition-related health outcomes. Production and consumption are separated, with the upstream component models calculating food availability (i.e. production). The health-impact model then combines the latter with socioeconomic variables to estimate consumption-related outcomes in entire populations. Panel B shows the model structure adopted in this paper. Constellations of producer-consumer farmers practicing different styles of farming develop over time under given climate, policy, style preference, and price transmission scenarios. Different facets of the farm development process give rise to patterns of hunger and other health-supporting conditions in the rural community.

Main findings

The 'Style preference and globalization' model runs assessed how patterns of farming styles influence production, price and farm incomes and were conducted in the absence of climate change and specific agricultural policies. That is, in contrast to previous climate-undernutrition modelling which assesses how production and price impact on hunger, we initially take a step back to assess how patterns of farming styles impact on production and price.

Four key patterns were seen, relating to: (i) the influence of farming style preference patterns of food production and price; (ii) the effects of global price transmission on food prices; (iii) differences in farm incomes by style and over time; and (iv) the mixed fates of the worst-off households depending on the style preference pattern. Table 5 describes the relevant patterns, their implications, and provides comments on the underlying mechanisms.

Table 5. The four key patterns seen in the results of the 'Style preference and globalization' model runs, their implications, and comments on the underlying mechanisms.

Pattern in the results	Implications	Comments on mechanisms[a]
(i) Food production and food price differ by style preference pattern		
As the proportion preferring agroecology increased, total food production decreased and local food price increased; this effect on production and price decreased over time (Fig 2, top and bottom rows, respectively).	Compared to agroecology futures, entrepreneurial futures provided both more and cheaper food, especially in the near term.	Agroecology is slower to develop than entrepreneurial farming, requiring an initial transition period and with potential yield gains accumulating gradually over time. Each style sets their optimal production and asking prices via different processes.
(ii) Global price transmission influences price but not production		
As global price transmission increased, local food prices fell, with the difference between prices under lower and higher transmission increasing over time (Fig 2, bottom row). Transmission did not influence total food production (Fig 2, top row).	Farm gross income declined as price transmission (i.e. globalization) increased (because price fell but production was unchanged), and this had a cumulative effect over time.	The model assumes global food prices are (on average) falling and oscillating over time. This means that as price transmission increases there is greater downward pressure on local prices. This effect interacts with the aggregate asking price of local farmers (the latter has only a small influence in this set of runs).
(iii) Farm income trajectories differ by farming style and over time		
Patterns of farm development – using income slopes over the previous 10 years as an indicator – were uneven (Fig 3). - Orphan farmers faced slow income decline at both 25 and 50 years (Fig 3, top row). - Agroecology farmers had increasing incomes: rapidly at 25 years and more slowly at 50 years (Fig 3, middle row). - Entrepreneurial farmers had increasing incomes at 25 years but falling incomes at 50 years (Fig 3, bottom row).	In entrepreneurial futures, there would be initial progress amongst most converted farms, but the beginnings of a farming crisis were evident at 50 years. In agroecology futures, there would be rapid progress initially, with progress slowing after 50 years.	All orphan farmers will convert to their preferred style if their resources allow it under current price conditions. Thus, remaining orphan farmers have had their development blocked (at least temporarily). Agroecology incomes rise rapidly from a baseline of precarious subsistence. This slows over time as potential production rises and the style is established. For entrepreneurial farmers, their margin is dependent on input:output price ratios (i.e. off-farm conditions). Over time they face an increasing "squeeze" (falling food prices, rising input costs) ([e.g. as described in 29]).
(iv) Fates of the worst-off households are mixed, with the pattern differing by style preference pattern		
As the proportion preferring agroecology increased, the decline in the incomes of orphan farmers increased, with a greater effect at 50 years compared to 25 years (Fig 3, top row).	Some orphan farmers had their development blocked to a greater degree in agroecology futures compared to entrepreneurial futures. However, more orphan farmers were able to convert to there preferred style in agroecology futures (result not shown). That is, some orphan farmers were harmed while others benefited.	Opposing effects are operating. Agroecology benefits some orphan farmers, allowing them to convert as it has lower entry barriers (i.e. costs) than entrepreneurial farming, and it may generate conditions (i.e. higher prices) that allow others to convert. However, at the same time, the higher food prices also tended to trap the very worst-off farmers as they sell little food on the market but face rising input prices (which are linked to food prices).

[a] This column discusses key mechanisms that shaped the patterns of interest but other processes and between-process interactions are also likely to have contributed.

Collectively, the findings in Table 5 suggest that farming futures must consider trade-offs between the quantity of food produced, its price, the development of farming communities, and the fate of the most precariously placed households. For instance, if actions were to be guided by a theory of undernutrition that suggested abundant (i.e. addressing availability), low priced (i.e. addressing access) food was the solution to hunger, then the results would suggest that futures in which a high proportion of households adopt entrepreneurial farming in a highly globalized market would be the preferred future (Fig 2). This suggestion is complicated, though, when the implications for rural communities are considered (Fig 3). Futures that may appear to offer the greatest food security are precisely futures in which the model suggests farming would be in crisis (i.e. incomes tend to be falling) after 50 years (Fig 3, bottom right panel). In contrast, agroecology-orientated futures appear to mitigate these negative effects, potentially sustaining rural communities, but production increases are slower and food prices higher, and the worst-off households may have their development blocked (Fig 2 and 3).

In other words, different farming futures – that is, different constellations of farming styles and their development trajectories – appear to have very different impacts on food production, price, and the fates of farms. This may in turn be expected to have significantly different impacts on the conditions supporting the health of farming households. Further, these impacts would be expected to be modified by both climate change and agricultural policy. These expectations were explored in the second set of simulations.

The 'Climate change and agricultural policy' runs showed four key patterns: (i) between-policy differences in production and price reversed over time; (ii) the 'peasant' policy had mixed effects on farm conversion and abandonment rates; (iii) different facets of the farm development process had different implications for nutrition; and, (iv) the farm development process shaped a range of conditions that may support or undermine rural health. Table 6 describes the relevant patterns, their implications, and provides comments on the underlying mechanisms.

Table 6. The four key patterns seen in the results of the 'Climate change and agricultural policy' model runs, their implications, and comments on the underlying mechanisms.

Pattern in the results	Implications	Comments on mechanisms[a]
(i) Under climate change, between-policy differences in production and price reversed over time.		
After 30 years, production was highest under 'peasant' policy, with the gap between the latter and other policies increasing as climate change worsened (although total production simultaneously fell) (Fig 4, top row). In the absence of climate change and after 50 years, local food price was highest under 'peasant' policy, with prices tending to converge across all policies under low climate change and being lowest in the 'peasant' policy under high climate change. Prices were more stable under the 'peasant' policy.	'Entrepreneurial' policy initially provided the most food at the lowest prices. However, after an initial development period, food availability was highest under 'peasant' policy at prices that were similar to other policies under low climate change, and lower than under other policies under high climate change. Additionally, the tendency for more stable prices in 'peasant' futures may have reduced the risk entailed in agricultural livelihoods.	As described in Table 5, agroecology is slower to develop than entrepreneurial farming and each style sets its production and asking price differently. Additionally, in these runs, the introduction of supportive policies leads to faster rates of agroecology yield increments, which appears to allow farmers to sustain their livelihoods at lower asking prices than under the 'entrepreneurial' policy. Prices are more stable under 'peasant' policy as agroecology is relatively insulated from markets.
(ii) For farm conversion and abandonment, mixed benefits and harms were evident under 'peasant' policy		
The greatest number of farms were able to convert to their preferred style under 'peasant' policy (Fig 4, third row). However, more farmers abandoned farming under 'peasant' compared to 'entrepreneurial' policy (Fig 4, bottom row).	As described in Table 5, 'peasant' policy had opposing effects on orphan farmers, both facilitating conversion for some and blocking the development of the worst-off.	Lower transition costs allow more farmers to convert to agroecology earlier. The resulting higher food prices as agroecology proliferated, however, leads to prices of necessary inputs (which are linked to food price) that may be too high for farms with the lowest productive potential.
(iii) Different facets of the farm development process had different implications for nutrition		
Patterns of nutrition were influenced by total food production, blocked development, farm abandonment, and successful farm conversion (Table 4). Nutrition related to total production and conversion was highest under 'peasant' policy for all climate scenarios. However, under the same policy, nutrition related to blocked development was at its lowest and nutrition related to abandonment was at similar levels to that seen under other policies.	These findings - particularly that under a given policy/climate combination different facets of the farm development process may either benefit or harm nutrition – underscore the need to look beyond food quantity and quality, and to specifically consider producer-consumers, in future climate-nutrition modelling.	On average, orphan farmers have limited production potential relative to reproduction requirements (i.e. production and consumption). Thus, if their development is blocked, many will have poor nutrition. Farmers decide to abandon their farms if they cannot provide at least half a basic diet to the family. For households that have been able to convert to their preferred style, their level of production far exceeds basic dietary requirements.
(iv) The farm development process shaped conditions that may support or undermine rural health		
Farm development trajectories shaped patterns of labour, farm income, income inequalities, and 'real land productivity' (Figure 5), each of which would be expected to influence community health in rural areas. All of these conditions were most supportive of rural health under 'peasant' policy under all the climate scenarios.	These findings suggest that future climate-nutrition models should consider not only how farm development trajectories impact on nutrition, but also how they may shape rural health more generally via impacts on conditions that are supportive of (or harmful to) community health.	On labour: agroecology develops via labour-intensification while entrepreneurial farming develops via capital intensification. On income: low input costs and the avoidance of debt contribute to relatively higher net incomes in agroecology. On income inequalities: more and smaller farms under 'peasant' relative to 'entrepreneurial' policy results in lower inequalities. On 'real land productivity': the use of off-farm produced inputs on entrepreneurial farms means proportionally less new value is generated on the farm than on agroecology farms.

[a] This column discusses key mechanisms that shaped the pattern of interest but other processes and between-process interactions are also likely to have contributed.

In additional to Table 6, a number of further discussion points arise. The first relates to food production (Table 6, pattern (i)). Under the entrepreneurial policy, production initially rose rapidly but then began to decline after about 20 years before again rising, albeit slowly (Fig 4, top row). The decline is not explained by trends in farm conversions: the rate of conversion was slowing (Fig 4, third row) and this may have slowed production growth but it would not directly cause a decline. Nor is it explained by farm abandonment (Fig 4, bottom row). The farm income curves (Fig 5, fourth row), however, show the decline in production was a rational action aimed at maximising incomes. Immediately before the drop in production, income growth was slowing; during the subsequent period of falling production, however, income grew rapidly. That is, for entrepreneurial farming, the interactions of farmer goals, on-farm conditions (e.g. assets), and off-farm conditions (e.g. price ratios) may at times drive production downwards while simultaneously increasing net incomes.

A similar production pattern was not evident in the 'peasant' scenario (Fig 4, top row). Peasant farmers aim to increase returns per labour object (e.g. returns per hectare) and attempt to render themselves less sensitive to off-farm conditions. As a result, total production rose continuously over the model runs. Of further note, production at 50 years was lowest under 'entrepreneurial eroding' policy (Fig 4, top row): this highlights the risks faced by styles that are highly dependent on changeable off-farm conditions that are beyond their control.

The second point relates to the opposing effects of agroecology on conversion and abandonment rates (Table 6, pattern (ii); see also Table 5, pattern (iv)). The potential for negative impacts on the worst-off households and the means of addressing them should perhaps be explored in future empirical work and incorporated into model. For instance, programmes that ensure the most precariously placed households are included in community knowledge networks which aim to develop peasant farming may be developed [39,53]. Of additional note, under the 'none' policy, in which entrepreneurial and agroecology styles coexist, conversions were slower and lower than under 'peasant' policy and there were the highest levels of abandonment. This suggests that the viability of a co-existence strategy, that may appear robust due to a mixture of both peasant and non-peasant farming, may actually be harmful; this should be investigated in future work.

The third point relates to the impacts on the health-supporting conditions (Table 6, pattern (iv)). We have suggested that the higher levels of farm labour under the 'peasant' policy compared to the 'entrepreneurial' policy are beneficial for health (Fig 5, second row). This, however, is contentious. Some argue that reduced farm labour releases people from undesirable toil to work in other sectors;

others argue that agroecology generates rewarding work [71]. While this issue, along with its health-related implications, is likely to remain subject to dispute, two relevant considerations are: (i) the nature of work differs by farming style, meaning both positions may be correct: labour on entrepreneurial farms may entail drudgery while labour on peasant farms may be more rewarding [29,71]; and (ii) for people no longer working on farms, decent alternative employment in cities may not be available [72].

The results also show that income inequalities initially rose rapidly in all scenarios (Fig 5, third row). It may be speculated that, during this initial transition period, hardship for the many in the context of rising prosperity for a few may harm community health, and may have unexpected (and unmodelled in the ABM) influences on the longer-term development trajectories (e.g. via high levels of competition and rapid accumulation of land by the first to develop [73]).

Of final note on the results for the health-supporting conditions, both farm income and real land productivity are lowest under 'entrepreneurial eroding' policy (Fig 5, bottom two rows). This again shows the potential for farming styles that are heavily dependent on external conditions to place farming livelihoods in jeopardy, as well to farm less intensively (in the environmentally-sensitive sense of real land productivity), if these external supporting conditions are not maintained.

Sensitivity analysis

The sensitivity analysis assessed the impacts on total production and price when the assumptions about maximum yields and climate sensitivities of agroecology and entrepreneurial farming were varied. There were three key findings.

Firstly, farmers tended to produce at a level closer to their maximum yield under the 'peasant' policy than under the 'entrepreneurial' policy (Fig 6, top row). For instance, in futures without climate change, when maximum production for agroecology was 50% lower that for entrepreneurial farming (yield ratio 1:2), total production under 'peasant' policy was just 25% lower than under 'entrepreneurial' policy.

Secondly, the between-style gap in actual compared to maximum production widened when climate change was introduced (Fig 6, top row, middle and right panels). This was seen regardless of whether it was assumed agroecology was more or less sensitive to yields losses due to climate change than entrepreneurial farming. For instance, when agroecology maximum production was 50% of that of entrepreneurial farming (yield ratio 1:2), total production for the 'peasant' policy was just 14% lower than for 'entrepreneurial' under low climate change; this gap closed to 8% under high climate change. For yields ratios $\geq$ 3:4, production in the 'peasant' scenario exceeded that in the 'entrepreneurial' scenario.

Together, these first two patterns show that the main results are not dependent on either agroecology having equal (or indeed, higher) productive potential to entrepreneurial farming or being less sensitive to climate change. Rather, it suggests that the between-style differences in the way production and consumption decisions are made - which rest on differences in underlying goals – play a key role in shaping the results. These between-style differences are not accounted for in previous climate-undernutrition modelling [e.g. 10,11-17,24,35].

The <u>third</u> finding relates to food price. Here, patterns by climate change scenario at 50 years (Fig 6, bottom row) are broadly similar to those seen in the main results (Fig 4, second row). In futures without climate change, food prices were considerably higher under the 'peasant' scenario compared to the 'entrepreneurial' scenario (Fig 6, bottom left panel). Of note, the influence of the agroecology to entrepreneurial yield ratio on the between-style price difference is minimal for ratios $\geq$ 1:2.

Under low climate change, prices tend to be 15% to 20% higher for 'peasant' compared to 'entrepreneurial' policy (Fig 6, bottom row, middle panel); in the main results, this price gap was smaller (Fig 4, second row, middle panel). Under high climate, 'peasant' policy prices were 10% to 20% lower than those for 'entrepreneurial' policy (Fig 6, bottom row, right panel); in the main results, this price gap was larger (Fig 4, second row, right panel). Once again, the yield ratio assumptions had little influence on the between-style price difference for ratios $\geq$ 1:2. Further, assumptions about between-style differences in sensitivity to climate change had only a small influence on the results.

When the production and price results are considered together, similar patterns are seen to those in the main results when the yield ratio is $\geq$ 3:4. In futures with climate change and a yield ratio of 1:2, production is slightly lower under 'peasant' policy compared to the 'entrepreneurial' policy, with slightly higher prices under low climate change but slightly lower prices under high climate change. That is, when agroecology is assumed to have 50% of the productive potential of entrepreneurial farming, future production and price are reasonably similar. When the yield ratio is 1:4, the outcomes differ significantly to those in the main results, but the available evidence suggests agroecology yields currently exceed this level [e.g. 39,44,45]. Additionally, it has been argued that ongoing research and on-farm knowledge generation has the potential to further increase agroecology yields over time [30] (We note that the sensitivity analysis assumes there are no yield increases over time for agroecology).

In sum, while the sensitivity analysis shows the yield- and climate change-related assumptions influence the results (as would be expected), they do not significantly alter the general patterns when held within plausible bounds. While we consider the tested parameters to be the most important, we recognise the model utilises many other parameters (Tables 1 and 2). It is possible that model output may be sensitive to one or more of these. Future work should further refine the parameters and assess model sensitivity to those that may have a strong influence on model output.

Implications

Considered together, the upshot of the model results is that when attempting to understand how climate change may impact on future nutrition and health, patterns of farming styles - along with the fates of the households that practice them - matter. We stress that our model is not intended to directly represent the real world and we do not claim that the findings demonstrate that peasant farming and agroecology are the optimal ways forward. Rather, the model demonstrates that this may be a viable way forward, yet – despite being a future that is desired by many farmers [27] – it has been neglected in previous health impact modelling; thus, it warrants more attention.

Crucially, this line of inquiry is not just of academic interest: firstly, the contributions and vulnerabilities of peasants have been formally recognised by the United Nations with the adoption of the Declaration of the Rights of Peasants and Other Working People in Rural Areas (UNDROP) [74]; secondly, it goes to the heart of a current debate on the future farming. A recent report by The High Level Panel of Experts on Food Security and Nutrition [28] makes the distinction between 'sustainable intensification and related approaches' (which includes, for example, 'climate smart agriculture'), and, 'agroecological and related approaches'. In terms of our representations, the former is analogous to 'entrepreneurial' and the latter to 'agroecology'. The report highlights, for instance, that sustainable intensification starts from the premise that '… productivity per land area needs to increase in a sustainable manner …', while agroecological approaches emphasise '… reducing inputs and fostering diversity alongside social and political transformation focussed on improving ecological and human health …', and that these two approaches '… are thus grounded in very different visions of the future of food systems' [28].

Two distinct strands underlie this debate. The first is the empirical question of which futures are viable and would, for instance, be able to feed growing populations sustainably. The second is value-based: of these viable futures, which should we choose? [cf. 75] Shifting from a health model with a central focus on quantity and/or quality of food produced (i.e. where food is essentially considered to be 'a thing' that is separate from the processes that produced it) to one which explicitly considers farming styles (i.e. where food, how it is produced, and the social and environmental implications of this are considered together) simultaneously shifts from an approach that largely focusses on the empirical strand to one that includes aspects of the value-based strand. Both these strands are important for future population health, which include issues around who should choose the future we pursue as well as the distribution of benefits and harms.

Model limitations

Our model has a number of limitations. The first relates to the representation of different farming styles. We drew on existing typologies [29,30,38] but simplified them to define styles that were rigidly distinct from one another. We accounted for differences in relations with the market, the type of farm inputs used, and goals, as these influence farmer decisions and behaviours. In the real world, however, there are additional differences and between-style distinctions are less rigid: given this, it would be useful to develop more subtle representations in future work.

When modelling the economic behaviour of agents practicing different farming style, we did not draw on the tradition of agricultural household modelling [40]. This was because the latter has theoretical inconsistencies with our agent typology. At same time, agricultural household modelling has many well-developed aspects that are directly relevant to our approach, and the ABM could potentially be improved by drawing on them. For instance, the methods explicitly represent household production and consumption, are able to account for on- and off-farm produced inputs (e.g. fertilizers, wage vs family labour), and they have been used to look at how policies impact on the well-being (including nutritional status) of agricultural and non-agricultural rural households [40]. Future work should explore means of adapting these methods to allow, for instance, the incorporation of style-specific goals.

Two final issues related to farming styles are: (i) we only allowed conversions from orphan to either entrepreneurial or agroecology farming; future models should allow for other between-style conversion (e.g. from entrepreneurial to agroecology); and (ii) the ABM does not represent the environmental impacts of farming (such as soil degradation and greenhouse gas emissions), which would be expected to differ by style.

A second limitation is model parameterization (Tables 1 and 2). We used approximations based on quantifications (e.g. yield loss per degree of warming [42,43]), 'rules of thumb' (e.g. production and consumption in orphan agriculture [38]), and qualitative knowledge (e.g. annual yield increments for peasant agriculture [30]). We argue, however, that given the nature of our model (a proof of concept model focussed on a hypothetical rural area) and its purposes (to assess patterns of outcomes and draw attention to previously neglected processes) our parameterization is a reasonable first-order approximation and is adequate to illustrate fundamental patterns. Future modelling should attempt to refine these parameters, partly using empirical research but also drawing on expert knowledge and opinion where gaps exist.

A key aspect of this is agroecology-related knowledge gaps. For Europe, modelling of an agroecology future found that while production would decline by 35% in 2050 compared to 2010 (from a starting point of highly productive agriculture), healthy food would still be available for all Europeans, export capacity would be maintained, and agricultural greenhouse gases would decline by 40% [76]. For regions with lower incomes, empirical work has shown considerable yields gains from agroecology and similar farming styles [e.g. 44,45,77]. However, this is an under-researched area, and some existing research conflates agroecology with other forms of sustainable intensification thus neglecting key aspects of agroecology such as greater farmer autonomy [39,53].

A third limitation is that the model represents only some aspects of the global food system. For instance, the model does not include a 'demand-side' (other than the demand of farming households) that influences production and prices. Instead, we assume prices are set by the supply-side and that all food for sale will be purchased. This was partly intentional because, as Gliessman [26] argues, conventional supply-demand models essentially see agriculture as 'one giant farm' and group all people together as homogenous 'consumers'. Such a representation excludes factors that would be expected to impact on population health. Additionally, the ABM doesn't consider, for example, value-chains and their effects on nutrition [e.g. 78], or dietary diversity and the environmental consequences of dietary patterns [e.g. 79]. We argue, however, that these limitations are justified as they are both necessary – no model can represent the entirety of a complex reality – and advantageous: they allow the exploration of a part of reality that has not only been neglected but may provide key insights to achieving healthy, sustainable futures.

A fourth limitation is that the climate (Table 1) and agricultural policy (Table 3) scenarios were represented simply. This was intentional as it renders our assumptions transparent, but it would be possible to, for example, use more detailed climate scenario data in future ABMs. Under our representation (Table 1), the results showed average yield losses under low and high climate change after 50 years (relative to no climate change) of 9% and 18% under 'peasant', and 20% and 32% under 'entrepreneurial' policy, respectively. Losses of this magnitude are at the upper end of warming-related yield declines found across crop models [80]. However, we argue that this is partly justified because our model is intended to represent populations who live in regions that are expected to be most impacted (i.e. tropical regions), and, our model attempts to account for the effects of droughts as well as warming trends. For agricultural policies (Table 3), additional entrepreneurial- and peasant-favouring measures and their expected benefit could be explored and introduced.

Conclusions

By developing a model that views the climate-nutrition relation from a novel standpoint, we have gained new insights. Firstly, along with food quantity and quality, how farming is done - that is, patterns of farming styles - is likely to have a strong influence on future health. Secondly, farm development trajectories may have contradictory effects at a given time point (e.g. potentially benefiting some subsistence farmers but harming others) and on the same group at different times (e.g. rapidly rising production and falling prices may initially lead to rising incomes for some farmers but eventually to falling incomes). Finally, patterns of farming styles and their associated development trajectories will influence not only nutrition but also conditions that support rural health (e.g. labour, inequalities). We argue that each of these issues should be given greater prominence in debates amongst health-focussed researchers and in future modelling exercises. Specifically, we suggest a key strategy (in addition to, not in place of, existing strategies) for understanding the climate-nutrition relation is to move from a tendency to centre thinking around pathways traced from climate change to hunger, to instead focus on the development trajectories of farming styles and their impacts on rural health, and then ask how climate change may affect this.

In purely pragmatic terms, the question of how healthy, diverse diets could be provided for all people while living within planetary boundaries could be answered in multiple ways and achieved by various approaches to farming. Essentially, this is an empirical question. The question is complicated, however, by introducing issues such as democracy, justice, and equity, as these are normative issues that are contested [28], including in terms of what each of these actually entails. These latter issues are included as explicit goals of some styles of farming (e.g. agroecology [39]), and, different constellations of styles of farming are like to influence them in different ways. Previous climate-nutrition modelling has tended to focus on the empirical aspects using quantitative modelling. We argue that in addition to the empirical aspects, the normative aspects should also be considered, including through building models with an explanatory focus (such as Agent-Based Modelling), as it is their combined effects that will ultimately shape patterns of health. With our model, we have attempted to take a first step in this direction; we suggest that future work should continue on this path.

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Contribution of Research Paper 4 and new questions raised

The model developed for Research Paper 4 made two key innovations to fill a knowledge gap identified by Research Paper 3: it utilised Agent-Based Modelling, which to my knowledge has not previously been used in climate-health impact studies[33]; and, it explicitly accounted for different styles of farming (van der Ploeg, 2018), attempting to capture the core distinctions between approaches to sustainable agriculture that are currently being debated (HLPE, 2019). The results add to our understanding of the relation between climate change and hunger, showing that – alongside the quantity and quality of food produced - patterns of farming styles and their development trajectories are likely to: shape future health; have contradictory impacts on different sub-groups of farmers; and influence not only nutrition but also a range of conditions that support the health of rural communities.

For new questions raised and ways forward, see "Conclusions, Directions for future research"

[33] Although it has been used in climate change-oriented work in areas other than health, and in population health-oriented work in areas other than climate change impacts.

Chapter 7. Conclusions

The starting point of this thesis was the idea that the causation of hunger and undernutrition is complex, as is the climate-nutrition relation (Chapters 1 and 2). A wide range of processes are implicated in undernutrition, and a number of theoretical lenses may be used to develop our understanding, including of how climate change may impact on it. Despite this, prior to this thesis, global-level health modelling had – in essence - tended to take a single perspective on the problem; this may be (crudely) characterised as a "less or lower quality food means more hunger" perspective. This is a useful angle but leaves much unexplored.

In a seminal paper, Richard Levins proposed a modelling strategy for dealing with such complexity (Levins, 1966). Levins argued against a "brute force" approach, where the aim would be for a model to give as complete a representation of the phenomenon of interest as possible. The utility of such an approach is restricted by, for example, the limits of scientific practice (e.g. the ability to measure or quantify the full range of relevant parameters and variables) and the interpretability of such a model (e.g. it is difficult to identify the most important causal processes in a highly detailed model). Instead, Levins argued that our understanding of a complex phenomenon is better developed via a series of "strategic idealisations", in which – by intent – some processes are omitted, with choices being guided by what is already known about the problem and the purpose of the model (for a detailed discussion, see: Weisberg, 2006).

The aim of the thesis is based on Levins' suggested approach:

> *To develop - and illustrate the benefits of developing - multiple global-level undernutrition models, each adopting a different perspective and making different assumptions, and each providing different but complementary insights into how climate change may impact on future undernutrition and health.*

In this chapter I begin by summarizing the ways in which the thesis has met this aim. Following this, I briefly discuss the possible directions for future research as well as limitations of this thesis. I end with some concluding remarks.

Research Papers: Key insights and modelling strategy

Research Papers 1 and 2 (Chapter 4) built on previous work by adding a statistically-based health impact model. This made estimates of a more health-relevant outcome (child stunting) while also attempting to better account for the role of socioeconomic factors. In doing so, the results showed that future social and economic conditions appeared to play a much greater part in shaping the prevalence of stunting than climate change. In this model (as well as in other models (see Chapter 2)), however, it was assumed that national GDPpc gave adequate representation to socioeconomic conditions, and it was further assumed that they (i.e. socioeconomic conditions) would not be affected by climate change. These assumptions were made for a number of reasons.

Firstly, the availability of both historical[34] and projection[35] data (the former for fitting models; the latter for making future predictions) for socioeconomic factors is fairly limited, making it difficult (if not impossible) to incorporate them into empirically-based quantitative health models. Secondly, the central purpose of the health models was to assess the potential impacts of climate change; at the time these health models were being developed, upstream modellers were assessing climate impacts on crop productivity. Thus, health modellers also tended to focus on this aspect[36].

The third factor is associated with the way in which different types of variables tend to be represented in health models. In 1989, Laurell argued that, in general, epidemiology tended to treat the biomedical aspects of a problem rigorously but the social aspects "with the superficiality of the 'evident'" (Laurell, 1989). This is no longer the case given developments in social epidemiology (e.g. Bambra, 2016, Krieger, 2011, CSDH, 2008), but arguably the health components of climate-health impact models retain at least some of this tendency (e.g. Hales et al., 2014). To overcome this, climate-health modellers could draw on approaches used in social epidemiology (as well as further afield), including "stepping back" from the most proximal causes of undernutrition (i.e. food quantity and quality) to consider underlying social processes (cf. McMichael, 1999), and by explicitly drawing on theory (e.g. theories of the causes of undernutrition; see Chapter 2) to guide model development (Krieger, 2011).

To address some of the blind spots in previous work, Research Paper 3 (Chapter 5) shifted the focus away from food quantity in order to consider how the impacts of climate change on incomes of the poorest parts of populations and food price may combine to increase the risk of stunting in 2030. That is, it assessed how climate change acting through two socioeconomic pathways may shape future

[34] In addition, research has found that apparently precise historical data are often of low quality and may provide an unreliable account of actual conditions (Jerven, 2013, Jerven, 2018). This will in turn influence the outputs of models that are dependent on them.

[35] Until recently, the socioeconomic projection data used in climate change impact assessments was limited to demographics, GDPpc, education, and percent of a population living in urban areas (Wittgenstein Centre for Demography and Global Human Capital, 2017, IIASA, 2018, Jones and O'Neill, 2016). However, ongoing work is expanding the range of projection variables to include, for example, income inequalities (Rao et al., 2019).

[36] More recently, however, the World Bank developed a model that assesses how climate change may impact on poverty (Hallegatte and Rozenberg, 2017). This was used as an upstream model for Research Paper 3, enabling an assessment of the potential impacts of climate change on nutrition through its (i.e. climate change's) affects on socioeconomic conditions.

stunting. In order to explicitly focus on this, rather than building onto existing models based on food quantity or quality, a new (statistically-based) health model was developed. In doing so, it was assumed that in 2030 there would be sufficient food available for all people who were able to afford it; i.e. it placed the central concern of previous modelling in the background. This assumption served two purposes: (i) it allowed the total effects of incomes and food prices on stunting to be assessed by excluding co-dependent and “downstream” (and likely collinear) factors (cf. Biggs et al., 2010), and (ii) it facilitated the interpretation of patterns in the results (as it simplified the structure of the health model).

The quantitative results of Research Paper 3 suggested that – alongside concerns about climate impacts on food quantity and quality as assessed in previous models - the impacts of climate change on poverty are likely to increase the risk of stunting, particularly in rural areas. In addition, we argued that the patterns seen in the results implied that slowly rising food prices tended to lead to decent farm incomes and rural wages, which in turn reduced the risk of undernutrition and the risk that climate change posed to nutritional status. This interpretation, however, was guided by theory (Mazoyer, 2001, Mazoyer and Roudart, 2006) and previous empirical work (Hertel, 2016) rather than the explicit details of the health model.

The results of Research Paper 3 suggested two general ways forward. Option 1: having first established that poverty matters in a new model, build on existing food quantity- or quality-based models by simultaneously including climate impacts on poverty; i.e. attempt to make existing models more completely represent reality. Option 2: build new models that further explore mechanisms associated with food price and rural incomes while omitting other processes; i.e. attempt to capture a different part of reality (cf. Weisberg, 2006).

In the thesis, I opted for option 2. Option 1 would be potentially useful if the goal were to make quantitative predictions of future undernutrition, but option 2 is more useful for further developing an explanatory understanding. This choice is underscored by the following practical considerations.

Firstly, producer-consumer farmers are at the core of the issues raised by the results of Research Paper 3 but existing climate-undernutrition models split production from consumption by design (for example, see Chapter 2: Figure 2, Panel B). Thus, explicitly representing producer-consumers would be difficult. Secondly, empirically-based theories have argued that the “farming styles” (comprised of, for example, farmer goals, the types of farming inputs used, and the way a farm is connected to markets) adopted by producer-consumers influence farm incomes, development trajectories, and by extension farmer nutrition and health (van der Ploeg, 2018). Gliessman (2015), however, points out that in standard economic models - including the type used in existing climate-nutrition modelling -

“food production … is reduced to a merely technical problem in a purely economic context: to meet consumers’ demand for food, farmers develop and use the methods that produce the most food for the least cost”; that is, “farming methods [i.e. farming styles] are hidden inside the ‘black box’ of agriculture”. While the standard economic perspective is a useful, well developed, and widely accepted approach for many applications, it precludes the representation of producer-consumer famers practicing different styles[37]. Yet, “farming styles” are a central part of debates around the future of the food system (HLPE, 2019, Rosset and Altieri, 2017).

Thirdly, conventional climate impact models are currently driven by a set of standard socioeconomic scenarios: the Shared Socioeconomic Pathways (SSPs) (O’Neill et al., 2017). This across-model scenario harmonization brings many advantages. A limitation, however, arises if a key aim is to represent producer-consumer farmers: the SSPs that may be characterized as the most optimistic (in one way or another) (SSP1 and SSP5) assume that 92% of the world population will live in urban areas by 2100. The only scenario with a substantial rural population in 2100 (40%) is a pessimistic one. That is, while the SSPs are based on historical data and standard projection methods, and are widely accepted as plausible, they exclude the potential of modelling optimistic futures in which (relatively) large numbers of producer-consumer farmers live in vibrant rural communities (Lloyd and Hales, 2019). Yet, this is the future desired by large numbers of peasant farmers (La Via Campesina, 2019)[38].

Given this, for Research Paper 4, I attempted to develop a novel modelling strategy which intentionally de-coupled the health model from existing upstream models and the details of standard socioeconomic scenarios. This strategy, along with the use of Agent-Based Modelling, allowed the direct representation of households practicing different styles of farming, their distinct ways of making decisions, and internal processes (rather than exogenously imposed scenarios) that shape nutrition and health. New insights associated with previously unexplored processes were gained, but this was enabled by abstracting away a range of other processes, and climate change was represented simply (see “Discussion, Limitations” in Research Paper 4, Chapter 6). Thus, ongoing modelling should build on the finding of Research Paper 4 to develop new perspectives.

In sum, the research papers have broadened our understanding of the climate-undernutrition relation. They began by centring on the largely technical issue of producing sufficient food to feed the global population, and moved - by way of incomes of people who produce the food - to contested

[37] This is not to suggest that standard economic perspectives could not be adapted to explicitly account for farming styles; it only intends to suggest that in current global-level climate-undernutrition models farming styles could not be represented without such an adaptation.

[38] I do not mean to suggest this is necessarily a viable future; merely that it is a desired future for some groups.

issues around choices of farming styles. That is, they have illustrated that, when modelling population nutrition and health in future worlds, we need to think about socioeconomic conditions not only in quantitative terms (i.e. 'as having a little bit more of this, and a little bit less of that') but also qualitatively (e.g. in terms of how farming is done, including farmer goals), and the latter involves making explicit choices.

These insights were gained by developing a series of models, which: (i) each abstracted away a different set of processes; (ii) increasingly drew on relevant theoretical understandings of the core issues; (iii) adopted different technical methods; (iv) shifted the goal of the model from quantitative prediction to mathematically-based qualitive understanding; and, (v) moved from a general strategy of tracing a path from climate change to undernutrition and asking how socioeconomic conditions might modify this, to, beginning with an evolving social structure (i.e. constellations of farming styles) and asking how climate change may influence this.

I argue that the adoption of these and similar approaches into climate-nutrition modelling, as well as climate-health and planetary health modelling more generally, alongside the more typical approaches of refining existing models and/or developing multiple models that take essentially the same perspective and comparing their results (e.g. Caminade et al., 2014, Nelson et al., 2014), would better serve the goal of understanding future health impacts and how to reduce or avert them. That is to say, the adoption and development of Levins' strategy (Levins, 1966) in health impact modelling may ultimately lead to tangible benefits for population health.

Directions for future research

In general terms, given the complexity of the climate change-undernutrition relation, there are many possible directions for future research. At present, active lines of inquiry include, for example, sustainable diets (e.g. Willett et al., 2019) and the role of value chains (e.g. de Brauw et al., 2015)), and findings from the research papers in this thesis could potentially be integrated into existing work. Here, however, I focus on the future development of Research Paper 4.

The findings of the ABM raised a number of issues that would benefit from further investigation. In line with the general modelling strategy adopted in this thesis, one option would be to develop a model that takes a new perspective. However, as the ABM rests on a number of simplifications, I would argue that some of these – particularly those that are apparently most strongly linked to the key findings – should be "complexified". The priorities for development essentially mirror the model limitations raised in the discussion section of Research Paper 4 (Chapter 6).

There are three major priorities. First, as farming styles lie at the core of the model, their representation should be refined, becoming less dichotomous and more strongly grounded in current agricultural innovations. For instance, “entrepreneurial” farming could be refined to better represent “climate smart agriculture”, and means of reflecting a wider range of goals associated with agroecology could be explored (HLPE, 2019). Additionally, farm development trajectories should be allowed to be multi- rather than uni-directional (e.g. by allowing entrepreneurial farmers to become more peasant-like over time).

Second, selected model parameters should also be refined. The model results suggested that in entrepreneurial-futures there is a tension between rapid increases in low priced food and the long-term viability of farms and thus rural communities. Conversely, during the first few of decades of agroecology futures, production was lower and food prices were higher. Refinement of the model parameters that underlie these patterns (e.g. productivity increases, input prices, credit markets) should therefore be prioritized in order to explore the robustness of these results.

Thirdly, a demand-side should be introduced into the model, perhaps initially representing adjoining urban areas that may be fed by a combination of food produced locally (i.e. by the modelled rural community) and imported food.

The above developments may assist in deepening our understanding of: whether agroecology would be able to increase production quickly enough to feed growing populations; whether rapid increases in production could harm sub-groups of farmers; whether or not rapid increases in the production of low priced food would be ‘the best way’ of eradicating undernutrition and ensuring food security; and, the potential impacts of gradually rising food prices on different populations groups.

A range of additional developments, including improved representation of climate change and other environmental processes, as well as incorporation of other parts of the global food system, could also be useful pursed in the future, but I would suggest that these are of lower priority than the above issues.

Limitations

This thesis has a number of limitations. The limitations of each of the research papers are discussed in detail in the relevant chapters (see Chapter 4, 5, and 6), and here I focus on the major limitations of the thesis as a whole.

First, the thesis only considered the global-level. Real farmers, however, exist in specific conditions in communities with histories; no understanding of climate change, nutrition, and the future of food systems is complete without including these aspects. A number of studies across various sites have demonstrated and quantified the links between climate, weather, quantity of food produced, and undernutrition (Belesova et al., 2018, Phalkey et al., 2015). Such detail is a blind spot in this thesis, which generated knowledge of a more general nature.

Nevertheless, the findings provide some insights into how future local-level research and modelling could advance. Firstly, farms and farming communities do not exist in isolation; even when only loosely connected to markets, global and national food systems may impact on them and influence their options and choices (Amin, 2003, Mazoyer and Roudart, 2006). Where possible, local-level studies may benefit from including such contextual issues which may assist in answering questions such as, "why are some families trapped in precarious subsistence farming?"[39]. Secondly, while local level studies often include social and livelihood variables as factors that modify the climate-nutrition relation, additional – and potentially more useful – insights may be gained by specifically considering farming styles (i.e. as a collection of qualities rather than a set of independent quantities).

Second, in all the research papers in this thesis, food was represented only in terms of calories; this is a clear gap as it only captures one aspect of how food intake contributes to undernutrition in individuals and to population health in general. For instance, estimates suggest that two billion people are deficient in at least one micronutrient (Myers et al., 2017), and, recent work has shown that what we eat collectively has major impacts on the environment and the sustainability of farming (Willett et al., 2019).

At the time Research Paper 1 was developed, it was useful to abstract away from the details of dietary composition to gain an initial understanding of how climate may impact on stunting, and, for Research Paper 4, looking at diet in simple terms better allowed a focus on farming styles[40]. Now, however, it would be useful to consider diet in more detail. This has already been done by some groups (e.g. Medek et al., 2017, Myers et al., 2015, Springmann et al., 2018). In particular, future work on farming styles should incorporate these aspects as, for example, the production of diverse foods under agroecology style farming not only provides good nutrition, it also underwrites farm resilience (Rosset and Altieri, 2017).

[39] This question is of relevance to health research as it focuses on sources of vulnerability, including to climate change and its health impacts.
[40] Research Paper 2 was an extension of Research Paper 1, and Research Paper 3 did not directly represent food.

Third, overall, the thesis did not generate a quantitively backed-up set of final statements. In particular, the most important findings of Research Paper 3 are statements based on patterns seen in the results, and Research Paper 4 provides only a qualitive understanding of potentially important processes. While this is not a limit to the ability of the research to address its objectives, it may be seen as an important limit in the context of climate-health modelling in general. In climate-health modelling, the key results are typically expressed along the lines of: under high climate change x million additional children would be stunted in the year y in region z. Outputs in this form have an immediately apparent grounding in the real world, stress the magnitude of impacts on particular groups of people, and are readily digestible by other researchers, stakeholders, and the media. This in turn may mean they are more likely to spur actions to avoid future impacts. To guide such actions, however, an understanding of the causes of the problem is required: traditional quantitative climate-undernutrition models, however, arguably offer little explanation beyond changed quantity or quality of food.

This tension is captured by two quotes (Sayer, 1992): Lord Kelvin claimed, "When you cannot measure it, when you cannot express it in numbers, your knowledge is of a meagre and unsatisfactory kind"; Jacob Viner, however, further claimed, "When you can measure it, when you can express it in numbers, your knowledge is still of a meagre and unsatisfactory kind". That is, to act on a complex problem, we need both quantitative predictive models (to aid prioritization), and models that attempt to explain why we see something (to guide actions) (Hedström, 2005), in particular by looking beyond the immediately apparent causes (e.g. a lack of food) to underlying causes (e.g. patterns of farming styles). And, as discussed throughout this thesis, there should be an interplay of results from predictive and explanatory models, with each guiding the other in an ongoing modelling process.

Thus, one means of overcoming this limitation – and which may hasten the development of our understanding of complex climate-health problems - is to attempt to increase the acceptability of a wider range of modelling goals amongst the climate-health research community.

Concluding remarks

I would like to conclude with some thoughts on a general issue arising from the research papers developed for this thesis. As noted above, the research papers moved from focussing on technical issues around the quantity of food that will be available in future worlds to contested issues around which farming styles will ensure future food security. This adds an additional dimension to Levins' (1966) original modelling strategy. Levins was writing in the context of population biology, which was attempting to understand existing ecological systems[41]. In contrast, the models in this thesis are considering possible future worlds; this brings an additional choice: that is, which possible futures should we model? For population health, this is a crucial consideration.

In broad terms, there two aspects to this: future climate and future social conditions. Future climate is a physical phenomenon, and while there are advances that could be made when representing it in health models – for instance, in relation to extreme weather events and tipping points – this aspect has tended to receive the greatest attention in previous modelling and there have been ongoing advances made (Anderson et al., 2019). Giving representation to future social conditions is arguably more challenging, and in any case is less advanced. Social processes have a strong influence on population health (CSDH, 2008), and there will be both supportive and undermining interactions between climate change, actions to mitigate and adapt to it, population vulnerability, and development trajectories (Lloyd and Hales, 2019).

Wright (2010) argues that, for the social world (which would, in terms of the thesis, include – for example - the organization of the global food system), "… what is pragmatically possible is not fixed independently of our imaginations, but is itself shaped by our visions". Rieff (2016) suggests we may need a "… different development debate, one focused less on the metrics of what new agricultural techniques or market reform work best … and more on what kind of society we want … - in short, a political debate focussed around justice rather than a debate about technical means … ", and goes on to say, " … we need to think through what a decent society consists of beyond the easing of extreme poverty and hunger". Ongoing investigation into, for example, new metrics and their utility is of course required; but alongside this, broader visions of potentially viable futures should also be considered, as well as their implications for population health.

Such issues are highly contested but cut to the core of the concerns of population health, which go well beyond the incidence and prevalence of diseases to include the underlying processes and living conditions that ultimately determine patterns of health (Bambra, 2016, Krieger, 2011, Stuckler and Siegel, 2011). Thus, I argue for the need to develop health models and accompanying scenarios that look beyond the expected prevalence of a given health outcomes, and give representation to a range of visions of contested but genuinely transformative futures. The latter may be based on, for instance, the desires of different social groups (e.g. peasant farmers (La Via Campesina, 2019)) or ideas developed by credible groups of academics that take a more critical view on possible futures (Tellus Institute, 2019). The aim of this approach would not always – or even often - be to settle matters

[41] Levins' interests extended well beyond modelling populations (e.g. Levins and Lewontin, 1985, Lewontin and Levins, 2007), but this was the context focus of the particular paper I am referring to.

scientifically: some elements may be settled empirically, and technology may open or restrict the available options, but many issues rest on values and will remain contested. Given this, at times the aim would be to give representation to futures desired by particular groups and contribute to assessing their viability[42].

Over recent decades, environmental epidemiology[43] has expanded the scope of the problems it attempts to address, first bringing in the implications of climate change (McMichael et al., 2004) and more recently focussing on "planetary health" (Whitmee et al., 2015). Over the same period, there have been multiple calls for epidemiology to draw on a wider range of technical methods (for example, Systems Dynamic Modelling and Agent-Based Modelling) as it confronts problems of increasing complexity (El-Sayed and Galea, 2017, Mabry et al., 2010, Maglio and Mabry, 2011)[44]. This thesis has arguably contributed to showing that a third set of innovations is required: alongside the expansion of the scope and the adoption of new technical methods, it is necessary to draw on a wider range of theories to guide analysis and modelling while simultaneously engaging more directly in contested issues around what kind of society we want. This is because the latter will be a crucial determinant of both climate change and population health, and because – at least partially – it is a choice that health modellers could – and should - influence.

[42] When considering a particular future world, Wright (2010) distinguishes between whether that future would be "desirable" (i.e. is this future wanted by some groups?), "viable" (i.e. if this future were actually realised, would it function as expected or undermine itself?), and "achievable" (i.e. if this future were both desired and viable, could we actually get there?).
[43] Arguably the core discipline underlying the majority climate-health impact models.
[44] An exception is infectious disease epidemiology, which has long drawn on complexity science.

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Appendices

Research Paper 1: Supplemental Material

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<u>**Supplemental material**</u>

Climate Change, Crop Yields, and Undernutrition: Development of a Model to Quantify the Impact of Climate Scenarios on Child Undernutrition

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Contents

Annex 1. Calculation of the development score

The formula for calculating the development score is:

$$w_{ij} = \begin{cases} -\frac{(a_{ij} - a_{max})}{(a_{max} - a_{min})} & if\ a_{ij} \leq \tau \\ 0 & if\ a_{ij} > \tau \end{cases} \qquad \forall i, j \qquad [S1]$$

where:

$$a_{ij} = \ln\left(\frac{\text{GDP/capita}_{ij}}{\text{Gini}_{ij}}\right) \qquad [S2]$$

a_{max} = maximum value of a_{ij} across all countries i with $a_{ij} \leq \tau$ in all regions j,
$a_{max} = \max_{i,j}\{a_{ij}\}$

a_{min} = minimum value of a_{ij} across all countries i with $\frac{GDP}{capita_{ij}} \leq \tau$ in all regions j,
$a_{min} = \min_{i,j}\{a_{ij}\}$

$\tau = 10$, the cut-off value for a based on a GDP/capita of $10 000 (USD 2000 US) and a Gini coefficient of 0.38

GDP/capita_{ij} = Gross Domestic Product per capita for country i in region j
Gini_{ij} = Gini coefficient (World Bank 2011) of country i in region j.

(Note the operators $max_{i,j}\{.\}$ and $min_{i,j}\{.\}$ respectively mean the maximum or minimum of the argument in {.}; ∀ means 'for every')

Analysis of data for the present for GDP/capita, stunting and undernourishment, suggests that when GDP/capita is above $10 000 (US 2000) that both undernourishment and stunting are rare. This GDP/capita is approximately the lower end of the range seen in Western Europe, and socioeconomic conditions in Western Europe can generally be considered to be adequate in terms of avoiding stunting. We use an associated Gini coefficient of 0.38 to define minimum distribution of wealth necessary (In 1997 in Portugal, GDP/capita was $10,200 and Gini was 0.385). Based on these observations, we assume that once wealth reaches the equivalent of a GDP/capita of $10 000 (USD 2000) with a Gini of 0.38, that non-food causes of stunting are absent; that is, at and above this level, the development score is set to 0.

The initial scaling of the development score was done using a dataset for all countries (i.e. all countries across the globe) for which current GDP/capita and Gini coefficient data were available. This means, in the scaling from 0 to 1, 1 represents the 'worst' conditions currently observed, and 0 represents the 'best' conditions (capped as described above).

We note that this means that if conditions worsen in countries with very poor conditions currently, there is little room for the scaled development score to represent this (as the score will already be close to 1). In practice, however, the scenario we examined (as is common to all currently available socioeconomic scenarios for the future) assumes there is growth in GDP/capita in all countries; that is, there is no need to scale the score to allow the worst off countries to worsen. If the need arises to allow for worsening conditions, the development score could be re-scaled appropriately.

Annex 2. Estimating proportion undernourished (PoU)

Our model required projections of future proportion undernourished (PoU) with and without climate change. Nelson et al (2009) estimated country-level average per capita calorie availability in 2050 using five crop models (wheat, rice, maize, soy and groundnut) and the IMPACT trade model. For details of the assumptions in the crop modelling (e.g. regarding CO_2 fertilization, irrigation and adaptation responses, etc), extrapolations to other food groups, and the trade model see Nelson et al (2009).

We used the estimates of country-level per capita calorie availability to estimate PoU using the FAO method (FAO 2003). The FAO method assumes that the within-population distribution of calories is described by a log-normal distribution, and is driven by estimates of (i) the coefficient of variation for within-population calorie distribution, (ii) the average minimum calorie requirement to avoid undernourishment in the population, and (iii) per capita calorie availability (see FAO (2003) for details). As scenario (future) data were not available for either (i) or (ii), we obtained current estimates (FAO 2010) and assumed they remained constant at current (baseline) levels.

Supplemental Material, Table 1. Percentage of Monte Carlo simulation estimates rejected for having values < 0 without and with future climate change[a]. All numbers are percentages.

	No climate change		With climate change	
Region	**Severe stunting**	**Moderate stunting**	**Severe stunting**	**Moderate stunting**
South Asia	27	0	8	0
Sub-Saharan Africa, Central	<5	0	<5	0
Sub-Saharan Africa, East	14	0	<5	0
Sub-Saharan Africa, South	18	0	<5	0
Sub-Saharan Africa, West	<5	0	<5	0

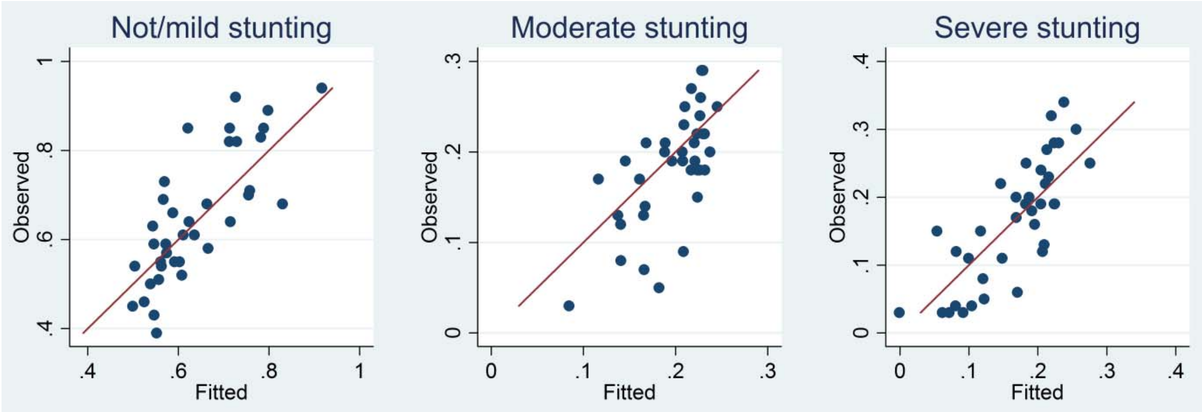
[a] In the Monte Carlo simulation, it was possible to obtain estimates where proportion stunted was <0 or >1. Thus we ran the simulation 500 000 times and selected the first 100 000 estimates that were >0 and <1 which potentially introduced bias. There were no estimates >1, meaning there was no risk of downward bias. This table shows the percentage of estimates that were rejected for being <0, which potentially introduces upward bias. More estimates for severe stunting were rejected in the 'no climate change' compared to the 'climate change' future which may have reduced the apparent impact of climate change on severe stunting.

Supplemental Material, Table 2. Countries in each region[a]. Countries marked with an asterisk* did not have complete data and were excluded from the simulation.

South Asia	**Sub-Saharan Africa, East**	**Sub-Saharan Africa, West**
Afghanistan*	Burundi	Benin
Bangladesh	Comoros*	Burkina Faso
Bhutan	Djibouti	Cameroon
India	Eritrea*	Cape Verde*
Nepal	Ethiopia	Chad
Pakistan	Kenya	Cote d'I'voire
	Madagascar	Gambia
Sub-Saharan Africa, Central	Malawi	Ghana
Angola	Mayotte*	Guinea
Central African Republic	Mozambique	Guinea-Bissau
Congo	Rwanda	Liberia
Democratic Republic of the Congo	Somalia*	Mali
Equatorial Guinea*	Sudan*	Mauritania
Gabon	Uganda	Niger
	United Republic of Tanzania	Nigeria
Sub-Saharan Africa, South	Zambia	Saint Helena*
Botswana		Sao Tome & Principle*
Lesotho		Senegal
Namibia*		
South Africa*		
Swaziland		
Zimbabwe		

[a] We used regions previously defined for the Global Burden of Disease Study 2010 (Institute for Health Metrics Evaluation 2010)

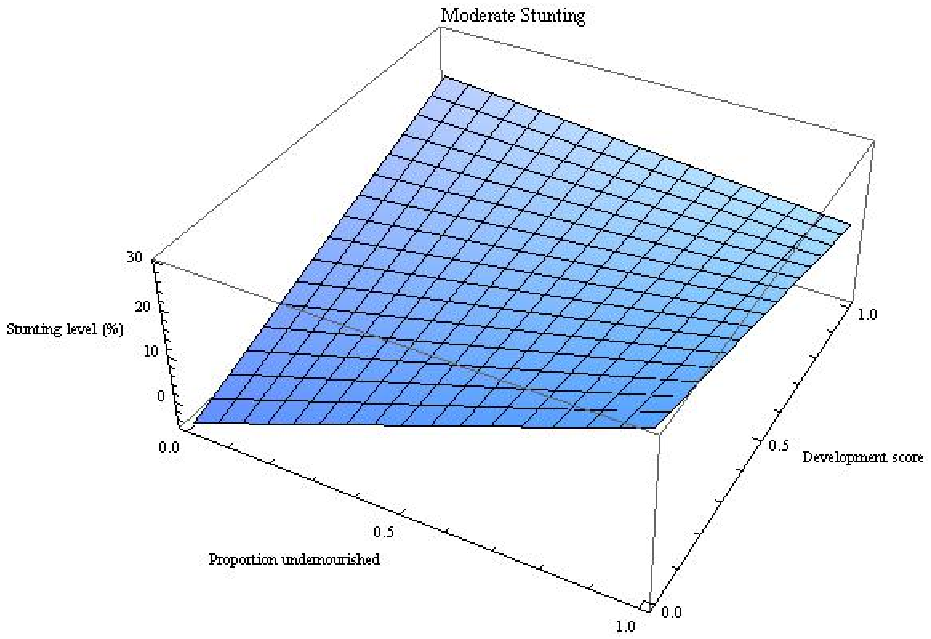
Supplemental Material, Figure 1. Model validation: scatter plots showing observed versus fitted estimates[a].



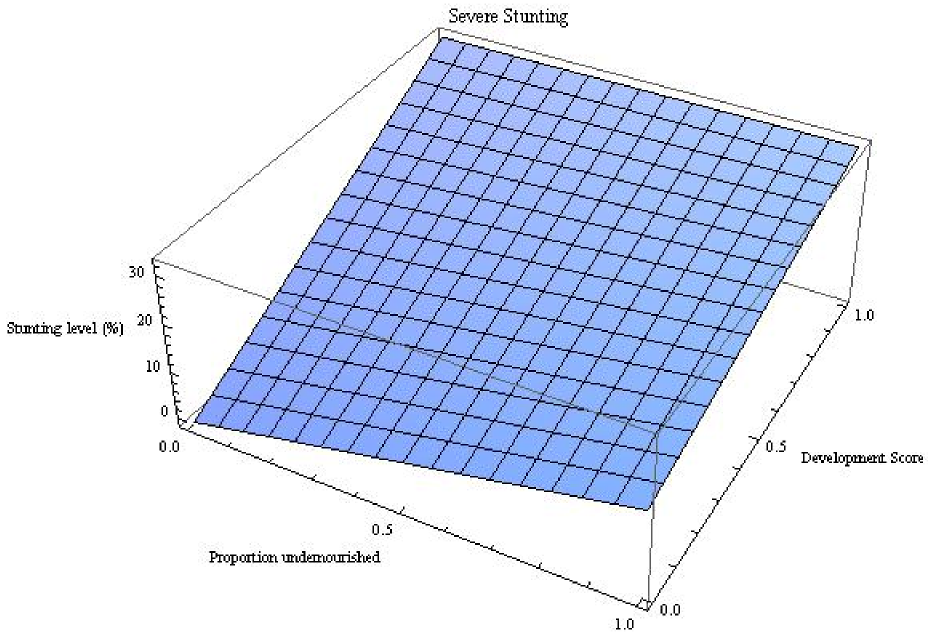
[a] The model was validated using the validation dataset (37 records). The x-axis is the model estimate, the y-axis is observed stunting, and the line shows a perfect fit.

Supplemental Material, Figure 2. Equation surface plots for A) moderate stunting and B) severe stunting

A) Moderate stunting



B) Severe stunting



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Research Paper 2: Supplemental Material

This section contains additional chapters of the report "Quantitative risk assessment of the effects of climate change on selected caused of death, 2030s and 2050s" that are relevant to Research Paper 2, including the reference list.

These are:

- Chapter 1 Introduction
- Chapter 8 Future Scenarios
- Chapter 9 References
- Annex

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Permission to reproduce sections of the report, "Quantitative risk assessment of the effects of climate change on selected causes of death, 2030s and 2050s" (Hales et al., 2014) was granted by the World Health Organization on February 1, 2019 (Catalina Gradin, WHO press; personal communication).

Introduction and key findings

1

Sari Kovats, Simon Hales, Simon Lloyd

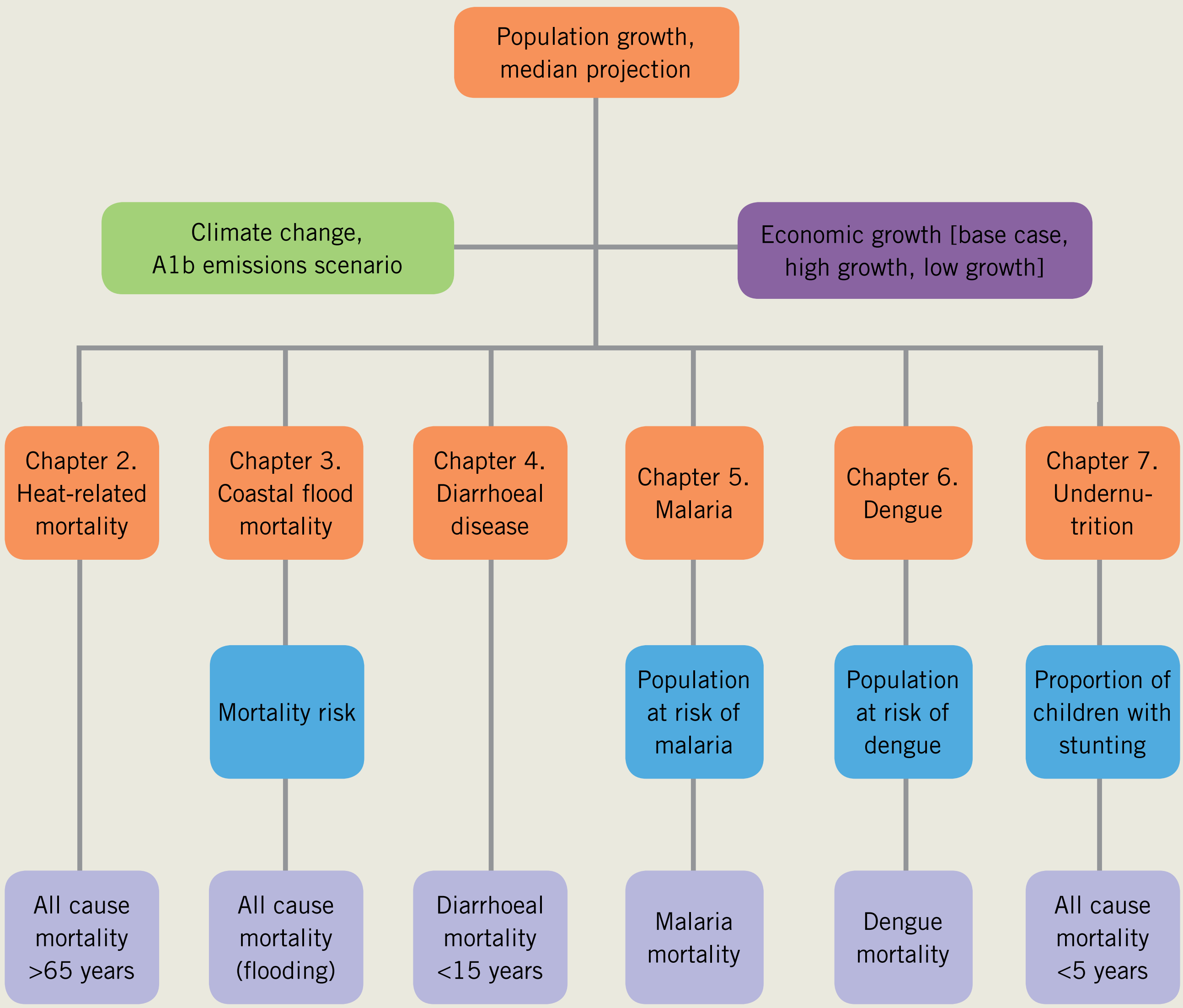
Climate change risks are systemic and long term in nature, requiring a different approach to assessment compared with other environmental exposures. Global burden of disease studies have focused on proximal risk factors and historical patterns (Lim et al., 2012), with relatively little attention paid to upstream causes. Burden of disease studies also focus on current exposures rather than future exposure and the long timescales required by climate change assessments. Climate change poses qualitatively different risks to human health, mainly via indirect pathways (McMichael, 1999, 2013). These features result in unique challenges for health risk assessment. There is a need to improve estimates of the effects of climate change on health on a global and regional scale (Campbell-Lendrum et al., 2007; Costello et al., 2009). The latest assessment of the Intergovernmental Panel on Climate Change (IPCC) found significant evidence gaps (Smith et al., 2014). For example, uncertainties about future vulnerability, exposure and responses of interlinked human and natural systems were acknowledged to be large, indicating the need to explore a wide range of socioeconomic futures in assessments of climate change-related risks.

This report summarizes the potential impact of climate change on health metrics and attributable mortality for two future time periods: 2030 and 2050. The assessment is an advance on previous studies (Campbell-Lendrum & Woodruff, 2006), but it is still constrained by limited quantitative information about, and understanding of, causal mechanisms linking climate with health impacts on a global and local scale. We did not assess the current burden of disease due to observed climate change (warming since the 1960s) (WHO, 2009a).

Since the first global risk assessment was published (McMichael et al., 2004), there has been some development of global models to estimate climate change impacts for a range of health issues, particularly for malaria (Caminade et al., 2014) and undernutrition (Nelson et al., 2010; Lloyd et al., 2011).

The health impacts of climate change described in this report are mortality caused by heat, coastal flooding, diarrhoeal disease, malaria, dengue and undernutrition (Figure 1.1). Models were run with a consistent set of climate, population and socioeconomic scenarios, as far as was technically possible. In keeping with current approaches to scenario-based climate impacts assessment, climate and non-climate scenarios were kept separate in the presentation of results. We also assessed, as far as possible, uncertainties associated with each impact model. We assessed the effect of climate model uncertainty by including a range of climate model projections. Estimates were done with and without inclusion of adaptation to climate change, as far as technically feasible (Table 1.1).

Figure 1.1 Models used in this assessment, with output metrics



1.1 Methods and data

This assessment, subsequently referred to as the Climate Change Risk Assessment (CCRA), involves the development of outcome-specific models to estimate future climate change-attributable health effects (a range of metrics indicated by blue boxes in Figure 1.1) and future annual mortality (light purple boxes in Figure 1.1). The individual health models are described briefly below and in detail in each chapter.

The overall conceptual framework of this assessment was to model mortality in future worlds with and without climate change. The climate change-attributable impacts were defined as the additional mortality in future years (2030s and 2050s) under climate change scenarios compared with the mortality in the same time periods under the 1961–1990 climate (the counterfactual).

In absolute terms, the future impacts of climate change will depend on underlying health status. Rather than assume no change in future health status, we base our assessment on forecasts of mortality in future decades. Mortality forecasts are based on empirical models of observed mortality trends in relation to major drivers such as socioeconomic development, education and technology, together with projections of the future trajectories of these drivers on a national scale (see below and Chapter 8 for details). It is assumed that recent trends in socioeconomic development, education and technology will continue for the next 15–50 years, resulting in a continued decline in mortality from infectious diseases and undernutrition (Mathers & Loncar, 2006; WHO, 2008, 2012). We acknowledge that the empirical method has limitations, including an inability to account for the subnational distribution of wealth and the optimistic assumption that there will be no major discontinuities in the trajectory of socioeconomic development until at least the middle of the 21st century.

A single greenhouse gas emission scenario, the Special Report on Emission Scenarios (SRES) A1b, was used in this assessment. Because of the long lead times between emission of greenhouse gases and changes in climate, the choice of emission scenario makes little difference to the projected range of climate change in the next few decades (IPCC, 2013). There is, however, strong justification for early emissions reductions, since the level of emissions in future decades has a major impact on the severity of climate alteration beyond the 2050s.

In order to take into account climate modelling uncertainty in future climate projections, five global climate model runs were used to estimate future impacts (see Chapter 8 for details). For some impact pathways, the results of intermediate models were used (for example, undernutrition estimates use outputs from food trade models, and flood mortality estimates use outputs from a coastal flood model). Final results were derived for 21 world regions, based on the regions used in the most recent round of the Global Burden of Disease study (Lim et al., 2012) (see Annex for details) and for two time periods (2030s and 2050s). We also report summary results for 10 world regions (Figure 1.2).

Table 1.1 Adaptation assumptions in the models used in this assessment

	Underlying trends	Adaptation assumptions included in model	Potential options not included in model	Foreseeable limits to adaptation
Heat-related mortality in elderly people	Population growth and ageing; improved health in elderly people due to economic development	Three levels of autonomous adaptation assumed – none, partial and full – based on shifts to optimum temperature	Improved heat health protection measures; early warning systems	Cost and feasibility of active and passive cooling measures in dwellings
Coastal flooding	Coastal population increase; increased vulnerability due to rapid urban development, which then declines	Evolving coastal protection measures	Population relocation	Technical and cost barriers to coastal defences, particularly in atoll countries, deltas and low-lying areas in poor countries
Diarrhoeal disease	Improved mortality outcomes due to technology and economic development	None	Improved water, sanitation and hygiene	Cost of installation and maintenance of water and sanitation facilities. Potential future decreases in water availability
Malaria and dengue	Assumed reductions in mortality rates resulting from socioeconomic development	Assumed reductions in mortality rates resulting from socioeconomic development	Specific novel interventions, e.g. vector control, vaccination, early warning systems	Insecticide or drug resistance
Undernutrition	Population growth; improved population health due to technology and economic development	Crop yield models include adaptation measures	Non-agricultural interventions, e.g. water and sanitation provision; reduced meat consumption in countries with currently high consumption	Limits of maximum productivity of agricultural systems

Table 1.2 Additional deaths attributable to climate change,[a] under A1b emissions and the base case socioeconomic scenario, in 2030

Region	Undernutrition[b]	Malaria	Dengue	Diarrhoeal disease[c]	Heat[d]
Asia Pacific, high income		0 (0 to 0)	0 (0 to 0)	1 (0 to 2)	1488 (1208 to 1739)
Asia, central	473 (–215 to 1161)	0 (0 to 0)	0 (0 to 0)	111 (49 to 150)	740 (364 to 990)
Asia, east	1155 (–5313 to 7622)	0 (0 to 0)	39 (23 to 48)	216 (95 to 298)	8010 (5710 to 9733)
Asia, south	20 692 (–39 019 to 80 404)	1875 (1368 to 2495)	197 (101 to 254)	14 870 (6533 to 20 561)	9176 (7330 to 10 620)
Asia, south-east	3348	550	0	765	2408

[Continues]

[Continued]

Region	Undernutrition[b]	Malaria	Dengue	Diarrhoeal disease[c]	Heat[d]
	(–2635 to 9331)	(398 to 779)	(0 to 0)	(336 to 1105)	(1629 to 3192)
Australasia		0 (0 to 0)	0 (0 to 0)	0 (0 to 0)	93 (58 to 151)
Caribbean		12 (12 to 12)	3 (3 to 3)	72 (31 to 104)	117 (73 to 148)
Europe, central		0 (0 to 0)	0 (0 to 0)	1 (0 to 1)	880 (570 to 1523)
Europe, eastern		0 (0 to 0)	0 (0 to 0)	3 (1 to 4)	1974 (1325 to 2904)
Europe, western		0 (0 to 0)	0 (0 to 0)	2 (1 to 13)	2625 (1152 to 5279)
Latin America, Andean[e]	445 (–327 to 1218)	17 (6 to 37)	2 (0 to 4)	49 (21 to 69)	181 (119 to 241)
Latin America, central[f]	859 (–837 to 2554)	39 (32 to 47)	6 (–1 to 9)	109 (48 to 156)	878 (540 to 1113)
Latin America, southern	14 (–49 to 76)	0 (0 to 0)	0 (0 to 0)	1 (0 to 2)	421 (303 to 686)
Latin America, tropical		95 (87 to 113)	5 (4 to 5)	19 (9 to 27)	739 (623 to 954)
North America, high income		0 (0 to 0)	0 (0 to 0)	2 (0 to 2)	2990 (2297 to 3287)
North Africa/ Middle East	1617 (–2030 to 5264)	14 (14 to 14)	0 (0 to 0)	1323 (582 to 1850)	2,058 (1381 to 2342)
Oceania		44 (44 to 44)	0 (0 to 0)	22 (10 to 32)	13 (9 to 20)
Sub-Saharan Africa, central	14 385 (–27 448 to 56 217)	56 705 (34 908 to 112 719)	0 (0 to 0)	6326 (2774 to 8946)	344 (281 to 389)
Sub-Saharan Africa, eastern	27 999 (–8701 to 64 699)	143 (142 to 143)	6 (5 to 7)	10 997 (4811 to 15 585)	1212 (1064 to 1552)
Sub-Saharan Africa, southern	1245 (–1505 to 3994)	0 (0 to 1)	0 (0 to 0)	489 (215 to 685)	254 (163 to 313)
Sub-Saharan Africa, western	22 944 (–31 728 to 77 616)	597 (597 to 597)	1 (1 to 1)	12 737 (5581 to 18 110)	987 (712 to 1214)
World	95 176 (–119 807 to 310 156)	60 091 (37 608 to 117 001)	258 (136 to 331)	48 114 (21 097 to 67 702)	37 588 (26 912 to 48 390)

a Unless otherwise stated, the central estimate is the mean, based on five global climate model runs, and the uncertainty interval (in brackets) is the lowest and highest estimates; for each region, the first line is the mean estimate and the second line is the lowest and highest estimates

b Undernutrition estimates are for children aged under 5 years; the central estimate is the mean of the probability density function of impact estimates; the uncertainty interval is mean ± 1 standard deviation of the probability density function

c Diarrhoeal disease estimates are for children aged under 15 years; estimates are based on median temperature across the five global climate model runs, with the central estimate based on the mid-estimate of the temperature/diarrhoea coefficient, and the range based on the low and high coefficient estimates

d Heat estimates are for people aged over 65 years; results assume 50% adaptation

e Undernutrition estimate for Andean Latin America and tropical Latin America combined

f Undernutrition estimate for central Latin America and Caribbean combined

1.1.1 Global health futures: population, economic and mortality projections

The health impacts of climate change will depend on the underlying health of affected populations, which will in turn depend on future socioeconomic conditions and other important factors, such as universal health coverage and environmental regulation. Three sets of mortality projections were developed for this project by the World Health Organization (WHO) (see Chapter 8):

- low (economic) growth;
- base case;
- high (economic) growth (consistent with the SRES A1 scenario) (Nakicenovic & Swart, 2000).

The approach built on previous methods (Mathers & Loncar, 2006; WHO, 2008, 2012). The method uses a series of regression equations that quantify the current and historical relationships between mortality and a set of independent variables. The major independent variables related to mortality were gross domestic product (GDP) per capita, years of education and time (which is assumed to be a proxy for health benefits arising from technological developments). In addition, specific assumptions are made regarding future patterns of acquired immunodeficiency syndrome (AIDS), tuberculosis, malaria, smoking and body mass index.

To represent future population totals and spatial patterns, we used the United Nations (UN) 2010 revision, medium variant (UN, 2011). This estimates a world population of around 9 billion people in 2050 that continues to grow and reaches about 10 billion people by 2100. Fertility and life expectancy are presently higher than anticipated in many countries; if this trend continues, then future population totals will exceed those of earlier projections (UN, 2011).

1.1.2 Climate scenarios

We used a single medium-high emissions scenario, SRES A1b, which captures the range of projections regarding global mean temperatures up to the middle of the 21st century (Nakicenovic & Swart, 2000).

We used five climate model runs – BCM2.0, EGMAM1, EGMAM2, EGMAM3 and CM4v1 (see Chapter 8). The climate scenarios were selected based on the availability of climate variables required for individual models.

The climate models chosen did not share a common spatial grid. Grid resolutions ranged from 48 × 96 to 160 × 320. All runs were therefore regridded (interpolated) to a 1° × 1° global grid (180 × 360). The coastal flood impacts were estimated using a sea-level rise scenario driven by SRES A1b (see Chapter 3).

The baseline climate (no anthropogenic climate change) was represented by the average over 1961–1990 from the Climate Research Unit, University of East Anglia TS 2.1 monthly time series. Some analyses have used alternative datasets, such as for heat-related mortality in

Chapter 2. The analysis of undernutrition relied on a model of the effect of climate change on food availability, which used two global climate models – Model for Interdisciplinary Research on Climate (MIROC) and Commonwealth Scientific and Industrial Research Organisation (CSIRO Mk3) – driven by A1 emissions (see below and Chapter 7 for details).

1.1.3 Climate health models

Heat-related mortality

A published temperature–mortality model was used to estimate heat-related mortality based on the observed association between daily mortality and temperature in Japan (Honda et al., 2014). Impacts were restricted to mortality in people aged over 65 years, and a single temperature mortality function was applied universally as the function was validated against other (temperate-zone) populations. The difference in mortality between the optimum temperature and a temperature beyond the optimum is defined as the heat-attributable mortality. Estimates were generated for three assumptions about the level of autonomous adaptation (no adaptation, partial adaptation and complete adaptation), and the optimum temperature was shifted accordingly (see Chapter 2).

Coastal flood mortality

A new global model to estimate the mortality attributable to storm surge was developed (Lloyd et al., 2014). Estimates of future populations exposed to coastal flooding due to sea-level rise were derived from the Dynamic Interactive Vulnerability Assessment (DIVA) global model (Vafeidis et al., 2008). Country-specific mortality from storm surges was estimated from the International Disaster Database (EM-DAT) (CRED, 2011) and used to fit a model, with the baseline exposure from DIVA (which assumes that all countries optimize coastal protection). The effect of economic development was modelled using the Human Development Index. Based on observed associations between disaster mortality and economic development, the model allows for an initial increase in mortality risk as low-income countries develop, followed by a decline in risk as disaster risk reduction is improved (Patt et al., 2010). The model was fitted with observed disaster mortality data using a short and long time series to balance the competing requirements of data completeness and the need to assess average mortality over a long time period. Impact projections were made for sea-level rise projections under the A1b emissions scenario (see Chapter 3).

Diarrhoeal disease

A linear exposure–response function was derived from the published literature that described the association between temperature and diarrhoeal disease. Due to the limited number of observational studies, a range of exposure–response functions was generated (high, median and low estimates). Estimates were restricted to mortality in children aged under 15 years. Climate scenario data were used to estimate the attributable fraction due to higher temperatures, which was then applied to projections of future diarrhoeal disease mortality (see Chapter 4).

Malaria

A published empirical-statistical model was used, which incorporates temperature, precipitation and GDP per capita as predictors of the past, present and future geographical limits of malaria (Béguin et al., 2011). Scenario-based projections of future climate, economic development and population were used to estimate changes in the population at risk of malaria in the years 2030 and 2050. Gridded population data for the A1b scenario were obtained from the International Institute for Applied Systems Analysis (IIASA, 2009) for the years 1990, 2030 and 2050. The population data were used together with the risk areas from the malaria model to estimate the future population at risk and the change in the population at risk from baseline climate. To calculate mortality associated with malaria infections, national current malaria mortality estimates were multiplied by the national ratio of the projected population at risk to the present population at risk (see Chapter 5).

Dengue

An empirical-statistical model was developed using temperature, precipitation and GDP per capita as predictors of the past, present and future geographical limits of dengue (Åström et al., 2012). Scenario-based projections of future climate, economic development and population were used to estimate changes in the population at risk of dengue in the years 2030 and 2050. Changes in the proportion of the national population at risk, along with estimates of current mortality from dengue, were used to estimate changes in mortality attributable to climate change, using the same method as for malaria above (see Chapter 6).

Undernutrition

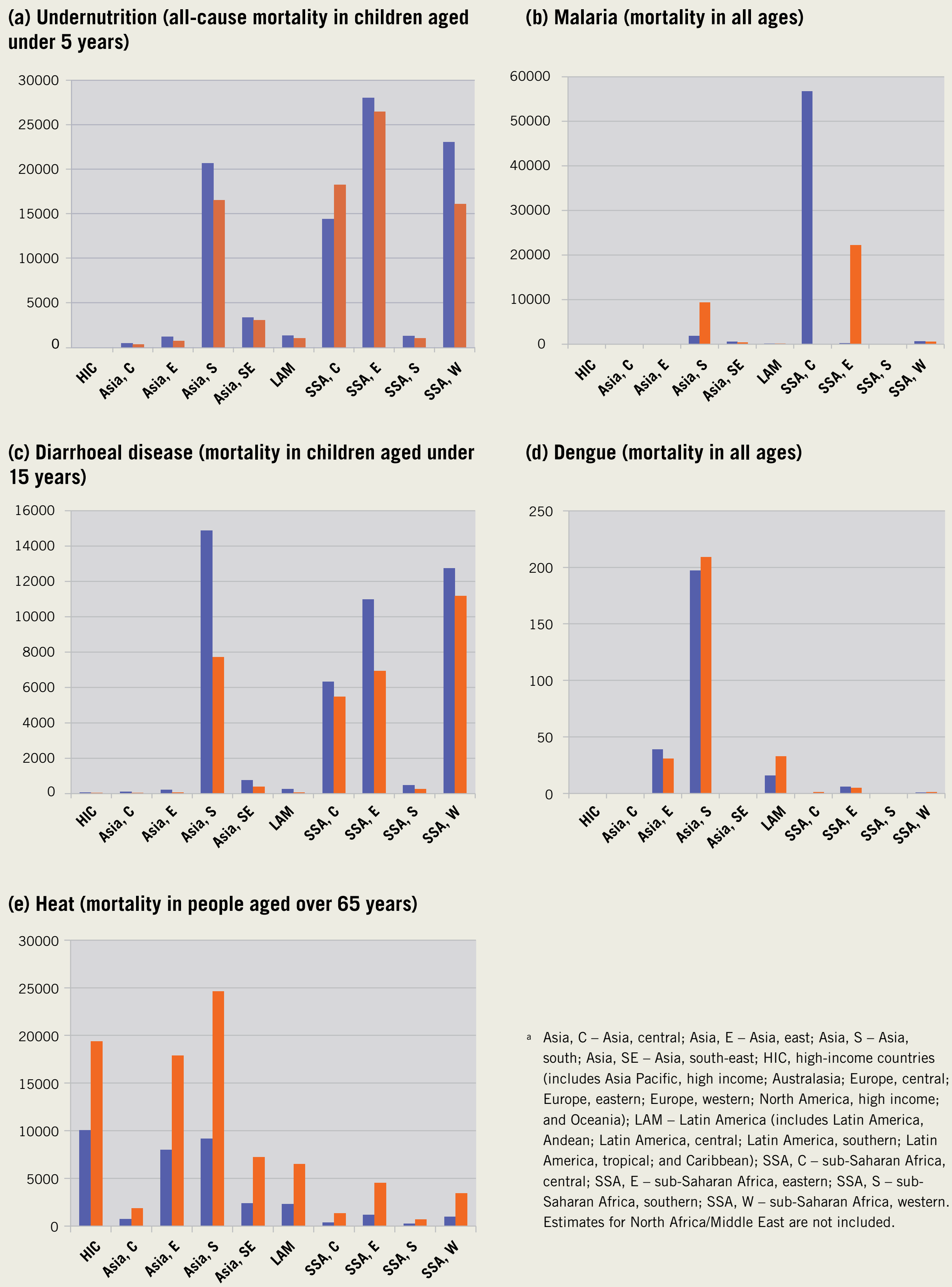
A previously published model estimated the effect of changes in per capita calorie availability (undernourishment) on undernutrition (stunting) in children aged under 5 years (Lloyd et al., 2011). The undernourishment estimates were derived from the International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT) integrated assessment model at the International Food Policy Research Institute (IFPRI) (Nelson et al., 2010). The model accounts for food and non-food (socioeconomic) causes of undernutrition. The model was used to estimate child stunting attributable to climate change based on projections of national food availability per capita published by IFPRI. This outcome was used to estimate the attributable burden of mortality in children aged under 5 years using published relative risks for association between stunting and all-cause mortality (Black et al., 2008), which were then applied to mortality projections provided by WHO (see Chapter 7).

1.2 Findings

Climate change is projected to have substantial adverse effects on human health that will be distributed unequally within and between populations.

Figure 1.2 and Tables 1.2 and 1.3 illustrate the regional distribution of annual climate change-attributable mortality in 2030 and 2050 under the base case scenario of economic development. Estimates are the annual impact for the specified year under each scenario, with a single population projection. The central estimates represent the average from five climate scenarios. Climate change may increase the burden of mortality from coastal flooding, but because these impacts are highly uncertain they are not included below.

Figure 1.2 Estimated future annual mortality attributable to climate change under A1b emissions and for the base case socioeconomic scenario in 2030 (blue bars) and 2050 (orange bars), by world region[a] and health outcome, for (a) undernutrition, (b) malaria, (c) diarrhoeal disease, (d) dengue and (e) heat



[a] Asia, C – Asia, central; Asia, E – Asia, east; Asia, S – Asia, south; Asia, SE – Asia, south-east; HIC, high-income countries (includes Asia Pacific, high income; Australasia; Europe, central; Europe, eastern; Europe, western; North America, high income; and Oceania); LAM – Latin America (includes Latin America, Andean; Latin America, central; Latin America, southern; Latin America, tropical; and Caribbean); SSA, C – sub-Saharan Africa, central; SSA, E – sub-Saharan Africa, eastern; SSA, S – sub-Saharan Africa, southern; SSA, W – sub-Saharan Africa, western. Estimates for North Africa/Middle East are not included.

Table 1.3 Additional deaths attributable to climate change,[a] under A1b emissions and the base case socioeconomic scenarios, in 2050

Region	Undernutrition[b]	Malaria	Dengue	Diarrhoeal disease[c]	Heat[d]
Asia Pacific, high income		0 (0 to 0)	0 (0 to 0)	1 (0 to 1)	2504 (1868 to 3046)
Asia, central	314 (66 to 563)	0 (0 to 0)	0 (0 to 0)	26 (12 to 38)	1889 (1077 to 2173)
Asia, east	700 (–427 to 1828)	0 (0 to 0)	31 (25 to 42)	72 (33 to 107)	17 882 (11 562 to 24 576)
Asia, south	16 530 (–1582 to 34 642)	9343 (2998 to 13 488)	209 (140 to 246)	7717 (3522 to 11 421)	24 632 (20 095 to 31 239)
Asia, south-east	3049 (605 to 5494)	287 (265 to 334)	0 (0 to 0)	383 (172 to 575)	7240 (5883 to 10 290)
Australasia		0 (0 to 0)	0 (0 to 0)	0 (0 to 0)	236 (180 to 359)
Caribbean		7 (7 to 7)	0 (0 to 1)	17 (8 to 26)	320 (259 to 380)
Europe, central		0 (0 to 0)	0 (0 to 0)	0 (0 to 0)	1680 (989 to 2769)
Europe, eastern		0 (0 to 0)	0 (0 to 0)	1 (0 to 1)	3218 (2438 to 4807)
Europe, western		0 (0 to 0)	0 (0 to 0)	1 (1 to 2)	5573 (3908 to 9737)
Latin America, Andean[e]	330 (–6 to 665)	1 (1 to 1)	3 (0 to 7)	12 (5 to 17)	597 (477 to 804)
Latin America, central[f]	706 (100 to 1311)	99 (56 to 167)	10 (7 to 14)	27 (12 to 40)	2713 (2137 to 3679)
Latin America, southern	11 (–27 to 49)	0 (0 to 0)	0 (0 to 0)	0 (0 to 0)	884 (624 to 1261)
Latin America, tropical		0 (0 to 0)	20 (15 to 23)	5 (2 to 7)	2007 (1489 to 2993)
North America, high income		0 (0 to 0)	0 (0 to 0)	1 (0 to 2)	6101 (4923 to 7259)
North Africa/Middle East	1167 (–480 to 2813)	209 (157 to 316)	0 (0 to 0)	812 (369 to 1206)	6669 (4731 to 8537)
Oceania		32 (32 to 32)	0 (0 to 0)	15 (7 to 23)	68 (58 to 101)
Sub-Saharan Africa, central	18 273 (–12 372 to 48 918)	0 (0 to 0)	1 (1 to 1)	5473 (2473 to 8174)	1363 (1139 to 1598)
Sub-Saharan Africa, eastern	26 480 (4936 to 48 024)	22 194 (18 747 to 26 002)	5 (4 to 5)	6951 (3138 to 10 392)	4543 (3497 to 5957)
Sub-Saharan Africa, southern	1032 (–516 to 2580)	0 (0 to 0)	0 (0 to 0)	267 (121 to 396)	706 (553 to 857)
Sub-Saharan Africa, western	16 105 (–19 500 to 51 709)	524 (524 to 524)	1 (1 to 1)	11 174 (5039 to 16 723)	3469 (2887 to 4261)
World	84 697 (–29 203 to 163 989)	32 695 (22 786 to 40 817)	282 (195 to 342)	32 955 (14 914 to 49 151)	94 621 (70 775 to 126 684)

a Unless otherwise stated, the central estimate is the mean, based on five global climate model runs, and the uncertainty interval (in brackets) is the lowest and highest estimates; for each region, the first line is the mean estimate and the second line is the lowest and highest estimates

b Undernutrition estimates are for children aged under 5 years; the central estimate is the mean of the probability density function of impact estimates; the uncertainty interval is mean ± 1 standard deviation of the probability density function

c Diarrhoeal disease estimates are for children aged under 15 years; estimates are based on median temperature across the five global climate model runs, with the central estimate based on the mid-estimate of the temperature/diarrhoea coefficient, and the range based on the low and high coefficient estimates

d Heat estimates are for people aged over 65 years; results assume 50% adaptation

e Undernutrition estimate for Andean Latin America and tropical Latin America combined

f Undernutrition estimate for central Latin America and Caribbean combined

An important component of the CCRA is the use of a consistent set of mortality projections with which to estimate future attributable mortality. We have used a range of GDP projections to drive the mortality forecasts.

The final mortality estimate is a combination of reduction in projected mortality in the absence of climate change, population growth in affected regions, and sensitivity of the health outcome to climate change.

Compared with a future without climate change, and in the absence of adaptation, approximately 65 000 additional deaths due to heat exposure in elderly people are projected for the year 2030 (see Chapter 2).

The coastal flooding modelling results show that much of the future burden of flooding can be avoided by adaptation to coastal flooding – assumed to be the construction and maintenance of coastal defences. This is not feasible for some populations, however, and so the results may represent an optimistic assessment of future health impacts. The results are, however, presented for a range of adaptation scenarios.

An additional 48 000 deaths due to diarrhoea and 60 000 deaths due to malaria are projected for the year 2030. There is very little projected increase in deaths due to dengue fever.

Undernutrition is one of the leading causes of death in young children and is likely to remain so in future decades. IPCC estimates suggest that climate change is likely to have significant effects on cereal crop productivity, potentially increasing the risk of undernutrition (Smith at al., 2014). Projected increases in infectious disease morbidity, especially for diarrhoeal illness, would exacerbate climate change effects on child nutrition.

1.3 Discussion

Climate change is projected to have substantial adverse impacts on future mortality, even under optimistic scenarios of future socioeconomic development. Under a base case socioeconomic scenario, we estimate approximately 250 000 additional deaths due to climate change per year between 2030 and 2050. These numbers do not represent a prediction of the overall impacts of climate change on health, since we could not quantify several important causal pathways (see Section 1.3.1).

The results of individual models are broadly consistent with previous published estimates for specific outcomes (see later chapters for details). A major limitation for a climate change risk assessment is the scope of the impacts that can be modelled quantitatively with sufficient confidence. The results reported here indicate that climate change will have an impact on health, even with adaptation and under conditions of high economic growth. Among these, the most substantial impacts of climate change on health are projected to be caused by undernutrition and infectious diseases (diarrhoeal disease and malaria). Impacts are greatest under a low (economic) growth scenario because of higher rates of mortality projected in low- and middle-income countries (see individual chapters). In 2030, sub-Saharan Africa is projected to have the greatest burden of mortality impacts attributable to climate change. By

2050, south Asia is projected to be the region most affected by the health effects of climate change.

Some models resulted in a wide range of uncertainty around the final estimates. Empirical models with improved statistical power can go some way to addressing this in the future. Due to the formulation of the models, uncertainty was estimated using a range of methods (see later chapters for discussion).

The previous estimate of the disease burden of climate change was for the year 2000 (McMichael et al., 2004) as part of the WHO Comparative Risk Assessment (2000–2004). Approximately 150 000 deaths globally were attributed to the climate warming experienced by 2000; most of these deaths were in sub-Saharan Africa and south Asia (Ezzati et al., 2002). In this project, we did not estimate a current burden due to observed climate change. Furthermore, with different models and different underlying assumptions and scenarios, the results of this project are not directly comparable with the previous WHO estimates.

1.3.1 Limitations of the assessment

The main limitation of the CCRA is the inability of current models to account for major pathways of potential health impact, such as the effects of economic damage, major heatwave events, river flooding or water scarcity. The assessment does not consider the impacts of climate change on human security, for example through increases in migration or conflict. The included models can capture only a subset of potential causal pathways, and none accounts for the effects of major discontinuities in climatic, social or ecological conditions.

Extreme events

The health impacts of extreme climate events are not included in this assessment, with the exception of the increase in coastal flooding due to sea-level rise. Extreme events are not well described by climate data averaged over space and time. Flood disasters from storm-surge events are included in the assessment, but an increase in river flooding due to climate change is not included because no global projections of populations at risk of flooding were available. The coastal flood risk assessment assumed no change in the frequency of storm events, apart from the relative change in impact due to rising sea levels. The crop yield models used within the undernutrition framework will include some measure of climate variability but not a scenario that includes multiple extreme drought events. The same methodological issues arise for the temperature-related impacts.

Burden of disease indicators

There are several reasons why mortality is only an incomplete indicator for a health impact assessment. For several outcomes, such as dengue, the health burden from morbidity far outweighs that attributable to mortality. Furthermore, for outcomes such as diarrhoeal disease, significant reductions in mortality rates have not been reflected in reduced morbidity rates. Future work will focus on summary measures of population health, such as disability-adjusted life-years (DALYs), and economic evaluation of impacts. It should be noted that many of the models provide useful intermediate endpoints that are not included here because they cannot be readily aggregated, such as the proportion of the population stunted and the population at risk of malaria. Several key outcomes included in this assessment are also closely interrelated, for example malaria and diarrhoeal disease are associated with increased mortality from undernutrition and vice versa. Thus estimates of mortality attributable to single diseases may under- or overestimate the true burden from climate change.

Our ability to model the effects of climate change on vector-borne disease is also limited. The models described below estimate the geographical areas within which the combination of average climatic and socioeconomic conditions is conducive to local transmission. Extrapolation to changes in mortality, based on the proportion of national populations at risk, is a crude, if reasonable, assumption. We assume no change in the mortality rate in the population defined as at risk at baseline and in the future.

1.3.2 Benefits of climate change to health

Climate change will have some positive impacts on human health. There are likely to be reductions in cold-related mortality and morbidity in high-income populations. The most recent assessment report of the IPCC concludes, however, that the impacts on health of more frequent heat extremes greatly outweigh the benefits of fewer cold days, and that the few studies of the large developing country populations in the tropics, point to effects of heat, but not cold, on mortality (Smith et al., 2014). The effect of cold temperatures is therefore not modelled in this assessment. Any beneficial effects of climate change on food supply and vector-borne disease distribution are included in the current estimates, which represent the aggregate results at the regional level. At the national or local level, benefits to health may be more apparent.

1.3.3 Incorporating adaptation into the assessment

Some of the impacts on health due to climate change in this assessment can be avoided by adaptation measures. This reinforces the need for strengthened public health measures. The quantification of the burden avoided by adaptation is difficult to assess, however. Adaptation can occur at all stages of the relevant causal pathways, such as disaster risk reduction or increased food production. Table 1.1 describes how adaptation was modelled explicitly for each health outcome.

This study shows that, even with effective adaptation policies, climate change can undermine current and future development programmes. Therefore, in the long term (decades to centuries), development policy is unlikely to succeed unless future global environmental risks are considered.

1.3.4. Implications for policy

The conclusion that climate change is projected to have substantial adverse impacts on future mortality, even considering only a subset of the expected health effects, under optimistic scenarios of future socioeconomic development and with adaptation, does have implications for the international effort to address climate change.

In relation to mitigation policy, the results indicate that minimizing climate-sensitive health risks is an additional reason to act to reduce climate change, alongside the immediate health benefits expected to accrue from measures to reduce climate pollutants (for example, through lower levels of particulate air pollution), and the avoided damages to other human and natural systems.

With regard to policies on climate change adaptation, the CCRA supports the case both for the overall strengthening of programmes to address health risks including undernutrition, diarrhoea, vector-borne disease, and heat extremes, and for explicit consideration of climate risks (both from climate variability and long-term climate change) within programme design.

The results also have implications for the linkages between climate, health and wider sustainable development objectives. The strong effect of socioeconomic development on the projections of many of the health risks emphasizes the need to ensure that overall economic growth, climate policies and health programmes, particularly benefit the poorest and most vulnerable populations.

Future worlds and scenario data

8

Sari Kovats, Simon Lloyd, Sophie Bonjour, Colin Mathers

8.1 Introduction

This chapter describes in more detail the scenarios used in this global climate change risk assessment. We have used three global climate models to generate five climate scenarios representing one emissions scenario (A1b) (Nakicenovic & Swart, 2000) and three economic futures (base case, low growth, high growth) to describe impacts across a range of plausible futures. An overview of the scenarios is given in Table 8.1.

Table 8.1 Summary of scenarios used in the assessment

Scenario name	Climate data	Population data	Mortality data	GDP data
Base case	A1b	UN 2010 revision, medium variant	Base case	Base case
Low growth	A1b	UN 2010 revision, medium variant	Low growth	Low growth
High growth	A1b	UN 2010 revision, medium variant	High growth	High growth

8.2 Climate data: observed

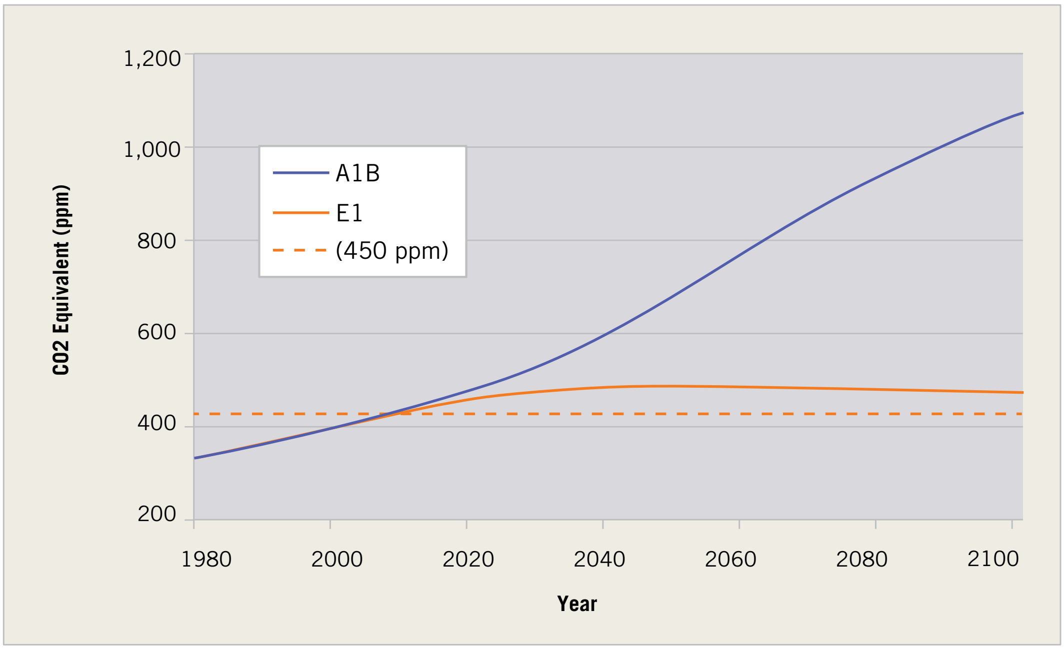
Observed climate data are used to represent the current climate. This was based on the Climate Research Unit TS 2.1 monthly time series for 1961–1990, which has a spatial resolution of 0.5° × 0.5° (Mitchell & Jones, 2005). We refer to this as baseline climate.

The baseline climate serves two purposes. First, it is used in combination with output from climate models to estimate future climate. The output of the climate models was not used directly. The temperature change (delta) was extracted as the difference between the projected future climate (for example, the 2030s) and the baseline time period (1961–1990), this change in temperature was then added to the observed baseline climate to represent future climate change. Second, the baseline climate is used to represent the future climate in a world without climate change – that is, it is used as the counterfactual climate.

8.3 Climate scenario data

There is much uncertainty about the future climate arising from the possible greenhouse gas emission pathways that society will follow and how a given level of emissions will influence climate. In terms of emissions, the effect of different pathways on global mean temperature is not significant before around 2040; as health impact estimates are made out to 2050, it was agreed to use a single emissions scenario: A1b from the SRES (Nakicenovic & Swart, 2000). The A1 scenario family comprises three groups that describe alternative directions of technological change in the energy system. The groups are distinguished by their technological emphasis: fossil-intensive (A1FI), non-fossil energy sources (A1T), and a balance across all sources (A1B) (where balanced is defined as not relying too heavily on one particular energy source, on the assumption that similar improvement rates apply to all energy supply and end-use technologies). Figure 8.1 shows the emissions trajectory under A1b.

Figure 8.1 A1b emissions trajectory; for comparison, an optimistic mitigation scenario known as E1 is also shown



To account for uncertainty in how emissions will affect climate, the outputs of several different climate model runs were used. The model runs used were selected based on the availability of the following variables: temperature, humidity and precipitation. Table 8.2 describes the five climate scenarios used.

Table 8.2 Climate model descriptions for the runs used in this assessment

	BCM	EGMAM	CM4
Modelling centre	Bjerknes Centre for Climate Research, University of Bergen, Norway	Freie Universitaet Berlin, Institute for Meteorology, Berlin, Germany	Institut Pierre Simon Laplace, Paris, France
Model version	BCM 2.0	EGMAM (2006)	IPSL-CM4_v1
Scenarios	20C3M, SRA1B	20C3M, SRA1B	20C3M, SRA1B
Run numbers	1	1, 2, 3	1
Original grid	64 × 128	48 × 96	72 × 96
References	Otterå, OH et al (2009)	Roeckner et al. (1996); Manzini & McFarlane (1998); Legutke & Maier-Reimer (1999)	Marti O et al. (2004)

The climate models used do not share a common spatial grid, with grid resolutions ranging from 48 × 96 to 160 × 320. All runs were therefore regridded (interpolated) to a 1° × 1° global grid (180 × 360). This was carried out using a bilinear interpolation routine, linint2 from the NCAR Command Language package (http://www.ncl.ucar.edu/Document/Functions/Built-in/linint2.shtml). Spherical harmonic-based regridding routines were available but are not advised for bounded parameters such as precipitation. It was felt that the same technique should be used across all parameters, so bilinear interpolation was chosen. Data processing was carried out by Ian Harris at the Climate Research Unit, University of East Anglia. The underlying data were from the ENSEMBLES project (Hewitt, 2004).

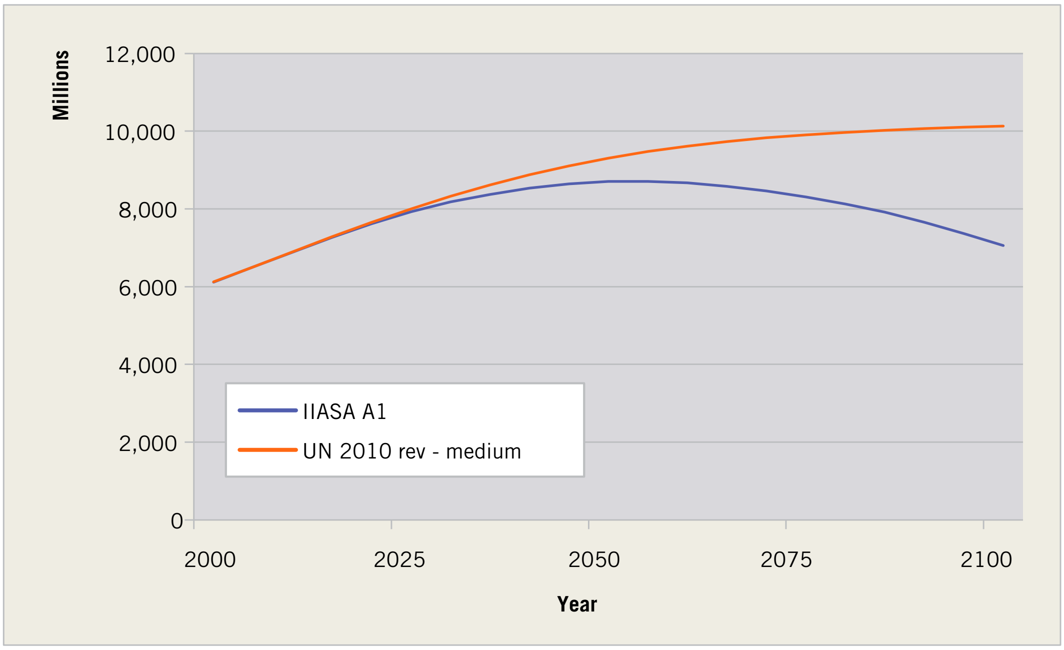
New post-SRES emissions scenarios (Representative Concentration Pathways) were developed for the IPCC fifth assessment report, but scenario data for these were not available at the time the estimates in this project were made.

8.4 Population projections

To represent future population totals and patterns, we used the UN 2010 revision, medium variant (UN, 2011). As analysis suggests that fertility and life expectancy are currently higher in many countries than was expected in the UN revisions made immediately before the 2010 revision, and expectations are that these will remain higher than previously anticipated in coming decades, future population totals exceed those made in the years immediately before this revision. The 2010 revision projects that in 2050, the world population will be around 9 billion people and will continue to grow to reach about 10 billion people by 2100 (Figure 8.2).

We have used the above projections as they were the most recent estimates (at the time of this analysis) of the most likely future trends. Totals differ from those used in previous climate change impact assessments for A1 worlds – particularly in the long term – and these differences must be borne in mind when interpreting our health impact estimates. Global total populations in the UN 2010 revision projections compared with IIASA A1 projections are 9.3 billion and 8.7 billion in 2050; 10.0 billion and 8.1 billion in 2080; and 10.1 billion

Figure 8.2 World population projections by year to 2100 for the UN 2010 revision (medium variant) and IIASA A1



and 7.1 billion in 2100. Previous work has generally coupled A1b emissions with population projections specifically made to accompany these emissions (van Vuuren et al., 2007), and these population projections were in turn based on low variants of the UN population projections from 2003 and 2004, which may, in light of the findings of the UN 2010 revision, be considered out of date.

Figure 8.2 compares the UN 2010, medium variant and one set of A1 population projections produced by IIASA (Grubler et al., 2007), with the A1 population peaking around 2050 and then declining to around 7 billion in 2100.

The implication of using the higher UN (2011) population projections in this assessment than in previous A1-based assessments is that the number of climate change-attributable deaths is likely to be higher. This is because there are more people potentially affected by climate change, and the countries with the highest population growth are, in general, those with high pre-existing disease burdens and thus most vulnerable to the health impacts of climate change.

8.5 GDP data

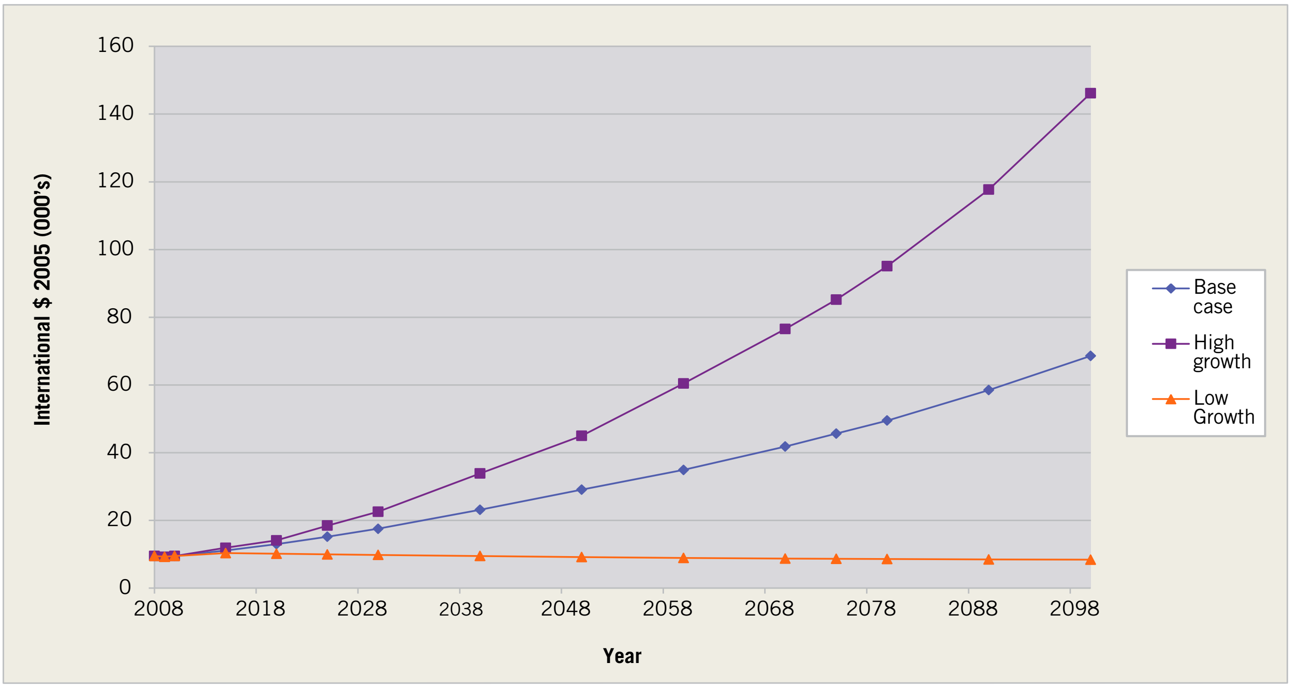
The GDP data are in 2005 international dollars as purchasing power parity. Three sets of historical estimates and projections were made, drawing on data from sources including the World Bank, International Monetary Fund (IMF), International Futures and the Organisation for Economic Co-operation and Development (OECD) (Table 8.3). Figure 8.3 shows the global level GDP per capita projections for the three scenarios. A high growth set of GDP projections was built based on the GDP country estimates developed for the emission scenario A1b (CIESIN, 2002). A low growth set of GDP projection was constructed in which growth tapers to zero in all countries by 2015.

Table 8.3 Data used in mortality projections[a]

Scenario	Base case	High growth	Low growth
Population	UN (2011)	UNDP (2010); UN (2011)	UNDP (2010); UN (2011)
GDP per capita	World Bank, OECD, IMF, International Futures	SRES A1	Growth from 2010 to 2015 tapers to zero at country level; country-level growth zero from 2015 to 2100
Human capital (average years of schooling at age 25 years)	International Futures base case with some adjustments	As for base scenario	As for base scenario
HIV/AIDS	UN (2010) for 48 countries, UNAIDS extended for others	UNAIDS projections, extended with optimistic trends	As for base scenario
Tuberculosis	Base scenario from previous projections extended to 2080	Base scenario	Base scenario
Malaria	Global Fund to Fight AIDS, Tuberculosis and Malaria scenario 2 (scale up to 147 million bednets per year by 2020)	Global Fund scenario 2 (scale up to 190 million bednets per year by 2020)	Global Fund scenario 2 (scale up to 110 million bednets per year by 2020)
Smoking	Base scenario updated projections (lower than previous projections)	Base scenario	Base scenario
Body mass index	Projections based on estimated trends for 1990–2010 regressed against GDP and time	Base scenario	Base scenario

a Projected changes in GDP/capita and human capital (years of education at age 25 years) and time (as a proxy for technological development) are used to drive the equations for estimating future mortality. In addition, specific assumptions are made when making estimates for HIV/AIDS, tuberculosis, malaria, and outcomes associated with smoking and body mass index

Figure 8.3 Global level GDP per capita for three future worlds



8.6 Mortality projections

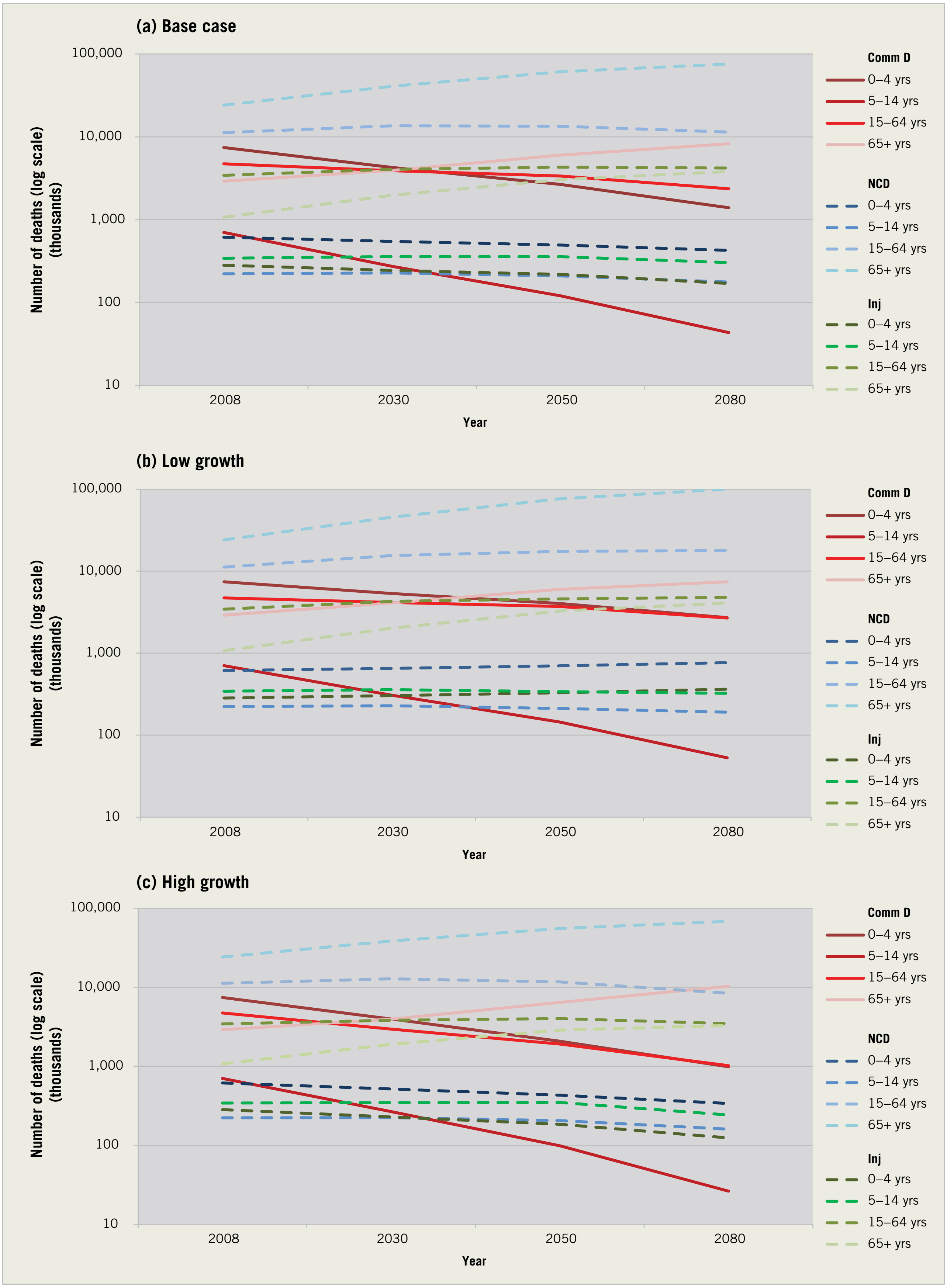
The health impacts of climate change will depend on the underlying health of affected populations, which in turn will depend on future socioeconomic conditions. A set of mortality projections was developed for this project. The cause- and age-specific projections for each world region were generated using a regression model and using the assumptions and scenarios described in Table 8.3 (consistent with those used to drive the climate change impact models). The models built upon previous methods (Mathers & Loncar, 2006; WHO, 2008, 2012). The method uses a series of equations that quantify the current and historical relationships between mortality and a set of independent variables. The major independent variables (which were shown to be structurally related to mortality) are GDP per capita, human capital (as years of education at age 25 years), and time, which is assumed to be a proxy for health benefits arising from technological developments. In addition, specific assumptions are made regarding future patterns of HIV/AIDS, tuberculosis and malaria, and for outcomes associated with smoking and body mass index.

These updated projections have been prepared using the WHO cause of death estimates for the year 2008 as a starting point (WHO, 2011a). The methods used are essentially the same as those published previously (Mathers & Loncar, 2006; WHO, 2008, 2012), with the following changes:

- GDP projections were revised to take account of World Bank revisions to purchasing power parity conversion rates and updated using recent projections of real growth per annum in income per capita from the World Bank (2010c,d), IMF (2010) and OECD (2009). Longer-term projections of GDP per capita to the year 2100 were taken from the International Futures project (Hughes, 2010) and converted from base year 2000 to 2005 for purchasing power parity dollars. Country-specific GDP per capita growth rates were varied smoothly from the World Bank and OECD estimates for 2015 to the International Futures estimates for 2030.
- Human capital (average years of schooling for adults) estimates and projections were updated using the latest update of the Barro & Lee (2010) time series and projections from the International Futures project base case (Hughes, 2010).
- The projection regression equations were recalibrated so that back projections of child mortality rates to 1990 matched observed trends for World Bank regions. In the recalibrated projections, the regression coefficient for human capital was left unchanged and the regression coefficient for time (a proxy for technological change) was set to zero for low-income countries in the WHO African, European, South-East Asia and Western Pacific regions.
- Smoking impact projections were updated to take into account more recent regional trends in tobacco smoking (WHO, 2011b).

Figure 8.4 shows the trends in mortality for diseases grouped as communicable diseases (this category includes maternal conditions, perinatal causes, and nutritional deficiencies), noncommunicable diseases and injuries, by age group. Each of the three scenarios is in a separate plot.

Figure 8.4 Trends in mortality for communicable diseases (Comm D), noncommunicable diseases (NCD) and injuries (Inj), by age group, from 2008 to 2080 under (a) base case, (b) low growth and (c) high growth scenarios



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Annex[6]

Definition of regions used in this assessment

Estimates in this assessment were made for the 21 world regions defined for the Global Burden of Disease Study (IHME, 2010). The regions are:

ASIA PACIFIC, HIGH INCOME
Brunei Darussalam
Japan
Republic of Korea
Singapore

ASIA, CENTRAL
Armenia
Azerbaijan
Georgia
Kazakhstan
Kyrgyzstan
Mongolia
Tajikistan
Turkmenistan
Uzbekistan

ASIA, EAST
China
China, Hong Kong Special Administrative Region
China, Macao Special Administrative Region
China, Province of Taiwan
Democratic People's Republic of Korea

ASIA, SOUTH
Afghanistan
Bangladesh
Bhutan
India
Nepal
Pakistan

ASIA, SOUTH-EAST
Cambodia
Christmas Island
Cocos Islands
Indonesia
Lao People's Democratic Republic
Malaysia
Maldives
Mauritius
Myanmar
Philippines
Reunion
Seychelles
Sri Lanka
Thailand
Timor-Leste
Viet Nam

AUSTRALASIA
Australia
New Zealand

CARIBBEAN
Anguilla
Antigua and Barbuda
Aruba
Bahamas
Barbados
Belize
Bermuda
British Virgin Islands
Cayman Islands
Cuba
Dominica
Dominican Republic
French Guiana
Grenada
Guadeloupe
Guyana
Haiti
Jamaica
Martinique
Montserrat
Netherlands Antilles
Puerto Rico
Saint Barthelemy
Saint Kitts and Nevis
Saint Lucia
Saint Martin
Saint Vincent and the Grenadines
Suriname
Trinidad and Tobago
Turks and Caicos Islands
US Virgin Islands

EUROPE, CENTRAL
Albania
Bosnia and Herzegovina
Bulgaria
Croatia
Czech Republic
Hungary
Montenegro
Poland
Romania
Serbia

6 The list in this annex has not been changed from the Global Burden of Disease Study and does not comply with WHO style for country references.

Slovakia
Slovenia
The former Yugoslav Republic of Macedonia

EUROPE, EASTERN
Belarus
Estonia
Latvia
Lithuania
Republic of Moldova
Russian Federation
Ukraine

EUROPE, WESTERN
Akrotiri and Dhekelia
Aland Islands
Andorra
Austria
Belgium
Channel Islands
Cyprus
Denmark
Faeroe Islands
Finland
France
Germany
Gibraltar
Greece
Greenland
Guernsey
Holy See
Iceland
Ireland
Isle of Man
Israel
Italy
Jersey
Liechtenstein
Luxembourg
Malta
Monaco
Netherlands
Norway
Portugal
San Marino
Spain
Svalbard
Sweden
Switzerland
United Kingdom of Great Britain and Northern Ireland

LATIN AMERICA, ANDEAN
Bolivia (Plurinational State of)
Ecuador
Peru

LATIN AMERICA, CENTRAL
Colombia
Costa Rica
El Salvador
Guatemala
Honduras
Mexico
Nicaragua
Panama
Venezuela

LATIN AMERICA, SOUTHERN
Argentina
Chile
Falkland Islands (Malvinas)
Uruguay

LATIN AMERICA, TROPICAL
Brazil
Paraguay

NORTH AFRICA/ MIDDLE EAST
Algeria
Bahrain
Egypt
Iran (Islamic Republic of)
Iraq
Jordan
Kuwait
Lebanon
Libyan Arab Jamahiriya
Morocco
Occupied Palestinian territory
Oman
Qatar
Saudi Arabia
Syrian Arab Republic
Tunisia
Turkey
United Arab Emirates
Western Sahara
Yemen

NORTH AMERICA, HIGH INCOME
Canada
Saint Pierre et Miquelon
United States of America

OCEANIA
American Samoa
Cook Islands
Fiji
French Polynesia
Guam
Kiribati
Marshall Islands
Micronesia (Federated States of)
Nauru
New Caledonia
Niue
Norfolk Island
Northern Mariana Islands
Palau
Papua New Guinea
Pitcairn
Samoa
Solomon Islands
Tokelau

Tonga
Tuvalu
Vanuatu
Wallis and Futuna Islands

SUB-SAHARAN AFRICA, CENTRAL

Angola
Central African Republic
Congo
Democratic Republic of the Congo
Equatorial Guinea
Gabon

SUB-SAHARAN AFRICA, EAST

Burundi
Comoros
Djibouti
Eritrea
Ethiopia
Kenya
Madagascar
Malawi
Mayotte
Mozambique
Rwanda
Somalia
Sudan
Uganda
United Republic of Tanzania
Zambia

SUB-SAHARAN AFRICA, SOUTHERN

Botswana
Lesotho
Namibia
South Africa
Swaziland
Zimbabwe

SUB-SAHARAN AFRICA, WEST

Benin
Burkina Faso
Cameroon
Cape Verde
Chad
Cote d'Ivoire
Gambia
Ghana
Guinea
Guinea-Bissau
Liberia
Mali
Mauritania
Niger
Nigeria
Saint Helena
Sao Tome and Principe
Senegal
Sierra Leone
Togo

Research Paper 3: Supplemental Material

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Supplemental Material

A Global-Level Model of the Potential Impacts of Climate Change on Child Stunting via Income and Food Price in 2030

Simon J. Lloyd, Mook Bangalore, Zaid Chalabi, R. Sari Kovats, Stèphane Hallegatte, Julie Rozenberg, Hugo Valin, and Petr Havlik

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Figure S2. Residuals for the national-level moderate (A, B, C) and severe (D, E, F) stunting equations, for the country random intercepts (A, D), country random slopes (B, E), and predicted stunting (C, F). **Figures A, B, D, and E are caterpillar plots:** these show the country residuals - i.e. random effects – for a given model parameter, ranked from smallest to largest along the x-axis by their difference from a random effect equal to zero (shown on the y-axis; a random effect equal to zero is indicated by the red line). The dots show the mean estimates; the bars the 95% confidence interval, where wide confidence intervals are partly caused by small sample sizes. The x-axis labels are as follows - **A:** 'u0_mod_rank' is the rank of the random intercept for moderate stunting; **B:** 'u1_mod_rank' is the rank of the random slope for moderate stunting; **D:** 'u0_svr_rank' is the rank of the random intercept for severe stunting'; and, **E:** 'u0_svr_rank' is the rank of the random slope for severe stunting. In each of the four figures the y-axis is the difference of the random effect from zero. The caterpillar plots show the random effects for the intercept and slope for both the moderate and severe stunting equations are significantly different from the average. **Figures C and F** show the for predicted stunting. The x-axes are **– C:** predicted percent moderately stunted in a country; and, **F:** predicted percent severely stunted in a country. In both figures the y-axis shows the residuals, with zero indicated by the red line. The residuals plot for moderate stunting (C) shows there may be a tendency to under predict at higher levels of stunting. For severe stunting (F), the equation appears to tends to under predict more often than over predict.

Figure S3. Predicted versus observed stunting for the within-country equations for rural (A and B) and urban stunting (C and D), based on the historical data used to fit the equations. For each pair, the first figure **(A and C)** is for moderate stunting, and the second **(B and D)** is for severe stunting. All figures show predicted percent stunted (y-axis) against observed percent stunted (x-axis), for the historical data used to fit the equations. The red line is a line of 'perfect fit'. Both equations appear to fit well across the range of the stunting, with slightly larger error in the severe compared to the moderate stunting equation. As noted in the main text, no independent data were available with which to validate the equations.

Figure S4. Residuals for the within-country rural equations for moderate (A, B, C) and severe (D, E, F) stunting, for the country random intercepts (A, D), country random slopes (B, E), and predicted stunting (C, F). **Figures A, B, D, and E are caterpillar plots:** these show the residuals - i.e. random effects – for a given model parameter, ranked from smallest to largest along the x-axis by their difference from a random effect equal to zero (shown on the y-axis; a random effect equal to zero is indicated by the red line). The dots show the mean estimates; the bars the 95% confidence interval, where wide confidence intervals are partly caused by small sample sizes. The x-axis labels are as follows - **A:** 'u0_mod__rur_rank' is the rank of the random intercept for moderate rural stunting; **B:** 'u1_mod_rur_rank' is the rank of the random slope for moderate rural stunting; **D:** 'u0_svr_rur_rank' is the rank of the random intercept for severe rural stunting'; and, **E:** 'u0_svr_rur_rank' is the rank of the random slope for severe rural stunting. In each of the four figures the y-axis is the difference of the random effect from zero. The caterpillar plots show the 95% confidence intervals for the random effects for both the intercept and slope frequently cross zero. **Figures C and F** show the for predicted stunting. The x-axes are **– C:** predicted percent moderately stunted in rural areas in a given country; and, **F:** predicted percent severely stunted in rural areas in given a country. In both figures the y-axis shows the residuals, with zero indicated by the red line. The residuals plot for severe stunting (F) shows the model has greater error for low levels of stunting than high. Consequently, estimates made for rural areas should be interpreted cautiously.

Figure S5. Residuals for the within-country urban equations for moderate (A, B, C) and severe (D,E, F) stunting, for the country random intercepts (A, D), country random slopes (B, E), and predicted stunting (C, F). **Figures A, B, D, and E are caterpillar plots:** these show the residuals - i.e. random effects – for a given model parameter, ranked from smallest to largest along the x-axis by their difference from a random effect equal to zero (shown on the y-axis; a random effect equal to zero is indicated by the red line). The dots show the mean estimates; the bars the 95% confidence interval, where wide confidence intervals are partly caused by small sample sizes. The x-axis labels are as follows - **A:** 'u0_mod__urb_rank' is the rank of the random intercept for moderate urban stunting; **B:** 'u1_mod_urb_rank' is the rank of the random slope for moderate urban stunting; **D:** 'u0_svr_urb_rank' is the rank of the random intercept for severe urban stunting'; and, **E:** 'u0_svr_urb_rank' is the rank of the random slope for severe urban stunting. In each of the four figures the y-axis is the difference of the random effect from zero. The caterpillar plots show the 95% confidence intervals for the random effects for both the intercept and slope frequently cross zero. **Figures C and F** show the for predicted stunting. The x-axes are **– C:** predicted percent moderately stunted in urban areas in a given country; and, **F:** predicted percent severely stunted in urban areas in given a country. In both figures the y-axis shows the residuals, with zero indicated by the red line. The residuals plot for both moderate and severe stunting (C and F) shows the pattern of errors differs by level of stunting. Consequently, estimates made for urban areas should be interpreted cautiously.

Appendix S1. Calculation of 95% coverage intervals for (i) the percent of children aged under 5 stunted in the year 2010, and (ii) the absolute change in the percent of children aged under 5 stunted from the year 2000 to the year 2010.

Additional File - Excel Document

Tables

Table S1: Countries included when fitting the stunting models, grouped by Global Burden of Disease Region[1]. The number of observations per country is shown in brackets.

Asia, Central	**Asia, South East**	**Latin America, Andean**	**Sub-Saharan Africa, East**	**Sub-Saharan Africa, West**
Armenia (4)	Cambodia (5)	Bolivia (4)	Kenya (5)	Burkina Faso (5)
Kyrgyzstan (4)	Indonesia (3)	Peru (5)	Madagascar (4)	Cameroon (5)
Mongolia (3)	Lao PDR (3)	**Latin America, Central**	Malawi (6)	Cote d'Ivoire (4)
Tajikistan (3)	Sri Lanka (3)	Colombia (4)	Mozambique (4)	Ghana (5)
Uzbekistan (3)	Vietnam (3)	El Salvador (4)	Rwanda (3)	Mauritania (3)
Asia, East	**Caribbean**	Guatemala (3)	Tanzania (4)	Niger (3)
China (3)	Dominican Republic (5)	Honduras (4)	Zambia (4)	Senegal (4)
Asia, South	Jamaica (6)	Mexico (3)	**Sub-Saharan Africa, South**	Sierra Leone (4)
Bangladesh (5)	**Europe, Central**	Nicaragua (6)	Lesotho (3)	
India (3)	Bosnia and Herzegovina (3)	**North Africa/ Middle East**	Namibia (3)	
Nepal (5)	Romania (4)	Egypt (4)	Swaziland (4)	
Pakistan (4)	TFYR of Macedonia (4)	Turkey (4)		

[1] IHME. 2015. Global burden of disease study 2015 geographies. Available: http://www.healthdata.org/sites/default/files/files/Projects/GBD/GBDRegions_countries.pdf [accessed July 7 2017]

Table S2: Signal-to-noise ratios (as parameter estimates divided by their standard errors) for the national-level stunting equation (equation 5).

Predictor[1]	Moderate stunting			Severe stunting		
	Parameter estimate (log odds)	**Standard error**	**Signal-to-noise ratio**	**Parameter estimate (log odds)**	**Standard error**	**Signal-to-noise ratio**
Year, centred on 2010 (t_{ij})	-0.0103	0.00303	-3.4	-0.0305	0.0053	-5.8
log(GDP per capita of the population in the lowest 20% of the income distribution) (G_{ij})	-0.0923	0.0352	-2.6	-0.510	0.0422	-12.1
log(food price indicator), mean centred (P_{ij})	-0.206	0.0572	-3.6	0.206	0.0697	3.0
Interaction of log(GDP per capita of the population in the lowest 20% of the income distribution) and log(food price indicator) (G_{ij} X P_{ij})	0.0300	0.00969	3.1	-0.0751	0.0116	-6.5

[1] The predictors are given as a description and as the variable name (in brackets).

Table S3: Signal-to-noise ratios (as parameter estimates divided by their standard errors) for the area-level stunting equation (equation 8).

Predictor[1]	Rural					
	Moderate stunting			Severe stunting		
	Parameter estimate (log odds)	Standard error	Signal-to-noise ratio	Parameter estimate (log odds)	Standard error	Signal-to-noise ratio
National level stunting ($Y^{(N)}_{ijk}$)	0.0261	0.00599	4.4	0.0670	0.00860	7.8
log(income indicator), centred just below its historical minimum ($I^{(A)}_{ij}$)	-0.295	0.0450	-6.6	-0.136	0.0537	-2.53
Interaction of national-level stunting and the income indicator ($Y^{(N)}_{ijk}$ X $I^{(A)}_{ij}$)	0.0151	0.00196	7.7	0.0112	0.00191	5.9
Rural-urban inequalities (D_{ij})	-0.105	0.0324	-3.2	-0.00850	0.0816	-0.1
Interaction of the income indicator and rural-urban inequalities ($I^{(A)}_{ij}$ X D_{ij})	-1.718	0.142	-12.1	-2.409	0.129	-18.7

Predictor	Urban					
	Moderate stunting			Severe stunting		
	Parameter estimate (log odds)	Standard error	Signal-to-noise ratio	Parameter estimate (log odds)	Standard error	Signal-to-noise ratio
National level stunting ($Y^{(N)}_{ijk}$)	0.0687	0.00433	15.9	0.0435	0.0135	3.2
log(income indicator), centred just below its historical minimum ($I^{(A)}_{ij}$)	-0.150	0.0523	-2.9	-0.130	0.0671	-1.9
Interaction of national-level stunting and the income indicator ($Y^{(N))}_{ijk}$ X $I^{(A)}_{ij}$)	.	.	.	0.0172	0.00377	4.6
Rural-urban inequalities (D_{ij})	-0.145	0.122	-1.2	.	.	.
Interaction of the income indicator and rural-urban inequalities ($I^{(A)}_{ij}$ X D_{ij})	0.123	0.0587	2.1	.	.	.

[1] The predictors are given as a description and as the variable name (in brackets).

Figures

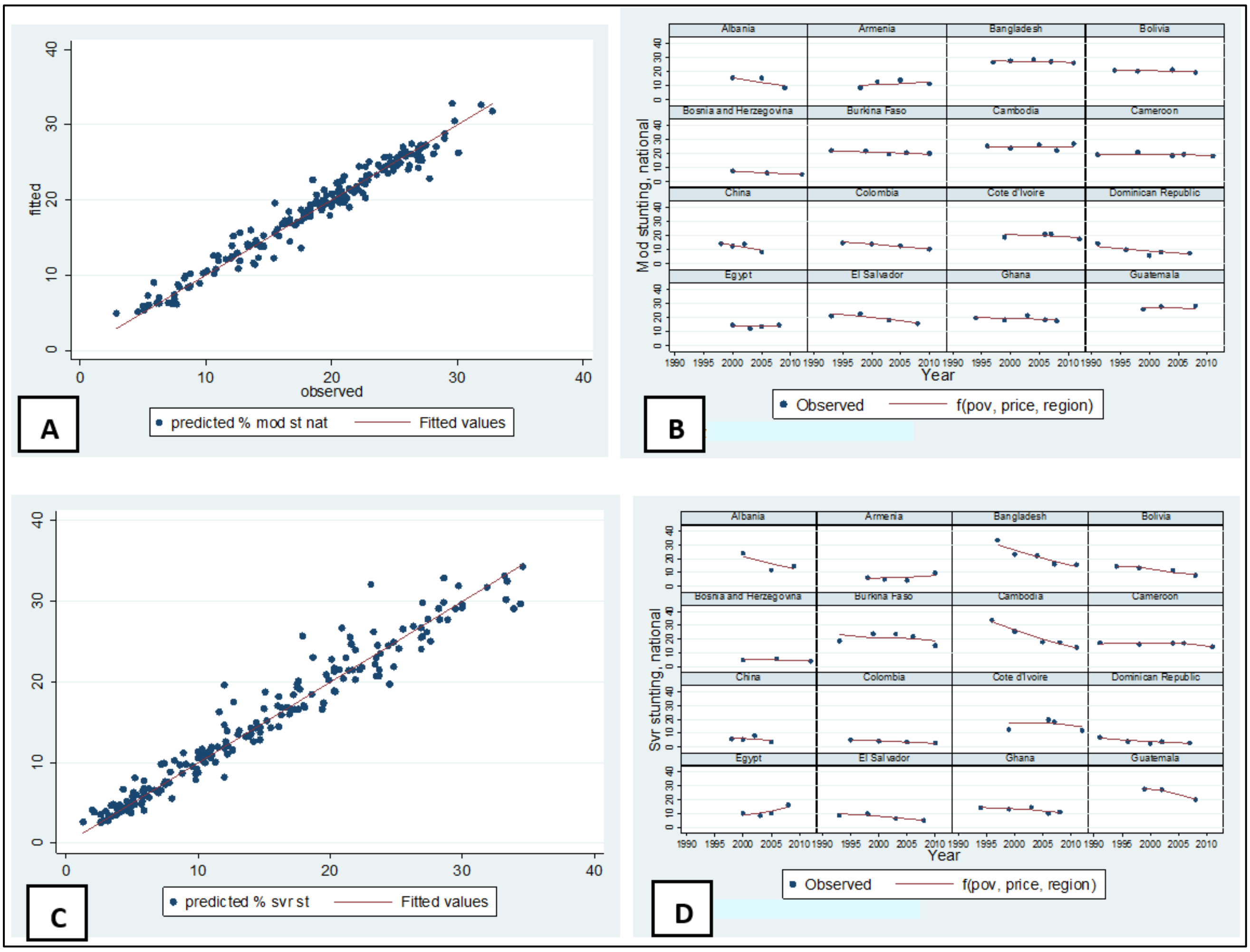

Figure S1: Predicted versus observed stunting for the national-level equations for moderate (A and B) and severe stunting (C and D), based on the historical data used to fit the equations.

Figures A and C show predicted percent stunted (y-axis) against observed percent stunted (x-axis), for the historical data used to fit the equations. The red line is a line of 'perfect fit'. Both equations appear to fit well across the range of the stunting, with larger error in the severe compared to the moderate equation.

Figures B and D show predicted within-country trajectories of stunting (as red lines) against observed percent stunted (blue dots) for a sub-set of countries. Year is shown on the x-axes; percent stunted on y-axes. It appears that the equations are able to reproduce historical stunting trajectories well for both moderate and severe stunting.

As noted in the main text, no independent data were available with which to validate the equations.

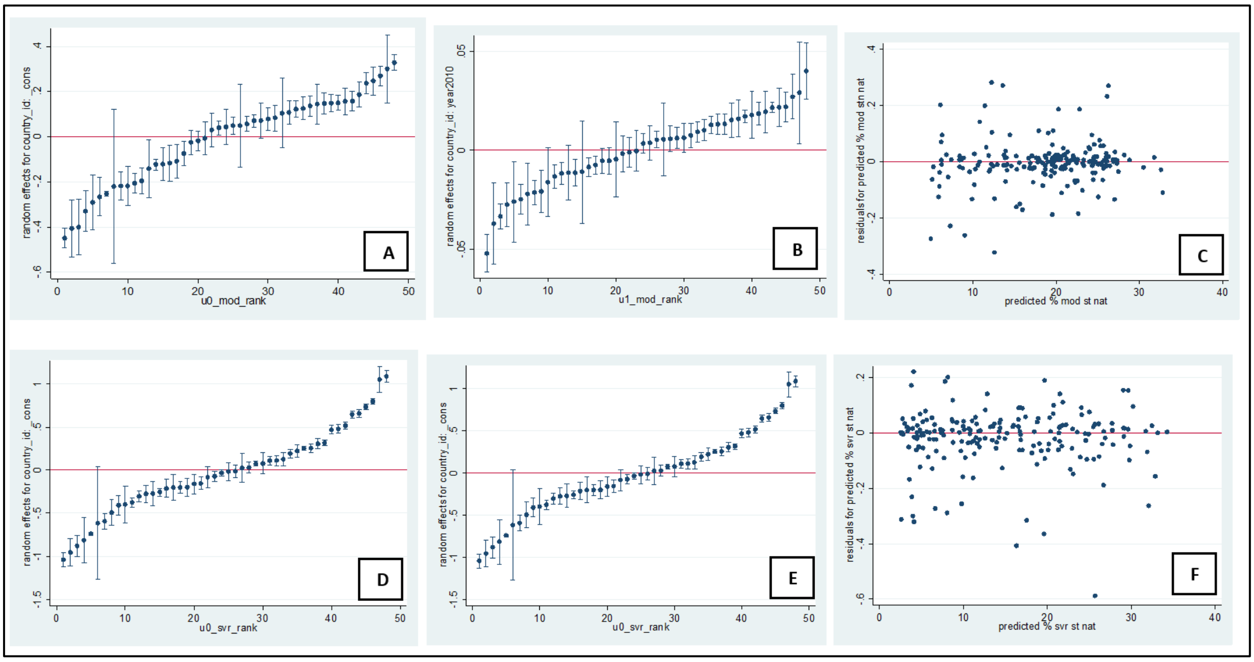

Figure S2: Residuals for the national-level moderate (A, B, C) and severe (D, E, F) stunting equations, for the country random intercepts (A, D), country random slopes (B, E), and predicted stunting (C, F).

Figures A, B, D, and E are caterpillar plots: these show the country residuals - i.e. random effects – for a given model parameter, ranked from smallest to largest along the x-axis by their difference from a random effect equal to zero (shown on the y-axis; a random effect equal to zero is indicated by the red line). The dots show the mean estimates; the bars the 95% confidence interval, where wide confidence intervals are partly caused by small sample sizes. The x-axis labels are as follows - **A:** 'u0_mod_rank' is the rank of the random intercept for moderate stunting; **B:** 'u1_mod_rank' is the rank of the random slope for moderate stunting; **D:** 'u0_svr_rank' is the rank of the random intercept for severe stunting'; and, **E:** 'u0_svr_rank' is the rank of the random slope for severe stunting. In each of the four figures the y-axis is the difference of the random effect from zero.

The caterpillar plots show the random effects for the intercept and slope for both the moderate and severe stunting equations are significantly different from the average.

Figures C and F show the for predicted stunting. The x-axes are – **C:** predicted percent moderately stunted in a country; and, **F**: predicted percent severely stunted in a country. In both figures the y-axis shows the residuals, with zero indicated by the red line.

The residuals plot for moderate stunting (C) shows there may be a tendency to under predict at higher levels of stunting. For severe stunting (F), the equation appears to tends to under predict more often than over predict.

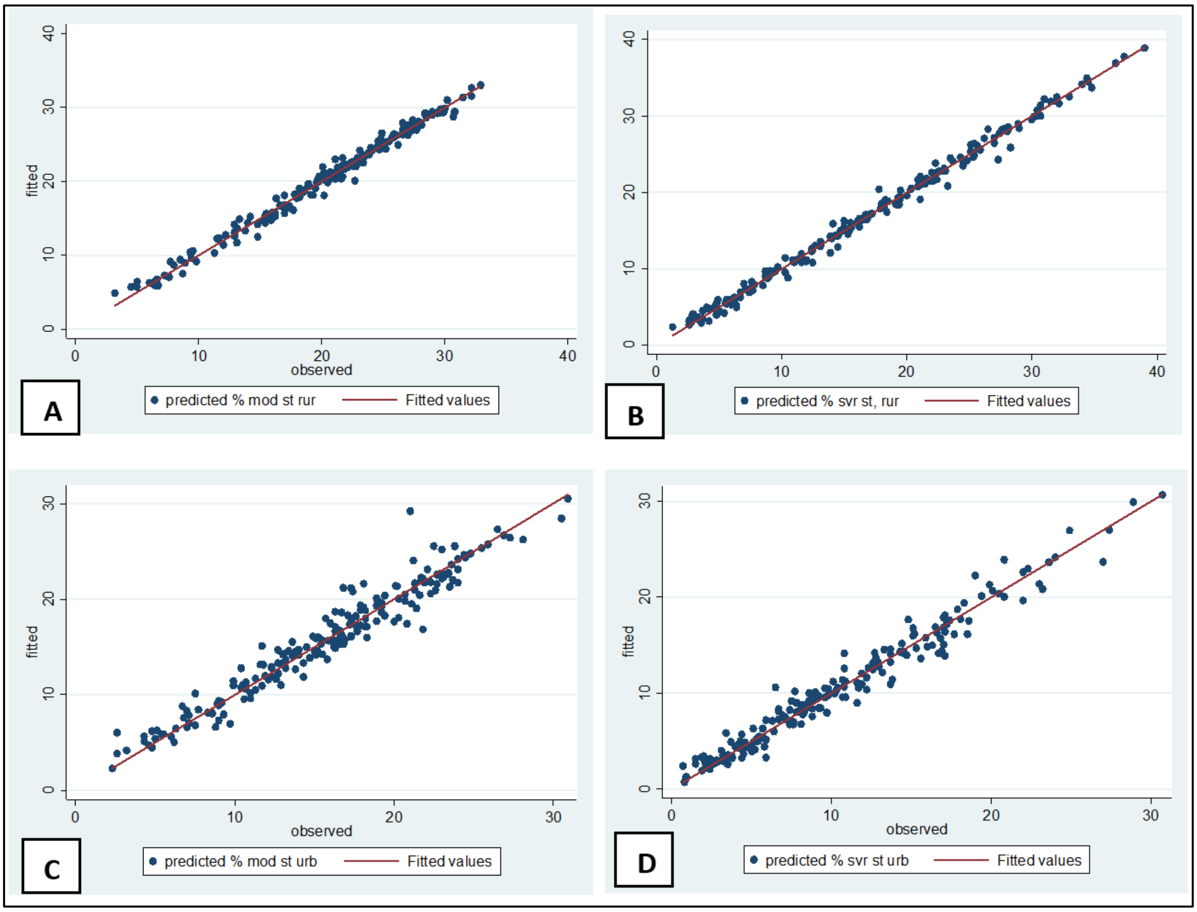

Figure S3: Predicted versus observed stunting for the within-country equations for rural (A and B) and urban stunting (C and D), based on the historical data used to fit the equations.

For each pair, the first figure (**A and C**) is for moderate stunting, and the second (**B and D**) is for severe stunting

All figures show predicted percent stunted (y-axis) against observed percent stunted (x-axis), for the historical data used to fit the equations. The red line is a line of 'perfect fit'. Both equations appear to fit well across the range of the stunting, with slightly larger error in the severe compared to the moderate stunting equation.

As noted in the main text, no independent data were available with which to validate the equations.

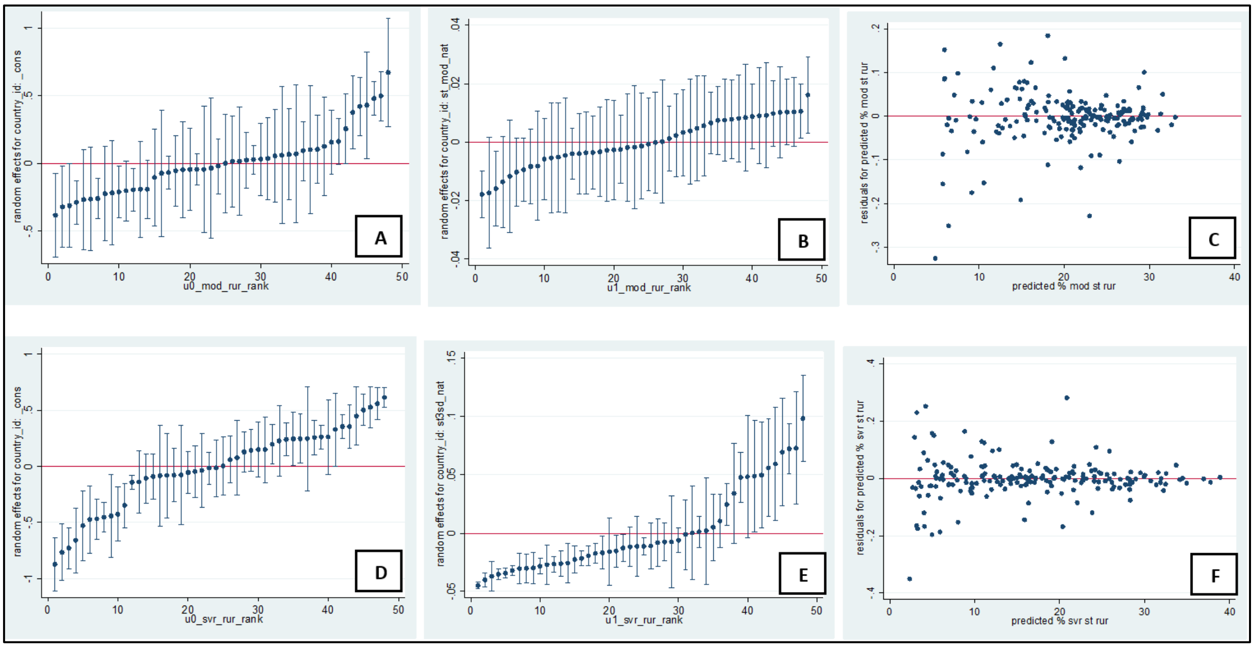

Figure S4: Residuals for the within-country rural equations for moderate (A, B, C) and severe (D, E, F) stunting, for the country random intercepts (A, D), country random slopes (B, E), and predicted stunting (C, F).

Figures A, B, D, and E are caterpillar plots: these show the residuals - i.e. random effects – for a given model parameter, ranked from smallest to largest along the x-axis by their difference from a random effect equal to zero (shown on the y-axis; a random effect equal to zero is indicated by the red line). The dots show the mean estimates; the bars the 95% confidence interval, where wide confidence intervals are partly caused by small sample sizes. The x-axis labels are as follows - **A:** 'u0_mod__rur_rank' is the rank of the random intercept for moderate rural stunting; **B:** 'u1_mod_rur_rank' is the rank of the random slope for moderate rural stunting; **D:** 'u0_svr_rur_rank' is the rank of the random intercept for severe rural stunting'; and, **E:** 'u0_svr_rur_rank' is the rank of the random slope for severe rural stunting. In each of the four figures the y-axis is the difference of the random effect from zero.

The caterpillar plots show the 95% confidence intervals for the random effects for both the intercept and slope frequently cross zero.

Figures C and F show the for predicted stunting. The x-axes are – **C:** predicted percent moderately stunted in rural areas in a given country; and, **F**: predicted percent severely stunted in rural areas in given a country. In both figures the y-axis shows the residuals, with zero indicated by the red line.

The residuals plot for severe stunting (F) shows the model has greater error for low levels of stunting than high.

Consequently, estimates made for rural areas should be interpreted cautiously.

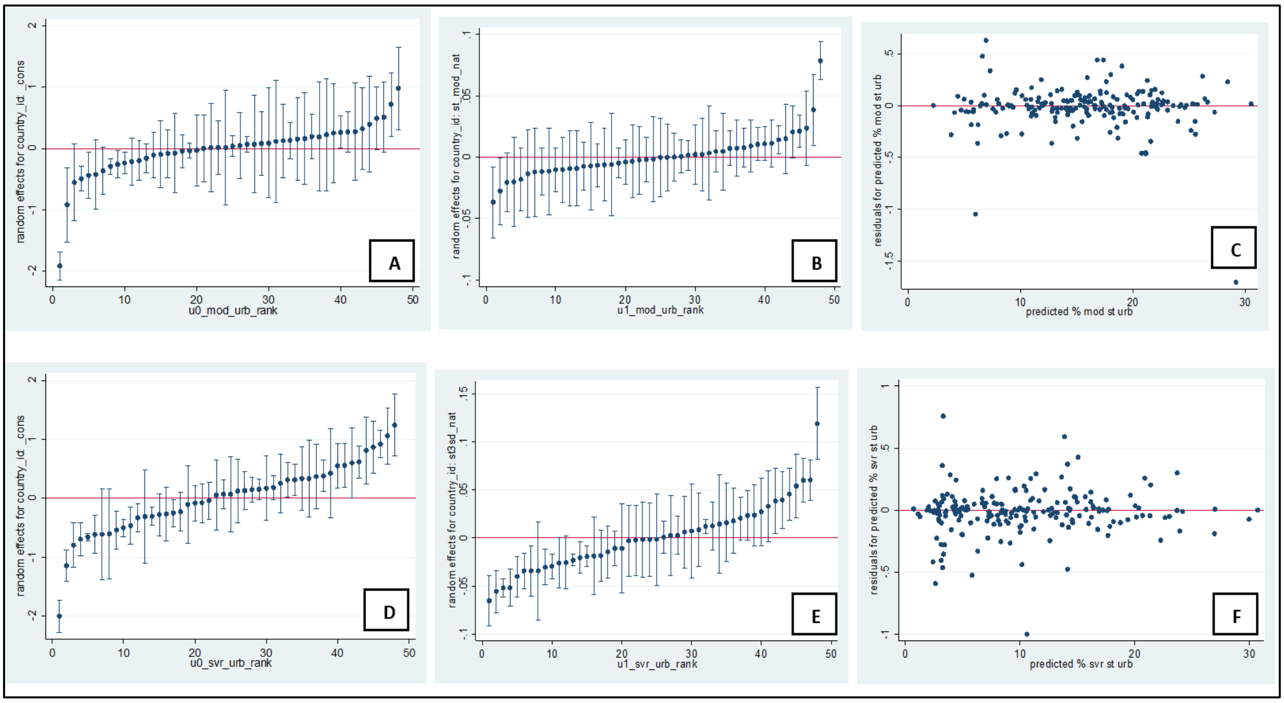

Figure S5: Residuals for the within-country urban equations for moderate (A, B, C) and severe (D,E, F) stunting, for the country random intercepts (A, D), country random slopes (B, E), and predicted stunting (C, F).

Figures A, B, D, and E are caterpillar plots: these show the residuals - i.e. random effects – for a given model parameter, ranked from smallest to largest along the x-axis by their difference from a random effect equal to zero (shown on the y-axis; a random effect equal to zero is indicated by the red line). The dots show the mean estimates; the bars the 95% confidence interval, where wide confidence intervals are partly caused by small sample sizes. The x-axis labels are as follows - **A:** 'u0_mod__urb_rank' is the rank of the random intercept for moderate urban stunting; **B:** 'u1_mod_urb_rank' is the rank of the random slope for moderate urban stunting; **D:** 'u0_svr_urb_rank' is the rank of the random intercept for severe urban stunting'; and, **E:** 'u0_svr_urb_rank' is the rank of the random slope for severe urban stunting. In each of the four figures the y-axis is the difference of the random effect from zero.

The caterpillar plots show the 95% confidence intervals for the random effects for both the intercept and slope frequently cross zero.

Figures C and F show the for predicted stunting. The x-axes are – **C:** predicted percent moderately stunted in urban areas in a given country; and, **F**: predicted percent severely stunted in urban areas in given a country. In both figures the y-axis shows the residuals, with zero indicated by the red line.

The residuals plot for both moderate and severe stunting (C and F) shows the pattern of errors differs by level of stunting.

Consequently, estimates made for urban areas should be interpreted cautiously.

Appendix S1

Calculation of 95% coverage intervals for (i) the percent of children aged under 5 stunted in the year 2010, and (ii) the absolute change in the percent of children aged under 5 stunted from the year 2000 to the year 2010

For equation [4], the 95% coverage interval for the random intercept or slope is the range over which 95% of the country-specific values would be expected to lie.

$$95\%\ coverage\ interval = parameter\ estimate\ as \log odds\ \pm\ 1.96\sqrt{variance}$$

[S1]

Note that in the calculations below:

- numbers shown to four decimal places; any small discrepancies in the results of a calculation are due to rounding, and,
- see equations [4] to [7] for the parameters referred to.
- all 'log' calculations are natural logs.

1. The range of predicted percent of stunted children in the year 2010
(i.e. the 95% coverage interval for the intercept)

<u>Moderate stunting</u>
Fixed constant as odds ratio = 0.1928 (see Table 1)

Fixed constant as log odds = log(0.1928) = -1.6463

95% coverage interval $= \beta_{0jk}^{(N)} \pm 1.96\sqrt{\sigma_{u_0}^2} = -1.6463 \pm 1.96\sqrt{0.3319}$

$$= -1.6463 \pm 1.1292$$

$$\text{i.e. } -1.6463\ (-2.7755, -0.5172)$$

As odds:

$$e^{-1.6463}(e^{-2.7755}, e^{-0.5172})$$
$$= 0.1928\ (0.06232, 0.5962)$$

As predicted probability:

$$\frac{0.1928}{1+0.1928}\left(\frac{0.06232}{1+0.06232}, \frac{0.5962}{1+0.5962}\right)$$
$$= 0.1616\ (0.05866, 0.3735)$$

As percent stunted:

$$\mathbf{16.2}\%\ (\mathbf{5.9}\%, \mathbf{37.4}\%)$$

<u>Severe stunting</u>
Fixed constant as odds ratio = 0.1092 (see Table 1)

Fixed constant as log odds = log(0.1092) = -2.2139

As log odds:

$$95\% \text{ coverage interval} = \beta_{0jk}^{(N)} \pm 1.96\sqrt{\sigma_{u_0}^2} = -2.2139 \pm 1.96\sqrt{0.702}$$
$$= -2.2139 \pm 1.6423$$
$$\text{i.e. } -2.2139\ (-3.8564, -0.5712)$$

As odds:

$$e^{-2.2139}\ (e^{-3.8564}, e^{-0.5712})$$
$$= 0.1093\ (0.02114, 0.568)$$

As predicted probability:

$$\frac{0.1093}{1+0.1093}\ \left(\frac{0.02114}{1+0.02114}, \frac{0.568}{1+0.568}\right)$$
$$= 0.09851\ (0.0207, 0.3609)$$

As percent stunted:

$$\mathbf{9.9}\%\ (\mathbf{2.1}\%, \mathbf{36.1}\%)$$

2. The range of absolute change in predicted percent of children stunted from the year 2000 to the year 2010
(i.e. based on the 95% coverage interval for the slope for year)

The null form of equation [4] for estimating the log odds of stunting in 2000 and 2010 is:

$$log\left(\frac{Y_{ijk}^{(N)}}{1-Y_{ijk}^{(N)}}\right) = \beta_{0jk}^{(N)} + \beta_{1jk}^{(N)}(t_{ij}) \qquad \text{[S2]}$$

Where t_{ij} equals -10 in the year 2000 and 0 in the year 2010.

<u>Moderate stunting</u>
Fixed slope as odds ratio = 0.9862 (see Table 1)

Fixed slope as log odds = log(0.9862) = -0.01386

$$95\% \text{ coverage interval} = \beta_{1jk}^{(N)} \pm 1.96\sqrt{\sigma_{u_1}^2} = -0.01386 \pm 1.96\sqrt{0.000429}$$
$$= -0.01386 \pm 0.00084$$
$$\text{i.e. } -0.01386\ (-0.05445, 0.02673)$$

For the fixed estimate, using [S2], the log odds of stunting in the year 2000 is:

$$log\left(\frac{Y_{ijk}^{(N)}}{1-Y_{ijk}^{(N)}}\right)=\beta_{0jk}^{(N)}+\beta_{1jk}^{(N)}(t_{ij})$$

$$=-1.6463-0.01386(-10)=-1.5077$$

As odds:

$$e^{-1.5077}=0.2214$$

As predicted probability:

$$\frac{0.2214}{1+0.2214}=0.1813$$

As percent stunted:

$$18.1\%$$

For the fixed estimate, log odds of stunting in the year 2010 is:

$$log\left(\frac{Y_{ijk}^{(N)}}{1-Y_{ijk}^{(N)}}\right)=\beta_{0jk}^{(N)}+\beta_{1jk}^{(N)}(t_{ij})$$

$$=-1.6463-0.01386(0)=-1.6463$$

As odds:

$$e^{-1.6463}=0.1928$$

As predicted probability:

$$\frac{0.1928}{1+0.1928}=0.1616$$

As percent stunted:

$$16.2\%$$

Finally, based on the fixed estimate, the absolute change in moderate stunting between the years 2000 and 2010 is:

$$18.1\%-\ 16.2\%=\mathbf{-1.9}\%$$

For the low and high estimates of absolute change in moderate stunting between the years 2000 and 2010, the above calculations were repeated using S2 with $\beta_{1jk}^{(N)}$ set to -0.05445 for the low estimate and to 0.02673 for the high estimate (i.e. based on the above calculation of the 95% coverage interval).

The resulting estimate for the absolute change in the percent of children moderately stunted between the years 2000 to 2010 is **-2% (-8.8% to 3.3%)** (where a positive number indicates moderate stunting increased).

<u>Severe stunting</u>
Fixed slope as odds ratio = 0.9622 (see Table 1)

Fixed slope as log odds = log(0.9622) = -0.03855

95% coverage interval $= \beta_{1jk}^{(N)} \pm 1.96\sqrt{\sigma_{u_1}^2} = -0.03855 \pm 1.96\sqrt{0.001175}$

$$= -0.03855 \pm 0.002303$$

i.e. $-0.03855\ (-0.1057, 0.02865)$

The calculations used to estimate the absolute change in moderate stunted were repeated, using equation [S2] with $\beta_{0jk}^{(N)} = -2.2139$ and $\beta_{1jk}^{(N)}$ set to -0.03855, -0.1057, and 0.02865 for the fixed, low and high estimates, respectively.

The resulting estimate for the absolute change in the percent of children severely stunted between the years 2000 to 2010 is **-4% (-14.1% to 2.3%)** (where a positive number indicates severe stunting increased).

Research Paper 4: Supplemental Material

S1 Appendix. ODD+D model documentation

Accompanying the paper, **"Climate change and hunger through the lens of farming styles and rural health: insights from an agent-based model"**; Lloyd SJ, Chalabi Z.

Table of Contents

1 Overview

1.1 Purpose

1.1.1 What is the purpose of the study?

The purpose of the model is to gain an understanding of *how* the development trajectories of constellations of producer-consumer farming households practicing different styles of farming *may affect* patterns of hunger and health in a farming community, *under scenarios for* climate change, agricultural policy, global price transmission, and style preference patterns, *in* a global food system in which food prices are tending to fall and oscillate.

The model represents a stylized farming community and aims to assess the potential importance of previously unexplored aspects of the relation between climate change and hunger. Previous models have focused on changes in food quantity and quality for consumers, as well as the impacts of dietary patterns on both consumer health and the environment. This ABM focusses on how patterns of farming styles – which differ in terms of farmer goals and degree of market dependence – may shape both nutrition and conditions that support the health of rural communities, and, it acts as a virtual lab for testing the implications of various scenarios.

The key outcomes assessed are total food production, local food price, household nutritional status, farm labour (number of full-time equivalent workers), income Gini (i.e. income inequalities), average net farm income (and its rate of change), and 'real land productivity' (an ecologically sensitive measure of farming intensity).

1.1.2 For whom is the model designed?

The model was designed for researchers with an interest in climate change and health. The results may be of interest to decision-makers and stakeholders involved in and/or affected by debates and choices about the future of farming.

1.2 Entities, state variables, and scales

1.2.1 What kind of entities are in the model?

Agents are farming households practicing a given style of farming: 'peasant' style, with sub-types of 'orphan' style (i.e. subsistence farming on one hectare using manual tools) and 'agroecology' style (labour-intensive; largely using on-farm produced inputs; using the market as an outlet to sell surplus yields; using savings rather than credit to make purchases; has a key goal of maximising autonomy), or, 'entrepreneurial-style' (capital-intensive; dependent on the market to both purchase farm inputs and to sell yields; if needed, uses credit to finance purchases; a key goal of expansion) (van der Ploeg, 2018, Mazoyer and Roudart, 2006). There is also an a-spatial mega-agent for global corporate agriculture, which is represented as a tendency for global food prices to fall and oscillate[1]. The **spatial units** are 1 hectare plots of farm land. The **environment** is represented as climate change, composed of a warming trend and change in drought risk, which affects crop yields.

1.2.2 By what attributes (i.e. state variables and parameters) are these entities characterized?

Farming households are characterized by: a list of adjacent 1 hectare plot they occupy, with farm size influencing their productive potential; their current and preferred farming styles; their farm equipment, which determines the amount of land one worker is able to farm: **manual tools** (e.g. a

[1] Note that global corporate agriculture is not strictly an agent in that it does not take actions based on decisions; however, it is characterized as an agent here as it represents a farming entity and future iterations of the model will make it increasingly agent-like.

hoe, which allows one worker to farm 1 hectare), **working animals** (e.g. oxen, which allow one worker to farm up to 5 hectares), or a **small tractor** (which allows one worker to farm to 16 hectares)**;** their preferences for saving money and rationing spending, which together represent their preference for developing the farm vs. feeding the family a basic diet; family nutritional status, as the proportion of a basic diet consumed; current farm income as well as a list of their income in previous years; their expected food price in the coming year, given actual food prices in previous years and their style-specific goals; their optimum (given their style-specific goals), target (given their resources and preferences), and actual (given weather and random variation (the latter representing unmodelled factors)) yields; their asking food price (i.e. when selling their yield) given their actual yield and farming style-specific goals; and, short-, mid-, and long-term debt.

Global corporate agriculture is characterised by: current global food price; average rate of price decline; and, the amplitude and frequency of oscillation.

The **1 hectare plots** are characterized by: whether the plot is occupied by a farmer; the maximum yield of the plot in the absence of inputs (e.g. fertilizer); and, the potential yield multiple of the plot under agroecology following an **agroecology transition period**.

1.2.3 What are the exogenous factors / drivers of the model?

Climate change, characterised as a warming trend which sets the temperature anomaly relative to year 0, and, an annual drought risk. Both the warming trend and annual drought risk increase as the climate scenario worsens. The temperature anomaly causes yield losses for farming households, and it (implicitly) causes the average rate of global price decline to slow. If a drought occurs in the farming community, households lose a proportion of their yields; if a drought affects corporate agriculture, global food price rises. The climate scenario is selected by the model user as: no, low, or high climate change.

Agricultural policy is selected by the user and favours one style of farming over another. 'Entrepreneurial' policy favours entrepreneurial farming by subsidising farm inputs and lowering interest rates on credit; 'Entrepreneurial eroding' policy is initially the same as the previous but support erodes over time; 'Peasant' policy favours peasant farming by stimulating research and supporting community networks, represented implicitly in the model as increased rates of yield increase for peasant farmers; 'No' policy which means there are no actions supporting any style of farming.

Global price transmission which determines the influence of global food price (i.e. associated with corporate agriculture) on local food price (i.e. the price faced by the community of farming households (agents)). This is a user selected elasticity (e.g. a setting of 0.5 would mean for each 1% rise in global food price, local price would rise by 0.5).

Farming style preference pattern which sets the proportion of farming households that prefer to develop via a given style. At model initialisation, all farmers practice orphan-style and they may develop either via agroecology- or entrepreneurial-style. The preference pattern is user selected; for instance, preferences may be set such that 40% prefer agroecology and 60% prefer entrepreneurial.

Interest rates for short-, mid-, and long-term credit (used for purchases of farm inputs, farm equipment, and land, respectively) are set according to the agricultural policy scenario.

1.2.4 If applicable, how is space included in the model?

The **landscape** is composed of 1 hectare farm plots. Each farming household initially occupies 1 hectare of land but may expand to unoccupied adjacent (in any direction, but the world does not 'wrap around') plots if they have the necessary resources to purchase and cultivate it. Each plot has a randomly assigned maximum productive potential. Climate change and global food price influence all plots equally (i.e. for the former it is assumed that climate change does not vary across space occupied by the farming community, and for the latter it is assumed that factors such as distance from the nearest market do not affect food price). The landscape is stylized and does not represent a real-world location.

1.2.5 What are the temporal and spatial resolutions and extents of the model?

Each **time step** represents one year and each simulation runs for 50 years. Each **cell** represents 1 hectare of farmland in a 21 by 21 grid (i.e. 441 cells).

1.3 Process overview and scheduling

1.3.1 What entity does what, and in what order?

In each year (i.e. time step), **six processes** occur in the following order, with the entity undertaking the process shown in square brackets (where the 'observer' is the model controller[2]). In processes involving farming households, the order in which each makes decisions and/or takes actions is randomly determined.

1. <u>Set weather</u> [observer]
   Given the climate change scenario, **weather** conditions are updated and the expected impacts are calculated: the **temperature anomaly** is incremented and the associated yield losses are calculated; **drought** risk is incremented and whether droughts affecting the farming community and/or corporate agriculture occur is assessed, along with the associated expected **average yield losses** and **global price rise**, respectively.

2. <u>Produce crops</u> [all farming households]
   All farming households attempt to produce their **target yield** (for setting of target yield, see 'Consumption and production decisions' ahead), with **actual yield** being a function of the temperature anomaly, drought (if occurred), and random variation (representing unmodelled factors). Following this, each household calculates their **asking price** (i.e. the selling price they aim for), given their target yield, actual yield, and style-specific goals.

   Finally, assessment is made of (i) the potential **yield increments** in the coming year for peasant farmers, and (ii) whether farmers have **transitioned a plot to agroecology**, with the transition period being set by the user[3],[4].

3. <u>Set food prices and other prices</u> [observer]
   Global and local food prices are set. **Global food price** is set such that: it tends to fall annually by a climate scenario-specific average amount (with actual change varying randomly around the average, including the possibility of a price rise); tends to oscillate with a given amplitude and period; and, is adjusted upwards if a drought affecting corporate agriculture has occurred

[2] This is standard terminology in NetLogo, the platform in which the model was coded.
[3] In the accompanying paper, the transition period is set to 3 years in all model runs.
[4] Note these steps are included in 'produce crops' as the labour-intensive production process on peasant farms leads to both ongoing yield increments and agroecology transitions.

(this adjustment is made according to a climate scenario-specific average amount, with actual rise being randomly determined).

Local food price is set by combining household asking prices to give a production-weighted average price (i.e. where each household's asking price is given a weight according the quantity of food produced by that household), and this is then adjusted according to global food price and the user selected level of **global price transmission**. Local food price represents both farm-gate and consumer price, which are assumed to be equal.

The following prices, which are functions of local food price, are then set: **low-skilled wage** (i.e. the cost of a full-time farm worker), **necessary inputs** (i.e. expenditure that is necessary to allow a worker to be productive, e.g. clothes, tool repair, building maintenance), **'fertilizer'** (which stands in for all non-necessary purchased inputs, such as herbicides and pesticides), **farm equipment** (working animals and small tractors), and **land price** (for a 1ha plot). Under the 'Entrepreneurial eroding' policy scenario, current **interest rates** are calculated[5].

4. <u>Consider farming style change</u> [households practicing 'orphan' style]
   Farmers practicing **orphan agriculture decide whether to change to their preferred style** (In the current iteration of the model, the only permitted changes are from 'orphan' to either 'agroecology' or 'entrepreneurial'). Orphan farmers with a **preference for agroecology** will convert if they have sufficient savings (i.e. they avoid credit) to cover additional input costs during the agroecology transition period. Orphan farmers with a **preference for entrepreneurial** farming will convert if, after providing a basic diet for the family, their income plus savings would be sufficient to employ a full-time worker; they will use **short-term credit** to purchase fertilizer if they require additional funds.

5. <u>Consider expansion</u> [households practicing 'agroecology' or 'entrepreneurial' style]
   Before converting to their preferred style, all orphan households occupy 1 hectare of land and use manual tools. Following conversion, a household may gradually expand the farm by acquiring adjacent (in any direction) unoccupied plots. In addition, to farm newly acquired land, households may require additional farm equipment and/or labour inputs.

   Agroecology farms: An additional unoccupied adjacent 1 hectare plot and/or working animals will be acquired if the costs can be covered by household savings (i.e. credit is avoided). A maximum of one new plot can be acquired in each time step, and farmers will not acquire a new plot until the most recently acquired plot has been transitioned to agroecology. Agroecology households may have up to 10 hectares of land and two pairs of working animals as such a farm can be managed using family labour.

   Entrepreneurial farms: An additional unoccupied adjacent 1 hectare plot and/or working animals or a small tractor may be acquired if farm income and savings cover half the cost; credit will be used to cover the remainder, if required. A maximum of one new plot can be acquired in each time step.

6. <u>Allocate resources to consumption and production</u> [all farming households]

[5] Interest rates remain constant over time in other agricultural policy scenarios.

All farming households make decisions about consumption (of food) and production, given their resources and style-specific goals. All households estimate their **expected food price** in the coming year, and then find their **optimum production level**.

Peasant households initially optimize given their farm land and equipment but without considering other resource constraints. Standard optimization methods are used except that farmers, who use family labour, do not cost labour when optimizing (i.e. they **maximise returns-to-labour**) (van der Ploeg, 2013). Instead, they must provide workers with a labour diet sufficient to allow them to produce at the optimal level (Strauss, 1986). Households then set their **target yield** at this optimal level unless (i) their resources do not permit this level production in which case they ration their resources across consumption and production, and will **abandon** the farm if, after selling farm assets, they are unable to meet at least 50% of a basic diet for the family; or (ii) optimal production would not provide an income sufficient to reproduce the farm and meet their autonomy-related goal of increasing value added per labour object, in which case they attempt to increase production.

Entrepreneurial households optimize, again using standard methods except that they aim to **maximise returns-on-investment** (van der Ploeg, 2013), given their resources (including the available credit). If at this optimal level returns-on-investment are negative (i.e. the farm would run at a loss), they sell an asset and re-optimize; if they have no assets to sell, they **abandon** the farm. They then assess whether income at optimal production would cover their expected expenses (e.g. debt obligations) and meet their income target: if not, they aim to produce at a level that would come as close to achieving this as possible; if, however, at this level returns-on-investment are negative, they sell an asset and re-optimize, unless they have no assets to sell, in which case they **abandon** the farm.

2 Design Concepts

2.1 Theoretical and Empirical Background

2.1.1 Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)?

The **general theory** underlying the model is that the root causes of hunger lie in patterns of poverty and inequality, and that these are partly generated by the food system itself; that is, the food system produces both wealth and poverty, and both good nutrition and hunger (Holt-Gimenez and Patel, 2009, Moore Lappe and Collins, 2015, Rossett, 2006, Buttel, 2000). **Two specific aspects of this are explored in the model**. Firstly, over-productive 'corporate' agriculture drives a tendency for food price to fall, which in turn reduces the viability of livelihoods for the least productive agricultures, pushing them into poverty and hunger (Mazoyer and Roudart, 2006). Secondly, policies that generally support 'entrepreneurial' farming tend to harm 'peasant' farming and may be generating a constellation of farms that is not sustainable and is highly vulnerable to changing institutional and market conditions (van der Ploeg, 2017).

The key **concept** employed in the model is **'farming styles'** (van der Ploeg, 2018). While farms may differ by size and farmers may differ in terms of, for example, risk averseness, van der Ploeg (2018) suggests that, alongside these quantitative differences, there are also crucial qualitative distinctions. A key distinction is between 'peasant' (represented in the model as 'orphan' farming and 'agroecology') and 'entrepreneurial' styles of farming[6]. Here, some key differences lie in (i) farmer goals, (ii) the means employed to intensify farming, and (iii) the way farms are connected to markets. **Peasant farmers** have a key goal of deepening autonomy. Means of achieving this include avoiding market dependence and increasing value added per labour object. Production is increased via labour-intensification. The farm production process produces food as well as most farm inputs: this means the next round of production is guaranteed[7] without recourse to markets (notwithstanding some necessary inputs that must be purchased, including as clothing, tool repairs, or for building maintenance). Peasant farmers also avoid credit, making purchases using their savings. Of note, peasants do not isolate themselves from markets: the market is used as an outlet for surplus production.

Entrepreneurial farmers have a key goal of expansion, and production is increased via capital-intensification which is generally partly financed using credit. The farm production process relies on purchased inputs (e.g. fertilizers) and employed workers, again often financed using credit. Yield is almost entirely sold on the market. This means the logic driving production decisions is largely shaped by off-farm processes, such as price ratios (determining the margin) and technology (determining scale); thus, the market acts as an ordering principle, and another goal of entrepreneurial farming is to maximise returns-on-investment.

Corporate agriculture has a central goal of maximising profit. In the ABM, however, corporate farms are not explicitly represented; rather, they are represented implicitly as a tendency for global food price to fall and oscillate.

The **hypothesis** of the model is that the development trajectories of different constellations of farming styles will have implications for both nutrition and the conditions supporting the health of rural communities, and that climate change, agricultural policy and global price transmission will modify these implications.

2.1.2 On what assumptions is/are the agents' decision model(s) based

Decisions on **optimal production** are assumed to be consistent with standard economic approaches (i.e. using a production function and a total factor cost curve) (Debertin, 2012, Ellis, 1993) but modified using van der Ploeg's (2013) Chayanovian-based approach, in which goals differ by farming style (see above).

Decisions on **asking price** (i.e. for food to be sold in the market), on whether to **convert to the preferred style of farming**, and on whether to **expand the farm or purchase equipment**, are assumed to be taken in line with farming style-specific goals (van der Ploeg, 2013, van der Ploeg, 2018). For instance, for the latter, peasant farmers will only use saving to make purchases while entrepreneurial farmers will use credit (if needed).

Decisions on **rationing resources** (between nutrition and production) are guided by arbitrarily assigned fixed preferences, with the exception that it is assumed that nutrition will be favoured over production when faced with starvation (De La O Campos et al., 2018). For peasants, the decision to **abandon a farm** is made when nutrition falls below a threshold for survival, which is set to consumption of half a basic diet, on the assumption that when faced with 'ultra hunger' (De La O

[6] In the real-world, this is not a binary distinction and farmers may be more peasant- or entrepreneurial-like. In this iteration of the model, however, as we are attempting to take a first look at the implications of farming style for hunger and health under climate change, we treat the distinction as being binary.

[7] That is, guaranteed except if faced with unforeseen circumstances such as significant crop losses.

Campos et al., 2018) farming is no longer viable. For entrepreneurial farmers, it is assumed that the farm will be abandoned when it is running at loss or debt obligations cannot be met.

2.1.3 Why is a/are certain decision model(s) chosen?

The decision models of central importance to the model are based on the empirically grounded theories on **farming styles** developed by van der Ploeg (van der Ploeg, 2013, van der Ploeg, 2016, van der Ploeg, 2017, van der Ploeg, 2018). These where chosen for the following related reasons.

Firstly, producer-consumer farming households comprise a large proportion of those affected by, and at risk of, poverty and hunger (IFAD, 2011), yet it has been argued this same group could hold the key to feeding populations healthily, mitigating climate change (and other environmental damages), and providing decent rural livelihoods (La Via Campesina, 2019, HLPE, 2019). In previous global-level climate-undernutrition models, however, production and consumption are separated by design, and both producer and consumers are represented essentially homogenously: production is not distinguished qualitatively by farming style, and, all people are cast as homogenous consumers (i.e. producer-consumers are not represented) (e.g. Lloyd et al., 2011).

Secondly, between-style distinctions go to the heart of debates on the future of farming. The High Level Panel of Experts on Food Security (HLPE, 2019) distinguish between 'sustainable intensification and related approaches' (SI) (which includes, for example, 'climate smart agriculture'), and, 'agroecological and related approaches' . The former is analogous to 'entrepreneurial' farming and the latter to 'agroecology'. The HLPE crucially notes that these two approaches are '… grounded in very different visions of the future of food systems' (HLPE, 2019).

Thus, the model employs decision models based on theories of farming styles in order to assess the health implications of these possible future food systems under climate change.

2.1.4 If the model/a submodel (e.g. the decision model) is based on empirical data, where does the data come from?

The model does not draw on explicit empirical data. Rather, it uses generalizations based on published empirically-based studies where possible.

2.1.5 At which level of aggregation were the data available?

Not applicable.

2.2 Individual Decision Making

2.2.1 What are the subjects and objects of decision-making? On which level of aggregation is decision-making modelled? Are multiple levels of decision making included?

The decision-making subjects are farming households. The objects of decisions are: target production, whether to convert to their preferred farming style, whether to expand the farm and/or purchase new equipment, how to ration (if required) resources between consumption and production, whether to liquid assets if additional funds are needed, and whether to abandon the farm.

All decisions are made at the household level.

2.2.2 What is the basic rationality behind agents' decision-making in the model? Do agents pursue an explicit objective or have other success criteria?

Households find their optimal production according to their objectives (i.e. goals), which differ by farming style. Decisions on target production, as well as farm expansion, are made given resource constraints, style-specific goals, fixed preferences (assigned at model initialization), and thresholds (e.g. for abandoning the farm).

2.2.3 How do agents make their decisions?

Decisions are made according to the rules represented in the decision trees (Figures A, B, and C). Within these decision trees, decisions on optimal production are initially made using modified standard economic methods; i.e. based on production functions and cost curves (Debertin, 2012, Ellis, 1993) (see 4.3.6.3).

2.2.4 Do the agents adapt their behaviour to changing endogenous and exogenous state variables? And if yes, how?

No.

2.2.5 Do social norms or cultural values play a role in the decision-making process?

Not explicitly. However, the goals of peasant farmers arise from underlying peasant norms and values (van der Ploeg, 2018).

2.2.6 Do spatial aspects play a role in the decision process?

When attempting to expand the farm, households may only acquire unoccupied adjacent plots (in any direction, but the world does not 'wrap around'). If no adjacent plots are unoccupied, they cannot expand.

2.2.7 Do temporal aspects play a role in the decision process?

When estimating expected food price in the coming year, agents consider the price trend over the previous 5 years. When making decisions guided by income-related goals, households base decisions on their average net income over the previous 5 years. When making decisions about production, agents account for previous yield losses due to climate change-associated warming trends.

2.2.8 To which extent and how is uncertainty included in the agents' decision rules?

No information that agents obtain (e.g. food prices) contains uncertainty. When agents are estimating their expected food price in the coming year, a random element is used to represent unmodelled factors which partly represent farmer uncertainty regarding future prices.

2.3 Learning

2.3.1 Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?

No

2.3.2 Is collective learning implemented in the model?

No

2.4 Individual sensing

2.4.1 What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?

Agents sense and use the following variables in their decision making: local food price and other prices (low-skilled wage, necessary inputs, fertilizer, working animals, small tractors, land, interest rates), warming trend-associated yield losses, the productive potential of a plot they are considering purchasing. Sensing processes are not erroneous.

2.4.2 What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?

None

2.4.3 What is the spatial scale of sensing?

All sensed variables are sensed globally, except the productivity of plots being considered for purchase, for which only plots adjacent to the farm may be sensed.

2.4.4 Are the mechanisms by which agents obtain information modelled explicitly, or are individuals simply assumed to know these variables?

Agents are assumed to know.

2.4.5 Are costs for cognition and costs for gathering information included in the model?

No

2.5 Individual prediction

2.5.1 Which data do the agents use to predict future conditions?

They predict their expected food price in the coming year based on the local price in the previous five years. They predict their maximum possible yield in the coming year based on the current temperature anomaly (i.e. due to climate change).

2.5.2 What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?

An agent's expected food price is based on a combination of: current local price and the price trend over the previous five years, random variation to reflect unmodelled factors, and their style-specific goals.

For predictions of temperature anomaly-associated yield losses, all agents are assumed to know the current anomaly and the associated yield losses.

2.5.3 Might agents be erroneous in the prediction process, and how is it implemented?

The actual local food price in the coming year arises from prices and expectations of all agents; thus, predictions of individual agents are likely to be erroneous. All households face the same local food price, regardless of the expectations or initial asking price.

Temperature anomaly-associated yield loss predictions are not erroneous. However, actual yields for each household are subject to random variation (to capture unmodelled factors, which implicitly includes, for example, growing season temperatures that diverge from the anomaly-associated average)).

2.6 Interaction

2.6.1 Are interactions among agents and entities assumed as direct or indirect?

Households interact indirectly through local food price (which is determined by the production and expectations of all agents).

Households with farms located close to each other may also interact indirectly when purchasing additional plots. Households purchase the adjacent plot with highest productive potential, and once a plot is occupied it is unavailable to other households. Entrepreneurial farmers may expand faster than those practicing agroecology as the latter will not purchase additional land until the previously purchased plot has been transitioned (to agroecology).

2.6.2 On what do the interactions depend?

Interaction via local food price depends on relative farm productivities; i.e. those with the highest production have the greatest influence on local food price, which is a production-weighted average.

Interactions via land purchase depend on spatial proximity of farms.

2.6.3 If the interactions involve communication, how are such communications represented?

Not applicable.

2.6.4 If a coordination network exists, how does it affect the agent behaviour? Is the structure of the network imposed or emergent?

Not applicable.

2.7 Collectives

2.7.1 If a coordination network exists, how does it affect the agent behaviour? Is the structure of the network imposed or emergent?

Not applicable.

2.7.2 How are collectives represented?

Not applicable.

2.8 Heterogeneity

2.8.1 Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?

Between-farming style heterogeneity is of central concern in the model. Peasant (orphan and agroecology) and entrepreneurial farmers are heterogenous; for details see 1.3.1 and 2.1.1, Figures B and C, section 4.3.

2.8.2 Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?

Peasant (orphan and agroecology) and entrepreneurial farmers are heterogenous in the decision making for: decisions on style change (i.e. depending on preferred style of the orphan farmer) and expansion (see 4.3.4 and 4.3.5), and decisions on allocation of resources to consumption and production (see Figures B and C) including when optimizing , setting target production and whether to abandon the farm (see Figures B and C, and 4.3.6.3), as well as when deciding their asking price (see 4.3.2.2).

2.9 Stochasticity

2.9.1 What processes (including initialization) are modelled by assuming they are random or partly random?

At model initiation: households are placed on randomly selected one hectare plots; the maximum potential yield and the agroecology yield multiple of each plot is randomly assigned (Table A); household preferences for the use of savings (use all, use half, don't use, save additional 10% of income) and rationing (favour production, favour consumption, favour both equally) are randomly distributed (but in fixed proportions), as are style preferences (in user specified proportions).

In each time step: droughts occur randomly given their risk, and average expected yield loss (Table A) and rises in global food price are randomly set (Table B); yields have a random component to represent unmodelled factors (varying by about $\pm$15%; normally distributed, mean = 0, std dev = 6.5); global food price has a general tendency to fall, but actual change is partly randomly determined (and included the possibility of a rise); if local or global food price fall below 5c/kg they are increased by a random amount (see 4.3.3.1 and 4.3.3.2); household expected food prices in the coming year contain a random component to reflect unmodelled processes (see 4.3.6.3).

2.10 Observation

2.10.1 What data are collected from the ABM for testing, understanding, and analysing it, and how and when are they collected?

The key model outputs are described in 4.3.7. All data are collated at the end of each time step.

2.10.2 What key results, outputs or characteristics of the model are emerging from the individuals?

The above outputs are assessed at the system level but they are not strictly 'emergent' (e.g. they are sums or aggregates of individual-level variables), but collectively they give an indication of the productive potential and health of the community as a whole.

3 Details

3.1 Implementation details

3.1.1 How has the model been implemented?

Netlogo 6.0.1 (Wilensky, 1999).

3.1.2 Is the model accessible and if so where?

On request from the author.

3.2 Initialization

3.2.1 What is the initial state of the model world, i.e. at time t=0 of a simulation run?

See Tables A and B.

3.2.2 Is initialization always the same, or is it allowed to vary among simulations?

Households are randomly located. Style preference patterns are user selected.

3.2.3 Are the initial values chosen arbitrarily or based on data?

Initial values are derived for the empirically-based literature where possible (see Tables A and B).

3.3 Input data

3.3.1 Does the model use input from external sources such as data files or other models to represent processes that change over time?

No

3.4 Sub-models

3.4.1 What, in detail, are the submodels that represent the processes listed in 'Process overview and scheduling'?

For model a description of model variables and parameters, their initial values, and how they change over time, see Tables A and B. For decision trees, see 4.2. For pseudo-code, see 4.3.

3.4.2 What are the model parameters, their dimensions and reference values?

See Tables A and B.

3.4.3 How were sub-models designed or chosen, and how were they parameterized and then tested?

The model sub-models for farming household decisions were designed as expressions of van der Ploeg's (2018) empirically-based theories of style-specific goals and behaviours, drawing on standard economic methods (Debertin, 2012, Ellis, 1993) but modifying them as required (Holt-Gimenez, 2019, van der Ploeg, 2013), empirical studies of farm productivity (Pimentel and Pimentel, 2008), 'rules of thumb' (for productive potential given equipment and land) (Mazoyer and Roudart, 2006). Additionally, *ad hoc* decision trees were developed, intended to represent style-specific goals and plausible farmer behaviour when faced with starvation or a farm that is running at a loss.

The climate sub-model was designed to be an approximation of possible changes in climate and weather and the possible impacts on farming.

The sub-models were test iteratively, which each section of code being tested (e.g. by tracking individual working variables), de-bugged, and modified as necessary.

4 Tables, figures, and pseudo-code

4.1 Tables

The tables in this section describe model variables and parameters, their functions, their initial values, and how they change over time. Table A shows factors associated with agents and the environment; Table B shows the prices of factors that may be purchased.

Table A. Key environment and agent factors, their initial values, and how they change over time

Factor	Function or effect	Initial value	Change over time	Notes
Landscape				
'Local area'	Grid of 1 ha plots.	441 plots.	No change.	A 21 by 21 grid of arable plots.
Plot max productivity	Each plot has a maximum productivity under orphan agriculture (i.e. in which no non-labour farm inputs are used).	Randomly set for each plot: 1000kg/year $\pm$20% (uniform distribution). [Based on Mazoyer and Roudart (2006)]	Gradual increase on 'optimized' peasant farms. 'Peasant' policy: orphan 1.5%/year, Agroecol 3% per year; other policies: Orphan 1%/year, Agroecol 1.5%/year. Max production = 10t/ha. [Based on van der Ploeg (2013)]	'Optimized' in terms of production; assumed that if farmer unable to optimize, then also unable to gain production increases. Assumes no land degradation under any style.
Plot agroecology yield multiple	Max productivity of a plot is raised by a given multiple after transitioning to agroecology.	Randomly set for each plot: mean=4, SD=1.5 (normal distribution, restricted to values between 2 and 7). [Based on Pretty et al. (2003), Pretty et al. (2018), Rosset and Altieri (2017)]	No change.	Productivity rises slowly during the transition phase, with the full yield multiple being achieved after the agroecology transition period (see 4.3.2.4)
Agroecology transition period	Number of years to transition a plot to agroecology.	3 years. [Based on Rosset and Altieri (2017)]	No change.	Transition achieved via labour intensification (see 'Agroecology labour multiple')
Agents				
Farming households	Farming households, each of four people, practicing a particular style of farming. Using manual tools, each household can farm one hectare.	250; each randomly assigned a 1ha plot; all practicing orphan agriculture; preference to develop via a particular style distributed according to scenario. All households are assumed to have consumed a basic diet, be aiming to produce their maximum yield, and have no savings	Households change to preferred style if they have access to sufficient resources (see 4.3.4), or, abandon farming if nutrition falls below 50% of a basic diet.	Initially ~40% of plots are unoccupied. Approximates conditions in lower income countries. (Bruinsma, 2003, Mazoyer and Roudart, 2006, World Bank, 2019)
Family basic diet	Quantity of cereal equivalents providing a basic diet to a family for one year.	700kg/year (equiv. to ~2200kcal/person/day). [Based on Mazoyer and Roudart (2006)]	No change. Households abandon their farm if they are unable to obtain 50% of a basic diet.	Household members do not age over time.
Labour diet	Worker calorie intake/day to allow a given amount of labour power.	5100kcal/day for max production on 1ha; diminishing returns as intake increases to this level (see 4.3.6.1) [Based on Strauss (1986) & Pimentel and Pimentel (2008)]	Acquiring working animals or a small tractor allows a worker to farm more than 1ha (Table B). Labour input requirements double under agroecology.	For orphan agriculture, max production on 1ha with manual tools requires 150 ten hour labour days/year. [Based on Pimentel and Pimentel (2008)]
Agroecology labour multiple	Increase in labour requirements for maximum production in agroecology.	2 (i.e. for max production, required labour time doubles). [Based on Rosset and Altieri (2017)]	No change.	'Necessary input' requirements rise proportionally with labour (Table B).

Table A, continued

Factor	Function or effect	Initial value	Change over time	Notes
Climate				
Warming trend and yield losses	Yields decline as warming increases, with lower losses for agroecology. (For effects on global food price, see Table B).	Warming = 0. Yield loss = 4%/degree of warming [Based on Moore et al. (2017) and Zhao et al. (2017)]; losses reduced by 10% under agroecology. [Based on Rosset and Altieri (2017)]	Linear rise in warming. High CC: 2 degrees/50years (i.e. 0.04 degrees per year); Low CC: 1 degree/50 years (i.e. 0.02 degrees per year); No CC: no warming. [Based on Knutti and Sedláček (2012)]	An approximation guided by average warming under the Representative Concentration Pathways (Moss et al., 2010). Agroecology loss reductions are an approximation.
Drought risk and yield losses	Proportion of yield lost if a drought occurs; lower losses under agroecology. (For effects on global food price, see Table B).	Drought risk = 5%/year Drought yield losses are - High CC: av. 15%, up to 30%; Low CC: av. 10%, up to 25%; No CC: av. 7.5%, up to 20%. Losses reduced by 20% under agroecology (see 4.3.1.1 and 4.3.2.1). [Based on Rosset and Altieri (2017)]	Linear increase in risk – High CC: doubles after 50 years; Low CC: 1.5 times after 50 years; No CC: no change. Yield losses are fixed over time.	Drought losses are contingent on multiple processes meaning no generally applicable quantification available. Plausible approximations used, including for agroecology.

Table B. Prices for key factors, their initial values, and how they change over time

Factor	Function or effect	Initial value	Change over time	Notes
Food price				
Local food price	Food price faced by farming households.	40c/kg (Given input prices (see below), this places the average farmer close to the threshold for development.)	Calculated as the production-weighted average of farmer asking prices, adjusted for global price given price transmission (see 4.3.3.2).	Farm gate and consumer prices assumed to be the same.
Global food price	Represents price arising from global corporate agriculture: influences trend in local price via global price transmission (Figure A)	40c/kg	General tendency to fall (most rapidly under 'no climate change' and most slowly under 'high climate change' (due to warming)) & oscillate. Drought causes price increases, with the greatest increases under 'high climate change' (see 4.3.3.1).	The simulations aim to assess the impact of the tendency for global prices to fall and oscillate on smallholder farming. [Based on Mazoyer and Roudart (2006)]
Inputs				
Labour: low skilled wage	Cost of a full-time farm worker (Labour time may be purchased in fractions given target yield).	Price = 180% of the cost of a basic diet for a family of four; i.e. price = 700kg * local food price * 1.8. [e.g. Wage Indicator Foundation (2019)]	Same formula (based on average local price over last 5 years), but with an additional rise of 2% per year [Based on ILO (2016)].	Peasants do not cost labour. Over time, food costs represent a smaller proportion of people's income.
Purchased inputs: necessary inputs	'Necessary inputs' represent expenditure required to enable production. Assumed to be scalable given target production.	Necessary inputs for max production: price/ha = 15% of a low skilled wage. [Based on Petersen and Silveira (2017) and van der Ploeg (2016)]	Under agroecology, necessary inputs for maximum production double (i.e. in proportion to increased labour requirements (Table A)).	Necessary inputs include clothing, tool repair, building maintenance, etc (Mazoyer and Roudart, 2006).
Purchased inputs: fertilizer	Increases productivity of a plot up to 10 times (Mazoyer and Roudart, 2006), with diminishing returns as quantity used increases to max (see 4.3.6.2)	Price of 1kg = local food price/kg * 10. Max productivity at 500kg [e.g. (Roser and Ritchie (2019), van der Velde et al., 2013, Yamano and Arai, 2011)]. Under 'Entre' and 'entre eroding' policy: 50% subsidy.	Same formula, but price rises 1%/year. Under 'entre eroding', subsidy falls by 1%/year.	'Fertilizer' assumed to represent all non-necessary purchased inputs (e.g. pesticides, seeds). Thus, the fertilizer:food price ratio accounts for this.
Working (i.e. draught) animals	Allows one worker to farm up to 5ha (cf. manual tools, which allow 1ha to be farmed).	Price = 30 years of net income (i.e. after feeding the family) of average orphan ag farm (See 4.3.3.3). [Based on Mazoyer and Roudart (2006)]	Same formula, based on average local food price over the last five years.	Working animals allow workers to farm a greater area but do not increase plot productivity.
Small tractor	Allows one worker to farm up to 16 hectares (cf. manual tools, which allow 1ha to be farmed).	Price = 150 years of net income (i.e. after feeding the family) of av orphan ag farm. (See 4.3.3.3) [Based on Mazoyer and Roudart (2006) and Pimentel and Pimentel (2008)]	Same formula, based on average local food price over the last five years.	Tractors allow workers to farm a greater area but do not increase plot productivity.
Land price	Farmers may expand by purchasing unused adjacent plots.	Price/ha = the cost of 30 tonnes of cereal (Equivalent to the value of 30 years of average max production of orphan agriculture) (See 4.3.3.3).	Same formula, based on average local food price over the last five years.	Price chosen as this roughly represents the gross value produced on the land over the working life of an orphan farmer.
Credit				
Annual interest rates	Interest rates on loans for fertilizer (short-term), animals and tractors (mid-term), and land (long-term) (van der Ploeg, 2018).	Short-term (1 year): 20%, mid-term (3 to 6 years): 15%, long-term (8 years): 10%. Rates halved under 'Entre' and 'Entre eroding' policy.	Fixed, except under 'Entre eroding' policy where rates increase linearly over time, returning to their full values after 50 years.	Peasant farmers do not use credit. Rates based on Chandio and Jiang (2018), Chisasa and Makina (2012), Duniya and Adinah (2015), Malik and Nazli (1999).

4.2 Figures

Figure A show household actions and decision related to production, and Figures B and C show household actions and decisions related to the allocation of resources to consumption and production for peasant and entrepreneurial farmers, respectively.

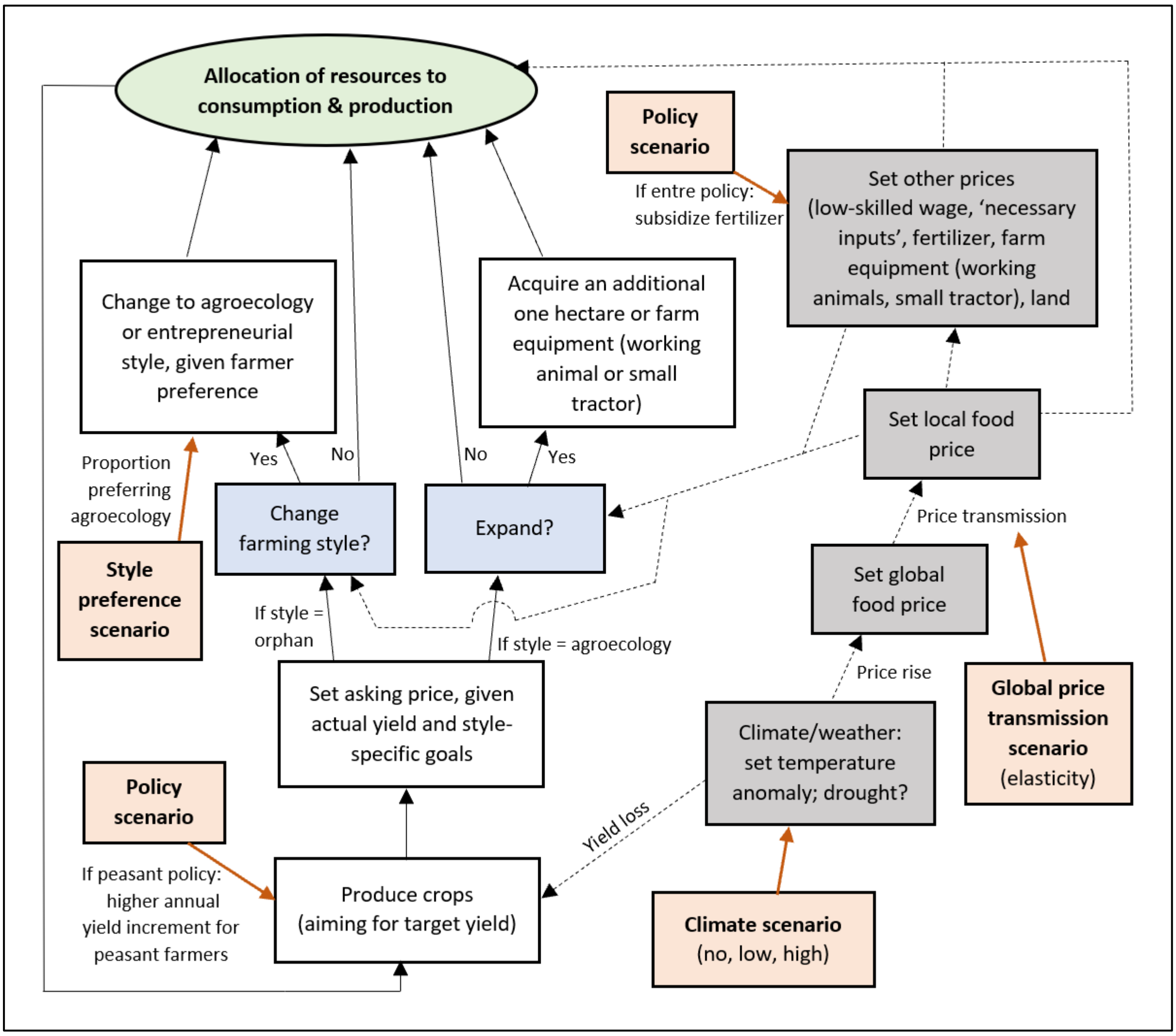

Figure A Household actions and decisions related to production. Scenarios are shown in orange; 'observer' (i.e. model controller) are shown in grey boxes and by dotted arrows; household decisions are shown in blue boxes; household actions are shown in white boxes and linked by solid arrows. Decisions related to the allocation of resources to consumption and production are shown in green and differ for peasant and entrepreneurial farmers (see Figures B and C)

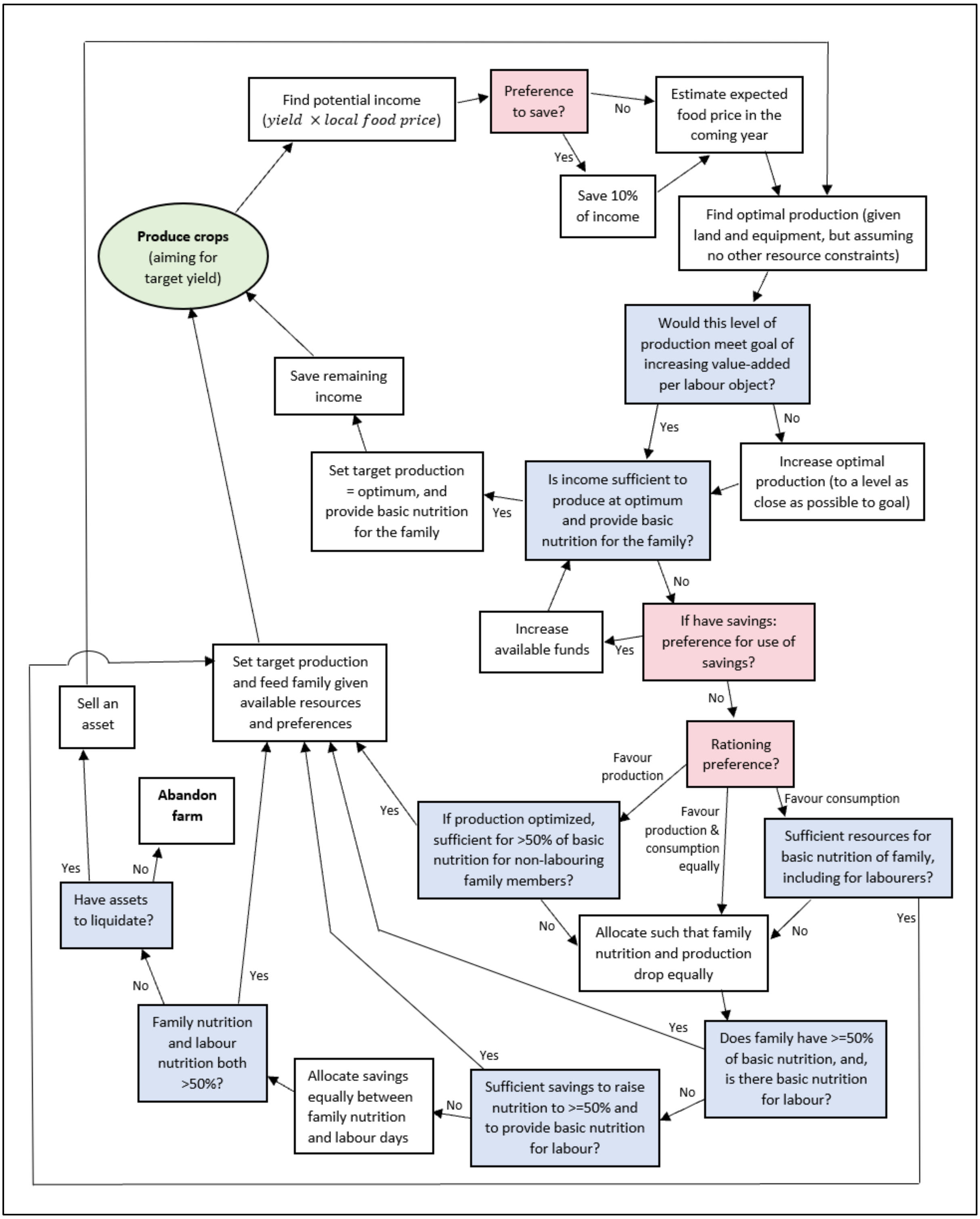

Figure B Peasant farmer actions and decisions related to the allocation of resources to consumption and production. Household decisions are shown in blue boxes except for decisions shaped by fixed preferences which are shown in red; household actions are shown in white boxes and linked by arrows. Decisions related to production are shown in green (see Figure A).

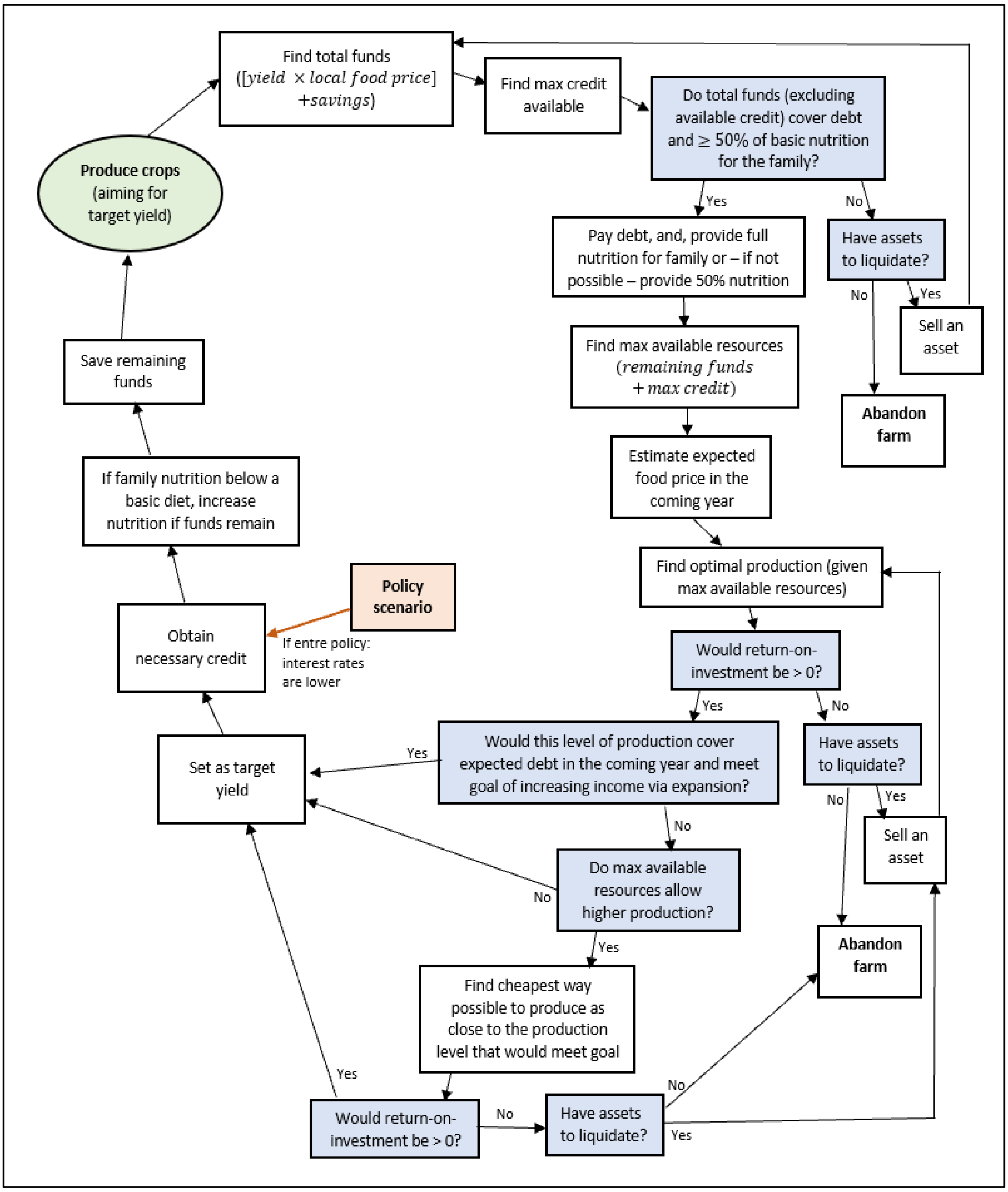

Figure C Entrepreneurial farmer actions and decisions related to the allocation of resources to consumption and production. Household decisions are shown in blue boxes; household actions are shown in white boxes and linked by arrows; scenarios are shown in orange. Decisions related to production are shown in green (see Figure A).

4.3 Pseudo-code

In this section, relevant pseudo-code is shown for each of the six major model processes (see 1.3) and for the main model outputs (see 1.1). See also Tables A and B for how additional variables and parameters change over time.

4.3.1 Set weather

4.3.1.1 Average yield losses if a drought occurs

Average yield losses if a drought occurs:

For high climate change, average yield loss = 15% to ~30%
= (15 + absolute value [normally distributed random floating point number with (mean = 0, std dev = 7)]) / 100

For low climate change, average yield loss = 10% to ~25%
= (10 + absolute value [normally distributed random floating point number with (mean = 0, std dev = 7)]) / 100

For no climate change, average yield loss = 7.5% to ~20%
= (7.5 + absolute value [normally distributed random floating point number with (mean = 0, std dev = 6.5)]) / 100

4.3.2 Produce crops

4.3.2.1 Household yield losses if a drought has occurred

For orphan and entrepreneurial households (note that 'average yield losses' are calculated in 4.3.1.1):

household drought yield loss = 80% to 120% of average losses for 90% of households

= average yield loss × (1 + ([normally distributed random

floating point number with (mean = 0, std dev = 10)] / 100))

For agroecology households, losses are calculated as for orphan and entrepreneurial households but then decreased by 20%.

4.3.2.2 Actual yield

Actual yield is target yield, reduced by warming-associated yield losses (Table A), drought-associated yield losses (4.3.2.1), and randomly adjusted (by up to ~±15%) to account for unmodelled factors.

actual yield = (target yield – (warming-associated yield losses + drought associated yield losses)) ×
((1 + normally distributed random floating point number with (mean = 0, std dev = 6.5) / 100)

4.3.2.3 Household asking price

Households finding their asking price in style-dependent manner. Asking prices are restricted such that they do not differ by more than ± 15% of expected price.

For peasant farmers:
yield for sale = what would remain of the yield if the family were provided with a basic diet and sufficient for 90% of a maximum labour diet were set aside
= actual yield – (quantity required to provide a basic family diet + quantity to provide 90% of a maximum labour diet)

desired income = the maximum of: either the cost of 90% of maximum necessary inputs, or, a net income of 105% of the average net income over the previous five years[8]
= max (90% of cost of maximum necessary inputs, 105% of five year average net income)

[8] The former is the quantity of necessary inputs required for 90% of maximum labour to be fully productive; the latter represents an increase on value added per labour object (i.e. a key goal of peasant farmers).

If yield for sale > 0 [asking price = (desired income) / (yield for sale)
if asking price > expected price × 1.15 [set asking price = expected price × 1.15]
if asking price < expected price × 0.85 [set asking price = expected price × 0.85]
]
If yield for sale < 0 [asking price = expected price × 1.15][9]

For entrepreneurial farmers:
yield for sale = actual yield
asking price = (target yield × expected price) / yield for sale)
if asking price > expected price × 1.15 [set asking price = expected price × 1.15]
if asking price < expected price × 0.85 [set asking price = expected price × 0.85]

4.3.2.4 Agroecology yield rise during transition period

Household yields rise gradually during the agroecology transition period, achieving the full agroecology yield multiple after the transition period:

During transition period, achieved yield multiple = (plot agroecology yield multiple) / (agroecology transition period – plot years under agroecology)

4.3.3 Set food prices and other prices

4.3.3.1 Global food price

Global food price is set such that it has a tendency to fall (fastest when no climate change; slowest under high climate change), oscillate, and rise in response to a drought.

Roughly linear tendency to fall (but may also rise):

For high climate change, working global food price = average fall of 1% per year
= global food price$_{(t-1)}$ –
(global food price$_{(t-1)}$ × 0.01) + normal distributed random floating point number with
(mean = 0, std dev = global food price$_{(t-1)}$ × 0.025)

For low climate change, working global food price = average fall of 1.25% per year
= global food price$_{(t-1)}$ –
(global food price$_{(t-1)}$ × 0.0125) + normal distributed random floating point number with
(mean = 0, std dev = global food price$_{(t-1)}$ × 0.0275)

For no climate change, working global food price = average fall of 1.5% per year
= global food price$_{(t-1)}$ –
(global food price$_{(t-1)}$ × 0.015) + normal distributed random floating point number with
(mean = 0, std dev = global food price$_{(t-1)}$ × 0.03)
(where t is the current time step)

Check working global food price > 5c/kg (i.e. assume a price lower than this would be unreasonably low):
while (working global food price) ≤ 5c/kg [
set (working global food price) =
working global food price + (random floating point number ≥0 and < 5)
]

Adjust for oscillation:

let amplitude = 0.3 and period = 10

[9] If a household would have nothing for sale after meeting a basic diet and 90% of a labour diet they will boost they asking price by as much as they think is viable: this is assumed to be 15% above their expected price. Households will sell at least some of their yield as they require at least some necessary inputs if they are to produce crops.

oscillator = amplitude × $sin\left(\frac{2\pi}{period} \times time\ step\ \times \frac{180}{\pi}\right)$
working global food price = working global food price + (oscillation * 0.05)

Check working global food price >5c/kg, as per code above.

Adjust for drought:

For high climate change, drought price increase = 10% to 17.5%
= (random floating point number ≥ 10 and <17.5) / 100
For low climate change, drought price increase = 7.5% to 12.5%
= (random floating point number ≥ 7.5 and <12.5) / 100
For no climate change, drought price increase = 5% to 7.5%
= (random floating point number ≥ 5 and <7.5) / 100

global food price = working global food price × (1 + drought-price-increase)

4.3.3.2 Local food price

Local food price is the production-weighted average of household asking prices adjusted by global price transmission:

Production-weighted average of household asking prices =

$$\sum\nolimits_{all\ households}\left[household\ asking\ price\ \times \left(\frac{household\ yield\ for\ sale}{\sum_{all\ households}(yield\ for\ sale)}\right)\right]$$

Check production weighted price > 5c/kg (i.e. assume a price lower than this would be unreasonably low):
while (production-weighted average of household asking prices) ≤ 5c/kg [
set (production-weighted average of household asking price) =
production-weighted average of household asking price + (random floating point number ≥0 and < 5)
]

Adjust for global price transmission:
% change global food price = (global food price$_{(t)}$ – global food price$_{(t-1)}$) / global food price$_{(t-1)}$, where t is the current time step
local food price = production-weighted average of household asking prices ×
((1 + % change in global food price) * global price transmission))

4.3.3.3 Prices of working animals, small tractors, and land

Prices are linked to average local food price over the previous 5 years.

price of working animals plus simple equipment = ~30 years of average income for an orphan farmer after feeding the family a basic diet
= 30 years × (1000kg – 700kg) × local food price
≈ ~10 years of average gross value product per ha for an orphan farmer
= 10 × 1000kg × five year average local food price

price of small tractor = ~150 years of average income for an orphan farmer after feeding the family a basic diet
= 150 years × (1000kg – 700kg) × local food price
≈ ~50 years of average gross value product per ha for an orphan farmer
= 50 × 1000kg × five year average local food price

price of 1ha of land = ~30 years of average gross value product per ha for an orphan farmer
= 30 × 1000kg × five year average local food price

4.3.4 Consider farming style change

Orphan with preference for agroecology:

Change style if:
savings ≥ additional inputs required during transition period, which is:
[additional necessary inputs] + [additional labour diet], which is:
[(necessary inputs × (agroecology labour multiple – 1)] +
[(daily labour diet – daily basic diet) * annual labour days * local food price *
(agroecology labour multiple – 1)]

Orphan with preference for entrepreneurial:
Change style if:
savings + (income – family basic diet) ≥ low skilled wage

4.3.5 Consider expansion

Orphan farmers cannot expand their farm beyond one hectare (the maximum area that can be managed by an orphan farmer using manual tools). Agroecology farmers may acquire up to 10 hectares plus two set of working animals (as this can be managed using family labour), and they only make purchased using their savings. Entrepreneurial farmers, who use wage labour, may acquire an unlimited number of hectares plus working animals or small tractors; they make purchases if they can pay at least half the cost using savings and acquire credit for the balance (mid-term credit for working animals and tractors; long-term credit for land).

Agroecology farmers:
IF all plots transitioned to agroecology [
AND IF have only 1 hectare of land AND savings > (price of working animals + one hectare of land) [
IF at least one plot adjacent to the farm is unoccupied, acquire the plot with the greatest yield potential
and one pair of working animals
]
ELSE IF have working animals that are able to farm more land than currently owned AND own < 10 hectares AND
savings > price of one hectare of land [
IF at least one plot adjacent to the farm is unoccupied, acquire the plot with the greatest yield potential
]
ELSE IF own 5 hectare of land AND own 1 pair of working animals AND savings > price of working animals [
acquire an additional pair of working animals
]
]

Entrepreneurial farmers:
IF own ≥ 1 tractor AND could farm more land than currently owned with these tractors AND
savings ≥ (price of one hectare / 2) [
IF at least one plot adjacent to the farm is unoccupied, acquire the plot with the greatest yield potential
]
ELSE IF (savings + current income + (price of owned working animals / 2)[10] ≥ (price of a small tractor / 2)) AND
mid-term debt = 0) [
acquire a tractor
]
ELSE IF own ≥ 1 pair of working animals AND could farm more land than currently owned with these working animals
AND savings ≥ (price of one hectare / 2) [
IF at least one plot adjacent to the farm is unoccupied, acquire the plot with the greatest yield potential
]
ELSE IF ((savings + current income) ≥ (price of working animals / 2)) AND no tractors owned AND mid-term debt = 0)[
acquire a pair of working animals
]

[10] If moving for using working animals to using tractors, farmers will sell their working animals at half their initial value.

ELSE IF ((savings + current income) ≥ (low skilled-wage × farm size)[11]) AND no working animals or tractors are owned AND savings ≥ (price of one hectare / 2) [
IF at least one plot adjacent to the farm is unoccupied, acquire the plot with the greatest yield potential
]

4.3.6 Allocate resources to consumption and production

4.3.6.1 Proportion of maximum yield achieved as a function of labour diet

Based on Strauss (1986).

Proportion of maximum yield achieved = *f*(proportion of maximum labour power)
= *f*(proportion of maximum labour diet consumed)
= -(proportion of maximum labour diet consumed)^2 +
2×(proportion of maximum labour diet consumed)

4.3.6.2 Yield increases with fertilizer

With maximum fertilizer input (assumed to be 500kg/hectare) the yield multiple is assumed to be 10 (e.g. if yield on a hectare of land were 1 tonne then the application of 500kg of fertilizer would lead to a yield of 10 tonnes). Fertilizer use up to this maximum brings diminishing returns.

The table below shows the relation between fertilizer inputs and the achieved yield multiple. The top row ('Prop') is the proportion of maximum fertilizer used (e.g. 0.2 means 100kg of fertilizer was used) and the second row ('Mult') shows the associated yield multiple (e.g. if a proportion of 0.2 were used the yield multiple would be 3.6).

Prop	.05	.1	.15	.2	.25	.3	.35	.4	.45	.5	.55	.6	.65	.7	.75	.8	.85	.9	.95	1
Mult	1.1	1.9	2.8	3.6	4.4	5.1	5.8	6.4	7	7.5	8	8.4	8.8	9.1	9.4	9.6	9.8	9.9	9.98	10

4.3.6.3 Optimization

First, all households find their expected price in the coming year.

Expected price

Each household estimates their expected food price in the coming year, where expected price reflects the price farmers would aim to sell their yield for, given price trends and their style-specific goals. Thus, expected price is based on an initial estimate given price trends, which is then adjusted as follows to reflect style-specific goals: orphan farmers make no adjustment; entrepreneurial farmers aim to expand by capturing more of the market so reduce their expected price; agroecology farmers aim to increase autonomy by increasing returns-to-labour-object so they increase their expected price.

Step 1: find initial expected price
Initial expected price = current local food price +
(slope of local food price over previous five years × (random floating point number > -3.5 and <1.5)
Where, the random number represents unspecified factors when making judgements about price trends, but there is a general tendency to assume that the current trend will slow.

IF initial expected price ≤ 0 THEN set initial expected price = current price × 1.05

Step 2: adjust initial expected price given farming style
Orphan farmers:
Expected price = initial expected price
Entrepreneurial farmers:
Expected price = initial expected price × 0.98
Agroecology farmers:

[11] This is the cost of wages to farm all the plots currently owned; i.e. using manual tools, each working can manage 1 hectare).

Expected price = initial expected price × 1.15

Following this, households find their optimal production.

Find optimal production: peasant households

Step 1: Find production level that would maximise returns-to-labour, given land and equipment but assuming no other resource constraints. Maximising returns-to-labour is equivalent to optimizing production using standard economic methods (i.e. to maximise profit) (Debertin, 2012, Ellis, 1993) but without costing labour (van der Ploeg, 2013).

The total value product (TVP) curve is derived by modifying the curve for 'proportion of maximum yield achieved' given labour inputs (see 4.3.6.1) so that it accounts for household maximum achievable yield and expected food price.

TVP = [-(proportion of maximum labour diet consumed)^2 +
2×(proportion of maximum labour diet consumed)] × (expected price × maximum yield)

It is assumed that, for a given proportion of maximum labour power (which is equal to the proportion of a maximum labour diet consumed) to be productive, an equivalent proportion of maximum necessary inputs is required. Thus:

TVP = [-(proportion of maximum necessary inputs)^2 +
2×(proportion of maximum necessary inputs)] × (expected price × maximum yield)
[where the x-axis is proportion of maximum necessary inputs, and the y-axis is $]

The total factor cost (TFC) curve is derived such that it begins at the origin and slope is equal to the cost of necessary inputs that would allow maximum production. For the TFC curve: x-axis is proportion of maximum necessary inputs and y-axis is $.

TFC = (cost of necessary inputs that would allow maximum production) ×
(proportion of maximum necessary inputs)

Then, production is optimal when: $\frac{d(TVP)}{dx} = \frac{d(TFC)}{dx}$

Step 2: IF optimal production is at a level such that workers would not be consuming a basic diet THEN boost optimal production to a level where workers consume a basic diet.

IF optimal proportion of maximum necessary inputs × calories for maximum labour < calories in basic daily diet
THEN [optimal proportion of maximum necessary inputs =
calories in basic daily diet / calories for maximum labour power
= 2200 / 5100 = 0.43
]

Step 3: Assess whether optimal production would provide sufficient income to reproduce the farm: i.e. provide a family basic diet, and, allow the purchase of sufficient necessary inputs to enable workers consuming a basic labour diet to be fully productive. If not, attempt to increase production.

IF (gross income at optimal production – (family basic diet × expected food price)) <
((2200 / 5100) × cost of necessary inputs that would allow maximum production)
THEN [set optimal production to a level that provides required income
OR if not achievable, set optimal production = maximum achievable production
]

Step 4: Assess whether optimal production would provide sufficient income to achieve autonomy-related goal of increasing value added per labour object. This is assumed to be achieved if a household's five year average net income is increased by 5%. If not, attempt to increase production.

IF (gross income at optimal production – (family basic diet × expected food price)) <
(five year average net income × 1.05)
THEN [set optimal production to a level that provides desired income
OR if not achievable, set optimal production = maximum achievable production
]

Step 5: see Figure A for subsequent household decisions on target production, rationing if necessary, and whether to abandon the farm.

Find optimal production: entrepreneurial households

Step 1: find production level that would maximise returns-on-investment given available resources including maximum available credit. Maximising returns-on-investment is based on the same curves used to optimize production in standard economic methods (i.e. to maximise profit) (Debertin, 2012, Ellis, 1993) but aims for a different target (van der Ploeg, 2013).

The total value product (TVP) curve has an x-axis for proportion of maximum labour used (which is equal to proportion of maximum necessary inputs used), a y-axis for proportion of maximum fertilizer inputs[12] used, and a z-axis for total value product in $. The total factor cost (TFC) curve has the same x- and y-axes but the z-axis is total factor cost in $. And for each combination of inputs, returns-on-investment (ROI) is given by:

$$ROI = \frac{TVP - TFC}{TFC}$$

The household sets optimal production at the level which, of the viable options (given available resources), maximises ROI.

$$viable\ ROIs = subset\ of\ ROIs\ that\ are\ achievable\ given\ resources$$

$$target\ ROI = \max\,(viable\ ROIs)$$

$$optimal\ production = production\ level\ at\ which\ target\ ROI\ is\ achieved$$

Step 2: Check whether the expected return on investment is positive. If not, sell assets and re-optimize.

IF viable ROI < 0, THEN
[IF they have assets to sell [sell assets (see 4.3.6.4) and return to step 1]
ELSE [abandon the farm]
]

Step 3: Assess whether optimal production would allow household to cover expenses and achieve desired income in the coming year. If not, attempt to increase production.

Desired income is either (i) average net income per hectare over the previous 5 years if no additional land was acquired in the current time step, or (ii) if an additional hectare was acquired in this time step, 95% of average net income per hectare over the previous five year. The latter is because entrepreneurial farmers aim to increase income via expansion, where income is determined by margin per ha multiplied by scale (i.e. farm size) (van der Ploeg, 2018). Thus, if entrepreneurial farmers have expanded by acquiring an additional plot in the current time step, the margin per ha may fall while income rises.

IF no land acquired in the current time step
THEN [desired net income = five year average net income per hectare × farm size]
ELSE [desired net income = five year average net income per hectare × farm size × 0.95]

IF TVP at optimal < (debt obligations + basic diet for the household + desired income)
THEN [set target TVP = min ((debt obligations + basic diet for the household + desired income),
maximum viable TVP)
find lowest cost way of achieving target TVP
IF ROI for target TVP < 0 THEN [IF they have asset to sell [sell assets (see 4.3.6.4) and
return to step 1]
ELSE [abandon the farm]

[12] 'Fertilizer' stands in for all purchased inputs (e.g. herbicides, pesticides).

For decisions and actions taken by peasant and entrepreneurial farmers following optimization see Figures B and C, respectively.

4.3.6.4 Sell assets

If households require additional funds to for the farm to survive they will sell equipment and land for half its value (i.e. assumed to require a quick sale by a struggling farm).

IF at least one small tractor owned [sell tractor for half its value AND sell any land that can no longer be farmed without this equipment[13]
]
Else IF at least one pair of working animals owned [sell pair of working animals for half their value AND sell any land that can no longer be farmed without this equipment[14]
]

4.3.7 Model outputs

4.3.7.1 Total food produced

Total food produce by all households in a given year, quantified as kilograms of cereal equivalents, where 700kg feeds a family of 4 a basic diet (Mazoyer and Roudart, 2006).

$$Total\ food\ produced_t = \sum_{all\ households} household\ total\ food\ production_t$$

(where t is the current time step)

4.3.7.2 Local food price

See 4.3.3.2.

4.3.7.3 Income slope

Shown as average change in average net income over the previous 10 years for farmers practicing each style (units: $/year).

household net income = household gross income – all household expenses

five year average household net income = [sum of (household net income) over the previous five years] / 5

mean of five year average household net income for all household practicing a given style =
[sum of (five year average household net income for households practicing a given style)] /
(number of households practicing that style)

For finding average income slope for all households practicing a given style , let x-axis = time step and y-axis = mean of five year average household net income for households practicing a given style, then:
style-specific income slope = $\frac{dy}{dx}$, over the previous 10 years

4.3.7.4 Orphan nutrition

Average nutrition across all orphan households, as the proportion of a basic diet being consumed.

[13] i.e. each small tractor allows one worker to farm 16 hectares.
[14] i.e. each pair of working animals allows one worker to farm 5 hectares. Note that after selling the last pair of working animals a household will have only 1 hectare of land.

Household nutrition = (kg of cereal equivalents consumed by a household) / 700kg, where 700kg provide a basic diet.
Orphan nutrition = mean (household nutrition) of orphan households

4.3.7.5 Farm labour

For orphan agriculture, max production on 1ha with manual tools requires 150 ten hour labour days/year (Based on Pimentel and Pimentel, 2008). Thus, a full-time worker is assumed to be working 150 ten hour labour days/year, regardless of the area they farm (which is dependent on their equipment). Full-time workers include both family labour on peasant farms and wage labour on entrepreneurial farms.

Farm labour = sum of (full-time equivalent workers) on all farms

4.3.7.6 Income Gini

The Gini coefficient is calculated using standard methods (e.g. Milanovic, 2005), based on five year average household net incomes. A value of 0 indicates perfect inequality and a value of 1 indicates maximum inequality.

4.3.7.7 Mean net farm income

Mean net farm income is the average of the five year average net income of all farming households.

household net income = household gross income – all household expenses

five year average household net income = [sum of (household net income) over the previous five years] / 5

mean of five year average household net income = [sum of (five year average household net income)] / (number of households)

4.3.7.8 Real land productivity

Real land productivity is net income per hectare adjusted for the proportion of value that was added on the farm ('endogeneity'), calculated (based on Petersen and Silveira, 2017) as follows.

For each household:

$$real\ land\ productivity\ [\$/ha] = \frac{household\ net\ income\ in\ a\ given\ year\ [\$]}{farm\ size\ \ [ha]} \times endogeneity \text{ , where:}$$

$$endogeneity = \frac{value\ added\ on\ the\ farm\ [\$]}{value\ of\ total\ farm\ production\ [\$]}$$

$$= \frac{value\ of\ total\ farm\ production - (purchased\ inputs\ excluding\ labour)\ [\$]}{value\ of\ total\ farm\ production\ [\$]} \text{ , where:}$$

$$value\ of\ total\ farm\ production = actual\ farm\ \times local\ food\ price$$

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