The role of climate science in understanding Climate Security

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I certify that all material in this thesis which is not my own work has been identified and that any material that has previously been submitted and approved for the award of a degree by this or any other University has been acknowledged.

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Abstract

Climate change is widely recognised to represent a threat to human security, but understanding how this threat may manifest itself is a non-trivial task. Climate Security spans natural and social science boundaries, where differences in analytical methods, language and scale between disciplines can result in barriers to accessing climate science knowledge.

This thesis attempts to address some of these knowledge problems and demonstrate the potential to improve the integration and utilisation of climate science in understanding climate and security. Using a systems-based approach, the example of long term food insecurity in Ethiopia is explored.

Despite large increases in national cereal production in recent decades, Ethiopia continues to experience regular acute food insecurity crises, often associated with drought events. However, the meteorology of these events is poorly defined and local populations frequently experience food insecurity crises in years when national rainfall and cereal production totals are high. The on-going recurrence of acute food insecurity is a feature of the heterogeneity of climate and climate variability in Ethiopia, but only in the context of a food system dominated by smallholder farming and climate-sensitive livelihoods. Over climate change timescales both the climate and the food system will be subject to change, and so information on climate change needs to be provided in the context of food system changes. To explore the potential for climate change to threaten longer term food security, a simple 'toy' model of the food system in Ethiopia was developed. The model was run with a number of climate model projections and under different scenarios of transformational change to the food system.

The results showed that climate change will have a negative impact on achieving food security in Ethiopia, but that the scale of this impact is smaller than potential positive food system changes. However, climate change does substantially off-set much of the modelled improvement associated with system

interventions, and without ambitious system changes the food security situation in Ethiopia will become more challenging. In addition, the model shows an increase in food system variability associated with increased climate variability, which is amplified by the multiplicative effect of the food system changes. This suggests that substantial policy interventions are required if Ethiopia is to meet its food security needs long term, and that incremental adaptation to improve resilience to climate variability is required alongside transformational system change.

The simple food system model was then run over Botswana, Tanzania and Mali for comparison. For Tanzania and Mali the scale of positive system changes was again larger than the negative climate change impacts, but as in Ethiopia climate change both exacerbated system variability and made transformational change necessary. In Botswana, where there is a strong signal for drying and the potential for transformational system change is more limited, the long term food security outlook under climate change is less optimistic.

The simple systems model approach shows the potential for climate model projections to be better utilised in evaluating the scale and direction of the climate security threat, and that a systems approach can facilitate transdisciplinary research in Climate Security aimed at policy-relevance.

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Author's Declaration

All analysis in this thesis has been carried out by Kirsty Lewis.

Acknowledgments

We acknowledge the World Climate Research Programme's Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modelling groups (listed in

Table 4-1 of this paper) for producing and making available their model output. For CMIP the U.S. Department of Energy's Program for Climate Model Diagnosis and Inter-comparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals

Publications

Chapters 2 and 3 in this thesis are created from the publications listed below. They have been adapted from their published form to allow them to form chapters.

Lewis, K. H. and Lenton, T. M. (2015), Knowledge problems in climate change and security research. WIREs Climate Change, 6: 383-399. doi:10.1002/wcc.346

Lewis, K. Climatic Change (2017) Understanding climate as a driver of food insecurity in Ethiopia. Climatic Change, 144: 317. https://doi.org/10.1007/s10584-017-2036-7

Chapter 1

Introduction

The potential for climate change to have an adverse impact on different kinds of security has long been recognised and has formed an important part of the discussion about the consequences of large-scale changes to the forcing of the climate system (Adger 2010, Adger, Pulhin et al. 2014, Gemenne, Barnett et al. 2014). Recognising that long term changes in climate could have consequences for security is one thing, but understanding what those consequences may be, and even more importantly, how to respond effectively, is quite another (Dellmuth, Gustafsson et al. 2018).

Climate and security are both terms which require definition and can be interpreted differently by different communities. In meteorological terms climate is defined as the statistical properties of a period (usually 30 years) of weather, and therefore climate change is the difference in the statistical description between two such periods (AMS 2000). Whilst this is the definition that will apply throughout this thesis, for most non-climate scientists, the concept of climate change is often more experiential. This could be weather patterns that are unusual compared to experience or the memory of seasons being different in the past. More scientific approaches, outside of climate science, may consider climate change as the change in weather or seasonal patterns over the past few years or decades, which still differs from the meteorological definition.

While climate change does have a set definition, albeit one that is not strictly applied, there is no single definition of security (Paris 2001). As is discussed in Chapter 2, security can be defined in terms of protection or freedom from conflict and violence, but can also refer to more complex ideas relating to human well-being (Owen 2008). The result is that climate security can mean many different things in different contexts (Adger 2010). This issue of understanding what is meant by climate security is particularly problematic because climate security is not a single disciplinary field of study, but crosses boundaries between the natural and social sciences. Ownership does not lie distinctly with one community of researchers, whether that be climate or social scientists, policy makers of all kinds, or security analysts. From each perspective, the need for information, the framing of the research questions, and the approaches taken to address those questions, can be quite different. Yet research that encompasses the interaction of physical, economic and social systems, requires a common space where a variety of stakeholders and disciplines can interact. This makes climate and security an area where new approaches for transdisciplinary research are required.

In 2008 the UK's National Security Strategy declared that 'climate change is potentially the greatest challenge to global stability and security, and therefore to national security' (NSC 2008). Climate science research on the scale and pace of anthropogenic climate change might support the general plausibility of this conclusion, but a sensible response is to ask two key questions. Firstly is climate change really the *greatest* challenge? A more general framing of this question might be, what is the scale of challenge associated with climate change? There is plenty of research available on climate change, mostly supported by numerical modelling of the Earth system, but it is not so easy to compare the threats associated with climate change with other changes or threats to security. Secondly, if it is true that climate change is a great, or even the greatest, threat to global stability and security of any kind, how will this manifest itself? Answering these two questions is a necessary (if not sufficient) requirement to be able to respond to the security challenges of climate change in an effective way, and form the key questions that this thesis will begin to address.

The primary tool of the climate scientist are climate models, which are built to understand and test the sensitivities of Earth system dynamics. This means that the information available to climate scientists is in the form of modelled data (on climate timescales even 'observations' are primarily model-derived products). Where that data applies to the future, at least on climate change timescales, it is not predictive in a deterministic sense. Climate models do not provide weather forecasts for the end of the century, but they can provide valuable information on climate trends and scale of change. The statement that 'All models are wrong, but some are useful' (Box 1976) is certainly true for climate models, and it is how the model output is interpreted that is key to unlocking their utility. As such it can be argued that climate science knowledge needs to be incorporated into the evaluation of security outcomes at a deep level (not just a provision of data). This includes engagement in the exploration of uncertainty and system sensitivities, and evaluation of climate model projections in the context of decision making.

Although climate change is a potential threat to humanity, research into our changing climate and the insight from climate models also brings an opportunity to inspire long term, transformational change. This requires that the powerful insights from climate science can be shared across disciplines, and accessed by non-climate scientists in a way that informs action.

This thesis will review the challenges in understanding the impact of climate change on long term human security, and explore the role of climate science to help to address some of these challenges with practical examples. In particular the challenges of interpreting climate science output from a security perspective. Interactions between climate and security are complex, and simply providing projections on changes in climate variables, particularly to an audience of non-climate scientists, may not be sufficient. This thesis will propose a framework for examining the impact of climate change on food security at a national scale and apply it to Ethiopia and then to three other African countries. The worked examples aim to demonstrate the role that climate science could take in climate and security research, but will also be considered in the wider context of advancing approaches in climate and security research. The result will be new insight into the potential impact of climate change on food security in these countries, presented in a way accessible to food security and policy analysts. It will also demonstrate the wider value of incorporating climate science in detailed security analysis, addressing the challenges of scale and of providing actionable detail on the climate change and security relationship.

Relationship to previous work

The research undertaken for the thesis forms part of a wider body of work which takes a climate science perspective on climate and security, related to my role as founder and manager of the Met Office's Climate Security team. Two key examples of this kind of research are the collaborative development of a Hunger and Climate Vulnerability Index (HCVI) (Krishnamurthy, Lewis et al. 2014, Richardson, Lewis et al. 2018) and research on the probability of climate-driven multi-breadbasket failure events (Kent, Pope et al. 2017). Both of these projects concern food security, also the main security focus of this thesis.

The Hunger and Climate Vulnerability Index was developed in collaboration with the World Food Programme (WFP), as a means of assessing the consequences of climate variability on food security at a national level, for food security experts who are not familiar with climate information. The index provides a visualisation of the global geography of climate impacts on food security, and thus allows WFP to prioritise climate adaptation efforts between countries. The Index defines vulnerability as a function of exposure to adverse weather, sensitivity of the system to weather and capacity to adapt in response to adverse weather events (Mach, Planton et al. 2014). The collaborative aspect of developing this Index was therefore critical, with expertise on weather and food security systems both vital to building an integrated output. The Index was then further developed so that rather than reported weather, climate model output could be incorporated (Richardson, Lewis et al. 2018). This meant that the Index could be driven with climate model simulation output under different scenarios of climate change. Alongside these climate scenarios, scenarios of adaptation were developed with expert input from WFP. The output allowed a translation of the raw climate model data into a meaningful food security outcome metric that WFP are able to use to understand and communicate the impact of climate change on the geography of food security. This approach for developing a useful food security metric that incorporates climate and non-climate drivers of change is similar to the one taken in Chapter 4 of this thesis.

The second research project was initially developed as part of a transdisciplinary collaboration with the UK Global Food Security Programme (Bailey, Benton et al. 2015), which subsequently evolved into on-going research to evaluate the probability of multi-breadbasket failure (Kent, Pope et al. 2017). This research used a large member ensemble of simulations of the present day

(1400 simulations), to explore potential inter-annual variability consistent with the current climate. As with the simple food system model developed in Chapter 4, a proxy for climate-driven adverse production events was identified in the climate data. This was then used to evaluate the probability of such an event occurring in one of two major maize breadbasket regions (in the US Midwest and/or the northeast China plain), or both simultaneously. The results showed that the probability of such an event is higher than would be inferred from the observational record. In this case the research was led and developed from a climate science perspective, but importantly the research question itself was inspired by transdisciplinary discussion on the global food system, providing an important perspective from which the climate science research was framed. The result was an interpretation of the climate model data from a systems perspective, with direct, quantified findings that could be interpreted within a wider security assessment.

Both the projects are aimed at developing approaches to improve the utility of science research to understanding the potential security impacts of long term climate change. They move away from a linear provision of climate data, to a more holistic view of climate and security that allows climate model data to be interrogated and interpreted from the systems context. The research in this thesis builds on these projects to reflect on the wider knowledge problems in climate and security research and develop a further application of this systems-led approach.

Outline of thesis

Chapter two reviews the literature in climate and security research and sets out the key knowledge problems in the field. It identifies the gap that exists between the types of information climate projections provide and the understanding of what that information means in human security and well-being terms. The difficulties of working across disciplines, particularly across the natural and social sciences, are set out. These include differences in analytical methods, language and most critically, scale differences. In order to meet the demand for policy-relevant information on climate change and security, in the face of quite disparate research output, climate change and security assessments are often conducted by security analysts. These analysts make their own interpretation of the climate projections, and do not always include social science insight. This raises a number of problems, not least that in-depth expertise is lost at the point at which conclusions are drawn. It also results in conclusions and recommendations which, due to the large scale nature of climate information and in the face of climate model uncertainty, can be overly general and vague. Conclusions from such climate security reports often fail to provide specific and novel insight, or actionable policy recommendations. The conclusion from this chapter is that a more holistic approach, integrating different disciplines into a systems-led analysis of climate and security, would help to address many of the current shortcomings in the research. Having identified the knowledge problems, and suggested a theoretical approach that might help address these, the next chapters take an example of climate and security interactions to explore some of the practical challenges of this approach.

Chapter three takes the example of food security in Ethiopia and looks at the relationship between climate and acute food insecurity events, as reported by humanitarian and aid organisations. This example was chosen for a number of reasons, not least the close relationship between weather and food production in Ethiopia. Ethiopia is a country with high levels of food insecurity in global terms (FAOSTAT 2014). As a result there is a lot attention paid by humanitarian and aid communities to research and monitoring of food security in the country. At the same time it is a country which has had reasonable amount of investment in forecasting and early warning systems, and long term climate change studies, but where the observational record of recent past climate is still not robust (Karl, Derr et al. 1995).

Ethiopia experiences seasonal rains associated with the passage of the Intertropical Convergence Zone (ITCZ), a band of rains formed on the thermal equator. Differences in the intensity of rainfall and position of the ITCZ from year to year mean that inter-annual variability is an important feature of the Ethiopian climate. Modelling the position of the ITCZ both on decadal and longer climate change timescales is challenging (Neelin, Latif et al. 1992, Lin

2007), and as such there is disagreement between models on the climate change signal for Ethiopia (Jury and Funk 2013). As a result much of the effort to adapt to climate change is focused on improving resilience to climate variability, rather than long term climate change. (For example through the Government of Ethiopia's Productive Safety Net Programme (PSNP) (Conway and Schipper 2011, WorldBank 2013)). Given the uncertainty in the climate model projections for the country, and the very immediate food security problems it faces, this is perhaps understandable (Conway 2011). However, this does mean that an opportunity to look at longer-term transformational change is possibly being missed. The issues of scale and the nature of climate and social science information identified in Chapter 2 are part of the limitations on realising this opportunity in Ethiopia. Like many regions, the dominant narrative for food security and climate is very general and negative (WFP 2013). There is a lack of detail on both the scale of climate change impacts on food security, relative to other changes, and the specifics of the interaction between climate change and the food system as a whole (rather than just production). Adaptation efforts focus on improving early warning systems and managing variability. Information about the long term outlook for food security that could be used to inform practical, transformational adaptation planning seems to be absent. The call to climate science is to reduce projection uncertainty and to increase model resolution (Shukla, Hagedorn et al. 2009), on the assumption that more specific information would be more valuable, something challenged by the knowledge problems identified in Chapter 2. With all this in mind, Chapter 3 compares the available climate and food security data to unpick the assumptions around climate as a driver of food insecurity in Ethiopia. This shows that food security is affected by extreme weather events, but that at present climate is not the limiting factor on achieving food security in Ethiopia, even accounting for the country's reliance on national food production.

This finding on the interaction between climate and the food system in Ethiopia provides new insight into the appropriate research questions to ask on long term climate change. If climate extremes are not the cause of food insecurity (albeit that in the current food system climate extremes do result in food insecurity events), then just providing higher resolution, more detailed projections of climate over Ethiopia, without any change in analytic approach, may not be the key to assessing the scale of impact of climate change on food security.

Instead, Chapter 4 considers climate change and food security from the long-term, large-scale perspective that climate models are best designed for, and which is perhaps more appropriate for transformational systems change. It takes a food systems-led approach, using the systems learning in Chapter 3, rather than leading with the climate change projections. At this larger scale the question is about the constraints climate change may impose on the potential for Ethiopia to be food secure, not a deterministic assessment of whether Ethiopia will be food secure or not in the future. (As Chapter 3 shows, the country may produce enough food to meet the population's food needs but still be food insecure for reasons not directly related to climate). A simple food systems model is developed and used to explore the direction and scale of impact of climate change on food security potential, relative to other large-scale system changes. A further benefit of developing a simple food systems model is that it provides a mechanism for quantitatively exploring the impact of uncertainty across climate model projections on food system outcomes. Developing methods for evaluating sensitivity of outcomes to climate model uncertainty are proposed as a more practical response than just calling for uncertainty to be reduced. This is important because climate model uncertainty will never be eliminated, the future will always be uncertain, necessitating techniques to manage uncertainty alongside the climate signal. An ensemble of 19 models from the Climate Model Inter-comparison Project 5 (CMIP5) were used in order to include a range of projections to capture some of the model uncertainty. The results across these models were compared to evaluate the impact of model uncertainty on the conclusions for food system impacts.

Together Chapters 3 and 4 develop a practical example of climate and security analysis that takes a systems-led (in this case food systems-led) approach, as suggested in Chapter 2. The analysis occurs at a naturally emerging scale associated with climate change (rather than climate variability), focusing on the options for long-term, transformational change, and integrating climate model uncertainty. The results provide new insight into the role of climate and system changes for long term food security in Ethiopia. Climate change is shown to have a negative impact on food security outcomes, but considered separately, other system changes can have a greater positive effect. Together climate change and system change can lead to a more food secure future on average, but ambitious transformational change is required, and increasing variability is a feature of the future food system.

Chapter 5 extends the simple food systems model to three additional countries; Botswana, Tanzania and Mali. The aim here is to test the general applicability of the model, as well as to provide reflection on the specifics of the results under different food systems, different climate change signals, and different levels of climate model agreement. These three countries were chosen as comparators for Ethiopia, due to the differences in climate signal, climate model agreement and food system conditions. For Botswana the climate model projections show a drying trend, along with increasing temperatures, both with good agreement across models, although the models do not capture the present day climatology well. The food system in Botswana is quite different from Ethiopia, and these two factors mean a more cautious interpretation of the food security output is required. In Tanzania there is greater uncertainty in the sign of the change in rainfall across the models. This could present difficulties in the development of an adaptation response for decision makers. However, this uncertainty in the projections is not translated into uncertainty in the food system impacts, which highlights some of the benefits of taking a systems view that considers uncertainty in impacts terms, rather than just from a climate model perspective. The climate model projections for Mali show little change in rainfall, but increasing temperatures over time. Temperature plays an important role in water availability in Mali, and the food production proxy metric developed for Ethiopia has some limitations here. Despite the different challenges in applying the simple food system model in each country, the output supports a consistent message on the negative impact of climate change. It also provides evidence that adaptation to both climate variability and long term change is necessary to achieve the conditions under which the food security situation in each country can ultimately be improved.

Chapter 6 is a discussion of the main findings and the evolution of thought from the previous four chapters. Limitations of the examples from Chapters 3, 4 and 5 are discussed, along with the lessons learnt from the examples. Finally the findings of this thesis are concluded and recommendations for further research provided.

Chapter 2

Knowledge problems in climate change and security research

This chapter is based on Lewis, K. H. and Lenton, T. M. (2015), Knowledge problems in climate change and security research. WIREs Clim Change, 6: 383-399. doi:10.1002/wcc.346

Introduction

The relationship between climate and human security is a complex and multiply inter-connected one, but also one that spans the divide between physical and social scientific enquiry. Demand for information on the human dimensions of global climate change has never been higher, but there remains a gap between the type of information contained in climate projections and environment and security studies, and practical conclusions on what this means for long-term human well-being and security.

The idea that climate change could pose a security threat is not a new one. Before 2007, environmental change, and specifically climate change, had already begun to be considered as an unconventional security threat (Mathews 1989, F. Homer-Dixon 1991, Rodal 1994), but did not feature prominently in security discourse (Levy 1995, Stipp 2004). As a disputed phenomenon with effects far into the future, climate change was not a mainstream consideration for security analysts. However, in 2007 an influential report by a group of eleven retired senior US military officials (CNA 2007) moved the subject up the political agenda. The report, published by the CNA Corporation in Washington identified climate change as a ‘serious threat to America’s national security’. In the same year, the UK chaired a UN Security Council session on climate and security (UNSC 2007) and the Nobel Peace Prize was awarded jointly to the IPCC and Al Gore (Gore 2007). In 2008 the UK National Security Strategy stated that ‘Climate change is potentially the greatest challenge to global stability and security, and therefore to national security.’ (NSC 2008) These high-profile events, and influential security reports, and others (Schwartz and Randall 2003, Gulledge, McNeill et al. 2007, Vivekananda and Smith 2007, Carius, Tanzler et al. 2008, Mabey 2008, Schubert, Schellnhuber et al. 2008, Paskal 2009, UNGA 2009, Mazo 2010), set the agenda for a wide-ranging debate about the human dimensions of climate change for well-being and security at a national and international level. Governments, policy-makers and the military began incorporating questions about the consequences of climate change into long-term strategic assessments (Barnett 2009, DCDC 2010). This demand for analysis was driven by the growing evidence that climate change would have a large impact on two key aspects of security; exposure to natural disasters, and resource access and availability.

The nature of the discourse on climate change and security has evolved since 2007. For example, in the lead up to the UN Council of Parties climate change negotiations in Copenhagen in 2009 (COP 15) (UNFCCC 2009), there was a push towards evaluating climate change as a security threat as a means to drive the negotiation agenda. Climate diplomats, looking to secure a deal on climate change that would meet the stated target of preventing ‘ dangerous anthropogenic interference with the climate system’ (Blobel, Meyer-Ohlendorf et al. 2006), felt that the case for this ambitious target could be better made by talking about climate change, not as an environmental threat, but as a security threat (Hayes and Knox-Hayes 2014). As a result there was a perception that the evidence for climate change representing a global security threat was somewhat exaggerated for the purpose of influencing negotiations on climate mitigation action (Hulme 2007, Koning 2010, Harris 2012). However, over time the evidence for climate change has grown, and climate change has become increasingly mainstream in discussions about global futures. The result is that although when climate change and security first became an issue for policy and decision makers, the requirement was mainly to support broad statements about climate change as a security threat (Floyd 2008), the increasing acceptance that the world must face the challenge of a changing climate (Pidgeon 2012), means that questions about climate change and security are now often more focused on the need to inform action to prepare.

The range of policy and decision makers with an interest in understanding more about climate change and security is wide, as is the range of definitions of security itself (Paris 2001, Owen 2004, Gasper 2005, Hoogensen and Stuvøy 2006, Inglehart and Norris 2012). Although much of the highest profile work has been done in a military context, governments and military are interested in more than simply conflict and are concerned with any events that disrupt core economic activity (Dabelko 2009). The role of climate change in water and food security, migration, poverty, humanitarian disaster, inequity and gender issues, are as much a concern for government as for others, such as UN agencies, NGOs and even business and industry. The result is that there is a wide demand for information and advice on climate change and security from a diverse set of policy and decision-makers. Each of these groups also brings their own agendas, which can influence the way analysis is undertaken.

As the demand for information on climate change and security had grown and expanded, the science of climate change has progressed and the remit of the scientists has also expanded. The Intergovernmental Panel on Climate Change Assessment reports (Parry, Canziani et al. 2007, Solomon, Qin et al. 2007, Stocker, Qin et al. 2013, Field, Barros et al. 2014) are a good example of how this evolution has played out. The publication of the Fourth Assessment Report (AR4) in 2007 (Parry, Canziani et al. 2007, Solomon, Qin et al. 2007) coincided with the increasing interest in climate change and security, and was the basis for the climate evidence for most of the climate change and security assessments from that time. AR4 was primarily a means to communicate the narrow findings of the natural science research into climate change. It presented the evidence for physical changes to the atmosphere and direct impacts on geographical and biological systems. The approach was slightly different for the Fifth Assessment Report (AR5) (Stocker, Qin et al. 2013, Field, Barros et al. 2014), published in 2013. In addition to this increasing confidence in the evidence base for an anthropogenic-driven changing climate, AR5 expanded the breadth of expertise that fed into the reports, and included chapters looking specifically at outcomes for security and well-being. Examples of this wider remit include chapters in the Working Group 2 report of AR5 on Food Security and Food Production Systems (Porter, Xie et al. 2014), and on Human Security (Adger, Pulhin et al. 2014); both of which will be discussed in more detail in this review.

Despite the developments in both the requirement for evidence on climate change and security, and in the science itself, there still remain challenges to matching the demand for knowledge with the expertise available. The main diversity in approaches to climate change and security assessments are between a ‘bottom-up’, on the ground adaptation response, and at ‘top-down’, perspective on global security dynamics. In either approach the broader question remains the same, and in the majority of assessments has two distinct aspects firstly, how does climate affect security?; and secondly how will the climate change? By accessing knowledge about both the relationship between the climate and security, and then how the climate may change, the aim is to develop an understanding of future security as a result of a changing climate. Dividing the problem into these two questions aligns well with the academic research silos between climate and social science research. However, society is a complex system, interacting with climate, another complex system, which makes climate change and security is a complex systems problem. A reductionist approach that divides the problem into separate component parts, runs the risk of over simplification that misses key drivers and system interactions.

This review of knowledge problems within research on climate change and security first looks at what knowledge is available to inform climate change and security studies. Research into the relationship between the environment and different forms of security by social scientists explores much of the complexity of social systems, and provides a strong evidence base for the relationship between the environment and security. However, this is based mainly on observations of past events at local scale. The conclusions are specific to the circumstances of individual studies, and are therefore difficult to generalise or integrate with information about the future. Research on the changing climate, on the other hand, provides information about large-scale and average conditions of the climate system. The information is quantified and includes projections of future change. However, the utility of the information on climate dynamics, in the context of human systems, can be a limiting factor in interpreting and integrating climate science into studies of human security futures. After comparing the information that is available on both climate and environmental security at a wider research level, this review considers the types of studies that have been undertaken to inform the mainstream climate security debate at policy and government level. In particular the difficulties in accessing and integrating expertise across disciplines, to provide actionable advice to policymakers is explored. Finally an alternative approach of tackling climate change and security as a complex systems problem that spans the restrictions of the climate and social science disciplines is considered. A general systems thinking approach to climate security has the potential to address some of the difficulties faced in climate security analysis, by considering the problem as a whole, at a naturally emerging scale, and allowing for the uncertainties and interactions within the system to inform the conclusions.

Social science research for security

An integral part of the question of how climate change could affect security, is whether there is a relationship between climate and security. This relationship between the environment, environmental change and security is a significant field of study, and one that has extensive and growing focus in the social science community, supported by a number of initiatives (Matthew, Barnett et al. 2009, Afifi and Jäger 2010, Oswald 2011, Scheffran, Brzoska et al. 2012, Sygna, O'Brien et al. 2013, UNESCO 2013, Davion 2014, IHDP 2014, GECHS 2015, Gleditsch 2015). Much of this research has focused on the more controversial direct relationship between climate and conflict (Gleditsch and Nordås 2014). Beyond that, there is some consensus around the idea that climate change has the potential to progressively impact on human security (Gleditsch and Nordås 2014) through the risk to livelihoods, resources and communities (Badjeck, Allison et al. 2009, Adger 2010, McLeman 2011).

How the relationship between environment and security is understood is not underpinned by a single methodological approach (Cornell, J. Downy et al. 2012), which is hardly surprising given the multiple notions of security that exist (Rothschild 1995, Dalby 1997, Paris 2001, Dalby 2002, Owen 2004, Gasper 2005, Smith 2005, Hoogensen and Stuvøy 2006, ISSC 2010, Inglehart and Norris 2012) (see Box 1), and the range of contexts in which the term is used (Buzan, Wæver et al. 1998). There are a number of different, and sometimes conflicting theoretical perspectives, from quantitative analysis, to alternative social theories on the nature of interactions between the environment and society (Goldman and Schurman 2000). For a summary of examples of different theoretical framings applied to the same socio-environmental phenomena see (Cornell, J. Downy et al. 2012).

Box 1: Defining climate security

One of the issues with talking about climate security is the lack of clear definition of what is meant by the concept of security (Paris 2001). In a national or international sense it refers to a state's ability to maintain its interests in the global arena, but from a human perspective this can manifest itself at a range of scales from global down to the individual (Gemenne, Barnett et al. 2014). Security can be defined in terms of protection or freedom from conflict and violence, but can also refer to more complex ideas relating to human well-being. Human security itself has been variously described, but can include concepts such as: Economic security (e.g. freedom from poverty); Food security (freedom from hunger); Health security (e.g. access to health care and protection from diseases); Environmental Security (e.g. protection from environmental pollution and depletion); Personal security (e.g. physical safety); Community security (e.g. survival of traditional cultures, etc.) and Political security (e.g. freedom from oppression and enjoyment of political rights) (Paris 2001).

In a political discourse and security analysis context, climate security often refers to instability or conflict, migration, or resource availability and access, often at state level, although this is not always the case.

In this paper we refer to security in its widest sense, to incorporate not only definitions of human security in terms of absence of threat or want, but also security at the level of national self-interest, and as it relates to economics, trade, migration, instability and conflict.

Across the theoretical perspectives and the different definitions of security, there are three main research approaches that are visible from the social science discourse on climate and security. The first is a focus on exploring the interaction between environmental change and security, simply to gain greater insight into processes and phenomena involved (Goldman and Schurman 2000, Scheffran and Remling 2013). The second is to explore causal mechanisms behind specific instances of insecurity within environmental change (Zhang, Lee et al. 2011, Hsiang and Burke 2014). The third, related approach, is to analyse security and climate data for statistical correlations that uncover links between the two (Hsiang, Meng et al. 2011, Hendrix and Salehyan 2012). For a more detailed summary of the development of these research strands, for the case of the relationship between environment and conflict at least, see Deligiannis (2012).

Researching causal mechanisms behind related climate and security variables generates understanding and real knowledge about the social-environment system, but also highlights the importance of context for security outcomes. The one unifying conclusion that has been drawn from these numerous different studies, is that climate change, and resultant environmental scarcity is ‘never a sole or sufficient cause of large migrations, poverty or violence; it always joins with other economic political and social factors to produce its effects’ (Homer-Dixon 1999). Climate change is seen as a ‘threat multiplier’, rather than a direct cause of human insecurity and conflict (CNA 2007). The individual circumstances of environmental change in the context of social structures and processes, lead to individual paths to insecurity (Gemenne, Barnett et al. 2014).

Not all social science research into climate and security looks in depth into the complex causal pathways. Statistical approaches step back from that complexity to look for correlations between climate and measures of security. For example Burke et al. 2009 found a correlation between the long term temperature trend in sub-Saharan Africa and civil war in the same region. They used this correlation to extrapolate forward to future based on climate projections, suggesting a 54% increase in armed conflict incidence as a result of climate change. Similarly, Feng et al. 2010, found a relationship between climate induced crop yield fluctuations and Mexico-US cross-border migration. Numerous other studies look for similar correlative relationships, both with conflict and wider indicators of human security (Hsiang, Meng et al. 2011), but not all find such a correlation, and some find correlations between instability and change, irrespective of the sign of that change.

While a number of studies show temporal correlations between changes in past climate and security factors, and these correlations can be relatively straightforwardly applied to projections of future climate, there are a problems with this approach. Correlations between security indicators and climate are a useful way of testing whether there is a relationship between the two, but are affected by the choice of indicator; how representative it is of security or climate variability, in both nature and spatial and temporal scale. (Climate may be relatively easy to measure, but security or insecurity is a more subjective property.) Empirical studies of correlation between indicators also do not provide the causal explanations that would increase understanding of the mechanisms behind the relationships (Butler 2007, Salehyan 2008), which is what is ultimately required to justify any application of the conclusions to an evaluation of the impact of future changes. For these reasons, although such statistical studies have received a good deal of coverage in well-regarded journals, this approach is controversial and has been strongly critiqued; not least by researchers at the Peace Research Institute Oslo (Gleditsch, Nord et al. 2009, Buhaug 2010, Buhaug, Hegre et al. 2010).

The chapter on Human Security in IPCC Working Group II, Fifth Assessment Report (Adger, Pulhin et al. 2014), makes a systematic assessment of the research undertaken in impacts of climate across the dimensions of human security, with the view to targeting a generalised policy audience. The chapter highlights the diversity of approaches taken by social scientists, both qualitative and quantitative, and captures the complexity of the interactions involved. It is also clear about the fact that most social science-led studies in climate and security depend upon empirical observation, and the difficulties in generalising from individual studies to the wider case.

One consequence of this empirical approach is that it relies on a relatively short time series of data, relative to climate change timescales. Most of the studies included look at the impact of either weather events, or variability in the climate, on human security. In these cases the social scientists are using a quite different definition of climate change than that used by climate scientists. To a climate scientist the climate is described by the statistical properties of a period (usually thirty years) of weather, and climate change is the difference in the statistical description between two such periods (AMS 2000). By this definition, social scientists are concerned with analysing climate variability, rather than climate change. As the report itself concludes 'Much of the current literature on human security and climate change is informed by contemporary relationships and observation and hence is limited in analysing the human security implications of rapid or severe climate change' (Adger, Pulhin et al. 2014, p. 779). Although social science research into the relationship between climate and security may be useful for adaptation to variability, without input from the climate science community, there is little to support decision making on planning for the long-term climate change.

A further consequence of the fact that the complex relationship between the environment and security can only be understood by careful analysis of the specifics of the local interaction, is that social science research focuses primarily on the local scale (Wilbanks and Kates 1999). Individual countries, but more often communities or social groups, share characteristics that cannot be generalized beyond their boundaries. These include culture, economic and political systems and governance, values and beliefs. In a globalised world many social processes such as trade, or the flow of information and ideas, are large scale, but the influence of agency remains mostly local. These case-specific studies may be more tractable, but they are not easily generalised (Wilbanks and Kates 1999).

The difficulty in integrating information about long term climate change into social science research on climate and security is seen in Table 12-4 of the IPCC AR5 chapter on Human Security (Adger, Pulhin et al. 2014). This lists risks such as displacement, loss of land and conflict, with adaptation outlooks for each risk. The information is a summary of the detailed and nuanced analysis done across the social science research, with an attempt to integrate this with projections of future climate change. The climate change information is shown as a set of 'climate drivers', represented by icons for weather events such as 'damaging cyclones', or 'extreme precipitation'. Information such as the frequency, intensity of the events, the uncertainty across the projections, the scale and geographic distribution, as well as how terms like ‘extreme’ are defined, are all excluded. Yet the analysis in the rest of the chapter shows how critical these details are to actual security outcomes. The conclusions about long term climate change from the table are therefore very general, and demonstrate how difficult it is, from a social science perspective, to offer practical information to policy makers on how to respond to future change.

Climate science research for security

While social science research explores the relationship between climate and security. It is climate science that strives to understand how the climate is changing. The primary tools of the climate scientist for understanding future climate are climate models. Over time these models have become increasingly complex and sophisticated, as the scientific understanding of the climate, and computational capacity, have developed (Scholze, Allen et al. 2012). Models provide not only an understanding of the physical earth system, they also produce projections, which form the basis of our understanding of the future climate. They provide quantitative and statistical information about climate parameters. Climate model projections are also used in conjunction with climate impacts models, which model processes more closely aligned with the impacts on human and environment systems, such as run-off, crop yield, flooding and drought (Betts, Arnell et al. 2012).

Climate scientists strive to understand the climate system, but are also tasked with providing information that is useful to inform responses to climate change (McNie 2007, GOScience 2012). This policy tasking means that climate scientists have had to consider the relevance and the communication of their findings in a way that is possibly unprecedented across the scientific disciplines (Lubchenco 1998). The IPCC climate change assessment reports (Parry, Canziani et al. 2007, Solomon, Qin et al. 2007, Stocker, Qin et al. 2013, Field, Barros et al. 2014), can be argued to have raised the level of credibility of the projections of climate change above the normal standard of scientific evidence in the public domain (Farber 2007), and are the primary source of climate information in security assessments.

To some decision makers looking for a practical solution to problems relating to climate change, the nature of the information provided by climate science can be alienating (Shackley, Young et al. 1998). Most decision and policy makers looking at future planning, from whatever perspective, are used to acting from a position of deep uncertainty. Through the use of physically-based models, climate science offers perhaps less, or better defined, uncertainty in predictions of the future than other disciplines such as social science or economics. However, this does not mean that uncertainty within climate projections, particularly on the temporal and spatial scales of most interest to decision-makers, is not a limit to how useful the projections are to those decision makers (Fetzek 2008). Global average temperatures, climatological means, extremes defined as a percentile of a climatology, are all examples of information provided by climate science that can be difficult to interpret in a practical context. The combination of uncertainty, the scale and the abstract nature of much of the information mean that for many, climate projections are not always usable in a policy context (Lemos and Rood 2010). Climate scientists are very aware that there remains an on-going need to make information about the changing climate accessible to a wider audience, demonstrated in the recommendations of many climate and security assessments (Stipp 2004, CNA 2007, Harrison 2008, Mabey 2008, NSC 2008, Paskal 2009, UNGA 2009), and increasingly make efforts to do so (NRC 2007). In order to do this, research effort is invested in improving understanding of the climate system (Bedritsky 2008, Shukla, Hagedorn et al. 2009), quantifying and reducing uncertainty (Giorgi 2005, Palmer, Doblas-Reyes et al. 2005, Taylor, Stouffer et al. 2012), increasing the resolution of the data available (Bedritsky 2008, Shukla, Hagedorn et al. 2009, GOScience 2010), and better communication of uncertainty (Webster, Forest et al. 2003, Lempert, Nakicenovic et al. 2004).

These are all important steps to improving the usefulness of climate model projections. However, criticisms of the value of climate change information include the idea that it is not simply usefulness (i.e. the value of the information), that is important, but also utility (i.e. the ability to be able to use the information) (Shackley, Young et al. 1998). Uncertainty is a common feature of decision-making; reducing uncertainty may improve functionality of climate information, but it does not improve the application or fit, within the decision-making process (Weiss 1978, Lemos and Rood 2010).

Similarly, the spatial resolution at which climate change information is available is limited by what climate models can sensibly represent, and increasing resolution, both temporally and spatially may make the information more specific, but will not make it more accurate (Castro, Pielke et al. 2005, Pielke and Wilby 2012). The grid box resolution of the latest global climate models is of the order of 100 km^2, and is used to describe the statistics of 30-year climatologies. Confidence in climate model projections is highest at even coarser resolution. Global variables such as average temperature or, to a lesser extent, precipitation, are better understood than local variables, such as weather patterns, storms or flooding events. The problem comes when trying to understand what these global changes will mean at the local scale of most social science climate and security studies.

Climate scientists are potentially producing too much of the wrong kind of information for individual decision makers, and concentrating on producing more of that information, rather than changing the type of information provided (Shackley, Young et al. 1998, Gulledge and Rogers 2010). Three criteria have been identified for climate science to be translated into action (Meinke, Nelson et al. 2006). The first two, credibility and legitimacy, are generally held to be true for climate projections (Farber 2007) (with local exceptions identified). The third criteria, salience - the perceived relevance of the information - is more challenging to a climate scientist, who view climate change from a natural science perspective.

Expansion of the expert input to the IPCC reports, and the recent establishment of Climate Services through the WMO Global Framework of Climate Services (Hewitt, Mason et al. 2012, Vaughan and Dessai 2014) are examples of a response to this challenge of saliency. Increasingly, climate scientists are interacting with users to gain a better appreciation of the application to which the information they provide will be used (Stainforth, Downing et al. 2007). For example, it has been proposed that in ecological systems research, extreme climate events should be defined by the magnitude of their ecological impact, rather than simply the magnitude of the event as a function of the climate profile (Smith 2011). This would ensure that the information sought from the climate models on future extremes is relevant to the application, not simply a measure of the change in climate.

One example of where the climate science community has struggled to provide information that works well in a policy context is in the Food Security chapter of the IPCC AR5 report (Porter, Xie et al. 2014). The UN Food and Agriculture Organisation (FAO) identify four pillars that support this state as being 'availability, access, utilization and stability' (FAO 2009). Yield may imply something about the availability of food, but not necessarily food security as a whole (Pinstrup-Andersen 2009). This definition of food security, and the need to consider climate impacts more widely than yield changes is recognized in the Food Security chapter (Porter, Xie et al. 2014), but the information available from climate impacts studies was still largely confined to yield. This chapter had minimal input from social scientists and was therefore a summary of the climate impact model assessments, with a concluding statement that climate change has the potential to negatively affect food security (Porter, Xie et al. 2014). Whilst this is at least a comment on future climate change, which is often missing from social science led assessments; the exclusion of the complexity of the food security systems themselves makes it difficult to translate this statement into something that can inform a response to the food security threat identified.

Climate change and security assessments

Most reports evaluating future security implications of climate undertaken by security analysts take projections of climate change coming from the climate science community, primarily through the IPCC assessment reports, and consider what these changes could mean in a military and human security context. Thus, many security analyst assessments start with one or more of these changes, and draw broad, 'logical' conclusions on the security implications. This ‘top-down’ perspective on global security dynamics, contrasts with more adaptation-focused assessments, such as those on ecosystems, water resources, or infrastructure resilience. These often undertake a ‘bottom-up’ analysis which starts with the particular decision context and applies the existing climate information accordingly. (For example GOScience 2011).

An example of this ‘top-down’ approach to climate change and security assessments is the ‘World in Transition: Climate Change as a Security Risk’ report, undertaken by the German Advisory Council on Global Change (WBGU) (Schubert, Schellnhuber et al. 2008). This frames changes in climate as a series of ‘conflict constellations’. They identify one such climate constellation as ‘Climate-induced degradation of freshwater resources’. Arguing that the numbers of people without access to safe drinking water could increase by hundreds of millions as climate change alters the variability of precipitation, and the quantity of available water. Other ‘conflict constellations’ arising from the consequences of climate change include declines in food production, increasing storm and flood disasters, and environmental migration. Similarly reports such as the UK MoD’s ‘Global Strategic Trends to 2040’ report (DCDC 2010), the US Center for Naval Analyses security report, ‘National security and the threat of climate change’ (CNA 2007), also take this climate-first approach. The ‘Global Strategic Trends to 2045’ report (MOD 2015) goes further in its attempt to integrate climate change information throughout, but still relies on an independent climate science input to inform the security conclusion.

These particular reports look at climate change and security from a primarily, although not solely, conflict-driven view of security, and with governments and military planners in mind. However, other climate change and security reports, considering other definitions of security, and for other policy and decision makers, also first look to the climate science to understand the environmental change, then attempt to put this information into a security context by considering the potential consequences of these changes for security dynamics (Gulledge, McNeill et al. 2007, Vivekananda and Smith 2007, Busby 2008, Carius, Tanzler et al. 2008, Mabey 2008, Schubert, Schellnhuber et al. 2008, Paskal 2009, UNGA 2009, Gemenne 2011, Scheffran and Battaglini 2011, Busby, Smith et al. 2013). These assessments broadly conclude that climate change is a factor in long-term security, but is essentially a resource issue and is more likely to be an 'exacerbating factor for failure to meet basic human needs and for social conflict, rather than the root cause' (Barnett and Adger 2007). Figure 2-1 illustrates this top-down, hierarchical flow of information and analysis, commonly used in climate change and security assessments.

While these types of security analyst reports speak to a policy community in a language more accessible to those communities than either climate science or social science academic-led analysis often does, there are three possible weaknesses to this approach.

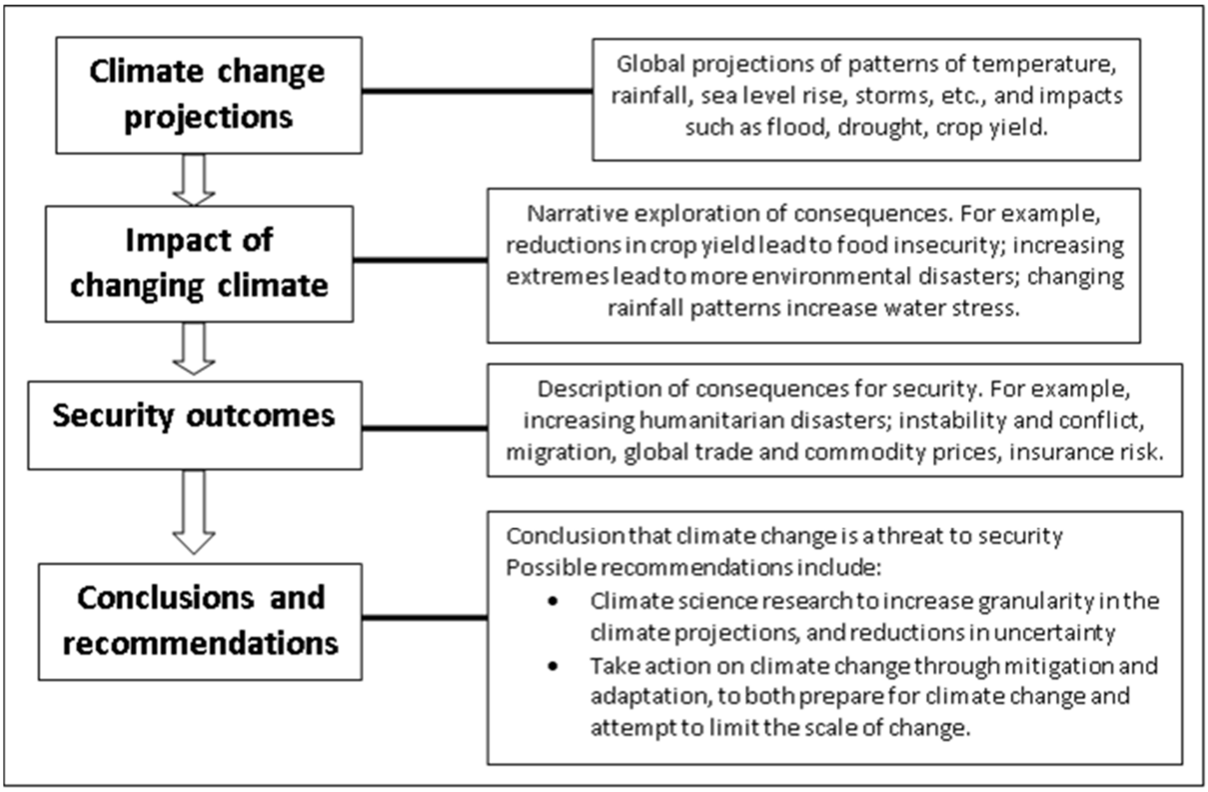

Figure 2-1: Flow diagram of structure for typical climate change and security assessment.

Firstly, by looking first to climate science to identify the critical aspects of climate change, and drawing security conclusions from these changes, security analysts are restricted in the connections they can make. The information in synthesis reports, such as the IPCC, as large and comprehensive a set of documents as they are, are necessarily simplified and edited. Climate scientists present the information they believe will be of the most value, but without specialist expertise in environmental security it is unlikely that the information supplied will be the most salient to this application. The security conclusions therefore follow a narrative driven by climate science and run the risk of overlooking security connections that fall outside this narrative.

Second, the direct interpretation of climate model projections by security analysts can over-simplify the relationship between environment and security, into a one-dimensional cause and effect problem (Barnett and Adger 2007). In reality, the impacts of climate change on security are not unilateral, and the evidence for climate change either exacerbating or even initiating violent conflict in particular, is widely criticised (Salehyan 2008, Buhaug 2010, Oswald 2011). The relationship between climate and security is a complex, multi-dimensional one that incorporates socio-economic, cultural and political interactions and for which there are a range of theoretical framings from which it can be understood (Cornell, J. Downy et al. 2012). Regarding WBGU's water security conflict constellation (Schubert, Schellnhuber et al. 2008) for example, more recent research (Wiltshire, Gornall et al. 2013) suggests that it is change in population and increases in water demand that dominate the signal for water insecurity, rather than climate change, which in many regions may increase water availability. However, even this does not account for water storage and distribution infrastructure, or other factors such as advances in desalination technology. All of which could be a greater determining factor for future water security.

Third, even though the language and the framing of climate change as a security concern in this type of analysis speaks clearly to a variety of policymakers, it is not obvious that the conclusions and recommendations provided can easily be translated into policy response, whatever that policy field pertains to. The analysis is limited by the large spatial and temporal scale of much climate change information. The main policy prescription in these examples is that addressing the causes of climate change is necessary to limit the threat to national and international security. However, there is little guidance on the specifics for policies to prepare or adapt to the security consequences of the climate change to which the world is already committed. Evaluating broad climate projections in a security context, does not naturally lead to identification of specific regions where security may be most threatened. As Wilbanks and Kates (Wilbanks and Kates 1999) say, ‘Focusing exclusively on larger scale can lead to ready generalizations that are just that – much too general.’

Despite the weaknesses associated with third-party interpretation of the expertise, climate change and security reports are written because policy makers need information tailored to their policy perspectives, which can be quite divergent. In the absence of research that crosses the discipline boundaries of climate and social science and focuses on the policy and decision makers’ need for information, security analysts are forced to try to reconcile whatever information is available to them, as best they can.

One option to address the deficiencies of the current approach to climate security might be to take a different perspective. Rather than attempting to synthesize the findings of two different research fields to generate insight into the security implications of climate change, an alternative approach would be to tackle the problem from the climate security perspective from the start. Instead of the linear process of assessing the evidence from different disciplines individually; take a holistic, systems based approach to the interaction of climate change and security. The following section sets out this approach and explores the potential benefits and shortcomings.

A systems approach to climate change and security

The climate science led approach of most climate change and security assessments, is not the only approach that has been used. Gradually, examples of research in climate change and security that consider the problem as a whole have emerged (GOScience 2011, Tacoli, Bukhari et al. 2013). This sort of approach to understanding how systems behave and interact both internally and with their environment, has its roots in General Systems Thinking (See Box 2).

Taking a systems approach to climate change is not a new idea. Earth System Models (Heavans, Ward et al. 2013) are themselves a product of this approach, and computer modelling naturally lends itself to the development of increasingly complex representations of a system. Defining the system boundary is often the most critical part of a systems analysis (Heavans, Ward et al. 2013) and the temptation is to include everything within the system description, leading to a failure to capture the critical aspects through analysis paralysis (Bankes 1993). However, some complex systems research does attempt to model very large and detailed systems, and to continually develop these models to add increasing detail and complexity, with the aim of more realistically representing the system and its dynamics. Examples of these models include Earth System Models themselves, but also General Ecosystem Models (Fulton, Link et al. 2011), such as the recently developed Madingley model (Purves, Scharlemann et al. 2013), also some of the more detailed Integrated Assessment Models (Dickinson, Fung et al. 2014), and some agent-based models (Bonabeau 2002, Doran 2006). Earth System Models have a physical basis and representation of complexity is primarily limited by computation power. However, ecosystems models and IAMs are very much more dependent on empirical system behaviours. There is good reason to suspect that the level of detail in the system representation is not necessarily correlated with the accuracy of the models, particularly as validation of models built from empirical observation cannot be then meaningfully validated against these observations (Bankes 1993). Agent based models perform a slightly different function, in that they explore feedbacks between actors and their environment, but again are based on assumptions about actor behaviour, limiting the value of increasing complexity (Weaver, Lempert et al. 2013).

Looking at climate security from a systems perspective means answering questions asked by policy makers in a different way, and the way most relevant to individual policy makers' individual needs. It involves looking at what constitutes security for that policy maker (define the system boundaries); how it is maintained and operates (exploring the system structure and behaviour) and then describing that system, its interconnections and behaviours over time, in a way useful to identifying the influence of climate change on security. This description of the system could be narrative, a schematic mapping, or a quantified mathematical or computational modelling approach. The key aspect is that the influence of the climate on the system is derived from the system perspective, and not limited by the properties of the information available from climate science. As the perspective on the system is driven by whoever is asking the questions, then this approach has the major advantage of providing a view tailored to the policy maker, however diverse a group policy makers may be.

Box 2: General Systems Theory

A systems approach involves embracing the Aristotelian view that the whole is often greater than the sum of its parts. General systems theory was first suggested as an approach to complex problems in the 1930s (Bertanlanffy 1972). Initially it was used to better understand mechanical systems, but subsequently developed as a way of thinking about social systems too (Forrester 1971). Since that time it has been used in a range of applications, from IT and engineering, to management and business (Faulconbridge and Ryan 2014). General systems theory is not so much a theory, in the most formal mathematical sense, but a way of thinking about a problem that identifies coherence and inter-connectedness, and applies a range of tools and methods to quantifying, analysing and representing that system (Meadows 2008). Instead of breaking problems down into their constituent parts, systems thinking means taking an expanded perspective and accounting for all the elements of the problem together. The way elements of a problem interact together is incorporated into the understanding of the problem, and the conclusions that can be drawn from this sort of approach are often quite different as a result (Mesarovic 1967). Many systems exhibit emergent behaviour and internal and external feedbacks. New critical thresholds and sensitivities may only become apparent from the dynamical interaction of the system elements, and not obvious from examining the elements in isolation (Weinberg 2011).

In a climate change and security assessment, building the system model is a task that involves input from across disciplines, and the result is a means by which to identify the sensitivities of that system to weather and climate events, in the context of other drivers of change. Using this systems view of the critical aspects of weather and climate to security can then inform the way the climate projections are analysed, including how they are communicated and how uncertainty within the projections is handled. This climate information can then be applied to the systems model, to gain a more informative understanding of what climate change could mean for security. Figure 2-2 outlines this approach.

The systems approach to climate security outlined in Figure 2-2 moves away from the idea of climate models as prediction machines, with an emphasis on producing more detailed and certain data, as they are in Figure 2-1. Instead it allows them to be used as tools for learning about the responses of the climate system. Weaver, Lempert et al. (2013) advocate the use of climate models as sources of insight into the climate system, that can be incorporated with learning from the social sciences, to better inform decision making, and a systems approach opens the way to implement this.

A systems approach also offers a means to address the issues of scale that divide the climate and social science approaches to climate change and security. Gibson, Ostrom et al. (2000) (p.224) suggest that 'One way to explain natural processes is to use the natural scales and frequencies that may emerge'. In the case of climate, there is a natural length scale of the order of 1000km; the size of synoptic weather patterns. While both communities have developed their scale perspectives at least in part because of the scale at which processes emerge, it is not true to say that they operate only at these scales. Climate and climate change may operate on large scales, but it is experienced through changes in weather patterns at local scale (both temporal and spatial). Similarly, agency and social interaction may occur on a small scale, but contribute to the larger, global state. As such processes at one scale have affects and influences on other scales, and these interactions themselves are more complex than simple aggregation to large scale, or downscaling to smaller scale, can address (Wilbanks and Kates 1999).

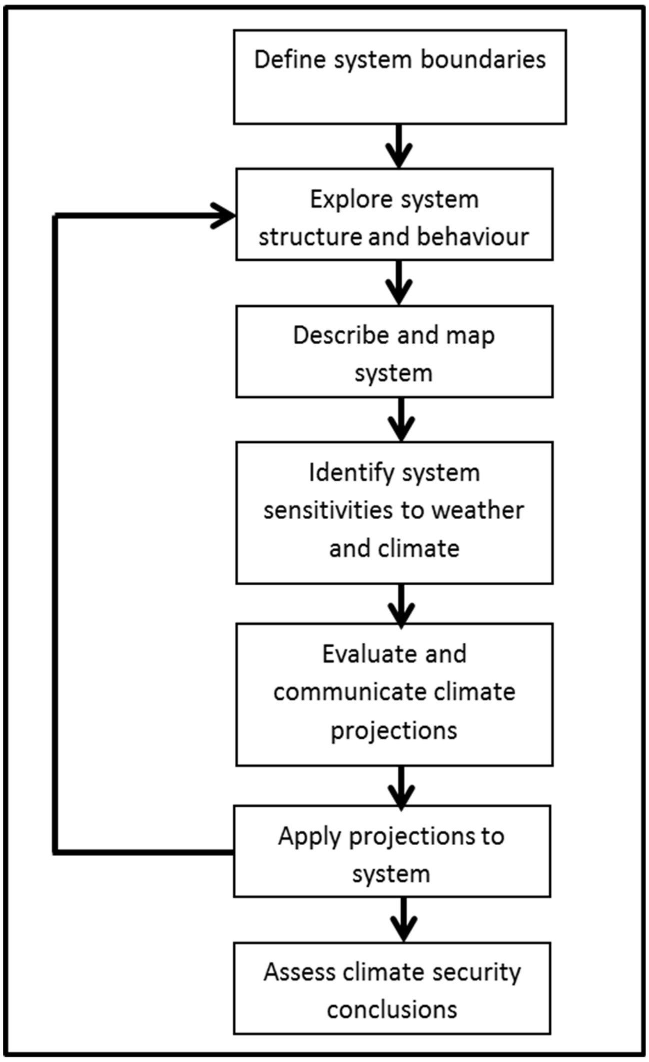

Figure 2-2: Flow diagram of systems approach to climate change and security assessments.

The policy- and decision-making customers of climate change and security assessments are diverse in their needs, but all have one thing in common. They are not driven by an interest in climate change, or even necessarily the relationship between climate and society, but rather by a need to respond to the potential threat of a changing climate on their area of responsibility or influence. A systems approach has the benefit of both leading with a focus on the subject of interest, and incorporating an understanding of how future changes may affect that subject. This is something that both the climate and the social science assessments in isolation fail to do.

Although the systems approach is a relatively new concept in climate and security studies, there are some examples where it has been used. The UK

Government Foresight study ‘Migration and Global Environmental Change’ (GOScience 2011) undertook an evaluation of the drivers and conditions surrounding migration, and used a systems-led conceptual framework to identify the influence of environmental change on those drivers. Although this understanding was not taken forward to assess the drivers in the context of specific environmental change generated by climate projections, the result was still a set of policy-relevant conclusions on the potential outcomes of future generalized change. Indeed, one output from this study was an action plan (GOScience 2011). Migration, like conflict, is a particularly difficult example of the interaction between climate and security and the Foresight study demonstrates that the complexity of the system is not a limiting factor in the utility of the systems approach, but rather the approach serves as a tool for better exploring and defining that complexity.

The International Institute for Environment and Development (IIED) recently published a report on ‘Urban poverty, food security and climate change’ (Tacoli, Bukhari et al. 2013) that similarly began with an assessment of the dimensions of the problem as a whole (in this case food security and food systems). This study considered climate change and urbanisation as drivers within, not external to, the food system. Although this study did not conclude with a set of policy recommendations, it did provide an explanation of mechanics of food security in developing countries, without over-simplifying either the social or climate aspects.

In both these examples a systems-based approach led to a better understanding of the complexity of the relationship between climate and security, and in the Foresight Migration study, led to a plan for action for policy makers. The next step in developing this systems approach would be to incorporate both social science and climate science expertise in the definition and exploration of the system, and go on to include climate model projections in the assessment of future system responses and states.

To examine how this systems approach might work in practice, consider the case of food security in a developing country. It is not difficult to see that weather and climate has a profound impact on food security and livelihood outcomes in a country like Ethiopia, for example (WFP 2014). Climate model projections indicate increases in extremes, including more frequent, intense and long-lasting droughts, and more frequent and intense heavy rainfall (Niang, Ruppel et al. 2014). A generalised conclusion that climate change will be a driver of greater food insecurity in the future is therefore easy to make (WFP 2014). However, this gives no information about the scale of the threat, relative to other drivers of food insecurity; or how this might relate to demographic, technological, cultural or economic change. It is therefore not clear what kind of outcome may result, or what options to respond would be most effective. In fact in Ethiopia there are a number of initiatives to tackle climate change and food insecurity, but in the absence of any real knowledge about future climate and its interaction with the food security system as a whole, almost all focus on building resilience (Bryan, Deressa et al. 2009, GCCA 2012, BRACED 2014, WFP 2014). These initiatives aim to improve farmers' ability to cope with variability in the weather in the present day.

However, in a changing climate, without identifying the who, the where and the how of climate impacts on food security, it is not at all obvious that resilience to present day variability at a farm scale level will be sufficient or even relevant, to tackle the consequences of long-term climate change on food security. A study that looked at the food security system as a whole, and the way it interacts with weather and climate might highlight quite different sensitivities within the system than were supposed. For example, drought has negative effects on yield (Deressa 2007), but does it matter where the drought is (in a rain fed or irrigated area; pastoralist or agro-pastoralist region) for national food security? Is the length of the drought or the intensity more important? Does the harvest in the previous year alter the impact of a poor harvest in this? If you make small changes in farming practices that increase resilience to present day climate, how does that affect resilience in future climates, under different climate projections? All of these questions are difficult to answer without considering the system as a whole, the way different aspects interact, and feedbacks that might occur. Building a model of the food security system in Ethiopia, through a collaborative process that includes social and climate scientists, whether that model be conceptual or computational, would ensure that the interactions are accounted for, and provide a tool for exploring alternative futures against different policy options.

An example of where a computational model of a food security system has been tried across developing countries and not just Ethiopia, is a study by Hertel, Burke et al. 2010 on the poverty implications of climate-induced crop yield changes by 2030. This study used a general economic global trade model (GTAP) (Hertel 1996) and a set of climate-induced yield impacts, based on a synthesis of values from the literature available. The results of this study focus very much on the outcome of production shocks on poverty, and highlight which aspects of the system are the most important drivers. In this case they conclude that yield is a poor predictor of national poverty, and that it is the interaction of production levels with commodity prices and earnings that determines poverty outcomes. This demonstrates how taking a systems approach can alter the perspective of analyst in a way that allows the complexity of the problem to be properly accounted for. In this case the approach did not allow for a fully integrated climate and social science input, and the climate science was somewhat marginalised. However, the result of making the system itself the focus, is that the results provide interesting feedback to both social and climate scientists on how their expert views could be integrated in a whole systems approach. If this sort of study had been integrated with the work summarised in the Food Security chapter of the IPCC reports (Porter, Xie et al. 2014), for example, it might have led to quite different conclusions on the role of climate change in food security, and perhaps recommendations for action.

Although the need to apply a more sophisticated view of the interaction between climate, climate change and security is recognised, applying a systems approach is not necessarily an easy solution. It can help disciplines find a common space, but communication between disciplines is challenging and requires an open mind. It can help define an appropriate scale, but it will not necessarily make information available at the right scale. It will however, at least allow recognition of scale issues. In this shared systems thinking space, decisions about systems boundaries will be made in the full knowledge of all experts, with no opportunity to 'dismiss' the importance of each other in the way that social scientists can be accused of reducing climate science, or climate scientists of reducing social science, to simplistic inputs into their analysis. The result, at the very least, will be a shared understanding of what we know and do not, or cannot, know. The result is that it becomes clear where the unknowns are in the system behaviour, and alternative approaches, such as scenario development, and other 'futures' research techniques can be applied (Bishop, Hines et al. 2007), to provide policy and decision makers with the information they need to act.

Conclusions

Climate science and social science research into environment and security have made great advances, but the problem of how to combine this learning to meet the ever growing demand for evidence about how climate change will affect security is more difficult. Policy and security analysts have put a lot of work into evaluating the available evidence, but their linear, climate science driven approach has limitations. The global scale of climate change projections dominates most climate analysis, and these general evaluations are just that; too general. They have led to an understanding that climate change has the potential to impact on security in its various forms, as one factor amongst others, but little additional detail that can support policy responses to this threat, at least on an adaptation timescale.

One alternative is to evaluate climate security from a systems perspective, and use the information about system sensitivity gained from this approach, to inform the analysis of climate projections. This brings a fresh approach, that will at least help identify issues of scale and agency, if not solve them, and provide an analytical space for different disciplines to meet and share expertise. The aim of this approach would be to provide more detailed and actionable advice tuned to the needs of individual policy-makers, on which they make policy decisions.

Chapter 3

Understanding climate as a driver of food insecurity in Ethiopia

This chapter is based on Lewis, K. Climatic Change (2017) Understanding climate as a driver of food insecurity in Ethiopia. Climatic Change, 144: 317.
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Introduction

Ethiopia suffers from both chronic, long term food insecurity (WFP and CSA 2014), and the regular incidence of severe food insecurity crises, often associated with drought events (Guha-Sapir, Below et al. 2015). During El Niño years in particular, summer rainfall over parts of the country is known to be low (Gleixner, Keenlyside et al. 2016) and these years are often associated with food security crises (Glantz 1994). As the climate changes, there is concern that changes in rainfall amounts and increasing frequency and intensity of droughts will lead to Ethiopia becoming a more food insecure country (WFP 2014). Climate model projections for changes in rainfall over the Greater Horn of Africa have low confidence (Otieno and Anyah 2013), and in the absence of a clear climate change signal, adaptation to climate change has focused on building resilience to variability (for example, (BRACED 2015), (CADAPT 2015)). However, drought in Ethiopia is often defined from a socio-economic perspective, and can be as much a consequence of the food system structure, as climate itself (Devereux and Sussex 2000). The assumption that drought, in a broad sense, is a major driver of food insecurity in Ethiopia affects not only the way climate model projections are interpreted and the challenges of climate change are viewed, but also the way agricultural development activity is prioritised today.

A large number of studies have been undertaken to evaluate how climate, climate variability and change could affect food security in Ethiopia . All these reports conclude that climate variability is a causal driver of food insecurity, and therefore that climate change represents a threat to future food security. In similar studies this conclusion is drawn from an understanding that water is critical to food production, and in many acute food security events ‘drought’ is reported as the cause. However, in each of these studies, no formal definition of what constitutes a drought is given, so it is not necessarily clear that these ‘drought’ events have the same meteorological characteristics.

This lack of definition for drought is a problem because it makes it difficult to evaluate what climate model projections mean for longer term food security outcomes. Furthermore, the reliance on anecdote also has the potential to undermine efforts to improve food security today. One example of a social study that looked at drought in Ethiopia was conducted by USAID (USAID 2000), and stated that in the Ethiopian state of Amhara 'there has been no single year since 1950 where there was no drought'. From a socio-economic perspective there is a chronic shortage of water in the region, but in meteorological terms a drought, defined as some deficit relative to the climate average, cannot occur every year. Unpacking the socio-economic and meteorological context associated with the food security outcomes of climate in Ethiopia is key to providing salient and actionable advice on both climate variability and change. It is also necessary to inform action to tackle food insecurity now and over the long term.

In this study we compare socio-economic information about the food system and food security outcomes in Ethiopia, with the physical temporal and spatial patterns of rainfall associated with these outcomes. The aim is to address some of the interdisciplinary barriers associated with analysis across natural and physical sciences (Lewis and Lenton 2015), to test some basic assumptions about the food security-climate relationship in Ethiopia, and to provide robust evidence on that relationship to support action to tackle food insecurity at a national level.

Data

National indicators of food availability (production and yields), population and economy are available from the UN Food and Agriculture Organisation (FAO) (FAOSTAT 2018) and the World Bank (World Bank 2016). These organisations in turn receive their data from national statistical authorities. Acute food security disasters as reported in the EMDAT database are also used (Guha-Sapir, Below et al. 2015). Table 3-1 shows the list of reported drought-attributed disasters for Ethiopia since 1981. The EMDAT database contains information about disasters (rather than hazard) which are measured in terms of the impact on people. This data is rather subjective, and not reported in a standardised way, but is the best information available that records the occurrence of such events.

The climate data available to compare with these reported events also has its limitations. The coverage of available observation sites and rain gauges for climate is poor in Ethiopia, and much of the data is available only to the National Meteorological Administration (NMA) in Ethiopia. Alternative representations of the meteorology include the use of reanalysis data (a hybrid of observational data and climate model interpolation), such as ERAInt (Balsamo, Albergel et al. 2015), 20CR (Compo, Whitaker et al. 2011) or MERRA (Rienecker, Suarez et al. 2011), satellite data, such as TRMM (Adler, Awaka et al., 2000), and combined satellite and observational datasets such as CHIRPS (Funk, Peterson et al. 2015). A comparison of reanalysis, satellite and CHIRPS data indicated quite large differences between the different data types, and in particular there are some serious shortcomings in the skill of reanalysis data to represent Ethiopian climate (Sylla, Giorgi et al. 2013). CHIRPS data is considered by many to be the ‘gold standard’ of data for drought monitoring in Ethiopia and is used extensively by humanitarian agencies in the region (Boniface 2016). This data set only includes rainfall, not other variables such as temperature or evapotranspiration, which might become increasingly important as the climate warms. However, as inter-annual variability in temperature is quite low in Ethiopia, it is reasonable that the focus is on rainfall as fluctuations in this variable are the dominant driver of drought in the country. For this reason, and because it is the rainfall data of choice for food security activity in the country, CHIRPS rainfall data is used throughout this study.

Food security and climate in Ethiopia

Around 30% of the 97 million population of Ethiopia are reported as undernourished (FAOSTAT 2018). The absolute number of undernourished people has declined very little in the past 25 years, from 40 million in 1990 to around 35 million in 2015. Although in percentage terms, there has been a substantial decrease from the 60% level seen in the 1990s, to a figure closer to 30%. By this measure Ethiopia has met the Millennium Development Goal target to ‘halve, between 1990 and 2015, the proportion of people who suffer from hunger' (UN 2000). At the same time the incidence of reported acute food insecurity events does not seem to have fallen, and although the numbers of people killed as a result of drought-driven famine have not subsequently reached the totals seen in 1984, events that affect greater than 1 million people continue to occur frequently (Table 3-1).

*Table 3-1: Reported drought disasters for Ethiopia with >= 100,000 people affected (source EMDAT (Guhar-Sapir, Below et al. 2015), WFP (2012)) * indicates some disagreement over exact dates with other sources such as Reliefweb (Reliefweb 2016)*

Dates	**Location**	**Total deaths**	**Total affected**
1983/1984	Wollo, Gondar, Goe, Eritrea, Tigray, Shoa, Haregre, Sidamo	300,000	7,750,000
1987*	Eritrea, Tigray, Ogaden, Wello, Shewa, Gama, Gofa, Sidamo, Gondar, Bale	367	7,000,000
1989-1994*	Northern Ethiopia, Eritrea, Tigray, Wollo, Gondar, Harerge		6,500,000
1997	Oromia, Bale, Borena, South Ome, Somali		986,200
1998*			
2003*	Tigray, Oromia, Amhara, Somali, Afar		12,600,000
2005*	Afar, Liben, Gode zones, Somali, Borena, Somali		2,600,000
2008/2009*	Oromia, Somali, Amhara, Afar, Tigray, SNNPR		6,400,000
2009/2010			6,300,000
2011/2012	Somali, Oromia, Afar, Tigray, Amhara		4,805,679
2012/2012			1,000,000
2015/2016	Somali, Afar		10,000,000

Rainfall variability as a driver of national food security

One assumption made about Ethiopia is that rainfall variability is a critical driver of food insecurity nationally. The evidence for this assumption comes from a variety of studies which find an inverse correlation between GDP growth and rainfall variability.

One study in particular that is widely cited as proof of an association between rainfall and food insecurity at a national scale in Ethiopia is the World Bank Water Report (World Bank 2006). In this study rainfall variability was plotted against GDP growth as evidence of a correlation between the two. This relationship is used to support the argument for the importance of rainfall variability to economic development, and therefore food security and other human well-being outcomes in Ethiopia in a number of studies.

In their study on adaption to climate change in Ethiopia (Conway and Schipper 2011) revisit this relationship, and find that if more recent data is included the correlation is far weaker. Revisiting this relationship for a second time to include the latest data, we find that the relationship between national rainfall anomaly and GDP growth rate does not recover, suggesting that the initial findings of a significant correlation do not hold. Figure 3-1 shows a correlation between rainfall variability (using CHIRPS rainfall data (Funk, Dettinger et al. 2008)) and GDP growth of 0.24, compared with 0.40 from the original World Bank analysis (as estimated by Conway& Schipper), and 0.10 found by Conway & Schipper in their subsequent analysis. Introducing a one-year lag does not improve the correlation.

Around 60% of the average daily calorific intake for Ethiopians comes from cereals, of which maize, sorghum, teff (a local grain indigenous to Ethiopia) and wheat are the most important (FAOSTAT 2018). Figure 3-2 shows annual rainfall variability and the yield and total production anomaly from the de-trended mean for these four crops. The correlation between rainfall variability and cereal production is in fact weaker than for GDP (Figure 3-3), with a correlation coefficient of only 0.23. For yield it is weaker again at 0.15. (For individual crops the correlation between production and GDP is highest for maize and wheat at 0.24, and lower for sorghum at (0.18) and teff (0.1)).

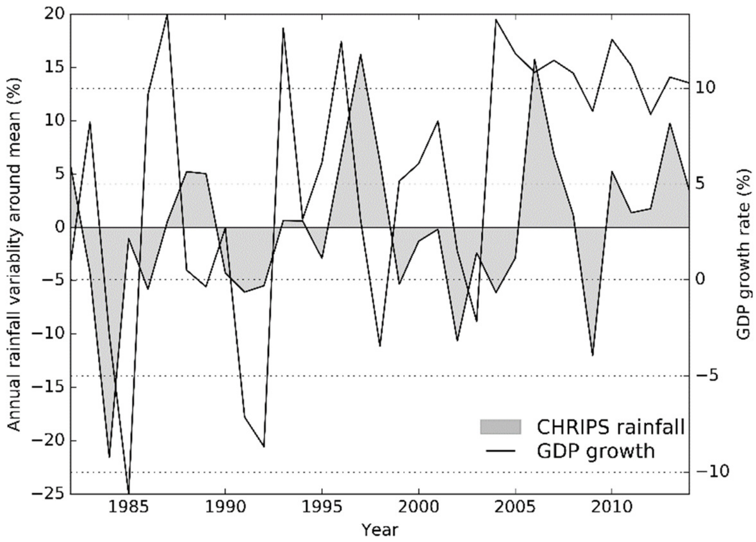


Figure 3-1: Ethiopian rainfall and GDP growth rate using CHIRPS rainfall (Funk, Peterson et al. 2015) data Correlation r = 0.244

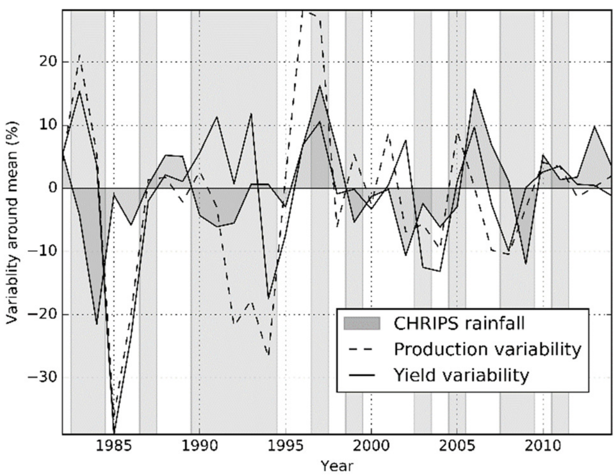


Figure 3-2: Rainfall variability over Ethiopia and total cereal production (maize, sorghum, teff & wheat) anomaly relative to de-trended mean (source CHIRPS rainfall (Funk, Peterson et al. 2015), FAOSTAT 2018) Reported drought-driven food security disaster years from table 1 are shaded in grey. Rainfall-yield variability correlation r = 0.147 Rainfall-production variability correlation r = 0.227.

From this it is possible to conclude that national rainfall variability is not necessarily a major driver of variability in total food availability in Ethiopia, or even a good indicator of crop yield. This conclusion is supported by a more in-depth study by (Bewket 2009) which looked at the relationship between rainfall variability and crop production (rather than food security) in Ethiopia in more detail, and also found annual rainfall to be weakly correlated with cereal production. One implication from this is that that large-scale climate trends may not be a useful means of assessing the impacts of weather on future food security as it relates to production, regardless of the confidence, or otherwise, in climate change projections.

National food availability – exploring the trend

Although production totals for all the major cereal crops have increased considerably over the past 20 years, Ethiopians' daily food calorie intake stood at 1,858 as an average during 1992 - 2013 (FAOSTAT 2018); below the standard requirement of 2,200 Kcal/capita/day. This means that Ethiopia does not quite produce enough food to meet a basic calorie allowance for the population as a whole.

The gap between actual yields for major cereals and the potential yield that could be achieved is high in Ethiopia. A recent study by the FAO looking specifically at wheat showed that the main producing regions achieved only between around 50 and 60% of their local attainable yields, given their altitude, weather conditions, terrain and plant health (Jirata, Grey et al. 2016). Ethiopian farming also has a very low level of technological input (low use of irrigation, specialist seed varieties, fertilizers and pesticides). Even accounting for the fact that agricultural production in Ethiopia is predominantly rain-fed, research as part of the Global Yield Gap Analysis project (Tesfaye 2015) concludes that if Ethiopia were able to halve its water-limited (i.e. rain-fed crop) yield gaps, it would be possible to produce sufficient cereals to meet the food requirement of a population of 174 million (the projected population of the country by 2050), without expanding the agricultural production area. Addressing the yield gaps in agricultural production in Ethiopia is a challenging task. It is possible that climate change will make this more difficult, but projections of average change in yield associated with future average climate are smaller than the potential gains associated with closing yield gaps, under the most climate projections (Kelbore 2012, Kassie, Asseng et al. 2015). A large number of initiatives are underway to boost agricultural productivity in Ethiopia, through ‘Climate-Smart’ investment, that aim to reduce yield gaps and eliminate chronic food security. (For a comprehensive summary of climate-smart agriculture programmes and projects underway in Ethiopia see (Jirata, Grey et al. 2016)).

The shortfall between potential and actual production is one aspect of the problems of chronic food insecurity in Ethiopia. However, the number of food insecure has been fairly static over the same period that total production, and production per capita, has increased sharply, suggesting that the benefits of increased availability are not necessarily translating into greater access for all. The fact that Ethiopia does not quite produce enough to meet the food requirements of the whole population, does not alone explain the on-going occurrence of food security disasters in the country. This disconnect between food production and food insecurity is discussed further in Sen (1981).

Acute food insecurity events

The incidence of food security disasters in Ethiopia shows little signs of decreasing over time, and the majority of these events are attributed largely to drought (Table 3-1) (Guha-Sapir, Below et al. 2015). Figure 3-2 not only shows rainfall and cereal production variability, but also includes shading to indicate periods of reported drought-driven food insecurity crises. This highlights the weak relationship between fluctuations in national cereal production and specific food security crises. This is possibly a surprising result. It indicates that while overall national production (and possibly therefore average climate suitability) is important, it is not availability of food that causes food insecurity disasters in Ethiopia. Each incidence of a food security disaster in Table 3-1 was recorded as an event where there was insufficient rain in an area which resulted in hunger, but there was no dip in national rainfall totals or cereal production during these events. These ‘drought’ incidences therefore must have been relatively local but had serious impacts on livelihoods, leaving the local populations unable to meet their food needs by buying from other regions, even though, on the whole, the country was no worse off than in any other year. This suggests that while increasing food production is being achieved; acute food insecurity is somewhat decoupled from national cereal production, possibly making it more difficult to manage successfully (Sen, 1981).

Meteorology of acute food insecurity events

Rainfall totals are highly variable across Ethiopia. Figure 3-3 shows the average annual precipitation over the country for the 1981-2015 climatology. The western highland areas receive the most rainfall (up to 2000mm or more per year), while areas to the East and Northeast are extremely dry (receiving 250mm per year or less). The majority of cereal production is concentrated in the wetter highlands, and most of the population is concentrated in these areas. Elsewhere livelihoods are predominantly pastoralist or agro-pastoralist (WFP and CSA 2014), with pastoralism concentrated in the Afar, Somali and eastern and southern Oromia regions.

Rainfall across Ethiopia is highly heterogeneous, but this is also true for rainfall anomalies. Comparing the spatial pattern of rainfall anomalies for each year in the climatological period (1981-2015) with the incidence of reported drought from Table 3-1 begins to unpick the reasons behind the disconnect between climate and food security at the national and sub-national level. In many years where the total annual rainfall was close to the climatological average for the country as a whole some areas experienced rainfall totals much lower than the climatological average, but higher than average totals elsewhere made up the deficit nationally (See Appendix A for rainfall distribution for individual years in the climatological record).

In every year in the period, some proportion of Ethiopia experienced rainfall 70% or less of the expected climatological average for that location (see Appendix B). However, this data also shows that in every year except one (1984), the majority of Ethiopia received at least 80% of the expected climatological average rainfall. This supports the conclusion that as a nation, Ethiopia does not have a climate adverse to food security. However, in most years local weather conditions can cause problems for sub-national level food production. If livelihoods are dependent on rainfall then in years when some regions do not receive sufficient, even if national food production totals are unaffected, these regions will be unable to access that food through the market and will experience food insecurity. Rather than this being a feature of the large scale climate that climate models can explore, this is predominantly a feature of how food is accessed as a result of the livelihood and food system conditions in Ethiopia.

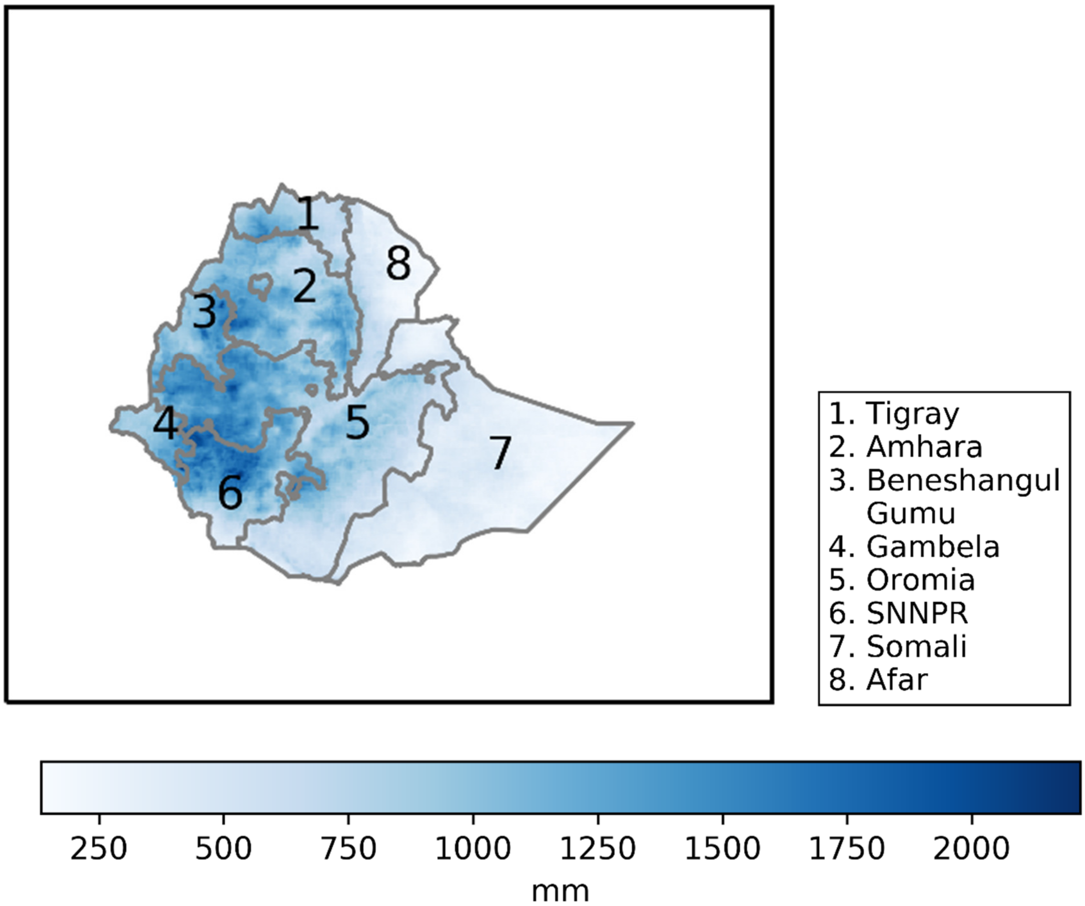


Figure 3-3: Average annual precipitation over Ethiopia for 1981-2015 climatology (source CHIRPS (Funk, Peterson et al. 2015))

The states that are most often reported as experiencing drought are Tigray, Afar and Somali. These three states are the driest, and the states where low precipitation totals correspond most closely with periods of reported drought (Figure 3-4). In the driest states, the coefficient of variability is, by definition, greater for smaller absolute changes in rainfall, meaning that in marginal dry lands even small fluctuations in absolute rainfall potentially have a large impact.

The assertion that ‘every year is a drought year’ (USAID 2000), whilst not meteorologically accurate, is a combination of the fact that somewhere in Ethiopia experiences substantially below average rainfall in almost every year, and that in some very dry parts of the country in particular (such as Afar), people are living on very marginal lands with highly rain sensitive livelihoods, where variability has the greatest impact.

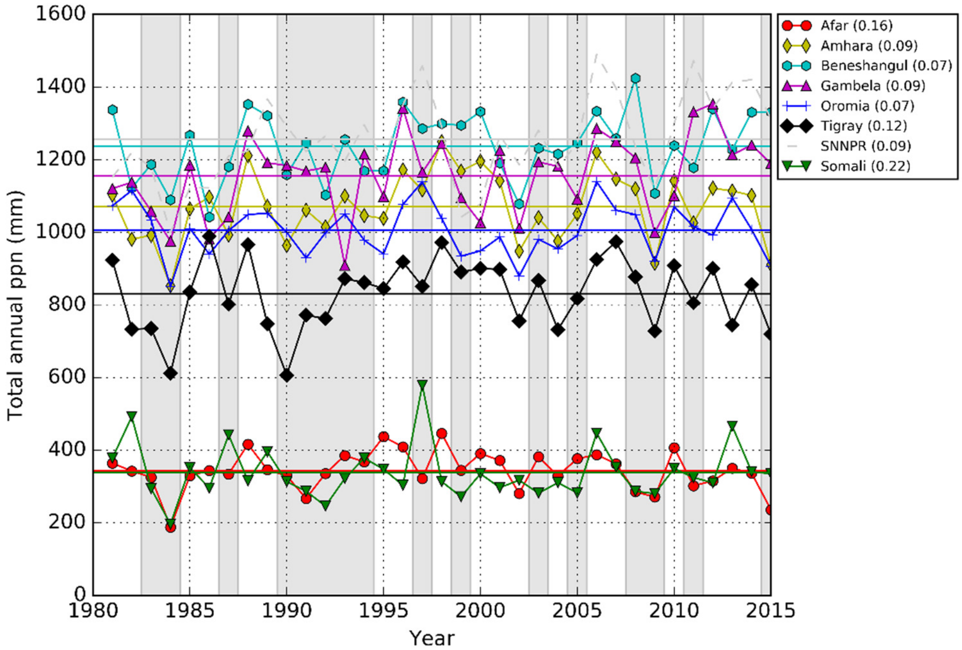


Figure 3-4: Annual average rainfall over the largest Ethiopian states with coefficient of variability for each state listed. Periods of reported drought events from table 1 shaded in grey (Source: CHIRPS (Funk, Peterson et al. 2015) & EMDAT (Guhar-Sapir, Below et al. 2015)).

An alternative way to show this data is given in Figure 3-5 a & b. This shows the number of years for which the rainfall is less than 60 or 80% of the annual average for the climatology. This is effectively a spatial projection of Figure 3-4, and shows that the variability in the very driest states (Somali, Tigray and Afar) is most significant. Figure 3-5 c and d shows the number of years where the total rainfall fails to exceed 600 mm (the approximate threshold for rainfall required for the production of wheat, sorghum and teff), and 800 mm (the approximate threshold for rainfall required for the production of maize (FAO 2016)). These figures clearly show that some areas of Ethiopia have been consistently suitable for cereal production (areas in white in Figure 3-5 c & d), whilst other are not suitable at all (areas in black in Figure 3-5 c & d), and that only small areas of the country, on the boundary between these two regions, experience variability in total rainfall that would impact on cereal production in some years. This further reinforces the conclusion that rainfall variability is not a driver of food availability nationally. However, in those regions not suitable for cereal production, predominantly the states of Somali, Tigray and to a lesser extent Afar, where pastoralist livelihoods dominate, rainfall variability is more significant (Figure 3-4 & Figure 3-5).

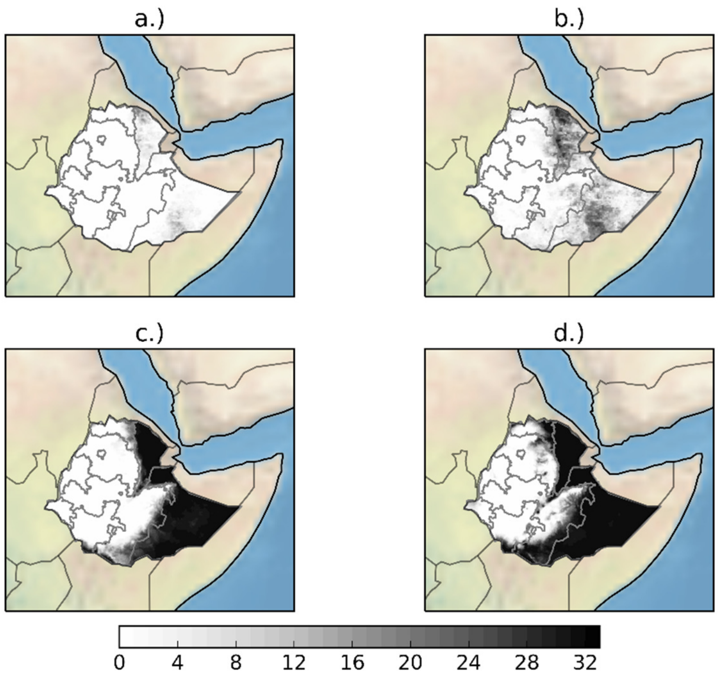


Figure 3-5: Number of years in 1980-2015 period in which the total annual precipitation was less that a.) 60% and b.) 80% of annual average for that location and less than c.) 600 mm and d.) 800 mm between 1981 and 2015 (Source CHIRPS (Funk, Peterson et al. 2015))

Discussion and conclusions

Studies into food insecurity and climate in Ethiopia are often founded on the presumption that drought causes food insecurity in Ethiopia, and that by extension efforts to reduce the impact of drought through early warning mechanisms, or in the introduction of drought-resilient crops, for example, can tackle food insecurity in the country. The definition of drought here is critical. Linking total rainfall to food insecurity in Ethiopia can explain some of the very large scale events that have occurred (such as in 1984), but this does not explain either the chronic production shortfall that is largely the result of failure to optimise yields, or the majority of acute crises that occur much more frequently and remain a significant challenge. Although the national annual rainfall total is a poor indicator of food insecurity disasters, a localised deficit in rainfall does correspond to localised food insecurity. These events most often occur in the same years that other areas of Ethiopia have average or above average rainfall, and are therefore not associated with widespread reduction in food availability. Drought does, of course lead to crop failure, but it does not have to result in food insecurity. Food security outcomes are as much, if not more, a result of how optimised the food system as a whole is to climate than it is a function of total availability. Therefore looking at national, or even to some extent sub-national, rainfall variability is a misappropriation of climate as the causal factor for food insecurity in Ethiopia.

Huge gains have been made in improving the national and international response to food security disasters in Ethiopia, and the fact that far fewer people now die in such events than twenty or thirty years ago is a major achievement (FAOSTAT 2018). However, if the ambition is to achieve 'zero hunger' by 2030 (UN 2015), then improving the response and resilience to disasters is not enough. It requires recognition that that the means to produce enough food to meet the nutritional needs of the whole population of Ethiopia is not limited by climate. Access to food is affected by climate and this is a feature of the food system, not an environmental limitation.

The two key aspects of underlying systemic causes of acute food insecurity in Ethiopia are the high proportion of smallholder farmers whose livelihoods depend on sufficient rainfall, and the fact that around 14% (CSA 2016) of the population make those climate-sensitive livelihoods on the very dry, marginal and highly variable land in the east and northeast of the country. Regardless of the levels of climate change projected for the next few decades (IPCC 2013), food insecurity could be addressed by firstly addressing the yield gaps in the most climate-suitable regions to increase national food availability, and secondly, diversifying the incomes of the approximately 13 million people in most climate-challenging regions away from agriculture. As long as these populations are dependent on local rainfall for both availability and access to food they will continue to experience regular acute food insecurity. Action to improve resilience will reduce the frequency of these events, and improvements in early warning and disaster risk response will reduce the impact of these events, but unless there is a transformational change in the food system in these regions, food insecurity will not be eliminated.

Such substantial systemic changes are not an easy thing to achieve, and are associated with political, social and cultural changes that are not trivial to implement. However there is a danger that while working with existing systems to build resilience to climate variability through incremental adaptation could reduce the incidence and severity of acute food insecurity crises, it may also further embed communities in livelihoods that are dependent on regular humanitarian assistance to avoid catastrophe. Climate variability, and indeed food insecurity, has long been a feature of life in Ethiopia, but the future threats and opportunities for the country require not simply adaptation but transformation. It is important to fully understand the contribution of both the climate and the food system itself to national food insecurity, in order to address the unprecedented challenge of climate change and achieve the ambitious target of zero hunger by 2030.

Chapter 4

A Simple model for assessing climate variability and change as drivers of long term food insecurity in Ethiopia

Introduction

Having explored the interaction between climate and food security in Ethiopia, it is clear that while weather and climate are critical factors in food security outcomes, it is within the context of the food system that their impact is realised. In order to meet the challenge set out in the United Nations Sustainable Development Goals of eliminating global hunger (UN 2015) in a future where the climate change signal dominates over present day variability, action to make large-scale, long-term, systemic changes is required (Kates, Travis et al. 2012). To do this information on the scale and direction of climate change, as well as the sensitivity of the food system to these changes relative to other system changes, is critical. A current focus on building resilience to climate variability as a climate adaptation priority is in part a pragmatic response to perceptions of the lack of utility in uncertain and low resolution climate model projections (Fetzek 2008). However, it may be that what is needed is an approach for interpreting and translating the climate model projections to address the information needs of long term planners.

In this chapter we revisit food security and climate in Ethiopia, building on what was learnt in Chapter 3 as a worked example of a possible approach to address the issues of utility, scale and uncertainty in climate model projections. The aim is to develop a methodology for interpreting climate projections that could provide quantitative analysis of the relative impact of climate change compared with other system changes, and the role of climate model uncertainty in the utility of this evidence.

Approach

In order to provide a quantitative, rather than just qualitative assessment, a simple 'toy' model[1] of the food system in Ethiopia was developed. This model is

[1] In this instance a 'toy model' refers to a highly simplified model designed to test the behaviours and responses of specific aspects of a system. This contrasts with more general models where the aim may be to create a more realistic representation of that system.

designed to capture some of the key national-scale features of the relationship between climate and food security, rather than model the whole system in detail. The model is driven with data from a number of climate models, and under a set of policy changes to the national food system, to test the sensitivity of the outcomes to these changes. The simple model provides information on relative impacts (e.g. food security outcomes are more/less sensitive to climate change than to improvements in yield), rather than providing 'predictions' of absolute national food security levels under climate change.

Following from the knowledge gained in Chapter 3 on the relationship between the food system and climate in Ethiopia, then next step in this process is to assess the availability and veracity of the climate model data available over the country. Selecting a set of climate model projections, it is necessary to evaluate the performance of these models compared to observations, and to consider the level of agreement there is on the climate change signal. Next the climate data is compared with reported cereal production in Ethiopia to establish a 'climate proxy' to allow the climate model projections to be interpreted from a food production perspective. This could be a measure of climate suitability for agriculture, or more generic climate indices. Following this the simple food system model is designed and built, and the basic system parameters determined. Finally the model is run with and without climate change, and with and without system changes. The outputs are evaluated and interpreted to assess how useful a tool this is for providing evidence about the potential impacts of climate change on food security, relative to the present day climate and to other changes to the food system, and in light of the uncertainty in the climate model projections.

Climate model data

Baseline climate

Climate model data from the CMIP5 (Climate Model Inter-comparison Project 5) multi-model ensemble of simulations were used to provide the climate simulations. Nineteen models (listed in

Table 4-1) were selected and data from historical and RCP8.5 (Moss, Nakicenovic et al. 2008) climate simulations were downloaded. The selection criteria for the models was based primarily on availability, but a check was made to ensure that models from the most reputable research institutes were included, and that they approximately covered the spread of model projections across the wider ensemble group (McSweeney, et al. 2012). RCP8.5 is the highest available greenhouse gas concentration scenario, and this was used in order to maximise the climate change signal for the purposes of comparison with other drivers of change. For the same reason, the projections were analysed for change to the end of the century, rather than a nearer time period.

Before the climate change projections from these models were explored, some initial work was done to evaluate how well the model simulations are able to reproduce the recent past climate, and how large the differences are between the models in this period. This assessment informs the level of confidence that might be ascribed to the climate model projections when it comes to interpreting the implications drawn from those projections.

Using a multi-model ensemble (MME) of nineteen models means it is possible to include a wide range of projections, increasing the probability that something of the future climate is captured within the ensemble range (Tebaldi and Knutti 2007).

There are a variety of techniques available for evaluating climate models, from visual comparisons to more rigorous quantitative performance metrics (Flato, Marotzke et al. 2013). There are limitations to all approaches, mainly associated with the reliability of the observational record, something of particular concern over Africa. In addition, however well an individual or ensemble of models may perform in such tests, uncertainty will always remain a key feature of long term planning, and developing means to deal with this is critical to Climate Security studies. Nevertheless, within this study a basic comparison of climate model performance was undertaken, both against observations and between models, for three reasons:

First, a good understanding of the level of agreement between models and between models and observations gives a qualitative sense of confidence in the resulting projections, and therefore the impact of model uncertainty on the food security outcomes.

Second, an evaluation of model performance introduces the option to exclude some of the models from the MME, if they are considered insufficiently credible such that they may mislead. It is important to note that there is no formal way to determine how well a model must perform in assessment to be deemed sufficiently reliable. This is a matter of subjective judgement. As such, although some models are excluded from the multi-model ensemble in the final analysis, all model results are included within the study as a whole.

Third, communicating the results from 19 models and an MME can lead to confusion. For clarity the results for the MME are primarily used for illustration, but as some features of these results can be a consequence of the inclusion of multiple models (for example an increase in model spread could be confused with a signal for an increase in annual variability), the results of one single model are shown alongside. For each country for which future food security is assessed, a qualitative assessment of a 'best performing' model is suggested. This model is then used as the single model comparator for the MME. This 'best performing' model is, in effect, an arbitrary choice with the purpose of showing the difference between the MME and any given model only, and no additional weight is given to the results from this model over any other. (In fact there is some evidence that over Africa excluding models that perform badly in comparison with observations does not necessarily constrain the range of the future projections (Rowell, Senior et al. 2016).)

Table 4-1: List of CMIP5 climate models included in this study

Modeling Center (or Group)	Institute ID	Model Name
Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM), Australia	CSIRO-BOM	ACCESS1.3
Canadian Centre for Climate Modelling and Analysis	CCCMA	CanESM2
National Center for Atmospheric Research	NCAR	CCSM4
Community Earth System Model Contributors	NSF-DOE-NCAR	CESM1(CAM5)
Centro Euro-Mediterraneo per I Cambiamenti Climatici	CMCC	CMCC-CESM
Centre National de Recherches Météorologiques / Centre Européen de Recherche et Formation Avancée en Calcul Scientifique	CNRM-CERFACS	CNRM-CM5
Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence	CSIRO-QCCCE	CSIRO-Mk3.6.0
NOAA Geophysical Fluid Dynamics Laboratory	NOAA GFDL	GFDL-CM3
NASA Goddard Institute for Space Studies	NASA GISS	GISS-E2-H GISS-E2-R
Met Office Hadley Centre (additional HadGEM2-ES realizations contributed by Instituto Nacional de Pesquisas Espaciais)	MOHC (additional realizations by INPE)	HadGEM2-CC HadGEM2-ES
Institute for Numerical Mathematics	INM	INM-CM4
Institut Pierre-Simon Laplace	IPSL	IPSL-CM5A-LR IPSL-CM5A-MR
Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	MIROC	MIROC5
Max-Planck-Institut für Meteorologie (Max Planck Institute for Meteorology)	MPI-M	MPI-ESM-MR
Meteorological Research Institute	MRI	MRI-CGCM3
Norwegian Climate Centre	NCC	NorESM1-M

In order to assess climate model performance, climate model data should ideally be compared with similar data drawn from observations. In this case reanalysis data (gridded data for a standard set of climate variables, generated through a hybrid of observational and model simulation) would, in theory, provide a suitable comparator for the model projections over the same period. However, one key limitation for climate change assessments over Africa is the sparsity of direct observations. This lack of long-term observational data means that the reanalysis products in this region are only poorly constrained, and rely more heavily on the model processes to fill in the gaps. As a result different reanalysis datasets show little agreement between each other on the climate of the recent past, at least on the scale of individual years, and therefore cannot be considered to represent a reliable approximation of the actual climate conditions on that scale. Figure 4-1 shows a time series of total annual precipitation over Ethiopia for three reanalysis datasets (ERAINT (Dee, Uppala et al. 2011), CMAP (Xie and Arkin 1997) and NCEP (Kalnay, Kanamitsu et al. 1996). This figure illustrates how different the values for annual precipitation are for different reanalysis datasets for the same period. Also shown in Figure 4-1 is the time series of annual rainfall from the CHIRPS dataset (Funk, Peterson et al. 2015) used in Chapter 3. The CHIRPS dataset of rainfall is derived from satellite and rain gauge data, and is considered the 'gold standard' in the rainfall observational record across Africa (Boniface 2016, pers. comms.). It is the primary source of rainfall data by analysts working on food security humanitarian response in country, and so a qualitative confidence in the accuracy of this data as the best available has been obtained by expert practitioners. The three reanalysis data sets agree very poorly with CHIRPS. As a result of this lack of agreement on the annual rainfall pattern between reanalysis datasets and with CHIRPS, reanalysis data has not been used as a proxy for observations of climate over Ethiopia in this study. This selection is supported by Maidment et al. (2015), who show that potentially spurious time-varying jumps exist in some reanalysis datasets. The main problem with this decision however is that while the CHIRPS data may be considered a reliable representation of the recent past weather, the data set does not include temperature. So it is only possible to evaluate the climate model data against this observational data set for precipitation.

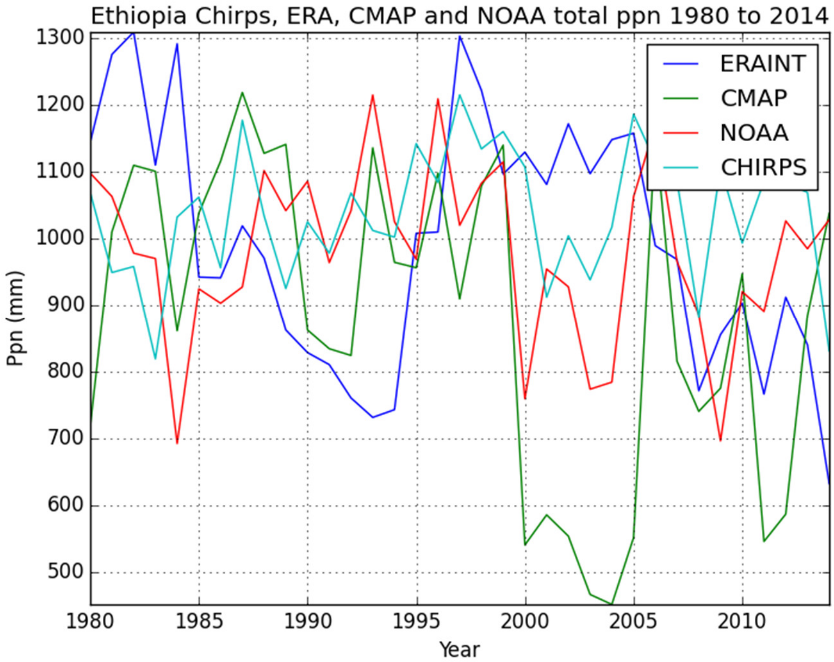


Figure 4-1: Total annual rainfall over Ethiopia for three reanalysis datasets and CHIRPS

Figure 4-2 shows box and whisker plots for time series of annual rainfall over Ethiopia for the period 1981-2005 for CHIRPS and for the 19 CMIP5 climate models. The period 1981-2005 was used because these are the years for which there is overlap between the CMIP5 historic runs and CHIRPS.

Climate models aim to simulate the characteristics of the climatology of a region, and would not be expected to reproduce the climate features in individual years. Comparing aspects of the rainfall climatology produced by the models with CHIRPS in Figure 4-2, it can be seen that some models are on the whole too dry (IPSL-CM5A-LR) while others are too wet (MIROC5). The models closest to CHIRPS in terms of mean and variability of climate appear to be the two HadGEM2 models and perhaps CNRM-CM3.

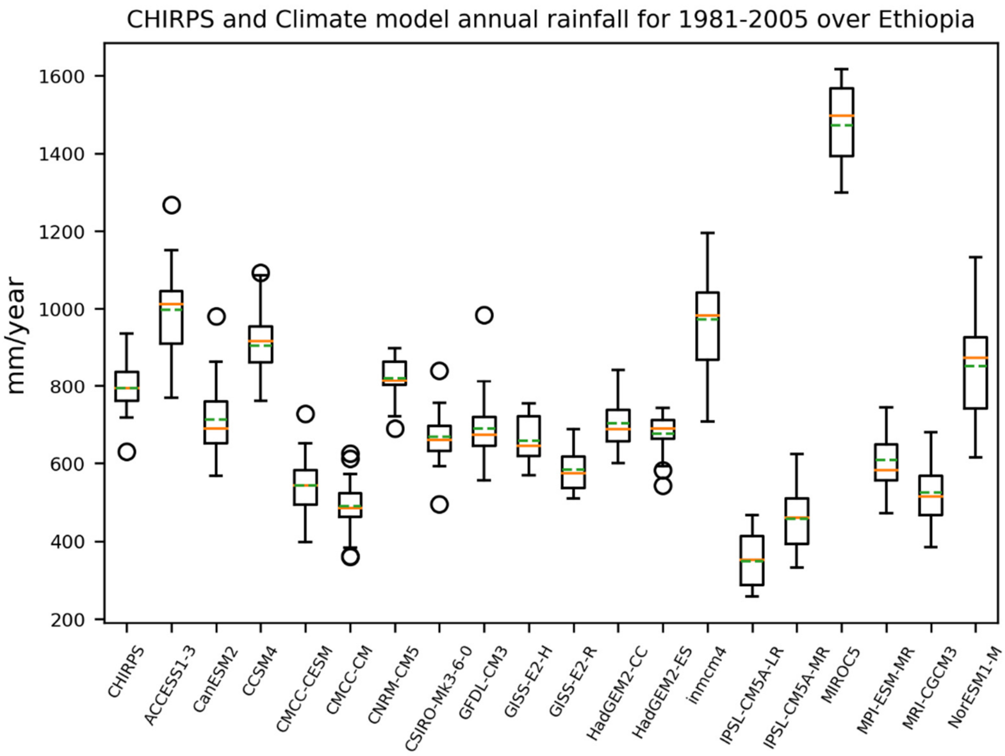


Figure 4-2: Annual rainfall over Ethiopia for CHIRPS and 19 climate models from CMIP5, for the period 1981-2005. Orange line shows climate median, dashed green line shows climate mean, box represents interquartile range, whiskers 1.5 times the interquartile range, and circles represent outliers beyond the whisker range.

Figure 3-3 showed the mean annual precipitation over Ethiopia for the 1981-2005 climatology from CHIRPS data. There is very high spatial variability over the country in terms of rainfall totals. The east is extremely dry, arid and semi-arid, while the central and western highlands are extremely wet. Figure 4-3 shows the difference in the average climatology between each climate model and CHIRPS, and illustrates the spatial pattern of rainfall differences. Figure 4-3 also shows the grid box size for each of the climate models, and the CMCC-CESM and IPSL-CM5A-LR models in particular have very low horizontal resolutions. In terms of annual rainfall, the best performing models from Figure 4-3 appear again to be the two HadGEM2 models, but also MPI-ESM-MR and GFDL-CM3.

Finally, the distribution of annual rainfall values at all the grid boxes over Ethiopia, for the whole time period (1981-2005) were compared for each of the models and CHIRPS (Figure 4-4).

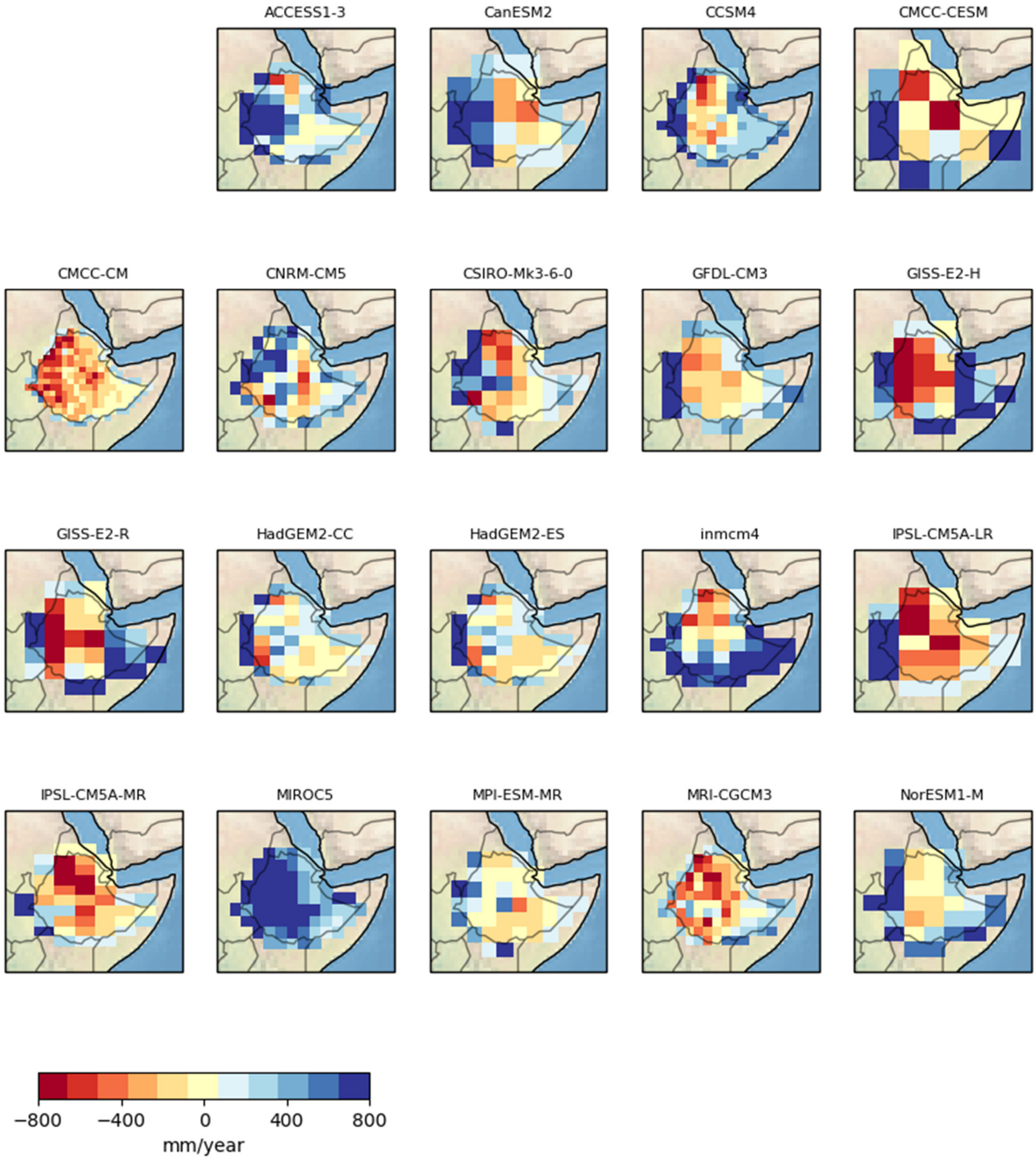


Figure 4-3: Difference between CHIRPS and each CMIP5 climate model for climatological average annual rainfall for the period 1981-2005. (CHIRPS data re-gridded to model resolution).

The CHIRPS data (in green), shows a bi-modal distribution of rainfall intensity, with a large number of dry grid boxes, and a second peak of wetter grid boxes, as a result of the large climatological range across the country. Few of the models capture this distribution, with the exceptions of the two HadGEM2 models and the MPI-ESM-MR model. The multi-model mean distribution also shown in Figure 4-4 does a reasonable job of capturing the footprint of the distribution of rainfall, although it smooths the distinction of bi-model distribution.

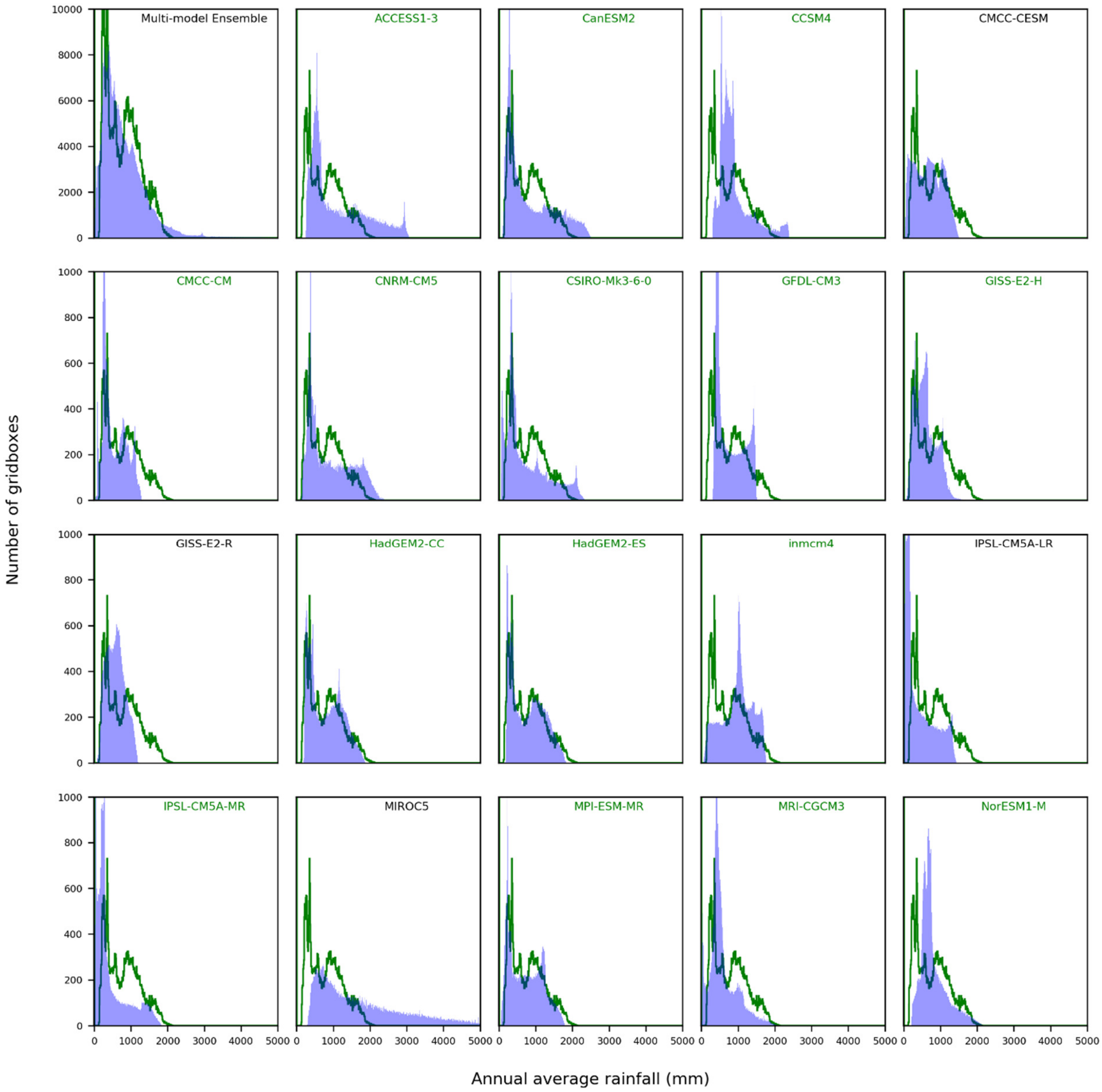


Figure 4-4: 1981-2005 annual rainfall climatology for CHIRPS (in green) and each climate model and the multi-model ensemble (in blue) for whole of Ethiopia

The purpose of this study is to consider the potential for climate change to impact on food production, but looking at the spatial pattern of rainfall in Figure 3-3 and the resultant bi-model distribution of rainfall climatology in Figure 4-4, it is clear that food production in Ethiopia has a strong spatial component, as was found in Chapter 3. Figure 4-5 shows a map of livelihood zones in Ethiopia (FEWSNET 2009) which confirms this. The zones in shades of green are predominantly cropping regions, while those in yellows and oranges are predominantly pastoral or agro-pastoral regions. Only around 12% of the population live in the pastoralist regions of Ethiopia (EEA 2005), and it is likely to be extremely difficult to capture the interaction between climate and pastoral food production, not least because pastoralists, by definition, move around. A simpler first approach would be to focus on cereal production, which makes up the majority of the calorie intake for Ethiopians, as well as the largest proportion of agricultural income (FAO 2018). From this perspective, a focus on model performance over the wetter, cropping regions of Ethiopia, rather than over Ethiopia as a whole, is also considered.

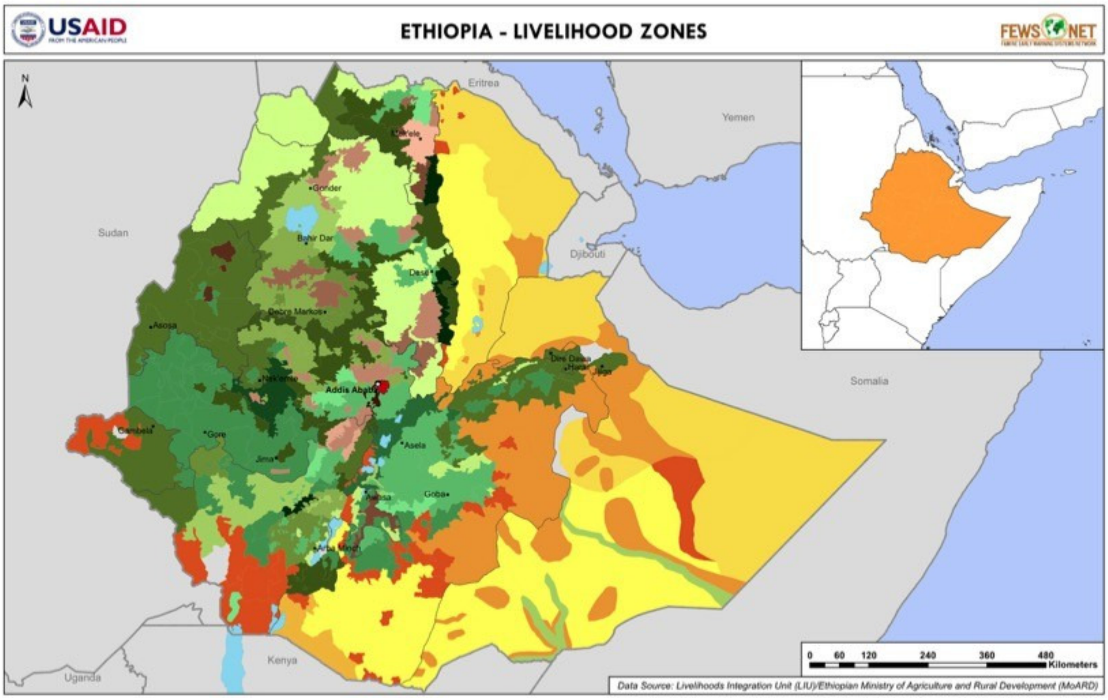


Figure 4-5: Livelihood zone map of Ethiopia (FEWSNET 2009)

The climatological distribution of rainfall for the 'Highlands' region alone (Here Highlands refers to all Ethiopia, excluding the driest eastern states of Somali, Afar and Tigray, see Figure 3-3 for map of states), shows some differences from the analysis of Ethiopia as a whole (Figure 4-6). For the Highlands region the CHIRPS rainfall data shows a unimodal distribution, as the driest grid boxes fall in the desert states that have been removed from the analysis.

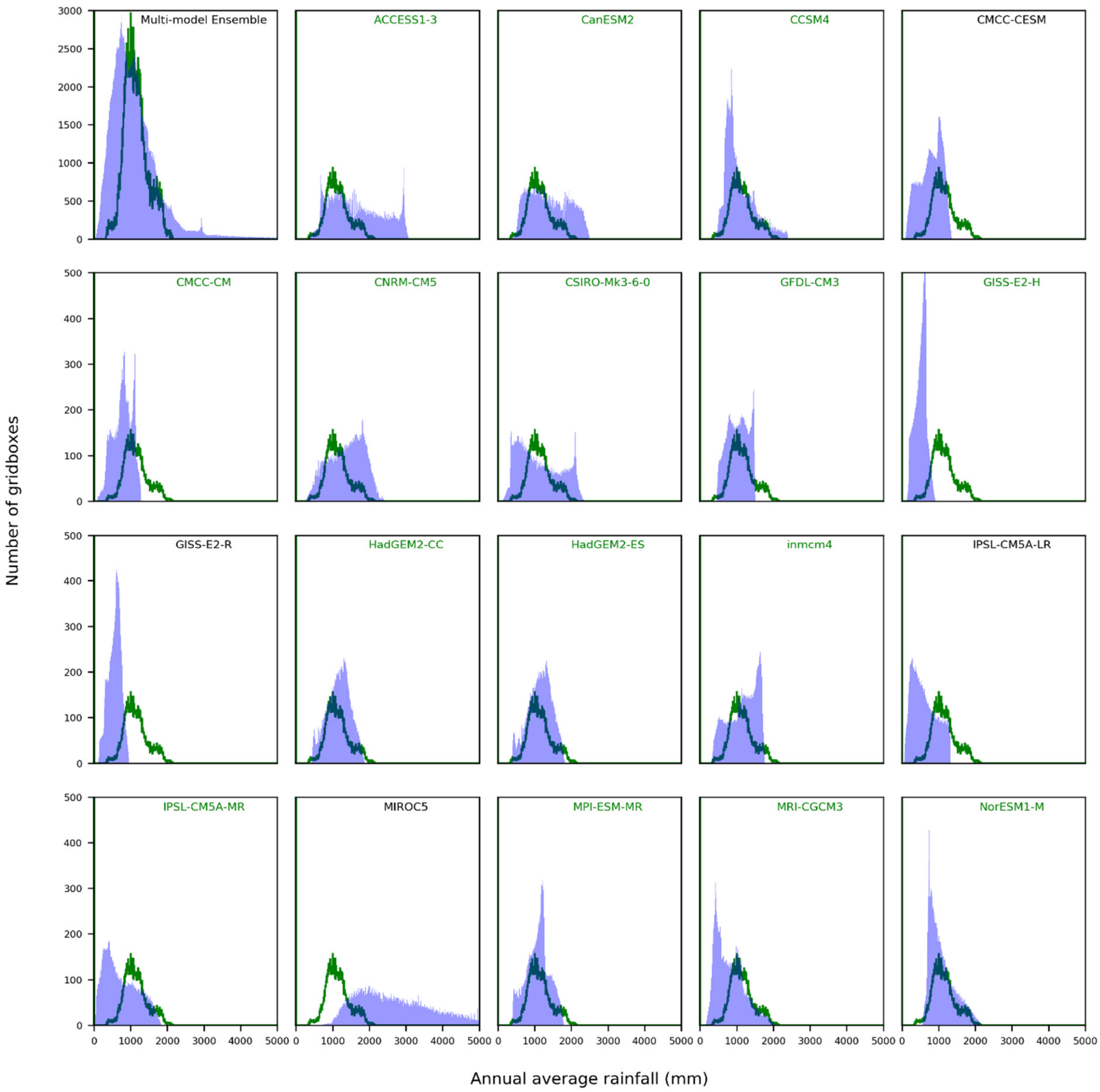


Figure 4-6: 1981-2005 annual rainfall climatology for CHIRPS (in green) and each climate model and the multi-model ensemble (in blue) for Highlands region of Ethiopia.

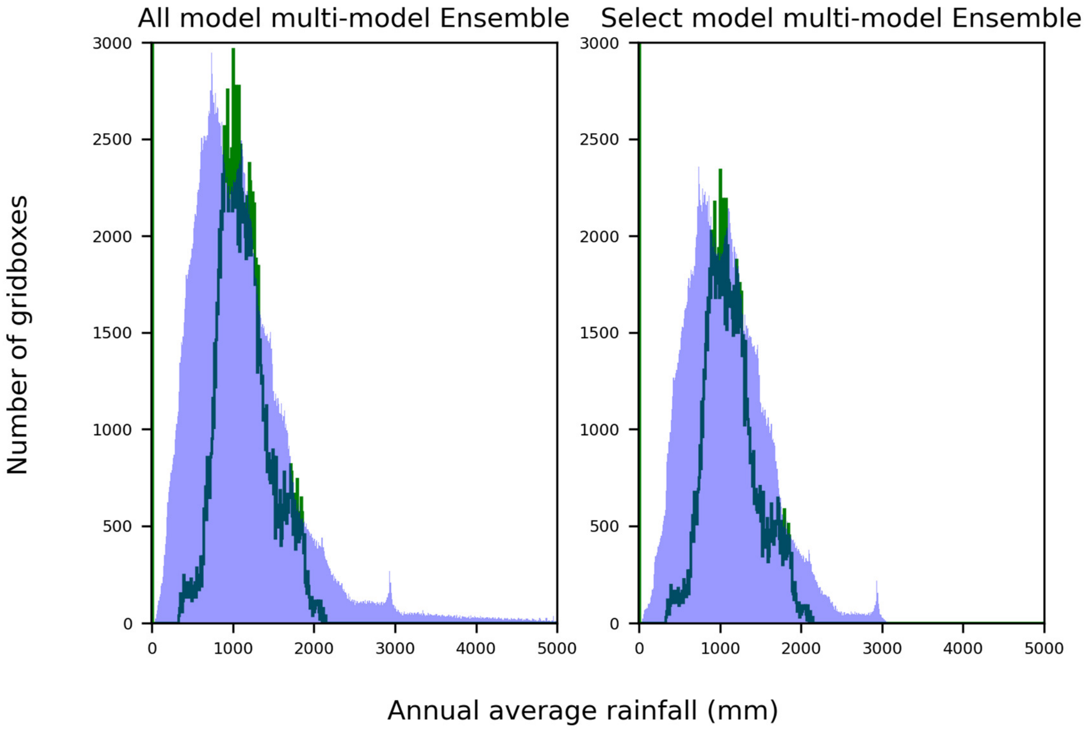


Figure 4-7: 1981-2005 annual rainfall climatology for CHIRPS (in green) and the full multi-model ensemble (left), and the sub-selected multi-model ensemble (right) (in blue), for Highlands region of Ethiopia.

The 19 climate models used in this study show a range of patterns of rainfall. They all show the western highland regions as wetter than the eastern arid regions, but a number of them are either too dry (for example GISS-E2-R) or too wet (for example MIROC), or have to large a range (for example ACCESS1-3). Some poorly capture the climatological profile of rainfall compared to CHIRPS (for example GISS-E2-R and CMCC-CESM), and the resolution of the models, particularly CMCC-CESM and IPSL-CM5A-LR, is low compared to the large variations in orography in Ethiopia. However, the MME does not perform too badly, in terms of capturing the climatological profile, as do a number of individual models. HadGEM2-ES in particular does well when considering how it captures the spatial pattern of climate, the climate profile and the model resolution. This model is therefore selected as the 'best performing' model.

Figure 4-7 shows the climatology for the multi-model ensemble for all 19 models overlaid with CHIRPS (same as first plot in Figure 4-6), alongside a sub-selected multi-model ensemble with the lowest performing models removed. CMCC-CESM, IPSL-CM5A-LR and MIROC are excluded from this second ensemble. Removing these three models does improve the representation of the climatology slightly, mainly by removing some of the outlying climate values. However, care needs to be taken when excluding models for a number of reasons. It is not necessarily the case that the models that best reproduce the recent past will also be the best at modelling the climate change signal, so only the very poorest, lowest resolution models have been excluded. Also the uncertainty range across different models is an important aspect of the analysis, particularly in this case where testing the sensitivity of food security outcomes to uncertainty in climate model projections is part of the motivation behind the study. It may be reasonable to have more confidence in the best performing models, but it is critical to capture a wide range of possible climate change projections to evaluate their potential impact on food security outcomes, to ensure that any long term policy decisions retain an awareness of the sensitivity of those decisions to uncertainty. Although as previously mentioned there is evidence that sub-selecting models that perform well against past observations may not necessarily constrain the range of future projections over Africa (Rowell, Senior et al. 2016). Too much certainty in long-term future projections runs the risk of leading to over-confident decision making. Knowing how sensitive outcomes are to differences in the projections helps to instil a sensible level of caution in any long term planning decisions. For this reason, although the sub-selection group of models are used in the analysis of the multi-model ensemble, all 19 models will be included in the individual model results.

Climate change projections

Figure 4-8, Figure 4-9 and Figure 4-10 show the change in rainfall and temperature between the baseline period (2006-2035) and the end of the century (2071-2100) under a high emissions scenario (RCP8.5) for each of the nineteen climate models included in this study.

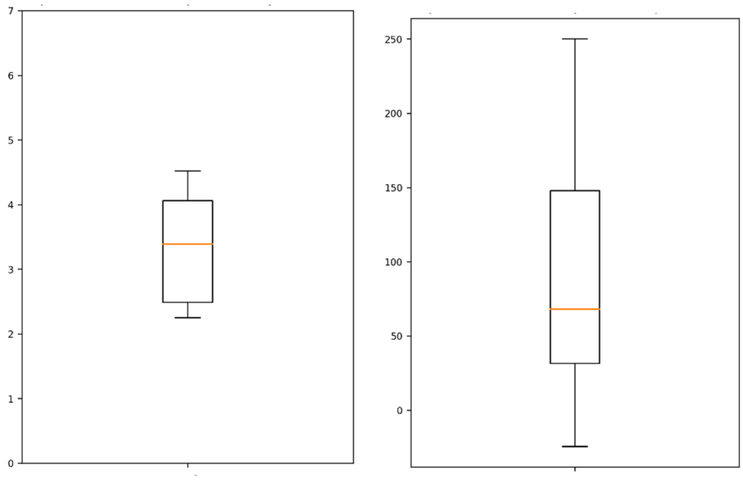


Figure 4-8: Change in average annual temperature (^{0}C) (left) and rainfall (mm/year) (right) range for all 19 CMIP5 models over Ethiopia.

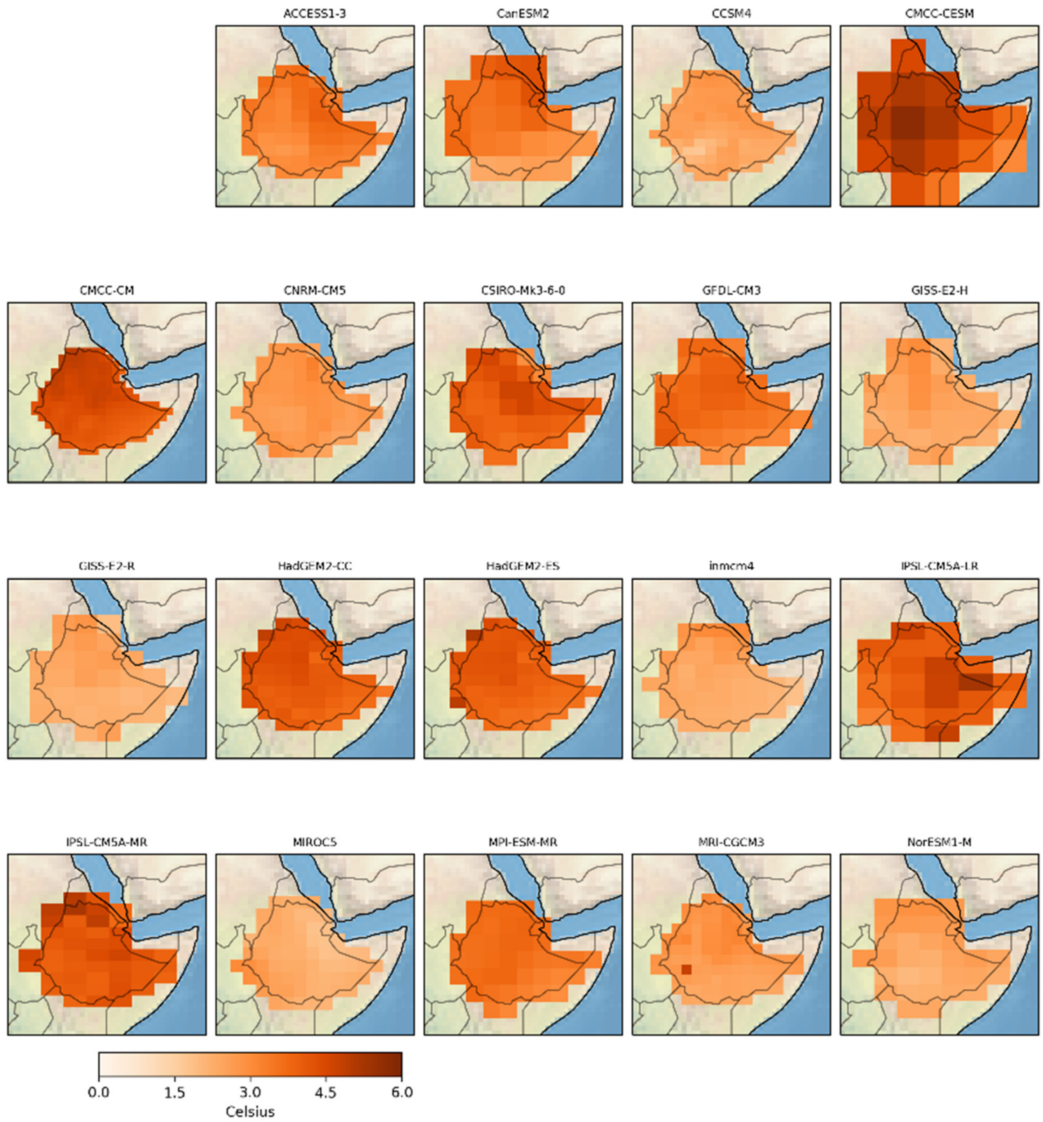


Figure 4-9: Change in temperature between the baseline climate (2006-2035) and the future climate (2071-2100) under RCP8.5, for each of the 19 CMIP5 models.

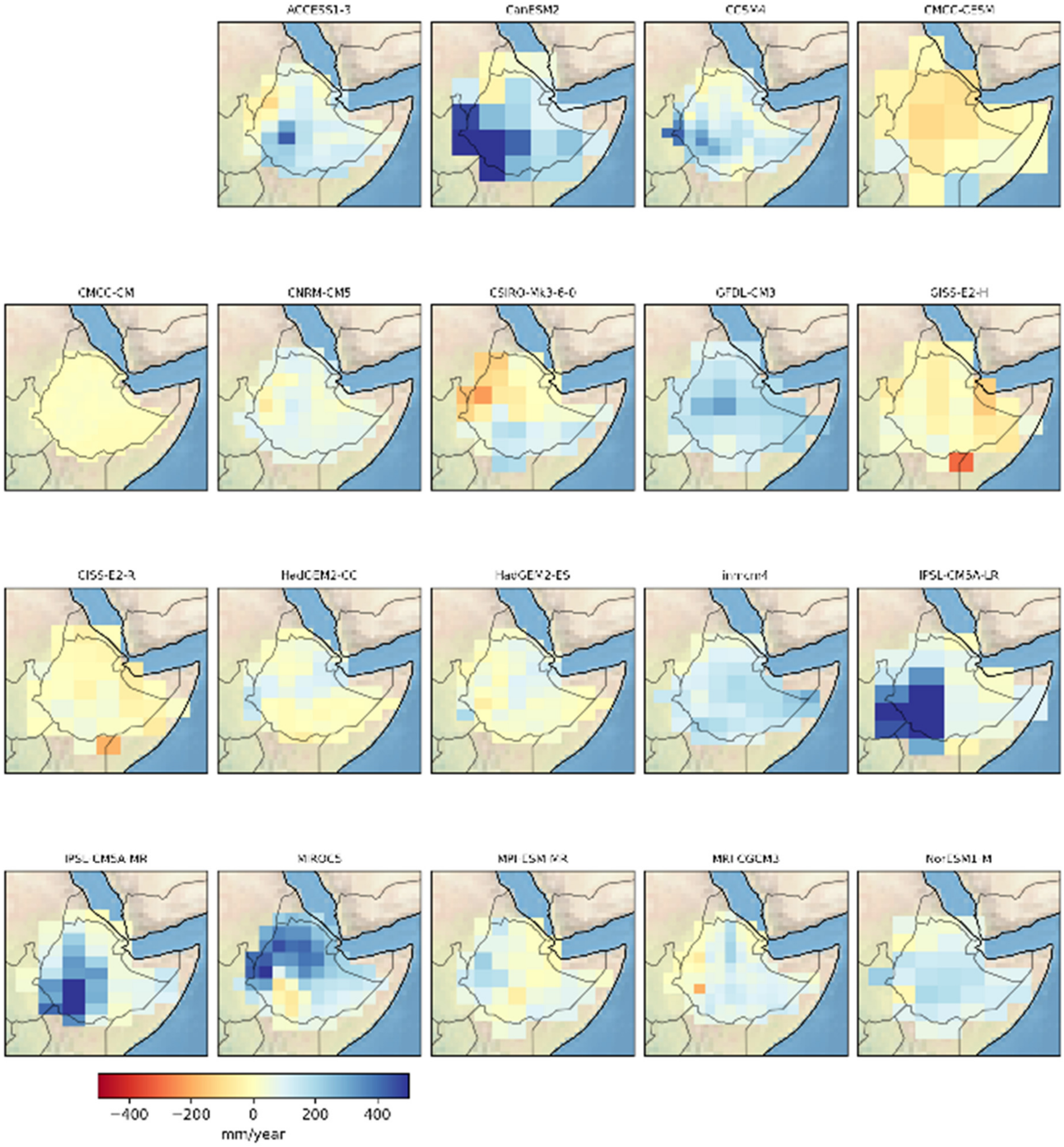


Figure 4-10: Change in precipitation between the baseline climate (2006-2035) and the future climate (2071-2100) under RCP8.5, for each of the 19 CMIP5 models.

All the models show an increase in temperature, while for rainfall different models show different levels, direction, and spatial patterns of change. The models with the smallest increase in rainfall, and a larger increase in temperature include HadGEM2-ES and HadGEM2-CC, which both performed well when compared with the CHIRPS rainfall data.

Climate variability

Model projections shown are for mean changes in annual rainfall and precipitation. However, what may be as important are changes to the inter-annual variability of rainfall and temperature. This is much more difficult to quantify for a number of reasons (Sippel, Zscheischler et al. 2015) and how climate variability will change is less well understood than changes in mean (Alexander and Perkins 2013). A number of studies conclude that climate change will result in more extreme events (IPCC 2012), but this increase in extreme events could occur due to a shift in the mean climate with no change in overall variability (Thornton 2014). Turco, Palazzi et al. 2015 and Huntingford, Jones et al. 2013 both find that globally temperature and precipitation variability have been relatively stable over the past few decades and many studies indicate a complex picture in terms of global changes in variability (Stouffer and Wetherald 2007, Wetherald 2009). More recently Bathiany, Dakos et al. 2018 looked at changes in temperature variability in a large ensemble (37 members) of global climate models from CMIP5, which included all 19 of the models used in this study. They found increasing variability in monthly temperatures for large parts of the world, including across most of Africa, by the end of the century under RCP 8.5. These results are supported by analysis undertaken by Siam and Eltahir (2017) which finds that flow variability in the Nile basin (a river fed by rainfall over the Ethiopian highlands) could increase by 50% by the end of the century under RCP 8.5. These findings are important because they support an interpretation of the food security outcomes in this study that includes increases to variability as well as changes in mean conditions.

Summary of climate analysis

The simulations over Ethiopia show a broad trend towards increasing annual rainfall totals, and increasing average temperatures, but there is disagreement between the models on the absolute level of change in both variables, and for precipitation, not all models agree on the sign of the change in all locations. One response to this could be to decide that uncertainty in the model projections means that climate scientists ‘don’t know’ what climate change will occur, and the projections are therefore unhelpful. In addition the climate model simulations provide data at a lower resolution than would be suitable for analysing the individual livelihood zones shown in Figure 4-5. However, a high level of temporal and spatial detail is not necessarily appropriate in climate model projections for long term planning decisions. As discussed in Chapter 2 climate change is a long term trend in the climate system and it is not the only thing that is changing over this timescale. For example, the livelihood zone landscape is likely to be different by the end of the century, for a number of reasons, which would invalidate any predictions of long term climate impacts on those livelihoods. Climate models provide a projection, rather than a prediction, of the climate trend. In this case, although the models show a spread of projections, there is information in them. They all agree that temperature is increasing, and that there will be some changes to precipitation. The majority project a modest increase in precipitation, with only a few showing decreases. None of the projections show decreases in temperature, and none show a large drying signal across Ethiopia. These projections can allow us to test the sensitivity of the food system to a range of climate change futures to see whether useful information for long term planning can be derived.

Developing a climate metric as proxy driver for climate-driven variability in production

The next step is to look at the relationship between climate and food production in Ethiopia, in order to develop a climate data proxy for food production. There are a number of possible approaches to this. The first might be to consider how suitable the climate is for the dominant crops. Chapter 2 looked at thresholds of rainfall, both relative to the climatology (annual rainfall totals below 60% and 80% of grid box climatological average), and absolute (annual rainfall totals below 600mm and 800 mm). The second approach would be to consider meteorological indices of drought and see how well these correspond to production output. The main challenge for any method for translating climate data into food security outcomes is the availability, suitability and quality of the non-climate data for this purpose. There are reported food production data available for Ethiopia for the four major cereal crops, although this is recorded on an annual basis for the country as a whole. The nature of the production data means that it would not be possible to consider the relative impact of local rainfall on local food production. It also means that the impact of the weather through the year on food production is aggregated up to a single value. So for example, delays in the rainfall, dry or hot periods, or unusual patterns of rainfall intensity may all affect production but the result is only expressed as a single annual production value.

In order to simplify things, in the first instance only total annual rainfall was explored. There were a number of reasons for this, including the fact that the production data is annual. Different regions of Ethiopia have different rainfall seasons, so isolating the timing of the rains at any given location is complex. Also, it would not be easy to identify how skilful the climate models are in reproducing intra-annual rainfall patterns, and therefore how reliable any modelled changes in these patterns might be.

In order to evaluate the best climate metric to use, the CHIRPS dataset was used to drive a set of metrics, which were then compared to the reported cereal production. Once a metric is identified from the 'observational' data, it can then be generated from the climate model data to look at both the present and the future under climate change.

Climate suitability metric

One potential metric for use as a proxy for food production is to look at the percentage of an area for which the climate is 'suitable' in any given year. In this case suitability is determined by whether or not the total annual rainfall at a grid box exceeds a threshold (60% or 80% of the grid box climatological average, or 600mm or 800mm total annual rainfall). The two absolute thresholds approximately correspond to the water requirement thresholds for the major crops (maize, sorghum, teff and wheat) (FAO 2016). The use of relative thresholds is also included in case there is a high level of adaptation to local climate by farmers.

For each suitability threshold the proportion of the area that is classed as suitable in each year from the CHIRPS rainfall data is determined. This is then plotted against cereal production and the correlation between the two determined.

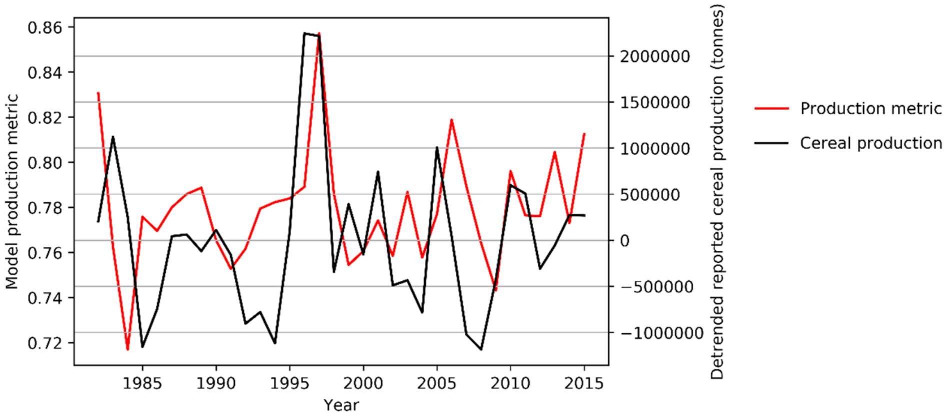


Figure 4-11: Production suitability metric for 600mm annual rainfall threshold and de-trended cereal production over Ethiopia.

Figure 4-11 shows a plot of the suitability metric for 600mm, calculated over the whole of Ethiopia, along with the reported cereal production anomalies for the same period. (These anomalies are relative to the 3 year de-trended mean. For the same anomalies expressed in percentage terms see Figure 3-2). This was repeated for each suitability threshold, and for suitability in different regions of Ethiopia, and for each of the cereal crops individually and together. The correlations were tested with and without a lag in the data, and it was found that introducing a lag did not improve the correlation. The results of the correlation testing for each combination (without any lag) are shown in Table 4-2. Correlation values above 0.3 are shown in green, above 0.4 in red, and above 0.5 in bold red. The metric does show some potential for use as a proxy for food production, particularly for a 600mm annual rainfall threshold. The higher correlations for particular states over other states or regions suggests that rainfall variability in key production areas is responsible for much of the variability in production. Examining this, a couple of interesting features emerge. The first is that the production metric over Beneshangul Gumu, an important cereal production region in the wetter highlands, shows almost no correlation with reported national cereal production. On closer investigation, this appears to be because Beneshangul Gumu such a wet region, that annual rainfall almost never falls below the suitability threshold. SNNPR state shows the largest correlation with national production, and this is possibly because SNNPR has the greatest variability in rainfall across the suitability threshold in cereal production regions, and so is the region which drives much of the variability in reported production. This corresponds to findings in Chapter 3, where marginal agricultural areas were affected most by inter-annual variability in rainfall. The mean annual rainfall over the period for Beneshangul and SNNPR is similar (1240mm/yr and 1255 mm/yr, respectively), but Figure 3-5 shows that while Beneshangul Gumu has no years in the historic record with mean annual rainfall below 600 mm/yr, there are several years where this is the case in some areas of SNNPR. If this metric was used then including rainfall over Beneshangul Gumu would reduce the effectiveness of the metric as a proxy for food production. Beneshangul Gumu is an important food production region and therefore should be included in order to capture any impact of climate change on this state. This raises questions about how appropriate the suitability metric would be for this study.

The second feature that emerges from the correlation table is that the metric in Afar (greyed out because, along with Tigray and Somali, cereal production levels are extremely low), has small but noticeable anti-correlation with reported production. It is not clear why this would be the case, but an initial thought is that it may be that the position of the rains in each year may mean that wetter years in Afar in the far north correspond to drier years in SNNPR in the south, if the annual rain bands track further north in those years. This is an interesting feature, but one outside the scope of this study to pursue.

Standard Precipitation Index

The next metric investigated was the Standard Precipitation Index (SPI) (McKee, Doesken et al. 1993). The SPI is a relatively simple measure of dryness and only requires precipitation as an input. This is important because as a result of the lack of reliable gridded meteorological data from observation, the CHIRPS rainfall data set is considered the most trustworthy representation of recent past climate available, and this only contains precipitation information.

SPI is calculated by fitting the monthly rainfall values to a probability distribution (usually a Gamma distribution or a Pearson Type III distribution), which is then transformed into a normal distribution. The mean SPI value for a location is therefore zero, positive SPI values correspond to wetter conditions and negative values correspond to dry conditions. The SPI can be calculated for a range of timescales, from 1-12 month rolling durations (WMO 2012).

In this case the monthly SPI values were calculated for each grid box over the 1981-2015 period using the CHIRPS rainfall data. (Python algorithms for calculating SPI were obtained from the US National Integrated Drought Information System (NIDIS) https://www.drought.gov/drought/climate-and-drought-indices-python). Both the Gamma distribution and Pearson Type III distribution fits were calculated, in order to test how much difference this made. The average monthly SPI values are taken for each year, over the whole area, as a measure of regional moisture availability, and this value plotted against reported cereal production. An annual value is required to compare with the annual reported cereal production data, and initially the sum of negative SPI values over each year was taken as this is a known measure of drought intensity (Kumar, Murthy et al. 2009). However, this only measures dryness, and fails to capture some of the benefit of years with higher moisture availability, so was not used.

An example of this for the whole of Ethiopia for SPI using a Gamma distribution fit is shown in Figure 4-12. The results for a Pearson Type III distribution fit were almost identical and so from this point all SPI values are calculated by using a Gamma distribution fit.

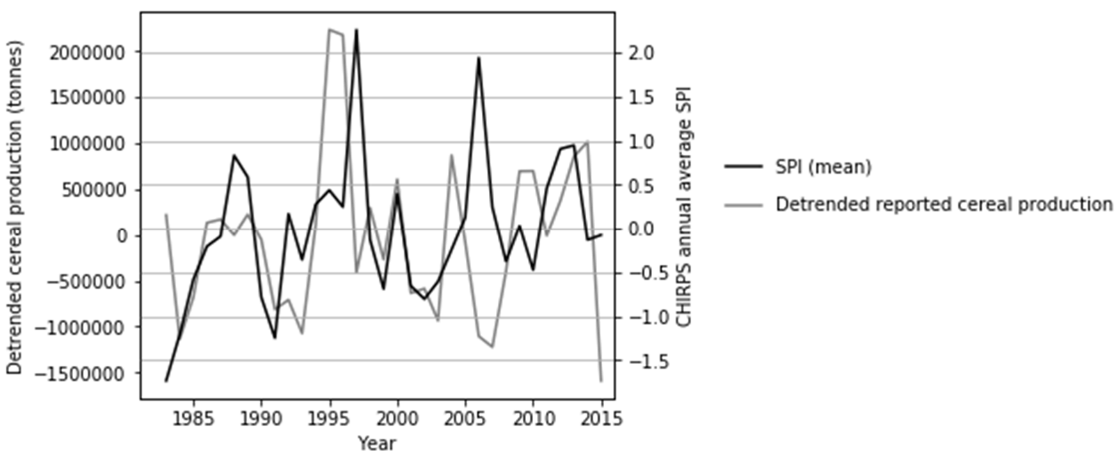


Figure 4-12: Standard Precipitation Index (SPI) calculated with a Gamma distribution fit for comparison, with de-trended reported cereal production, over Ethiopia.

Table 4-2: Correlations between production metric and reported national cereal production (1981-2015) (Pearsons r, 2-tailed P). Correlation values above 0.3 are shown in green, above 0.4 in red, and above 0.5 in bold red. (Calculated without any time series lag.)

	maize		sorghum		teff		wheat		Sorghum, teff, wheat		all cereal	
	600mm	800mm	600mm	800mm	600mm	800mm	600mm	800mm	600mm	800mm	600mm	800mm
Ethiopia	0.08 , 0.63	0.06 , 0.72	0.07 , 0.67	0.04 , 0.81	0.09 , 0.61	0.06 , 0.73	0.05 , 0.79	0.03 , 0.85	0.07 , 0.68	0.04 , 0.8	0.08 , 0.66	0.05 , 0.77
Production area	0.01 , 0.93	0.02 , 0.89	-0.0 , 0.99	-0.0 , 0.98	0.04 , 0.83	0.02 , 0.9	0.01 , 0.97	0.0 , 0.99	0.01 , 0.94	0.01 , 0.97	0.01 , 0.94	0.01 , 0.94
Afar	-0.25 , 0.16	-0.22 , 0.2	-0.27 , 0.12	-0.2 , 0.26	-0.23 , 0.19	-0.19 , 0.27	-0.26 , 0.13	-0.23 , 0.19	-0.25 , 0.14	-0.21 , 0.23	-0.25 , 0.14	-0.21 , 0.22
Amhara	-0.06 , 0.72	-0.02 , 0.91	-0.13 , 0.47	-0.11 , 0.52	-0.1 , 0.57	-0.07 , 0.7	-0.1 , 0.59	-0.07 , 0.69	-0.11 , 0.53	-0.09 , 0.63	-0.09 , 0.6	-0.06 , 0.72
Beneshangul Gumu	-0.0 , 1.0	0.34 , 0.04	0.0 , 1.0	0.31 , 0.07	0.0 , 1.0	0.23 , 0.19	-0.0 , 1.0	0.3 , 0.08	0.0 , 1.0	0.28 , 0.1	-0.0 , 1.0	0.31 , 0.07
Gambela	0.14 , 0.42	0.32 , 0.06	0.19 , 0.28	0.27 , 0.12	0.14 , 0.44	0.29 , 0.09	0.13 , 0.45	0.26 , 0.14	0.15 , 0.38	0.28 , 0.11	0.15 , 0.39	0.29 , 0.09
Oromia	0.1 , 0.57	-0.04 , 0.84	0.11 , 0.54	0.0 , 0.98	0.11 , 0.53	0.01 , 0.97	0.09 , 0.61	-0.03 , 0.87	0.1 , 0.56	-0.01 , 0.97	0.1 , 0.56	-0.02 , 0.92
E_Oromia	-0.0 , 1.0	-0.11 , 0.51	0.0 , 1.0	-0.08 , 0.63	0.0 , 1.0	-0.14 , 0.43	-0.0 , 1.0	-0.13 , 0.44	0.0 , 1.0	-0.12 , 0.5	-0.0 , 1.0	-0.12 , 0.5
SNNPR	0.48 , 0.0	0.38 , 0.02	0.43 , 0.01	0.33 , 0.05	0.45 , 0.01	0.36 , 0.03	0.41 , 0.01	0.33 , 0.05	0.43 , 0.01	0.35 , 0.04	0.45 , 0.01	0.36 , 0.03
Somali	0.08 , 0.64	-0.1 , 0.58	0.11 , 0.54	0.0 , 0.99	0.1 , 0.59	-0.04 , 0.82	0.04 , 0.82	-0.1 , 0.57	0.08 , 0.64	-0.05 , 0.8	0.08 , 0.64	-0.06 , 0.71
Tigray	0.03 , 0.87	0.07 , 0.67	-0.05 , 0.77	0.0 , 0.98	0.04 , 0.83	0.03 , 0.87	0.01 , 0.94	0.04 , 0.83	-0.0 , 0.99	0.02 , 0.9	0.01 , 0.96	0.04 , 0.81
BG, SNNPR	0.48 , 0.0	0.43 , 0.01	0.43 , 0.01	0.37 , 0.03	0.45 , 0.01	0.38 , 0.02	0.41 , 0.01	0.37 , 0.03	0.43 , 0.01	0.38 , 0.02	0.45 , 0.01	0.4 , 0.02
BG, SNNPR, Gambela	0.48 , 0.0	0.45 , 0.01	0.43 , 0.01	0.39 , 0.02	0.45 , 0.01	0.4 , 0.02	0.41 , 0.01	0.39 , 0.02	0.44 , 0.01	0.4 , 0.02	0.46 , 0.01	0.42 , 0.01
BG, SNNPR, Gambela and E Oromia	0.23 , 0.18	0.14 , 0.43	0.21 , 0.23	0.11 , 0.54	0.2 , 0.24	0.11 , 0.53	0.17 , 0.34	0.09 , 0.6	0.2 , 0.26	0.1 , 0.55	0.21 , 0.23	0.12 , 0.5
All Ethiopia (except Afar, Tigray and Somali)	0.12 , 0.5	0.07 , 0.69	0.1 , 0.55	0.04 , 0.8	0.11 , 0.51	0.07 , 0.7	0.09 , 0.59	0.04 , 0.82	0.11 , 0.54	0.05 , 0.77	0.11 , 0.53	0.06 , 0.74

As with the suitability metric the correlation between SPI and reported cereal production was calculated for regions over Ethiopia, and for the four major cereal crops, see Table 4-3.

The correlations between SPI and reported cereal production are substantially better than those for the previous threshold suitability metric, for all areas where cereals are grown. This includes areas like Beneshangul Gumu. This is likely to be simply because SPI is a much more realistic representation of the climate suitability for crop production in each year. The Production Suitability indicator depended on the proportion of the area being deemed 'suitable' or 'unsuitable' depending on a single threshold. The SPI metric gives provides a graduated measure of climate suitability, which better reflects the actual production variability. The best correlations between SPI and national production come when comparing annual average SPI over the combined area of Beneshangul Gumu, SNNPR and Gambela, which is where much of Ethiopia's cereal production is located (r = 0.5). Although the correlation is not quite as high there is still a good relationship between SPI and reported cereal production when the 'Highlands' region as a whole is considered (this is all Ethiopia except the arid regions of Afar, Tigray and Somali) (r = 0.47). This is important because the climate models have relatively low spatial resolution, as can be seen in Figure 4-3. The larger the area analysed the more model grid boxes will be included and the better the representation of the climate model signal will be. Finding the appropriate spatial scale is a critical aspect of climate and security assessments (Lewis and Lenton 2015). Here there is a tension between representing drought events at sufficient local detail to pick up the impact on individual states or even livelihood zones, and analysing climate model data over a sufficiently large area to make the interpretation of any projection meaningful. In this case it is clear from the initial climate analysis that looking at Ethiopia as a whole, with its extreme variation in climate and orography is not a reasonable approach from a food production or meteorological perspective. However, looking at individual states is not compatible with the resolution of the climate model data (indeed the resolution of the coarsest models is insufficient to represent Afar and Tigray at all because of their small size). A compromise scale could therefore be to interpret the climate model projections over the Highlands region. The fact that the SPI metric shows a correlation with reported food production of r = 0.47 (and r = 0.5 for the most important crop, maize) supports this.

Table 4-3: Correlations between annual average SPI (Gamma distribution fit) and reported national cereal production (1981-2015) (Pearsons r, 2-tailed P).

	maize	sorghum	teff	wheat	Sorghum, teff, wheat	all cereal
Ethiopia	0.48 , 0.0	0.43 , 0.01	0.4 , 0.02	0.42 , 0.02	0.42 , 0.01	0.45 , 0.01
Production area	0.48 , 0.0	0.42 , 0.01	0.42 , 0.02	0.42 , 0.01	0.43 , 0.01	0.45 , 0.01
Afar	0.2 , 0.26	0.09 , 0.61	0.09 , 0.61	0.11 , 0.54	0.1 , 0.58	0.13 , 0.45
Amhara	0.37 , 0.03	0.28 , 0.12	0.28 , 0.12	0.32 , 0.07	0.29 , 0.1	0.32 , 0.07
Beneshangul Gumu	**0.5 , 0.0**	0.4 , 0.02	0.46 , 0.01	0.45 , 0.01	0.44 , 0.01	0.47 , 0.01
Gambela	**0.54 , 0.0**	0.45 , 0.01	**0.52 , 0.0**	0.48 , 0.0	0.49 , 0.0	**0.51 , 0.0**
Oromia	0.35 , 0.05	0.38 , 0.03	0.34 , 0.05	0.33 , 0.06	0.36 , 0.04	0.36 , 0.04
E_Oromia	0.42 , 0.01	0.33 , 0.06	0.42 , 0.02	0.39 , 0.03	0.38 , 0.03	0.4 , 0.02
SNNPR	0.44 , 0.01	0.41 , 0.02	0.46 , 0.01	0.42 , 0.01	0.44 , 0.01	0.44 , 0.01
Somali	0.31 , 0.08	0.33 , 0.06	0.22 , 0.22	0.25 , 0.15	0.27 , 0.12	0.29 , 0.1
Tigray	0.37 , 0.04	0.34 , 0.06	0.28 , 0.12	0.34 , 0.05	0.32 , 0.07	0.34 , 0.05
BG, SNNPR	**0.5 , 0.0**	0.44 , 0.01	**0.5 , 0.0**	0.46 , 0.01	0.48 , 0.01	0.49 , 0.0
BG, SNNPR, Gambela	**0.51 , 0.0**	0.45 , 0.01	**0.51 , 0.0**	0.47 , 0.01	0.48 , 0.0	**0.5 , 0.0**
BG, SNNPR, Gambela and E Oromia	0.49 , 0.0	0.42 , 0.01	0.49 , 0.0	0.44 , 0.01	0.46 , 0.01	0.47 , 0.01
All Ethiopia (except Afar, Tigray and Somali)	**0.5 , 0.0**	0.44 , 0.01	0.46 , 0.01	0.44 , 0.01	0.45 , 0.01	0.47 , 0.01

Alternative drought metrics

The SPI metric does a better job as a proxy for cereal production in the climate data than the suitability threshold metric, but there are some important downsides to the SPI. The main one, shared by the suitability metric, is that as it is based on precipitation only and does not account for potential evapotranspiration. For a stationary climate this may not be a problem. The inter-annual variability of precipitation in Ethiopia is much higher than for temperature, and so a measure of drought that only looks at rainfall is likely to be sufficient to represent the conditions experienced. The problem comes when looking at climate change, where temperature is not stationary. All the climate models show an increase in temperature over time, and if this is not accounted for in the water availability analysis (which it will not be if SPI is used as the measure), the impact of climate change on water availability for crop production will be underestimated.

Other indices that do incorporate temperature include Standardised Precipitation and Evapotranspiration Index (SPEI) (Vicente-Serrano, Begueria et al. 2010) and the Palmer Drought Severity Index (PDSI) (Dai, Trenberth et al. 2004). The SPEI retains many of the features of the SPI in its flexibility and the potential to look at drought over a range of timescales, whilst also incorporating evapotranspiration, making it more suitable for looking at the impact of climate change on drought. The PDSI takes this further by also incorporating local soil properties. Some issues with the PDSI have been identified (Trenberth, Dai et al. 2013), not least the sensitivity of the index to the calibration period. Some of these have been addressed in the formulation of the self-calibrating PDSI (scPDSI) (Wells, Goddard et al. 2004), but the index still presents problems for consideration in this analysis.

The first problem with the PDSI also applies to all the indices under consideration and that is the lack of consistency between reanalysis datasets. Sufficient reliable, long term records of rainfall and temperature providing good coverage over Africa as a whole are not available, and, as discussed, there are large differences between gridded data products. There is little that can be done about this, and the decision here is to use the CHIRPS rainfall data set to represent the recent past was taken for this reason. The problem with this is that both the SPEI and the PDSI (and scPDSI) require temperature and precipitation as inputs. Without consistent gridded datasets of both variables, it is not possible to produce values of SPEI or PDSI for which there is any expectation of a correlation with reported food production, even if the indices themselves are robust measures of drought as it would affect crop production. Second, PDSI (and scPDSI) also requires an empirically derived value for available water capacity (AWC) (the difference between moisture content at 333 mbar and 15,000 mbar suctions). This value varies across Ethiopia, and over time, and there is little or no reliable data on AWC for Ethiopia at a national scale. Any formulation of PDSI (or scPDSI) can only be approximate on the measurement of AWC, therefore very difficult to use in this situation.

These data issues illustrate a common difficulty in providing information on climate change that can be interpreted in a security context. To be able to study the relationship between weather and climate and security outcomes depends on having data on the recent past climate in which there is sufficient confidence, and non-climate data on the security outcomes with which the climate can be compared. The suitability and SPI metrics do correlate well with reported national food production, and so address many of the potential challenges around temporal and spatial compatibility between the two data types. However, they are not suitable for looking at long term climate change because they fail to capture an important part of the climate trend for future drought. The more sophisticated SPEI and PDSI better represent the climate drivers of drought in a non-stationary climate where both temperature and rainfall are important factors, but the present day climate data is not available to validate them against the food production impacts.

As the aim of this study is to take a pragmatic approach to providing useful guidance on the role of climate change, one option is to compare the SPEI with the SPI in the climate model data. Given that SPI correlates well with reported cereal production, if the SPEI also correlates well with the SPI in the model data over the same period, there are some grounds for looking at SPEI as an alternative proxy for food production.

Standardised Precipitation and Evapotranspiration Index (SPEI)

The comparison between SPI and SPEI for each of the climate models for the 1981-2005 period (Figure 4-13), shows that they do produce similar results. (The mean correlation between the two values across all the models is $r = 0.86$). In some years temperature plays more of a role in the index value than in others, and this can be seen in the higher index values for SPEI over SPI later in the time period for some models (particularly the drier ones), as temperature has of course been increasing even in the recent past. The 1981-2005 period was used because this is the period for which the modelled historical climate model runs overlap with the available CHIRPS data.

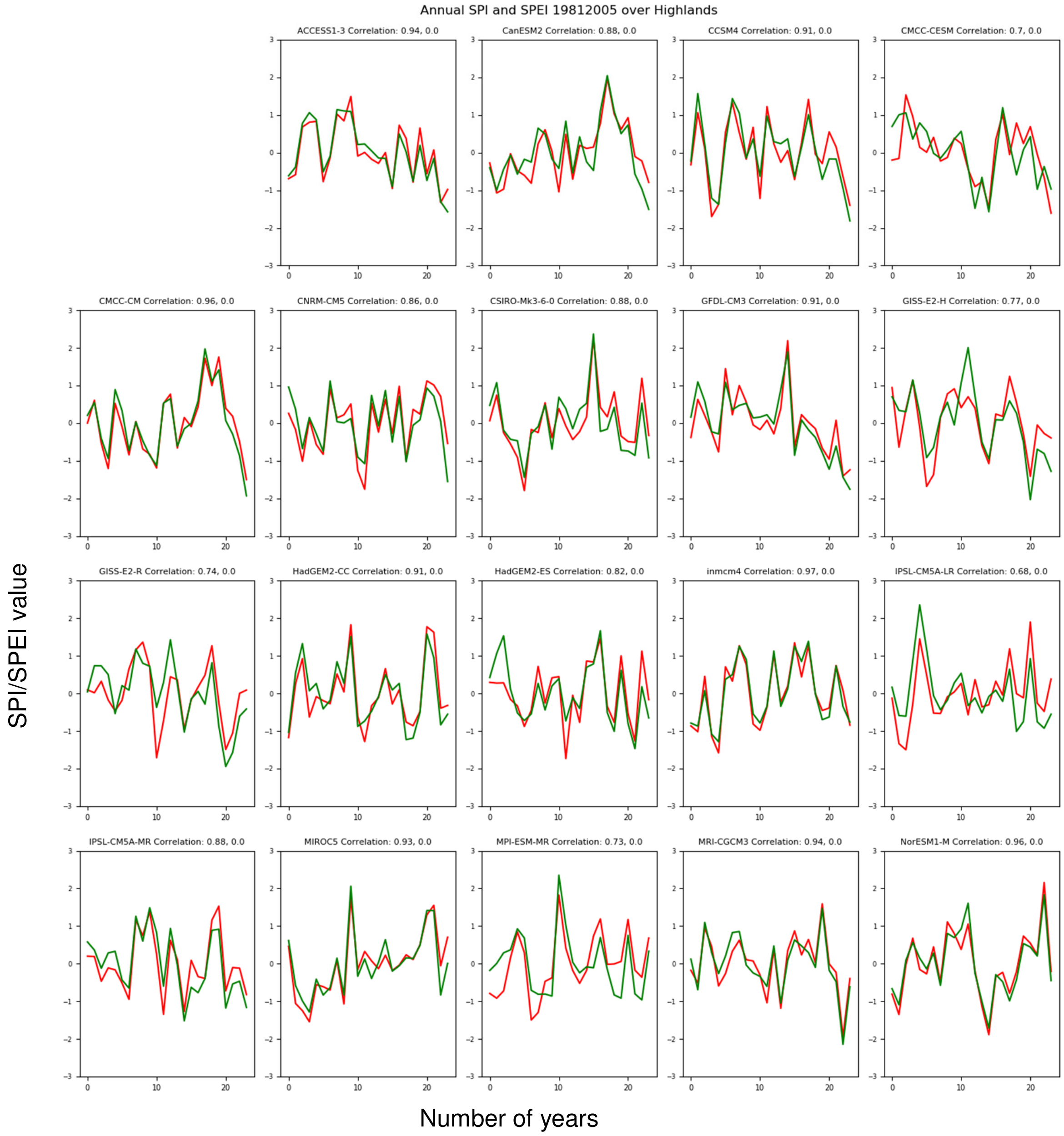


Figure 4-13: SPI (red) and SPEI (green) values for the period 1981-2005 for each of the climate models for the 'Highlands' region of Ethiopia.

However, the two indices are sufficiently similar in this comparison that using SPEI in an analysis of future climate change impacts on food security could be justified.

One thing to note here about the use of both the Standardised Precipitation Index (SPI) and the Standardised Evapotranspiration and Precipitation Index (SPEI), is that by definition they are standardised metrics. The data is fitted to a distribution (in this case a Gamma distribution) and calibrated against a reference period to transfer the data to normal distribution. In the comparisons between the two indices in Figure 4-13 the time period used is only 24 years long, and while there is some trend in temperature (and to a much lesser extent in rainfall in some models), these trends are small compared to those over longer climate change time periods. To evaluate long term food security output it is therefore necessary to calculate both SPI and SPEI over a single long time series from the present to the end of the projection period, rather than calculating the index values for two individual climatological periods separately.

Figure 4-14 shows the full time series of SPI and SPEI from 2006 to 2100. It clearly shows the increasing influence of temperature on the measure of drought for the SPEI. SPI shows either little change or some decrease in the intensity of drought events as measured by the index, depending on the change in precipitation projected. (The two indices do not match as closely in the initial period as they did in Figure 4-13, because the scale is standardised over the whole time period, as previously discussed. This also affects the way variability is comparatively represented in the two indices. Putting both indices on the same scale means that SPI with little or no trend over the period has the appearance of larger variability. For SPEI the large trend suppresses the range of variability that can be shown on the same scale.)

Figure 4-15 shows the same data in the form of box plots, and just for the first 30 years of data (2006-2035) and the final 30 years (2071-2100). Most models, particularly those with a strong warming trend show a marked increase in drought intensity, as measured by the SPEI, but little change, or a reduction in drought intensity when measured by the SPI, which only uses precipitation as an input.

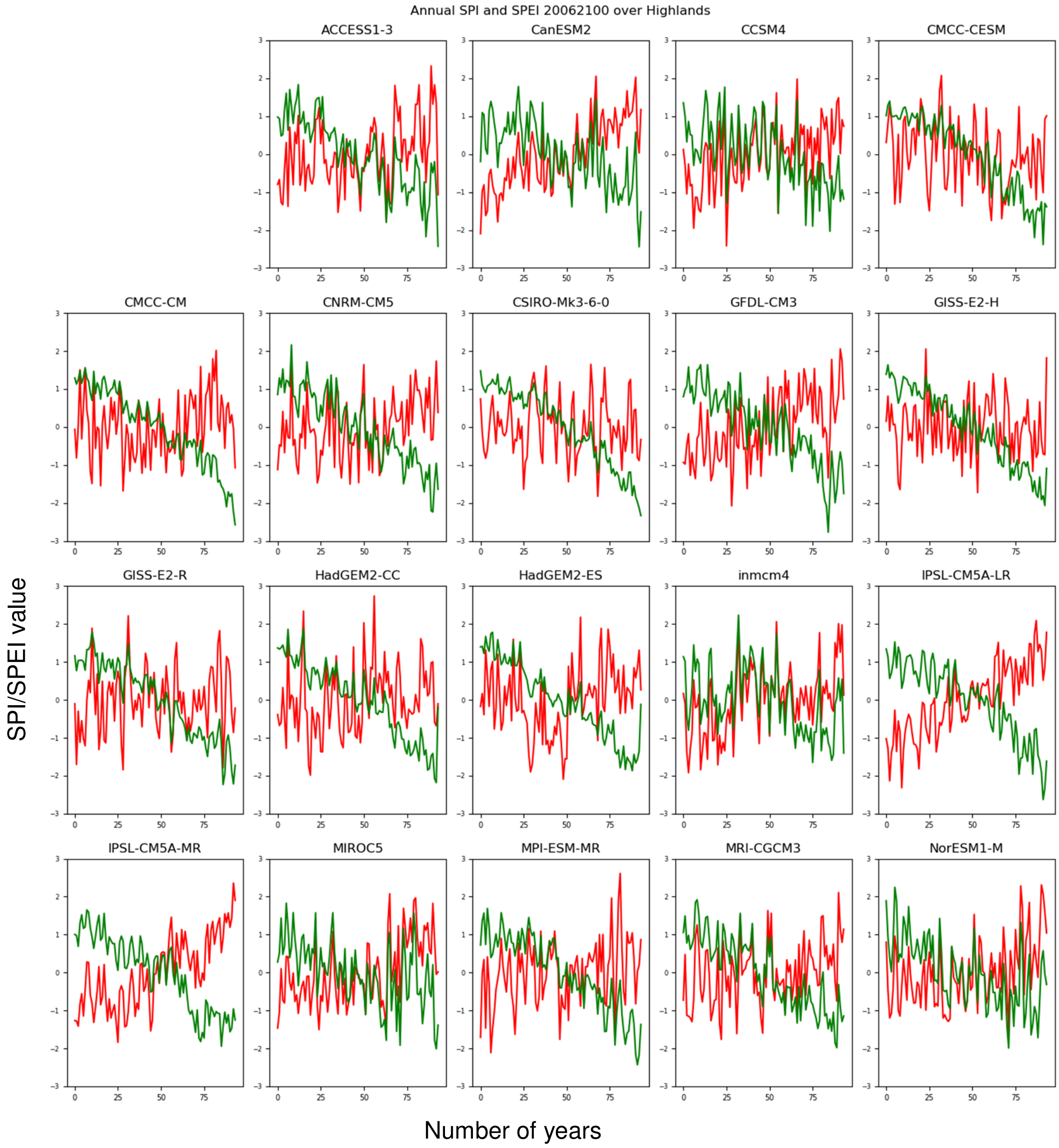


Figure 4-14: SPI (red) and SPEI (green) for 2006-2100 for each of the climate models over Highlands region of Ethiopia

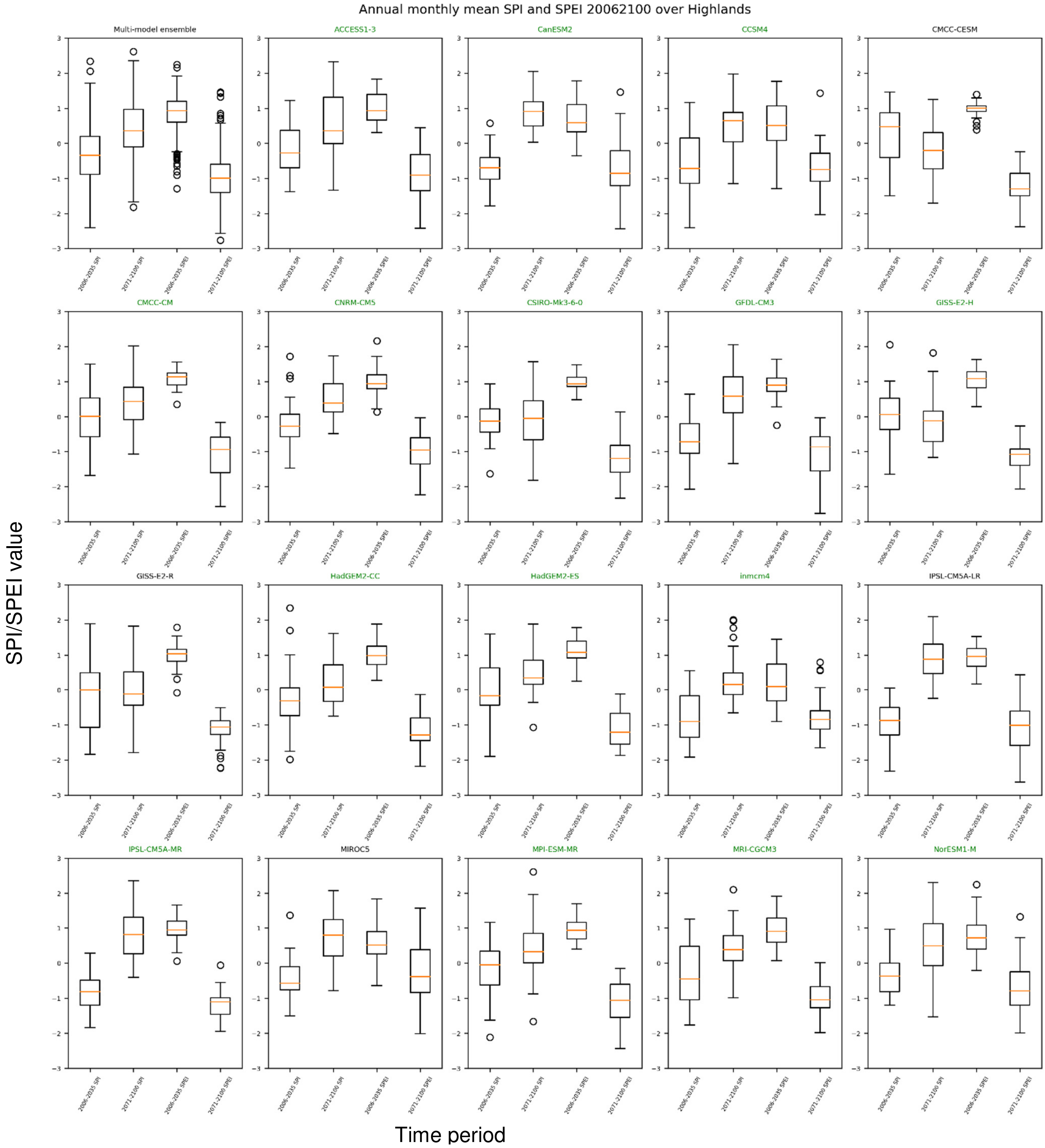


Figure 4-15: Boxplots of SPI and SPEI for the 2006-2035 and 2071-2100 periods for the 'Highlands' area of Ethiopia for the sub-selected multi-model ensemble and each of the climate models individually. (Model names in green indicate the model contributed to the multi-model ensemble in the top left corner).

Selecting a proxy metric for food production

Having explored a number of possible options for developing a proxy metric for food production, some of the necessary compromise associated with developing a pragmatic but meaningful metric has emerged. Any proxy metric needs to be validated against the actual value that it is proxy to (in this case cereal production), but the climate data available to do this is limited. The Standardised Evapotranspiration and Precipitation Index (SPEI) is a much better measure for evaluating a water availability in a non-stationary climate than the Standardised Precipitation Index, and indeed the climate change signal is quite different between the two (Figure 4-14). However, reliable data that could approximate to observed climate for temperature and precipitation, required to produce SPEI data, and that could be checked for correlation with cereal production data, is not available. The availability and assumed reliability of the CHIRPS data makes calculation of the SPI possible, and this correlates well with reported cereal production. In addition SPI and SPEI are similar when calculated from climate model data for the recent past, and as such one option is to use SPEI as the proxy metric for food production, through a second hand verification process via the SPI measure. SPEI and SPI yield similar results in the model baseline period, suggesting that SPEI would be a reasonable proxy for cereal production, as SPI is.

Developing a simple food systems model

Having developed a metric for national cereal production in Ethiopia, the next step is to consider a simple model for translating this into food security terms. Defining food security is not necessarily straightforward, as it is not only food production (Smith, Pointing et al. 1993). The number of different definitions that exist reflect the complexity of the problem and the many differing perspectives on how food security can be understood. The most widely accepted and broadest definition is possibly that developed in 1996 at the World Food Summit which states that ‘Food security exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food which meets their dietary needs and food preferences for an active and healthy life’. There are clearly a large number of things incorporated in this definition, most of which are social, political or economic in nature, which a study on climate cannot address. Perhaps a more practical way of considering the problem is to use the World Food Programme’s understanding, which is to think of food security as having three dimensions: Availability, Access and Utilisation (WFP 2018). Here availability refers to the need for there to be sufficient food produced. Access is the requirement to be able to acquire sufficient food, for example through purchase, which includes the need for funds for access to markets. Finally utilisation refers to the nutritional value of the food consumed. Whilst climate variability and change can have an impact on food utilisation, this is something more difficult to measure, and of the three components of food security, probably the one least directly affected. However, both availability and access are directly impacted by climate, and this is particularly true in developing countries like Ethiopia. In Ethiopia around 76% of the population are employed in agriculture (World Bank 2017), and the majority of these are on smallholder, subsistence farms of less than 1 hectare in size (CSA 2013). This means that for the majority of the population their income is directly related to food production. In low production years the result is not only lower availability of food (potentially pushing up prices), but also a reduction in income and therefore purchasing power, reducing access to food (Bachewe, Berhane et al. 2016). This is a simplistic view of the interaction between climate and food security, and of course communities and households have a number of ways of managing this. These include releasing assets (including stored food), turning to gifts, remittances or donations, seeking alternative employment in poor years or participating in insurance schemes (Corbett 1988). However, this double impact of low food production affecting both the total food available and the income required to purchase food to make up the shortfall, is an important feature of food insecurity in subsistence farming economies in developing countries. Any simple model of food security climate outcomes in Ethiopia needs to capture this and translate the changes in climate into a combined outcome on both food availability and access. It is important to note that the development of such a model would not capture the wider complexity of the food system, and would not have predictive capability on long term food security outcomes. Instead, the aim here is to provide a method to translate climate model data into meaningful food system terms. This would make it possible to explore the potential broad impact of changes in climate on the food system, and the ways changes to the system might affect the relationship between climate and food security. As was shown in Chapter 2, it is common for statements to be made about the level of threat that climate change represents, without quantified analysis, based on a subjective interpretation of climate risk (Lewis and Lenton 2015). Such statements are often made by security analysts, without the input of climate scientists moderating the way the climate data are interpreted. In this case, it is hoped that a simple food system model that captures both the availability and access components of food security will meet that need to quantify the scale of climate change in food security terms. This model represents a simple tool for evaluating scale, direction and sensitivity to uncertainty and system change. Such a model could be a useful way of not only bridging the gap between climate data and an understanding of scale and priority, but also demonstrate the potential of such an approach for wider application.

Model design

As discussed, food security depends on both availability and access. Ethiopia imports very little food (CSA 2014), and so food availability is primarily a function of in-country production. Access is, among other factors, largely a measure of purchasing power, and any simple food systems model needs to capture the climate impact on both these factors. The food system design for this study is as follows:

$$Food\ Security\ Metric = \frac{(Production\ metric + Income\ metric)}{2} \tag{1}$$

The Food Security Metric is a value of 0-1 indicating the level of food security potential associated with climate for a given set of food system parameters in an individual year (where zero represents strongly adverse food security conditions, and one represents optimal food security conditions, given the climate state).

$$Production\ metric = Climate\ metric\ \times\ (1 - yield\ gap) \tag{2}$$

The Production metric is based on the SPEI climate metric developed in this chapter that correlates with reported production, normalised to a 0-1 scale, as a measure of relative climate stress. This is then multiplied by the proportion of the optimal yield that can be achieved in a given food system. In ideal climate conditions, with no yield gap this value will be one. In conditions where production efficiency is very low the value will be closer to zero.

$$Income\ metric = w + \left((1 - w) \times Production\ metric\right) \qquad (3)$$

Where w is the proportion of income from non-agricultural sources.

The Income metric includes both agricultural and non-agricultural income, with the agricultural income being scaled by the Production metric. In years when the climate conditions lead to crop failure (Production metric is zero), income will be solely driven by the proportion of income that comes from non-agricultural sources, and if there are no alternative income sources, then this value will also be zero. For food systems where no income is derived from agricultural activity, this value will always be one.

This simple model does not capture any of the complexity of a real food system, the range of crops, trading relationships, physical aspects of the access of households to markets, food stocks from previous years, aid, or import or export conditions. However, this simple model of the relationship between climate suitability and food security potential captures two important features. The first is the influence of production variability on both availability and access to food. The second is that both of these are moderated by the food system conditions, specifically the gap between the maximum yield possible and the yield actually achieved, and the dependence on agricultural for income. For Ethiopia both of these factors are important limitations on food production and access.

Another important feature of this simple model is that it measures food security stress relative to the optimal, rather than as an absolute measure. So if the country cannot grow enough food for the population, even in perfect climate conditions, with no yield gap, this will not be captured. Instead, it looks at the scale of stress on the food system that climate variability and change imposes, under different food system conditions.

Setting the model parameters for Ethiopia

The input for this simple food system model is the SPEI climate metric, which is driven by the climate model data for the region of interest (in this case the Highlands region of Ethiopia). In addition, two aspects of the food system can be varied. These are the yield gap and the proportion of income that comes from non–agricultural sources.In both cases this is a value from zero to one, and needs to be set externally. Both these values vary across Ethiopia, across livelihoods and income groups. However, as the focus of this study is to understand something general about the relationship between climate change and the potential to meet food security needs, an indicative value for the country as a whole is sufficient.

Data on current yield gaps was obtained from the Global Yield Gap Atlas (GYGA 2017), for the major cereal crops in Ethiopia. The proportion of the population employed in agriculture was used as a measure of national dependence on income from farming. This metric was selected because of the variability of income types across the country and the lack of data on livelihood incomes. This metric is also more meaningful as a national indicator, and expresses the economic dependence of the population as a whole on agricultural income. This data for the present day was obtained from the World Bank (World Bank 2017).

To look at long-term future food insecurity the climate metric was driven by the climate change projections, under RCP8.5 to the end of the century. The food system conditions were then varied systematically, in order to test the sensitivity of the Food Security metric to these system changes, relative to the changes associated with long term climate change. Figure 4-16 outlines the various combinations of scenarios of climate change, yield gap reduction and reduction in economic dependence on agriculture that were tested using the simple food system model.

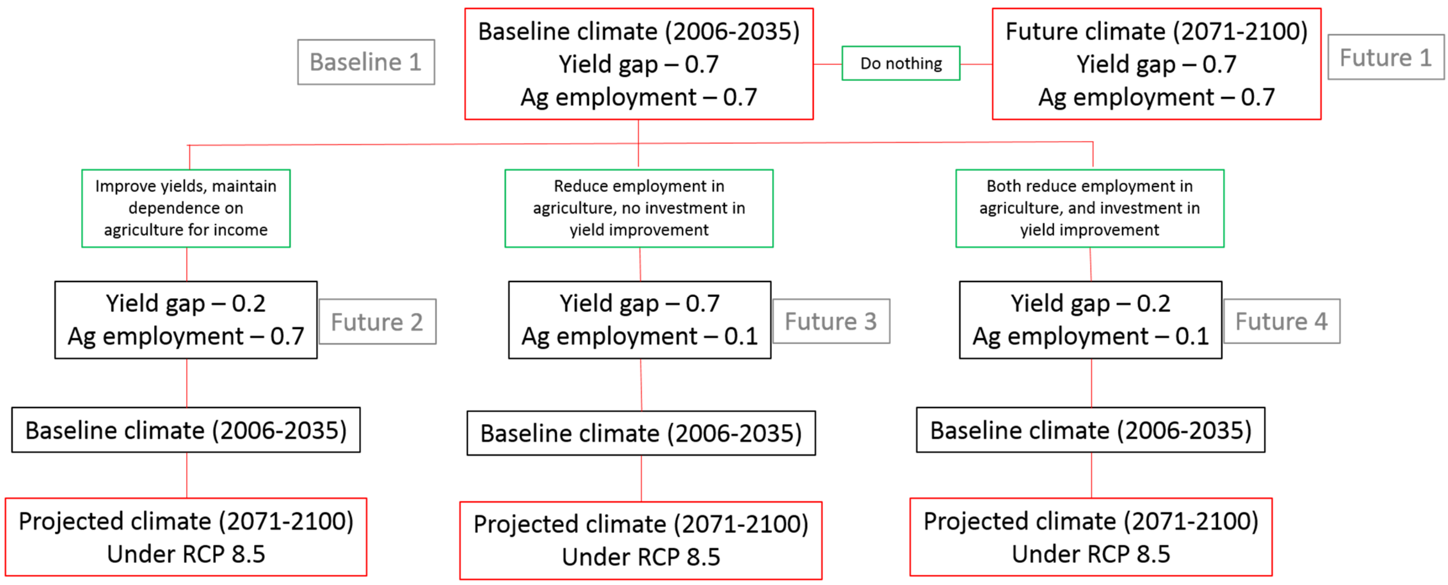


Figure 4-16: Diagram of options for systematically varying driving climate, yield gap and dependence of population on agriculture for income

Running the simplified food system model

The simple food system model was run for Ethiopia using climate data from all 19 of the climate models from CMIP5 used in this study, for a baseline period (2006-2035) and the end of the century (2071-2100) under RCP 8.5, and for each scenario combination shown in Figure 4-16. The climate metric in this case was the Standardised Evapotranspiration and Precipitation Index (SPEI), calibrated over the whole time period (2006-2100). The outputs are shown in Figure 4-17, Figure 4-18 and Figure 4-19. For each of these figures the boxplots of the model output are grouped in pairs. The first two boxplots show: the baseline climate and food system conditions (labelled ‘Baseline 1’ in Figure 4-16); and the ‘do nothing’ future (labelled ‘Future 1’ in Figure 4-16), where the same food system conditions are applied but under the RCP8.5 climate projections for the end of the century (2071-2100). The next two boxplots show the output for a food system where the yield gap has been reduced, but no change has been made to the overall dependence on agriculture for income. The first is for the baseline (2006-2035) climate conditions (labelled ‘Baseline 2’ in Figure 4-16), the second for the climate of the end of the century (2071-2100) (labelled ‘Future 2’ in Figure 4-16). The next pair are the output where dependence on agriculture for income is reduced, but the yield gap is not reduced, again for the baseline (labelled ‘Baseline 3’) and future climate conditions (labelled ‘Future 3’). The final pair show the output where both dependence on agricultural income and the yield gap are both reduced, for the baseline (labelled ‘Baseline 4’) and future climate conditions (labelled ‘Future 4’).

Food system model results

The Production metric outputs from the simplified food system model shows climate change having a negative impact on weather-driven production. Figure 4-17 shows the Production metric output for the sub-selected multi-model ensemble of climate models, and for the ‘best performing’ model, HadGEM2-ES. (Here, as previously stated, the ‘best performing’ model has been identified as a means of selecting a single model from the group for comparison with the multi-model ensemble, rather than as a definitive judgement on the most accurate model). This can be seen by comparing the Baseline 1 boxplot and the Future 1 boxplot, where the only difference is the climate change input. The results for the individual models are shown in Appendix C. The mean metric value and the worst year values both decrease in 15 of the 19 models, including those identified as validating well against ‘observed’ climate (HadGEM2-ES, HadGEM2-CC and MPI-ESM-MR). Of the four models that show either little change or a small increase in the mean and/or lowest production proxy value, two of these (IPSL-CM5A-LR and MIROC5) were identified as validating poorly against recent rainfall observations, and were both too wet compared with observations.

(Figure 4-17 shows the Production metric. For this metric changes to the proportion of the population employed in agriculture make no difference. Baselines and Futures 1 & 3, and Baselines and Futures 2 & 4, where the proportion of the population employed in agriculture is the only difference, are identical, as would be expected.)

The negative impact of climate change on the Production metric is, however, smaller than the improvement in that metric associated with a reduction in the yield gap. This can be seen by comparing the difference between the first and second boxplots, and the third and fourth boxplots in each graph. This indicates that the reduction in production potential associated with the increase in annual drought severity (as measured by the SPEI), is less than the increases in production that could be obtained by addressing the very large yield gap in agriculture in Ethiopia. This finding allows us to make a scale comparison between two different drivers of change. It shows how large a limiting factor climate change and variability could be on cereal production in Ethiopia, compared with the potential for agricultural reform to increase yields. Climate change will make achieving food security more difficult, but it will not be the cause of future food insecurity. That said, even with improvements in yield, the production outcomes are poorer with climate change than they are without (compare boxplots 3 & 4) in Figure 4-17).

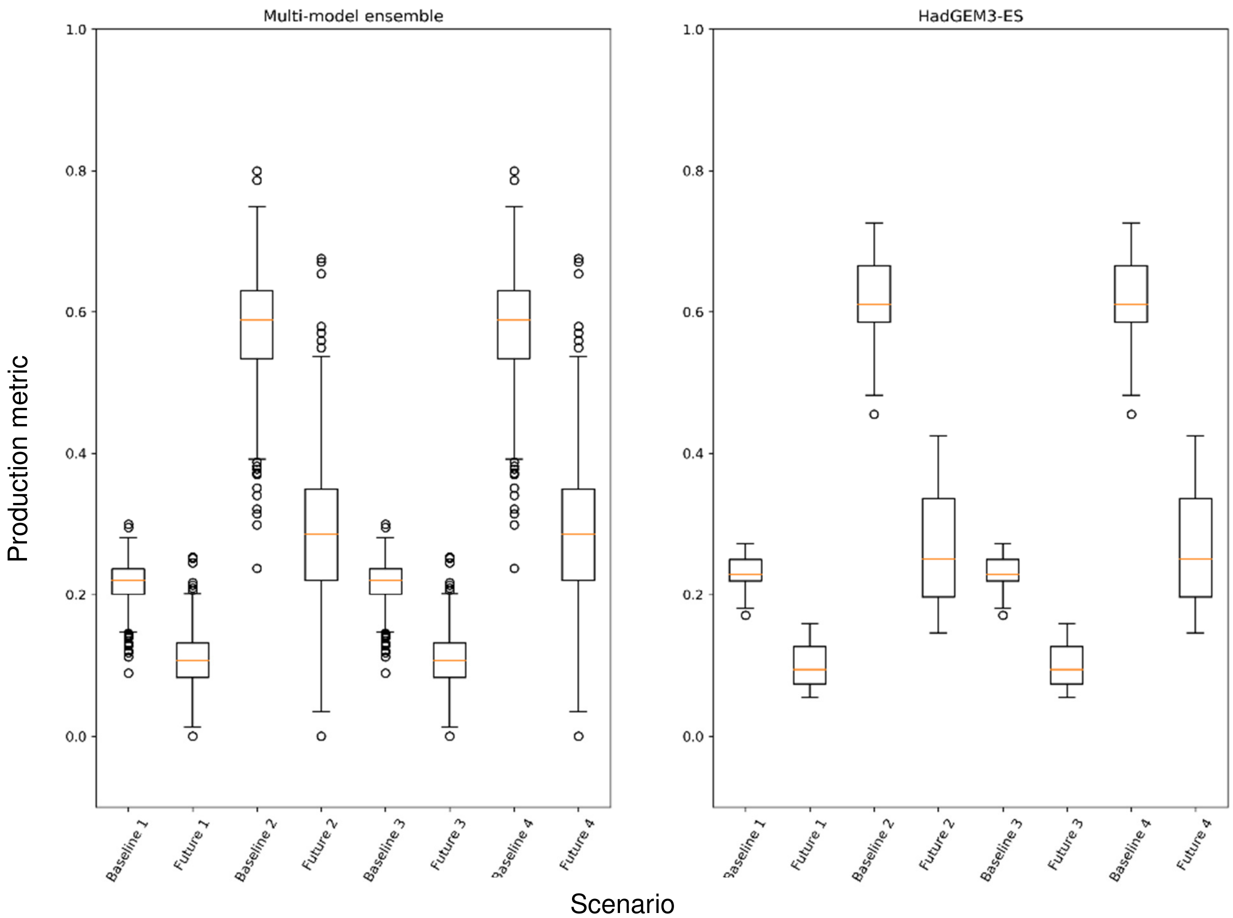


Figure 4-17: Production metric range for Ethiopia under each of the scenarios in Figure 4-16, for selected multi-model ensemble (left) and 'best performing' model over the Highlands region of Ethiopia (HadGEM2-ES) (right).

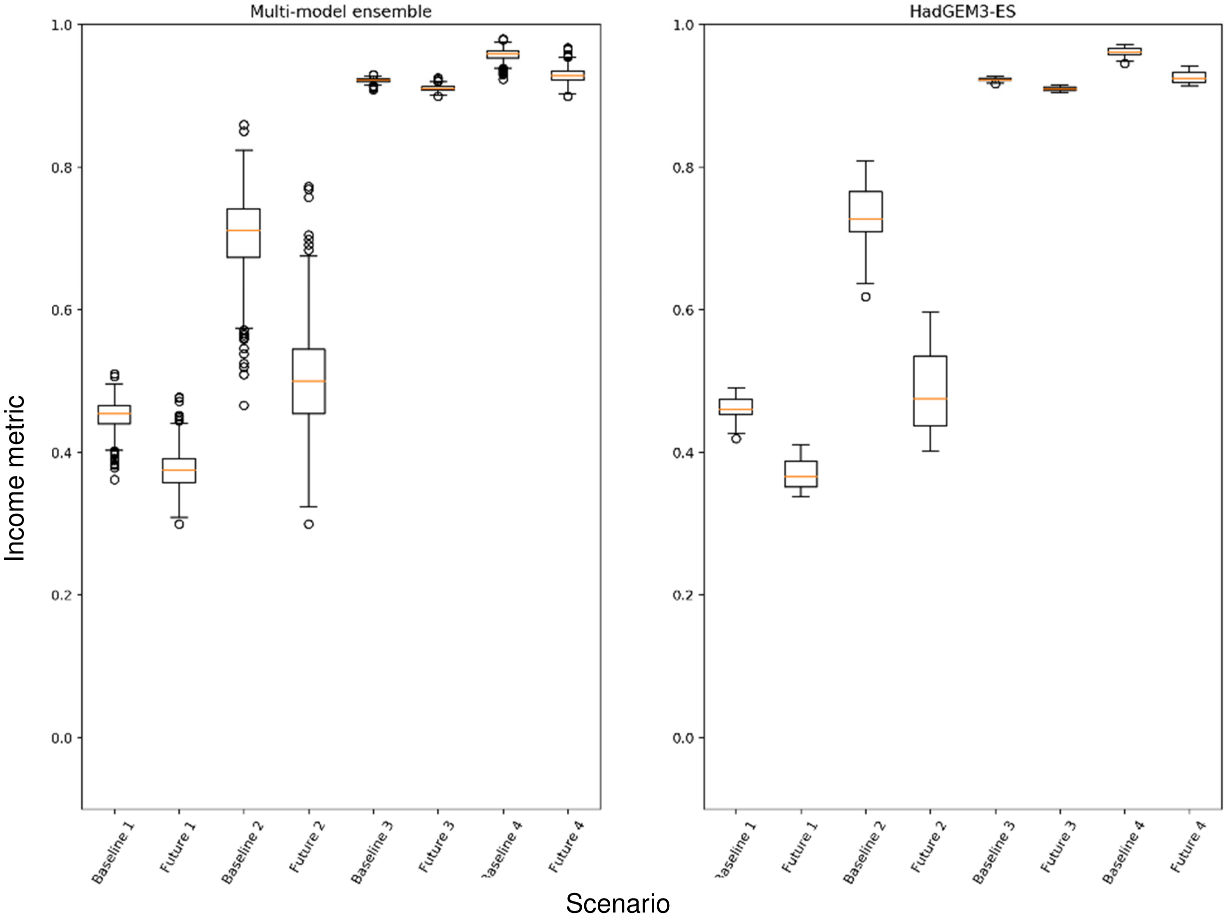


Figure 4-18: Income metric range for Ethiopia under each of the scenarios shown in Figure 4-16, for selected multi-model ensemble (left) and 'best performing' model over the Highlands region of Ethiopia (HadGEM2-ES) (right).

The income metric (Figure 4-18), shows same negative impact associated with climate change (Baseline 1 compared with Future 1), as the decrease in water availability (as measured by the SPEI) affects annual cereal production. However, the potential for action to address the yield gaps in agriculture in Ethiopia again has a much larger effect. For this metric, changes to the proportion of the population employed in agriculture also affects the way income is impacted by climate change (Baseline and Future 3, compared to Baseline and Future 1). In this case, by diversifying income sources nationally (i.e. reducing the very high proportion of the population dependant on agriculture for their livelihood), two important things happen. Firstly, there is a positive impact on the mean of the income metric (as there is when the yield gap is addressed (Baseline and Future 2)). Secondly, and perhaps more critically, the range of the income metric is reduced dramatically. This is because when a much larger proportion of income comes from non-agricultural sources, more of the country's income is unaffected by climate variability and change. This is perhaps a rather obvious result, but again, the important thing here is that the model gives a sense of the relative scale of the changes associated with climate and non-climate changes. Climate change reduces the mean income metric and increases the variability of that metric from year to year. Reducing the yield gap has a larger positive impact on mean income, but the multiplicative effect of the larger production range amplifies this change in variability. Diversifying the economy, more in line with that of developed countries, not only increases the income metric, by an amount equivalent to the reduction associated with climate change, but also dramatically reduces the variability of income, which more than off-sets the increase associated with climate change. With both changes applied, income potential is substantially improved and variability minimised.

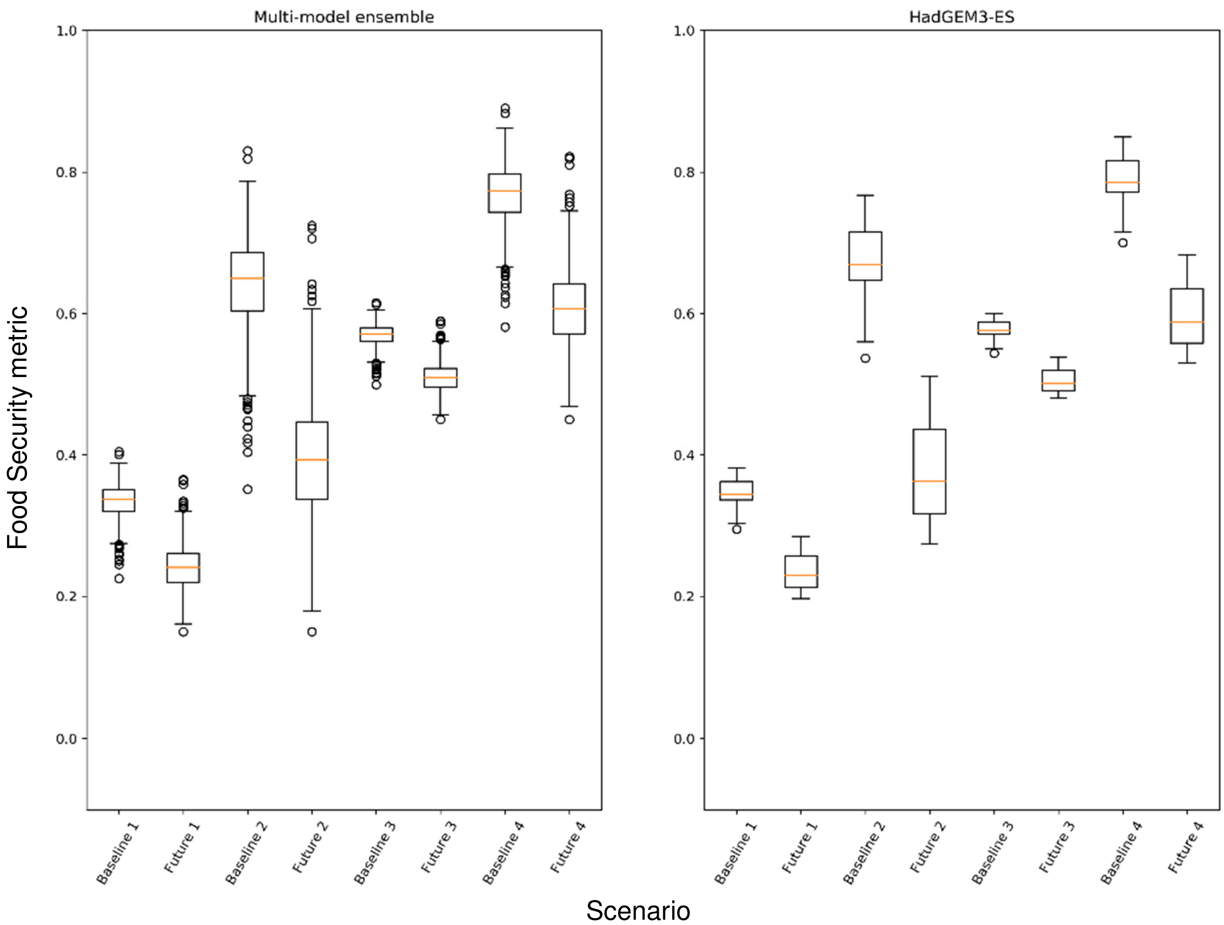


Figure 4-19: Food Security metric range for Ethiopia under each of the scenarios shown in Figure 4-16, for selected multi-model ensemble (left) and 'best performing' model over the 'Highlands' region of Ethiopia (HadGEM2-ES) (right).

The Food Security metric (Figure 4-19) combines access and availability, both of which are affected by changes in production. Here the negative impact of climate change on food security potential can be seen in most models (difference between the first two boxplots in each graph). Again, this is more than off-set by addressing the yield gap in cereal production in Ethiopia, and this affect is amplified in the Food Security metric because it contributes both to increasing food availability (by increasing production) (difference between Baseline 1 and Future 2), and by increasing access (through increases in agricultural income associated with higher production) (difference between Baseline 1 and Future). Reducing the proportion of the population dependant on agriculture increases the Food Security metric, although not as much as reducing the yield gap does. This is because it improves access by disassociating more of income from climate variability and change. Moving more of the population away from a dependence on agriculture for income also dramatically reduces the variability of the Food Security metric, for the reasons explained for the Income metric. By implementing policies to both reduce the yield gap and diversify income away from agriculture (Baseline and Future 4), large improvements are made on the Food Security metric, and the variability of this metric is decreased. If both measures are taken, at the scale set out in Figure 4-16, then even under climate change Ethiopia would have greater potential to meet its food security needs than at present. It should be noted that variability under this scenario is also higher than at present. The climate model component of the increase in variability is mainly due to changes in climate variability, rather than an increase in model projections spread. This can be seen by comparing the change in variability for the sub-selected multi-model results, with the individual models, represented by the ‘best performing’ model, in Figure 4-19. However, the worst years in the Future 4 scenario are still better than the best years in the Baseline 1 scenario. What this might mean in practice, might depend on the size of the future population and the demand for food.

Conclusions

The simplified food system model is designed to account for the double impact of changes in production on both food availability and access. Running it with climate model data from a number of models to the end of the century, under RCP 8.5, and additionally with changes to the cereal yield gap and proportion of the population dependent on agricultural income, does two key things. Firstly it gives a sense of the scale of the impact on food security of changes in climate, relative to other possible system changes, and it also allows us to see how uncertainty in the climate model projections affects their utility in providing evidence to support decision-making in this context.

Climate change is shown, for most models, to have negative consequences for food security potential, in that it both reduces the mean Food Security metric, and increases the variability of that metric. If we look at the food security outcomes of the recent past (Lewis 2017), we see that although the food security situation has improved markedly in recent decades, around 30% of the 97 million people in Ethiopia are reported as undernourished (FAO 2018) and large scale, acute food insecurity events (affecting > 1 million people) are still a feature of life in Ethiopia (Reliefweb 2016, Guha-Sapir 2018). The simple food system model indicates that climate change will exert a negative pressure on food security. Perhaps more worryingly the variability in the metric in the present day is small compared to the end of the century, RCP8.5 projections, which shows a large increase in variability under most model projections. Considering this change in variability in light of the present day frequency of food insecurity events is particularly concerning.

However, more positively, the simple food system model output also shows that the negative changes associated with climate are small when compared with the potential positive impact of large-scale system changes. How feasible these changes are, particularly to the degree included in this simple model, is not clear. Although they unlikely to be easy or straightforward to implement, they are at least representative of positive action that can be taken by a government.

Looking at the food system model output across all the models, the result that climate change is small compared to the potential for other system changes holds true. The climate model projections over Ethiopia show uncertainty in the sign of the change in rainfall, but this uncertainty does not translate into uncertainty on the value of system changes to address food insecurity in a changing climate. This simplified, toy model effectively follows the translation of the climate model data, into practical information of food security potential outcomes, and in doing so the view on the uncertainty in those projections changes. Uncertainty in the sign of the rainfall signal might appear to be a major limitation on the value of those projections, but having 19 model projections provides a means by which sensitivity to a range of future outcomes can be tested. When talking about long term planning, single predictions can be more dangerous than helpful, and having a tool to test sensitivity is key.

Although the model is here run with very ambitious scenarios of food system change, it is entirely straightforward to re-run it with a range of different levels of yield gap and agricultural employment proportions, based on consultation with experts in these areas. The model shows some initial results from an enhanced climate and development perspective, but can be run under a different set of scenarios more relevant to real policy options. The simple food system model developed here not only presents some useful results on the scale of stress to the food system associated with climate change, but also demonstrates potential as a tool to facilitate interpretation of climate model projections for food security in Ethiopia for use in climate and security studies.

Chapter 5

Applying the simple climate and food system model to other countries

Introduction

A simple climate and food system model was developed and run for Ethiopia, and the results appear to provide some interesting insight into the potential challenges for food security of climate change. As an extension of this work, this chapter applies the simple food system model approach to other countries to see if it provides useful insight beyond the specific example of Ethiopia. Figure 5-1 shows the summary outline of this process for reference.

There are two aspects of the model which application to additional countries is designed to test. First, whether the approach developed in Chapter 4 could work outside of Ethiopia. Second, how sensitive the model outputs are to differences in driving climate and system conditions and changes, and in particular to differences in regional uncertainty in the climate model projections.

Before the model can be applied as outlined in Figure 5-1, the countries to which it will be applied must be selected. Comparator countries suitable for this purpose must have a food system similar enough to Ethiopia's (i.e. with a dependence on in-country production to meet food demand) for the model to be relevant, and there needs to be data available on the food system to set the model parameters by. Countries most useful for comparison purposes need between them to have differences from Ethiopia that include: climate; climate change projections; and model agreement in the climate projections. Given that Africa as a whole engages in very low levels of international trade, the comparisons with Ethiopia will all be with other countries within Africa.

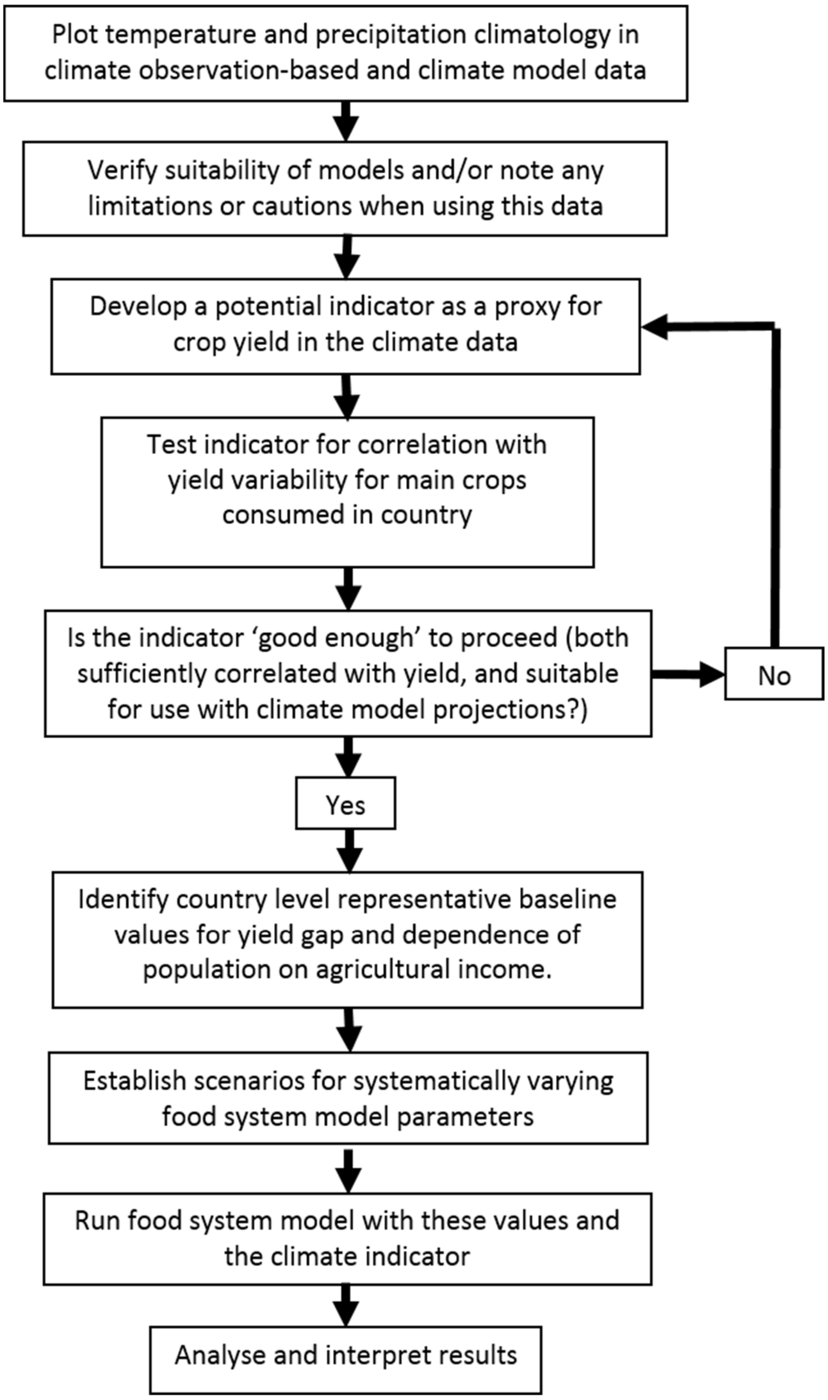


Figure 5-1: Flow diagram of process of applying simple food systems model approach.

Baseline climate - Africa

The scarcity of reliable, long term records of observational climate data is a problem across the whole of Africa. The lack of reliable reanalysis data over the continent, at least on a year by year scale, was also identified as a problem in the climate analysis over Ethiopia So as for Ethiopia, the CHIRPS rainfall data

(Funk, Peterson et al. 2015) is used as the main source of information on observed climate. The annual average rainfall over Africa for the 1981-2005 climatology is shown in Figure 5-2. The Intertropical Convergence Zone (ITCZ) (the band of tropical rains associated with the thermal equator) over tropical Africa, the drier northern and southern regions, and the boundaries between the two, are all clearly identifiable from this figure. Whilst climate models can reproduce this broad pattern, the relatively course-resolution GCMs struggle with the more detailed representation of the annual rainfall patterns over Africa (Flato, Marotzke et al. 2013, Kumar, Kodra et al. 2014, Mehran, AghaKouchak et al. 2014, Dike, Shimizu et al. 2015, Koutroulis, Grillakis et al. 2016). Some aspects of this can be seen in Figure 5-3, where data from the same nineteen climate models used throughout this study (

Table 4-1) was compared with CHIRPS rainfall data for the 1981-2005 period.

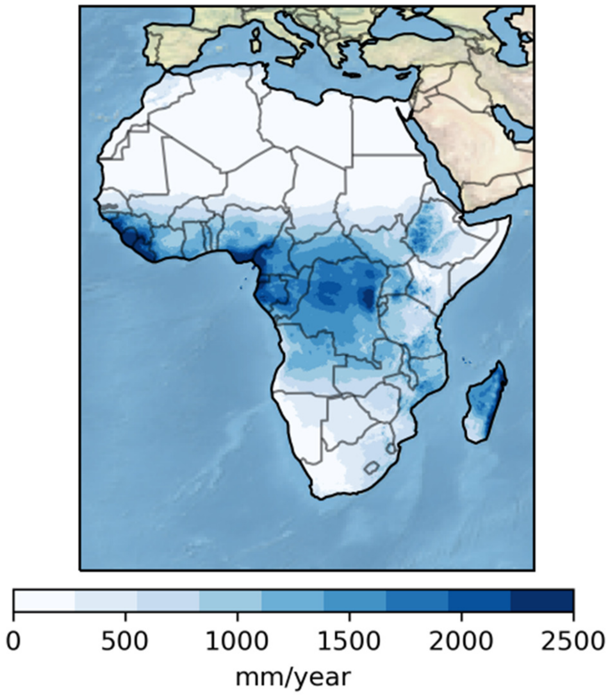


Figure 5-2: Annual average rainfall over Africa for 1981-2005 from CHIRPS.

The climate model projections show a range of differences from CHIRPS. MIROC and NorESM1-M appear to be too wet on the whole. CMCC-CM and MRI-CGCM3 both show a dry bias over much of Africa. Most models though show a range of regional differences from CHIRPS. In terms of the spatial pattern it is possible that HadGEM2-CC, HadGEM2-ES and MPI-ESM-MR are the closest to CHIRPS, but this similarity in average climate rainfall pattern may hide differences in the inter-annual and seasonal features of the rainfall climatology. Other than over the desert region of the Sahara (where rainfall is close to zero anyway), there is no region of Africa where all, or even the majority, of the models closely resemble CHIRPS.

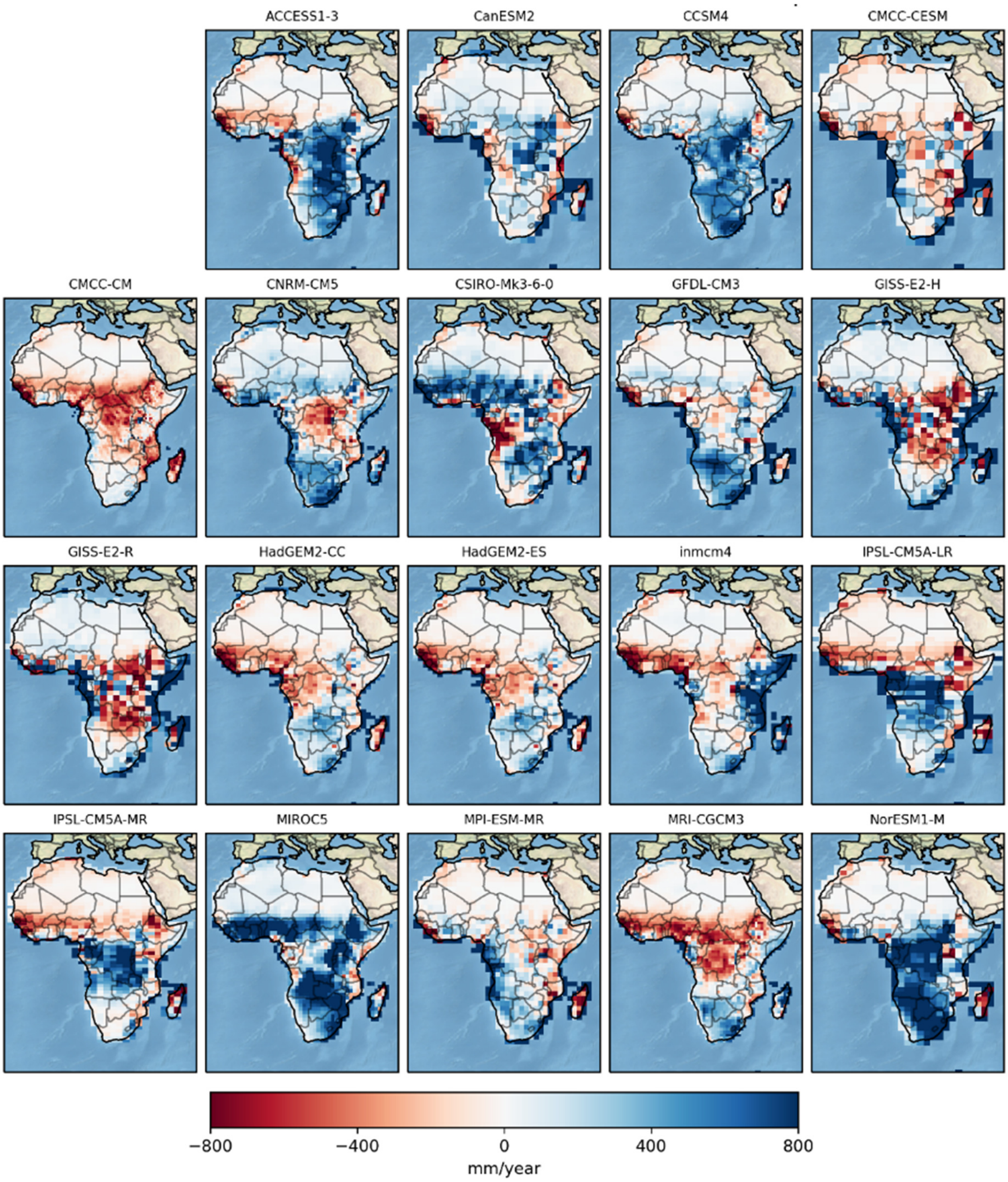


Figure 5-3: Difference between CHIRPS and each climate model mean rainfall for 1981-2005 period.

Climate projections - Africa

Figure 5-4 and Figure 5-5 show the climate model projections for change in temperature and rainfall over Africa between a baseline period of 2006-2035 and the end of the century (2071-2100), under the greenhouse gas concentration scenario RCP8.5. The projections show a consistent signal for warming over the continent, with all models agreeing on the sign of the change, although with differences in level of that warming.

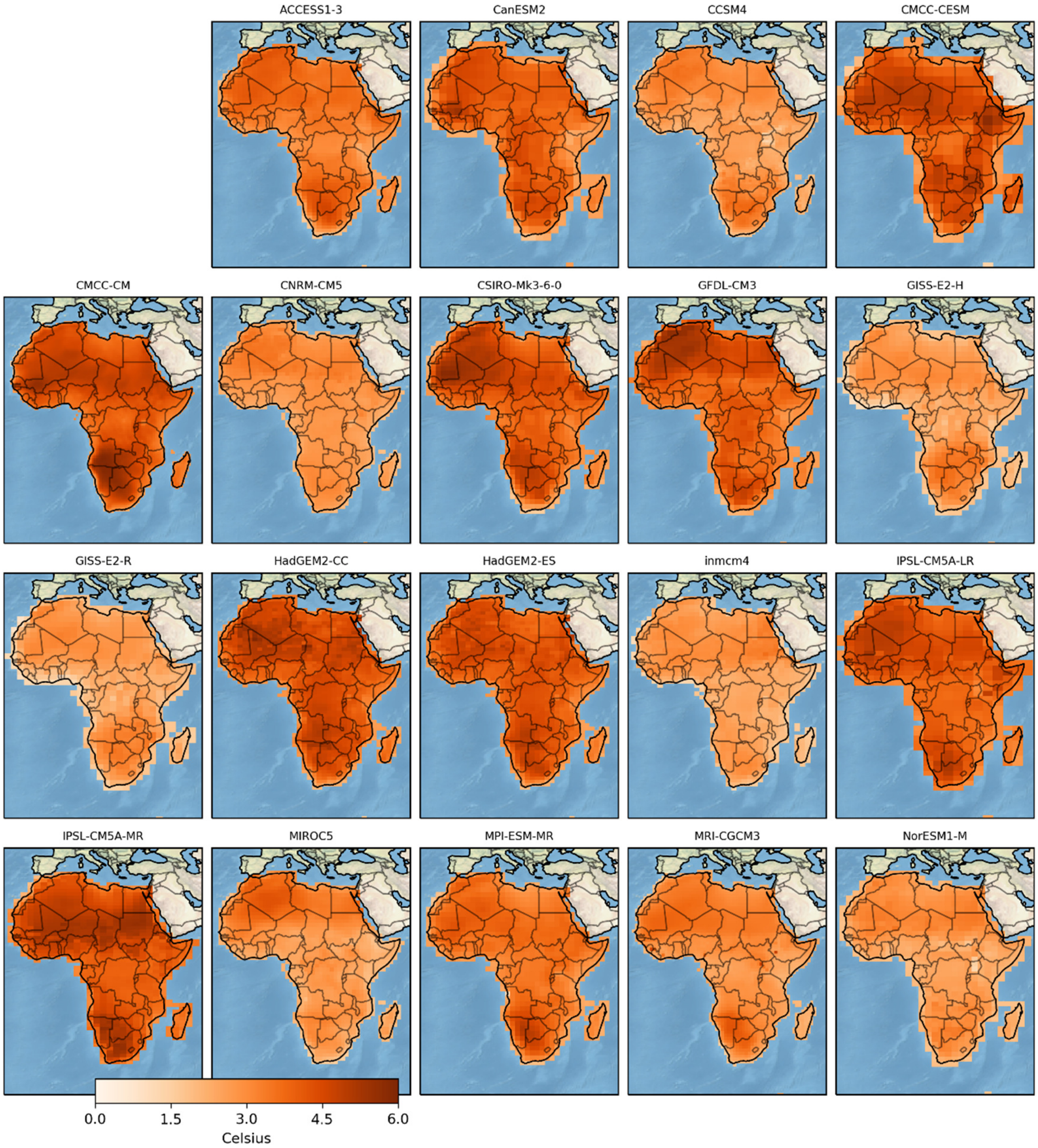


Figure 5-4: Change in temperature between 2006-2035 and 2071-2100 for 19 models from CMIP5 database under RCP8.5.

The projections for change in mean annual rainfall are more mixed. A number of the models show increased precipitation associated with the Intertropical Convergence Zone (ITCZ). There is also some agreement on a pattern of decreased rainfall over southern Africa. However, there are large differences in the regional detail, particularly associated with changes in the position and intensity of the ITCZ and there are a number of reasons for this associated with limitations of climate model dynamics (Niang, Ruppel et al. 2014, Kent, Chadwick et al. 2015).

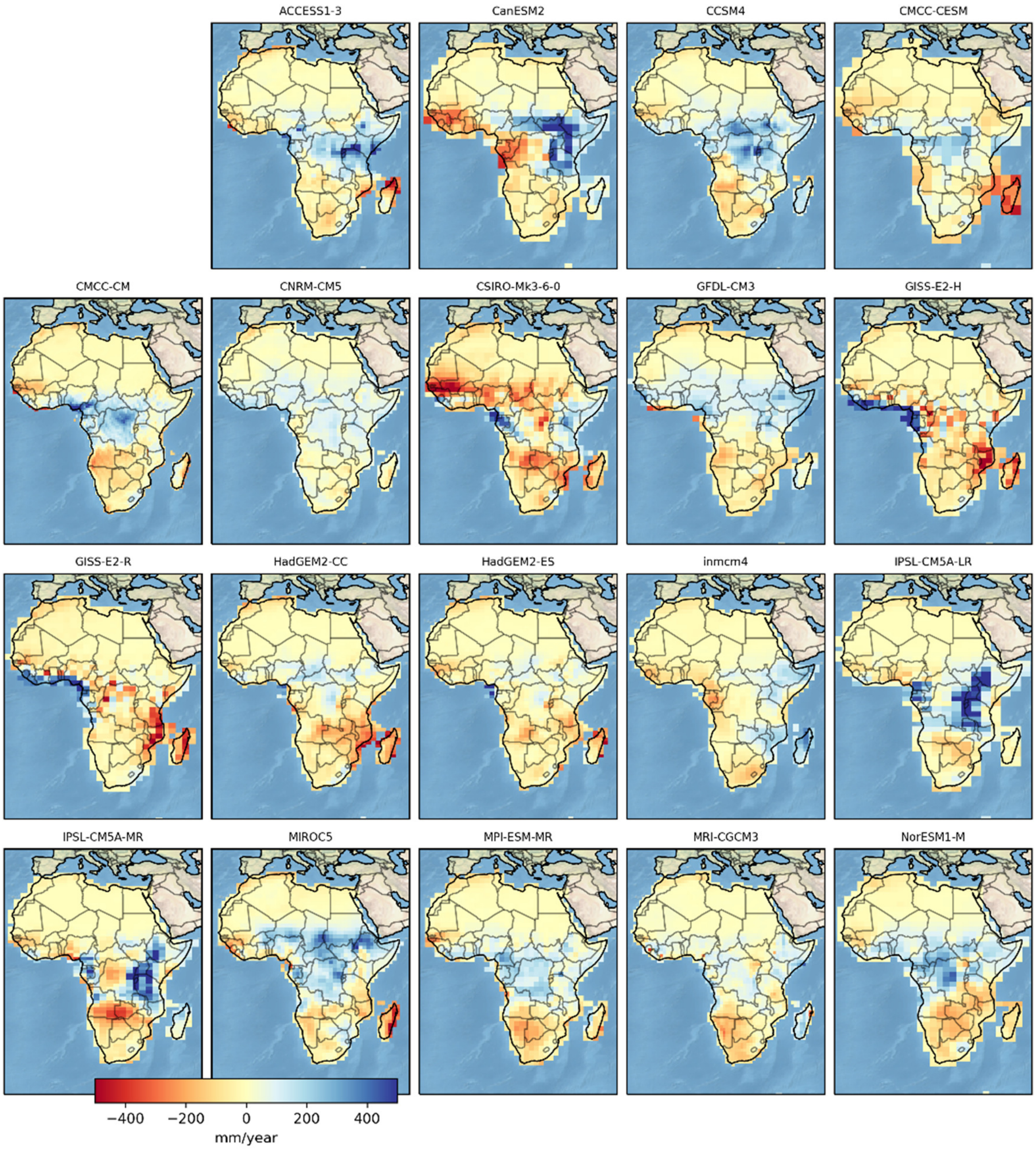


Figure 5-5: Change in precipitation between 2006-2035 and 2071-2100 for 19 models from CMIP5 database, under RCP 8.5.

In order to assess the spread across the climate models of the climate change projections, Africa was then divided into seven climate regions, shown in Figure 5-6, over which climate averages were taken. Figure 5-7 shows the change in temperature and precipitation between 2006-2035 and 2071-2100 in each of these regions, across 19 climate models from the CMIP5 database.

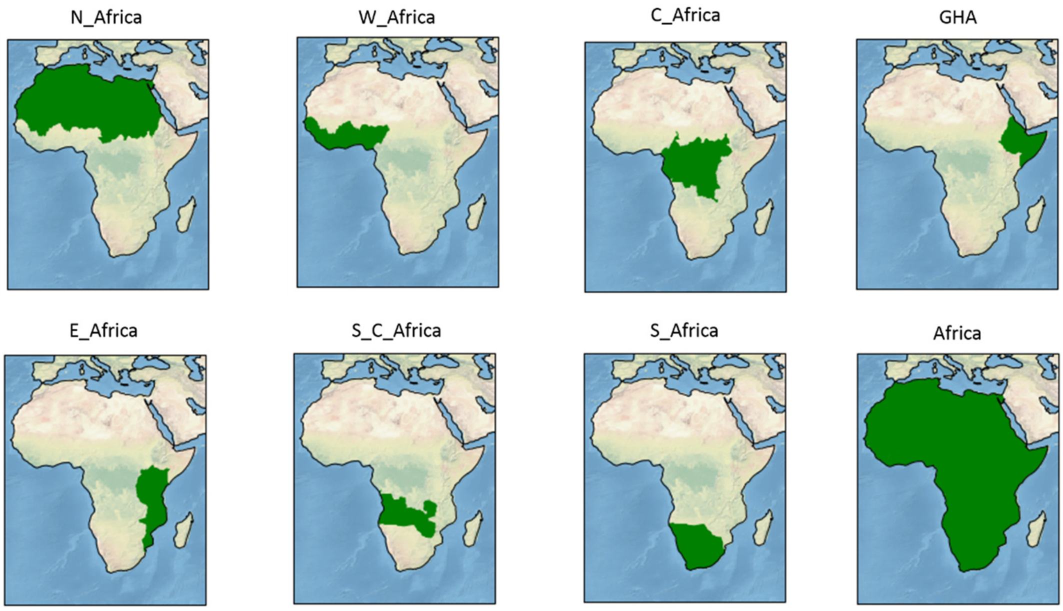


Figure 5-6: Climate regions of Africa for analysis.

Figure 5-7 shows the range of change in annual temperature and rainfall over each region of African from Figure 5-6 for all nineteen models. These projections are consistent with the same data shown in the IPCC Fifth Assessment Report on Africa (Niang, Ruppel et al. 2014), as would be expected. There is reasonably good agreement between the models for the amount of warming across all the models in all the regions between 2006-2035 and 2071-2100. However, different regions have different levels model confidence on changes to rainfall over the same period. In North Africa the consensus is for small amounts of change, spanning zero. West, Central and Eastern Africa, and the Greater Horn of Africa (GHA) all show little agreement, either on the scale of change or the sign of that change, the median projected change in rainfall is for a small average increase in each region. The projections for East Africa are particularly striking in the level of model disagreement. In Southern Africa there is a strong signal for drying and for large increases in temperature, with good agreement among the models for this change. In contrast West Africa, which has quite a different climate, has a rainfall signal more similar to Ethiopia, with uncertainty on the sign of the change, but a small mean increase, and agreement on warming.

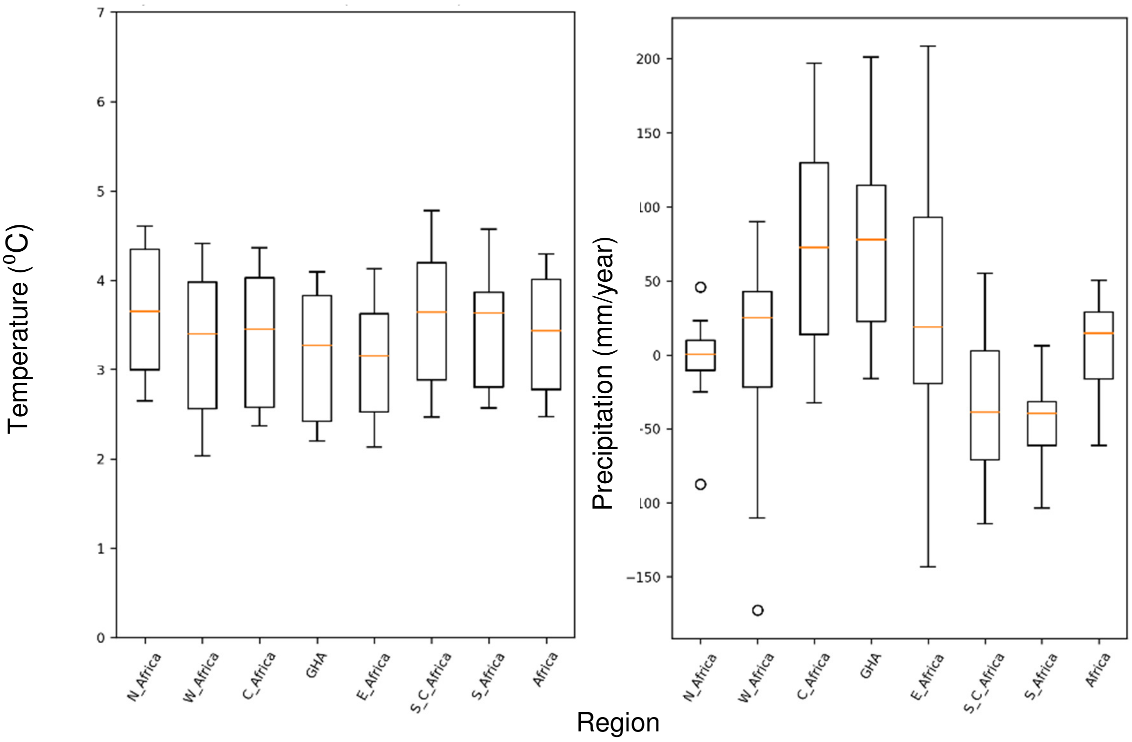


Figure 5-7: Spread of values for change in annual average temperature (^0C) (left) and annual precipitation (mm/year) (right), between 2006-2035 and 2071-2100, for each region of Africa over 19 models from CMIP5 database.

Country selection summary

Countries in the driest regions in the North are primarily dependant on food imports, as little is grown in these climates. Similar to countries in the far South, such as Namibia, there is a greater emphasis on livestock farming than on cereal production. These countries are therefore less suitable for the simple food system model in its current design. Elsewhere, broadly speaking, many countries have food security and food system challenges more similar to Ethiopia, such that they are dependent on in-country production to meet most of their food needs, which comes predominantly from subsistence farming of cereal crops.

One exception is Botswana, where there is a greater dependence on imports, and income from mining plays an important role in the economy. Despite this, Botswana still faces food security challenges and would make a useful comparison with Ethiopia to test the scale of impact of system changes, relative to climate change. As discussed, the differences in the climate change projections for southern Africa provide a useful contrast to Ethiopia. With these differences in mind, and the fact that non-climate data is readily available for Botswana, this country is included in the study as a comparator.

From the spread in climate model projections shown in Figure 5-7, a second useful comparison could be made by including a country in East Africa, where the uncertainty in the model projections is highest. Here the main difficulty is finding countries where there is available non-climate data. The sources of data used for Ethiopia (FAOSTAT 2014, GYGA 2017)) did not all also contain the same data for countries in East Africa. However, despite the fact that FAO do not have data on reported production in Tanzania, it has been possible to find some World Bank data on reported total crop production for this country, so Tanzania is also included in this study, but using production data from a different source. (For more information on the challenges associated with socio-economic and other non-climate data and statistical information for Africa see Jerven (2013).)

Finally a third country, Mali was selected as one much more similar to Ethiopia in both food system and climate model uncertainty. Here however, the climate model projections span zero, but with broad agreement on little change in rainfall. In this case the question is whether the similarities in food system parameters will translate to similar model results or whether smaller differences in climate and climate change will result in differences in the model output.

Country overviews

Botswana

Botswana is a land locked country in southern Africa. Unlike Ethiopia or Mali the economy is not primarily agriculturally based. Botswana’s economy is boosted by its diamond mining industry and it is one of the wealthier countries in Africa. The main cereals grown and consumed are maize, sorghum and millet, although Botswana does import some of these cereals to meet total demand. Arable land only makes up around 1% of the country, and cattle farming is also an important farming activity (FAO, 2015).

This means that the food system conditions in Botswana are slightly different from Ethiopia and Mali. The proportion of the population employed in agriculture is much lower (around 30%) (FAOSTAT 2018), which along with a stronger signal for drying in the region, makes an interesting comparison with the other three countries. The interpretation of the food system model output may also be different in practical terms. A lower (or higher) Food Security metric might have a different implication for policy in a wealthier country with greater purchasing power to import food, than it would in a country like Mali or Ethiopia where this may not be the case. As in-country production makes up a lower proportion of consumed food the Food Security metric could be interpreted as only applying to a proportion of the food system.

The climate of Botswana is semi-arid, with rainfall predominantly occurring in the peak rainy season during the summer months. Figure 5-8 shows the annual average rainfall over Botswana for 1981-2015.

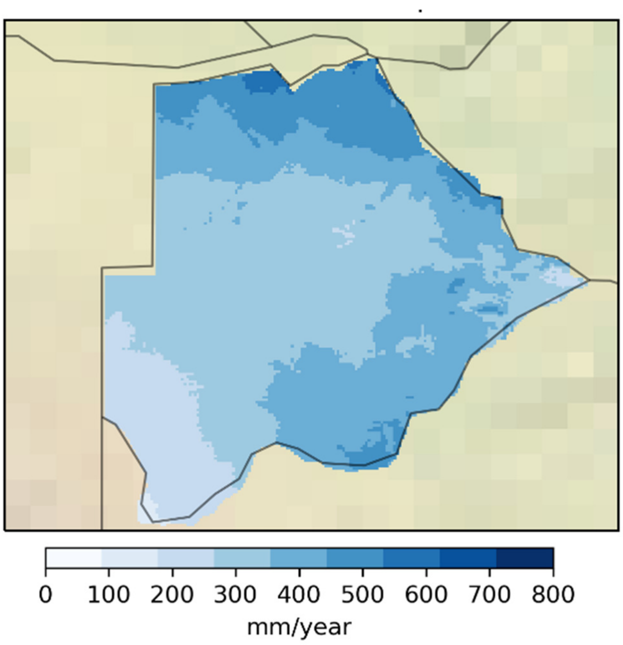


Figure 5-8: Mean annual rainfall from CHIRPS data for 1981-2005 over Botswana

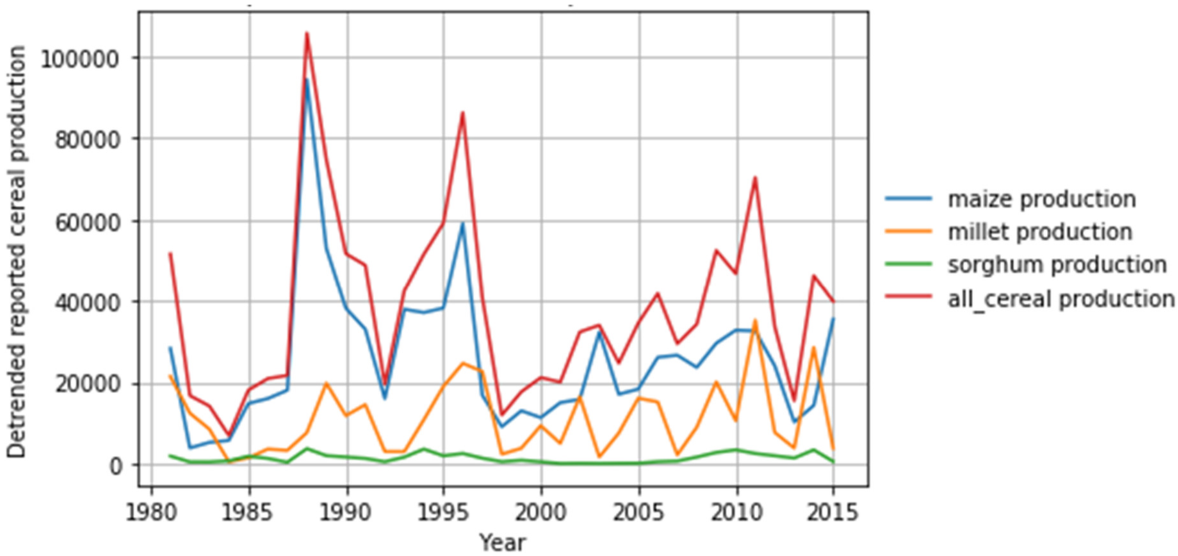


Figure 5-9: Reported national cereal production (tonnes) for Botswana 1981-2015. (FAOSTAT 2018)

Unlike many other countries in Africa, Botswana has not seen a trend of increasing cereal production. As can be seen from Figure 5-9, maize is the dominant crop grown in the country, followed by millet and sorghum.

Tanzania

Tanzania is a coastal country in East Africa. Agriculture is an important part of the economy with a high proportion of the population employed in agriculture (FAOSTAT 2018), but this is largely undertaken by small holder, subsistence farmers (WFP 2018). Although Tanzania currently produces enough food to feed the 54 million population (WFP 2018), food security is an on-going problem in the country, and around 34% of children are reported a stunted as a result (FAOSTAT 2018).

Tanzania experiences two rainy seasons per year in most of the country, and the climate is moderated by the proximity of the coast, the great lakes to the north, and the central highlands. Figure 5-10 shows the mean annual rainfall over the country.

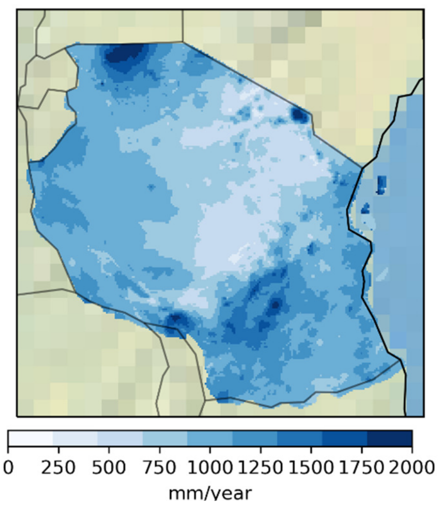


Figure 5-10: Mean annual rainfall from CHIRPS data for 1981-2005 over Tanzania

The dominant crop grown in Tanzania is maize, followed by rice, sorghum and millet and the majority of these crops are consumed in-country. FAO data on production totals for individual crops was not available for Tanzania, so alternative data was sought. Figure 5-11 shows the reported total production of all cereals in Tanzania for 1981-2015 from World Bank data (The_World_Bank 2016).

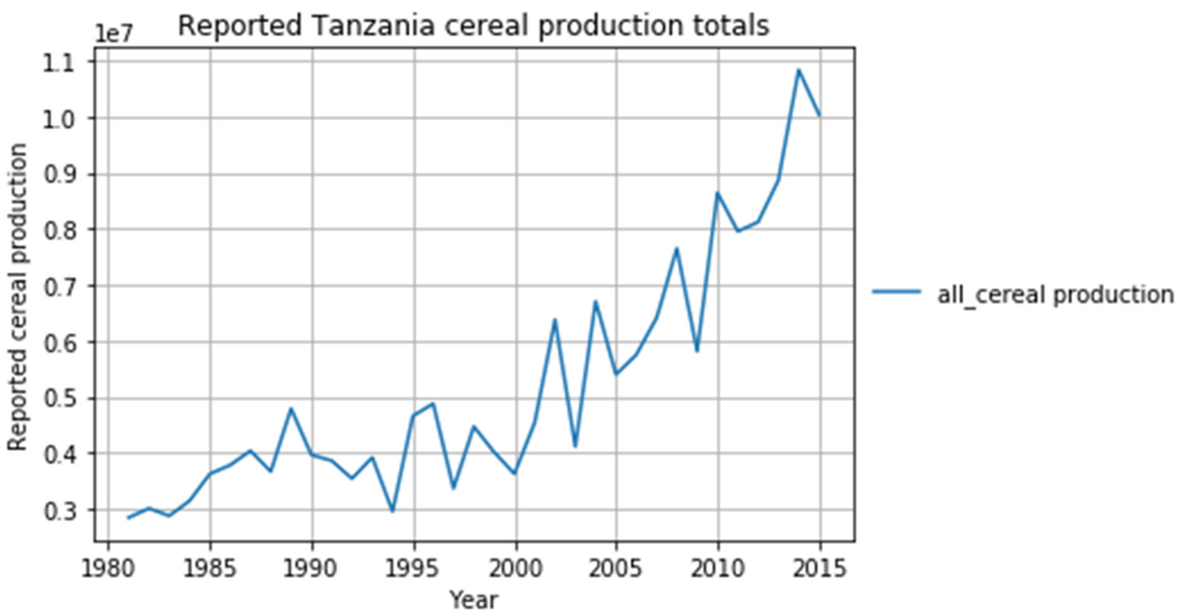


Figure 5-11: Reported national cereal production for Tanzania 1981-2015 (tonnes). (The World Bank 2016)

Mali

Mali is a land locked country in the Sahel region of West Africa. Like Ethiopia and Mali it has high levels of poverty and food insecurity. The economy is also primarily based around agriculture, with the majority of farmers engaged in subsistence farming on farms less than 1 ha in size (FAOSTAT 2018, World Bank 2018). Around two-thirds of consumed calories are from cereals, mainly millet, rice, sorghum and maize (FAO 2018). Also like Ethiopia and Tanzania, Mali has a high proportion of the population employed in agriculture and the cereal yield gap is high (GYGA 2017, FAOSTAT 2018).

The climate of Mali is highly diverse as the country spans the seasonally wet Sahel area in the south, to the arid Sahara desert in the North. Figure 5-12 shows the annual average rainfall over Mali for 1981-2015 and the strong north-south rainfall gradient.

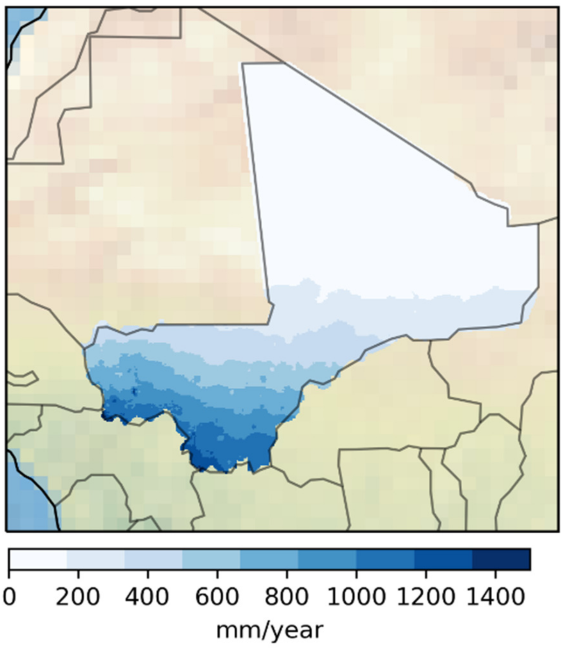


Figure 5-12: Mean annual rainfall over Mali for 1981-2015 from CHIRPS data (Funk, Peterson et al. 2015).

As a result of this gradient of rainfall, the majority of cropping livelihoods and population are in the south of the country, with the north sparsely populated with primarily pastoralist farmers (see Figure 5-13).

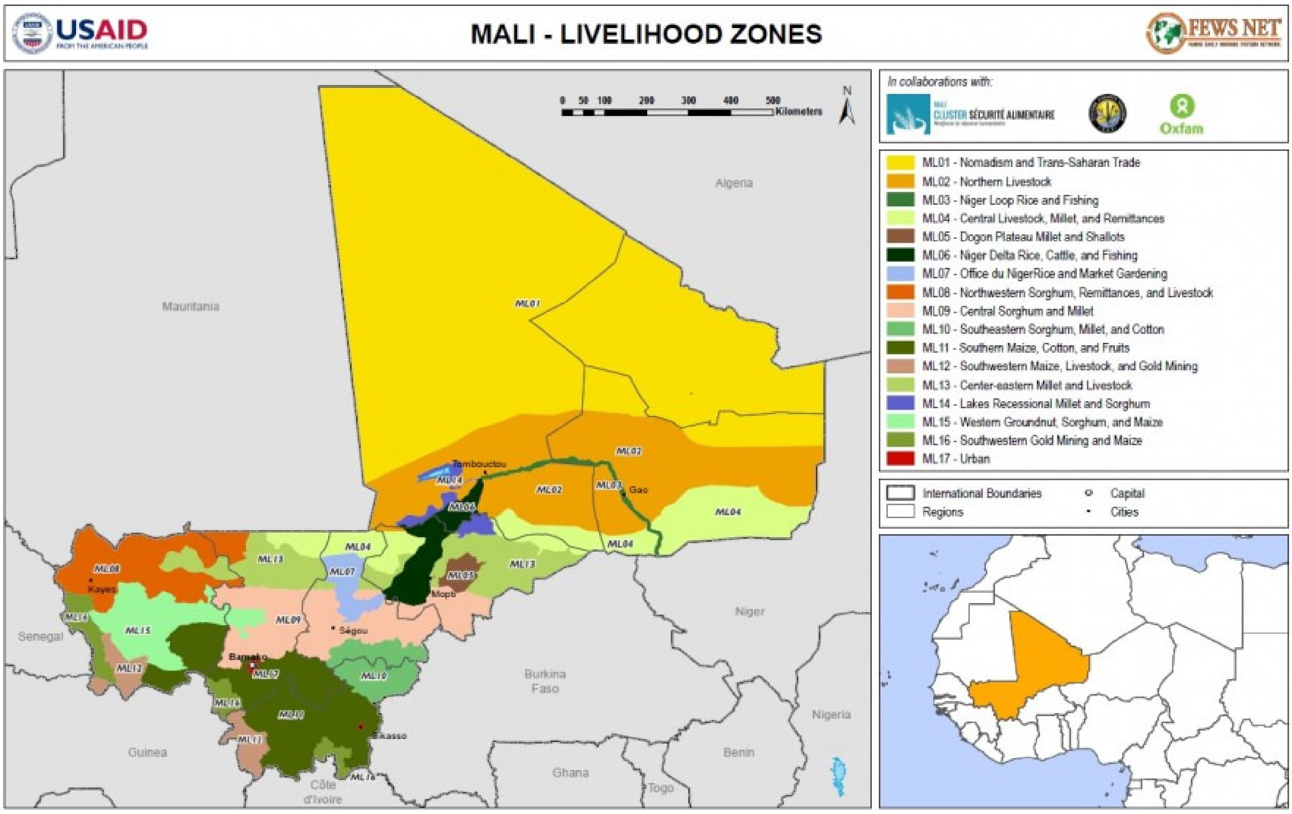


Figure 5-13: Livelihood zones in Mali (FEWSNET 2014).

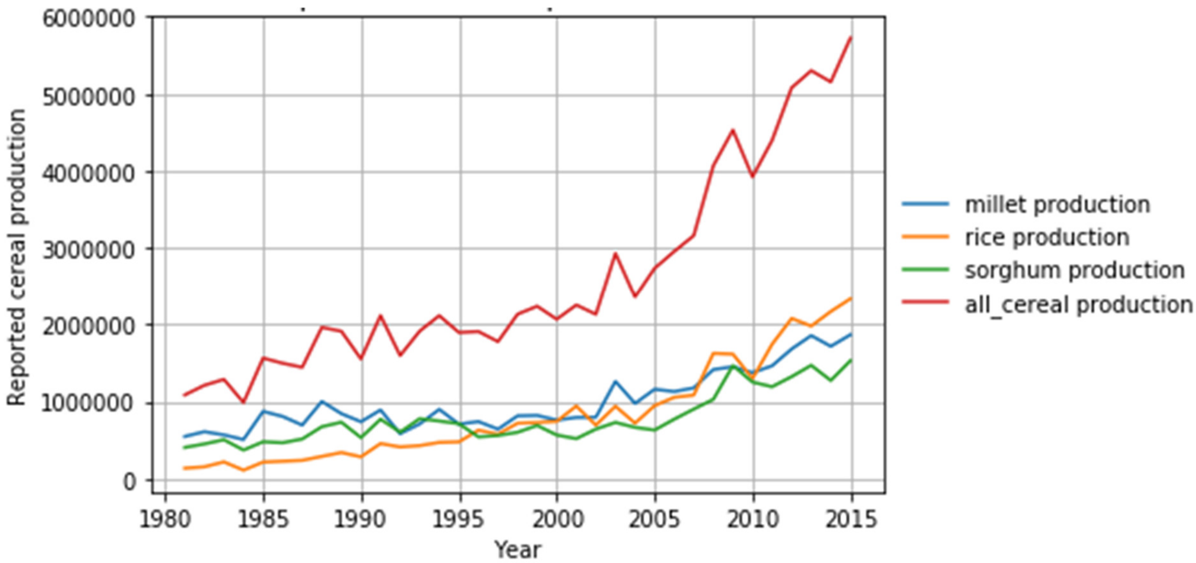


Figure 5-14: Reported national cereal production for Mali 1981-2015. (FAOSTAT 2018)

Like many countries in Africa, Mali has seen a trend of increasing cereal production, although with annual variability on that trend (Figure 5-14).

Climate model representation

The same nineteen climate models from the CMIP5 database used throughout this study (Table 4-1) were also analysed for the climate change signal over Botswana, Tanzania and Mali. The models were first analysed to get a sense of how well they are able to represent the present day climate of each country. As with Ethiopia, the main purpose of this is to get a sense of the confidence that can be given to the interpretation of the food security impact. A 'best performing' model is also selected, but only for the purposes of choosing a single model when comparison with the multi-model ensemble is useful.

Botswana

Figure 5-15 and Figure 5-16 show the difference annual average rainfall over Botswana from CHIRPS (Funk, Peterson et al. 2015) for each of the nineteen models for the 1981-2005 time period.

From Figure 5-15 it can be seen that most of the models have a wet bias when compared with CHIRPS. In particular GFDL-CM3, MIROC5 and NorESM1-M. Only the GISS models show an extensive dry bias, and this is less than the wet bias of the other models. Overall CMCC-CM seems to do the best job of reproducing a similar annual average rainfall pattern as CHIRPS.

Comparing the climatological profiles produced by the climate models with CHIRPS (Figure 5-16), the climate models do not do a particularly good job of reproducing the CHIRPS climate profile, particularly when compared to the same plots for Ethiopia Figure 4-4). Looking at both Figure 5-15 and Figure 5-16 the 'best performing' model over Botswana appears to be CMCC-CM.

In Figure 5-16 the multi-model ensemble (MME) in the top left hand corner includes the data from all the models together. The MME has a much larger distribution of annual rainfall values that CHIRPS and fails to capture the peak in annual rainfall around 300 mm/year seen in the CHIRPS data. Some of the 19 models do a particularly poor job of capturing the climatological profile, and these can be excluded from the multi-model ensemble.

Figure 5-17 shows the full multi-model ensemble climate profile on the left, next to a multi-model ensemble of sub-selected model on the right. The three models that show a strong wet bias (GFDL-CM3, MIROC5 and NorESM1-M) and CMCC-CESM which has only four grid boxes over Botswana were all excluded from the sub-selected ensemble. Removing some of the models from the ensemble does remove the longer wet-bias tail to the distribution and slightly shift the weighting towards the CHIRPS distribution peak. However, the very poor representation of the present day climate in the climate models is a cause for concern, and perhaps increases the weight that might be given to the CMCC-CM model, over the multi-model ensemble. (As for Ethiopia, analysis of the multi-model ensemble will be for this sub-selected group of models, but all models will remain in the study individually for all countries).

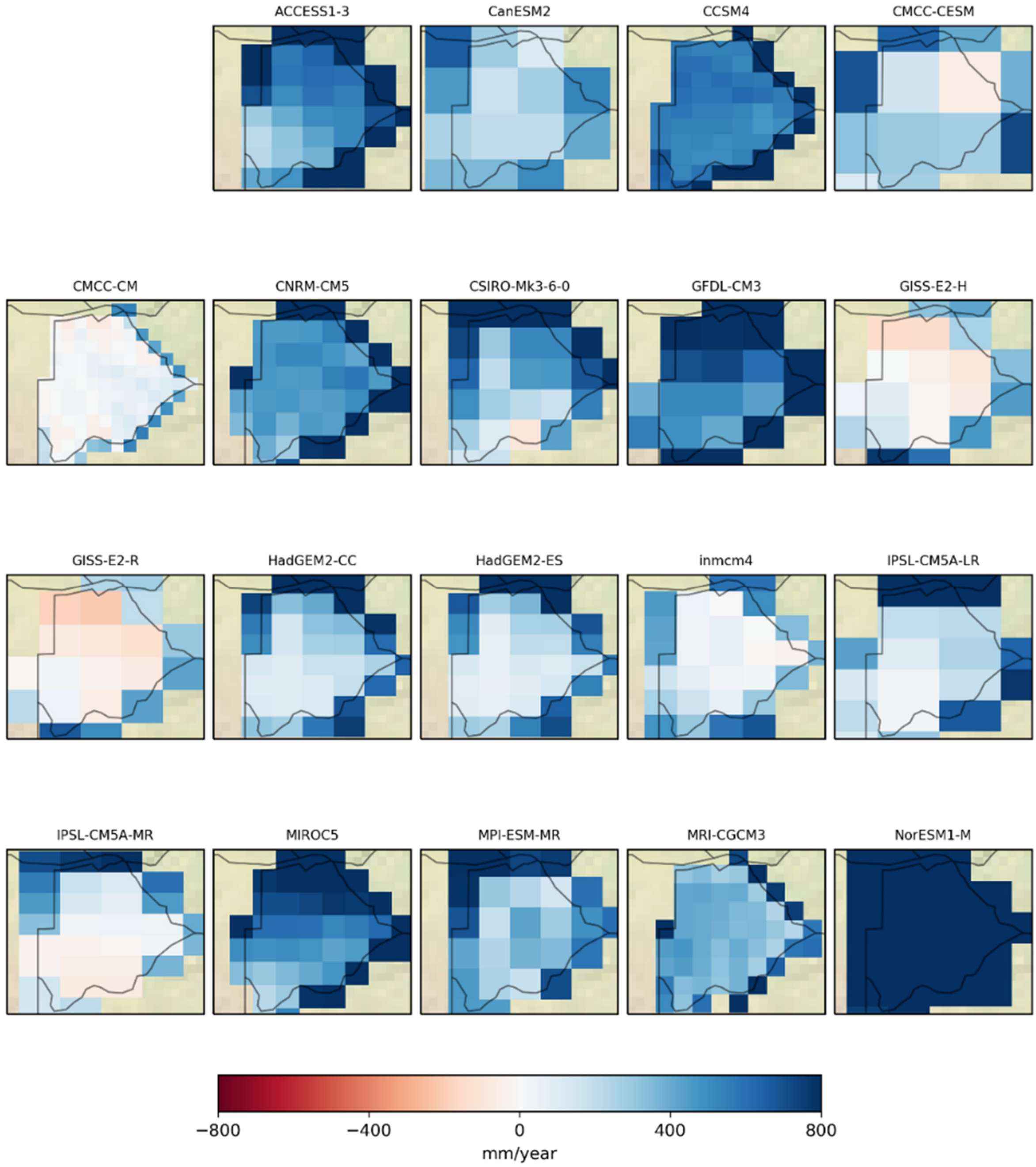


Figure 5-15: Difference between CHIRPS and each climate model for 1981-2005 climate mean for Botswana. (CHIRPS regridded to the resolution of each model).

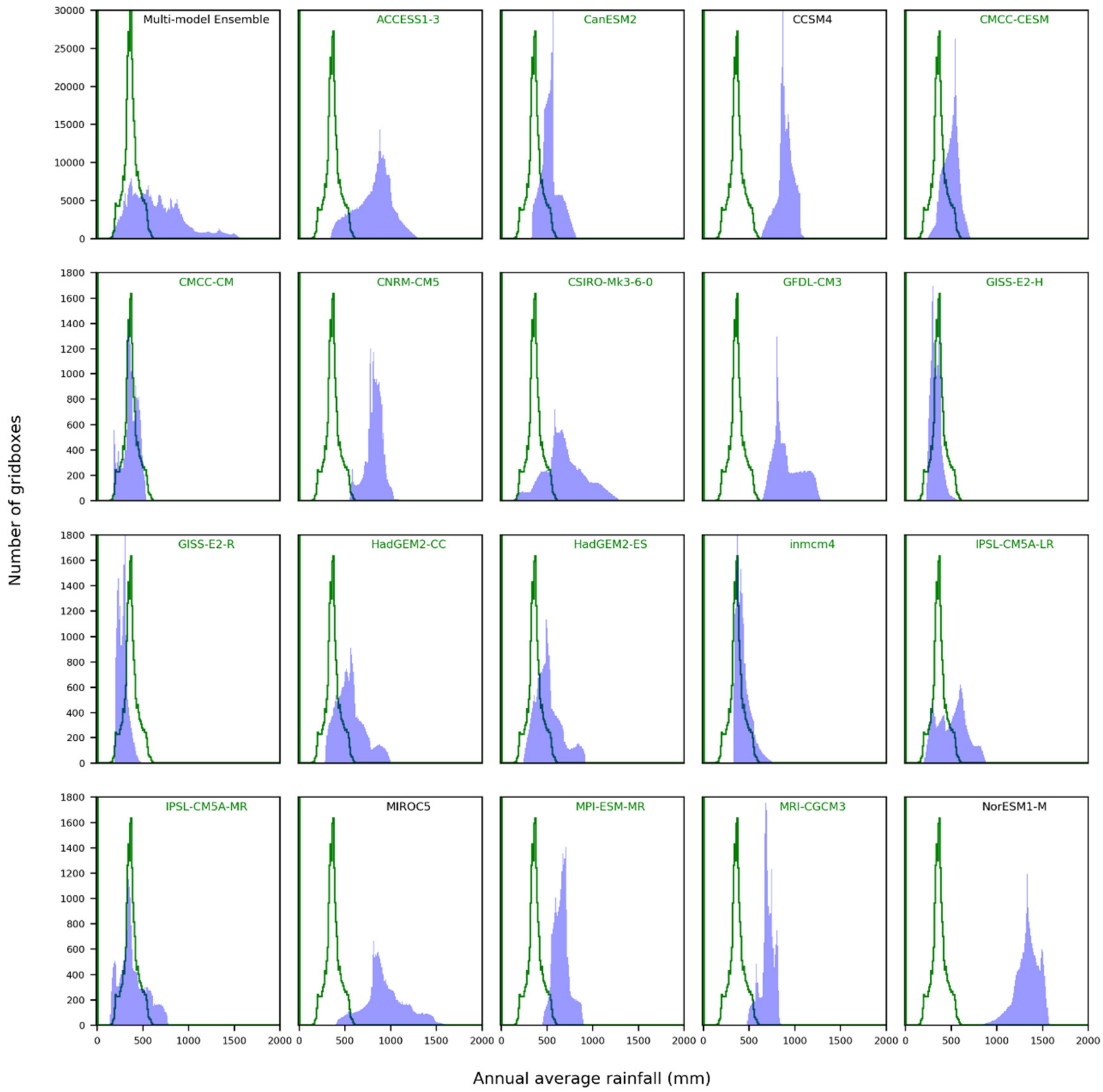


Figure 5-16: 1981-2005 annual rainfall climatology for CHIRPS (in green), each climate model and the multi-model ensemble (in blue) for Botswana.

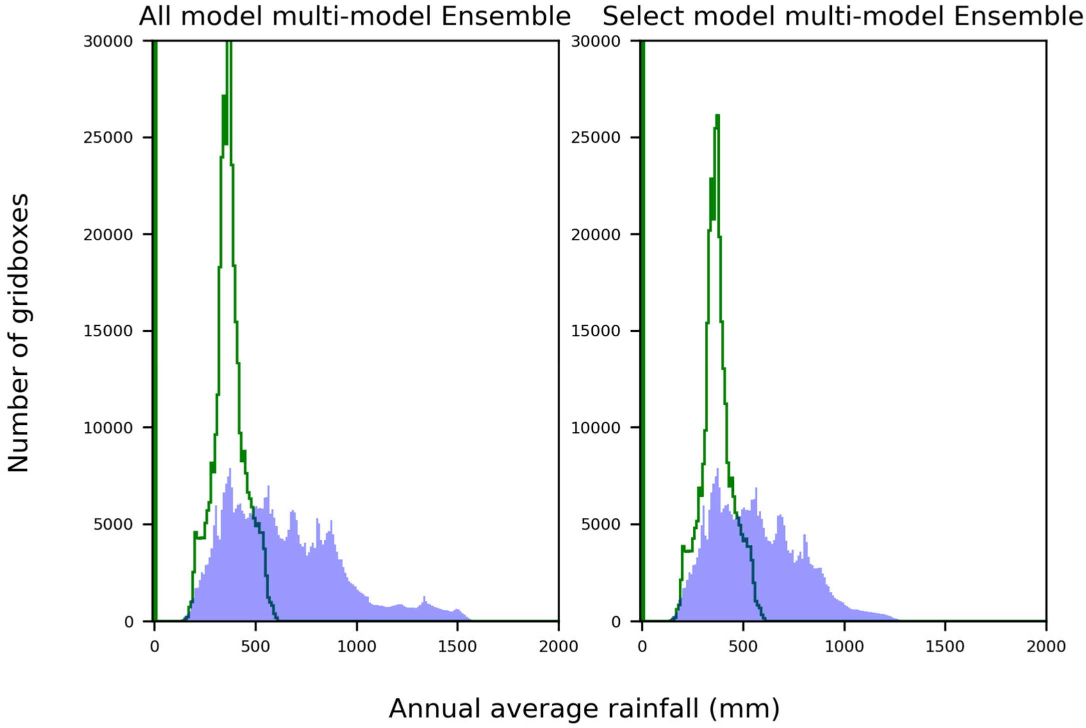


Figure 5-17: 1981-2005 annual rainfall climatology for CHIRPS (in green), and the multi-model ensemble (in blue) with all 19 climate models (left) and with 16 of the 19 models (right), for Botswana.

Tanzania

Figure 5-18 and Figure 5-19 show the difference annual average rainfall over Tanzania from CHIRPS (Funk, Peterson et al. 2015) for each of the nineteen models for the 1981-2005 time period.

A number of models show a dry bias compared with CHIRPS and these include CMCC-CM, CMRN-CM5 and MPI-ESM-MR in particular. In contrast inmcm4 has a relatively large wet bias. The climate profiles in Figure 5-19 indicate that the climate models do a much better job of reproducing the annual climate profile of Tanzania than they do for Botswana, and the fit of the multi-model ensemble in Figure 5-20 (left-hand plot) is much closer to the CHIRPS profile. Nevertheless, three models, GISS-E2-H, GISS-E2-R and inmcm4 have been excluded from the selected MME in Figure 5-20 (right-hand plot), and this has slightly improved the climate profile by removing some of the wet tail of the distribution.

It is a little less clear for Tanzania which model might be considered the 'best performing', but in this case GFDL-CM3 has been selected.

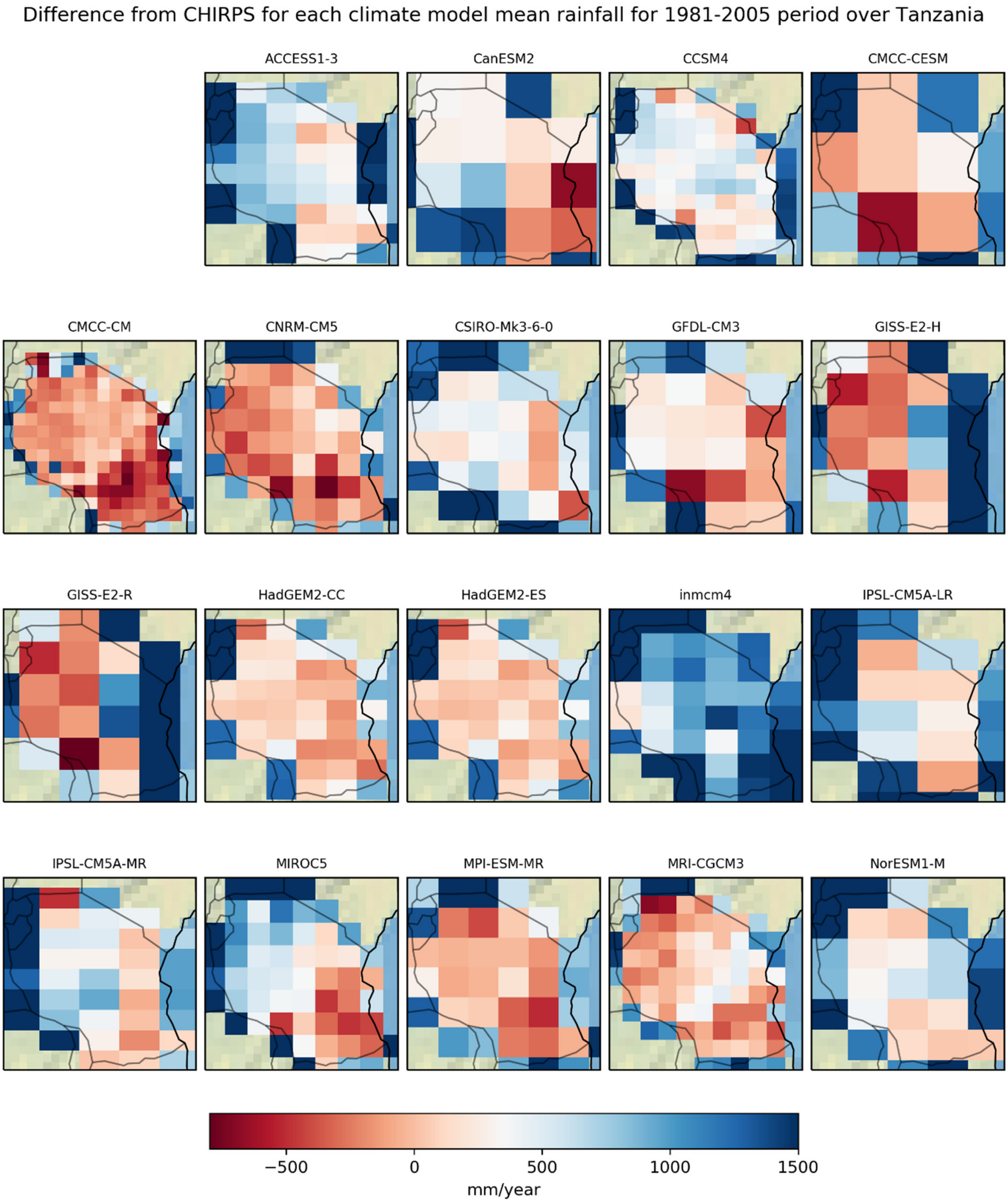


Figure 5-18: Difference between CHIRPS and each climate model for 1981-2005 climate mean for Tanzania. (CHIRPS re-gridded to the resolution of each model).

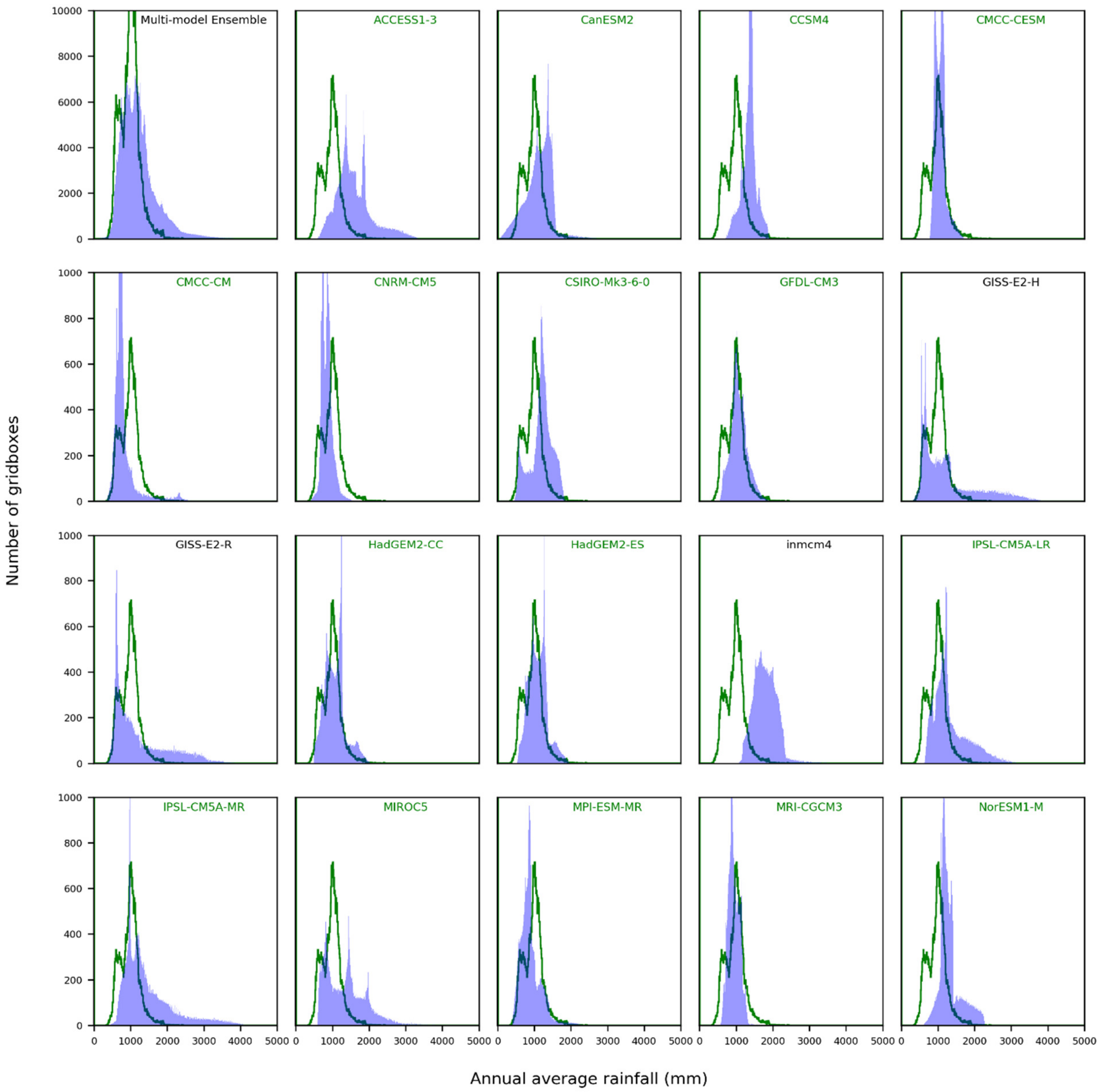


Figure 5-19: 1981-2005 annual rainfall climatology for CHIRPS (in green), each climate model and the multi-model ensemble (in blue) for Tanzania.

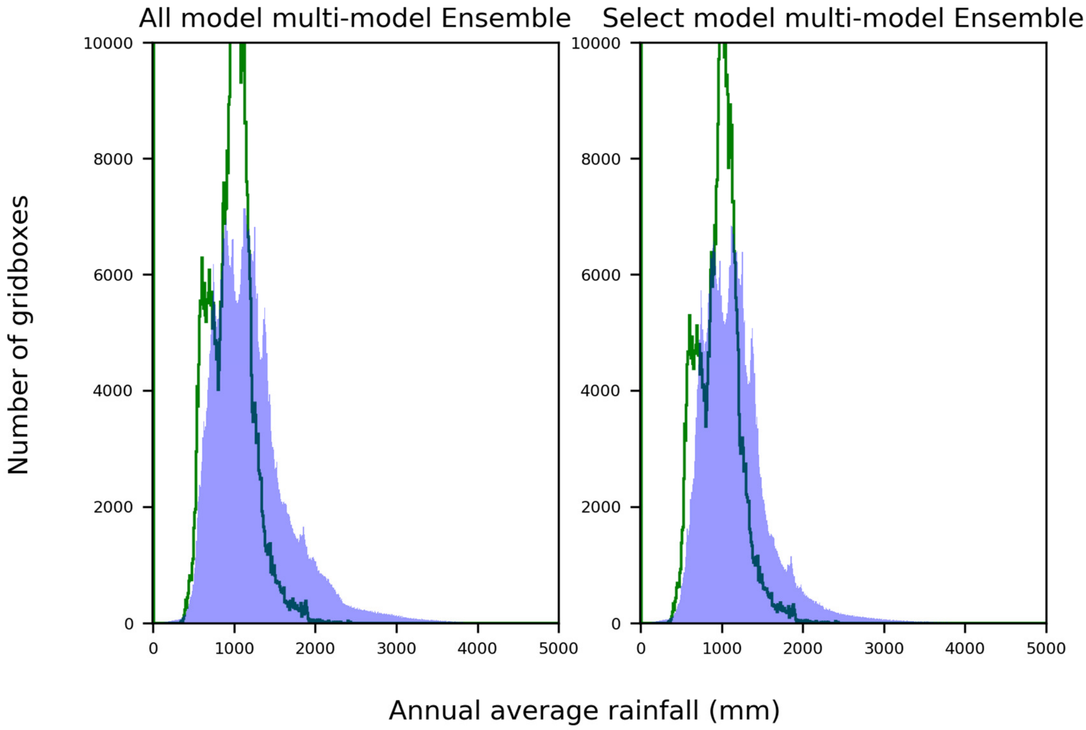


Figure 5-20: 1981-2005 annual rainfall climatology for CHIRPS (in green), and the multi-model ensemble (in blue) with all 19 climate models (left) and with 16 of the 19 models (right), for Tanzania.

Mali

Figure 5-21 shows the difference in annual average rainfall over the country between the CHIRPS rainfall data and each of the nineteen models over the 1981-2005 climatology for Mali.

From Figure 5-21 it can be seen that CISRO-Mk3-6-0 and MIROC5 have a wet bias, relative to CHIRPS. In contrast the HadGEM models, inmcm4 and the IPSL-CM5A models in particular have a dry bias. The resolution of the CMCC-CESM model is very low, with only one grid box substantially covering the main growing regions shown in Figure 5-13. Overall CCSM4 seems to do the best job of reproducing a similar annual average rainfall pattern as CHIRPS.

The strong north-south gradient in annual rainfall totals, and the resultant concentration of cropping livelihoods in the far south, indicate that it is only the climate of the far south that is really of interest for farming. Figure 5-22 shows the annual rainfall climatology for just the southern region of Mali (south of 15^{o}N).

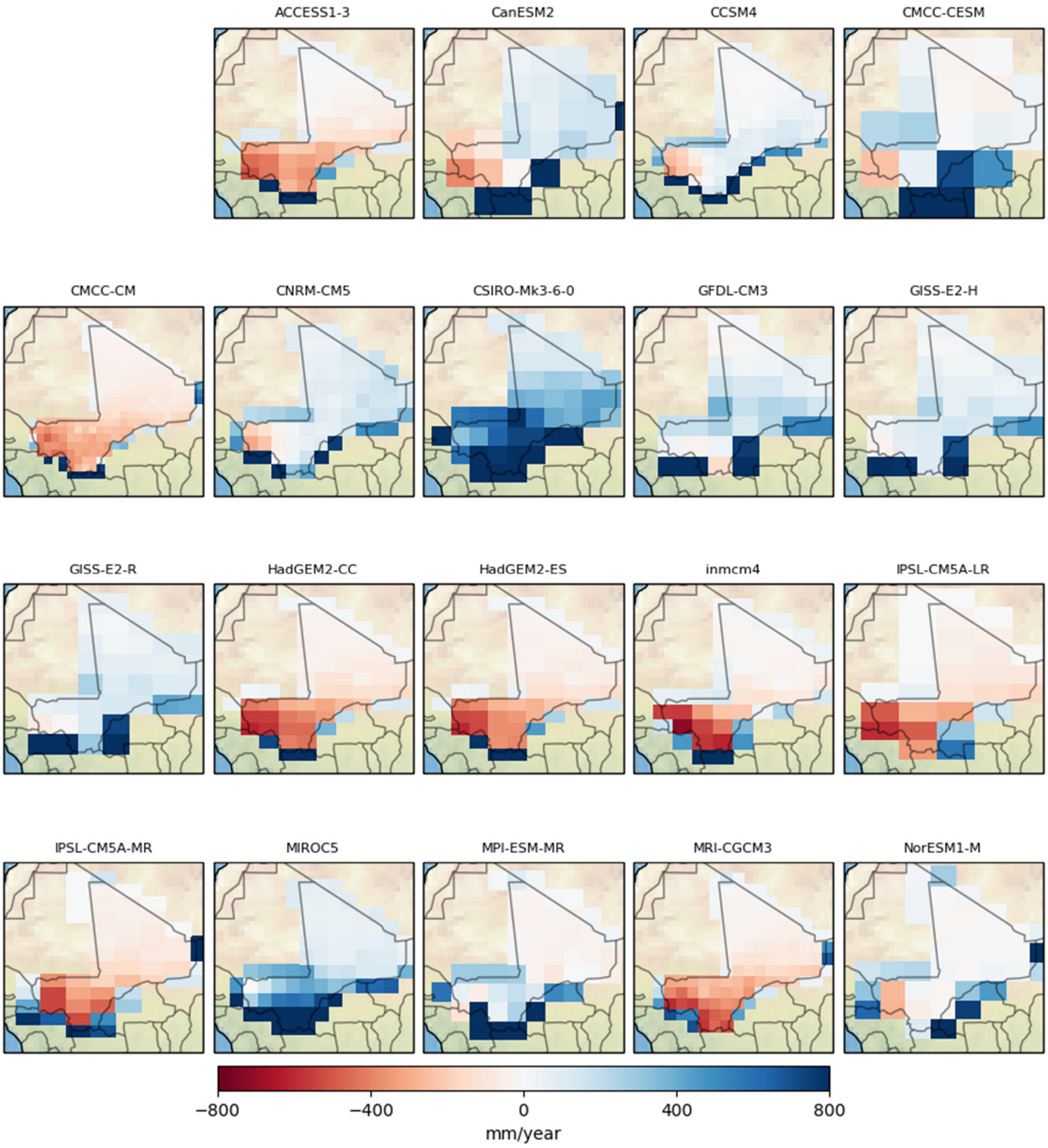


Figure 5-21: Difference between CHIRPS and each climate model for 1981-2005 climate mean. (CHIRPS re-gridded to the resolution of each model).

In general the models do a poorer job of reproducing the annual average rainfall climatology for CHIRPS in Mali than in Ethiopia and Tanzania, but better than Botswana. Climate models struggle to capture the West African monsoon, the dominant driver of inter-annual rainfall in the region (Cook and Vizy 2006, Niang, Ruppel et al. 2014), so this is not surprising. CISRO-Mk3-6-0 and MIRCO5 in particular show a wet bias, and a number of models including inmcm4 show a dry bias. Excluding these models, and CMCC-CESM (because of the low resolution which means there is only one grid box predominantly covering the cropping region in Mali), the multi-model ensemble was recalculated and compared with CHIRPS. The sub-selected multi-model ensemble climatology and the comparison with the full multi-model ensemble can be seen in Figure 5-23. This shows some improvement in the representation of the CHIRPS climatology by excluding some of the poorer performing models, in particular the long tail of wet-bias grid boxes is reduced.

Overall looking at Figure 5-22, the best performing model for Mali, from this limited comparison, seems to be CCSM4. (For a more detailed analysis of the West African monsoon simulations in CCSM4 see (Cook, Meehl et al. 2012)).

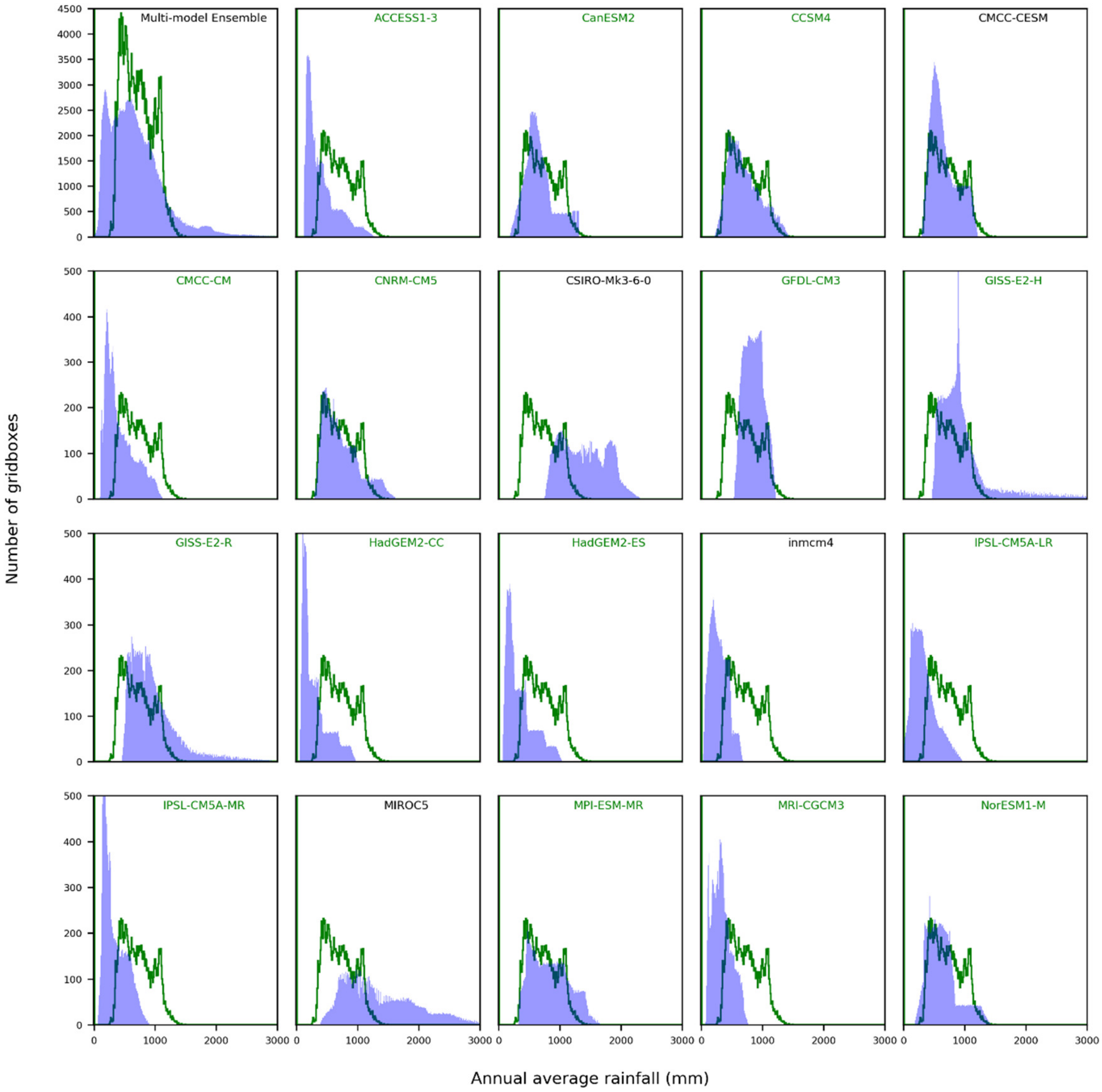


Figure 5-22: 1981-2005 annual rainfall climatology for CHIRPS (in green), each climate model and the multi-model ensemble (in blue) for southern Mali (South of latitude 15^{0} N)

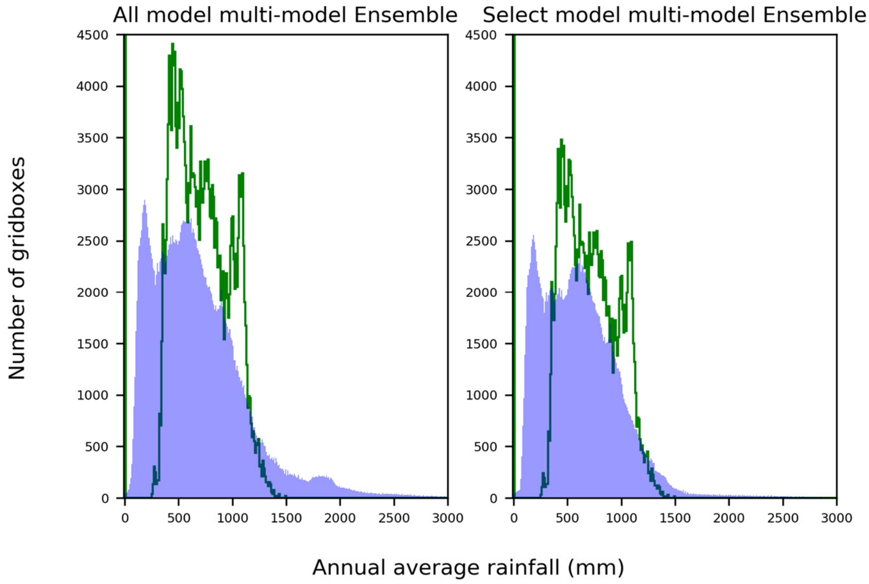


Figure 5-23: 1981-2005 annual rainfall climatology for CHIRPS (in green), and the multi-model ensemble (in blue) with all 19 climate models (left) and with 16 of the 19 models (right), for southern Mali (South of latitude 15^{0} N).

Climate change projections

The change in annual average temperature and rainfall across all the projections for all 19 of the climate models included in this study for Botswana, Tanzania and Mail are shown in Figure 5-24, Figure 5-25 and Figure 5-26. Appendix D includes maps of change in annual average temperature and rainfall, for each of the 19 models for each country.

For Botswana (Figure 5-24) there is good agreement amongst the models for a drying signal to 2100 under RCP8.5, and for an increase in temperature, although there is some disagreement on the level of reduction in average annual precipitation.

For the individual models (shown in Appendix D), all models showing an increase in temperature between 2006-2035 and 2071-2100, and all but one or two of the models show a decrease in annual average rainfall over the same period across the whole of Botswana. (The main exception is the MIROC5 model, which is also one of the models that exhibited a strong wet bias in the 1981-2005 period relative to CHIRPS, and was excluded from the multi-model ensemble on that basis).

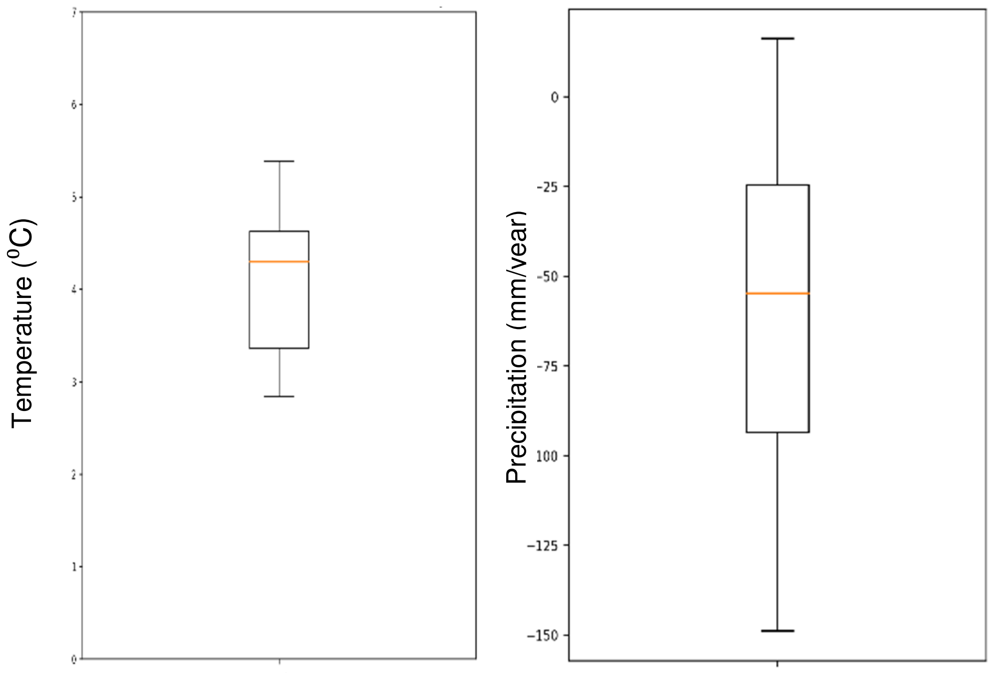


Figure 5-24: Change in annual average temperature (^{0}C) (left) and rainfall (mm/year) (right), over Botswana, from all 19 CMIP5 models included in this model between 2006-2035 climate and 2071-2100 climate. Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range

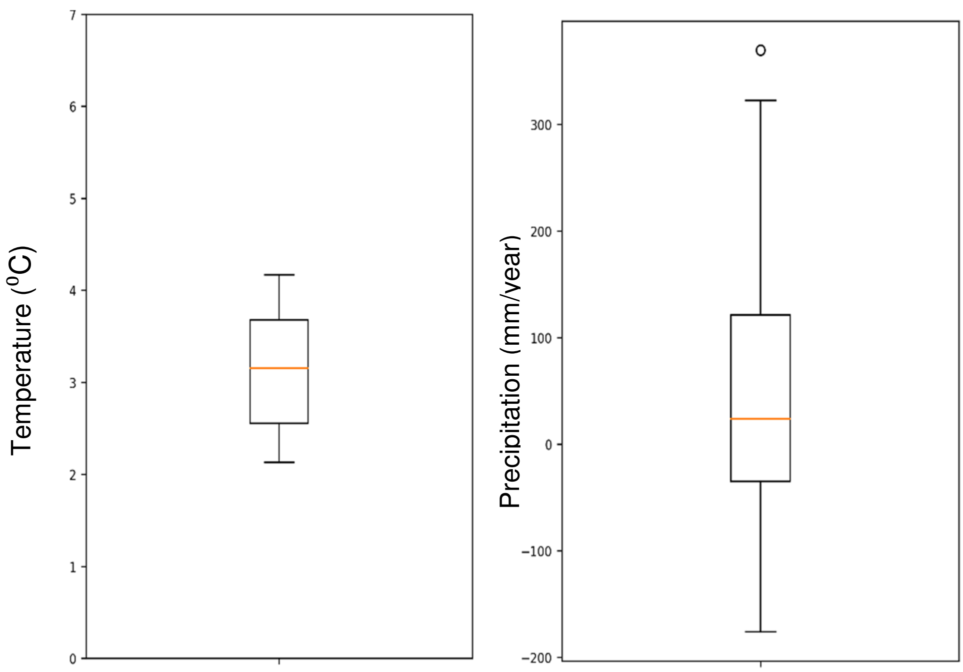


Figure 5-25: Change in annual average temperature (^{0} C) (left) and rainfall (mm/year), over Tanzania, from all 19 CMIP5 models included in this model between 2006-2035 climate and 2071-2100 climate. Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

For Tanzania there is a high level of uncertainty in the climate projections is for the change in rainfall over the country (Figure 5-25). The projected change in annual rainfall between 2006-2035 and 2071-2100 under RCP8.5 over Tanzania ranges from a decrease of almost 200mm/year, to an increase of over 300mm/year. The two GISS models (GISS-E2-H and GISS-E2-R), which have already been excluded from the sub-selected MME for their dry bias in the baseline climate, show the greatest drying under climate change. The two IPSL models (IPSL-CM5A-LR and IPSL-CM5A-MR) which are included in the sub-selected MME, show the greatest increases in rainfall.

As with the other countries in this study, all the models project increases in temperature over Tanzania, with relatively good agreement on the level of warming.

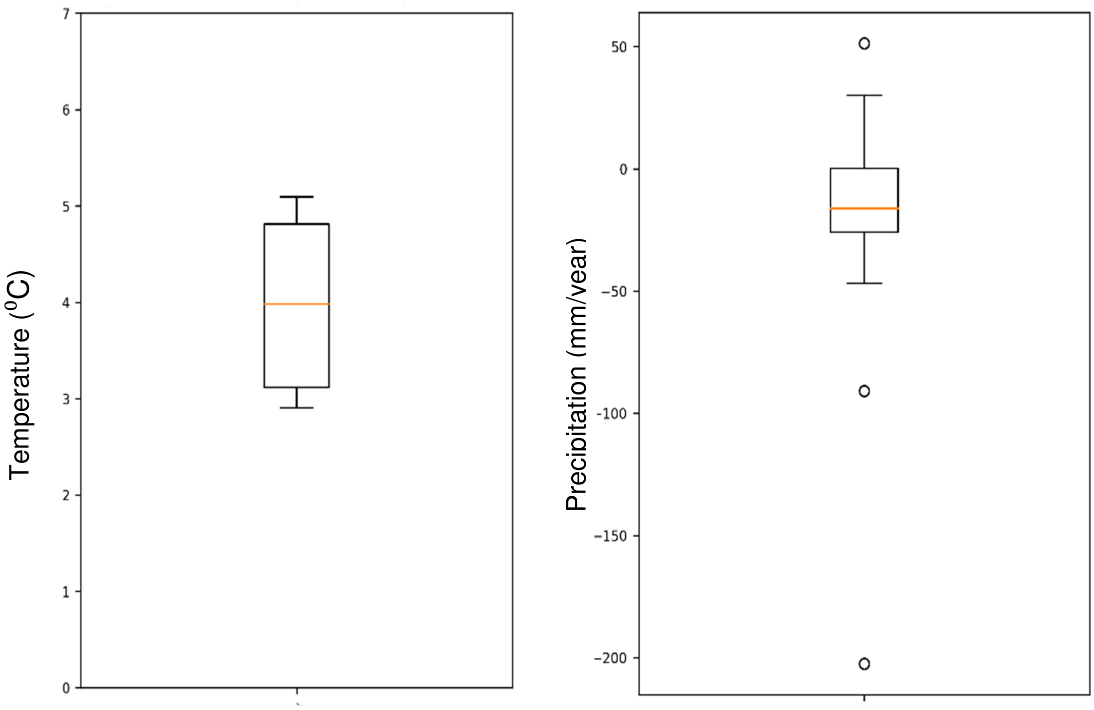


Figure 5-26: Change in annual average temperature (^{0}C) (left) and rainfall (mm/year), over Mali, from all 19 CMIP5 models included in this model between 2006-2035 climate and 2071-2100 climate. Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range

For Mali, aside from a few outliers, there is reasonable agreement on there being a low level of change in rainfall, albeit spanning zero, to the end of the century (Figure 5-26). This is despite the high level of uncertainty in climate model projections over the area as a whole seen in Figure 5-7. (It should be noted that while Mali is included in the country grouping for North Africa, the wet region in the south more properly lies in the West African tropical belt, and so it might be expected that uncertainty in the projections in Mali would be consistent with the climate model uncertainty in the larger West African region.)

The model consensus in both temperature and rainfall is for all models to show an increase in temperature between 2006-2035 and 2071-2100, and most models showing modest changes in annual average rainfall over the same period (see Appendix D). The exception is the CISRO-Mk3-6-0 model, which is also one of the models that exhibited a strong wet bias in the 1981-2005 period relative to CHIRPS, and was excluded from the multi-model ensemble on that basis.

Climate proxy for production

The Standardised Precipitation Index (SPI) was calculated using the CHIRPS data for Botswana, Tanzania and southern Mali. As for Ethiopia the average areal value of monthly SPI was calculated, and the annual mean value taken to get a single value for SPI for each year. Figure 5-27, Figure 5-28 and Figure 5-29 show this SPI value plotted against the de-trended reported cereal production for 1981-2015 for Botswana, Tanzania and Mali respectively. The correlations between SPI and reported all cereal production for each country are given in Table 5-1.

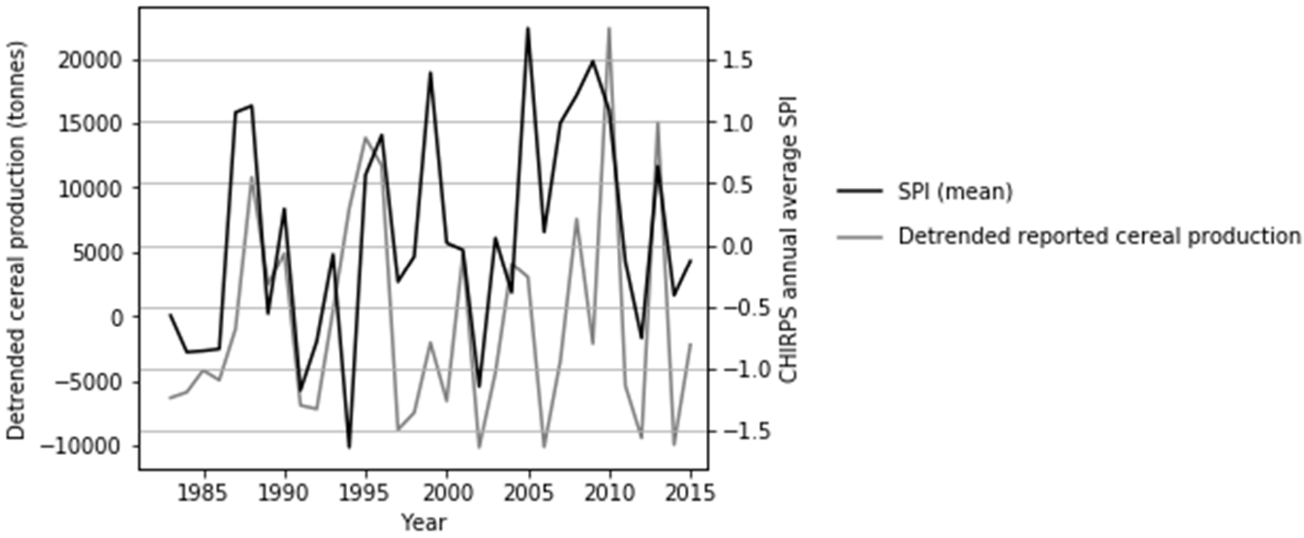


Figure 5-27: Standard Precipitation Index (SPI) calculated over Botswana, and de-trended reported cereal production anomalies (shown with 1 year lag).

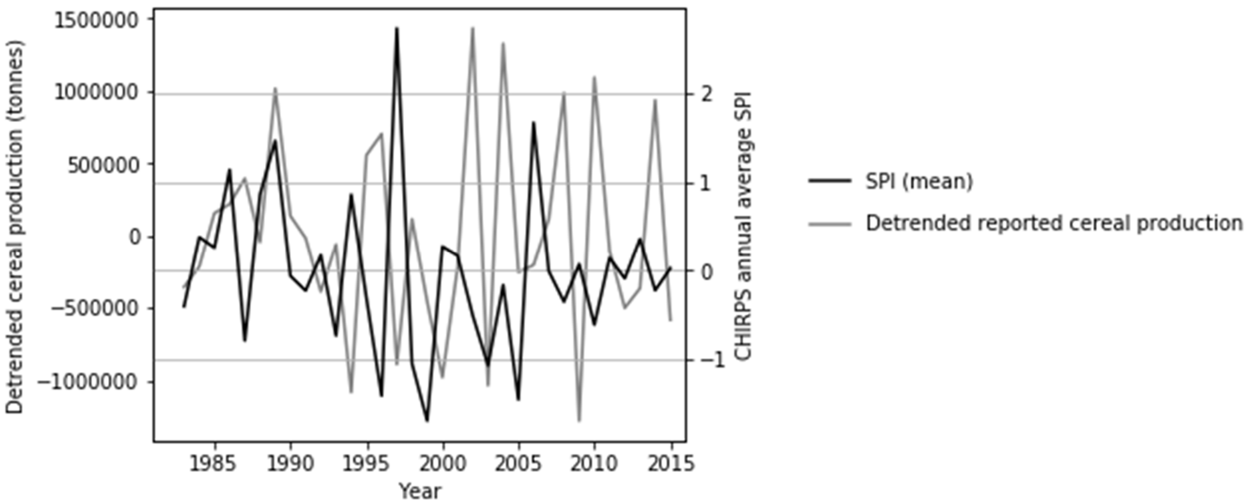


Figure 5-28: Mean annual Standard Precipitation Index (SPI) over Tanzania (black) and de-trended reported cereal production anomalies (grey) (shown without 1 year lag).

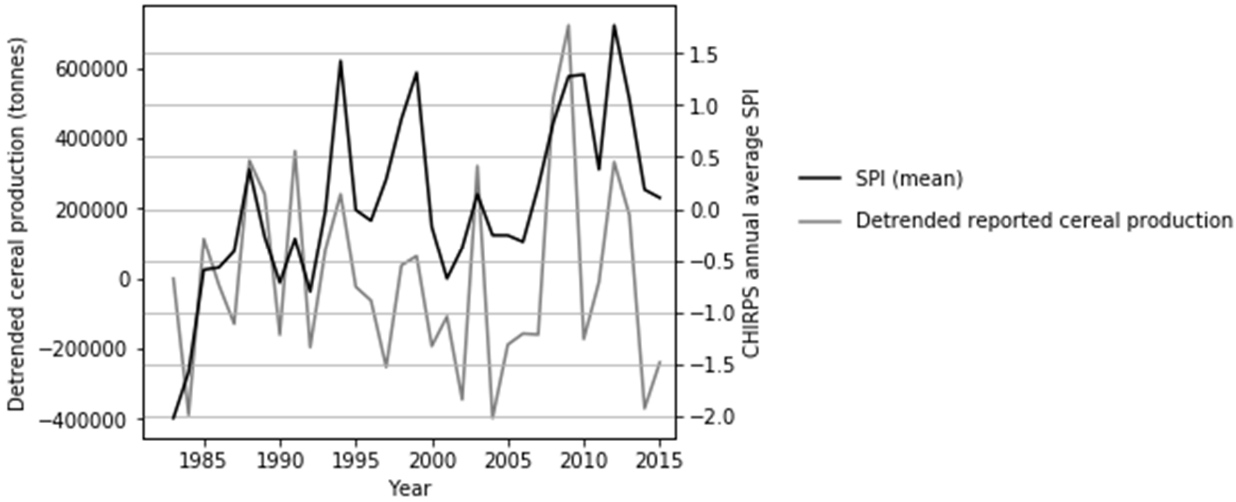


Figure 5-29: Mean annual Standard Precipitation Index (SPI) over southern Mali (black) and de-trended reported cereal production anomalies (grey) (shown without 1 year lag).

Table 5-1: Correlations between SPI and cereal production for 1981-2015 period.

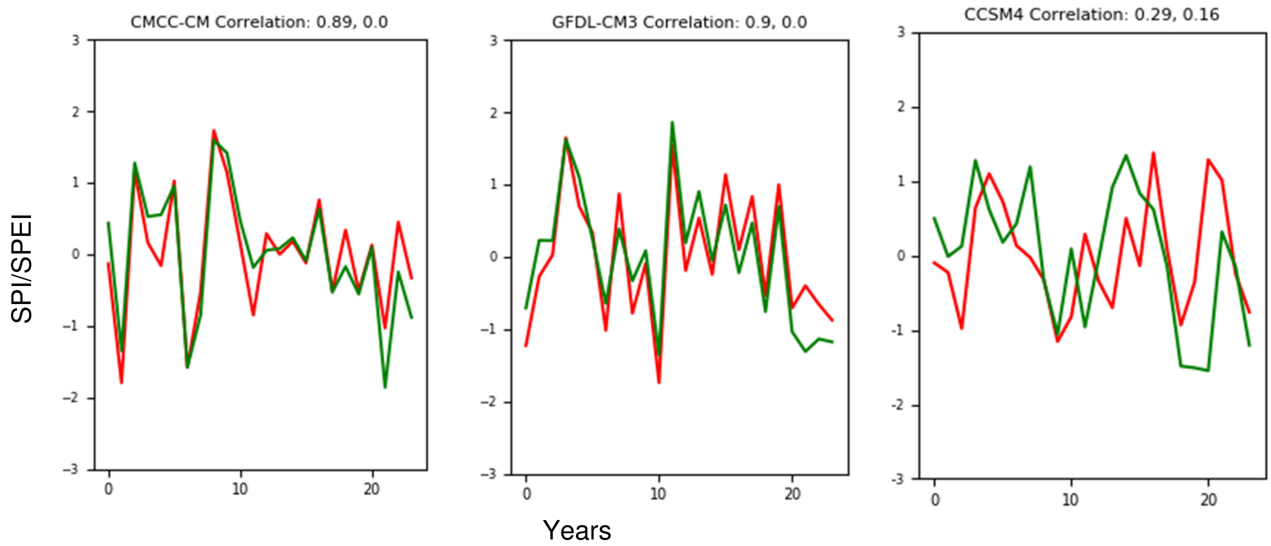
Country	SPI-cereal production correlation	
	Pearson r coefficient	2-tailed P value
Ethiopia	0.47	0.01
Botswana*	0.51	0.0
Tanzania*	0.36	0.04
Mali	0.6	0.01

The aim of looking at the correlation between the two datasets is to test whether SPI would make a ‘reasonable’ proxy for food production in the climate models. There are number of data reasons why SPI, or indeed any climate indicator, would not capture all the variability in cereal production, aside from their suitability for the task. This include the fact that annual production could vary as a result of factors not related to climate, and that the reliability of the production data being used is unknown. Despite this it might be expected that the fingerprint of climate impact on national production could be found, and an optimal climate indicator designed. In this case the Standard Precipitation Index is used for the reasons discussed in Chapter 4, and the purpose here is to check whether this is a valid metric for countries other than Ethiopia, rather than to begin again in finding the optimal metric for each country.

Both Botswana and Mali show correlations higher than that found for Ethiopia. The correlation for Tanzania is the lowest. What is not clear is what should be considered an acceptable level of correlation between SPI and production for SPI to be considered a valid proxy. Given the uncertainties of the data, this can only ever be a subjective assessment, and is therefore a weakness in the approach. However, in this instance SPI seems to explain at least a third of the production variability over the time period in all the countries. The lower correlation for Tanzania (and to a lesser extent Ethiopia) is noted and should inform the level of confidence attributed to the results.

One further point to note is that the correlation values for Botswana and Tanzania (indicated by *) are achieved when a lag of 1 year is introduced to the cereal data. Without this lag, the correlation is lower in the case of Botswana ($r = 0.47$, $P = 0.01$), and anti-correlated in the case of Tanzania ($r = -0.12$, $P = 0.27$). Investigation into the relationship between SPI and cereal production for a number of countries indicates that those with cereal production dominated by maize only correlate well with SPI when this one year lag is introduced. This is likely to be a feature of the crop calendar, and something that would benefit from investigation in a more detailed study of the relationship between crop productivity and rainfall, but is outside the scope of this study. In this case it is the climate profile of production that is of interest, not the timing of events, and so the lag between SPI and cereal production does not affect the validity of using SPI as a proxy for food production.

The next step in the development of a proxy for cereal production from the climate data is to compare the Standard Precipitation Index (SPI), which only uses rainfall in its computation, with the Standardised Precipitation and Evapotranspiration Index (SPEI), which includes the effects of both rainfall and temperature, thus making it more suitable over climate change timescales. Figure 5-30 compares the 1981-2005 time series for both, for each of the ‘best performing' models, for each country. The correlation between the two time series (Pearson r coefficient, 2-tailed P value) are shown above each plot. This illustrates the relationship between the two indices in each country. The same data, but for every individual model is available in Appendix E.



a. Botswana b. Tanzania c. Mali

Figure 5-30: Standardised Precipitation Index (SPI) (red) and Standardised Evapotranspiration and Precipitation Index (SPEI) (green) calculated with climate data from the 'best performing' models from CMIP5 for each country for 1981-2005 period

In the case of Botswana and in Tanzania there is very little difference between the two, but for Mali the two measures of aridity are not as similar. Table 5-2 lists the mean correlation across all the models for each country. The mean correlation for Mali is only 0.5, and this casts some doubt on the appropriateness of substituting SPEI for SPI in the proxy selection. However, as with the relationship between SPI and reported cereal production, there is no threshold over which the correlation could be objectively considered to be sufficient. Again, the only option is to make a subjective decision and to note the weakness of the correlation for Mali, such that it informs the confidence attributed to the final food security output.

Table 5-2: Mean correlations between SPI and SPEI values over each country for 1981-2005 period for 19 climate models.

Country	Mean SPI-SPEI correlation value for 1981-2005 period over 19 climate models (Pearson r coefficient, 2-tailed P value)
Ethiopia (Highlands region rainfall)	0.86, 0.0
Botswana	0.95, 0.0
Tanzania	0.94, 0.0
Mali (South Mali rainfall)	0.5, 0.1

Figure 5-31 shows the SPI and SPEI values over 2006-2100 for the 'best performing' model for each country for illustration. (These plots for all the models in the study are shown in Appendix F.) The two indices are normalised across the whole time period. (This accounts for the differences in the annual values and inter-annual variability between the two, as discussed in Chapter 4). This allows a comparison of the impact of using SPEI rather than SPI as a measure of water availability over a longer period where there is a strong trend in temperature change. In all three countries SPEI (in green) shows a decreasing trend over time, associated with drying and warming. The trend is sharper for the SPEI values as both temperature and rainfall changes contribute.

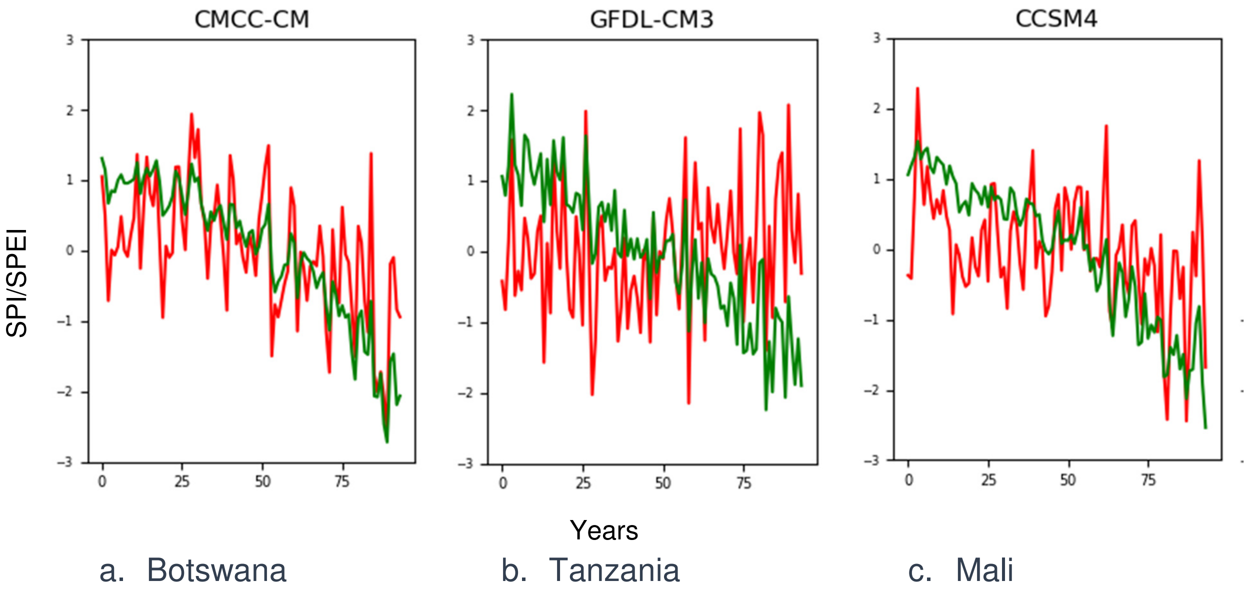
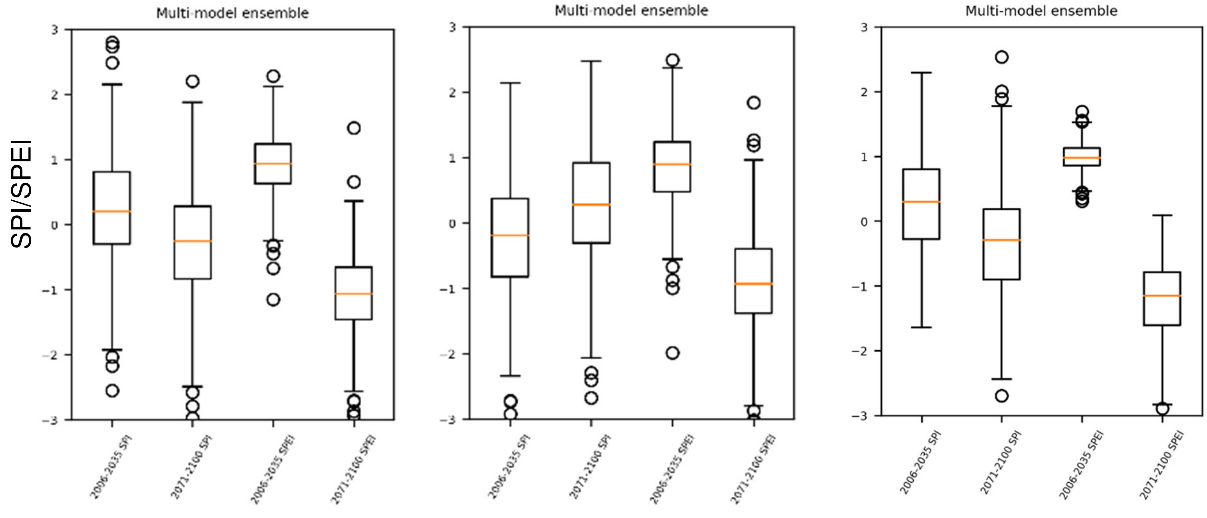


Figure 5-31: Standardised Precipitation Index (SPI) (red) and Standardised Evapotranspiration and Precipitation Index (SPEI) (green) calculated with climate data from the 'best performing' models from CMIP5 for each country for 2006-2100 period

Figure 5-32 shows the same SPI and SPEI data for 2006-2100, but for the sub-selected multi-model ensemble for each country, and as a box and whisker plots. The first two box and whiskers in each plot show the SPI range for 2006-2035 and for 2071-2100 respectively. The second two box and whiskers show the same data but for SPEI. This illustrates how SPI and SPEI median and range changes between the present day and future periods in the models. (Again, these plots for all the models in the study are shown in Appendix F.) For Botswana and Mali the trend for SPI is for a decrease over time, associated with the reduction in rainfall in the climate model projections. In Tanzania, SPI increases by the end of the century. However, the trend for SPEI is for a decrease in water availability associated with climate change between 2006-2035 and 2071-2100, in all three countries. There also appears to be an increase in the annual variability of the SPEI index over time. This is particularly noticeable for Mali, where the differences in SPI and SPEI even in the comparison (1981-2005) period, indicate that evapotranspiration plays an important role in water availability in the country.



a. Botswana Period nia c. Mali

Figure 5-32: Boxplots for 2006-2035 and 2071-2100 SPI (left) and SPEI (right) ranges calculated with climate data from the sub-selected multi-model ensemble from CMIP5 for each country for 2006-2035 and 2071-2100 periods. Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

Simple food system model

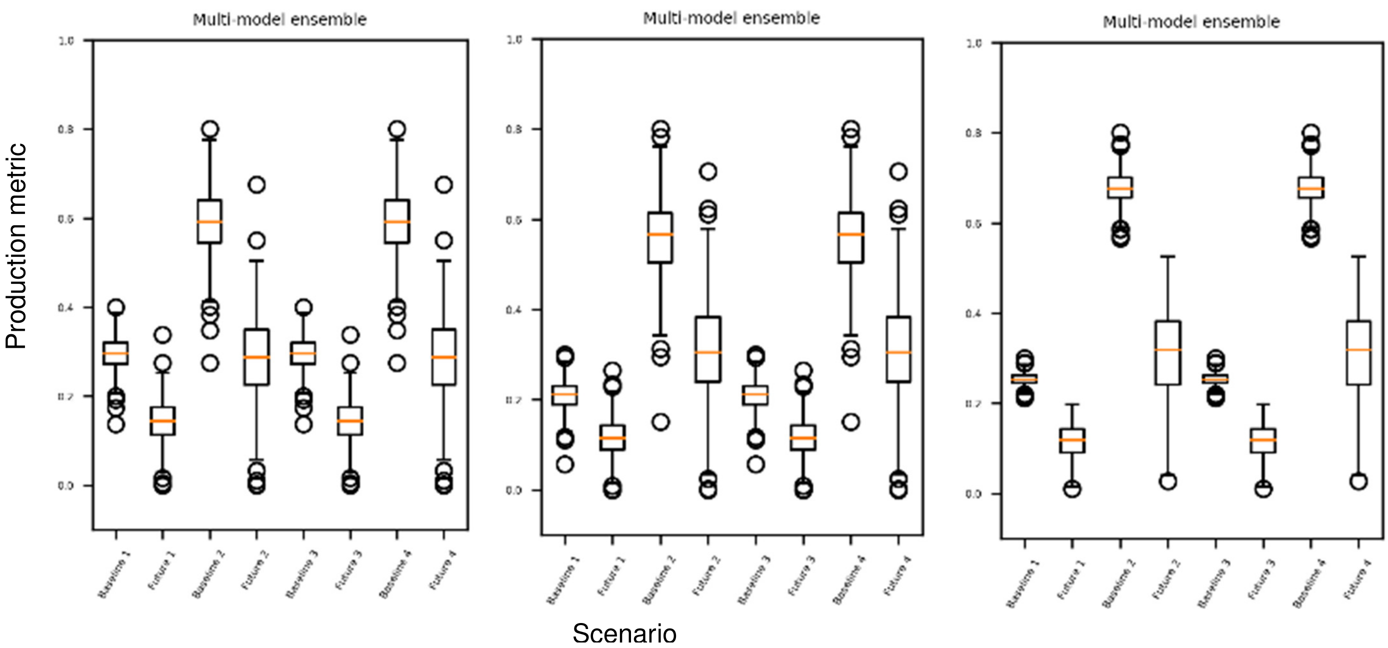
The simple food system model developed in Chapter 4 was run for Botswana, Tanzania and Mali, using the same set of climate and food system scenarios as in Figure 4-16. Values for the yield gap and proportion of the population employed in agriculture appropriate to the individual country food systems were used and are shown in Table 5-3.

Table 5-3: Scenarios for food system changes to simple food system model. Data from (GYGA 2017, World Bank 2017)

	Botswana		Tanzania		Mali		
	Yield gap	% employ in ag	Yield gap	% employ in ag	Yield gap	% employ in ag	Comment
Baseline 1	0.6	0.3	0.7	0.7	0.7	0.6	2006-2035 climate and food system
Future 1	0.6	0.3	0.7	0.7	0.7	0.6	As Baseline, but with 2071-2100 period climate
Baseline 2	0.2	0.3	0.2	0.7	0.2	0.6	Improve yields, maintain dependence on agriculture for income, in 2006-2035 climate
Future 2	0.2	0.3	0.2	0.7	0.2	0.6	As Baseline 2, but with 2071-2100 period climate
Baseline 3	0.6	0.1	0.7	0.1	0.7	0.1	Reduce employment in agriculture, no investment in yield improvement, in 2006-2035 climate
Future 3	0.6	0.1	0.7	0.1	0.7	0.1	As Baseline 3, but with 2071-2100 period climate
Baseline 4	0.2	0.1	0.2	0.1	0.2	0.1	Both reduce employment in agriculture and invest in yield improvement, in 2006-2035 climate
Future 4	0.2	0.1	0.2	0.1	0.2	0.1	As Baseline 4, but with 2071-2100 period climate

Food system model results

Figure 5-32 shows the Production metric output from the simple food system model for the sub-selected multi-model ensemble, for Botswana, Tanzania and Mali. All the results from the simple food system model for these countries, for all the models in the study, are shown in Appendix G.



a. Botswana b. Tanzania c. Mali

Figure 5-33: Production metric range for each country under each scenario from Table 5-3, for the selected multi-model ensemble. *Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.*

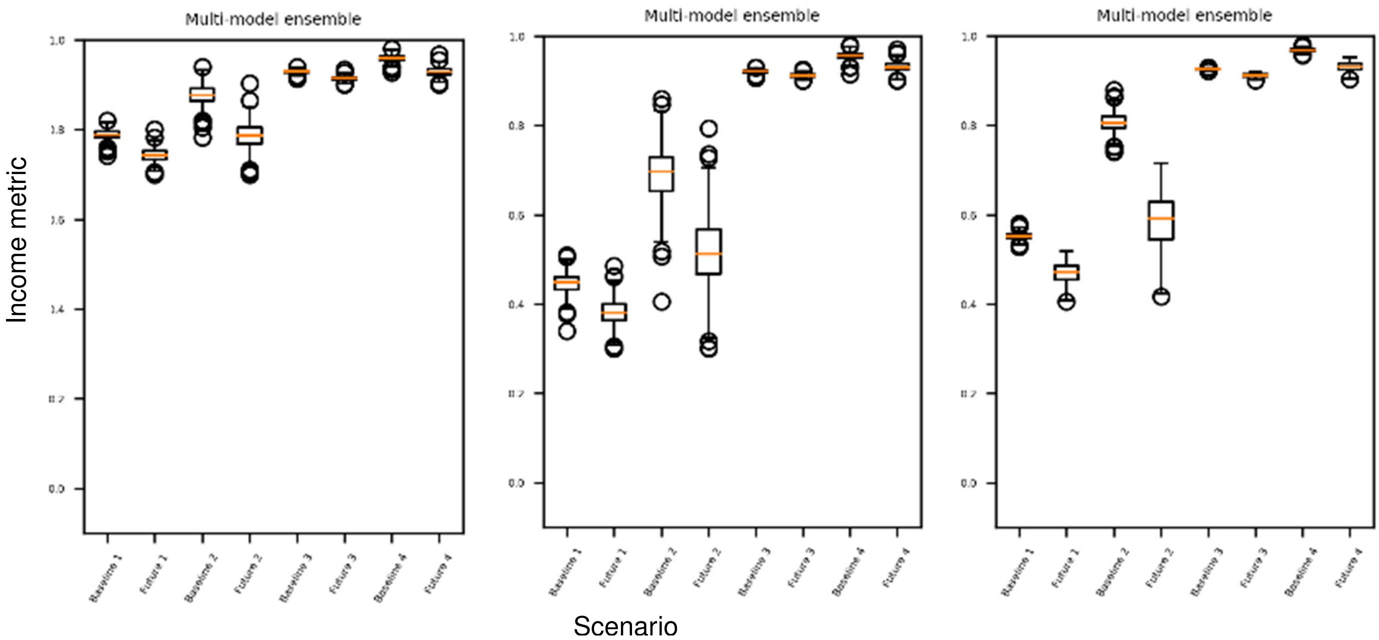
For all three countries, as with Ethiopia, climate change has a negative impact on the median metric value (difference between Baseline 1 and Future 1). As expected from the SPEI data, there is some increase in the variability in production associated with climate change, and this is most noticeable for Mali.

Note, as with Ethiopia the change in variability is seen in the individual climate models, shown in Appendix G, and not simply a feature of model divergence in the ensemble members. Having said that, for Botswana there is a higher level of disagreement on the baseline climate (2006-2035) between the models, which means the Production metric spread in the MME is larger than is seen in individual models. (Appendix G shows all the food system output for all the models and the MME for comparison). This means that the increase in variability is less obvious in Figure 5-32 than it is in the individual climate model results.

For all three countries the adverse impact of climate change alone is smaller than the positive impact of improvements in yield (difference between Baseline

1 and Future 1, compared with the difference between Baseline 1 and Baseline 2). However, when climate change is combined with action to reduce the yield gap, the benefits of this action are off-set by climate change. In Botswana, in particular the combined impact of changes to yield and climate change result in a future for which the median Production metric value is no better than the present, but where inter-annual variability plays a much larger role. This is likely to be as a result of the much stronger signal for drying in the climate model projections for Botswana. For all three countries the increase in variability is large, and the worst years in this future are far worse than at present.
For the Production metric, as in Ethiopia, the changes in scenarios 3 and 4 have no impact on production, so for this metric these scenarios are identical to scenarios 1 and 2.

Figure 5-34 shows the Income metric from the simple food system model for the sub-selected multi-model ensemble, for the same three countries. As for the Production metric, climate change has a negative impact on the Income metric across all three countries. (Difference between Baseline 1 and Future 1). Both improvements in yield and reductions in the proportion of the population working in agriculture have a positive impact on the Income metric (Baseline 2 and Baseline 3 compared Baseline 1). Climate change off-sets much of the improvement associated with yield gains, but diversification of income has a bigger impact, both in terms of reducing variability and improving the metric, even when climate change is applied. This is true across all the countries, even in Botswana where employment in agriculture is already at much lower levels than in Tanzania or Mali.

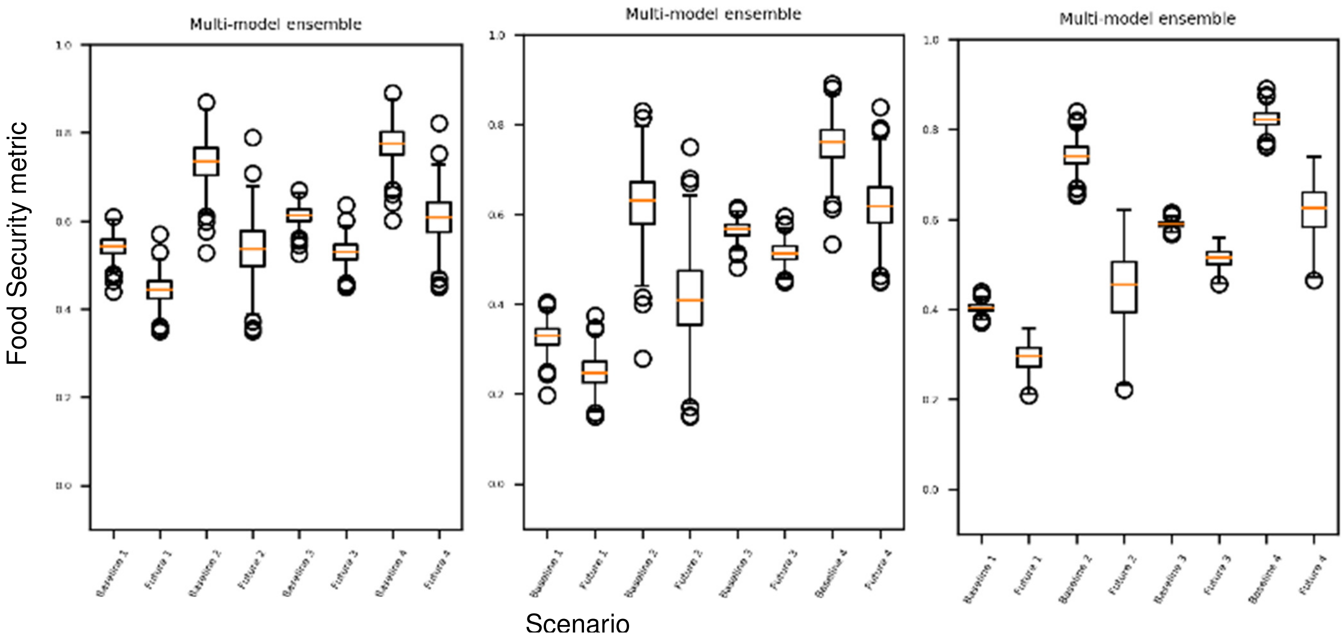


a. Botswana b. Tanzania c. Mali

Figure 5-34: Income metric range for each country under each scenario from Table 5-3, for the selected multi-model ensemble. Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

Figure 5-35 shows the Food Security metric for the sub-selected multi-model ensemble, for each of the three countries. This combines the results from the Production and Income metrics to show the overall modelled potential of each country to meet its food security needs, on a relative 0-1 scale.

As seen for the component metrics climate change reduces both the median and increases the variability of the Food Security metric (difference between Baseline 1 and Future 1). Increasing yields produces improvements in the metric larger than the adverse impact of climate change when each is considered separately, with the greatest benefit in Mali. When combined the higher variability of the climate on the larger production levels however, the benefits of increasing yield are off-set by climate change. This means that large increases in yield need to be achieved to make up for losses associated with climate change, and even then the Future 2 scenario in all three countries, is one where variability is a larger feature of food security than today. This increase in variability is particularly striking for Mali. Again, this is not a feature of the ensemble spread increasing over time, but can be clearly seen in the Food Security metric for each of the individual models in Appendix G.



a. Botswana b. Tanzania c. Mali

Figure 5-35: Food Security metric range for each country under each scenario Table 5-3 for the selected multi-model ensemble. Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

The increase in variability can be seen to a lesser extent for Tanzania. Here there is greater uncertainty for the climate model projections for rainfall change, although there is more consensus between the models on the signal for temperature change. This means that the projections for SPEI, which combine both variables, show much less uncertainty than for rainfall alone. The increase in variability is seen in the Food Security metric for each of the individual models (see Appendix G), and is not a feature of the MME in Tanzania. This demonstrates the value of looking at the projections from the perspective of the system impacts, rather than accepting the uncertainty in the projections is necessarily a limitation on the uncertainty in security outcomes.

Diversifying income away from agriculture (scenario 3) has a dramatic impact on reducing variability by disassociating more of the national income from an increasingly variable climate. Combined with reductions in the yield gap, the median future Food Security metric is higher in all three countries. However, even the proportion of the population dependant on agriculture for their income is dramatically reduced, the food system model indicates that variability will become an increasing feature of future food insecurity. As with the Production and Income metrics individually, substantial system changes are required in order for the future Food Security metric to even keep pace with climate change, and increasing volatility in this metric are unavoidable in the simple food systems model. This is before considering the practical and political feasibility of the large system changes each scenario describes.

Summary of food system model application outside of Ethiopia

The application of the simple food system model to three additional countries highlights some important weaknesses, but also strengths in the model approach. For each of the three countries there are reasons to be cautious about the informational value of the output from the simple food system model. For Botswana the climate models do a very poor job of reproducing the present day climate, and so confidence in the climate projections may also be low. For Tanzania the relationship between SPI and production was relatively weak, and so questions could be asked about the value of SPI (or SPEI) as a proxy for production. For Mali, although the correlation between SPI and production was good, the correlation between SPEI and SPI was not as strong. As it is not possible to test the relationship between SPEI and production due to the unreliability of gridded coherent temperature and rainfall datasets, there is no way of knowing how good a proxy SPEI is when actually used in the food system model.

Even accounting for the large assumptions in the application of the food system model to the four countries, the results provide good evidence that climate change will not in itself be the cause of future food insecurity. Some care may be required in interpretation, but the model output could help inform an understanding of the policy effort required to make large scale system changes appropriate to the challenge of climate change. For example, it could be used to evaluate the costs and benefits of large-scale economic reform to diversify income as an adaptation to climate change. In Botswana, the particulars of the national food system mean that the model is only describing part of the wider food system, and not accounting for the role of imports or livestock. In Tanzania though, where the climate model projection uncertainty is high, this approach demonstrates the importance of looking at the climate in a systems context. Here the climate model uncertainty is not a limitation on the value of the information that can be provided for decision-making.

Despite the problems encountered in the application of the model, it was possible to look at the climate change projections through a food security lens using this approach. The results are a quantification of the relative scale of climate impact, compared to two other factors, although it is not really possible to ascribe a confidence level to that data. Some of these difficulties could be addressed, or at least reduced, by taking a more detailed look at the food system model, and this will be discussed in the next chapter.

Chapter 6

Discussion & Conclusions

This thesis aimed to explore the role of climate science in understanding climate security. Chapter 2 reviewed the challenges of utilising climate model data to inform analysis of the potential security threats associated with climate change. Climate Security spans natural and social science boundaries, and differences in analytical methods, language and scale between disciplines can result in barriers to accessing climate science knowledge. For social scientists and security analysts, the temporal and spatial scale that climate model data is available at, together with the uncertainty inherent in projections of the long term future, can mean that the data lacks utility (Fetzek 2008). Climate models are designed to explore the climate system, and are not always well suited to providing information to support action to prepare for climate system changes (McNie 2007). The response is often to ask for more detailed (higher resolution) data with reduced uncertainty, so that non-climate scientists can interpret the data directly for their own analysis (Shukla, Hagedorn et al. 2009). However, in Chapter 2 it was argued that this is not a workable solution to the identified knowledge problems. Instead, there is a need to engage climate scientists in climate and security research, rather than view them as simply data providers. One approach taken here is to embrace a wider systems view to better incorporate different perspectives on a complex problem, not least to properly define the question to allow researchers to respond to the right information requirements. Rather than breaking a problem down into discrete disciplinary questions which are tackled sequentially, a systems approach can be used to look at the research questions from a systems function view (Meadows 2008). In this case different disciplines contribute their knowledge together to design a shared model of the system that can then be explored. At the very least there is the need to consider climate in light of the system dynamics, not as a standalone driver imposed on the system. One hope is that this would also improve the value of the output to inform policy action.

Approach

Chapter 3 began this task by exploring and defining a systems view of food insecurity in Ethiopia. This was to better understand the drivers, but it also to develop a much clearer view on how to frame questions on food security on climate change timescales for the country. Food security and climate data were considered together to build a more complete picture of the role of climate as a driver of food insecurity. This moves away from the simple, qualitative, linear view that adverse weather causes crop failure, which in turn causes hunger and food insecurity. Instead Chapter 3 found that Ethiopia is not food insecure because of the climate, even though extreme weather events often result in acute food insecurity events. Climate is not the limiting factor on Ethiopia meeting its food security needs, but in the context of the current food system Ethiopia is indeed vulnerable to climate variability, such that climate change may exacerbate this vulnerability. It is not accurate to argue that because climate variability drives food insecurity now, greater variability in the future will drive more food insecurity, however logical this may seem. This conclusion depends on the food system context remaining the same over climate change timescales. Not only is this unlikely, but the assumption negates the agency of long term planners to make system changes. These are precisely the changes that climate and security assessments could inform, were they well-designed to do so.

On weather or seasonal timescales, where resilience, early warning and emergency response are important, but over which the system structure will not change, prediction of climate-related security outcomes may be possible in some circumstances. A good example is the FEWSNET early warning food security outlooks provided to many developing countries (Brown 2008). On longer climate change timescales, prediction is not a useful concept. Predictions of the long term future will, by definition, be wrong simply because we are agents of that future, with the power to change the system in which the climate acts. On climate change timescales information on emerging trends and shocks, their direction and scale, may be of greater value for long term planners (Babüroglu and Ravn 1992).

This information can then be used to determine the kind of adaptation action that may be necessary. Incremental climate adaptation is defined as 'doing slightly more of what is already being done to deal with natural variation in climate and with extreme events' (Kates, Travis et al. 2012). This will not always be sufficient in the face of climate change, and on longer timescales there is also the option (and possibly necessity) to initiate transformational change. The language around climate and security does need to be clearly defined to ensure that the right types of analysis are being done for these different information needs. Incremental adaptation actions in disaster risk reduction have hugely reduced the number of people dying from food insecurity in Ethiopia, and reduced the proportion of the population suffering from undernourishment over the past 40 years (Webb, Stordalen et al. 2018), but as can be seen in Table 3-1, there has been little change in the numbers of people who are food insecure, or the frequency of acute food insecurity events. This suggests that to permanently address food security in Ethiopia transformational change is required, and with a future climate that does not look like the past, this needs to include transformational climate change adaptation (Adger et al. 2005).

The concept of transformational change is not always clearly defined by researchers (Feola 2015), but in this instance refers to the general idea of a major or fundamental change in the way a system operates. This is in contrast to smaller scale changes, which ‘nudge’ or refine system behaviours (doing the same things but a little better, as previously described). Although transformational change can sometimes be used to describe changes that are not only large, but also rapid, no assumption is made here about the pace of any system changes.

In the case of Ethiopia, achieving food security by 2030, in line with the Sustainable Development Goals (UN 2015), would require average total production to increase, but it also means providing better responses to acute food security crises, preferably ahead of them occurring. For Ethiopia, transformational change could mean system structure changes so that the need for such crisis response is eliminated. Acute food insecurity could be managed through the development of effective disaster risk management strategies, but a greater ambition would be to build a food system which did not experience these disasters (Mustelin and Handmer 2013). In this context, assessment of climate and security based on specific present day vulnerabilities is of limited use. To inform transformational change such an assessment would be better look at the role of climate as a limiting factor in meet food security needs, and the potential for transformational system change in the future climate. This approach does not attempt to predict future levels of food insecurity, but rather focuses on the constraints that climate change could impose and the opportunities to adapt to these constraints.

The approach taken to assess the climate and system constraints on future food insecurity in Ethiopia followed from the system learning in Chapter 3. It involved designing a simple food systems model which captured the generalised interaction between climate and food. This was done at a temporal scale appropriate for long term planning over which the climate change signal emerges from natural variability, and a spatial scale (large regional to national) suited to the resolution of the available global climate models. The aim was to provide a means to translate the climate model output, including all the uncertainty and disagreement between models, into information on the direction and scale of stress on the food system that climate change could represent. The format was designed to address the information needs of long term planners to make decisions now. This model was by necessity a simplification that could not resolve many of the complex interactions of the real food system. Instead it aimed to capture and quantify the essential features of that system. In particular the systems model incorporated the double effect of climate-driven impacts on production for both availability and access, in combination with system changes. This simple food systems model, although not a quantitative predictor of future food insecurity, goes beyond a qualitative assessment. The output quantifies the direction and scale of stress on the system associated with climate change, other system factors, and the two combined. Critically this provides information on the relative importance of climate change compared with system changes. It also demonstrates how uncertainty in the climate model projections affects their utility in providing evidence to support decision-making.

An assumption worth noting in the example investigated within this study is that the analysis of climate change and food security in Ethiopia will address the information needs for a normative planning process. That is, the information will be designed to support policy decisions aimed at achieving a desired outcome. In this case Sustainable Development Goal 2 for zero hunger (UN 2015). (For more information on normative planning approaches see (Klosterman 1978)). This differs from other types of Climate Security assessments considered in Chapter 2, which include alternative 'Futures' approaches to explore value-free 'worst case', or simple alternative, future scenarios (for example, Schwartz and Randall 2003, DSB 2011, Gemenne 2011).The choice to provide information tailored towards normative planning does not affect the generality of the example, but a feature of this particular case.

Results

The results in Chapter 4 showed that climate change will have a negative impact on the potential food security of Ethiopia, but that the scale of this impact is smaller than potential positive changes associated with policy interventions to improve crop yields and diversify the economy away from subsistence farming. Climate change does substantially off-set much of the improvement associated with system interventions, and without these (rather ambitious) system changes, the food security situation in Ethiopia will become more challenging. In addition, these model results showed an increase in food system variability associated with increased climate variability, which is amplified by the multiplicative effect of the food system changes. Although the ability of the climate models to reproduce variability is not well understood (Sippel, Zscheischler et al. 2015), this result is seen across all the models and is consistent with the findings from Bathiany, Dakos et al. 2018 on increasing temperature variability in Ethiopia. (Note that Bathiany, Dakos et al. 2018 included all 19 models from this study in their research, and temperature is a dominant driver of the trend in the Standard Precipitation and Evaporation Index (SPEI) which is used as a proxy for production in the simple food system model).

These results suggest that climate change will have a negative impact on both chronic and acute food insecurity that can be off-set by system changes, to allow the food security situation in Ethiopia to improve. However, it also shows that large scale substantial system changes are necessary if Ethiopia is to meet its food security needs long term, and that incremental adaptation to improve resilience to climate variability also needs to continue alongside this transformational system change.

One further key finding from the food system model output was that despite there being uncertainty in the sign of the change for precipitation over three four for which the model was run, there was little uncertainty in the output from the simple food system model. This highlights the need to understand the role of climate in security outcomes to fully appreciate the informational value in the projections. At present it is often assumed that all uncertainty in climate projections is relevant to the outcomes of interest and reduces confidence in the utility of those projections (Etkin and Ho 2007), but these results show that this is not necessarily the case.

The simple food system model was additionally run for Botswana, Tanzania and Mali for comparison in Chapter 5. These three countries have differences in their food systems, their climate change projections, and the levels of agreement amongst climate models for those projections. Despite these differences the results for these three countries were broadly similar to those for Ethiopia.

The one modest exception was Botswana. Differences in the food system its position as a more developed country than Ethiopia, Tanzania or Mali mean that here the potential for system changes is smaller. This combined with a strong signal and high consensus for drying over the country, meant that climate change not only had a negative impact on food security potential, but the scale of transformational system changes (within the parameters of the food system model) were reduced. Under a scenario of high climate change and transformational system adaptation, the long term food security potential in Botswana was at best a marginal improvement on the present day, but with greater variability. Care should be taken when interpreting the results for Botswana in particular however, as the simple food system model captured less of the food system description than was the case of the other countries in the study.

For Tanzania and Mali, as for Ethiopia, the model showed that transformational adaptation to climate change could result in more favourable food security conditions for the country. Albeit with the caveat that on-going management of variability would be required.

Evaluation and research recommendations

The results for the change in food security driven by the climate model projections alone are consistent with a wide range of climate change and food security assessments across Africa, which identify climate change and variability as threats to long term food security (e.g. (Devereux and Sussex 2000, Ludi 2009, Conway and Schipper 2011, Niang, Ruppel et al. 2014)). In this study the impact of climate change is given in the context of other possible system changes, to give a sense of scale. However, it is important to note that the system changes included in the simple food system model are illustrative. The initial system conditions are derived from reported data for each country (The_World_Bank 2016, GYGA 2017, FAOSTAT 2018), but the changes to these conditions are imposed with reference to optimal values observed globally. As a result they are extremely ambitious and no attempt is made here to assess the feasibility of achieving these levels of system change.

This simple tool could be a useful way of translating climate model output for policy planners wanting to evaluate the costs and benefits of large scale transformational system changes in a changing climate, but there are limitations as a result of this simplicity too. Some of these limitations could be addressed by working more directly with relevant experts to include more sophisticated representation of the food system,

Transdisciplinary research is challenging (Pohl and Hirsch Hadorn 2008), and engaging with other disciplines to develop the food systems model was not straightforward. The design and construction of the simple food system model was developed through discussion and exchange of ideas with food security experts and economists, for example from the World Food Programme, the UK Global Food Security programme, and others, as part of ongoing wider climate and security research collaboration relationships. In addition national stakeholders were engaged at a number of workshops in Ethiopia, associated with the C-Adapt, HELIX and BRACED projects. Ideally a systems model would be co-developed with direct expert input and ownership from a range of relevant disciplines, as occurred in the development of the Hunger and Climate Vulnerability Index (Krishnamurthy, Lewis et al. 2014). Due to the nature of the PhD, this model benefited from advice and input from relevant experts, but was designed and built from a climate science perspective. Co-design of the model may have resulted in substantial improvement, but the practicalities of trans-disciplinary research may also have provided many more challenges to actually developing a working model. This simple model demonstrates the potential for a systems approach, and offers a basis on which to develop further engagement, discussion and criticism from other expert disciplines to elicit future collaboration.

There are some specific developments that could be investigated, including a more sophisticated representation of agricultural economics within the model, the inclusion of processed-based modelling of crops, and engagement with political scientists and agricultural technologists to include information about the feasibility of the food system changes.

From an economics perspective, the model assumes that low productivity means lower income, mainly because the majority of farmers in the countries included in the study rely on subsistence production. This means that a loss of crops also means a loss of income. However, on a macro scale national reductions in availability are likely to result in the market responding with higher food prices. This is worth further investigation, although it is probably not a simple problem to address. Subsistence farmers may be able to command higher prices for surplus crop in a time of reduced national production, but the model assumes that national and local production are equivalent (on average). For a subsistence farmer this means that low production results in a reduced (or no) surplus to sell, and a higher cost for any purchased food. In reality the relationship between prices and food access is complex and works across scales. What might be more important is the relative income of individual households compared to the national food price. That is, food poverty resulting from low production at a household level is most severe in years when national production totals are high. The simple food system model only looks at national scale, where some of the impact of low production on income will be offset by the market. This choice of scale is an important feature of looking long term, with coarse climate models, but may limit the way economic activity can be included. Nevertheless, this would be something interesting to explore with an economist, and relates back to the concept that a systems model needs to be, as Einstein is reputed to have said, 'as simple as possible, but no simpler'. As an example of an alternative approach Hertel, Burke et al. 2010 consider the interaction between climate-induced crop yield changes and poverty outcomes by using a global trade general equilibrium model (the Global Trade Analysis Project (GTAP)) to translate climate model projections into poverty outcomes. Applying this type of methodology to a food system model that is driven by an ensemble of climate projections (as in this study), rather than simple scenarios of yield change (as in Hertel, Burke et al. 2010) might help address this limitation within the current simple food system model.

A second possible development could be to include process based models, such as a crop impact model (Asseng, Zhu et al. 2015). One advantage of the current model is that the climate model output is translated directly into production, and no additional complexity, on which the output may be sensitive, is introduced. However, this may also mean that some critical plant responses are not being captured (for example the response of certain cereal crops to a CO_2 enriched atmosphere (Dhakhwa et al. 1997)). This is particularly true as the climate moves out of its historic envelope and previously unobserved conditions apply, which may weaken the correlations seen between national crop production and the Standardised Precipitation Index used in this study. It is worth noting that many process based models are also empirically derived, and may struggle for the same reasons (Challinor, Müller et al. 2018). Further investigation would be required to fully explore this.

One feature of the simple food system model is that it considers relative rather than absolute change. Yield performance is measured as the gap between actual yield and the maximum that could be achieved. The key limitation of this is that of course the maximum achievable yield may change under climate change. So it could be possible to reduce the yield gap, but not actually increase yields. If crop impact models were incorporated into the approach it would allow yield, rather than yield gap, to be included. It would also open the option to consider not just relative change in food security potential, but to consider whether climate change would impose and absolute limit on the ability of the country to feed its population. At present, in Ethiopia, it is possible to produce more than enough food to feed the population, so however technologically or politically difficult it is, it is at least theoretically possible to meet the Sustainable Development Goal of zero hunger by 2030 (UN 2015). A key question not answered by the simple food system model is whether this would also be true at the end of the century. The introduction of crop models may help allow this to be addressed but it would not be a trivial change to make. The main issue would be the validation of the performance of the model in the present day. There are clear advantages to having absolute rather than relative measures of food security. The current model output measure cannot be translated into food per capita, for example. An absolute measure of food availability would allow projections of population dynamics to be incorporated.

Other alternative approaches would be to consider even greater complexity to model all aspects of the climate and food system. However, as discussed in Chapter 2, there is good reason to suspect that the level of detail in the system representation is not necessarily correlated with the accuracy of highly complex models, particularly when such models are built from empirically observed relationships and cannot be meaningfully validated. Large complex system models such as General Ecosystem Models (Fulton, Link et al. 2011), Integrated Assessment Models (Dickinson, Fung et al. 2014) and some agent-based models (Bonabeau 2002, Doran 2006) all have a role to play in exploring complex system dynamics, but do not necessarily offer practical solutions to evaluating climate and security from a policy planning perspective.

Highly detailed models of the future are at risk of over-interpretation and too much confidence can be ascribed to their results, although they are useful tools for exploring system sensitivities. They are less transparent than simpler models, and some of the output dependence on the model design may not be obvious. The simple food system model developed in this study, whilst limited in its scope to answer detailed questions about future food security, particularly on an absolute production or per capita basis, does have some advantages as a result of its simplicity. The main one being that it is easy to understand and it is straightforward to interpret. Nevertheless, further investigation to ensure that the simplicity of the approach is appropriate to complexity of the system would be beneficial.

Aside from increasing the complexity and sophistication of the climate and food system model, further development could centre around engagement with experts on the system parameters and the interpretation of the output. One obvious area for further research would be into developing the food system scenario parameters. The scenarios of yield gap reduction, for example, are extremely ambitious. The yield improvements imposed are equivalent to those seen in the highest yielding regions globally. Input from agricultural technologists could consider how specific technological innovations could practically improve yields. It might also be possible to incorporate the impact of climate change on the effectiveness of such innovations (Islam, Cenacchi et al. 2016). A similar study could be undertaken from an economic perspective to look at future national economic models and perhaps constrain the system parameters for the proportion of the population employed in agriculture, based on a plausible economic future. This research could be used to develop a more realistic set of yield gap reduction and economic diversity scenarios, which would be more relevant for comparison with climate change impacts.

The other aspect of the feasibility of the system changes is the political implementation of transformational social change which is as important as the physical considerations. A set of scenarios could be developed which better reflect political appetite and feasibility for implementing social and economic change. A larger set of scenario options could be generated to inform more detailed discussion on the cost/benefit of different system changes in the face of climate change.

With appropriate engagement with stakeholders the simple food system model could be used to explore transformational planning options at a national level. It could also potentially be used as a means to express climate change projections in terms of food security consequences. The model could be run with different RCP projections, for different levels of climate change, and discussed in the context of the associated Shared Socioeconomic Pathways (SSPs) (O'Neill, Kriegler et al. 2017).

Summary

The findings from the exploration of the food system and climate in Ethiopia and the development of a simple food system model, demonstrated the potential for a systems approach to address some of the current knowledge problems in climate and security. It showed that it is possible to translate climate model outputs into policy-relevant outcomes, and that the key to this is to address the issues of scale so that climate and systems dynamics can be analysed together without compromising either. The weather that drives conditions of insecurity on weather timescales may not be the same over climate change timescales, as was seen in Chapter 3. High temporal and spatial resolution may be necessary to resolve small scale processes, over short timescales, but this is not always necessary, or even helpful, for interpretation over climate timescales, as it can make the description of a complex system unmanageable (Mesarovic 1967).

Despite the limitations of the simple food systems model, it does show the potential to move away from a linear approach to climate security where information is handed from one expert discipline to the next, or where an external policy-focused analyst is left to interpret complex and disparate research findings. The conclusions from security analyst-led assessments are often the recognition of climate change as a security threat, without any real sense of the scale of climate impact, relative to other factors (Wilbanks and Kates 1999). The simple systems model approach shows the potential for climate model projections to be better utilised in evaluating the scale and direction of the climate security threat, and that a systems approach can facilitate transdisciplinary research in climate and security aimed at policy-relevance.

Appendix A

Rainfall analysis for individual years for Ethiopia

For each year in the climatological period (1981-2015), the rainfall anomaly relative to the climatology (in mm, and as a percentage) was mapped, and the rainfall through the year (absolute and cumulative) was plotted. In this way the temporal and spatial patterns of rainfall associated with drought and non-drought years could be examined. Figure A-1 shows the temporal and spatial rainfall distribution for two typical years where there was a reported drought in Ethiopia. In both years the total rainfall that fell was close to the climatological average for the country as a whole. However, in both years, areas within Ethiopia suffered rainfall totals much lower than the climatological average, but higher than average rainfall totals elsewhere made up for the deficit nationally. The regions of Amhara, Afar, Oromia, Somali and Tigray were reported to have experienced drought in both years, which correspond to the areas of rainfall shortfall. In 2003 it is reported that a total of 12,600,000 people in these regions were affected by the drought. In 2011 this figure was 4,805,679 (Table 1-1).

These two years are representative of this general pattern of highly heterogeneous anomalies in rainfall across the country, and a relationship between localised deficit of rainfall and reported droughts, but not between national rainfall and reported droughts. This pattern is not exact, and there is some ambiguity in some of the years where local deficits seem to exist, but no drought has been reported. Some of this ambiguity can be attributed to the non-standard nature of the reporting of socio-economic drought. For example, the start and end dates of a reported drought are likely to coincide with the periods when the population suffered the greatest food shortage, which will not necessarily be the same as the driest period. It seems that in some years an event reached a crisis after multiple dry years, rather than the severity in that particular year. 1993 may be an example of this, where the year was not particularly dry, but the previous two years had been extremely dry in some areas, and therefore the food insecurity crisis may have continued on. Similarly in 1987 no drought was reported, when regions in the East and Northeast had low rainfall totals, but this followed a relatively wet year and so there may have been sufficient harvest the year before to carry the population through a less productive period.

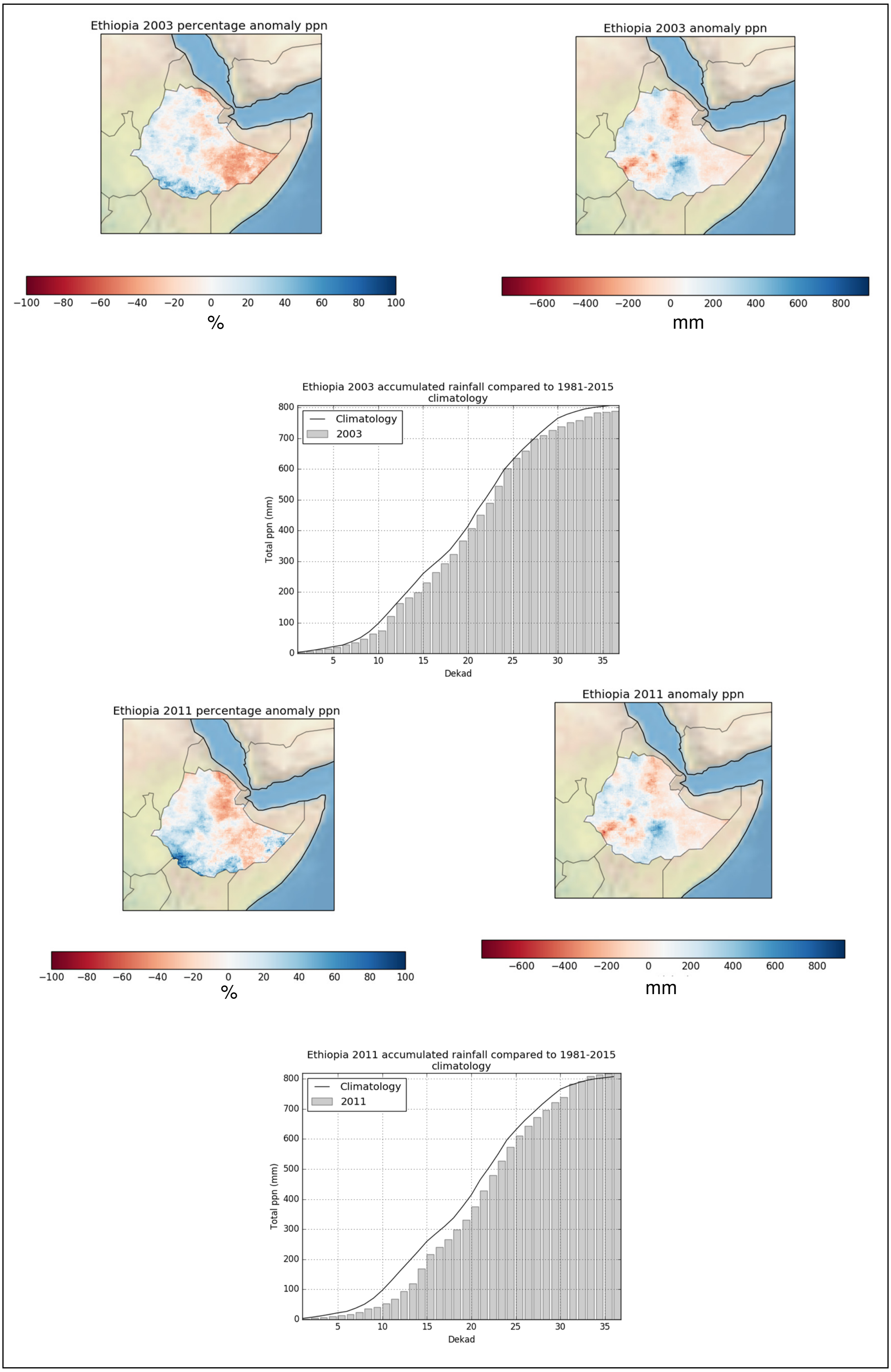


Figure A-1: Rainfall in 2003 (top) and 2011 (bottom) as a) absolute anomaly from climatological average, b) percentage anomaly and c) profile of rainfall accumulation through year. (Data CHIRPS (Funk, Peterson et al. 2015)

Appendix B

Plots of proportion of Ethiopia experiencing a deficit in rainfall in each year

An alternative way to consider the pattern of rainfall variability in Ethiopia is to look at the proportion of the country experiencing a deficit in rainfall in each year. Figure B-1 shows the proportion of the area of Ethiopia that experiences rainfall as a percentage of the local climatological average (1981-2015). In every year in the period, some proportion of Ethiopia experienced rainfall 70% or less of the expected climatological average for that location. However, this data also shows that in every year except one (1984), the majority of Ethiopia received at least 80% of the expected climatological average rainfall. (The data for 1995 is corrupt, so is disregarded).

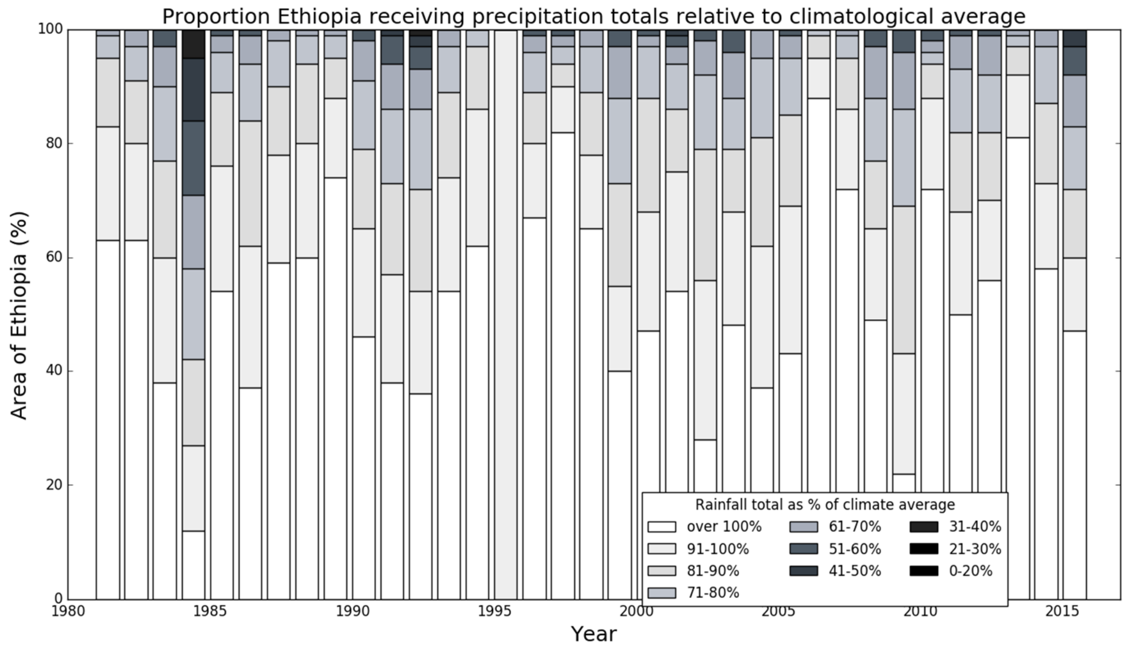


Figure B-1 Proportion of Ethiopia experiencing rainfall at different proportions of the local climatological average over time. (Data CHIRPS (Funk, Peterson et al. 2015))

Figure B-2 shows the proportion of Ethiopia that received less than 60% of climatological average annual rainfall in each year, and compares this with the incidence of reported drought-driven food insecurity events. The nature of the differences in the two data sets, mean that they are not directly comparable, and looking for a mathematical correlation between the two may not be meaningful. Despite the difficulties in comparing these two types of data, it does appear from this figure that there is a stronger association between reported drought and larger areas with below average precipitation, than there is between total national precipitation and these same events.

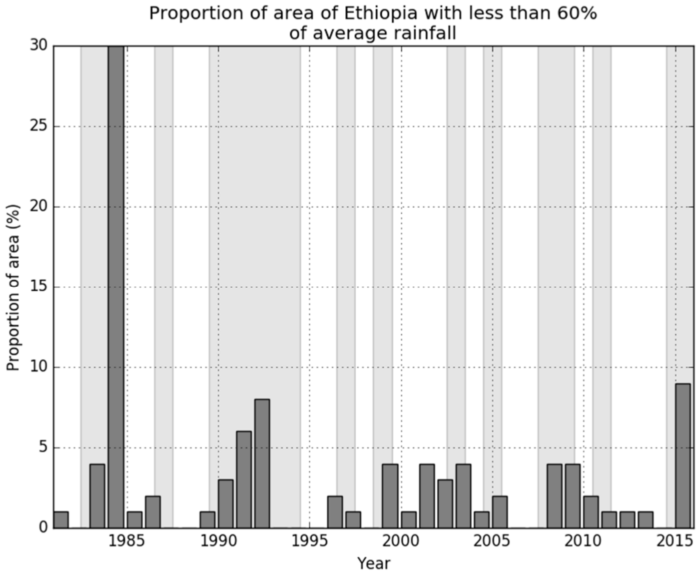


Figure B-2 Proportion of area of Ethiopia with less than 60% of climatological average annual rainfall. (Data CHIRPS (Funk, Peterson et al. 2015), & EMDAT (Guha-Sapir, Below et al. 2015))

Appendix C

Food System model output for Ethiopia

Figure C-1: Production metric output under each scenario outlined in Figure 4-16 for Ethiopia. (Model names in green indicate the model contributed to the multi-model ensemble in the top left corner). Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

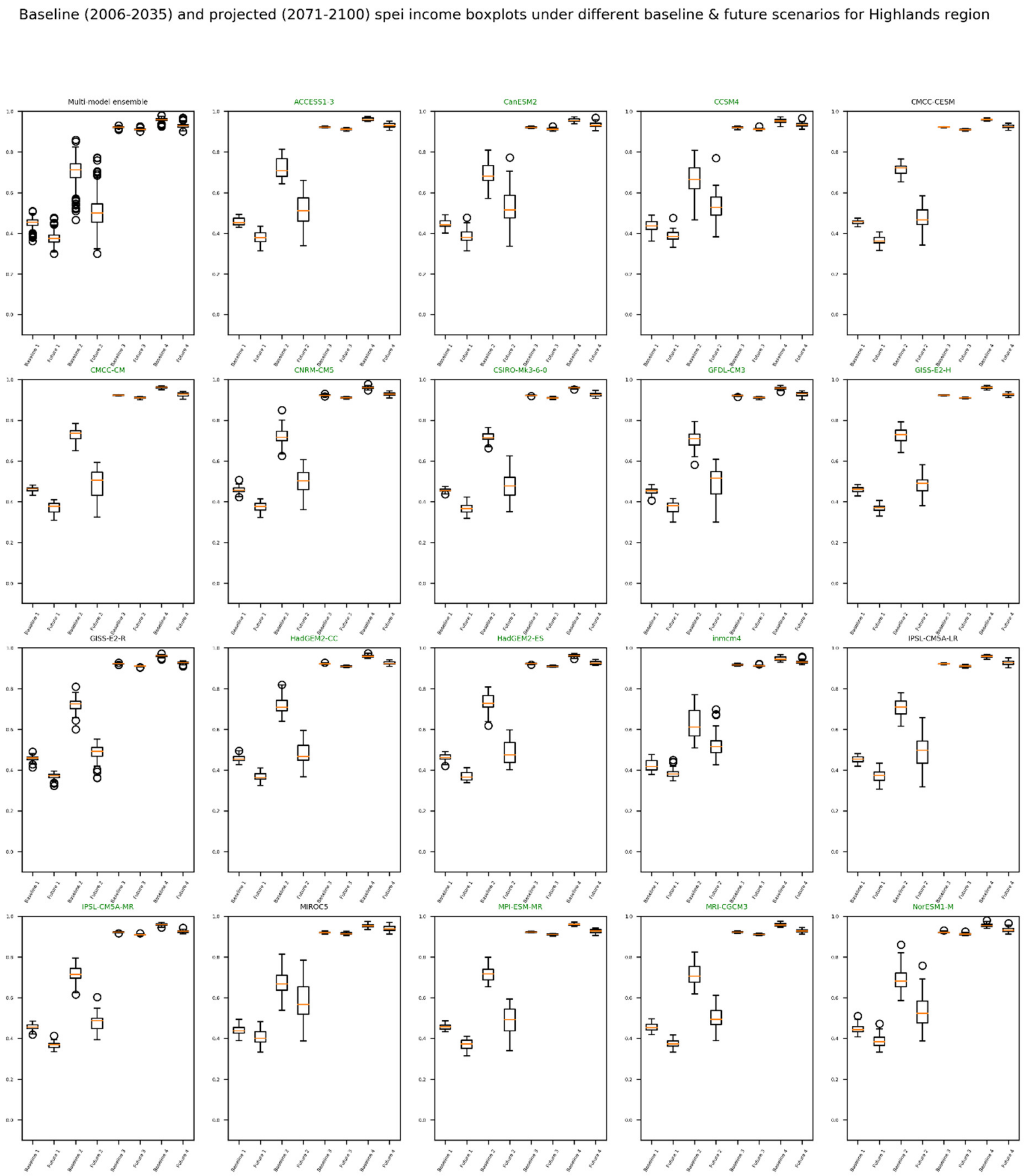


Figure C-2: Income metric output under each scenario outlined in Figure 4-16 for Ethiopia. (Model names in green indicate the model contributed to the multi-model ensemble in the top left corner). Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

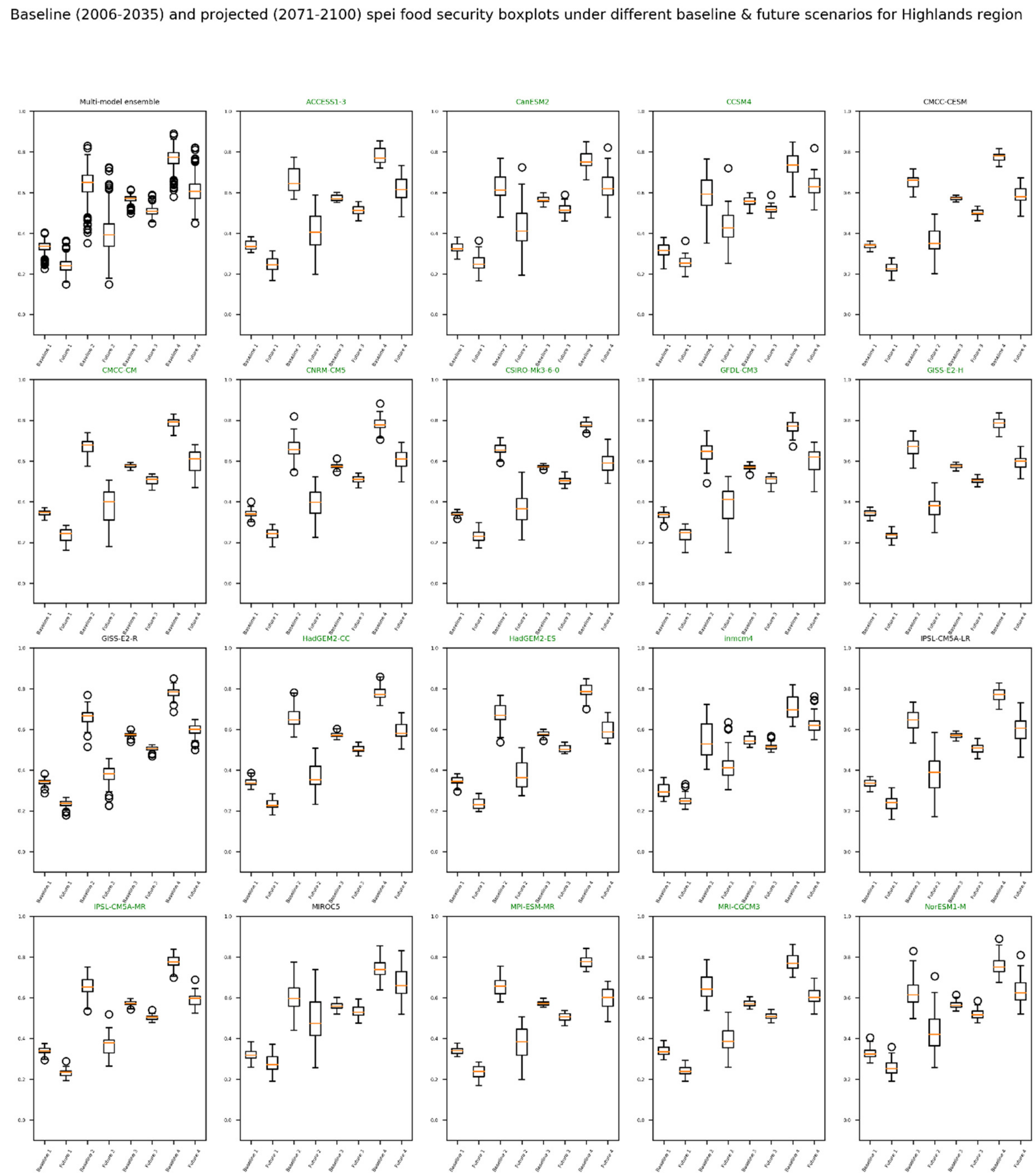


Figure C-3: Food Security metric output under each scenario outlined in Figure 4-16 for Ethiopia. (Model names in green indicate the model contributed to the multi-model ensemble in the top left corner). Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

Appendix D

Climate change projection maps for Botswana, Tanzania & Mali

Botswana

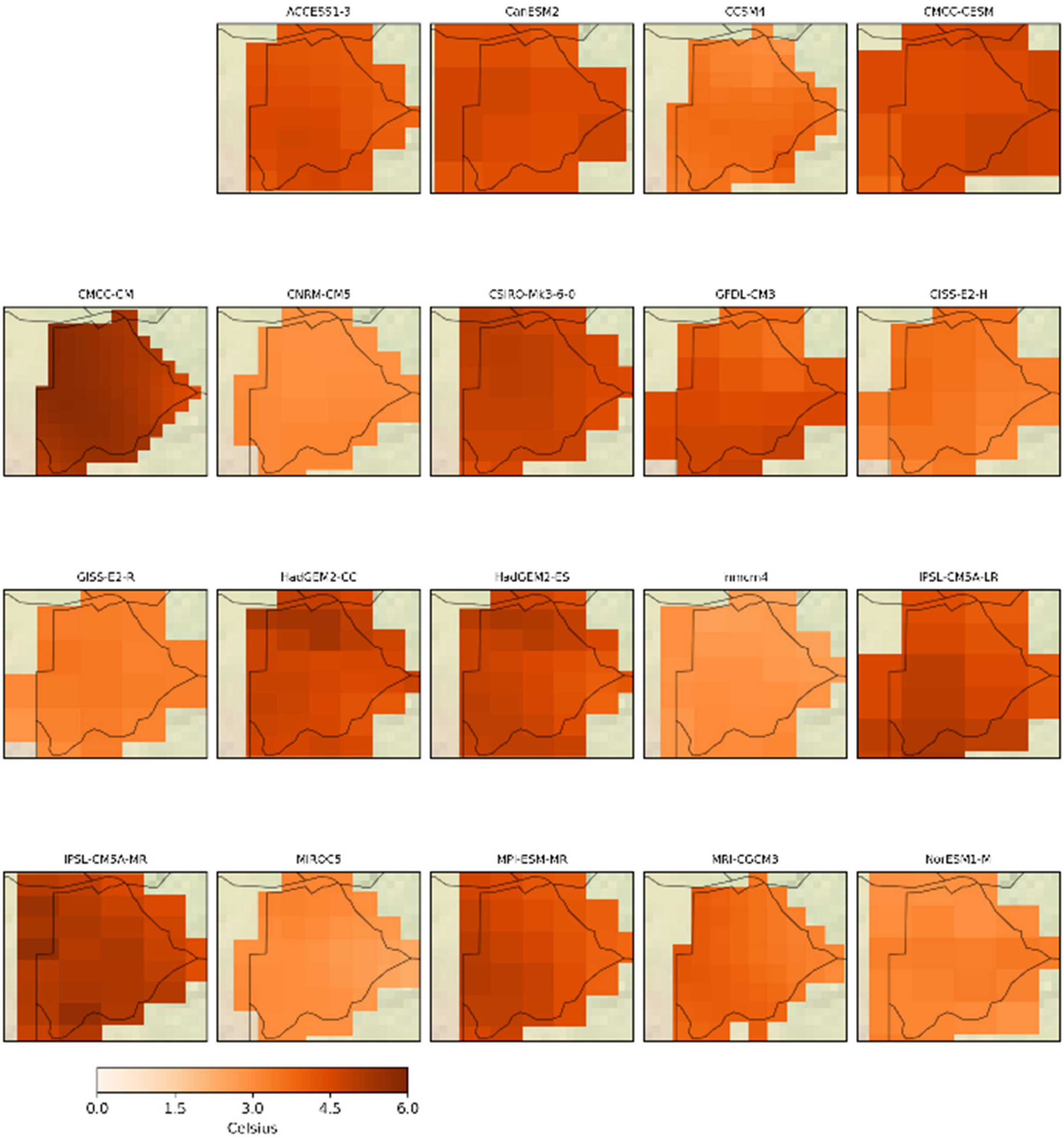


Figure D-1: Change in mean annual temperature (°C) from baseline (2006-2035) climate to 2071-2100 climate under RCP8.5 for each model in study for Botswana.

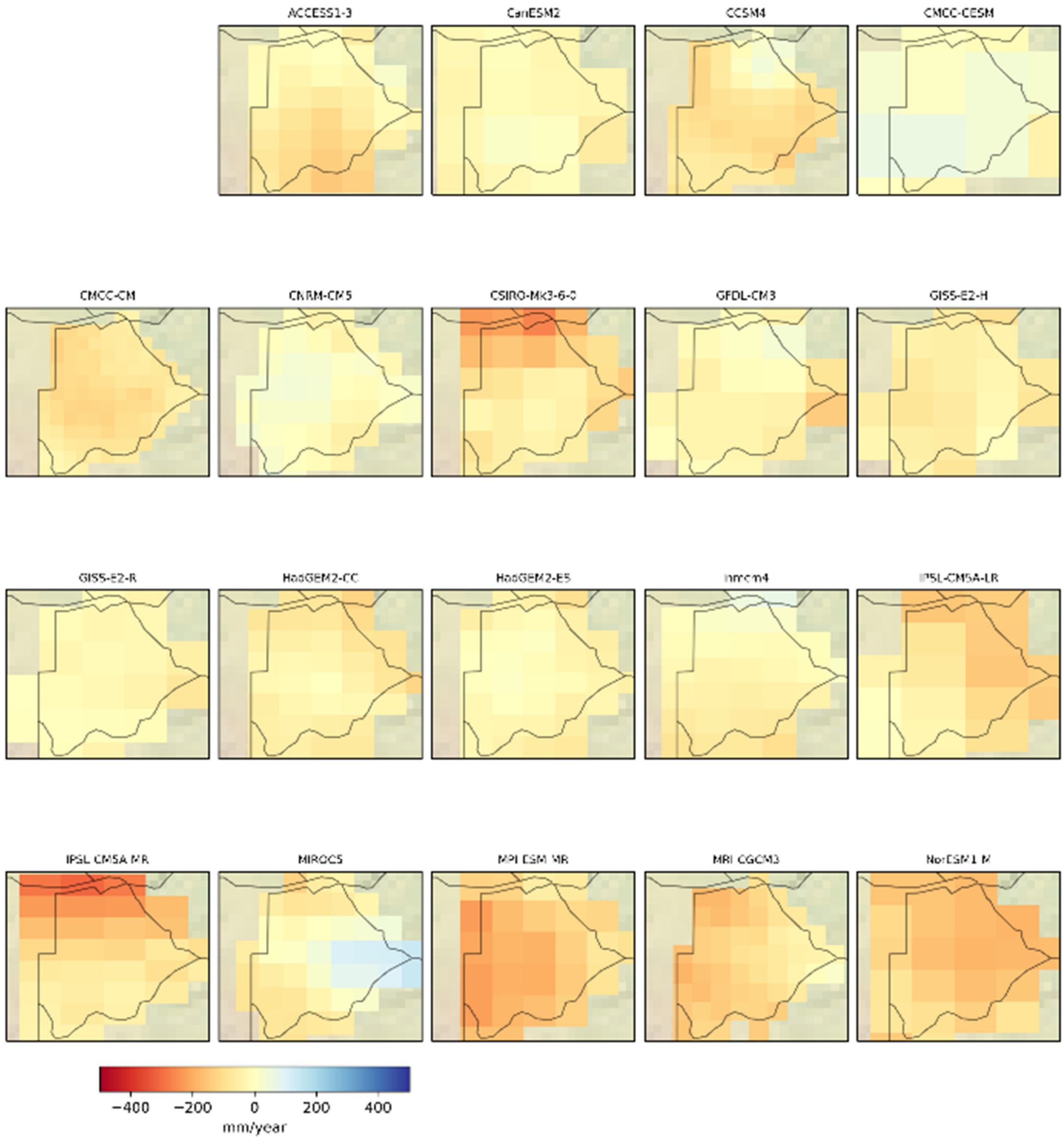


Figure D-2: Change in mean annual rainfall (mm/year) from baseline (2006-2035) climate to 2071-2100 climate under RCP8.5 for each model in study for Botswana.

Tanzania

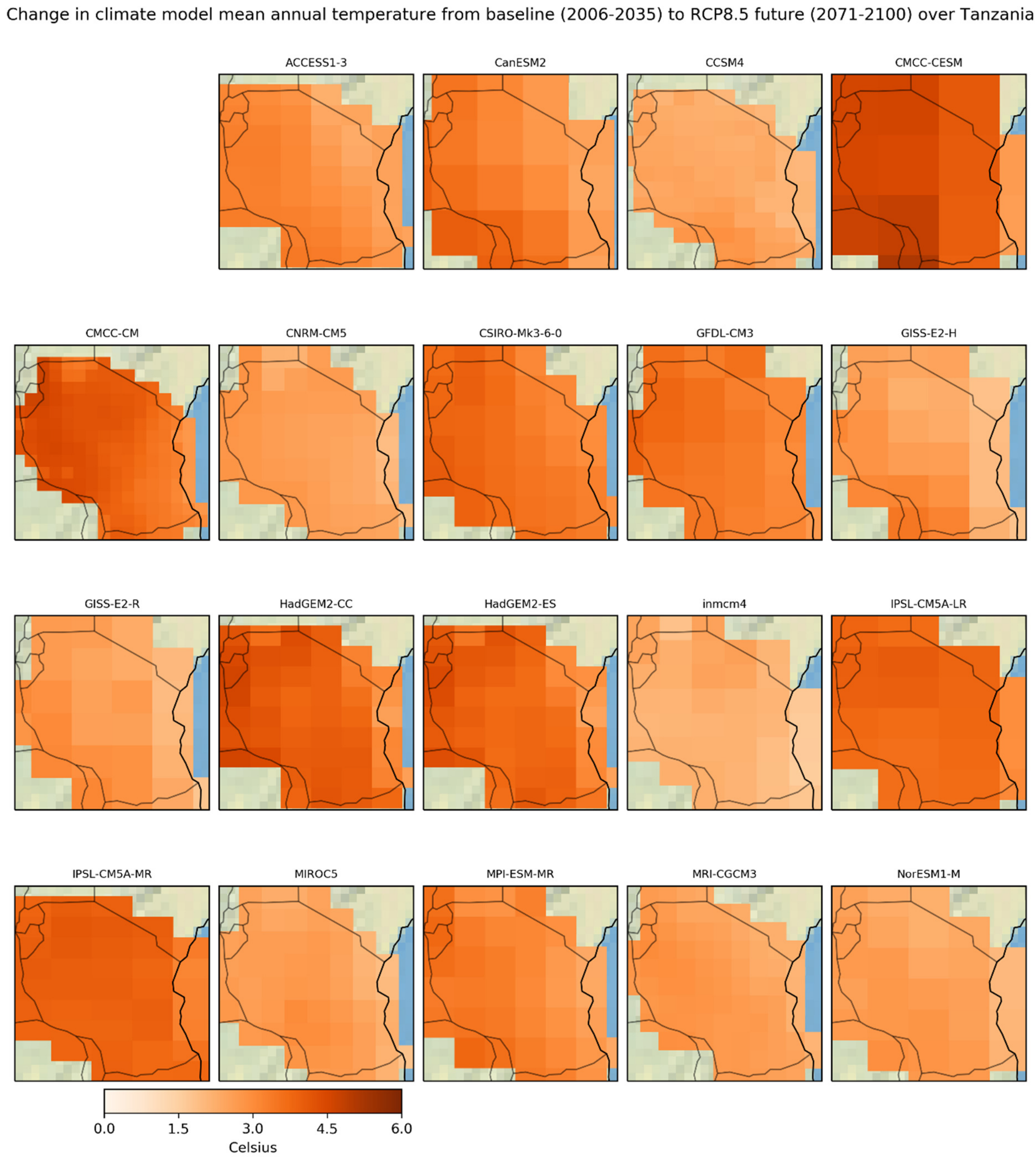


Figure D-3: Change in mean annual temperature (^0C) from baseline (2006-2035) climate to 2071-2100 climate under RCP8.5 for each model in study for Tanzania.

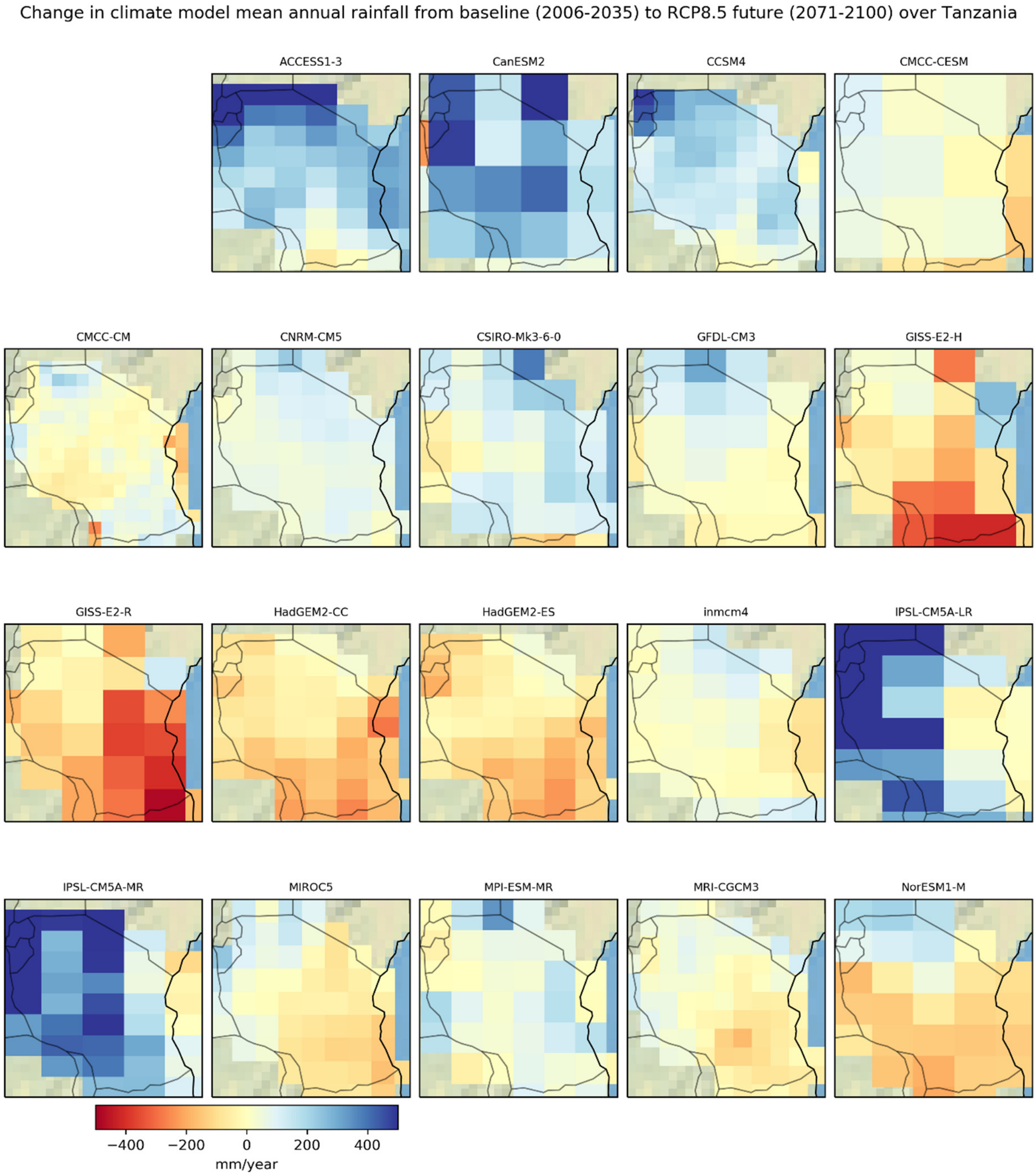


Figure D-4: Change in mean annual rainfall (mm/year) from baseline (2006-2035) climate to 2071-2100 climate under RCP8.5 for each model in study for Tanzania.

Mali

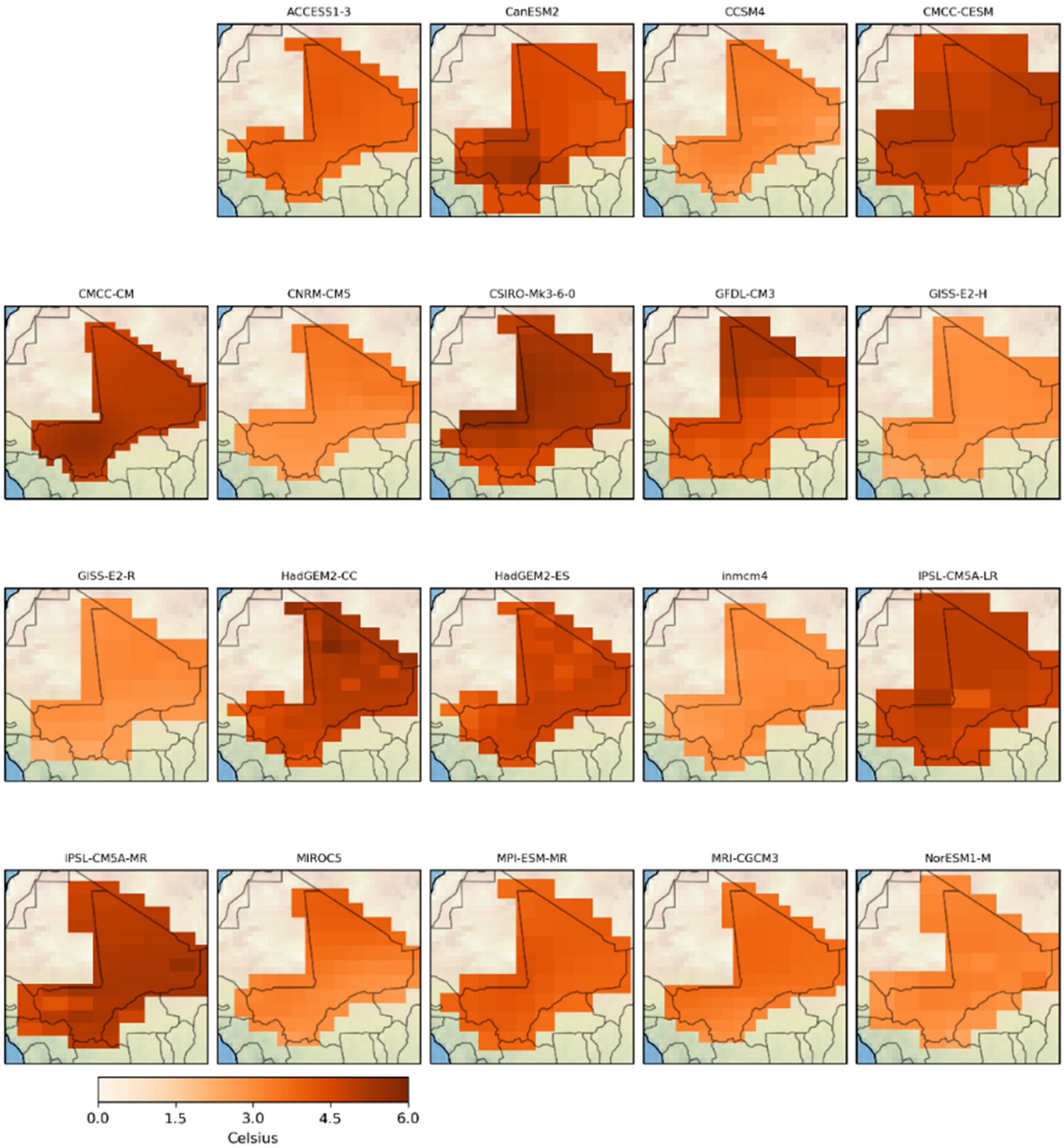


Figure D-5: Change in mean annual temperature (^{0}C) from baseline (2006-2035) climate to 2071-2100 climate under RCP8.5 for each model in study for Mali.

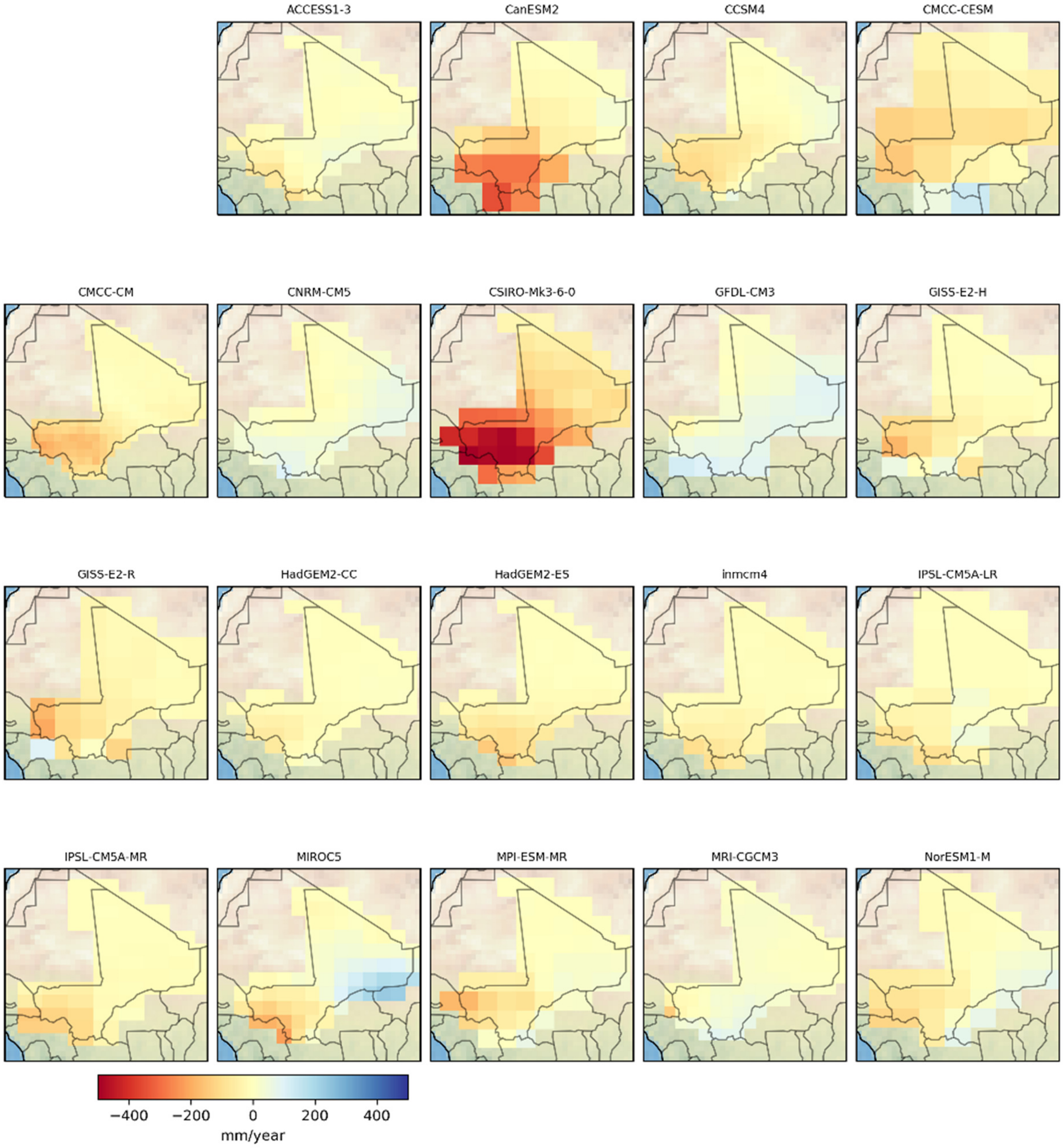


Figure D-6: Change in mean annual rainfall (mm/year) from baseline (2006-2035) climate to 2071-2100 climate under RCP8.5 for each model in study for Tanzania.

Appendix E

Correlation plots for Standard Precipitation Index (SPI) & Standardised Precipitation Index (SPEI) for Botswana, Tanzania & Mali

Botswana

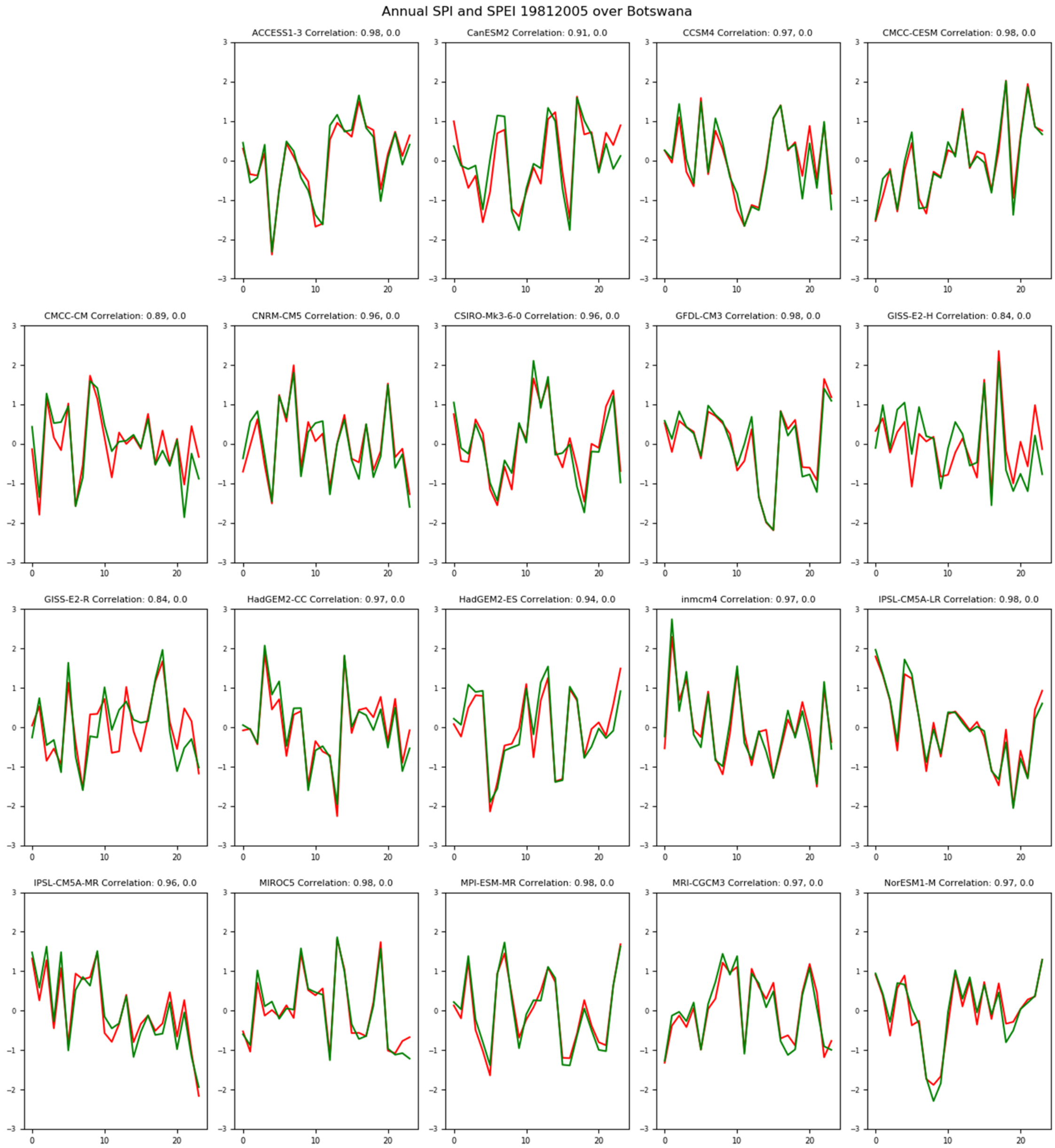


Figure E-1: Standardised Precipitation Index (SPI) (red) and Standardised Evapotranspiration and Precipitation Index (SPEI) (green) calculated with climate data from the 19 climate models from CMIP5 used in this study for 1981-2005 period over Botswana.

Tanzania

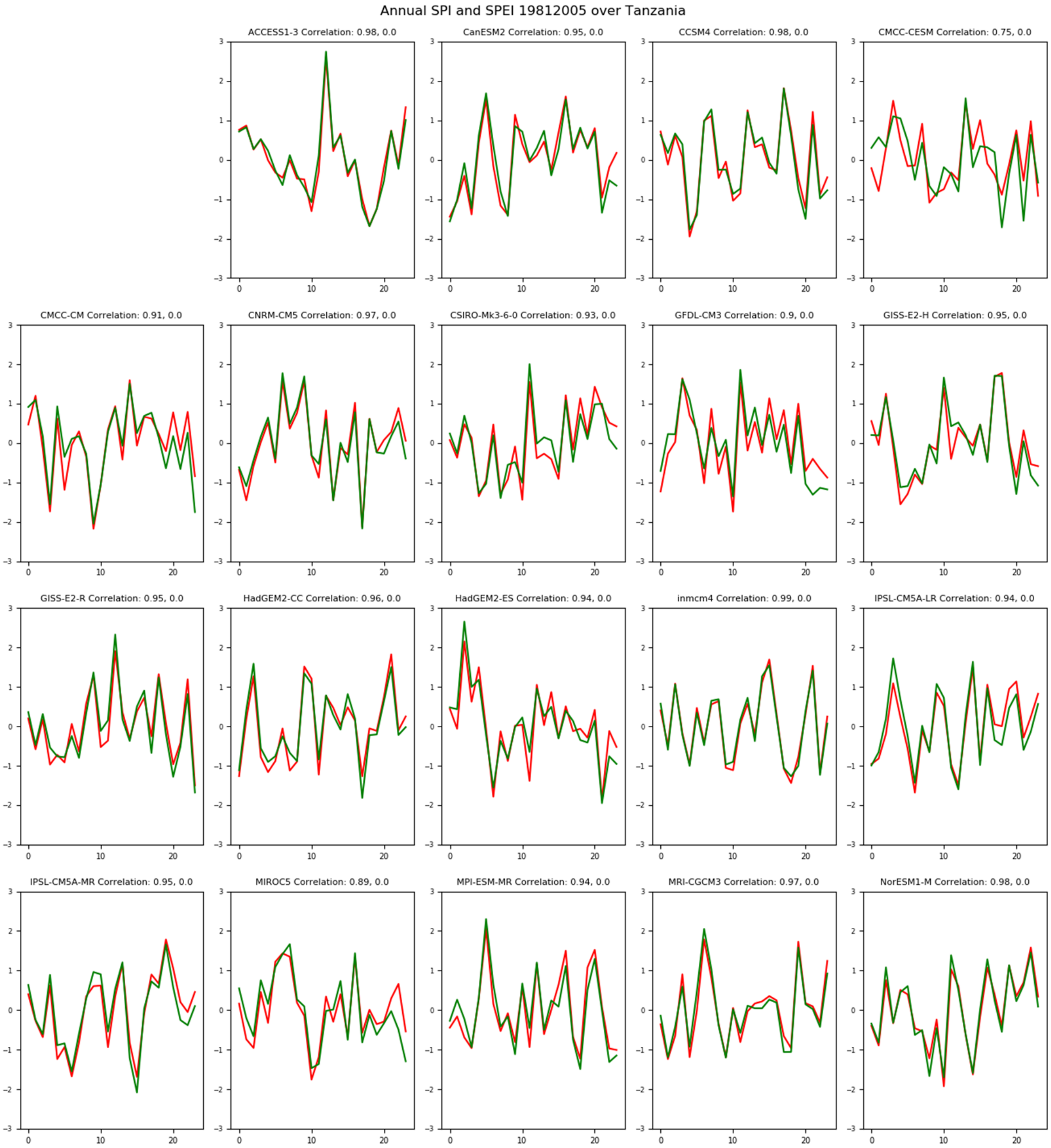


Figure E-2: Standardised Precipitation Index (SPI) (red) and Standardised Evapotranspiration and Precipitation Index (SPEI) (green) calculated with climate data from the 19 climate models from CMIP5 used in this study for 1981-2005 period over Tanzania.

Mali

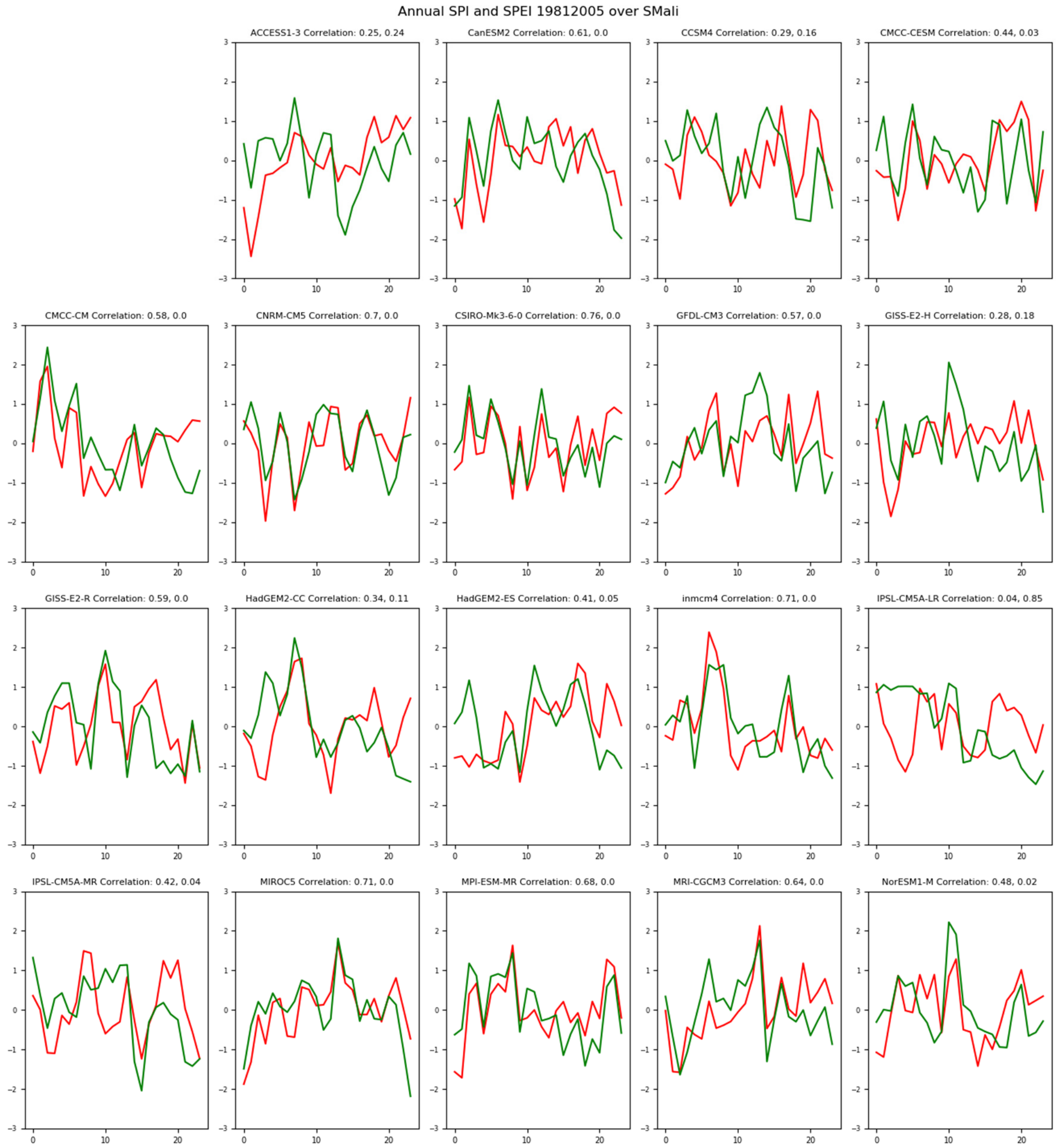


Figure E-3: Standardised Precipitation Index (SPI) (red) and Standardised Evapotranspiration and Precipitation Index (SPEI) (green) calculated with climate data from the 19 climate models from CMIP5 used in this study for 1981-2005 period over southern Mali.

Appendix F

Standard Precipitation Index (SPI) & Standardised Precipitation Index (SPEI) plots for 2006-2100 period, for Botswana, Tanzania & Mali

Botswana

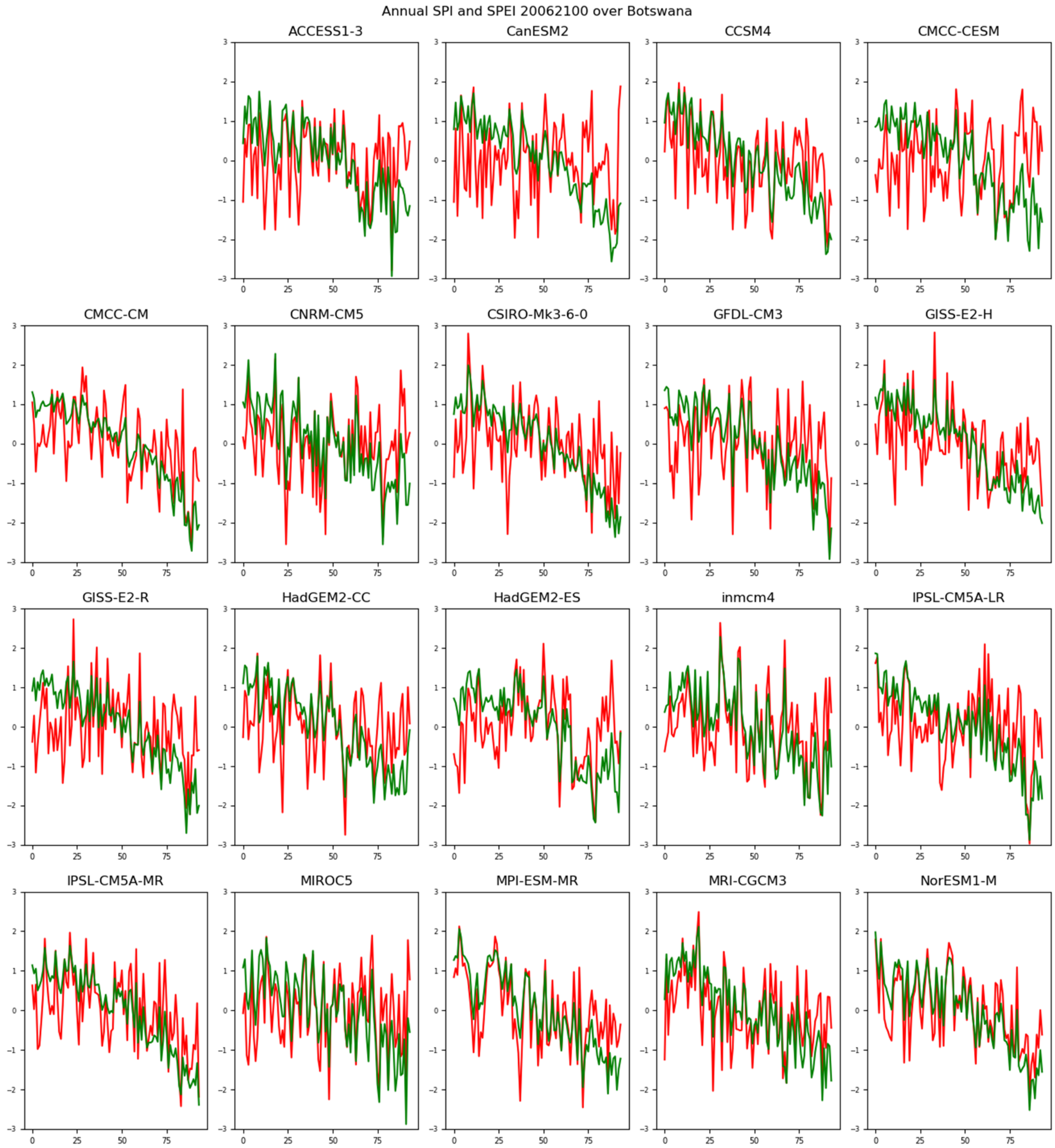


Figure F-1: Standardised Precipitation Index (SPI) (red) and Standardised Evapotranspiration and Precipitation Index (SPEI) (green) calculated with climate data from the 19 climate models from CMIP5 used in this study for 2006-2100 period over Botswana.

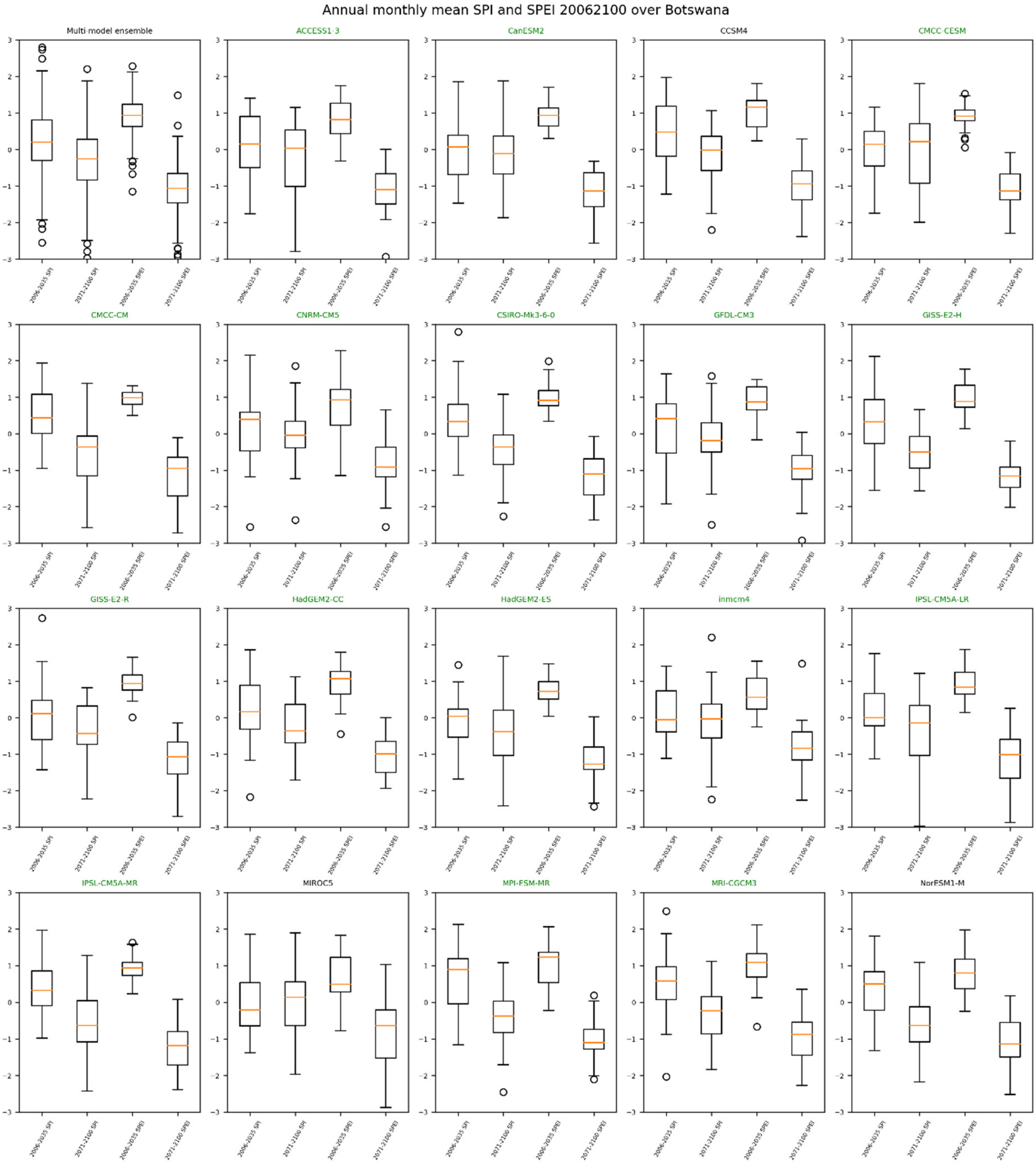


Figure F-2: Boxplots for 2006-2035 and 2071-2100 SPI (left) and SPEI (right) ranges for Botswana. (Model names in green indicate the model contributed to the multi-model ensemble in the top left corner). Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

Tanzania

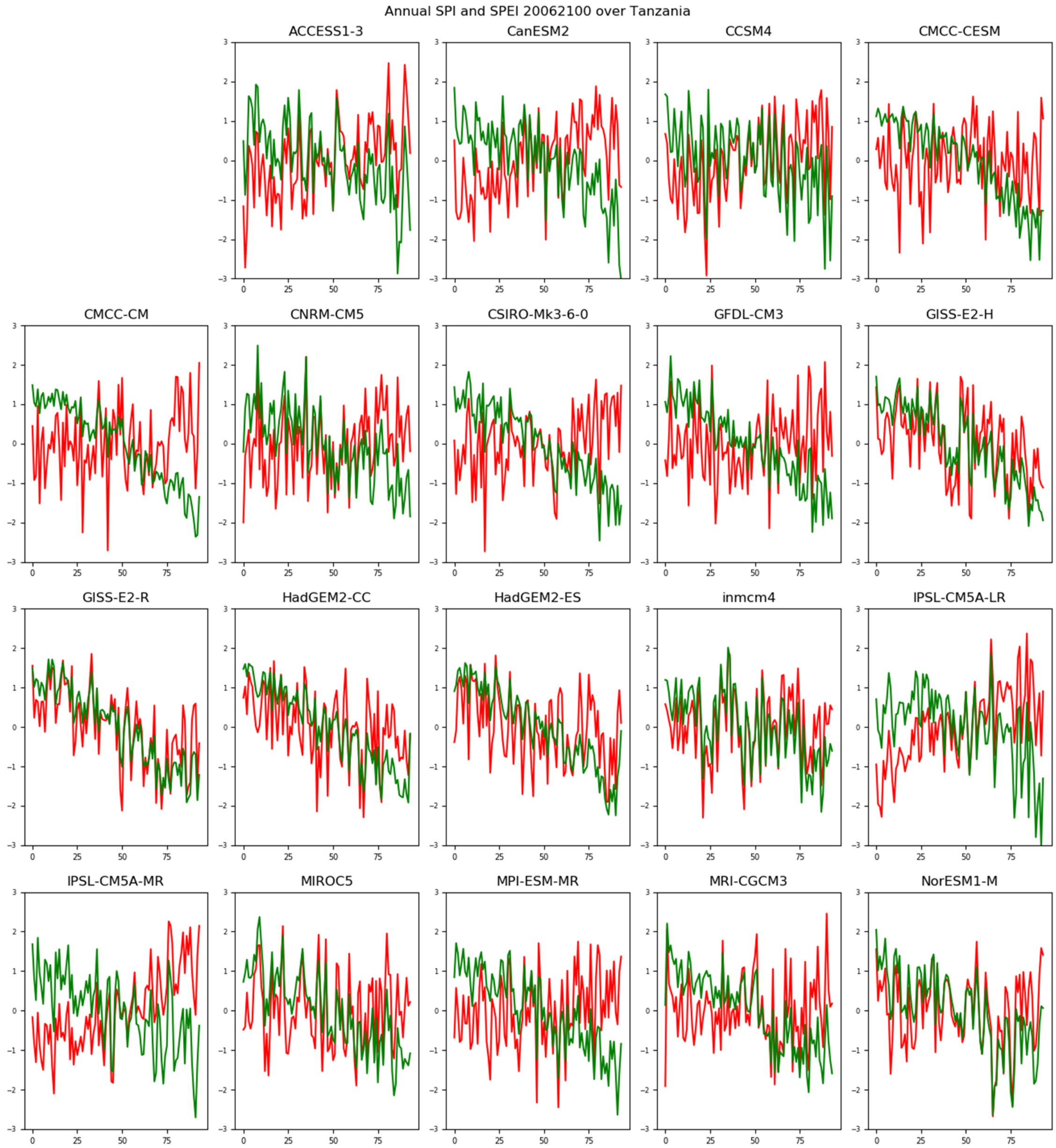


Figure F-3: Standardised Precipitation Index (SPI) (red) and Standardised Evapotranspiration and Precipitation Index (SPEI) (green) calculated with climate data from the 19 climate models from CMIP5 used in this study for 2006-2100 period over Tanzania.

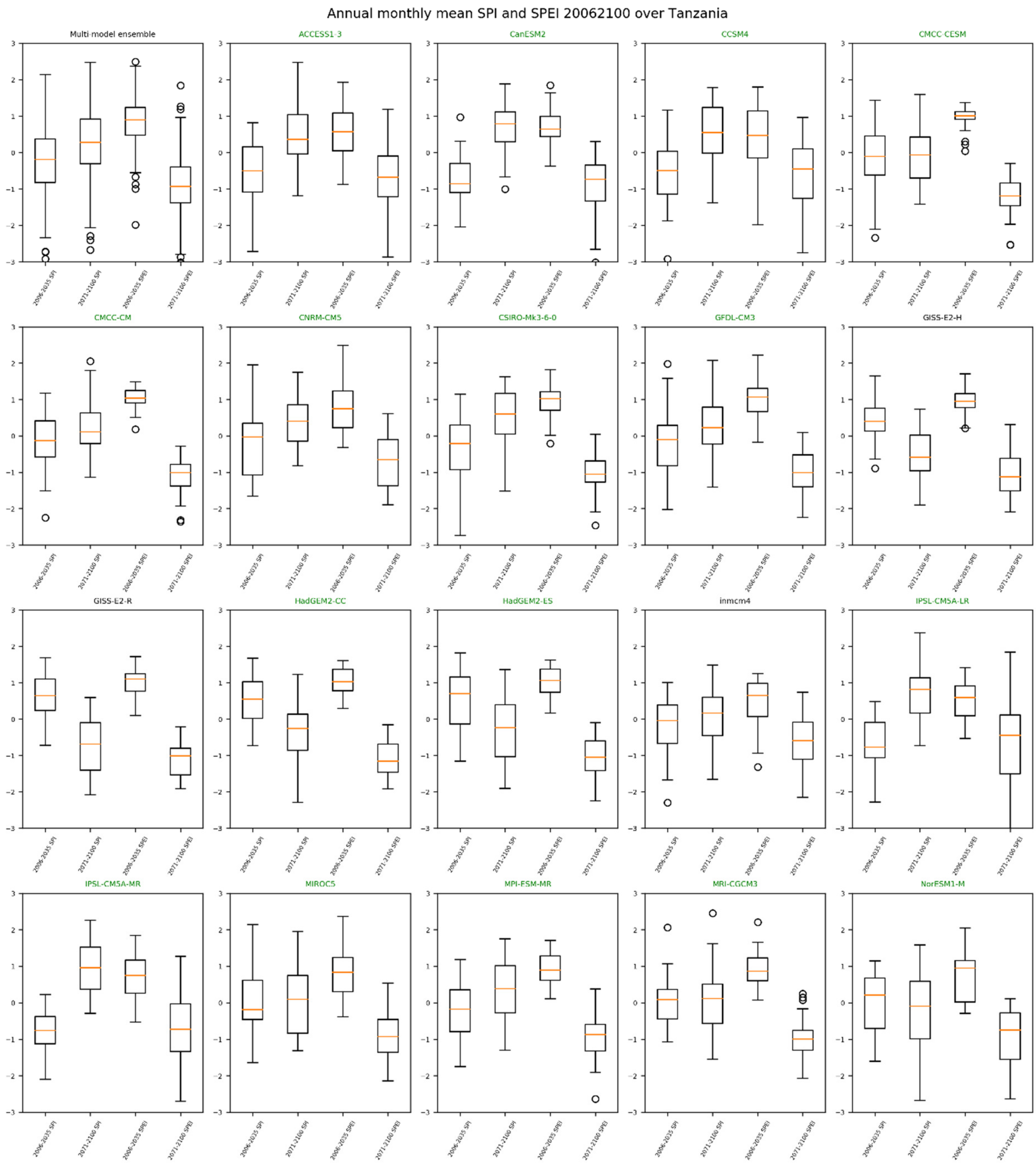


Figure F-4: Boxplots for 2006-2035 and 2071-2100 SPI (left) and SPEI (right) ranges for Tanzania. (Model names in green indicate the model contributed to the multi-model ensemble in the top left corner). Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

Mali

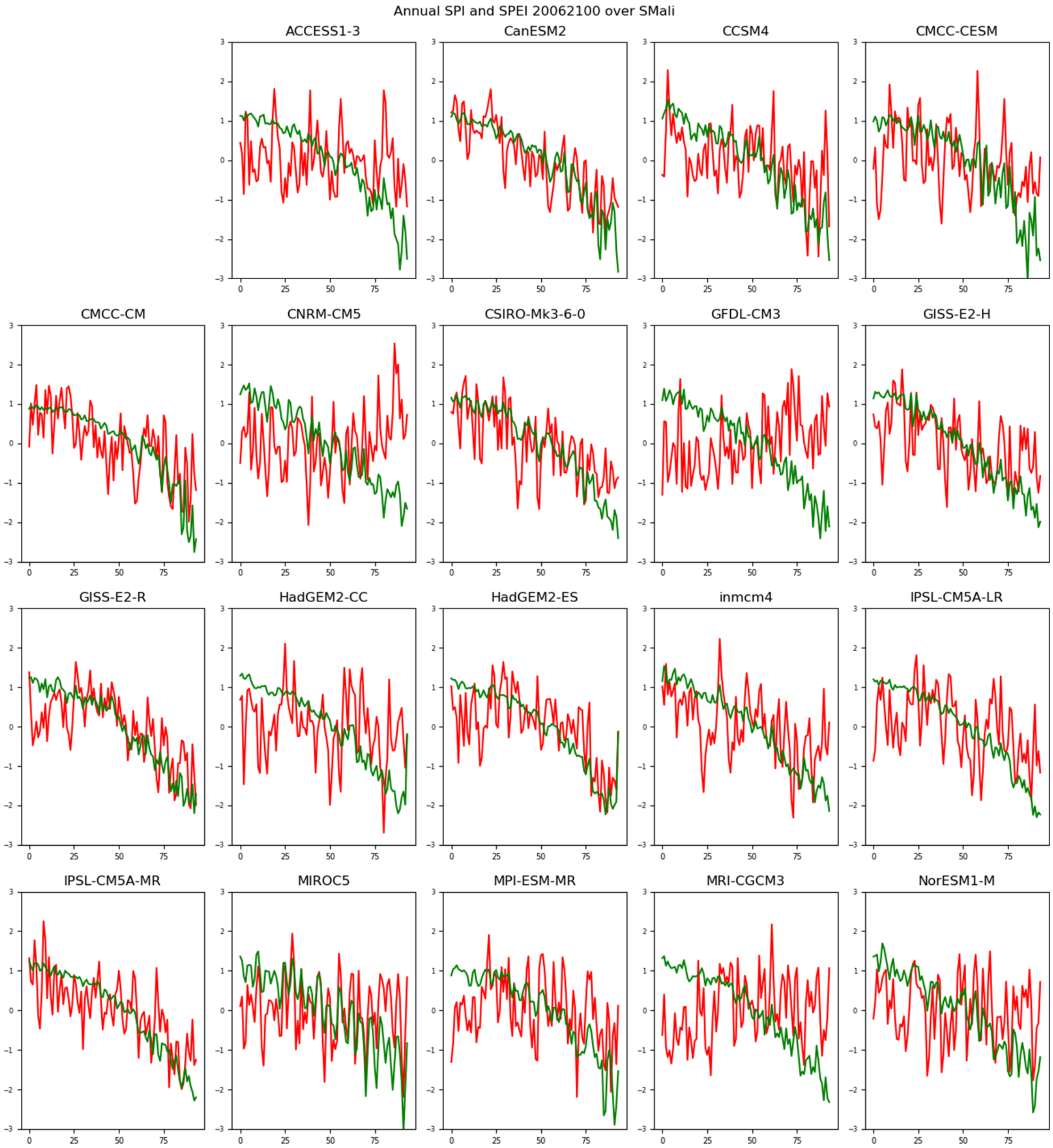


Figure F-5: Standardised Precipitation Index (SPI) (red) and Standardised Evapotranspiration and Precipitation Index (SPEI) (green) calculated with climate data from the 19 climate models from CMIP5 used in this study for 2006-2100 period over southern Mali.

Figure F-6: Boxplots for 2006-2035 and 2071-2100 SPI (left) and SPEI (right) ranges for southern Mali. (Model names in green indicate the model contributed to the multi-model ensemble in the top left corner. Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

Appendix G

Food System model output for Botswana, Tanzania & Mali

Botswana

Baseline (2006-2035) and projected (2071-2100) spei production boxplots under different baseline & future scenarios for Botswana region

Figure G-1: Production metric output under each scenario outlined in Table 5-3 for Botswana. (Model names in green indicate the model contributed to the multi-model ensemble in the top left corner). Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

Figure G-2: Income metric output under each scenario outlined in Table 5-3 for Botswana. (Model names in green indicate the model contributed to the multi-model ensemble in the top left corner). Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

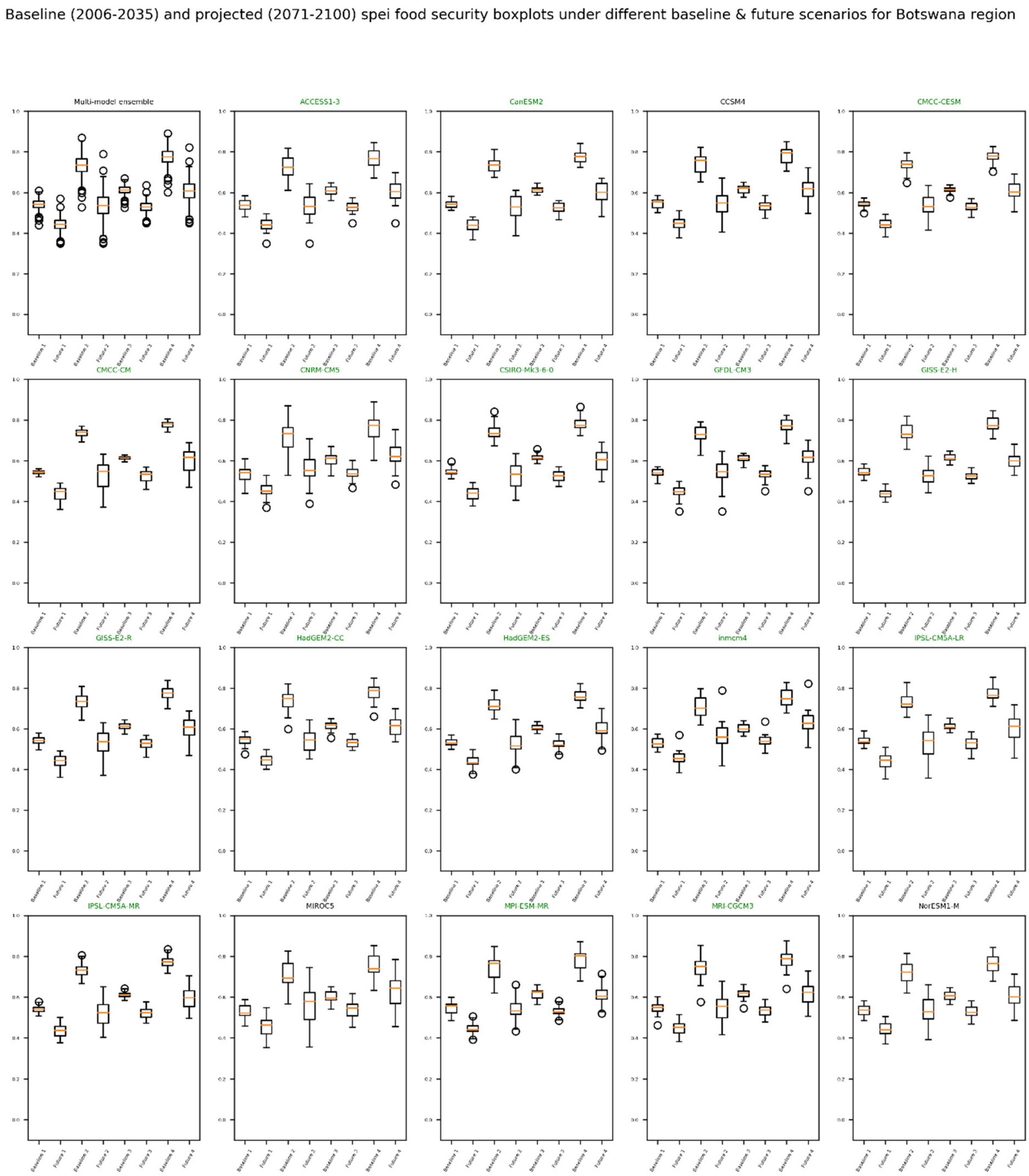


Figure G-3: Food Security metric output under each scenario outlined in Table 5-3 for Botswana. (Model names in green indicate the model contributed to the multi-model ensemble in the top left corner). Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

Tanzania

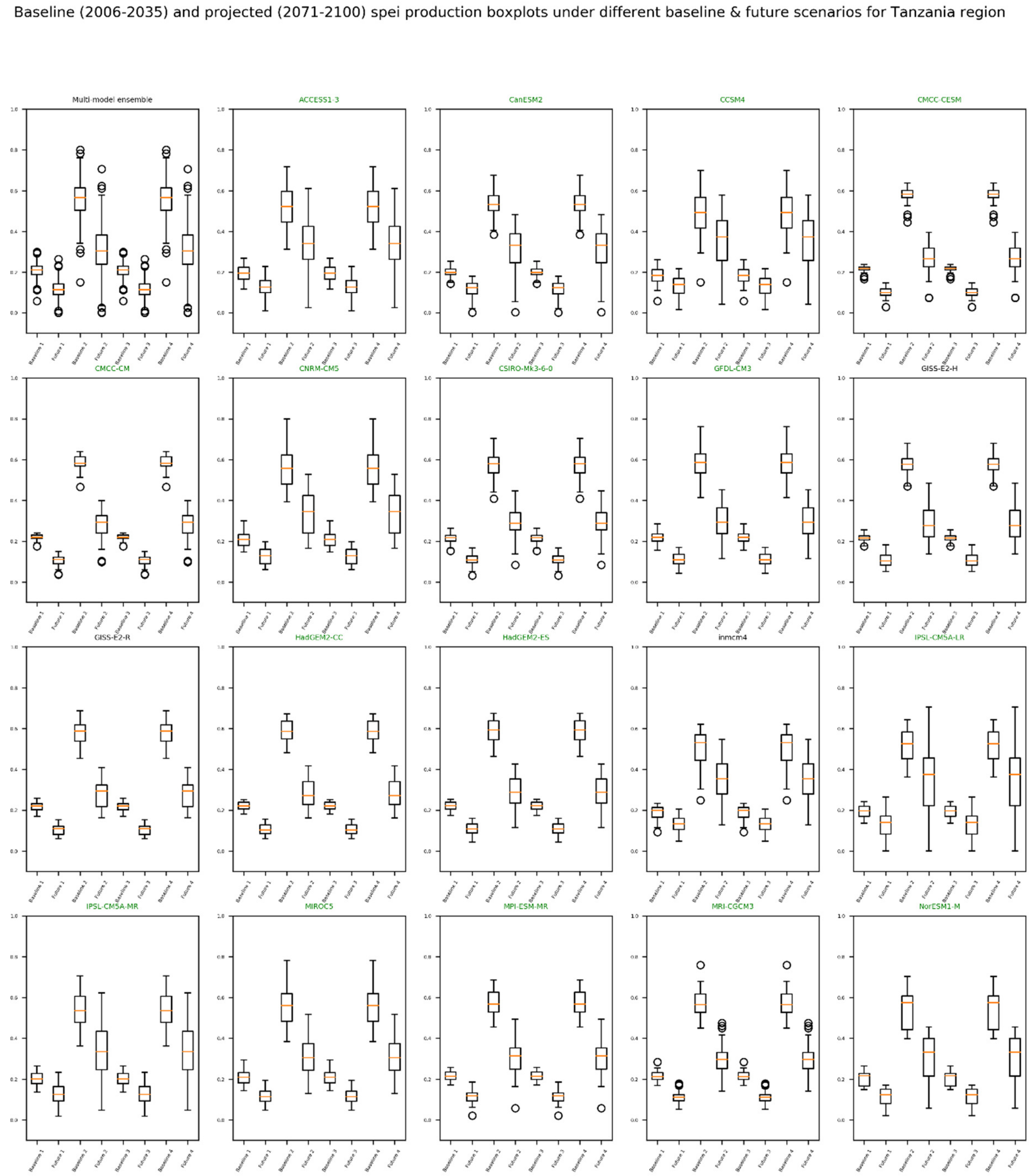


Figure G-4: Production metric output under each scenario outlined in Table 5-3 for Tanzania. (Model names in green indicate the model contributed to the multi-model ensemble in the top left corner). Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

Figure G-5: Income metric output under each scenario outlined in Table 5-3 for Tanzania. (Model names in green indicate the model contributed to the multi-model ensemble in the top left corner). Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

Baseline (2006-2035) and projected (2071-2100) spei food security boxplots under different baseline & future scenarios for Tanzania region

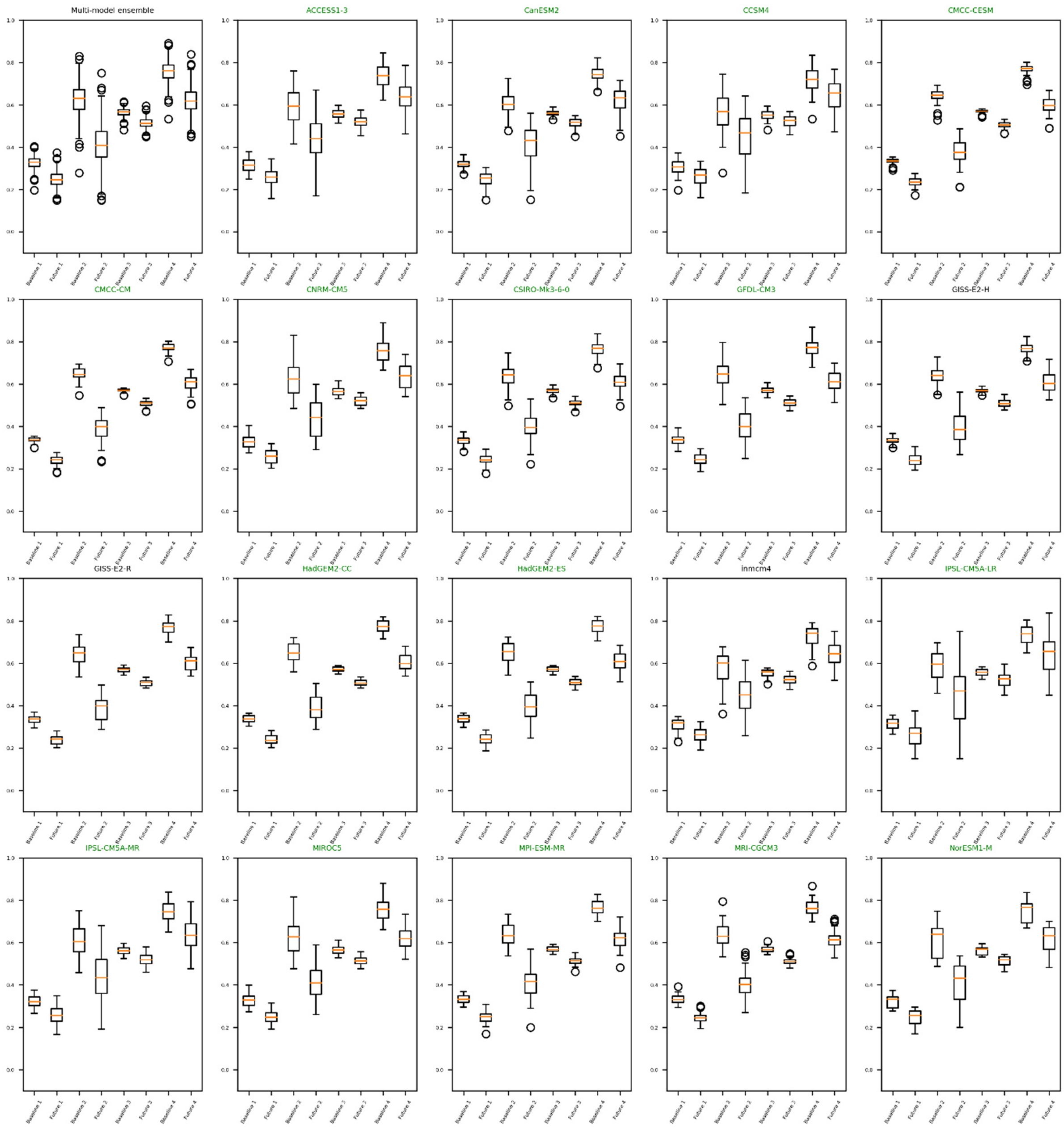


Figure G-6: Food Security metric output under each scenario outlined in Table 5-3 for Tanzania. (Model names in green indicate the model contributed to the multi-model ensemble in the top left corner). Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

Mali

Figure G-7: Production metric output under each scenario outlined in Table 5-3 for Mali. (Model names in green indicate the model contributed to the multi-model ensemble in the top left corner). Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

Figure G-8: Income metric output under each scenario outlined in Table 5-3 for Mali. (Model names in green indicate the model contributed to the multi-model ensemble in the top left corner). Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

Figure G-9: Food Security metric output under each scenario outlined in Table 5-3 for Mali. (Model names in green indicate the model contributed to the multi-model ensemble in the top left corner). Orange line indicates the median value, box shows the extent of the interquartile range. The whiskers indicated 1.5 x the interquartile range. Circles show values beyond the whisker range.

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