FEEDING THE FUTURE

Risks, resilience, and adaptation pathways in farming systems

Shalika Vyas

Propositions

1. Adaptive recovery from risk is more important than immunity to impact.
   (this thesis)

2. Farming systems adopting resilience-enhancing strategies must navigate multiple stressors across time scales for sustainability.
   (this thesis)

3. In the digital age, data generation is as important as research ideation in science.

4. External PhDs are uniquely positioned to apply science for impact.

5. Culinary elitism hinders community cohesion.

6. Activism that targets heritage alienates allies.

Propositions belonging to the thesis, entitled

Feeding the future: risks, resilience, and adaptation pathways in farming systems

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Feeding the future:

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List of abbreviations and acronyms

CCAFS	Climate Change, Agriculture and Food Security
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
CIMMYT	International Maize and Wheat Improvement Center
CMIP	Coupled Model Intercomparison Project
CSA	Climate-Smart Agriculture
CSV	Climate-Smart Village
ENSO	El Niño–Southern Oscillations
FAO	Food and Agriculture Organization of the United Nations
IMD	India Meteorological Department
IPCC	Intergovernmental Panel on Climate Change
LMICs	Low- and Middle-Income Countries
NAPs	National Action Plans
NAMAs	Nationally Appropriate Mitigation Actions
NDCs	Nationally Determined Contributions
ND-GAIN	Notre Dame-Global Adaptation Index
SDGs	Sustainable Development Goals
SSPs	Shared Socioeconomic Pathways
UNFCCC	United Nations Framework Convention on Climate Change

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Chapter 1

General introduction

1.1 Background

Food systems are facing many challenges since the dawn of the Anthropocene. The number of extreme weather events is rising across many regions of the world. For instance, 2023 continued to be the hottest year on record[1], with extremes such as five consecutive droughts in the Horn of Africa followed by floods, extreme heat in Southern Europe, wildfires in Northern America, among many others. Climate change is projected to increase the likelihood and intensity of many such extreme weather events (Fischer et al., 2021). The projected impacts from climate change across all sectors of food systems (Cheung et al., 2021; Jägermeyr et al., 2021; Thornton et al., 2021) have the potential to detrimentally affect food production in many regions (Glotter & Elliott, 2016; Rahimi et al., 2021). For instance, humid heatwaves are estimated to significantly decrease labour productivity in major breadbaskets of South and Southeast Asia (Freychet et al., 2022; Horton et al., 2021; Wang et al., 2022).

At the same time, the world is witnessing a rapid depletion of natural resources. Almost half the species on earth are undergoing population decline[2] (Ceballos et al., 2015; Pimm et al., 2014) and six of the nine crucial planetary boundaries have already been breached (Richardson et al., 2023). Accelerated groundwater depletion is a concern in many food basket regions of the world (Jasechko & Perrone, 2021; Mukherji, 2022a, 2022b), while nitrogen and pesticide pollution (Bijay-Singh & Craswell, 2021; Kanter et al., 2019) remain a global policy challenge. All these factors also contribute to soil health decline (Amundson et al., 2015; Kaiser, 2004; Mueller et al., 2012; Wuepper et al., 2019) and plateauing of crop yields in many parts of the world (Grassini et al., 2013).

It is also an era of rapid urbanization and socio-economic changes, causing significant changes in human food consumption (Ivanovich et al., 2023). Geo-political tensions are also projected to escalate with resource depletion and extreme weather events (Brück & D’Errico, 2019). Climate change is often seen as a “risk amplifier” (Hsiang et al., 2013; Jagermeyr et al., 2020; Mach et al., 2019), exacerbating already existing risks, inequalities, and poverty traps.

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[1] European Centre for Medium-Range Weather Forecasts (ECMWF) media article, 2024.
[2] The Guardian media article, 2022.

These risks are likely to affect all areas of food systems. Consequently, pathways to optimize food processing, reduce food wastage, shift food consumption patterns, and guarantee food safety are important. At the heart of food systems lies food production, interventions in food production can have a cascading effect on the entire food system chain. Building resilient agriculture to climate variability and climate change is an important research-policy agenda to minimize the impacts on food production, stabilize farm income and employment, and ensure food security across the world. The agricultural sector is the economic and social mainstay of more than 570 million farmers. The most vulnerable of these farmers live in Sub-Saharan Africa, South Asia, and Southeast Asia (Lowder et al., 2016). Accordingly, climate change adaptation needs are the greatest in these regions (Niles & Salerno, 2018; Rosenzweig et al., 2014; Warren, 2014).

Thus, reducing the vulnerability of agricultural production systems and strengthening adaptive capacities to climate change are top priorities to safeguard and improve the livelihood standards of millions of people. Scientists and policy makers are giving increasing attention to the need for more resilient agriculture by breeding efforts to improve productivity under extreme weather events (Langridge et al., 2021), promoting crop diversity and preserving genetic diversity through seed banks (Galluzzi et al., 2016), scaling out farm risk management policies, energy transitions in food production like solar irrigation (Yang et al., 2023), and promotion of climate-smart agriculture (CSA) (Lipper et al., 2014)—among many other technologies and practices.

Despite these efforts, scaling these technologies and practices is a monumental task. The complex intertwining of adaptive capacities of local communities, institutional and governance inefficiencies, readiness to scale and lack of enabling conditions including service delivery mechanisms—all affect the adoption and scaling of these climate resilient technologies (Acevedo et al., 2020). Further, reductionism and oversimplification of the way these technologies interact and operate in local agro-ecological and socio-economic conditions can also lead to maladaptive and unsustainable pathways. For example, irrigation can make crops more resilient to weather and climate stresses. However, excessive water withdrawals have led to significant groundwater depletion—22% of global food production and 2.3 billion people rely on unsustainable use of water resources (Rosa et al., 2020). To add to these challenges, the world faces the daunting task of feeding more than 9 billion people by 2050 in the face of mounting climate risks, and on the other hand, reducing emissions—

the agricultural sector (including land use change) contributes to over one-third of global emissions (Menegat et al., 2022).

1.2 Problem statement

To counteract the challenges discussed above, de-risking food production systems is one of the most important policy and research agenda across many nations. Insights on the state of resilience of farming systems, identification of blind spots and priority action areas is crucial for the development of any de-risking strategy. Increasing the resilience of farming systems in the face of climatic and environmental changes—including incremental and transformative changes in the way food is produced, is a crucial step forward. Fostering enabling environments to innovate, adopt and scale agricultural technologies for addressing risk[3], involves multiple actors and mechanisms. It is known that many regions in the world already face high degree of food production risks (Cottrell et al., 2019). This coupled with barriers to adequately adapt to these risks, in the form of policy, finance and societal constraints, often leads to low resilience[4] of farming systems to these risks (Meuwissen et al., 2020). Herein lies the need of a systematic analysis of how farming systems are exposed to and respond to different risks. Risks can also emerge from the unpredictability and uncertainty of outcomes, due to complex interactions between various factors that influence food production—including climate variability, biological threats, and market dynamics, among others (Hardaker et al., 2004). The risk reducing pathways include a range of mechanisms to manage, adapt and change to risks as a response, which ultimately contribute to farming systems resilience. Together, these three umbrella concepts of risk, resilience, and adaptation[5] are important for scientific advancement and cornerstone of debate on the future of farming systems (Intergovernmental Panel on Climate Change (IPCC), 2023).

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[3] Risk is defined as potential to have adverse consequences for human and ecological systems, from a given action, event, or decision. Risk also includes uncertainty and unpredictability of these consequences. Risk can be of different types including biological risks (livestock epidemics) and climate risks (extreme weather events and projected climate change impacts), among others. Source: IPCC glossary, Hardaker et al., 2004.

[4] Resilience is defined as capacity of a system (social, economic, and ecological) to cope with a hazardous event, respond to and reorganize in ways to maintain their essential functions, identity, and structure. Source: IPCC glossary.

[5] Adaptation is defined as the process of adjustment to actual or expected risks (like climate change), to minimize harm and capitalize on opportunities, wherever possible. Source: IPCC glossary.

1.3 Research gap

Various studies have focused on risks, resilience, and adaptation in food systems. However, I find critical gaps in literature which I classify as a) lack of a global overview on how farming systems respond to risks, b) fragmented evidence on this response, in the form of different coping and adaptation mechanisms across diverse scales, and c) lack of focus on the interconnectedness of these components and a general mono-disciplinary and reductionist approach to risk and resilience in farming systems.

Diverse farming systems have their own unique characteristics and capacities to manage and respond to risks. A global perspective is crucial to understand these dynamics to address food security concerns and draw policy lessons at a larger scale. Individual global studies in the past have a segmented focus on risks (usually a specific type of risk), the projected impacts from these risks and investigate a specific dimension of resilience. For example, some global studies have focused on the impact of extreme weather events like drought and heat stress, on crop production (Lesk et al., 2016), while global assessments of the livestock sector have focused on risk exposure to heat stress (Thornton et al., 2021). Similarly, various crop modelling studies at the global scale have focused on the future impacts of climate change on major crops (Hasegawa et al., 2021, 2022; Iizumi et al., 2017).

Review of existing literature on resilience in food systems indicates a lack of integrative global and broad scale analysis (Béné et al., 2016). To this effect, comprehensive global assessments focusing on diverse elements of risk, resilience enhancing strategies like adaptation, and their interconnections, help in identifying blind spots from previous research, enabling us to identify synergies across different regions based on contextual similarities and differences—shaping future research agendas, and identifying hotspots for priority action.

Evidence on adaptation across farming systems (especially in the context of climate change) is an important research agenda (Nalau & Verrall, 2021). However, key research gaps are documented in terms of fragmented evidence across geographies and sectors, and lack of clear risk reduction and resilience building pathways identified in the literature (Berrang-Ford et al., 2021). The research on farming systems adaptation is limited to certain geographies and based on biophysical modeling studies, in the absence of farm data in low- and middle-income countries (henceforth LMICs). The global stocktake and review of adaptation in many cases, for instance, agricultural insurance, is scattered across regions, agricultural sectors, and insurance product types (de Leeuw et al., 2014; Sarr et al., 2012). Another example is the lack of evidence on risk reducing effects of climate-smart agriculture (henceforth CSA), mostly restricted by data availability, especially in the LMICs.

To summarize, the existing literature across the dimensions of risk and farming system resilience is primarily anchored in a unidimensional view, isolating important elements, and rarely exploring their interconnections. A unidimensional analysis often overlooks the complexities and multifaceted ways in which farming systems operate, including the sociological, political, economic, and environmental domains. This thesis addresses these critical research gaps, identifies different elements across risks and resilience, highlights their interconnections, and provides entry points for future policy and research action.

1.4 Research objectives

The objective of this thesis is to understand risks faced by farming systems, the processes in response to these risks (like adaptation), and resilience of the farming systems as an outcome of these processes. To achieve this, the following specific research objectives are addressed:

I. Assess the alignment of global climate action policies with projected risks, readiness to scale adaptation based on economic, governance and social capacities of nations, and biophysical scope for adaptation. (Chapter 2)
II. Map global research on agricultural insurance across agricultural sectors, geographies, insurance product types, and research themes. In addition, analyze the geographical alignment of research intensity on agricultural insurance with historical and projected risk hotspots. (Chapter 3)
III. Identify the impacts of heat extremes on crop production under climate-smart agriculture. (Chapter 4)
IV. Assess how farming systems recover from production shocks. (Chapter 5)

In the following sections, I discuss in detail the multi-dimensional and multi-disciplinary focus of this thesis (Section 1.5), followed by discussion on the theoretical framework of this thesis (Section 1.6) and the thesis outline in Section 1.7. The following chapters (2 to 5) focus on individual research objectives. Finally in Chapter 6, I discuss the implications from this research and its societal impact.

1.5 Multi-dimensional and multi-disciplinary focus of the thesis

In this thesis, I look at risk, resilience and adaptation in agriculture while taking into consideration multiple dimensions and disciplines (Table 1.1). First, I address different types of risk, i.e., different chapters focus on different types of risks, including long-term climate change (Chapter 2 and 3), biological risks like livestock epidemics (Chapter 3), extreme weather events (Chapter 3 and 4), and production shocks due to multiple climatic, geo-political and economic fluctuations (Chapter 5). This thesis also looks at multiple sectors and farming systems—maize (Chapter 2, 3, 5), rice (Chapter 2, 3), wheat (Chapter 2, 3, 4), soybean (Chapter 3, 4), other crops (Chapter 3), livestock sector (including dairy milk production) (Chapter 3, 5), and fisheries (Chapter 3). Focusing on the entire spectrum of these risks across multiple sectors is important to draw geographical and sectoral lessons, each requiring their own set of risk management strategies.

Different spatial scales are also compared—Chapter 2, 3 and 5 are global in scope, whereas Chapter 4 focuses on climate-smart agriculture in India. While I discuss the advantages of having a global scope in the previous section, I also emphasize the importance of having a focused case study approach. In many contexts, due to data limitations (in this case, a lack of a global evidence on climate-smart agriculture), and the highly context-specific nature of some climate adaptations, it is important to also understand the local factors, the social and economic capacities of the communities, and the institutional and governance mechanisms to scale-out adaptations. I therefore explore a balanced approach—and combine insights from global scale to identify hotspots and a more dedicated local study to understand the contexts in which farm adaptation occurs—I discuss this further in Chapter 6. Another dimension used in this thesis is the timescale (Table 1.1). My research on climate policy and agricultural insurance (Chapter 2 and 3) assesses the future risks faced by farming systems. Chapter 3 also looks at risks from a hindsight dimension, focusing on observed events, along with my other Chapters (4 and 5). Prioritizing different time horizons is important to understand past successes and failures, identify current challenges and anticipate future risks (Rippke et al., 2016).

In addition to this, I derive learnings from multiple disciplines (right-hand column of Table 1.1) including policy analysis (Chapter 2), risk management (Chapter 3), agronomy and climate econometrics (Chapter 4) and agroecology and risk management (Chapter 5) to draw original insights and a diverse perspective on risks and resilience in farming systems. It is important to note that this thesis is not designed to address the entire combination across these diverse elements, but rather provide entry points to frame these issues from multiple points of view.

Table 1.1 Multiple dimensions and disciplines in this thesis.

Chapters	Dimensions				Disciplines
	Risk	Sector	Geographical scope	Temporal scope	
Chapter 2 (Climate policy)	Long-term climate change	Major crops (maize, rice, wheat)	Global	Foresight	Policy analysis
Chapter 3 (Agricultural insurance)	Long-term climate change, extreme weather events (droughts, floods, heat stress) and biological risk (livestock epidemics)	Agriculture (multiple crops, livestock, and fisheries)	Global	Both	Risk management
Chapter 4 (Climate-smart agriculture)	Heat stress	Crops (wheat, soybean)	Sub-national (India)	Hindsight	Agronomy and climate econometrics
Chapter 5 (Recovery)	Production shocks covering all risk types	Crops and livestock (maize, dairy milk)	Global	Hindsight	Agroecology and risk management
Chapter 6	All the above				

1.6 Theoretical framework

The central theme of this thesis is based on the risks faced by farming systems, the processes in response to these risks (like adaptation), and resilience of the farming systems as an outcome of these processes. I briefly introduced these concepts of risk, resilience, and adaptation above in Section 1.1 and 1.2. In this section, I further discuss these concepts in detail and position this thesis based on the framework I developed.

Risk in context of agriculture is often conceptualized based not only on its source (e.g., institutional, geopolitical, market, economic and climate risks) but also framed as the uncertainty of outcomes; it generally implies a likely negative consequence, often referred to as downside risks (Hardaker et al., 2004). Risk events can be both known and unknown in nature, and some risk events are unknown until they occur, and thereby having unknown outcomes and probabilities (commonly described as “unknown unknowns”) (Bond et al., 2015).

Farming systems and communities manage the consequences of these risks and subsequently change as a response to these risks. In this context, I define response pathways as actions that systems or communities take to manage, mitigate, or navigate risks. Although diverse, these response pathways can be characterized as react, cope, and adapt (Green et al., 2021). Coping is defined as the usage of available skills and resources to address, manage, and overcome adverse conditions (as a consequence of risk exposure), and maintain basic functioning of the system in the short- to medium-term (Intergovernmental Panel on Climate Change (IPCC), 2023). Reaction is an unplanned response to a risk (often immediate) (Green et al., 2021). Adaptation is defined as processes of adjustment to actual or expected risks (like climate change), to minimize harm and capitalize on opportunities, wherever possible. In farming systems, an example of such adaptation maybe the change in planting dates (McDonald et al., 2022).

I modify this response categorization by omitting “reaction” and adding “transformation” as another response pathway. There are two reasons for this—firstly, the research in this thesis focuses on long-term risks from climate change and therefore requires longer timescales of response pathways. Since reactive responses are often immediate and unplanned, their importance within the scope of this thesis is limited. Secondly, there is growing evidence that there are limits to adaptation which necessitate other response pathway, namely "transformation". Transformation is a change in fundamental attributes of natural and human pathways (Intergovernmental Panel on Climate Change (IPCC), 2023). It can be a possible pathway to respond to long-term risks, large uncertainties, and the surprise element ("unknown unknown" risk elements described above) associated with risks such as climate change (Nelson, 2011). Some examples of such transformations are already underway such as plant-based meat alternatives (Kozicka et al., 2023). By framing response pathways in this manner, I introduce a forward-looking perspective in the theoretical framework.

Finally, resilience is described as the capacity of interconnected social, economic, and ecological systems to cope with a hazardous event (risk) and reorganize in ways that maintain their essential function and structure. Additionally, resilience also has the capacity for adaptation, learning and transformation (Intergovernmental Panel on Climate Change (IPCC), 2023). Resilience is thus an outcome of the response pathways to risks.

By focusing on the time element of risks, I combine the three response pathways described above with the time reference with regard to risk—before, during and after the risk event. Next, I frame resilience as an outcome of these two dimensions: (i) time reference with regard to risk (Y-axis of Figure 1.1) and (ii) the consequent response pathways (X-axis of Figure 1.1); and resilience framed as an overarching concept (Figure 1.1). With this background and the framework described, I position my research chapters and research objectives.

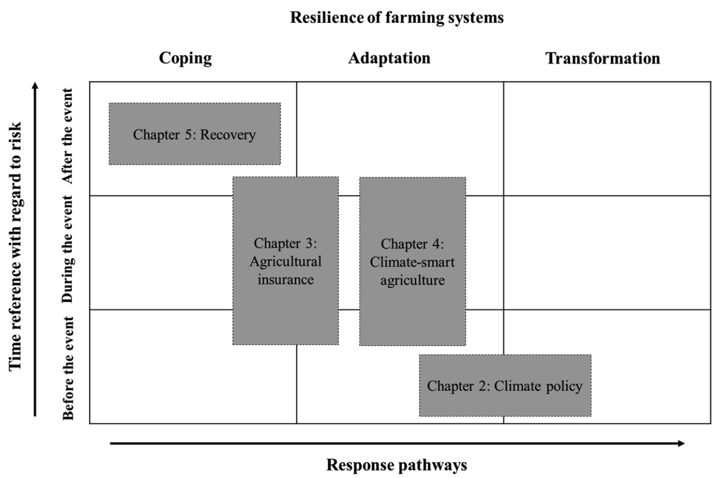

Figure 1.1 Theoretical framework used in this thesis and positioning of research chapters therein based on their core focus.

I place my research Chapter 2 on climate policy, between the adaptation and transformation 'boxes'. Chapter 2 looks at national climate policies, how they align with future climate risks, the readiness (in the form of economic and social capacities), and biophysical scope to implement them across different countries, transcending both the boxes of adaptation and transformation. The core focus of these climate policies is managing future risks through adaptive and transformative responses. For Chapter 3 on agricultural insurance, I frame this chapter under coping and adaptation. Agricultural insurance is often a coping mechanism to deal with current risks being faced by the farming systems. However, the payoffs from an insurance program can also catalyze adaptation actions, if designed well (Hellin et al., 2017; Linnerooth-Bayer & Mechler, 2006; Siebert, 2016). Further, insurance can also give incentives for risk prevention, hence it is placed across all the three risk timescales (before, during and after the event).

Chapter 4 of this thesis looks at risk reducing effects of Climate-smart agriculture (CSA), and I frame this under adaptation. The type of adaptive strategies included in this chapter (like agro-advisories, agronomic practices like reduced tillage, improved cultivar, and precision water and nutrient management practices) are positioned to deal with risks before, during and after risk occurrence. Finally, my last research chapter (Chapter 5) focuses on recovery of maize and dairy milk systems from observed production shocks. This chapter looks at how these farming systems recover from production shocks and is placed under coping, because the response is focused on recovering upto (pre-shock) baseline production levels. While there may be long-term adaptive and transformative processes involved in the recovery of these systems, they are not the core focus of the chapter. Additionally, the categories defined in this framework have many interlinkages, synergies, feedback loops, and may not always be linear. I further highlight these interlinkages and connections in Chapter 6.

1.7 Thesis outline

In this section I briefly summarize each research chapter, the key research objectives, the data and methods used, and contribution to the literature.

Chapter 2 aims at developing a framework to monitor climate action in agriculture at a global scale. The research chapter contributes to the literature by illustrating how to measure and track adaptation in agriculture. The framework combines the need for adaptation (based on the projected risks faced by farming systems from climate change), the scope for adaptation in terms of biophysical limits, readiness to adapt based on different socio-economic macro indicators including GDP (Gross Domestic Product), governance indicators, among others (Sarkodie & Strezov, 2019) and finally, the intent for adaptation based on the NDC (Nationally determined contributions) commitments of different countries (pledges to adapt to climate change, as part of the Paris agreement to limit global warming)[6]. The results are illustrated for adaptation in agriculture and identifies the misalignment of need with other dimensions of adaptation, i.e., scope, intent, and readiness for adaptation.

Chapter 3 builds on the adaptation gaps identified in the previous chapter and digs deeper into an important agricultural risk management and adaptation strategy—agricultural insurance. The objective of the study is to assess the extent to which agricultural insurance is a successful agricultural risk management option across sectors (crops and livestock), risk types (observed extreme weather events, biological risks like livestock epidemics, projected climate change) and geographies. The study is the first multi-sectoral, comprehensive review of agricultural insurance literature in the last two decades across different factors, sectors, and risks.

Chapter 4 focuses on another important strategy—testing the benefits of climate-smart agriculture. Using a unique farm-level panel dataset collected from climate-smart villages in India from 2015-2020, the study investigates the response of crop yields towards heat stress under climate-smart management practices. It investigates whether wheat and soybean farm yields in India are robust to the effects of extreme heat stress during the crop growth period, contributing significantly to evidence which has previously focused on high-income countries and temperate regions (Tack et al., 2017).

Chapter 6 further delves into production system resilience at a macro-level, focusing on maize and dairy milk production. Whereas several existing studies have analyzed the occurrence and impact of specific shocks, no study has assessed the recovery times and recovery likelihood to general production shocks. This study is the first to estimate the recovery likelihoods at a global scale for maize and dairy milk production systems, making an important contribution towards resilience research in agricultural production systems. Notably, it analyzes both maize and milk production, which are highly interdependent, with milk production generally being heavily understudied. It assesses recovery likelihoods from

[6] https://unfccc.int/process-and-meetings/the-paris-agreement/nationally-determined-contributions-ndcs

production shocks in maize and dairy milk production systems at national scale using 60 years of data available from FAOSTAT. Table 1.2 provides an overview of the data sources for each of the research chapters, the time-period covered, and the methods used to address the research objectives in each chapter.

Table 1.2 Data, time-period, and methods of the research chapters.

Chapters	Data sources	Time-period	Methods
Chapter 2 (Climate policy)	Previous research and globally available indicators (Aggarwal et al., 2019; Richards et al., 2015)	2050s (2041–2060)	Policy review and risk mapping
Chapter 3 (Agricultural insurance)	▪ Agricultural insurance research indexed in Scopus ▪ International disaster database ▪ Projected climate change impacts from Intergovernmental Panel on Climate Change (IPCC) ▪ Food and Agriculture Organization (FAO) Emergency Prevention System for Transboundary Animal and Plant Pests and Diseases (the EMPRES project)	2000–2020, 2050s (2041–2060)	Systematic literature review and risk mapping
Chapter 4 (Climate-smart agriculture)	Farm-level panel data collected through surveys	2015–2020	Fixed effects regression with cubic splines
Chapter 5 (Recovery)	Production data available from Food and Agriculture Organization (FAO)	1961–2021	Shock estimation using LOESS regression and survival analysis

The following four chapters (Chapter 2 to Chapter 5) focus on each of the research objectives described above. Next, I bring together the findings in a synthesis, and discuss limitations and opportunities for future research, scientific contribution, and recommendations in Chapter 6. The thesis ends with main conclusions in Chapter 6.

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Chapter 2
The gap between intent and climate action in agriculture

This chapter is adapted from Vyas, S., Khatri-Chhetri, A., Aggarwal, P., Thornton, P., Campbell, B.M., 2022. Perspective: The gap between intent and climate action in agriculture. Global Food Secur. 32,100612. http://dx.doi.org/10.1016/j.gfs.2022.100612

Abstract

Following the UNFCCC Paris Agreement, most nations made commitments within their Nationally Determined Contributions (NDCs) to adaptation and mitigation in agriculture. However, these commitments need to be assessed in relation with ground truth, including biophysical and socio-economic limits to climate action. We propose a new framework for monitoring climate action by countries/regions, based on four dimensions—intent, need, scope and readiness for implementing adaptation and mitigation in agriculture. While "intent" reflects intended climate action by countries such as those mentioned in NDCs or NAPs and NAMAs, "need" highlights vulnerability of a country's agriculture to climate change and historical GHG emissions. The third dimension, "scope", is related to the biophysical opportunities and limits to adapt or to mitigate. Finally, the "readiness" dimension considers a country's current ability to implement various adaptation/mitigation actions and policies. The framework is illustrated with a global analysis, using selected indicators for each of these dimensions. Results indicate that 61 countries globally (including key food producers) should consider corrective action. The framework presented in this chapter can serve as a monitoring and evaluation mechanism for NDC implementation and tracking progress.

Keywords: Climate change, NDC, adaptation, mitigation, Paris agreement, readiness, climate hotspots, agriculture, climate action

2.1 Introduction

Recent studies project a significant impact of climate change including more frequent extreme weather events, on food production, distribution, and consumption across the world (Cottrell et al., 2019; Godde et al., 2021). Food production, agriculture, and other land-use activities also account for 23% of anthropogenic emissions (Rivera et al., 2019). Rising to these challenges requires adaptation and mitigation actions at different scales by stakeholders (Bapna et al., 2019; UNFCC, 2017). Nationally Determined Contributions (NDCs), submitted by member nations under "The Paris Agreement" outline individual country pledges to climate action[7]. Agriculture is one of the critical sectors in prioritizing national mitigation and adaptation plans across the NDCs for 148 and 131 countries respectively (FAO, 2016). This intent is very encouraging, however implementing these actions is highly contingent upon the alignment of critical drivers which affect their feasibility. In this chapter, we propose a new framework for monitoring and tracking climate action in agriculture. The framework can help assess the types and feasibility of climate actions required in agriculture, and in understanding suitable pathways to achieve the goals of the Paris Agreement.

Framework for monitoring climate action in agriculture

The proposed framework examines four inter-related dimensions for climate action in agriculture—the intent, the need for action, the scope for action and the readiness to implement (Figure 2.1). Intended climate action should be aligned with a country's need and scope for adaptation and mitigation in agriculture; and its readiness to implement activities, which is influenced by its policy landscape and enabling conditions. We focus on climate action (adaptation and mitigation) required until the 2050s, as this period is critical to keep planetary changes within environmental limits (Rogelj et al., 2016; Steffen et al., 2015) and supporting sustainable development. Each dimension and the potential data and indicators are discussed below:

Intent

It is critical to understand a country's intent to undertake action for climate adaptation and mitigation independent of its capacity for implementation. This intent can be judged by the policy actions and/or budgets allocated for this purpose. Inclusion of agricultural adaptation

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[7] https://unfccc.int/documents/9176

and mitigation actions in NDC documents, National Action Plans (NAPs) and Nationally Appropriate Mitigation Actions (NAMAs) submitted to UNFCCC, along with other domestic policy measures can be used to represent the intent dimension of the monitoring framework (Kuramochi et al., 2020). There are multiple studies available to assess the intent for climate action through NDCs (Richards et al., 2015b) (FAO, 2020), but most are limited to specific regions or sectors.

Need

Climate action is needed by many countries to achieve collective global objectives of the Paris agreement, but the specific need for adaptation is also influenced by vulnerability at national and sub-national scales. Similarly, for mitigation, focus on land-use change and emission targets becomes important. Risk is often characterized as an intersection of climate hazards, exposure and vulnerability (consisting of socio-economic factors, among others) (Collins et al., 2019). In addition, understanding the balance between food demand and supply and its exposure to climatic risk is also critical to identify potential food insecure regions. For example, if a country is food self-sufficient or produces surplus with high projected climatic impacts, it may be less likely to prioritize an increase in food production, but rather focus on maintaining growth and implementing risk management interventions. On the other hand, if a country has a food deficit coupled with high projected climatic impacts, it may need to prioritize adaptation actions, even though trade can modify its response. Similarly, mitigation needs might be appropriately linked to a country's historical emissions, land-use systems (IPCC, 2019), food production priorities and capabilities to implement mitigation in agriculture. The need for mitigation and allocation of mitigation targets is context-dependent and there are various methods and tools available to estimate mitigation targets in agriculture (Frank et al., 2017; Richards et al., 2018).

Scope

The growth in crop production seen since the Green Revolution can be attributed mainly to an increase in productivity (yield gap closure) and crop area expansion (Bren d'Amour et al., 2017). The magnitude of the crop yield gap can be used as an indicator of scope—larger the gap, higher the scope for change. There are some studies and data available to measure crop yield gaps like (Mueller et al., 2012) and (http://www.yieldgap.org/), but these are limited by the number of countries analyzed. Diversification opportunities to expand livestock and fish culture could be additional indicators of scope. Expansion of the arable area for crop cultivation can be another criterion to assess the scope of adaptation through land-use change. Emission intensity in terms of food production (CO_2 equivalent emissions from croplands and livestock production per calorie or per unit of production) is a potentially useful criterion to understand the scope for mitigation in agriculture. It is better than absolute emissions per ha of land because it reflects both emissions and food production, an important consideration for countries to meet their national food security targets.

Readiness

There are many indicators which can be chosen to represent readiness. Ideally, the readiness index to analyze the framework presented in this chapter should a) combine both biophysical and socio-political dimensions which adequately represent the readiness to implement climate action and b) be able to represent most of the countries and should not be limited in its spatial scale. Available indicators which can be considered are global adaptation index (https://gain.nd.edu/about), change readiness index (https://home.kpmg/xx/en/home/insights/2019/06/2019-change-readiness-index.html) and World Bank's enabling the business of agriculture (https://eba.worldbank.org/).

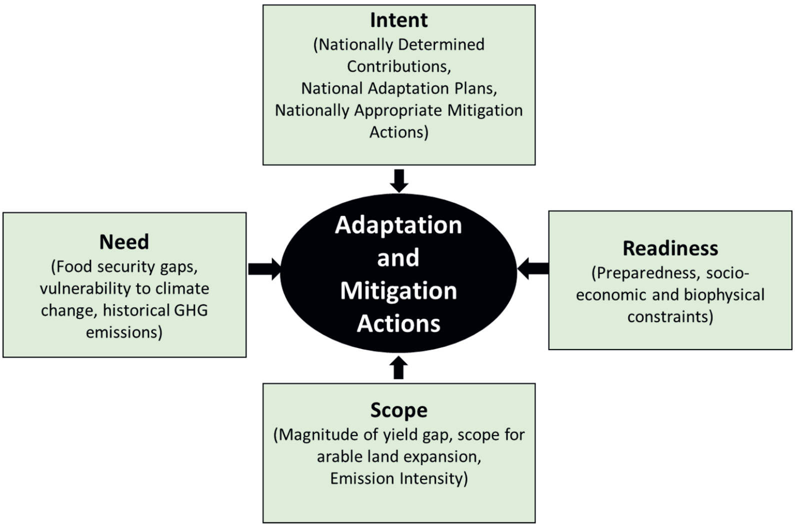


Figure 2.1 Framework for analyzing climate action for adaptation and mitigation in agriculture.

2.2 Data and methods

The framework outlined above allows for monitoring climate action in agricultural adaptation and mitigation. We apply the framework using publicly available indicators and data, to represent the need, scope, readiness, and intent for adaptation in agriculture. We have chosen global agriculture NDC data (Richards et al., 2015a) to represent the intent for adaptation. Indicator for the need dimension is based on a recent analysis of the gap between national future food demand and supply, assessed along with projected impacts of climate change on food production in the 2050s (Aggarwal et al., 2019). The scope for adaptation is envisaged as potential for adaptation in agriculture (we have limited the analysis here to crops and not included livestock due to limited data availability), based on a country's biophysical limits. It includes increasing crop production by reducing crop yield gaps and increasing cultivated area. To represent this, yield gap as % of attainable yields for cereal crops (maize, wheat and rice) was calculated (Mueller et al., 2012) and arable land as fraction of total agricultural land was estimated using land statistics from FAO (year 2019). Notre Dame-Global Adaptation Index for the year 2019 (ND-GAIN) (Sarkodie and Strezov, 2019) is a generic readiness indicator. In the absence of another suitable global indicator for agriculture, we have assumed that ND-GAIN also represents the differences in readiness (for implementing climate action) among countries for agriculture sector as well. Although we have chosen indicators that we believe adequately represent the various dimensions of the framework, there could be other suitable indicators that can be used. Future research on developing a specific readiness index for climate action in agriculture would be useful.

2.3 Results

Figure 2.2 shows results for countries based on the four dimensions of the framework. The scope for adaptation, however, is represented by two variables—cereal yield gap and available arable land. Most of the higher-income countries are in the upper left corner of the graph, indicating high scope (due to possibility of expanding arable area despite having low yield gaps) and high readiness despite low-medium need. On the other hand, lower-income countries, especially those of the African continent, are in the right lower quadrant of the graph indicating high scope and low readiness despite high need and intent. Many key food producers (like India, China, Brazil) have medium scope and readiness. The framework illustrated here is dynamic—the indicator used for readiness is publicly available and updated every year (the ND-GAIN Index is available since 1995), which allows for tracking the progress of each country over a period, based on its position.

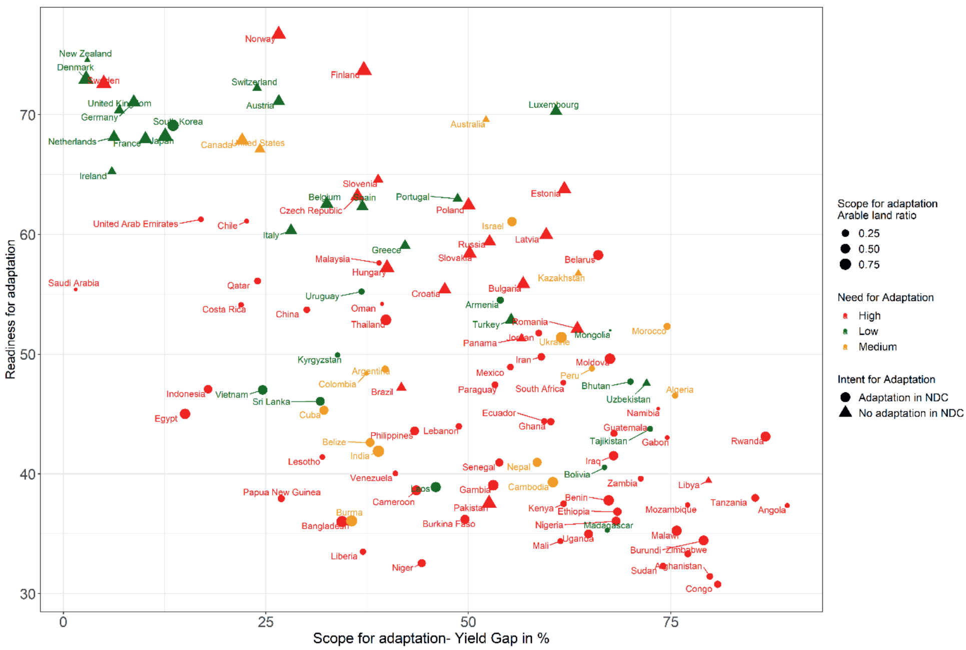
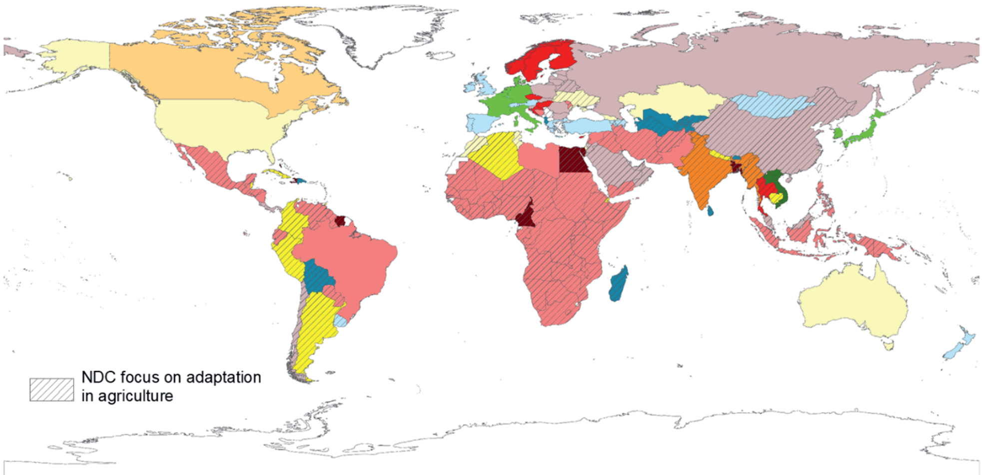


Figure 2.2 Illustration of framework with a scatterplot of intent, need, scope and readiness of different countries for adaptation in agriculture. Focus on adaptation in agriculture of Nationally Determined Contributions (NDCs) of countries is taken as an indicator of intent. Need for adaptation is represented by traffic light color of the symbols. High need countries are those with a projected future food production deficit and high negative impacts of climate change (more than 10% loss), medium need countries also have similar food production deficit but low negative climate impacts (less than 10%), and low need countries have negligible food production deficit and no negative climate impacts. Scope for adaptation is represented by cereal yield gap (percentage), and by the available arable land as symbol size. Higher the yield gap or available arable land, higher is the scope. Readiness for adaptation is illustrated by Notre Dame Global Adaptation Initiative's (ND-GAIN) Country Index.

For ease of interpretation and visualization these results are grouped into twelve distinct classes—combinations of three classes of need (high, medium, and low), and two classes for each of scope and readiness (high and low) (Figure 2.3). Alignment of need with intent, scope and readiness is the key objective of the clustering analysis. Results show that most of the countries need to act urgently on adaptation. Countries (and regions) like Brazil, most of Sub-Saharan Africa and Central Asia, Bangladesh and Indonesia require focus on adaptation actions in agriculture, as their needs are high whereas scope and/or readiness are low. A few higher-income countries of northern and eastern Europe are also hotspots due to projected climate change impacts (Iglesias and Rosenzweig, 2009; Parry et al., 2004), and limited scope for yield gap closure and cropland expansion, despite high readiness. For these countries, food imports from other countries may be an effective adaptation pathway. In comparison, most of the higher-income countries of Western Europe, North America and Australia have high readiness to adapt and variable scope, but their needs are low to medium due to limited food security concerns. Such countries have by and large not committed to adaptation actions in their NDCs. Globally, most of the countries have high to medium need for adaptation, and concerted efforts are required to align adaptation initiatives in agriculture with ground realities.



	Need	Scope	Readiness
	High	Low	Low
	High	Low	High
	High	High	Low
	High	High	High

	Need	Scope	Readiness
	Medium	Low	Low
	Medium	Low	High
	Medium	High	Low
	Medium	High	High

	Need	Scope	Readiness
	Low	Low	Low
	Low	Low	High
	Low	High	Low
	Low	High	High

Figure 2.3 Global assessment based on intent, need, scope and readiness in adaptation for agriculture. For details of indicators, please refer to Figure 2.2. Thresholds for high, medium, and low yields are also given in Figure 2.2. High scope denotes yield gap more than 50% of the attainable yield and/or current arable land is less than 50% of the total agricultural land. Readiness for climate action of a country is considered high when Notre Dame Global Adaptation Initiative's (ND-GAIN) Country Index is greater than 0.5. Countries which intend to undertake climate action in agriculture in the Nationally Determined Contributions (NDCs) are shown by hatching.

2.4 Discussion and conclusion

We highlight several crucial takeaways from this study. First, the framework presented in this chapter can serve as an important monitoring and evaluation mechanism for NDC implementation. The framework serves as a starting point to develop a comprehensive monitoring mechanism to track NDC progress. Similar mechanisms are already developed for other collective global goals such as the Sustainable Development Goals (SDG) (https://sdg-tracker.org/). Most indicators which can be used for this framework are reported annually, thus enabling a temporal analysis. Future research integrating synergies and trade-offs between different components of the framework through modelling can further help enhance the current work. Second, results for adaptation show a mismatch between the four dimensions of climate action—particularly amongst developing nations. We found that 61 countries (52% of the total reviewed) have high need for adaptation but a mismatch between scope, intent and/or readiness. On the contrary, 11% of the countries have low needs in adaptation, and a focus on adaptation in the NDC.

Adaptation finance today accounts for only 5% of global climate finance, of which only 23% is invested in agriculture, forestry, land-use and natural resource management (CPI, 2018), and is well below what is required (Campbell et al., 2018; Odhong' et al., 2019). For developing countries with limited financial resources, alignment of policy initiatives with need, scope and readiness is essential, so that their fast-depleting financial resources are used to support what they need at priority. The framework presented in this analysis would need periodic updating as its dimensions are likely to change with development and climate change scenarios. For example, the need for adaptation based on projected climate impacts for the 2050s (and future food security) may change based on actual emissions reduction achieved (which will affect the projected climate impacts).

The trajectories countries chose for adaptation will likely affect their mitigation results and vice-versa (Deng et al., 2017). Dietary changes in future may drive feed expansion at the expense of food production (The Eat-Lancet Commission, 2019). Projected land-use changes will influence the area available for farming (and can also cause deforestation and peatland degradation), and it should also be included in the scope. Policymakers across the world are also focusing on transforming food systems using sustainable and climate-smart pathways, through innovations in technology (Godde et al., 2021; Herrero et al., 2020). Once successful, these innovations would affect all dimensions of the framework. To conclude, the Paris

Agreement is widely viewed as an important policy and institutional framework for collective global climate action, especially for agriculture (Chand, 2020). The proposed framework provides a holistic way to contextualize and align climate change strategies with existing conditions and to help identify future trajectories. As countries learn to adjust to the new realities of climate change, scaling adaptation and mitigation will play a key role in changing the landscape of climate action across regions.

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Supplementary information

Supplementary table S2.1 Definition, indicators used and data source (including year) for results shown in Figures 2.2 and 2.3.

Definition	Indicator	Source
Intent for adaptation Commitment for agricultural adaptation in the Nationally Determined Contributions (NDC) of a country	Presence or absence of agriculture in adaptation targets and actions, in the Nationally Determined Contributions (NDC) of a country	(Richards et al., 2015)
Need for adaptation Need or requirement of adaptation in agriculture based on national food security and climate change	Future food production gap and projected impacts of climate change on cereal yields in 2050s	(Aggarwal et al., 2019)
Scope for adaptation Potential for adaptation in agriculture, based on a country's biophysical limits. It includes increasing crop production by reducing crop yield gaps and increasing cultivated area through expansion of available arable land	Yield gap, as a percentage of attainable yields for cereal crops and available arable area for cultivation (arable land as ratio of total agricultural land)	(Mueller et al., 2012) FAO (2019)
Readiness for adaptation An index to assesses the enabling environment and preparedness for scaling out technologies, practices, and services for adaptation and mitigation in agriculture	Composite index of different enabling factors for climate action—economic, social, governance, financial, information and physical indicators	Notre Dame Global Adaptation Initiative's (ND-GAIN index (2019)

Supplementary table S2.2 Descriptive statistics for each of the indicators used to represent different dimensions.

Indicator	Count	Type	Mean	Standard deviation	Minimum	Maximum
Intent for adaptation	118	Categorical 0=no focus in Nationally Determined Contributions (NDC), 1= adaptation focus in Nationally Determined Contributions (NDC)	.66	.475	0	1
Need for adaptation	118	Categorical 1= low need, 2 = medium need, 3= high need	2.34	.861	1	3
Scope for adaptation Yield gap	118	Percentage	47.69	21.73	1.54	89.37
Scope for adaptation Arable land as ratio of total agricultural land	118	Ratio	.40	.26	.005	.98
Readiness index Notre Dame Global Adaptation Initiative's (ND-GAIN index (2019)	118	Index	50.53	12.06	30.77	76.70

Supplementary references

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Chapter 3

Mapping global research on agricultural insurance

This chapter is adapted from Vyas, S., Dalhaus, T., Kropff, M., Aggarwal, P., Meuwissen, M.P.M., 2021. Mapping global research on agricultural insurance. Environ. Res. Lett. 16, 103003. http://dx.doi.org/10.1088/1748-9326/ac263d

Abstract

With a global market of 30 billion USD, agricultural insurance plays a key role in risk finance and contributes to climate change adaptation by achieving Sustainable Development Goals (SDGs) including no poverty, zero hunger, and climate action. The existing evidence in agricultural insurance is scattered across regions, topics and risks, and a structured synthesis is unavailable. To address this gap, we conducted a systematic review of 796 peer-reviewed papers on agricultural insurance published between 2000 and 2019. The goal of this review was twofold: 1) categorizing agricultural insurance literature by agricultural product insured, research theme, geographical study area, insurance type and hazards covered, and 2) mapping country-wise research intensity of these indicators vis-à-vis historical and projected risk and crisis events—extreme weather disasters, projected temperature increase under SSP5 (Shared Socioeconomic Pathways) scenario and livestock epidemics. We find that insurance research is focused on high-income countries while crops are the dominating agricultural product insured (33% of the papers). Large producers in production systems like fruits and vegetables (South America), millets (Africa) and fisheries and aquaculture (Southeast Asia) are not focused upon in the literature. Research on crop insurance is taking place where historical extreme weather disasters are frequent (correlation coefficient of 0.75), while we find a surprisingly low correlation between climate change induced temperature increases in the future and current research on crop insurance, even when sub-setting for papers on the research theme of climate change and insurance (-0.04). There is also limited evidence on the role of insurance to scale adaptation and mitigation measures to de-risk farming. Further, we find that the study area of livestock insurance papers is weakly correlated to the occurrence of livestock epidemics in the past (-0.06) and highly correlated to the historical drought frequency (0.51). For insurance to play its relevant role in climate change adaptation as described in the Sustainable Development Goals (SDGs), we recommend governments, insurance companies and researchers to better tune their interest to risk-prone areas and include novel developments in agriculture which will require major investments, and, hence, insurability, in the coming years.

Keywords: Agricultural insurance, climate change, systematic review, mapping, livestock epidemics, extreme weather disasters

3.1 Introduction

Agricultural insurance is a global billion-dollar industry growing at a fast rate. In 2019 alone, the insurance market was worth 30 billion USD (Wang et al., 2020). Climate change is an important driver of agricultural system instability and is expected to increase the frequency and intensity of risks in many regions across the globe (IPCC, 2018). Among different on-farm risk management tools available, one important strategy to manage these risks is agricultural insurance. State-supported insurance subsidies are common in many countries, amounting to over 20 billion USD annually (Hazell and Varangis, 2020). Effective insurance policies stabilize farm income, reduce poverty (SDG 1) and ensure a climate safety net for food producers (SDG 13). The welfare effects gained by insurance pay-offs can have multiple spill-over effects, including hunger reduction (SDG 2) (Siwedza and Shava, 2020). Therefore, insurance is a key element in agricultural adaptation to climate change, among other risk management tools.

A synthesis of current agricultural insurance research can help in assessing the current work and in reshaping the future research agenda. However, evidence from existing reviews is scattered across different regions and sectors and is limited in scope. In fact, most systematic reviews on agricultural insurance are focused on index-based insurance only (Benami et al., 2021; Jan de Leeuw et al., 2014; Marr et al., 2016; Vroege et al., 2019). Furthermore, no study has compared the literature with existing risks and historical crisis events. This chapter addresses this gap by focusing on two objectives: 1) categorizing agricultural insurance literature by agricultural product insured, research theme, geographical study area, insurance product type and hazards covered, and 2) mapping research intensity by country for these indicators vis-à-vis historical and projected risk and crisis events—extreme weather disasters, projected temperature increase under SSP5 (Shared Socioeconomic Pathways) scenario and livestock epidemics. We first describe the data and methods, followed by an overview of global insurance research and a comparison of research intensity with risks. The results contribute to our understanding of different indicators of agricultural insurance dynamics, including the role of insurance in dealing with likely environmental change and alignment with risk hotspots.

Agricultural systems today face myriad risks, both biotic and abiotic in nature. Losses from pests and diseases in agriculture and livestock are significant, especially among smallholder farming systems in the LMICs (De Groote et al., 2020; Mason-D'Croz et al., 2020). At the same time, climate change and weather extremes drive major food shocks across the globe (Cottrell et al., 2019). Extreme weather events (including heatwaves, drought, floods and cold waves) cause an average loss of 10% in cereal production alone (Lesk et al., 2016), and reduce the food quality of many other crops (Dalhaus et al., 2020; Kawasaki and Uchida, 2016). Climate change (gradual change in temperature and precipitation over time) reduces global consumable food calories by 1% every year (Ray et al., 2019), with additional losses in other sectors like livestock and fisheries (Godde et al., 2021; Lam et al., 2020). Weather extremes are increasing in magnitude, especially in the food-deficit, developing regions, which has major ramifications on food prices (Malesios et al., 2020) and international trade (Burkholz and Schweitzer, 2019). The magnitude and likelihood of extreme events are further expected to increase under projected climate change scenarios in many breadbasket regions (Kharin et al., 2018). These risks and crisis events enlarge the need for farm risk management, which can include multiple strategies including crop and livestock management (improved nutrient and water management), diversification, using seasonal weather forecasts as decision support and ultimately, risk financing tools (including insurance). These farm management tools complement each other, and insurance solutions are often used if other risk management tools reach their limits (Meuwissen et al., 2019). With the increasing severity and frequency of risk events in agriculture (Fischer et al., 2021), there is an additional focus on viable insurance solutions to de-risk agriculture from weather and disease/pest risks. Comparing insurance research intensity with risks and crisis events can help in understanding this mismatch and can reshape the research agenda.

3.2 Data and methods

Selection of literature

A systematic review was conducted using a combination of search terms related to agricultural insurance in Scopus, a widely used scientific database for published research. The literature review was done based on the PRISMA guidelines (http://www.prisma-statement.org/), allowing a replicable list of results (also provided as a Supplementary file). We focus on the peer-reviewed literature and thus excluded grey literature sources. Thus, only peer-reviewed papers in journals that were indexed in Scopus at the time of publication are included in this review[8].

The combination of search terms used for the systematic review are provided in the Supplementary information (Supplementary section 1 of Vyas et al. 2021)[9]. We use a combination of 45 search terms, which comprehensively cover global agricultural insurance literature. We included papers published between 2000 and 2019 to focus on recent research on agricultural insurance. Since 2000, there have not only been more agricultural production shocks (due to both climatic and non-climatic factors) (Cottrell et al., 2019), but the economic damages from extreme natural disasters (floods, extreme temperatures, droughts, storms, wildfires, and landslides) have also increased (Coronese et al., 2019).

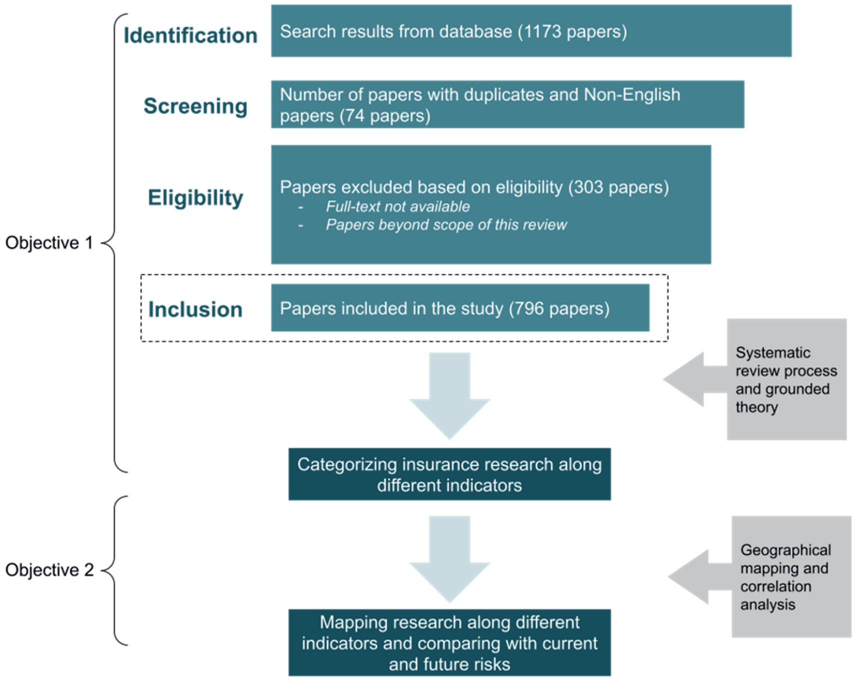

Figure 3.1 Schematic flowchart of the key steps of the systematic review. Grey blocks represent the methods used.

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[8] While this ensures a maximum replicability, we might miss single papers that were published before a journal got indexed (e.g., Turvey, 2001 published in Applied Economic Perspectives and Policy, which was indexed in Scopus not before 2010). The omission of single papers is not expected to change the general validity of our results.

[9] The Supplementary information of this chapter is not reproduced in this thesis. Please refer to the published version of this chapter (Vyas et al. 2021), available here.

The initial search resulted in 1173 papers (Figure 3.1). The next step required an initial abstract screening to eliminate duplicates and papers not available in English, leading to exclusion of 74 papers. After the initial screening, full-texts were accessed through the libraries of Wageningen University and Research (WUR) and the International Maize and Wheat Improvement Center (CIMMYT). All available papers were then scrutinized based on their content, and their fit with the scope of this review. We excluded papers that were a) not related to agricultural insurance (for example, papers on health insurance or livestock disease epidemiology without a focus on insurance), b) papers on meteorological databases and climatic events without any relation to agricultural insurance, c) papers on crop yield distribution and statistics, without any implications of the findings on crop insurance, d) papers based on crop production forecasting and monitoring, without any link with agricultural insurance and e) papers on insurance for carnivore-livestock conflicts. This led to the further exclusion of 303 papers, resulting in a total of 796 papers included in this study.

Categorizing the literature

The list of 796 papers was reviewed thoroughly and information was collected to categorize papers by different indicators—agricultural product insured (e.g., livestock, fisheries, or crops like cereals, fruits etc.), geographical focus (country and income group based on International Labour Organization and World Bank grouping- https://ilostat.ilo.org/resources/concepts-and-definitions/classification-country-groupings/), insurance product type and hazard covered (e.g., drought, flood, total production risk etc.). In case of multiple indicators, the paper was categorized under a separate category of multiple indicators. For instance, if a paper focused on multiple insurance product types, we put the paper in a separate category of multiple insurance product types. Similar steps were followed to collect information for other indicators (e.g., papers covering multiple hazards were grouped under multi-peril). For grasslands, the agricultural product was considered as livestock, and depending on the nature of the insurance product used, the papers were classified accordingly (indemnity-based livestock insurance or index-based livestock insurance).

Another indicator was the research theme. The research theme of the papers was identified based on grounded theory (Laplaza et al., 2017). The initial coding process involved drawing key objectives and/or findings verbatim from the text. As the papers were reviewed, repeated ideas began to emerge from the data and these initial codes (or text) were then merged into two levels of categories (themes-level 1 and sub-themes-level 2). For example, Castañeda-Vera et al. (2015) focused on selecting a suitable crop model for drought risk assessment to better capture crop-weather relations and improve insurance design. The paper was classified under the theme of "basis risk" and sub-theme of "crop-weather relations". The categories developed through this process were constantly compared with each other and the process was iterated. At the end of the process, the papers were classified into six research themes, which consisted of 29 sub-themes in total. The papers with a broad discussion of agricultural insurance (including multiple theme overlaps) were classified under the theme of *Insurance policy analysis* (in particular, sub-theme *review*). Figure 3.1 was created using Google drawings and Figure 3.2 with OriginPro software. R software was used for spatial data processing and visualization through maps.

Geographical mapping

To map the research intensity of these indicators by country vis-à-vis historical and projected risk and crisis events, the results obtained from categorizing the literature in the above step were mapped along with different indicators (agricultural product insured, research theme, type of insurance product, and hazard covered). To do this, the number of case studies per country for each of these indicators was determined from the review results and mapped using R software. Country-wise official boundaries were obtained from the World Bank (https://datacatalog.worldbank.org/dataset/world-bank-official-boundaries). The country was determined based on the research/focal study site(s) and not on the authors' affiliations. If a paper covered more than one country, both were included in the map. The maps, however, do not show regional papers (for example, papers on Africa or Europe in general), as the focus on the entire region can dominate countries with fewer papers in the mapping. For instance, we find a group of papers on developing countries in general that cover multiple crops/sectors, which would thus have been overrepresented in our maps. The distribution of regional papers along different indicators is shown in the Supplementary information (Supplementary table 5-9 of Vyas et al. 2021, please see footnote 9).

Risk mapping

The results obtained from mapping the research intensity of papers along with different indicators in the above steps, were compared with three risk indicators—1) the historical occurrence of weather-related disasters, 2) the projected mean temperature rise in the future, and 3) the occurrence of historical transboundary livestock diseases. These three risk indicators help in putting insurance literature into the context of the spatial patterns of key risks in agricultural systems. The data for the three risk indicators was collected from publicly available datasets and then mapped.

Historical weather disasters

To capture weather-related disasters since 2000 for every country, the international disaster database (https://www.emdat.be/) was consulted. These disasters were limited to meteorological and climatic events affecting agriculture (droughts, floods, extreme temperature, and storms). The events were mapped jointly (sum of all the four disaster types).

Projected future weather risk under climate change

To capture future weather-related risk, the projected increase in the land surface temperature for 2050 was used as a proxy for a country's future climate risk exposure. The annual average projected temperature increase in the middle century (2041–2060) was calculated using the projected temperature from CMIP-6 (Coupled Model Intercomparison Project) data (https://interactive-atlas.ipcc.ch/). The temperature change for every country was calculated as the difference between the average annual temperature of mid-century (2041–2060) and the average baseline annual temperature between 1981 and 2010, based on the SSP5-8.5 scenario and mean of all the available (34) global climate models. The SSP5-8.5 scenario models the projected temperature change based on intensive fossil-fueled development with high mitigation challenges, and with a median global temperature response of five degree warming (Kriegler et al., 2017). Although this scenario marks the upper extreme of greenhouse gas emission and fossil-use modelling, it helps in identifying hotspots of warming with limited pathways to green transition and sustainable energy alternatives. For comparison, results for other SSP scenarios are also provided in the Supplementary information (Supplementary table 4 of Vyas et al. 2021, please see footnote 9).

Historical animal disease outbreaks

The data on historical livestock disease outbreaks was collected from the FAO's Emergency Prevention System for Transboundary Animal and Plant Pests and Diseases (the EMPRES project—http://empres-i.fao.org/eipws3g/). The project provides a global comprehensive dataset of observed transboundary animal disease outbreaks at a gridded level, available from the year 2004. The total number of outbreaks for every country from 2004 to 2019 was calculated for livestock (including different sub-sectors—cattle, poultry, swine, sheep, and goats). The diseases covered in the dataset include African swine fever, Anthrax, Bluetongue, Bovine spongiform encephalopathy, Bovine tuberculosis, Brucellosis, Brucellosis (Brucella abortus), Brucellosis (Brucella melitensis), Brucellosis (Brucella suis), Classical swine fever, Contagious bovine pleuropneumonia, Foot and mouth disease, Influenza–Avian, Influenza–Swine, Japanese Encephalitis, Leptospirosis, Lumpy skin disease, Newcastle disease, Peste des petits ruminants, Porcine reproductive and respiratory syndrome, Rabies, Rift Valley fever, Rinderpest, Schmallenberg, Sheep pox and goat pox, and West Nile Fever. Due to a lack of data on appropriate risk indicators, fisheries and commercial aquaculture diseases were not included. Similarly, a risk indicator for pests and diseases of plants was not included.

Hypotheses

The research intensity and risk events for every country globally (calculated and mapped in the steps above) were compared using correlation analysis. Pearson's correlation coefficient (along with its significance level) was calculated using STATA software for three groups—1) the number of papers on livestock insurance with historical livestock disease outbreaks and relevant extreme weather events (drought), 2) the number of papers on crop insurance with the historical frequency of extreme weather events, and 3) the total number of papers on agricultural insurance with projected mean temperature change by mid-century. Correlation analysis was also undertaken for specific subsets of papers (e.g., papers on insurance and climate change were compared with projected temperature increase and papers on different (extreme weather) hazards with historical hazard frequency). We, therefore, test the hypothesis that insurance research is targeted to the most relevant regions, based on the geographical distribution of current (and future) risks, as the assessment of the risk exposure is an important part of insurance policy development (Lloyds, 2015). Historically, extreme weather events have had a significant impact on global and regional agricultural production (Cogato et al., 2019; Lesk et al., 2016; Vogel et al., 2019). Therefore, they have a significant role to play in the design of both indemnity-based (where insurance claims are paid based on actual loss) and index insurance products (claims are paid based on a pre-defined index), and in building overall resilience (Hudson et al., 2019). Disasters (including extreme weather events) are estimated to cost 520 billion USD per annum to the global economy and reported losses from extreme weather events have increased by 250% in the last two decades (UNISDR and CRED, 2017). Climate change may further increase the frequency and intensity of weather extremes during crop growing seasons, causing even greater losses in the future (Bouwer, 2019). Thus, comparing recent and current research intensity with future climate risk (projected mean temperature increase) can show whether there is an alignment between current research and projected temperature increase hotspots.

For livestock, both crisis events (including extreme weather disasters such as drought and extreme temperature) (Food and Agriculture Organization (FAO), 2017) and animal diseases can cause significant production losses. Comparing research intensity of livestock insurance with the global distribution of relevant disaster events helps to identify any mismatch between the two, even though it is difficult to insure transboundary disease risk because of its systemic nature, lack of data availability on disease occurrence and losses, and influence of governmental surveillance strategies on the overall disease risk (Meuwissen et al., 2003, 2013).

Spatial patterns of research intensity may not reflect the size of the agricultural insurance market or the need and capacity for insurance in a region. At the same time, not all historical (and future) risks are insurable and risk exposure alone may not imply insurability. However, an increase in temperature due to global warming has already increased the severity and magnitude of weather events (IPCC, 2021). Further, our research helps in assessing the alignment between current research and risks. A mismatch can guide investments into insurance research in some regions, while also highlighting the need for alternative risk management solutions where agricultural insurance is not feasible, for instance, due to high frequency of disasters.

3.3 Results

Categorizing the agricultural insurance literature along different indicators

All included papers were classified into agricultural product insured, research theme, income group, insurance product type, and hazard covered (Figure 3.2). Among the different agricultural products insured, cereal crops were the most prominent group with 24.7% of the papers, followed by livestock with 5.7% of the total papers, while most of the papers focused on multiple crops/sectors (55.3%). Among crops, limited focus on other crops was evident (for example, fruits and vegetables accounted for only 3% of the papers and non-cereals like millets, pulses, roots, and tubers were focused in 4.4% of the papers). Among the papers focused on livestock, classical livestock types (most often cattle) were most frequently retrieved, followed by fisheries and aquaculture.

We find six research themes to be of key interest: basis risk, demand estimation, insurance and climate change, insurance financing, insurance impact evaluation and insurance policy analysis. The highest number of papers were found under insurance financing (24.9%) and demand estimation (22.5%). The lowest number of papers were on insurance and climate change (4.5%). Additionally, we classified the papers based on the country income group and found that most papers focused on high-income group countries (44.6%), followed by middle-income countries (34.5%). Only a limited number of papers were focused on low-income countries (10.2%).

When classifying the papers along the insurance product type, we find that 42.3% focused on index insurance (insurance payouts based on an index measurement), followed by 32% on indemnity-based insurance (insurance payouts based on actual loss at the insured unit). Only 5.1% focused on revenue-based insurance (insurance payouts based on the yield and price of the commodity). Approximately one-fifth of the studies (20.4%) focused on multiple insurance products. Regarding hazards covered, 67.5% of the papers addressed multiple perils. Among single hazards, droughts were most frequently studied (11.6%), followed by extreme rainfall (5.8%). Livestock mortality including risk from livestock diseases was studied in 7.8% of the papers. Other hazards like floods, hail and ENSO (El Niño–Southern Oscillations, periodic change in oceanic temperature, affecting global precipitation and temperature patterns) (Nguyen et al., 2021), were less frequently addressed in the reviewed literature.

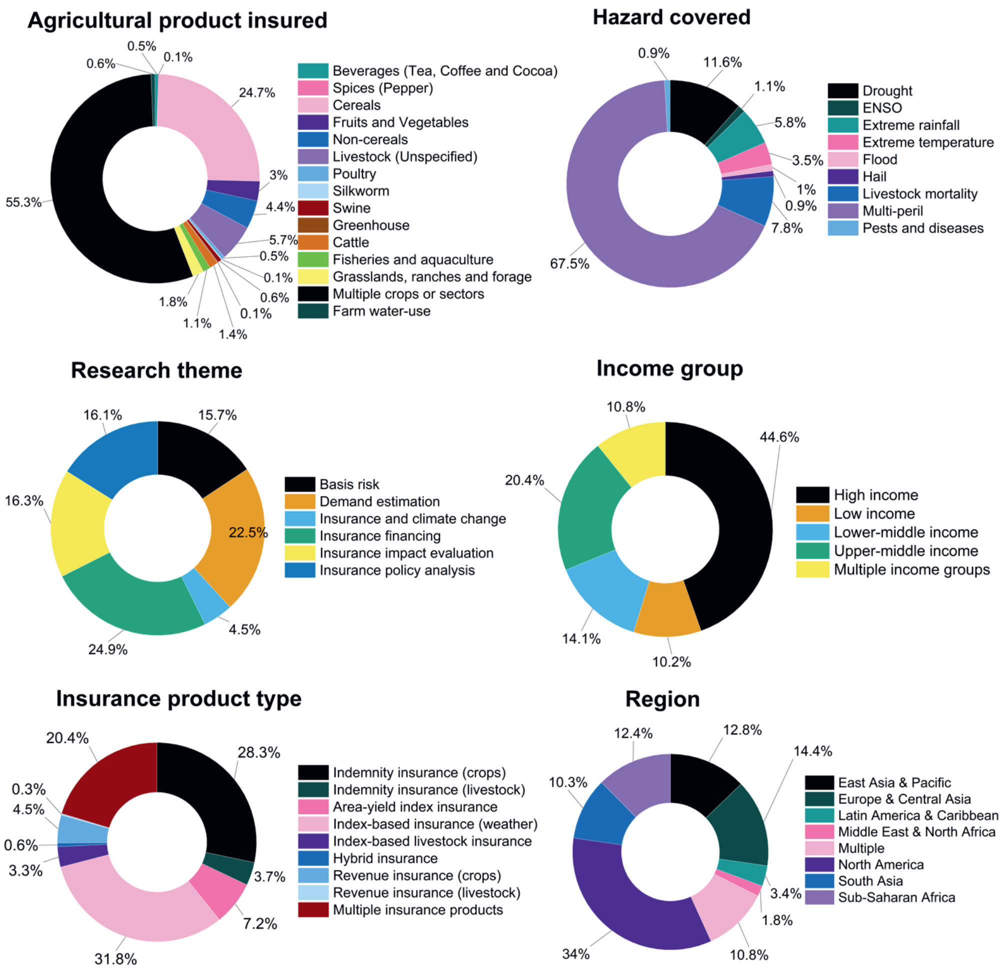

Figure 3.2 Summary of agricultural insurance research by agricultural product insured, research theme, income group, insurance product type, and the hazard covered.

Research themes

The research themes were identified during the review process based on a two-step classification procedure. We first identified a sub-theme which we then grouped into six main themes (Table 3.1). In the following section, we briefly describe the main themes, sub-themes, and key findings, illustrated by selected papers.

Table 3.1 Classification and number of papers in the review by research themes and sub-themes.

Research theme and sub-theme	Count
Basis risk	125
Aggregation bias and risk assessment Reducing basis risk by removing aggregation bias from crop yields and combining different sources of data for risk assessment	14
Crop models Using crop models to better capture crop-weather relations and reduce basis risk (especially under data scarcity)	3
Crop-weather relationship Capturing crop-weather and physiological relationships to reduce basis risk, by accurate crop yield predictions	5
Weather and climate data Using long-term climate data and weather risks to reduce basis risk, including remote sensing data and station-based weather data	47
Contract design Improved contract design to reduce basis risk, including the trigger and index design	56
Demand estimation	179
Preferences, farms, and farmer characteristics Farmers preferences, farm types (size of the farm) and farm characteristics (age, gender, education etc.) that influence demand for insurance	103
Decision theory Demand estimation using decision theories (including both prospect theory and expected utility theory)	39
Willingness to pay Farmer’s willingness to pay for agricultural insurance	37
Insurance and climate change (n=36)	36
Climate change impact on policy design Impact of climate change on production risk, insurance pricing and policy design of insurance	8
Insurance for adaptation and mitigation Role of agricultural insurance to scale-out adaptation and mitigation in agriculture	11
Insurance as financial adaptation Insurance itself as a financial adaptation to climate change and a safety-net for climate extremes/projected risks	17
Insurance financing	198
Financial instruments Using bonds, futures, and securitization for insurance financing	26
Disaster finance, risk pooling and systemic risk Risk pooling and disaster risk finance to overcome systemic risk and finance insurance policies	18

Research theme and sub-theme	Count
Risk transfer Financing insurance policies using risk transfer mechanisms including combining insurance with credit	15
Agribusiness and private finance Insurance funding from public-private partnerships, private sector, and contract farming	6
Insurance pricing Pricing of insurance policies including premium rate making, and its impact on insurance feasibility	85
Reinsurance Role of reinsurance in determining insurance feasibility	14
Revenue plans Revenue insurance and feasibility of revenue plans	24
Insurance subsidy State-supported insurance policies including subsidy for insurance and its impact on feasibility	10
Insurance impact evaluation	130
Bundling Impact of bundling insurance with agricultural technologies	18
Cropping mix and land use Impact of insurance on cropping mix, land-use patterns, tillage practices and crop acreage	25
Farm efficiency Impact of insurance on farm efficiency (including technical efficiency of farms)	10
Farm income Impact of insurance on farm income (including the combination of insurance with cash transfers) and income inequality	28
Input-use and negative environmental externalities Impact of insurance on input-use (e.g., fertilizers, pesticide, irrigation) and externalities (pollution, soil quality etc.)	31
Resilience Impact of insurance on the resilience of farms	2
Welfare Impact of insurance on welfare (welfare effects), social equity, economic growth, and well-being of farmers	16
Insurance policy analysis (n=128)	128
Policy analysis Overview of agricultural insurance policies, qualitative and empirical policy analysis (including key trends, claim analysis and structural changes)	45
Review Reviews (including literature and systematic reviews), opinions, essays and policy briefs on insurance and its role in agricultural risk management	70
Institutions for insurance policy delivery Institutional mechanisms for delivery of insurance policies (including mutuals, cooperatives, informal groups etc.)	13

Basis risk

Basis risk is the inability of index insurance to initiate payouts when a loss occurs to the farmer or vice versa when payouts are triggered in case of no losses. This can happen if the index used for insurance payouts, is not able to capture farmer's production losses. In this review, 125 papers focused on the issue of basis risk in agricultural insurance. For area-yield index insurance, basis risk arises from a lack of correlation between the area-trigger (spatially aggregated crop yield) and observed farm yield. Papers classified under the sub-theme of *aggregation bias* propose various ways to deal with this issue. For instance, Woodard et al. (2011) use statistical methods such as copulas to design the area trigger. Other studies focus on improving the *contract design* of insurance. Wang (2000) proposes a grouping of farms based on similar crop yield profiles rather than based on an administrative area. Data scarcity is another contributing factor to basis risk, as the lack of quality data impedes efficient contract design. As a response, the use of crop modelling and publicly available remote-sensing based weather and vegetation data is proposed in studies classified under the themes of *crop models* and *weather and climate data* (Enenkel et al., 2019; Nieto et al., 2012). Generally, we observe that recent papers integrate advanced modelling techniques and emerging data sources into index insurance design to make loss estimates more precise and reduce basis risk. For example, capturing crop-weather relationships (another sub-theme identified) by integrating phenology data in the contract design has been proven useful to reduce basis risk (Conradt et al., 2015; Dalhaus et al., 2018).

Demand estimation

Estimating demand for insurance helps policymakers and insurance agencies to devise implementation strategies to pilot and scale insurance in new areas, and simultaneously, to understand and identify factors that reduce insurance demand in many regions. Seventy papers studied how farmers' *preferences,* and *farms and farmer's characteristics* affect insurance adoption. Factors like age (more farming experience), gender (male), education (higher education level) and loss experience with previous disasters positively affected the demand for insurance in all three sectors—agriculture, livestock and fisheries (Akintunde, 2015; Akter et al., 2016; Olayinka et al., 2018). *Decision theory* was identified as another sub-theme. An emerging topic of interest is behavioural economic theories that might drive insurance demand such as compound risk, loss, or ambiguity aversion as well as probability weighting, where farmers depart from standard economic theory because payouts are unknown and ambiguous (as compared to premiums, which are certain and known) (Babcock, 2015). This plays an important role in accurately estimating the demand for insurance, in addition to traditional risk aversion theory (Carter et al., 2015; Elabed and Carter, 2015). *Willingness to pay* (the third sub-theme) for an insurance product helps in determining the price farmers are willing to pay for insurance and target subsidies to pilot new insurance programs. In most cases, the commercial premiums in existing insurance schemes were found to be significantly higher than the farmer's estimated willingness to pay (Budhathoki et al., 2019).

Insurance and climate change

The theme comprising the lowest number of papers (36) was insurance and climate change. The first sub-theme concerns the anticipated *impact of climate change on insurance policy design*. Modelled increases in agricultural losses from climate change were found to enhance insurance costs and increase premium rates for farmers in both developed (Tack et al., 2018) and developing regions (Siebert, 2016). To align insurance pricing with increasing risks and to address climate uncertainty while designing weather index insurance, climate modelling needs to be integrated with insurance policy design (Bell et al., 2013).

The second sub-theme under climate change related insurance research was *insurance for adaptation and mitigation* (Linnerooth-Bayer and Mechler, 2006). Such studies addressed the potential of insurance to complement or substitute ongoing adaptation and mitigation strategies. For example, crop insurance was compared with other adaptation strategies like crop diversification, which was found to negatively influence insurance adoption (Falco et al., 2014). In the third sub-theme, insurance itself was recognized as a *financial adaptation* strategy to stabilize farm income under climate change (Muchuru and Nhamo, 2019). However, climate insurance as an adaptive strategy (based on global risk-sharing principles) was argued to favor developed countries. Such insurance would be more expensive in developing countries, which are more exposed to higher risks (Duus-Otterström and Jagers, 2011).

Insurance financing

The biggest group of papers (198) focused on different sources for insurance financing from *financial instruments* like catastrophic bonds and futures (Komadel et al., 2018; Stein and Tobacman, 2016), to *disaster risk finance* including combining risks over large geographical areas in a common pool. Moreover, the role of systemic risk in decreasing the viability of a common risk pool was also addressed (Feng and Hayes, 2016; Porth et al., 2016). Combining insurance with credit as a *risk transfer* mechanism was another sub-theme to support insurance financing in developing countries (Collier, 2019; Stein and Tobacman, 2016). Credit-linked index insurance models where insurance is built into a loan as contingent credit were found to decrease loan defaults and expand credit access (Farrin and Miranda, 2015). Six papers explored the feasibility of *agribusiness or public-private partnership* for agricultural insurance, mainly in the US, where the federal crop insurance program allows public-private models in agricultural insurance. Other studies outside the US analyzed the legislative and legal reforms needed for an effective public-private model (Călin and Izvoranu, 2018; Inshakova et al., 2018). The viability of such public-private models was also explored with respect to their risk-sharing structures (Weng et al., 2017).

Within the insurance finance theme, another sub-theme focused on *insurance pricing* (ratemaking) and tools and methods for calculating actuarially fair premium rates. The use of copulas for capturing extremes to aid effective premium estimation was identified as an emerging trend in more recent papers (Bokusheva, 2018; Goodwin and Hungerford, 2015). Ratemaking under data scarcity was another research problem, especially in area yield-index and indemnity insurance. Under data-scarce conditions, the use of expert advice (Shen et al., 2016) and a pricing strategy based on relationships between aggregated and farm yields were the two of the investigated examples (Gerlt et al., 2014). Another sub-theme relate to the combination of insurance with add-on *revenue protection plans*, which cover price risk along with production (yield) risk, to also provide coverage against market risks (Bulut and J. Collins, 2014; Yehouenou et al., 2018). Most of the large agricultural insurance programs across the world depend on *insurance subsidy*, which was another sub-theme, with a large focus on developing countries (Mahul and Stutley, 2010). Subsidized insurance was found to have higher welfare gains for farmers in the risk-prone regions (as compared to farmers in less risky areas). However, in some cases, a higher expected utility was found for alternative risk prevention measures like cash-transfers, farm-input subsidies, and reduction in credit rates than for subsidized insurance (Ricome et al., 2017).

Insurance impact evaluation

Among all papers on insurance impact evaluation, the *impact of insurance on input-use* including fertilizer, pesticides and irrigation use, and their consequent negative externalities including pollution and decline in soil quality, was the most frequently recurring sub-theme (31 papers). Many papers reported marginally increased input-use and crop acreage, particularly for cash crops, upon insurance (Cole et al., 2017; Deryugina and Konar, 2017). Positive environmental effects of insurance were also noted, e.g., insurance was found to increase the use of soil conservation practices (Schoengold et al., 2014), and insurance premium discounts were shown to support pest management practices (Beckie et al., 2019). *Bundling* insurance with agricultural technology was another sub-theme, where insurance was found to increase the adoption of hybrid seeds, especially when subsidized (Foltz et al., 2013; Freudenreich and Mußhoff, 2018). Some papers discussed how insurance enhanced *farm efficiency* and, in some cases, also increased the technical efficiency of farms (Roll, 2019). The role of insurance in increasing farm *resilience* was an emerging field of study (Kron et al., 2016). Insurance was also found to increase the *welfare* of households in the presence of poverty traps (Chantarat et al., 2017) and to increase the well-being of livestock farmers (Tafere et al., 2019).

Insurance policy analysis

The papers in this research theme focused on *policy analysis* of existing insurance schemes. These included empirical analyses of insurance policies and examination of structural changes in insurance policies over the years (Coble et al., 2013; Siwach et al., 2017; Zarkovic et al., 2014). The other types of papers *reviewed* insurance policies—from qualitative reviews to opinion pieces and essays on insurance and its larger role in risk management. Some reviews focused on specific issues in insurance like basis risk (McElwee et al., 2020a), the use of remote sensing for insurance (J de Leeuw et al., 2014), and insurance for a specific sector like grasslands (Vroege et al., 2019). Another sub-theme in the field focused on the role of *institutions and policy delivery* of insurance. These included the use of collectives (Pacheco et al., 2016), insurance delivery by collaborating with existing local institutions (Bélanger, 2016), and the role of mutuals (Meuwissen et al., 2013).

Mapping and comparing the research intensity with historical and future risks

Agricultural products insured

From all the agricultural products insured (Figure 3.3), we find that insurance research on multiple crops/sectors has the highest geographical coverage (based on the number of countries covered), followed by papers that cover cereals. Only very few papers cover fruits and vegetables, and other (non-cereal) crops—most of them in India, China, and the US. Papers on insurance for beverages (tea, coffee and cocoa) is limited to China, India and Ghana (Okoffo et al., 2016). For livestock, the spatial extent of the insurance research is limited as well, with papers on cattle insurance focusing on six countries—the US, India, Ethiopia, the UK, the Netherlands, and Kenya. Papers on livestock (with multiple or unspecified sectors) are distributed in different countries across the globe. Papers on fisheries and aquaculture are limited to the US, China, Vietnam, Norway and Nigeria (Beach and Viator, 2008; Nguyen and Jolly, 2019).

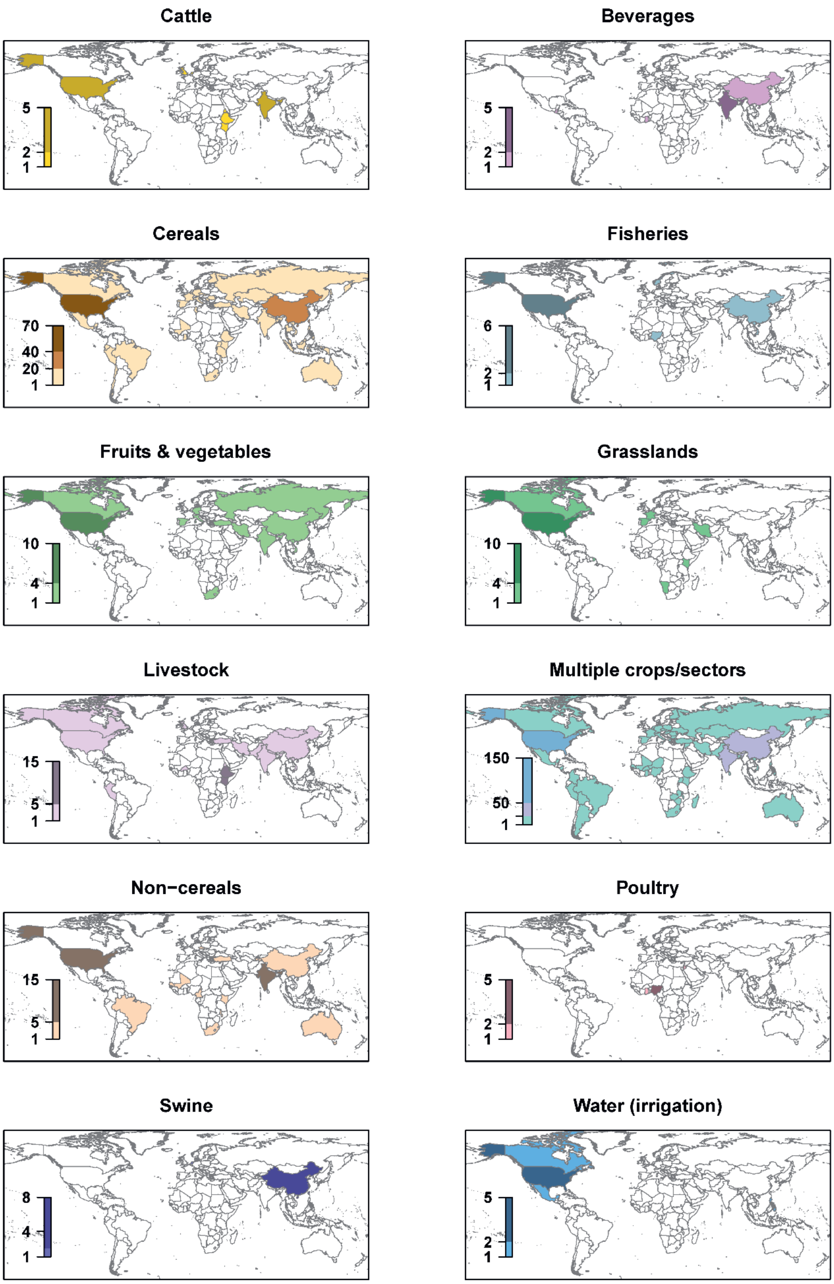

Figure 3.3 Panel of maps showing the geographical distribution of agricultural insurance research literature by agricultural product insured.

Research theme

Figure 3.4 presents the geographical distribution of papers according to the research theme. The themes with the highest number of papers were *insurance financing* and *demand estimation*, while *insurance and climate change* had the lowest number of papers. Most of the themes covered North America and Asia, and very few themes focused on Africa, South America, and Southeast Asia. The US was most frequently studied for every theme, along with India for the research theme on insurance and climate change (Jangle et al., 2016; Ogra, 2018). These results indicate which types of insurance research is conducted in a given country.

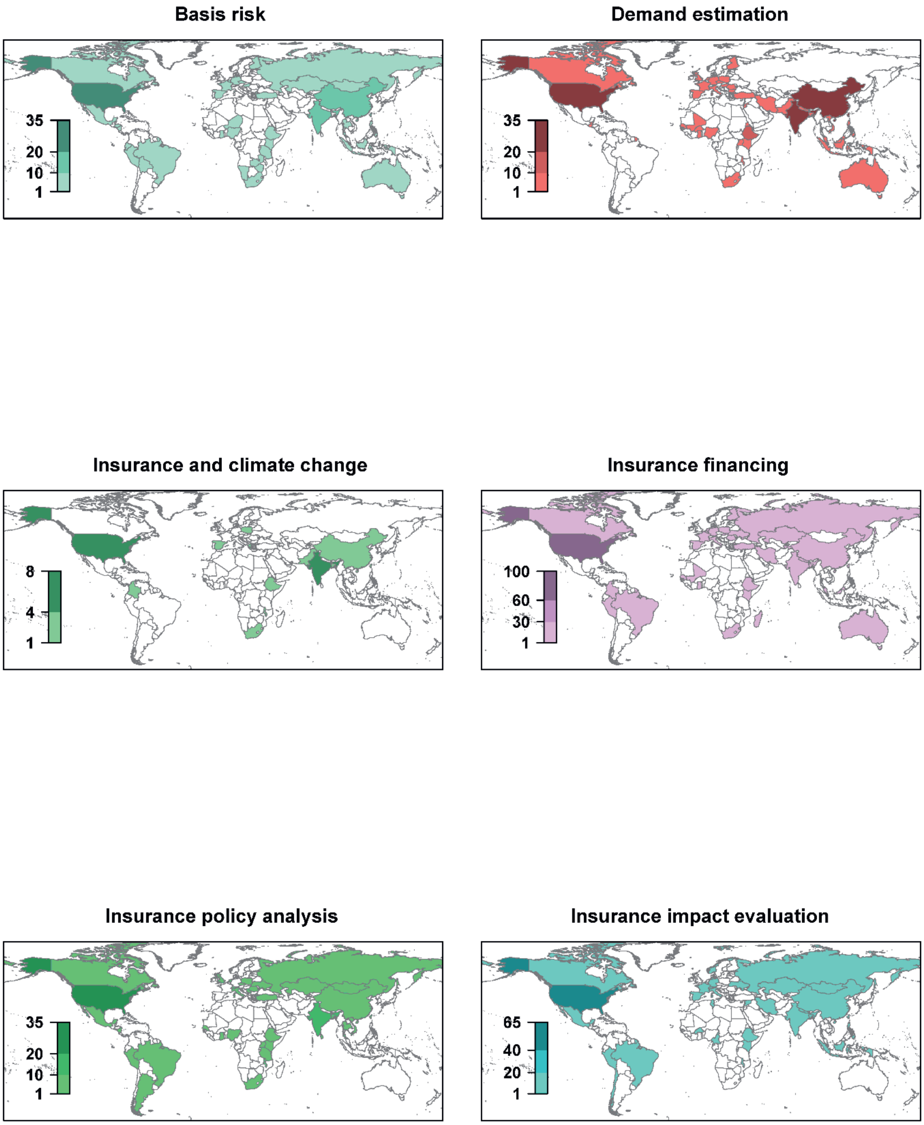

Figure 3.4 Panel of maps showing the geographical distribution of agricultural insurance research literature by research theme.

Insurance product type

Figure 3.5 shows maps of countries by types of insurance products. For index insurance (for crops), the highest number of studies was found for China, India, and the US. Index insurance for livestock (commonly known as Index-based Livestock Insurance-IBLI) was concentrated in eastern Africa (Ethiopia and Kenya) and Mongolia (Bageant and Barrett, 2017; Johnson et al., 2019). The highest research intensity for indemnity insurance (for crops) was found in China and the US, although several papers were also found in Europe (Capitanio et al., 2011; Mahul and Vermersch, 2000). Most papers on area yield index insurance related to the US and India, where the area-yield insurance policy is most common. It is important to note that, unlike index insurance, none of the papers from Africa (except South Africa), focused on area-yield insurance and revenue insurance, mainly due to data scarcity of crop production statistics. Papers on revenue insurance (crops) were found in the US, Canada, Spain, Italy and Iran (Goodwin et al., 2018).

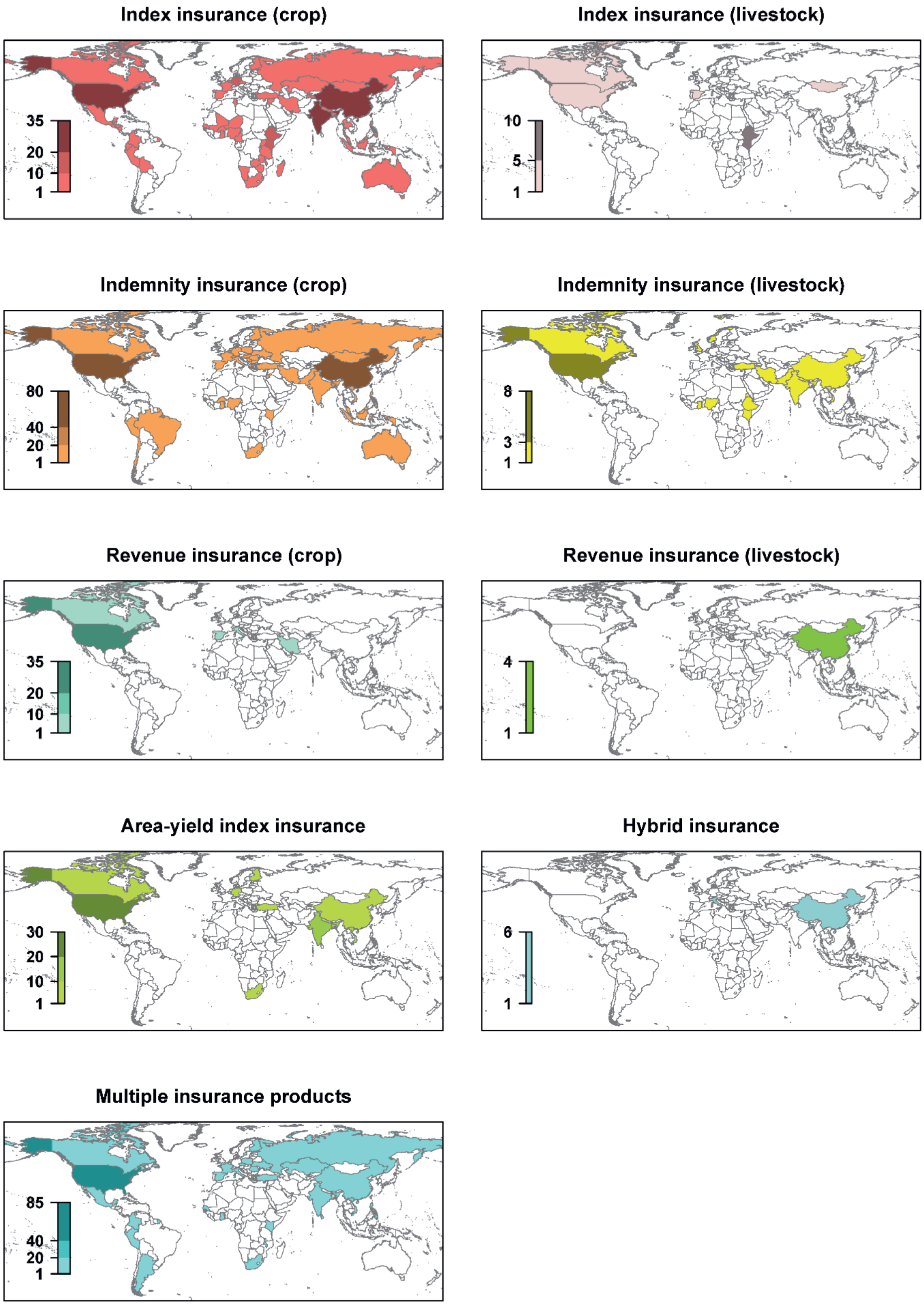

Figure 3.5 Panel of maps showing the geographical distribution of agricultural insurance research literature by insurance product type.

Hazards covered

Papers were also classified based on the hazards they covered (Figure 3.6). Studies focusing exclusively on hail insurance were found in Canada, the Netherlands, Germany, Switzerland, Australia and South Africa (van Asseldonk et al., 2018). Incidentally, the highest probability of hail is found in the US, India, Pakistan, Argentina, Laos, Vietnam and many countries in middle Africa (Prein and Holland, 2018). For floods, only a few papers were found for India, Pakistan, China, Vietnam and the US (Matheswaran et al., 2019). Very few papers, from North and South America, focused on El Niño Southern Oscillation (ENSO) events (Khalil et al., 2007; Tack and Ubilava, 2015). There were a considerable number of papers on drought, and these were evenly distributed throughout the world (although South America was not focused in the reviewed papers). Very few studies examined the role of agricultural insurance for pest and disease management and these occurred in developed countries (Beckie et al., 2019; Norton et al., 2016). In comparison, the highest losses from pests and diseases in cereal crops are observed in South Asia and Sub-Saharan Africa (Savary et al., 2019). Papers in the review which focused on extreme temperature were from China, the US, India, Germany, Turkey, Malaysia and Kazakhstan (Conradt et al., 2015). Other hazard types—uneven rainfall, multiperil hazards and livestock mortality, were distributed globally.

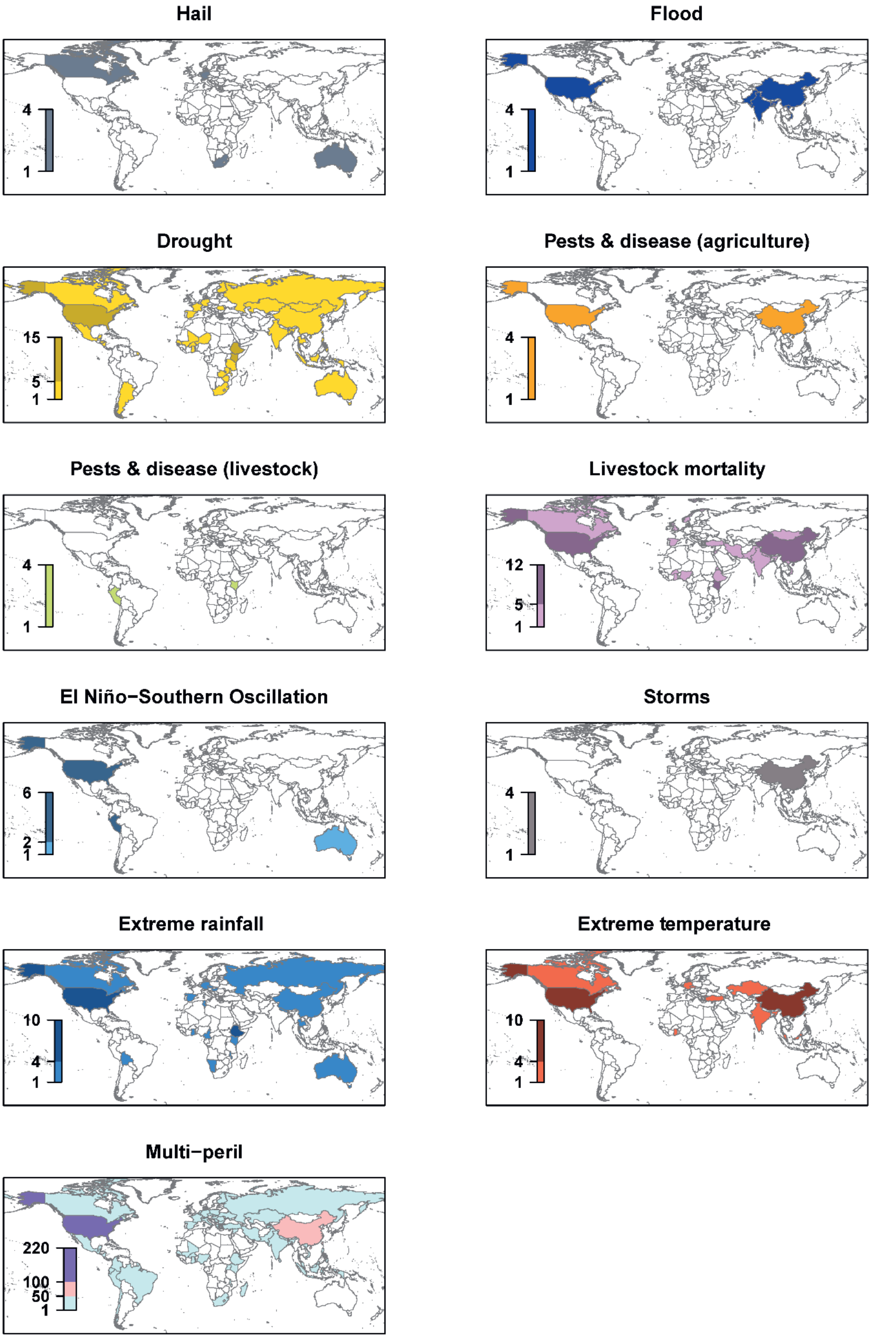

Figure 3.6 Panel of maps showing the geographical distribution of agricultural insurance research literature by hazards covered.

Risk mapping and hypothesis testing

Figure 3.7 compares the above results with current and future risks. There is a significant correlation between weather-related disasters and the distribution of papers on crop insurance, with a correlation coefficient of 0.75***. However, when the total number of papers per country identified in this review (including both crops and livestock) are compared with projected mean temperature change, a poor correlation is observed (0.18). The correlation further decreases when selected papers from the theme *insurance and climate change* are compared with projected temperature increase hotspots (non-significant correlation of -0.044). Similarly, a negative correlation (-0.06) is observed between the number of papers on livestock and the total number of livestock epidemics throughout the world. This is expected as very few papers from the livestock sector focused on pests and diseases. However, it is interesting to note that livestock epidemic hotspots like China, Indonesia, France, Germany, and Italy are not eminent in research on this matter. In comparison, many papers in the livestock literature are focused on droughts, which explains the higher correlation with drought events (0.51).

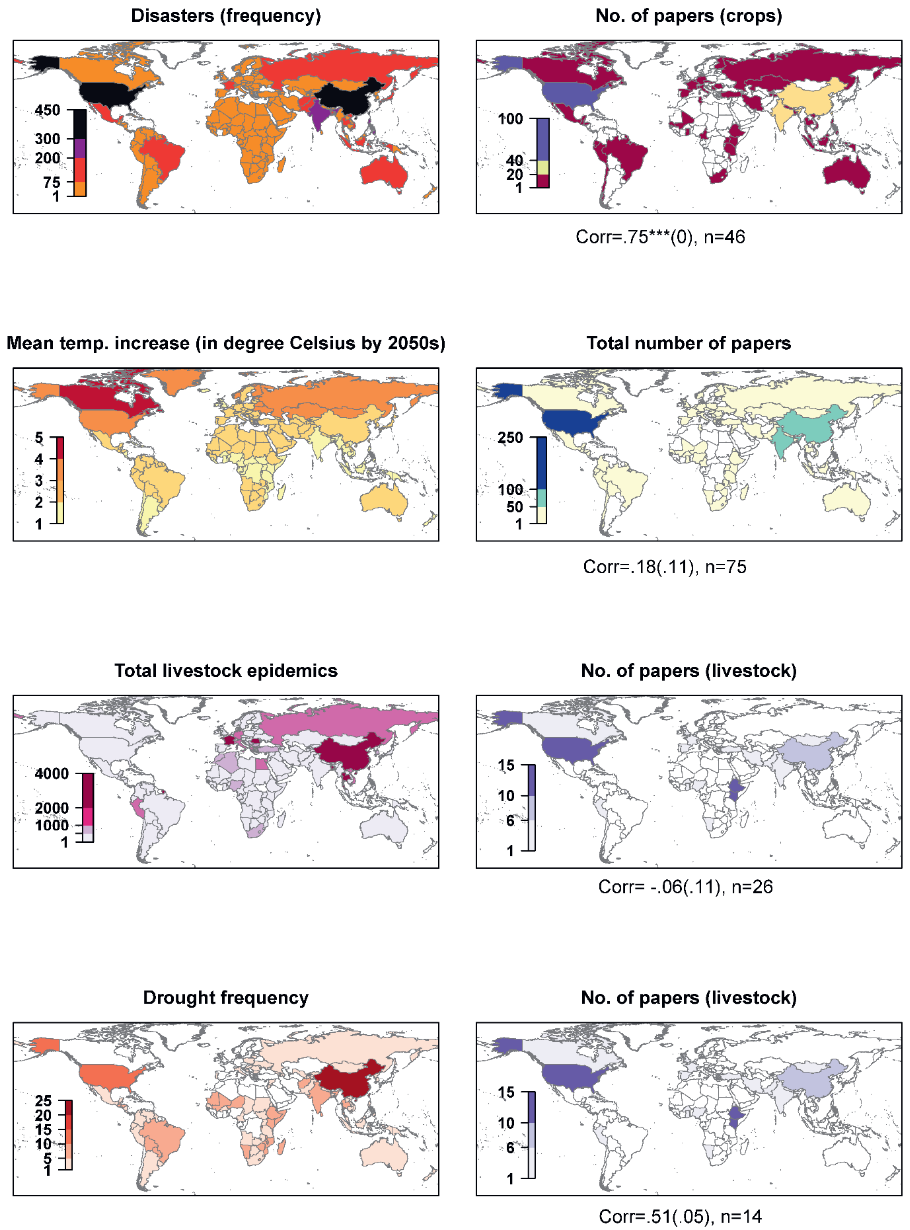

Figure 3.7 Research intensity of papers on agricultural insurance with four risk indicators. Correlation (with corresponding risk indicator), standard error (in brackets) and n (number of countries) are provided below each map. The significance-level are shown by stars (p-value ≤.05 is denoted with one star, p-value ≤.01 with two stars and p-value ≤.001 with three stars).

The above results provide a broad overview of the correlation of literature with four risk indicators. Even when the number of papers by different indicators are compared with extreme weather events, poor correlations are observed (Supplementary table 3 of Vyas et al. 2021, please see footnote 9). For instance, the correlation between the studies on drought with observed drought incidences was 0.32, with the highest drought disasters observed in the US and China while studies focused on Eastern Africa. Similarly, for floods, most flood-prone countries of South and Southeast Asia are not identified as focus areas in our literature review. By comparison, the correlation between papers on extreme rainfall and observed storm disasters is higher (0.58). Insurance research on extreme temperature is also poorly correlated with observed temperature events (0.03).

3.4 Discussion and conclusion

This review synthesized agricultural insurance research since the year 2000 and identified key research themes, along with their geographical focus, agricultural product insured, insurance product type and the hazards covered. The results were mapped and compared with historical and future risks. Overall, we find that case studies in the US and China dominate agricultural insurance research, calling for future research to focus more on areas most affected by climate change. Regarding the research themes, insurance financing has been most studied, including topics such as insurance pricing, revenue plans and reinsurance. So far, climate change has attracted little attention in agricultural insurance research.

There is clear research focus on crops, especially cereals. Other crops like fruits and vegetables, millets, pulses, oilseeds and roots-tubers have an important role to play in promoting sustainable diets and nutritional security across the world (Willett et al., 2019). Notably, we do not find any insurance research on these agricultural products. For example, large fruits and vegetable producing countries in Southern America (Brazil and Mexico) and non-cereal producers (small grains including pulses and millets) in Africa (Ethiopia, Nigeria) are missing in recent literature. These production systems are also vulnerable to extreme weather yet receive less focus in agricultural insurance research (Park et al., 2019). Among livestock, cattle insurance has the highest research intensity, as compared to swine, poultry, sheep, and goats. Fisheries and aquaculture receive the least attention. Incidentally, no studies on fisheries and aquaculture insurance were retrieved for the top fish producing countries like Indonesia, India, Russia, and Japan.

Index insurance was the most prominent among insurance product types found in the review, followed by indemnity insurance, while research intensity was lowest for revenue insurance. Literature on index insurance focused on different developing countries, that are often characterized by poor infrastructural resources and data scarcity, which limits the scope of indemnity-based products in these regions. This has led to considerable policy and donor-driven investments to develop index insurance in low and lower-middle income countries (Barnett and Mahul, 2007; Skees, 2008). Further, advances in remote sensing and data science have opened new opportunities to integrate satellite-based data with agricultural risk management (Enenkel et al., 2019; Vroege et al., 2021). This may also be the reason for the low correlation between drought disasters hotspots (China, the US and India), and papers in the review focusing on drought (correlation coefficient of 0.32), since a significant proportion of index insurance literature (found in the developing countries) is on droughts. Recent literature highlights the need to further improve index-based insurance and disaster risk management tools for drought protection (Belasco et al., 2020; Bucheli et al., 2021; Leppert et al., 2021). Here synergies between research on index insurance in developing and developed countries might advance products in both regions.

Apart from drought, most of the studies in the review address multiple perils and few are focused on single perils, especially flood, hail and pests and diseases of crops. Pests and diseases significantly undermine the sustainability of food systems, causing 17–30% productivity losses globally among major crops (Savary et al., 2019) and are expected to cause further damage in temperate regions due to global warming (Chaloner et al., 2021). Similarly, livestock diseases cause a significant loss in animal production systems. While the role of insurance in agricultural pest and disease management is found to be limited in this review, it can become an important future research topic to incentivize risk prevention and insure losses wherever feasible (Möhring et al., 2020). The COVID-19 pandemic has brought forth the need for risk prevention measures for global epidemics (Gu and Wang, 2020), and such crisis events are expected to become more frequent in the future due to ongoing biodiversity loss (McElwee et al., 2020b; Morand, 2020) and climate change. Targeting livestock insurance and other risk management strategies to epidemic hotspots is, therefore, an important area for future research.

We also find a mismatch (low correlation) between the spatial patterns of insurance research and future climate change risk hotspots. Very few papers in the review (4.5%) focus on the role of insurance in addressing challenges arising from climate change. The importance of insurance (among many agricultural risk management strategies) in addressing climate extremes is increasingly being realized because of the potential ‘double-role’ of insurance, i.e., as a tool to provide incentives for risk prevention and adaptation, and as an instrument to cover severe losses. However, limited evidence is found in this review for the role of insurance in scaling climate adaptation and mitigation. It remains an empirical question whether insurance, when combined with climate action (adaptation and mitigation activities), can reduce risks and encourage climate-smart pathways among farmers (Loboguerrero et al., 2020). Climate change is projected to impact various regions differently, due to diverse agro-ecological conditions, adaptive capacities, and vulnerability. Yield gains and shifts in favorable growing conditions are expected to occur in many temperature regions (Aggarwal et al., 2019; King et al., 2018). With limited climate and disaster finance available (especially in developing countries), aligning insurance with the identified research gaps can help to ensure risk protection for the most vulnerable groups. Findings from insurance research in developed countries also have a significant potential for application in developing countries, keeping into consideration the location and region-specific issues and challenges. At the same time, improving the insurability of currently under-represented regions is another important pathway for future work.

Agricultural research is increasingly focused on strategies to transition towards more sustainable food production pathways (Herrero et al., 2020). Some of these innovations include protein-based production systems, sustainable animal feed techniques like insect farming, land-saving technologies like vertical farming and glasshouse cultivation, as well as circular farm models (Chia et al., 2019). They have become an important part of the food systems narrative and future insurance research can focus on some of these promising technologies. The mapping exercise conducted in this review can help to set targets, recognize potential research topics and areas, and streamline research with current and potential risks. Finally, it is important to recognize the role of agricultural insurance in the larger risk management agenda, as a complement to other farm management tools. Risk hotpots based on weather and related crisis events, imply important policy decisions—a scoping analysis of the feasibility of agricultural insurance (when other farm risk management strategies do not work or are costly) is needed to offer adequate risk coverage. Linking risk management strategies (like agricultural insurance) with risk exposure, context-specific vulnerabilities, and resilience capacities of the food systems, can offer important lessons for policy design and prioritization. As countries strive to achieve SDGs and transform food systems along sustainable pathways, agricultural insurance will play an important role in risk management. The research gaps highlighted in this review can help stakeholders, including donors, policymakers, and researchers, in planning and aligning future action.

Supplementary information

For detailed Supplementary information, please refer to the published version of this chapter, Vyas, S., Dalhaus, T., Kropff, M., Aggarwal, P., & Meuwissen, M. P. (2021). Mapping global research on agricultural insurance. *Environmental Research Letters*, *16*(10), 103003. DOI 10.1088/1748-9326/ac263d

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Chapter 4

Limited impact of heat extremes in Indian wheat and soybean under climate-smart agriculture

Adapted from Vyas, S., Ramirez-Villegas, V., Kropff, M., Aggarwal, P., Shirsath, P., Meuwissen, M.P.M., Dalhaus, T., 2024. Submitted to a journal.

Abstract

The adoption of climate-smart agriculture (CSA) is a potential solution to manage productivity reductions in agriculture resulting from extreme temperatures. However, there is limited evidence on how effective CSA management practices are, in increasing the resilience of crop yields to extreme weather, especially in developing regions. We therefore assess how CSA managed crops respond to heat stress based on a unique multi-year dataset of 5,175 farm-level wheat and soybean yield observations in India, from 2015 to 2020. We find no significant impact of heat exposure during the growing season for both the crops, even for sub-samples based on different CSA bundles (different combinations of CSA practices). In addition, the findings remain constant for all district-level wheat and soybean yield statistics across India for the same time-period. The results remain consistent along various robustness checks including different weather data sources and different regression model specifications. We conclude that wheat and soybean production in India is resilient to heat stress, even without CSA. We hypothesize this is due to the widespread use of irrigation and improved varieties.

Keywords: Climate-smart agriculture, heat stress, maize, soybean, India

4.1 Introduction

Weather shocks such as extreme heat can cause widespread damage in crop, and livestock production (Cottrell et al., 2019; IPCC, 2021; Park et al., 2019; Vogel et al., 2019). The impacts of these shocks on yields (Schlenker & Roberts, 2009), cropped areas (Lesk et al., 2016), cropping patterns (Cui, 2020) and crop quality (Dalhaus et al., 2020) depend on the farms' vulnerability and coping mechanisms (Tack et al., 2017). To offset these weather effects, farmers can adapt their farming practices, for instance, by adjusting the planting dates (Korres et al., 2017) or by using irrigation or other agronomic practices, such as tillage and cultivar choice (Fisher et al., 2015). Where these practices increase productivity, contribute to climate adaptation and/or reduce greenhouse gas emissions, they are considered to be climate-smart agriculture (CSA) (Lipper et al., 2014). CSA has the potential to achieve food security in the face of climate change and extreme weather events (De Pinto et al., 2020). While CSA has been promoted as the cornerstone of agriculture under changing climate for over a decade, there is little understanding of how different CSA farming practices affect the crop production response to extreme weather. Some CSA practices have shown increases in productivity and soil health (Arenas-Calle et al., 2021, 2022). However, evidence on the risk-reducing impact of bundled CSA practices is still limited (Lobell, 2014). This understanding is crucial for global food security, even more so due to the greater likelihood of frequent and severe weather shocks due to climate change (Jehanzaib et al., 2020; Sun et al., 2019; Tabari, 2020).

Many studies have presented evidence on the impacts of weather shocks on crop (Schlenker & Roberts, 2009; Schmitt et al., 2022a; Turvey et al., 2021) and livestock production (Bucheli, Uldry, et al., 2022a) using different statistical modelling methods (Kolstad & Moore, 2020). However, this evidence is limited for low- and middle-income countries (Ortiz-Bobea et al., 2019; Powell & Reinhard, 2016) and different farm management and risk management practices, this is mainly due to data scarcity on farming practices. Data scarcity is one of the most significant challenges in scaling adaptation and risk management policies throughout the world, especially for smallholder agriculture (Jung et al., 2021). Importantly, how farmers manage their fields is assumed to be a key determinant of farm production and resilience to weather shocks. The management effects on crop production are known to be much higher than weather effects especially in low input systems, and a key constraint in designing risk management policies such as agricultural insurance (Aggarwal et al., 2019;

Norton et al., 2016; Vyas et al., 2021). In addition, evidence on how CSA farm management practices and weather events interact is even more limited (Keil et al., 2021).

Here, we use a farm-level dataset that includes 5,175 wheat and soybean yield observations collected between 2015 and 2020 from 643 climate-smart villages in India. Wheat and soybean crops are primarily winter and summer crops in the study area. The dataset includes information on the production of the major crops, soybean, and wheat, grown under different CSA practices. We complement the crop yield information with weather conditions at the farms' locations using the exact spatial coordinates of the farms. The analysis focuses on heat stress, as these farms are located in hot, arid, agro-climatic zones in India (in Rajasthan and Madhya Pradesh states), characterized by low precipitation, high aridity and high temperatures. In addition, extreme heat events are reported to be significant risks that affect farm production, according to farmers in the study area. Further, high intensity heat waves as observed in 2022 in the Indian sub-continent, are assumed to significantly affect crop yields (Kumar Dash et al., 2022; Kumar-Bal et al., 2022). We use statistical modelling to causally link temperature shocks (i.e., deviations from the average exposure at a farm) to yield shocks (i.e., deviations from the average yield of a farm under CSA management). By doing so, we generate novel empirical evidence on the effectiveness of CSA management practices on increasing crop productivity resilience to heat extremes (Rosenstock et al., 2016; Swami & Parthasarathy, 2022).

Impact of extreme weather events on crop production

Extreme weather events are known to impact food systems, causing food production shocks, and declines in crop quality and farming efficiency (Schmitt et al., 2022a). In particular, heat stress is known to trigger a range of morphological and physiological processes across growth stages in crops. This can lead to poor germination and a decline in germination potential, shortening of the crop growing season owing to reductions in photosynthetic rates, reductions in sink strength (sterility), reductions in grain filling rates and a resulting decline in grain yields (Daryanto et al., 2016; Dubey et al., 2020; Fahad et al., 2017). Global studies show that droughts and extreme heat can reduce national cereal production by 10% (Lesk et al., 2016), at a cost of 190 billion USD globally, unevenly distributed among major food-producing countries (Mehrabi & Ramankutty, 2017).

Farm management practices, including practices labelled as Climate Smart Agriculture (CSA), can influence how crops respond to extreme heat events. For instance, stress tolerant cultivars (Martey et al., 2020; Wossen et al., 2017), changes in planting dates, irrigation (Tack et al., 2017; Troy et al., 2015) and fertiliser management can help limit the damage from heat stress by escaping risk exposure and shifting harmful temperature thresholds upwards. Reported evidence of CSA suggests improvement in yields, farm income and enhanced drought resilience for CSA practising farms in low- and middle-income countries (Acevedo et al., 2020; Lopez-Ridaura et al., 2018; Pal et al., 2021). Moreover, changes in productivity, soil quality, and resource-use efficiency are also observed (Jat et al., 2021; Roy et al., 2022; Singh et al., 2020). Combining different adaptation technologies together in the farm, often have many synergies and interactions, resulting in co-benefits (Awondo et al., 2020; Foltz et al., 2013; Jagustović et al., 2021). In this chapter, we test three hypotheses—a) crop yields of CSA farms are resilient to heat stress, b) I response of crop yields to heat stress differs along different CSA bundles (combinations of CSA technologies) and c) crop yields of general farmer population (at district-level) respond negatively to heat stress.

4.2 Data and methods

Yield data

For this study, we use farm-level soybean and wheat yield data collected within the Climate Smart Villages project across two different states in India (Madhya Pradesh and Rajasthan) from 2015-2020. Besides yields, the dataset includes a wide variety of management practices including three levels of CSA packages. The packages CSA 1 (super champion), CSA 2 (champion) and CSA 3 (baseline CSA) indicate bundles of climate-smart practices. The super champion farmers are the influential promoters of CSA activities in the project area and have the highest number of CSA activities in their farms, followed by champion and CSA farmers (see Supplementary table S4.5) (Chanana et al., 2020). Due to requirements of the regression model, we remove farms from the sample with less than 3 years of data. Moreover, we remove outliers below the 1st and above the 99th percentile. Summary statistics of the yields for soybean and wheat are given below in Table 4.1:

Table 4.1 Summary statistics of farm yield data

Statistics	Soybean (Kg/ha)	Wheat (Kg/ha)
Minimum	34	24
First quartile	395	1,264
Median	741	2,718
Mean	771	2,591
Third quartile	1,186	3,707
Maximum	1,853	5,905

The final dataset used for the results (after outlier removal) includes 4,653 soybean observations and 522 wheat observations (refer to Supplementary table S4.3 for a more extensive description of the farm-level data).

Since the objective of the original CSV project was to scale out CSA practices across target villages, all farms in the sample apply these practices. As a robustness check, we therefore estimate the yield response to temperature not only for the farm-level sample, but also using district level average yields for the two crops. The district-level yields were collected from the Ministry of Agriculture, Government of India (https://eands.dacnet.nic.in/), for all of India, resulting in 333 districts for soybean and 528 districts for wheat every year. For the summary statistics of this alternative yield data source, see Table 4.2.

Table 4.2 Summary statistics of district yield data.

Statistics	Soybean (Kg/ha)	Wheat (Kg/ha)
Minimum	587	137
First quartile	752	1,720
Median	1,002	2,520
Mean	1,131	2,675
Third quartile	1,349	3,580
Maximum	7,521	5,800

Weather data

For each farm in our sample, we create time series of daily minimum temperature, maximum temperature and rainfall from different weather raster datasets using the spatial coordinates of the farms (Table 4.5). For temperature, we use the ERA5 (ECMWF Reanalysis version 5) reanalysis data, which combines data from climate models with global observations (Hersbach et al., 2020). The daily temperature grids have a global coverage with a 0.25°x0.25° spatial resolution. As a robustness check we use temperature grid data provided by the India Meteorological Department (IMD) (Srivastava et al., 2009) with a spatial resolution of 1°x1°. For rainfall, we use CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) data which combines satellite and rain gauge measured data, into a gridded dataset with near-global coverage and a 0.05°x 0.05° spatial resolution (Funk et al., 2015). Similar to the temperature robustness check, we use rainfall grid data provided by the IMD with a spatial resolution of 0.25°x0.25°.

For the district level analysis which we use as a robustness check we extract daily temperature minimum, temperature maximum, and rainfall data at the centroid of each district as a representative location for the entire district. We are aware that using the centroid of each district may not fully represent the spatial variation of the weather within one district, however the temperature data is highly correlated within each district (Mahto & Mishra, 2019) and we therefore assume the results not to be affected by this methodological choice. Refer to Supplementary information for further details on the climatic conditions in our study region (Supplementary figure S4.2-S4.3). The summary statistics for hourly temperature for soybean and wheat farms are provided in the following tables (Table 4.3-4.4).

Table 4.3 Summary statistics for hourly temperatures for soybean and wheat farms.

Statistics	Hourly temperature for soybean farms	Hourly temperature for wheat farms
Minimum	13.86	1.81
First quartile	24.43	17.69
Median	26.83	22.11
Mean	27.41	22.02
Third quartile	29.81	26.35
Maximum	47.00	42.08

Table 4.4 Summary statistics for seasonal rainfall for soybean and wheat farms.

Statistics	Seasonal rainfall for soybean farms (mm)	Seasonal rainfall for wheat farms (mm)
Minimum	745.71	9.51
First quartile	986	32.82
Median	1,107	67.05
Mean	1,260	68.74
Third quartile	1,578	117.91
Maximum	1,952	140.86

Table 4.5 Weather data sources.

Weather variable	Source	Year	Resolution
Daily maximum and minimum temperature	ERA5 (ECMWF Reanalysis version 5 (ERA5) IMD (India Meteorological Department)	1959 – present 1951 – present	.25 X .25 degree 1 X 1 degree
Seasonal rainfall (calculated from daily data)	CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) IMD (India Meteorological Department)	1981 –present 1901 – 2020	.05 X .05 degree .25 X .25 degree

Weather data aggregation and transformation

We aggregate daily weather data into yearly values to meaningfully connect them to yearly yield data. More specifically, we use the June to September summer growing season for soybean and the October to March winter growing season for wheat. We aggregate the daily rainfall values per farm to the seasonal rainfall sum for each farm and year. For temperature, first daily minimum and maximum temperature are extracted for the farm locations. Hourly temperature estimates are then derived by fitting daily double sine curves between daily minimum to maximum temperature; and then to the daily minimum of the consecutive day (Bucheli, Dalhaus, et al., 2022). This results in hourly temperature estimates T_{ith} for 2015 to 2020 (T_{ith} where *I* is a particular farm, and *h* is the hourly temperature exposure over each day of the growing season for year *t*).

We allow the response curve of crop yields to temperature, to be highly non-linear using restricted cubic splines. This acknowledges that temperatures above critical thresholds can be particularly harmful, while allowing the model to find these thresholds flexibly. For this we define temperature knot locations between which we fit cubic functions that indicate how yields respond to a specific temperature exposure. Defining at least three knots is essential, which can be identified based on several techniques—either based on known or hypothesized crop physiological temperature responses or based on the temperature data distribution. In our analysis, we use multiple model specifications based on temperature data distribution where we place three and four knots at a) intervals which divide the temperature data into equally sized groups (equal knots) and b) specific quantile intervals (quantile knots) and c) knot placements which have lowest residual sum of squares for the model (best fit).

Once the number of knots (k) and the knot locations ($kn_1, kn_2, kn_3, \ldots, kn_k$) are identified we generate new variables S_{ithj} with $j \in (1,\ldots,k\text{-}2)$, as a transformation of the original hourly temperature T_{ith}. The new series S_{ithj} are then calculated using Equation 4.1:

$$S_{ithj} = (\max\left(\frac{T_{ith} - kn_j}{(kn_k - k_{n1})^{\frac{2}{3}}}, 0\right))^3 - (\max\left(\frac{T_{ith} - kn_{k-1}}{(kn_k - k_{n1})^{\frac{2}{3}}}, 0\right))^3 * \frac{kn_k - kn_j}{(kn_k - k_{nk-1})} + (\max\left(\frac{T_{ith} - kn_k}{(kn_k - k_{n1})^{\frac{2}{3}}}, 0\right))^3 * \frac{kn_{k-1} - kn_j}{(kn_k - k_{nk-1})} \tag{4.1}$$

In the next step we sum up the values of each new time series S_{ithj} and the original temperature series T_{ith} per farm and year (Bucheli, Dalhaus, et al., 2022). The result is k-1 aggregated variables (of original and transformed temperature series), which are then used in the regression model.

Regression model: Restricted cubic splines

We use fixed effects panel regression to estimate the response of yield to temperature exposure while controlling for precipitation. The fixed effects specification turns the temperature exposure into a temperature shock variable as a deviation from the average exposure at a respective farm's location. We are therefore able to estimate the impact of a random and exogenous weather shock on deviations in wheat and soybean yields compared to the average yield per farm. The model uses piecewise cubic polynomial functions that smoothly connects piecewise cubic marginal response curves (of crop yields) for each temperature interval as described in the last section. Before the first and after the last knot, the response function is linear. Therefore, the model is flexible in its functional form to capture potentially non-linear effects of temperature while at the same time minimizing prediction errors in the tails of the temperature distributions which are (often) data scarce. The regression model is 85icardined below in Equation 4.2:

$$y_{ict} = g(T_{ithc}) + \gamma_{1c}(PREC)_{ict} + \gamma_{2c}(PREC)_{ict^2} + \delta_{1c}t + \delta_{2c}t^2 + a_{ic} + \varepsilon_{ict} \qquad (4.2)$$

Where y_{ict} is the log yield of farm I in year t of crop $c \in \{wheat, soy\}$, $g(T_{ithc})$ reflects the non-linear response yield to of hourly temperature exposure for which we use the described restricted cubic spline specification. In various robustness checks we systematically shift the temperature knot locations. In further robustness checks, we replace the cubic splines by piecewise linear splines and extreme heat day temperature loads (refer to Supplementary table S4.7-S4.8, Supplementary figure S4.11-S4.12) The term $\gamma_c(PREC)_{ict} + \gamma_c(PREC)_{ict^2}$ from Equation 4.2 controls for the potentially quadratic rainfall impact, as temperature exposure is likely correlated with rainfall. $\delta_{1c}t + \delta_{2c}tt^2$ capture the quadratic time trend to control for technological advances. The quadratic time trend (to control for technological growth) may also capture some of the effects of CSA, we therefore as a robustness check, also include the results without the quadratic time trend (please refer Supplementary figure S4.6). Finally, ε_{ict} is the error term, likely correlated in time and space. We, therefore, use a year-by-district block bootstrapping to allow for spatial and temporal dependence (Ortiz-Bobea et al., 2018). The marginal effects of hourly temperature exposure on log yields are centered around average hourly temperature (of the growing season) for ease of comparison. The methods used for robustness checks and other details are described in the Supplementary information (Supplementary information S4.4). The codes used for the analysis are publicly available at https://github.com/Shalika-WUR/Limited-impact-of-heat-extremes-in-Indian-wheat-and-soy-under-climate-smart-agriculture.

4.3 Results

Hourly temperature effects

Figure 4.1 shows the response function of log soybean yields to hourly temperature shocks at X-axis temperatures. Observed hourly temperatures in the growing season range between 14 and 47 degrees Celsius. We do not find a significant effect of temperature shocks on CSA managed soybean yields. More specifically, when temperatures deviate from normal, we do not find yields to deviate from their normal levels per farm. Our results remain robust to a wide variety of model specifications and the use of alternative weather data. Other model specifications are included in the Supplementary information (Supplementary figure S4.4).

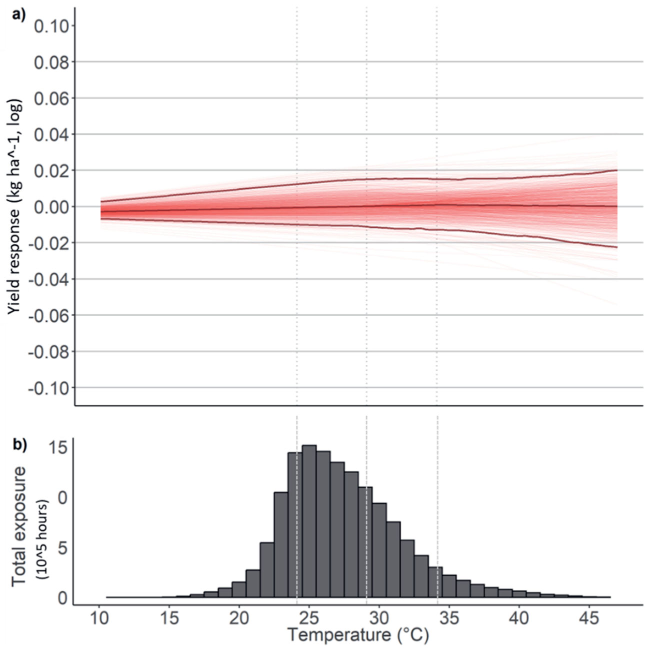

Figure 4.1 Hourly temperature effects on soybean yields from Climate-Smart Agriculture (CSA) farms based on ECMWF Reanalysis version 5 (ERA5) and Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) weather data: Panel (a) shows results based on knot locations of the best fit model (for details refer to the Methods section). Panel (b) shows a histogram of hourly temperature data (total) for the soybean growing season. Dotted vertical lines indicate knot locations and the 95% confidence bands are derived from 1,000 block-bootstrapped model runs, with observations blocked by year*district indices to allow for spatial dependence in the standard errors within a year. The dark-red line shows the median response function. The sample size for soybean is n=4,653. Other model specifications are available in the Supplementary information (Supplementary figure S4.4).

We find a similar response function of log winter wheat yields to temperature shocks. Figure 4.2a shows no significant effect of hourly heat shocks on CSA-managed wheat yields. Further robustness checks with different model specifications and weather data sources confirm these results (Supplementary figure S4.5). The temperature histogram shows hourly exposure of up to 42 degrees Celsius (Figure 4.2b). Yearly temperature histograms are available in in the Supplementary information (Supplementary figure S4.3).

We use different robustness checks to support our findings. First, we replicate the entire analysis (for both soybean and wheat) using weather data from the India Meteorological Department (henceforth IMD data). The IMD data is derived from weather stations (station and satellite merged data) across India (Pai et al., 2014), and we use this data to ensure that our results are not affected by the possible lack of weather extremes in the gridded ERA5 and CHIRPS datasets. Although IMD data showed higher temperature exposure in the study (IMD temperature histograms are available in Supplementary figure S4.7-S4.8), the marginal effects of heat exposure remained insignificant—consistent with our results (Supplementary figure S4.9-S4.10). In addition, our results remain insignificant for different model specifications including different knot placing strategies of the restricted cubic spline function, using piecewise linear instead of restricted cubic splines (Supplementary figure S4.11-S4.12) and using growing degree days instead of restricted cubic splines to specific temperature exposure.

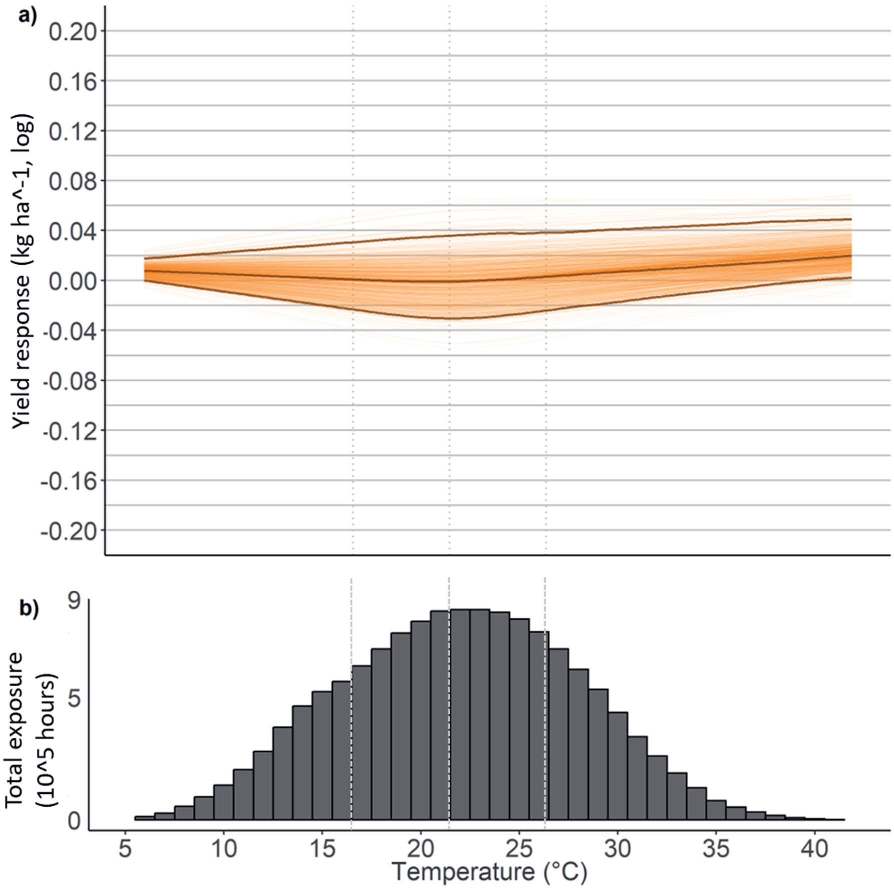

Figure 4.2 Hourly temperature effects on wheat yields from Climate-Smart Agriculture (CSA) farms based on ECMWF Reanalysis version 5 (ERA5) and Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) weather data: Panel (a) shows results based on knot locations of the best fit model (for details refer to the methods section). Panel (b) shows a histogram of hourly temperature data (total) for the soybean growing season. Dotted vertical lines indicate knot locations and the 95% confidence bands are derived from 1,000 block-bootstrapped model runs, with observations blocked by year*district indices (to allow for spatial dependence in the standard errors within a year). The dark-red line shows the median response function. Sample size for wheat is n=522. Other model specifications are available in the Supplementary section (Supplementary figure S4.5).

CSA bundles

We sub-sample our data by different CSA bundles, i.e., based on combination of different CSA practices (for details refer to Supplementary table S4.5). Figure 4.3 shows the soybean yield response functions to temperature shocks for two different CSA bundles for soybean—CSA 1 (Figure 4.3a) and CSA 2 (Figure 4.3b). Again, we find no significant effect of heat shocks on soybean yields under any CSA bundle. For wheat, results for CSA bundle 2[10] also show no significant effect of heat shocks (Figure 4.3c).

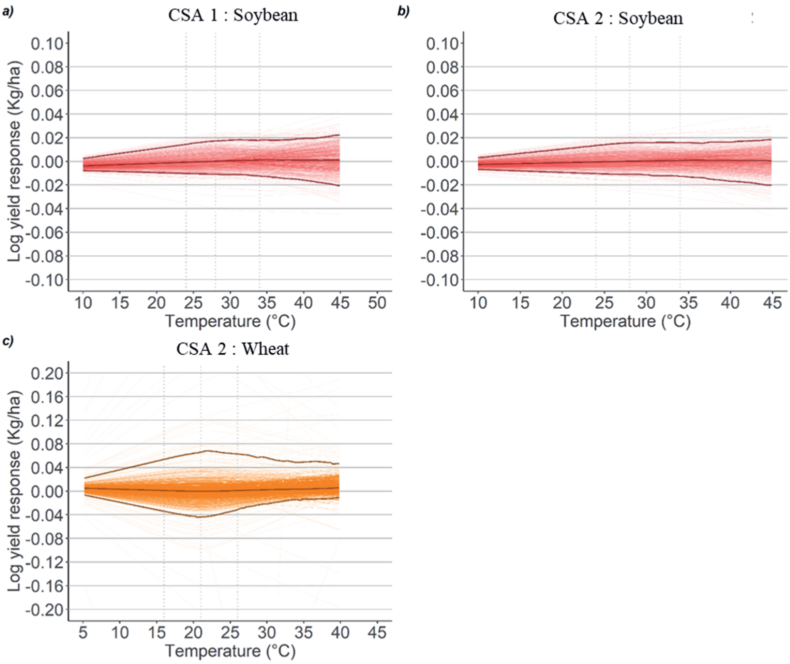

Figure 4.3 Hourly temperature effects on soybean and wheat sub-sample yields from Climate-Smart Agriculture (CSA) farms based on ECMWF Reanalysis version 5 (ERA5) and Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) weather data. Results for soybean are shown in plot a) CSA 1= 223 and plot b) CSA 2= 4380; and plot c) shows results for wheat for CSA 2 bundle (n=479). For soybean, the sample size for CSA 3 is too small to derive estimates (n=50). Likewise, the sample size for CSA 1 (n=31) and CSA 3 (n=12) for wheat is too small to derive estimates. Dotted vertical lines indicate knot locations and the 95% confidence bands are derived from 1000 block-bootstrapped model runs, with observations blocked by year*district indices (to allow for spatial dependence in the standard errors within a year). The dark-red line shows the median response function.

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[10] For wheat CSA bundles 1 and 3, the sample size is too low to derive estimates.

Comparison with district-level yields

Besides estimating yield response functions to temperature for CSA managed farms, we are interested in the temperature effect on yields, also for non-CSA managed farms to find differences in their heat susceptibility. Since our dataset does not include such farms, we use district-level yield statistics, which is the equivalent of county aggregated data in other regions, to assess the impact of heat exposure on the general farmer population (Ortiz-Bobea et al., 2019, 2021; Turvey et al., 2021).

Overall, we find no impact of heat shocks on soybean yields (Figure 4.4a). For wheat yields, we even find a slightly positive effect of high temperature shocks (Figure 4.4b). The results remain consistent for sub-samples of different geographical regions. It is important to note that wheat in India is more than 90% irrigated. Irrigation has been shown to offset the effects of heat on winter wheat yields in earlier studies (Agnolucci et al., 2020; Tack et al., 2017).

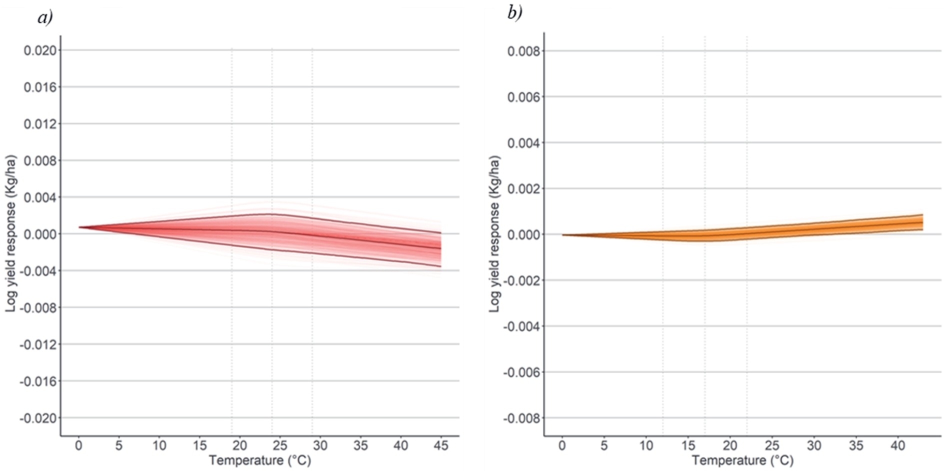

Figure 4.4 Hourly temperature effects on district yields of: a) soybean and b) wheat crop on ECMWF Reanalysis version 5 (ERA5) and Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) weather data. Results are based on knot locations of the best fit model (for details, refer to the Methods section). Dotted vertical lines indicate knot locations and the 95% confidence bands are derived from 1,000 block-bootstrapped model runs, with observations blocked by year*district indices (to allow for spatial dependence in the standard errors within a year). The dark-red line shows the median response function. The sample size for soybean is n= 1,232 and wheat is n=2,465.

For the district level analysis, we run a large variety of robustness checks. Results of different model specifications for both the crops and sub-sample results along different geographical regions do not show any different results (Supplementary figure S4.15-S4.16).

4.4 Discussion and conclusion

Various studies have estimated responses of different cropping systems to weather shocks. Recently, several studies for other regions and crops have used restricted cubic splines to quantify the marginal effects of weather on technical efficiency (Ortiz-Bobea et al., 2021), estimate weather impacts on crop quality (Dalhaus et al., 2020), crop/livestock production (Bucheli, Dalhaus, et al., 2022; Bucheli, Uldry, et al., 2022b; Schmitt et al., 2022b), diversification (Ortiz-Bobea et al., 2018), and soil moisture on crop productivity (Ortiz-Bobea et al., 2019). These and other model-based studies (Asseng et al., 2013; Wheeler, 2012) point towards negative impacts of heat exposure on crop yields—particularly wheat (Liu et al., 2016), whereas soybean is comparatively more resistant to heat than other crops (Cohen et al., 2021). Yet, no study to date has used farm-level data to assess how farming practices and practice bundles, including those labelled as CSA, affect the impact of heat on crop yields. The evidence on how management practices affect the sensitivity of farms to heat exposure is limited due to data scarcity, although a few studies indicate the importance of management in explaining crop yield failures (Visker et al., 2020).

In this analysis, we find no significant impact of heat exposure on both wheat and soybean, indicating that the crop productivity in India is resilient to heat stress under CSA. Notably, the fact that we find no heat stress effects on yields at the district level suggests that under prevalent (i.e., non-CSA) production conditions, crop yields are also resilient. This resilience may be due to several reasons. Farmers are assumed to adjust their management in response to weather conditions, and we know that the estimated production responses to heat can be significantly affected by the farm adjustments made (Ortiz-Bobea, 2021). We therefore hypothesize that farmers' management practices in India and in particular their widespread use of irrigation in wheat allow them to cope with extreme weather. Another factor that could explain crop yield resilience is the use of improved crop varieties. Across the sample of farms represented in our farm-level dataset, the most common wheat variety grown, Lok-1, has been reported to show heat tolerance characteristics (Kumar et al., 2015). Crop variety is fundamental to enhancing productivity and mitigating the impacts of heat and drought stress in crops (Xiong et al., 2021). Short duration varieties can reduce exposure to heat due to early maturity while other varieties can be specifically bred for heat tolerance (Langridge & Reynolds, 2021; Pandey et al., 2021). For soybean, the most common variety used in the CSA farms is JS-9560 (distribution of farms under different varieties is provided in Supplementary table S4.4), with early maturity, higher resistance to abiotic stress[11], higher yields[12] and seed longevity[13]. Although negative impact of heat stress on seed yield for this variety is observed in some studies, the experiments were done without management interventions like precision nutrient management and use of agro-advisories for planting and fertilizer timings (Jumrani et al., 2018). Another important point to note is the interaction of heat stress with drought. In some regions, soil moisture levels in the field may be sufficient to counteract the impacts of heat stress through transpirational cooling, whereas, in other regions, drought may be a more important driver of productivity losses compared to heat stress. While beyond the scope of this chapter, understanding the impacts of drought and its interactions with heat stress is an important item for the research agenda (Leng & Hall, 2019; Soares et al., 2021).

Irrigation also plays a key role in the physiological response of crops to heat stress, especially wheat (Wang et al., 2021). Studies show that, in many cases, irrigation can offset negative impacts to heat exposure through transpirational cooling. This has also been shown for India, where benefits from irrigation compensate for heat stress in wheat (Birthal et al., 2021; Kuriachen et al., 2022; Zaveri & B. Lobell, 2019), although yield gains have stagnated in recent years. In our dataset, all the wheat farmers irrigated their crops (see Supplementary table S4.2). Apart from the use of improved varieties and irrigation, most of the farmers in our sample (more than 50% for both wheat and soybean) use precision nutrient management (using leaf color charts to determine the timing and dosage of nitrogen fertilisers), in addition to weather agro-advisory services. These include SMS updates on short-term weather forecasts, market intelligence for input prices and other agronomic updates, like planting and fertiliser timings. While the survey does not capture how the farmers use specific weather agro-advisory services (i.e., whether their planting and irrigation decisions are linked to these advisory services), it is possible that these contribute to the resilience towards heat stress of the CSA farms as observed here (Balla et al., 2019).

[11] http://jnkvv.org/Departments/Dep_DRS_Soybean.aspx
[12] https://agris.fao.org/agris-search/search.do?recordID=US202100007050
[13] https://iisrindore.icar.gov.in/varieties.html

An important finding of this study is that of no heat stress impact for soybean and for wheat when using district level yield statistics (likely composed primarily non-CSA farms). While this might be due to the widespread use of irrigation technology, at least for wheat, future research could further refine the analyses presented here once more precise land-use and farm-level yield data under non-CSA conditions becomes available. Furthermore, there are a few limitations in the district-level analysis: a) using representative weather data based on the centroid of the district, which may not be representative of the weather conditions over the specific growing areas of these crops, and b) aggregation bias (yield data aggregation at higher geographical units, i.e., districts) may not capture farm heterogeneity and hide potential non-linear effects (Fezzi & Bateman, 2015; Finger, 2012). Therefore, the actual impact of heat stress may be higher than observed here for soybean. For wheat (being a highly irrigated crop), as stated earlier, it is possible that the farmers compensate the heat effect by additional irrigations to the crop. It is noteworthy that a few studies also find complex interactions of drought and heat stress significantly affecting winter wheat yield (Kent et al., 2017; Siebert et al., 2017). It is important to note that crop yield resilience to weather shocks (like heat stress, as analyzed in this chapter) may not directly lead to farm resilience as many CSA practices and technologies (like use of improved seeds) have economic costs which might deter their adoption. Further, continuous increase in area under irrigation (which has been hypothesized to play a key role in productivity resilience in this analysis), might not be feasible in the future due to severe groundwater depletion (Mukherjee & Mukherjee, 2018), and other ecological trade-offs and externalities associated with it (Devineni et al., 2022; Meuwissen et al., 2019).

Our findings have several important implications. First, CSA practices can buffer against the effect of heat extremes. This likely means that climate-smart village programmes will yield benefits for farmers and India’s overall resilience to heat stress, not least because heat stress is projected to intensify in coming decades (P.R. Shukla, J. Skea, E. Calvo Buendia, V. Masson-Delmotte, H.- O. Pörtner et al., 2019; Thornton et al., 2022; Yin et al., 2022). Furthermore, policies promoting CSA in India could be strengthened, and CSA programmes could be scaled up across other Indian states and farming systems. While we cannot disentangle individual CSA practice effects, the use of various CSA practices or practice bundles by farmers can become an indicator to track and report progress toward climate adaptation as part of India’s contribution to the United Nations Framework Convention on

Climate Change (UNFCCC)—Paris Agreement targets and broader development targets like Sustainable Development Goals (i.e., SDG 13).

Notably, the extent to which the CSA measures buffer against heat impacts and how they interact with drought in the future (Xu et al., 2019) should be further explored. More comprehensive and continuous impact evaluation studies (using randomized control trials with CSA treatments) are needed to quantify the extent to which CSA helps in building farm productivity resilience to heat stress. In addition, studies should also focus on drought and its interaction with heat stress as a possible driver of crop yield shocks. Further to the above, a last important implication of our work relates to existing approaches for estimating heat stress effects. More specifically, most studies showing evidence of negative heat effects on Indian agriculture do so using process-based crop models under future climate scenarios (Byjesh et al., 2010), with virtually no studies analysing farm-level observations as done here. We therefore suggest adapting process-based crop modelling approaches in a way that the yield response functions to temperature that we estimate here can be incorporated in the models.

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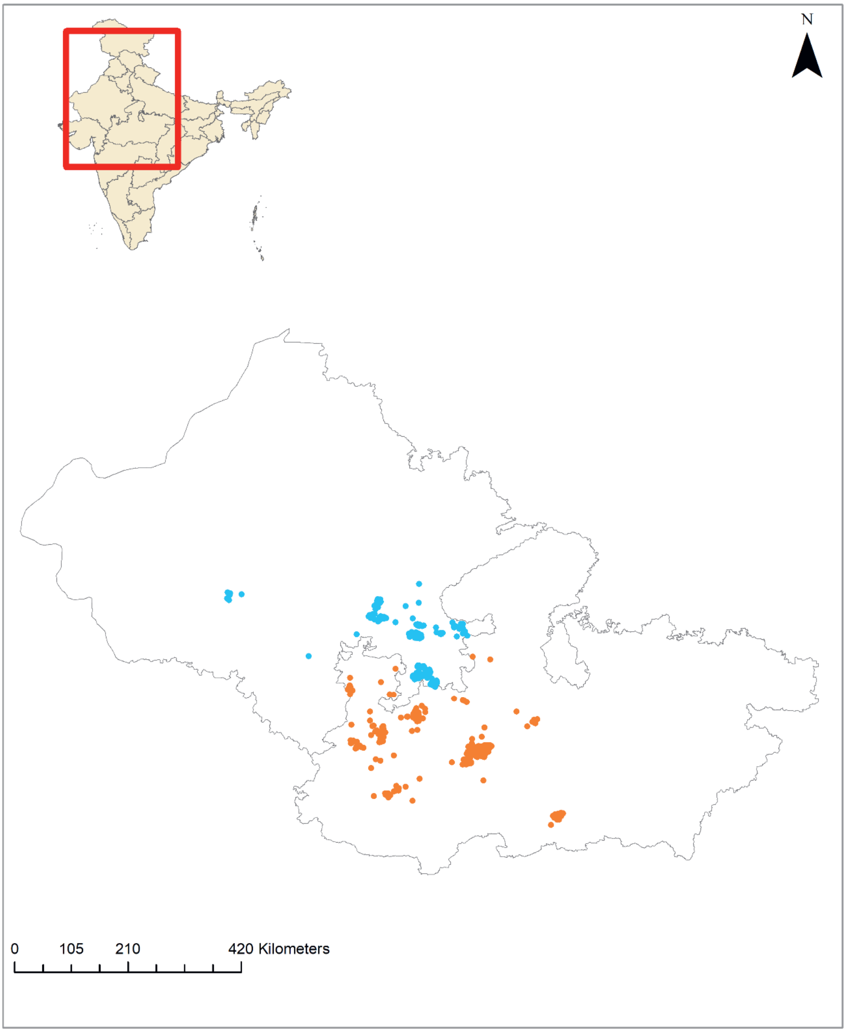
Supplementary information

S4.1 The Climate Smart Village Project

The CGIAR research program on Climate Change, Agriculture and Food Security (CCAFS) has implemented the “Climate-Smart Village project” with different national and international partners to promote CSA. CSA aims to integrate climate change into policy design, planning and implementation of sustainable agricultural practices from local to regional scales. It focuses on three key aspects of food production—adaptation, mitigation, and food security, in addition to building food system resilience to climate extremes. Climate-Smart Village (CSV) is a community approach to leverage local institutions, public and private partnerships to scale climate-smart agriculture across different geographies. The climate-smart village activities are planned along five pillars—weather, water, seed, carbon, and institutions. These interventions are implemented through different mechanisms (involving individual farmers and farmer groups) and local institutions, depending on location and context-specific characteristics. The CSV approach is thus flexible and is implemented in different regions depending on their specific objectives and/or needs.

The study areas (states of Madhya Pradesh and Rajasthan) have semi-arid and dry crop-growing conditions with high temperatures, dry spells, and droughts, especially in the summer season (Supplementary figure S4.1). The seasonal rainfall volume ranges from 300 to 1,500 mm in summer and 15 to 200 mm in winters and the maximum temperature varies from 25 to 45 degrees in summers (with records of even upto 50 degrees in a few places). The region is also characterized by intense and frequent droughts. In the baseline survey for the CSV project, the farmers reported high temperatures, heat waves as most important weather hazards, in addition to low rainfall and drought, hailstorms, frost, strong winds, and extensive rainfall. Global and regional scale gridded weather data sources are used in this analysis.



Supplementary figure S4.1 Spatial distribution of the villages selected for this study. Colors differentiate two project states-blue (Rajasthan) and orange (Madhya Pradesh).

Yields for soybean and wheat (total of 45,046 yield observations) were collected from 2015–2020. The farm data is unbalanced panel data consisting of information on crop yields and management interventions used in the farms from 2015–2020. Since the inception of the project, new farmers were added each year resulting in unbalanced panel (yearly distribution given below) in Supplementary table S4.1:

Supplementary table S4.1 Yearly yield observations.

Year	Total yield observations
2015	482
2016	481
2017	1068
2018	16855
2019	22115
2020	7379

Since fixed effects regression requires a minimum of 3 years yield data, only farms with 3 or more years of yield observations were included. Next 99% percentile cutoffs were used to identify outliers.

The survey includes farm-specific information on management conditions such as farm inputs used (crop variety, fertilizer and irrigation amount, labour), farm size, outputs (yield and income) and type of adaptation/mitigation strategies implemented (including precision nutrient management, agro-advisories, insurance, intercropping, conservation tillage, among others). The farm data (unbalanced panel data) is available for 29,524 households in 693 villages from the year 2015 to 2020, with a total of 51,707 individual household-by-year observations. The data covers maize, rice, wheat, gram, green gram, and soybean crops. Of this, the two major crops (focus of this study) soybean and wheat include 45,046 observations. This analysis, however, uses fixed effects regression, which requires atleast three years of data from a particular farm, resulting in 4733 soybean observations and 541 wheat observations. It is noteworthy that majority of the farmers (51.4%) in the total sample joined the project in 2019 and 2020, resulting in a highly unbalanced panel data. Crop yield data is used for the regression analysis along with other weather-based indicators and the outliers (for yield observations) are excluded based on 99th percentile cut-off. The final dataset used for the results (after outlier removal) includes 4653 soybean observations and 522 wheat observations.

Supplementary table S4.2 Summary statistics of farm management data (key categorical variables).

Variable code	Variable name	Categories and count
Soybean crop		
Q8	Type of farmer	Super champion= 223, Champion= 4380, CSA= 50
Q18	Seed treatment	Yes= 4541, No= 112
Q22	Zero tillage	Yes= 827, No= 3826
Q26	Use of broad-based furrow (BBF)	Yes= 3185, No= 1468
Q29	Crop insurance	Yes= 3161, No= 1492
Q31	Irrigation	No= 4653
Q56	Intercropping with legumes, vegetable	Yes= 1058, No= 3595
Q53	Use of precision nutrient management	Yes= 1824, No= 2829
Q68	Climate information, agro-advisory and market information	Yes= 3583, No= 1070
Q89	Season	Summer= 4653
Q90	Year	2015= 333, 2016= 347, 2017= 377, 2018= 1200, 2019= 1224, 2020= 1172
Wheat crop		
Q8	Type of farmer	Super champion = 31, Champion= 479, CSA= 12
Q18	Seed treatment	Yes= 403, No= 119
Q22	Zero tillage	Yes= 214, No= 308
Q26	Use of broad-based furrow (BBF)	Yes= 145, No= 377
Q29	Crop insurance	Yes= 276, No= 246
Q31	Irrigation	Yes= 522
Q56	Intercropping with legumes, vegetable	Yes= 394, No= 128
Q53	Use of precision nutrient management	Yes= 429, No= 93
Q68	Climate information, agro-advisory and market information	Yes= 382, No= 140
Q89	Season	Winter= 522
Q90	Year	2017= 128, 2018= 188; 2019= 206

Supplementary table S4.3 Summary statistics of farm management data (key numeric variables).

Variable code	Variable name	Count	Mean	Minimum	Maximum	Median
Soybean crop						
Q71	Total cost of cultivation (INR*/Acre)	4653	6619	2288	14277	6207
Q76	Market price of grain (INR/Qt**)	4653	3246	2456	4100	3150
Q30	Cost of crop insurance (INR/Acre)	4653	239.8	107	6250	257
Q9	Total cultivated area (in Acre)	4653	1.498	1	30	1
Wheat crop						
Q71	Total cost of cultivation (INR/Acre)	522	6468	3120	16691	5827
Q76	Market price of grain (INR/Qt)	522	1862	1600	2900	1850
Q30	Cost of crop insurance (INR/Acre)	522	155.5	103	428	157.5
Q9	Total cultivated area (in Acre)	522	2.828	.724	40	1

*INR (Indian National Rupee); **Qt (Quintals)

S4.2 Climate Smart Agriculture (CSA) measures

As discussed in the methods section, many climate-smart technologies were implemented in the CSV project. The selection of technologies, prioritization processClick or tap here to enter text., implementation plan, how the technologies were bundled in different groups, and other details are available in project documents[14]. Some of the CSA activities implemented are described below:

Improved seed: During the project implementation, a list of improved seed varieties was developed with farmers, extension agents (from local agricultural universities), and other experts based on the farmer's need for specific traits (i.e., drought tolerance, disease resistance, early maturity-among others) and the availability (market access, price) and suitability of the selected varieties for the region. The Supplementary table below provides the list of varieties used by farmers in our sample.

[14] https://ccafs.cgiar.org/resources/publications/developing-resilient-agriculture-climate-change-india

Supplementary table S4.4 List of soybean and wheat varieties grown by farmers in the Climate-Smart Agriculture (CSA) project.

Wheat varieties used by the farmers	Count	Soybean varieties used by the farmers	Count
C-306	18	JS-9305	159
GW-322	53	IC-210	9
HI-1544 (Purna)	94	JS-9560	3821
HI-8498 (Malwa shakti)	3	JS-1025	208
HI-8663	6	JS-2029	19
HI-8713 (Pusa Mangal)	12	JS-2034	201
HI-8737 (Pusa Anmol)	3	JS-335	41
Lok-1	271	JS-2029	37
MP-3382	1	JS-6124	4
Pusa-111	9	Kishan-228	4
Raj-3077	2	NRC-2	10
Raj-3765	6	NRC-7	3
Raj-4037	15	NRC-86	1
Raj-4079	4	PS-1569	4
Raj-4238	2	RVS-18	30
Super 111	9	RVS-2001-4	182
WH-147	13	JS-9305	159
WH-273	1	IC-210	9

Seed treatment: This includes chemical and biological treatment of seeds before sowing (as an example, for wheat crop chemical treatment with Endosulphan 35EC or Chlorpyriphos 20 EC was recommended for damage against termites).

Precision Nutrient Management: Precision nutrient management was a major technology implemented in farms. This included soil testing based on farm-specific fertilizer recommendations (including both macro and micro-nutrients like Sulphur and Zinc for wheat) and monitoring nutrient levels after sowing using leaf color chart and green seeker for nitrogen management.

Crop insurance and climate information services: Climate information services implemented in the project included—a) weather forecasts: The weather forecasts given daily (one voice message and 2 SMSs in the local language) except Sunday with reasonable accuracy at the village level; b) Weather and Crop Advisories: The weather and crop advisories in regional language, issued once or twice a week depending on crops, c) Insect and pest advisories: Crop protection advisories were issued with targeted biocides along with major dealers in nearby areas with their contact details, d) Input suppliers and market intelligence: The project partner along with ICT firm (MKSP) provided details of input suppliers and daily commodity prices in nearby Mandis with contact details of traders; and e) Information Dissemination: ICT also disseminated the information about the ongoing and upcoming Government Schemes for subsidies and other farmer support. In addition, all the farms were enrolled in the national crop insurance scheme (Pradhan Mantri Fasal Bima Yojana-PMFBY).

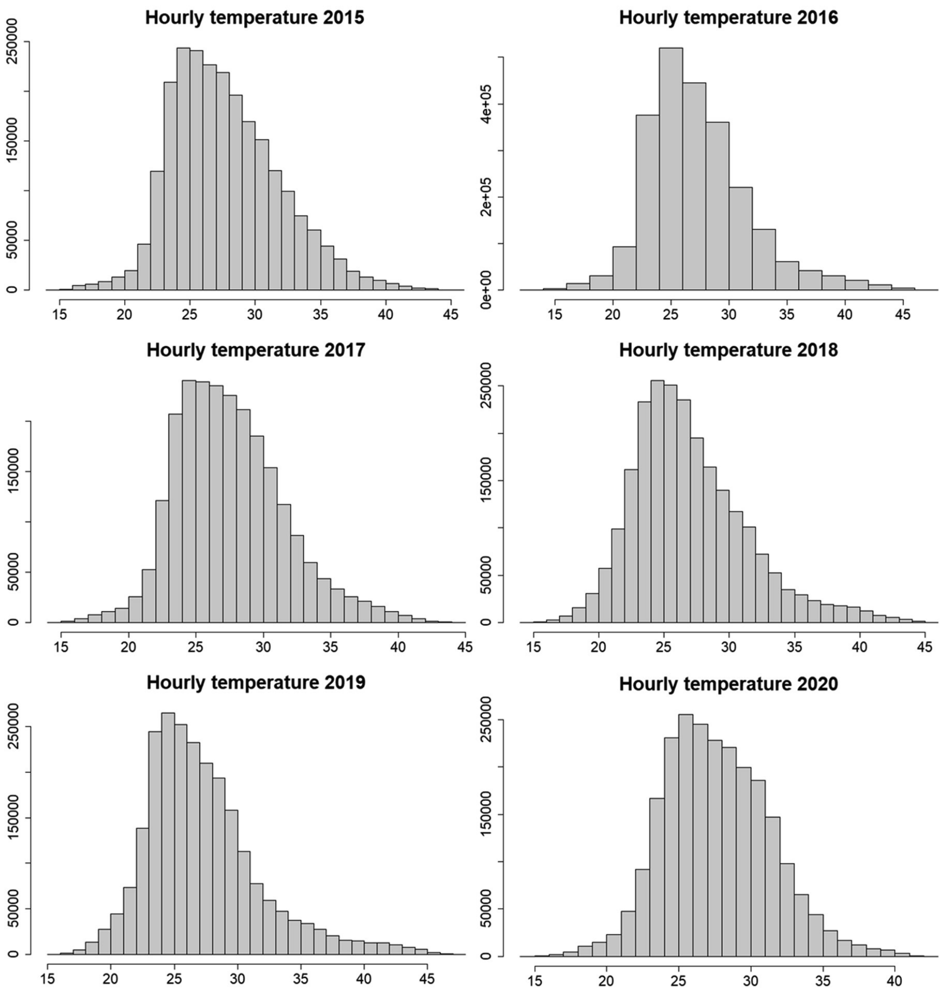
CSA Bundling: For irrigation and water management, various practices based on the area, soil type, and other conditions were implemented, e.g., tension-meter based irrigation scheduling, and micro-irrigation using sprinkler and furrow-based methods. Supplementary table S4.5 below shows how different CSA technologies were grouped together for implementation.

Supplementary table S4.5 Climate-smart technologies implemented in each Climate-Smart Agriculture (CSA) bundle.

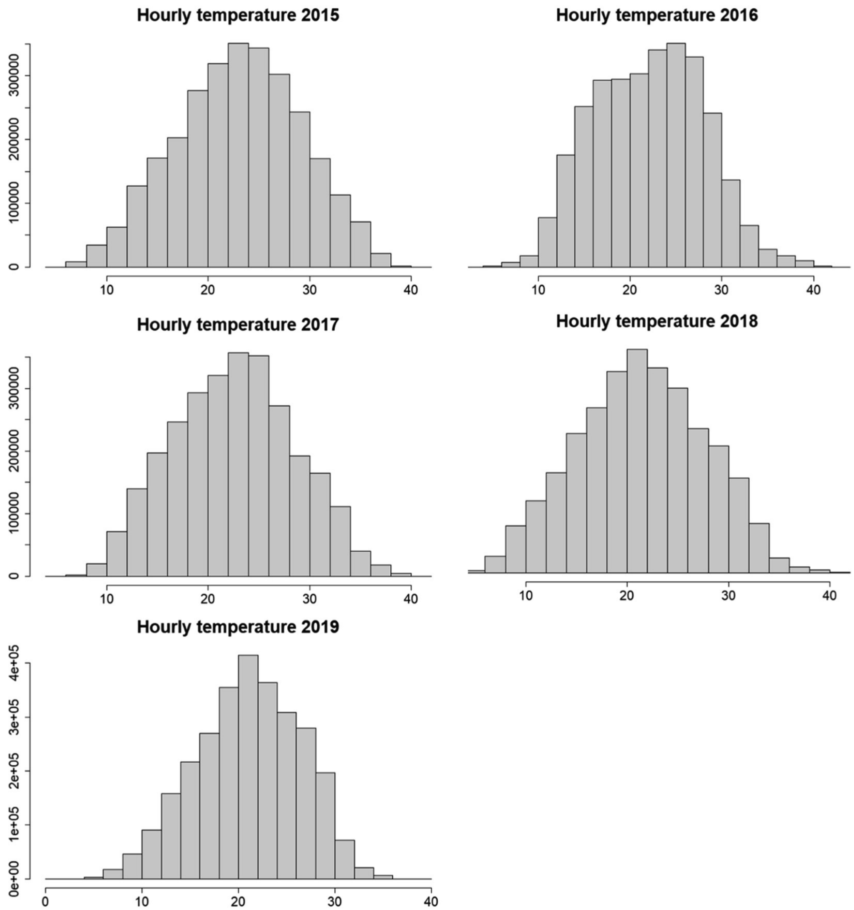
CSA 1	CSA 2	CSA 3
Seed-smart		
Improved seed Seed treatment	Improved seed	Improved seed
Nutrient-smart		
Precision nutrient management Intercropping with legumes, vegetables	Precision nutrient management	None
Water-smart		
Broad-based furrows Irrigation and drainage management Water-use efficient technologies	Broad-based furrows Water-use efficient technologies	None
Knowledge-smart		
Farmers capacity building Contingent crop planning	Farmers capacity building	Farmers capacity building
Weather-smart		
Crop insurance Climate information services and advisory	Climate information services and advisory	Crop insurance Climate information services and advisory

S4.3 Weather data and yearly heat exposure

As explained in the main methods section, daily minimum and maximum temperature was used to compute hourly temperature values. Yearly histograms of hourly temperature for soybean and wheat growing seasons are shown below in Supplementary figure S4.2 and S4.3.



Supplementary figure S4.2 Yearly histogram of hourly temperatures (in degree Celsius) during growing season for soybean crop, from 2015 to 2020 based on ECMWF Reanalysis version 5 (ERA5) temperature data.

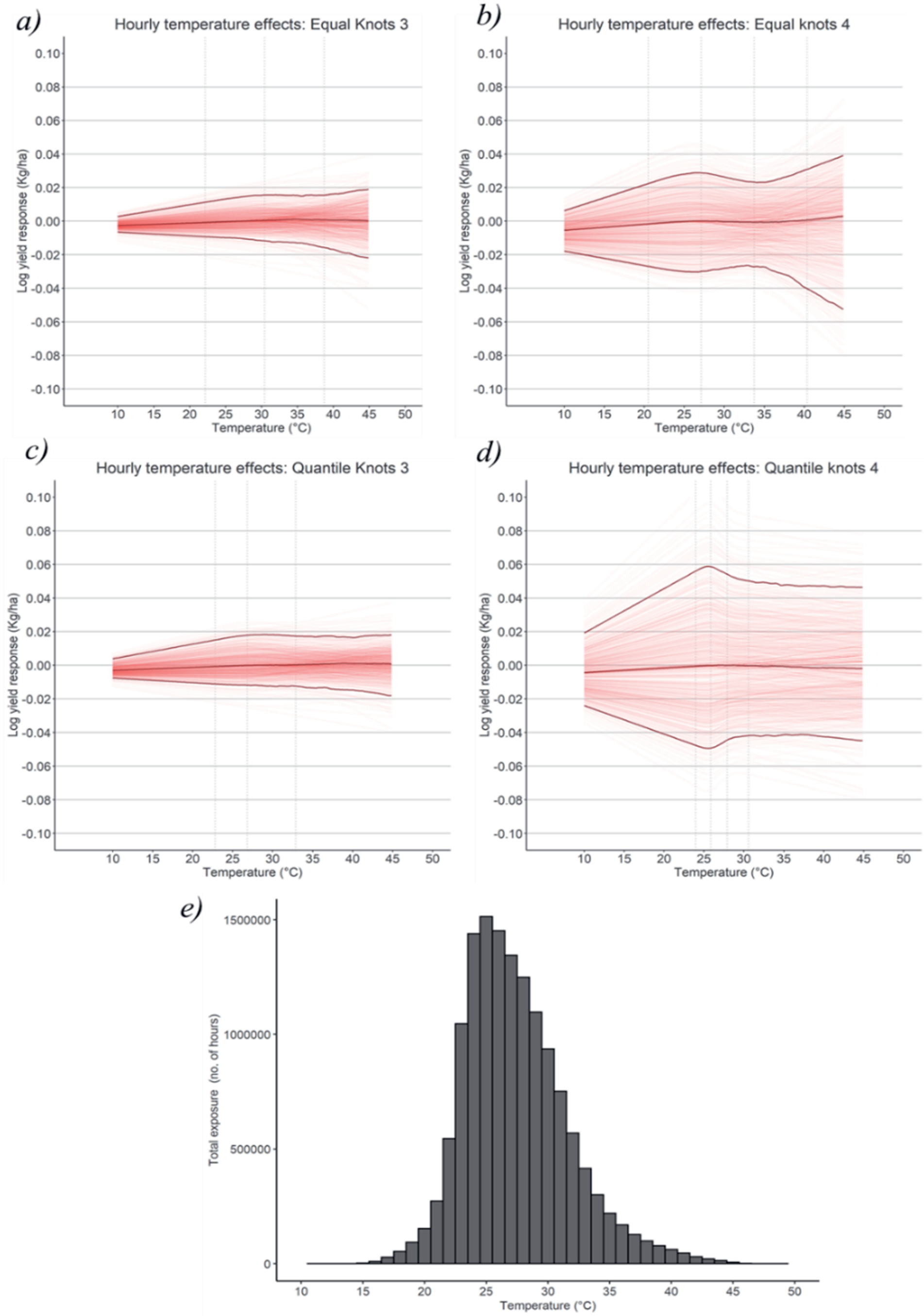


Supplementary figure S4.3 Yearly histogram of hourly temperatures (in degree Celsius) during growing season for wheat crop, from 2015 to 2019 based on ECMWF Reanalysis version 5 (ERA5) weather data.

S4.4 Robustness checks for regression model

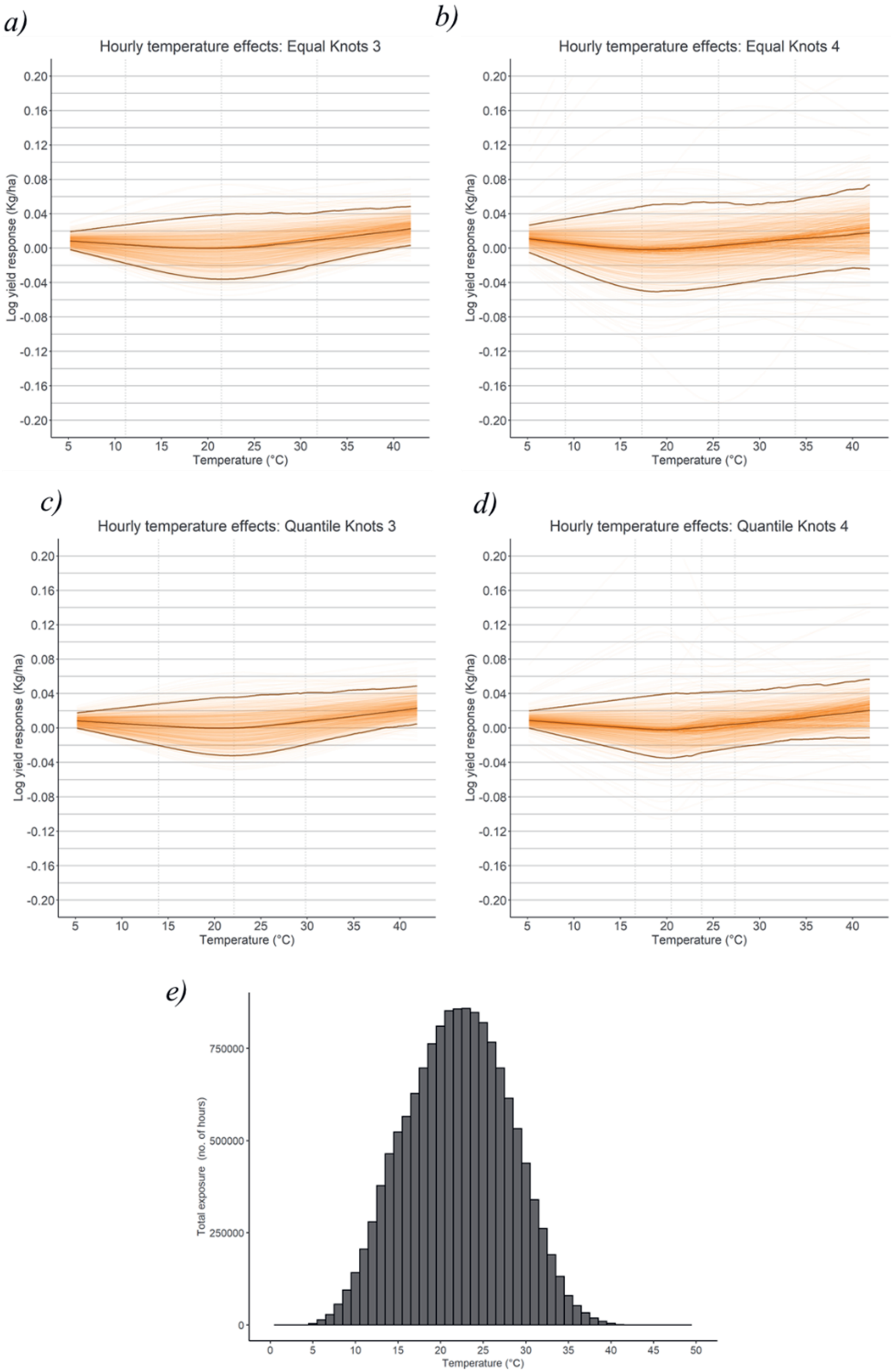
Model specifications

Supplementary figure S4.4 and S4.5 show different model specification results for soybean and wheat crops, respectively. All the model specifications show no significant impact of heat exposure on soybean and wheat yields. Specifications with three knots (quantile, equal distribution and best fit) have narrower confidence intervals than models with four knots.



Supplementary figure S4.4 Hourly temperature effects on soybean yields from Climate-Smart Agriculture (CSA) farms based on ECMWF Reanalysis version 5 (ERA5) and Climate Hazards Group InfraRed

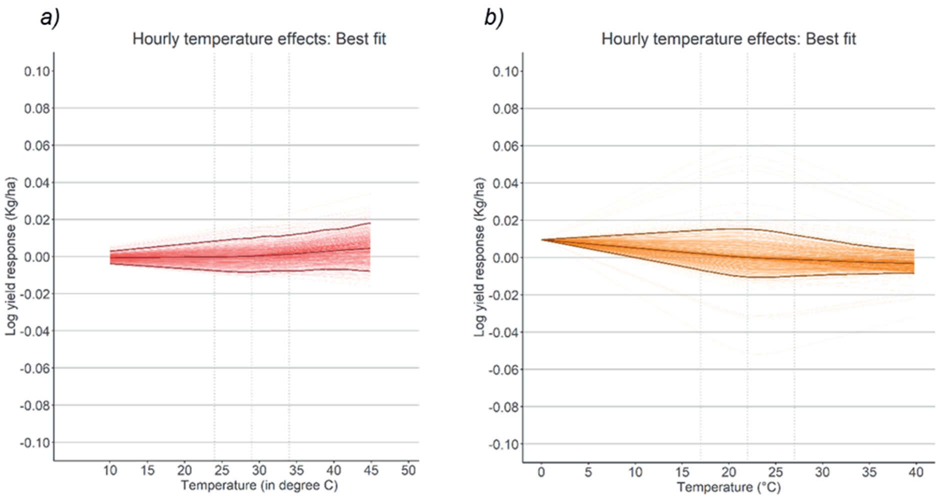
Precipitation with Station (CHIRPS) weather data: Panel shows different model specifications based on knot locations-a) three equally spaced knots on hourly temperature data, b) three knots at 10, 50 and 90% quantile of temperature c) four equally spaced knots d) four knots at 20, 40, 60 and 80% quantile of temperature. Plot I shows histogram of hourly temperature data for soybean growing season. Knot locations are specified by dotted vertical lines. 95% confidence bands are derived from 1000 block-bootstrapping, with observations blocked by year and district (to account for spatial dependence within a year). The dark line in the middle show median response function. Sample size for soybean crop, n=4733.


a)
Hourly temperature effects: Equal Knots 3
b)
Hourly temperature effects: Equal Knots 4
c)
Hourly temperature effects: Quantile Knots 3
d)
Hourly temperature effects: Quantile Knots 4
Log yield response (Kg/ha)
Temperature (°C)
e)
Total exposure (no. of hours)
Temperature (°C)

Supplementary figure S4.5 Hourly temperature effects on wheat yields from Climate-Smart Agriculture (CSA) farms based on ECMWF Reanalysis version 5 (ERA5) and Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) weather data: Panel shows different model specifications based on knot locations-a) three equally spaced knots on hourly temperature data, b) three knots at 10, 50 and 90% quantile of temperature c) four equally spaced knots d) four knots at 20, 40, 60 and 80% quantile of temperature. Plot I shows histogram of hourly temperature data for wheat growing season. Knot locations are specified by dotted vertical lines. 95% confidence bands are derived from 1000 block-bootstrapping, with observations blocked by year and district (to account for spatial dependence within a year). The dark line in the middle show median response function. Sample size for wheat crop, n=522.

No technology control

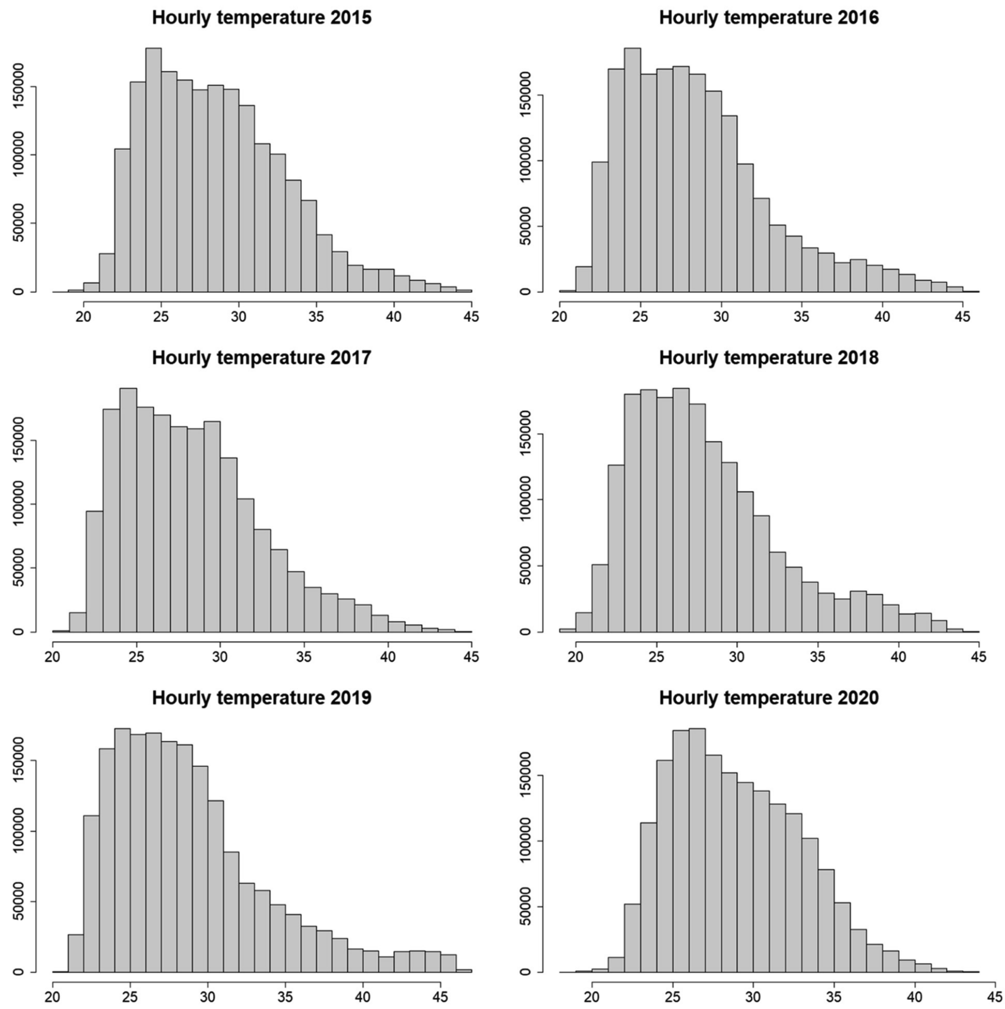
The following figure (Supplementary figure S4.6) show the results of best fit model without quadratic time trend for both soybean and wheat. There is no significant effect of hourly temperature exposure on the yields of these crops.



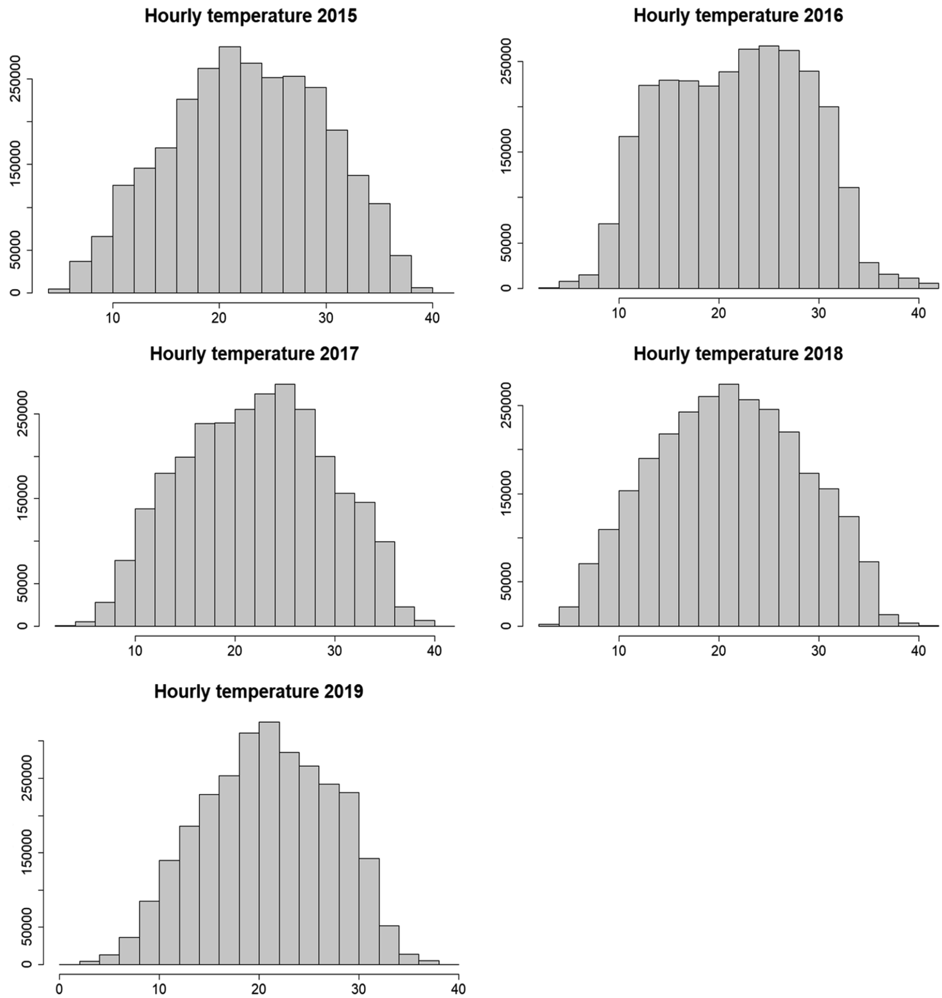
Supplementary figure S4.6 Hourly temperature effects on a) soybean and b) wheat yields Climate-Smart Agriculture (CSA) farms based on ECMWF Reanalysis version 5 (ERA5) and Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) weather data. The model does not include quadratic time trends to control for technology effects. The knot locations are based on the best fit model for the both the crops. Knot locations are specified by dotted vertical lines. 95% confidence bands are derived from 1000 block-bootstrapping, with observations blocked by year and district (to account for spatial dependence within a year). The dark line in the middle show median response function. Sample size for soybean crop is n=4733 and wheat crop, n=522.

Results with India Meteorological Department (IMD) data

The analysis for both soybean and wheat crops were replicated with IMD weather data as a robustness check. Supplementary figures S4.7 and S4.8 show yearly histograms for soybean and wheat crops with IMD data.



Supplementary figure S4.7 Yearly histogram of hourly temperatures (in degree Celsius) during growing season for soybean crop, from 2015 to 2020 based on India Meteorological Department (IMD) temperature data.



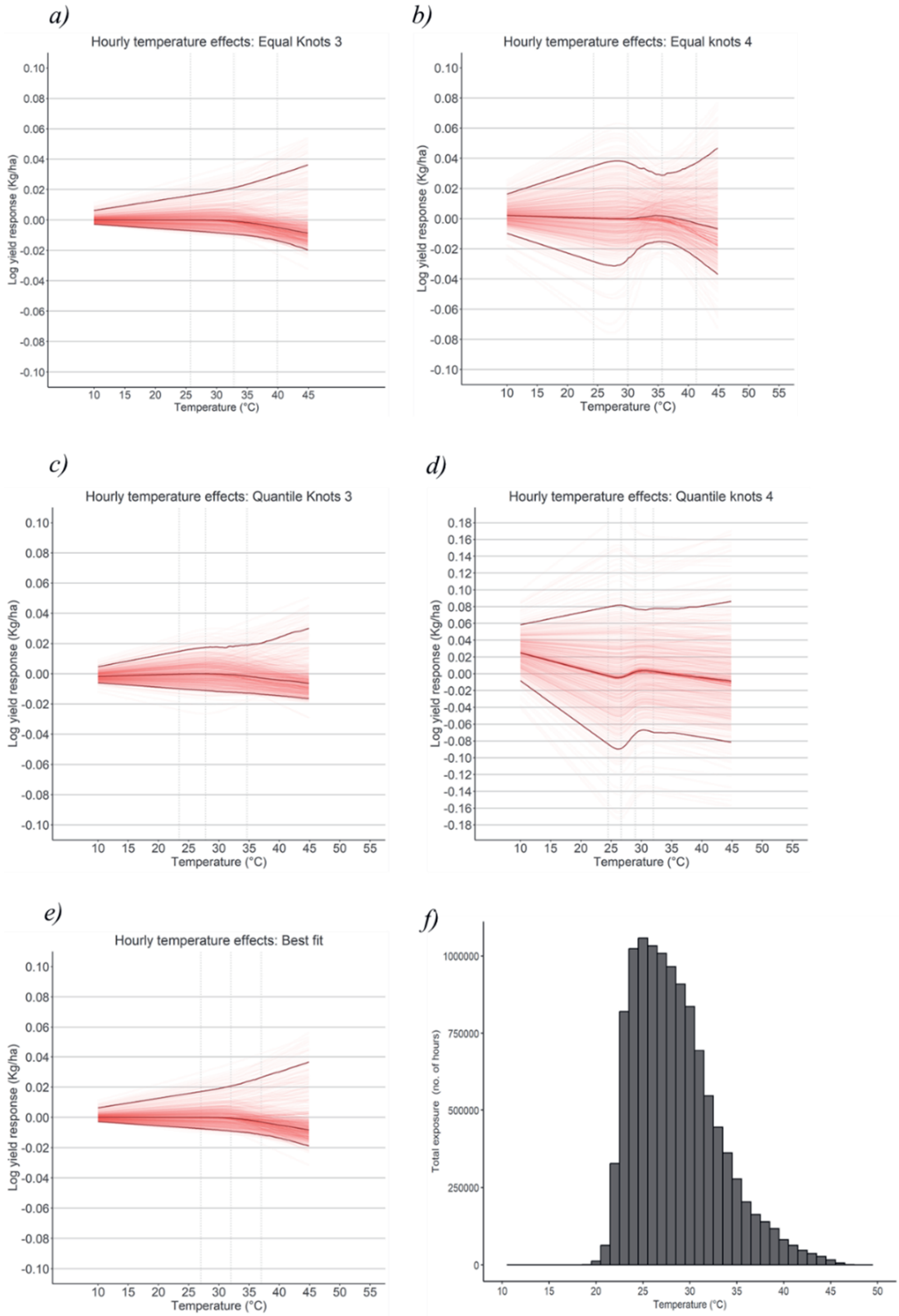
Supplementary figure S4.8 Yearly histogram of hourly temperatures (in degree Celsius) during growing season for wheat crop, from 2015 to 2019 based on India Meteorological Department (IMD) temperature data.

The following table shows summary statistics for hourly temperature during soybean and wheat growing season, for the study period using IMD data.

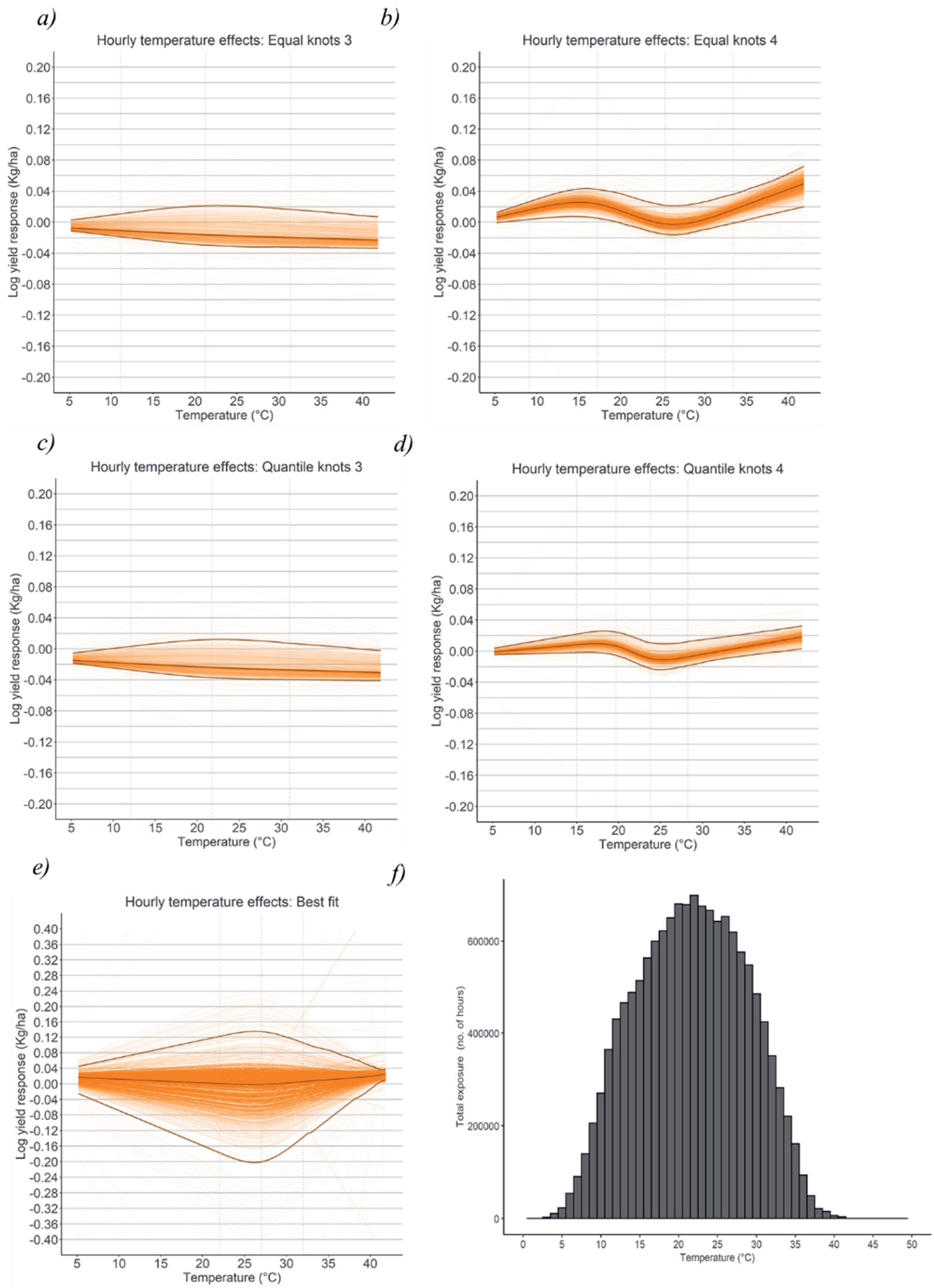
Supplementary table S4.6 Summary statistics for hourly temperatures during soybean and wheat growing season based on India Meteorological Department (IMD) data.

Statistics	Hourly temperature exposure for soybean	Hourly temperature exposure for wheat
Minimum	14.04	0.98
First quartile	24.91	16.29
Median	27.62	21.74
Mean	28.28	21.65
Third quartile	30.70	27.04
Maximum	46.96	41.51

Supplementary figure S4.9 and S4.10 show marginal effects of heat exposure on soybean and wheat crops respectively, based on IMD data. No significant effect is observed for both the crops, consistent for different model specifications.


a)
Hourly temperature effects: Equal Knots 3
Log yield response (Kg/ha)
Temperature (°C)
b)
Hourly temperature effects: Equal knots 4
Log yield response (Kg/ha)
Temperature (°C)
c)
Hourly temperature effects: Quantile Knots 3
Log yield response (Kg/ha)
Temperature (°C)
d)
Hourly temperature effects: Quantile knots 4
Log yield response (Kg/ha)
Temperature (°C)
e)
Hourly temperature effects: Best fit
Log yield response (Kg/ha)
Temperature (°C)
f)
Total exposure (no. of hours)
Temperature (°C)

Supplementary figure S4.9 Hourly temperature effects on soybean yields from Climate-Smart agriculture (CSA) farms based on India Meteorological Department (IMD) weather data: Panel shows different model specifications based on knot locations-a) three equally spaced knots on hourly temperature data, b) three knots at 10, 50 and 90% quantile of temperature c) four equally spaced knots d) four knots at 20, 40, 60 and 80% quantile of temperature and e) three knots placed at 5 degree Celsius interval which show lowest Residual Sum of Square (RSS) (largest goodness of fit). Plot (f) shows histogram of hourly temperature data for soybean growing season. Knot locations are specified by dotted vertical lines. 95% confidence bands are derived from 1000 block-bootstrapping, with observations blocked by year and district (to account for spatial dependence within a year). The dark line in the middle show median response function. Sample size for soybean crop, n=4733.



Supplementary figure S4.10 Hourly temperature effects on wheat yields from Climate-Smart agriculture (CSA) farms, based on India Meteorological Department (IMD) weather data: Panel shows different model specifications based on knot locations: a) three equally spaced knots on hourly temperature data, b) three knots at 10, 50 and 90% quantile of temperature, c) four equally spaced knots, d) four knots at 20, 40, 60 and 80% quantile of temperature, and e) three knots placed at 5 degree Celsius interval which show lowest Residual Sum of Square (RSS) (largest goodness of fit) (largest goodness of fit). Plot (f) shows histogram of hourly temperature data for wheat growing season. Knot locations are specified by dotted vertical lines. 95% confidence bands are derived from 1000 block-bootstrapping, with observations blocked by year and district (to account for spatial dependence within a year). The dark line in the middle shows median response function. Sample size for wheat crop, n=522. Please note unequal X-axis in each plot.

S4.5 Other methods

Growing Degree Days

The impact of heat exposure on soybean yield in the CSA farms of the project was also assessed using the concept of growing degree days. Degree days are calculated as a sum of exposure above a certain threshold. The following table shows the regression results for a threshold of exposure above 30 degrees. This threshold was shifted between 27 to 35 degrees. The results remained consistent with no significant effect of heat exposure on soybean yields. Similar results were observed for wheat crop in the CSA farms. The following table shows the regression results for a threshold of exposure above 27 degrees. This threshold was shifted between 25 to 32 degrees. The results remained consistent with no significant effect of heat exposure on wheat yields.

Supplementary table S4.7 Farm fixed effects regression model using growing degree days for soybean yields in the Climate-Smart Agriculture (CSA) farms. Standard errors clustered by farm and year to account for spatial dependence.

Dependent variable	Log (Soybean yield)
Degree days above 30	-5.81e-6 (0.0003)
Year	-15.66 (168.9)
Square of year	0.0039 (0.0419)
Summer rainfall	-0.00002028
Square of summer rainfall	2.66e-6* (9.38e-7)
Observations	4653
R2	0.42
Within R2	0.26

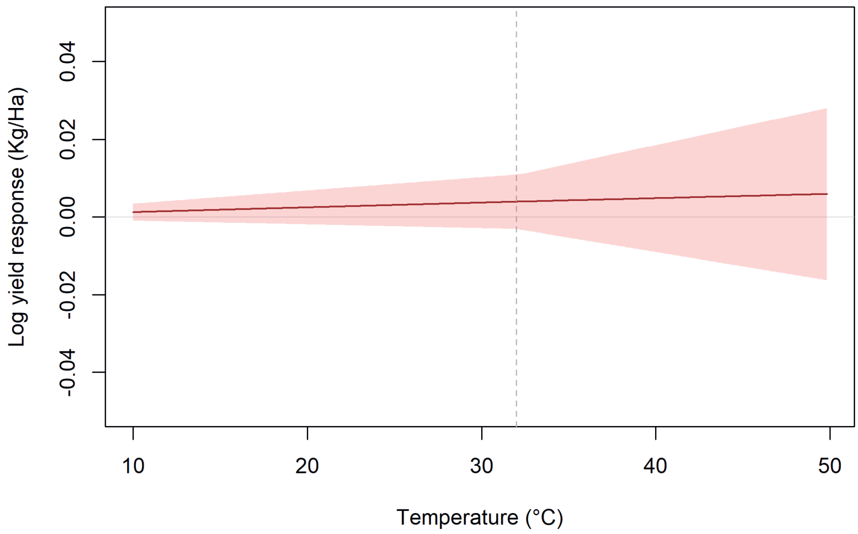
Supplementary table S4.8 Farm fixed effects regression model using growing degree days for wheat yields in the Climate-Smart Agriculture (CSA) farms. Standard errors clustered by farm and year to account for spatial dependence.

Dependent variable	Log (Wheat yield)
Degree days above 27	0.0006 (0.0004)
Year	4,555.9 (1,613.8)
Square of year	-1.129 (0.3999)
Winter rainfall	0.0096 (0.0111)
Square of winter rainfall	-3.36e-5 (4.64e-5)
Observations	522
R2	0.76
Within R2	0.65

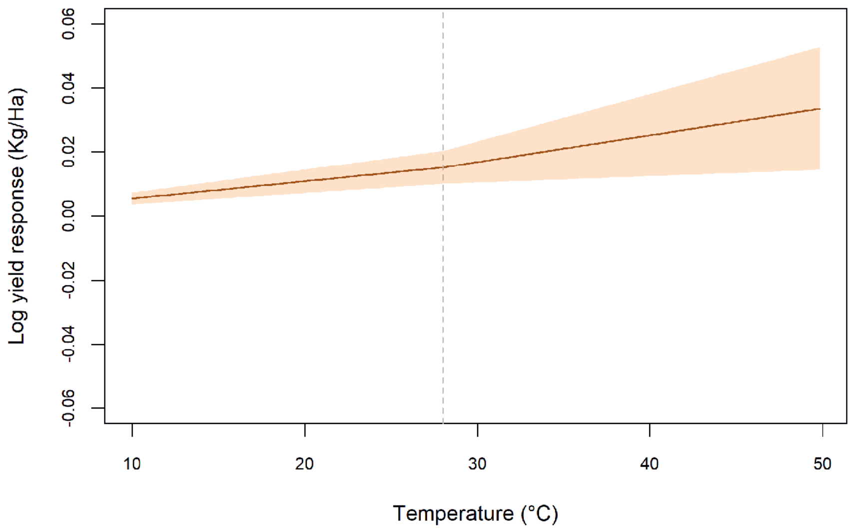
Piecewise linear regression

In the main analysis, restricted cubic splines were used to derive marginal effects of temperature on CSA crop yields. As another robustness check, we replicated the analysis using piecewise linear regression method (Perry et al., 2020), which uses cut-offs (or thresholds) to fit different linear functions across these cut-offs. Supplementary figure S4.11 shows the results for soybean crop, with the cut-off set at 32 degrees. The result shows no significant effect of temperature exposure on soybean CSA yields (consistent across the cut-off). For wheat, a positive effect is observed after the cut-off of 28 degrees, consistent with the findings of the main analysis (Supplementary figure S4.12).

Like the growing degree days analysis, these cut-offs were shifted from 27 to 35 degrees in soybean and 25 to 32 degrees in wheat; and the results remained consistent across these cut-off points for both soybean and wheat.



Supplementary figure S4.11 Effect of hourly temperature exposure in the growing season on soybean yields of Climate-Smart agriculture (CSA) farms, using piecewise linear regression method. The cut-off is represented by the dotted line. The shaded bands indicate 95% confidence interval.

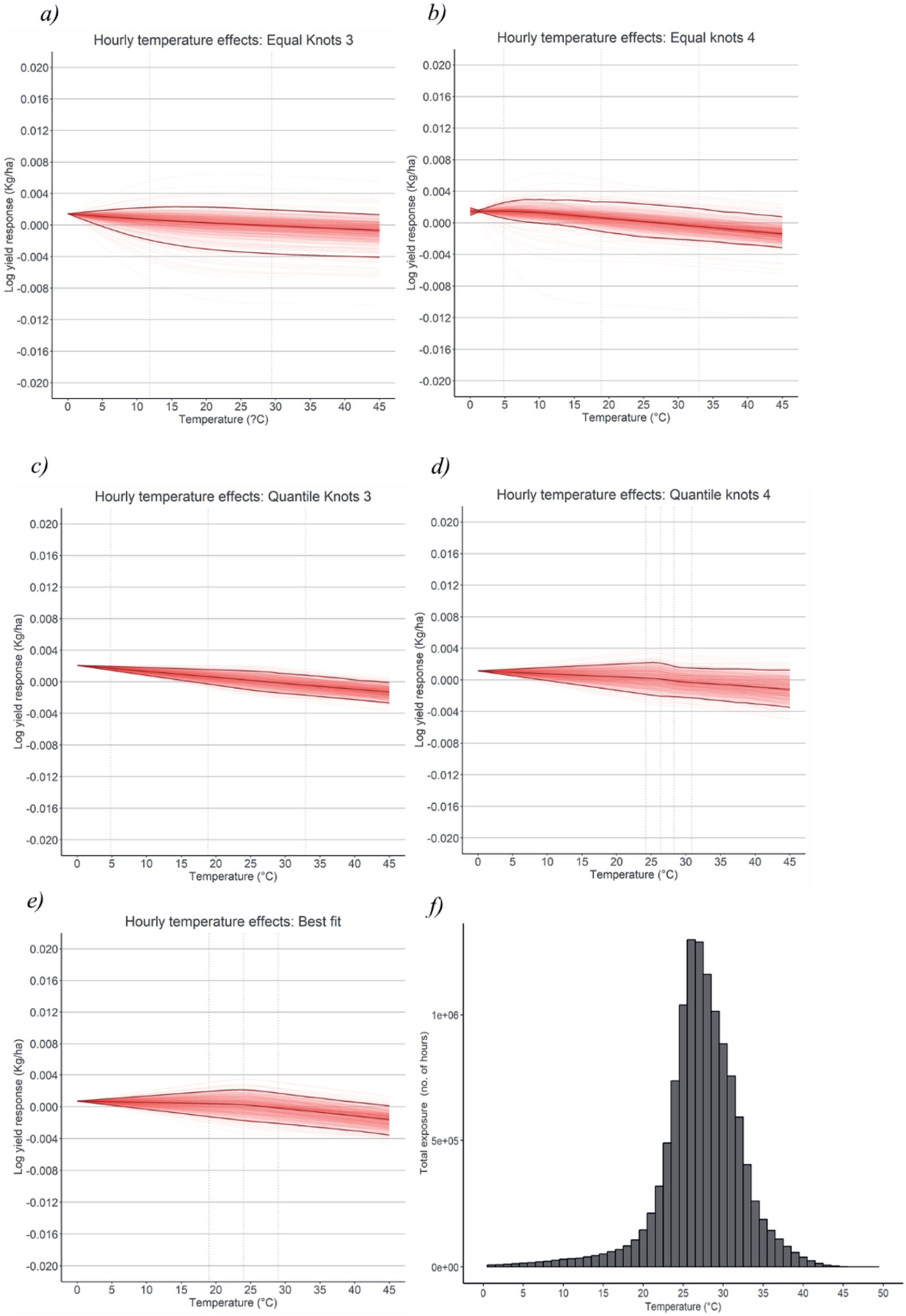


Supplementary figure S4.12 Effect of hourly temperature exposure in the growing season on wheat yields of Climate-Smart agriculture (CSA) farms, using piecewise linear regression method. The cut-off is represented by the dotted line. The shaded bands indicate 95% confidence interval.

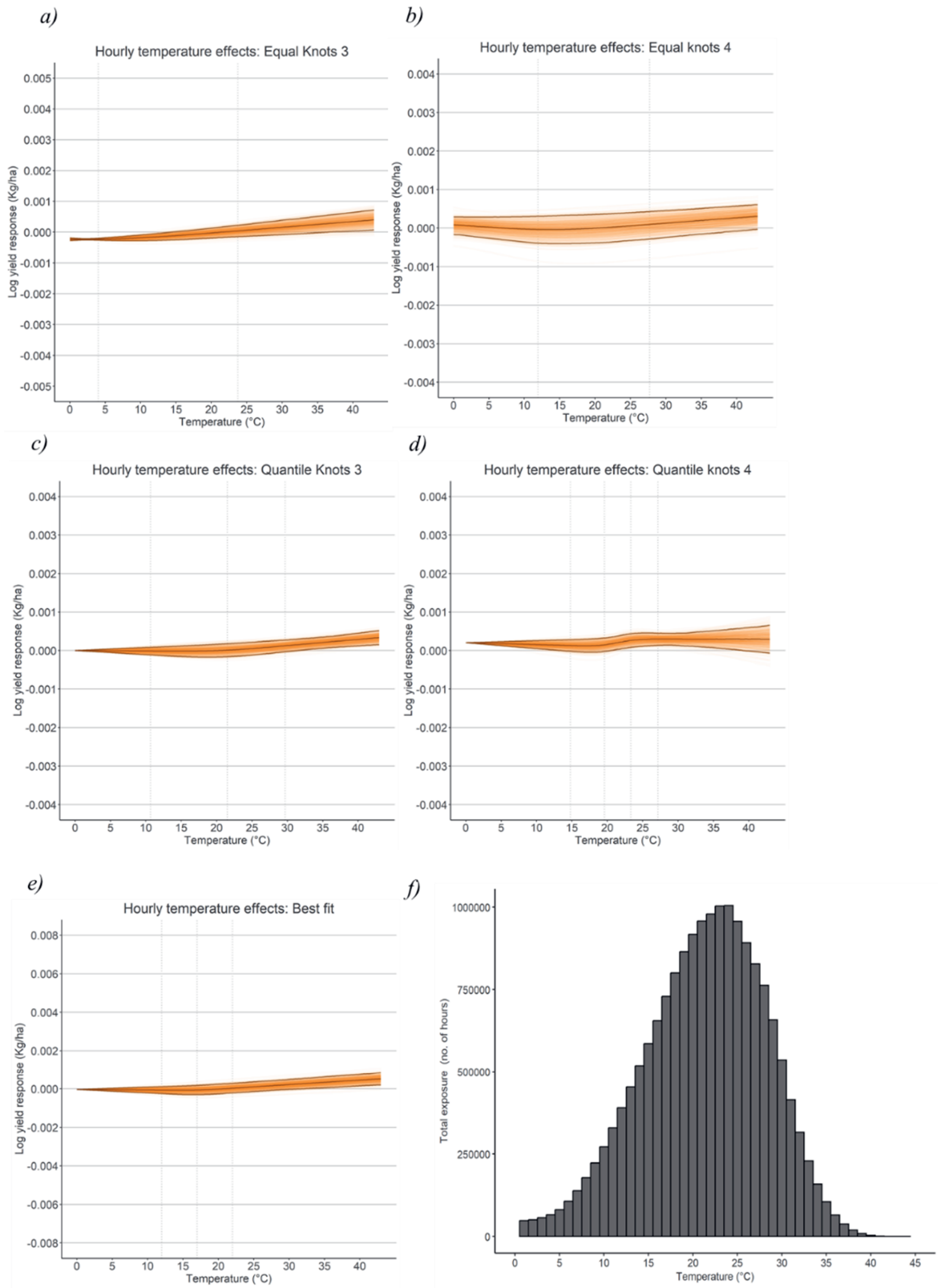
S4.6 District analysis

Robustness checks

Hourly temperature effects were calculated for district yields for soybean and wheat crop in India and as a robustness check, different knot placement strategies were used. Supplementary figures S4.13 and S4.14 show different model specifications for marginal effects of hourly exposure on soybean yields in India, including knot placements at equal, quantile and best fit (lowest RSS locations). All model specifications (with different knot locations) show a consistent negative response of soybean district yields to hourly temperature exposure.



Supplementary figure S4.13 Hourly temperature effects on soybean district yields, based on ECMWF Reanalysis version 5 (ERA5) and Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) weather data: Panel shows different model specifications based on knot locations-a) three equally spaced knots on hourly temperature data, b) four equally spaced knots, c) three knots at 10, 50 and 90% quantile of temperature, d) four knots at 20, 40, 60 and 80% quantile of temperature and e) three knots placed at 5-degree interval which show lowest Residual Sum of Square (RSS) (largest goodness of fit). Plot (f) shows histogram of hourly temperature data for wheat growing season. Knot locations are specified by dotted vertical lines. 95% confidence bands are derived from 1000 block-bootstrapping, with observations blocked by year and district (to account for spatial dependence within a year). The dark line in the middle shows median response function.

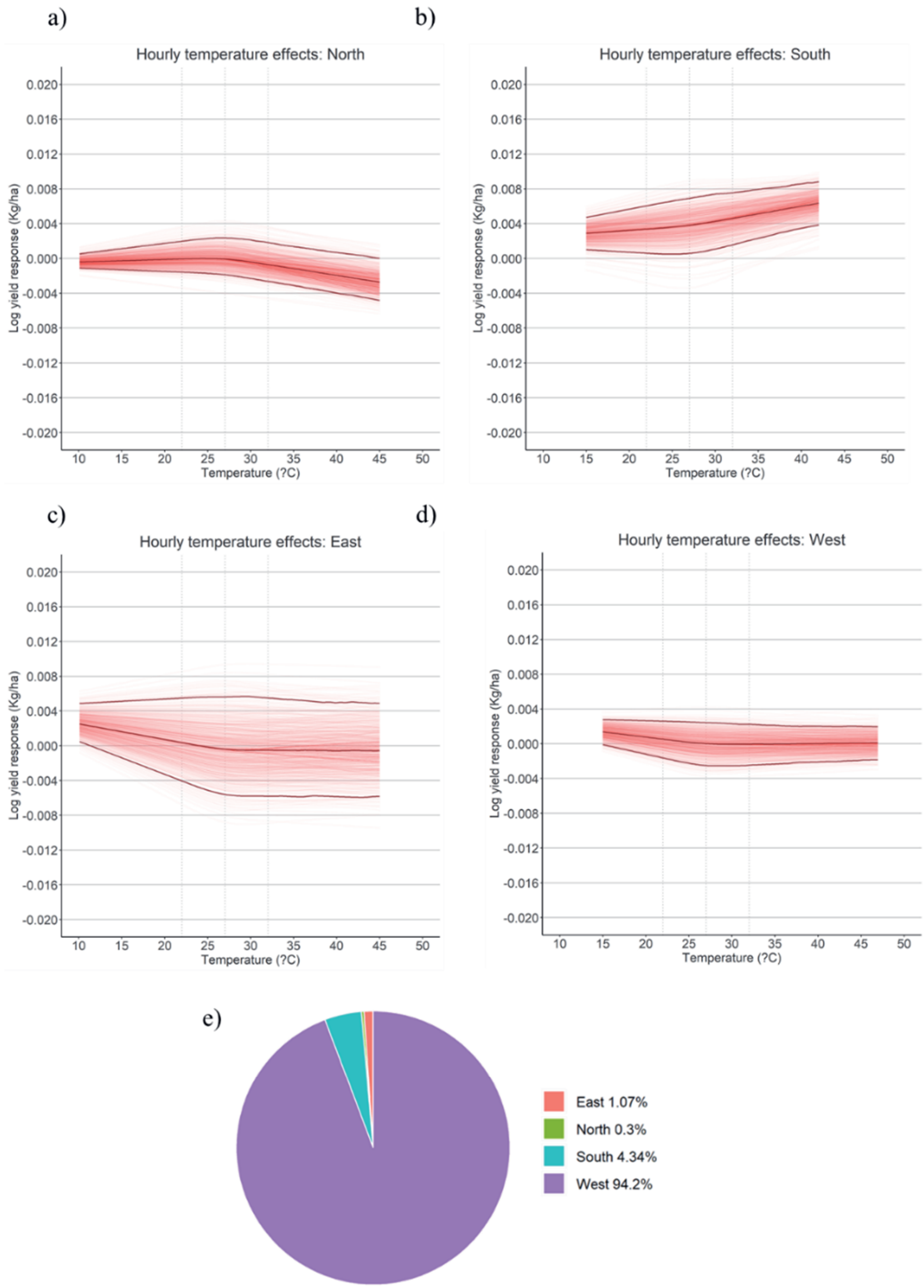


Supplementary figure S4.14 Hourly temperature effects on wheat district yields, based on ECMWF Reanalysis version 5 (ERA5) and Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) weather data:

Panel shows different model specifications based on knot locations-a) three equally spaced knots on hourly temperature data, b) four equally spaced knots, c) three knots at 10, 50 and 90% quantile of temperature, d) four knots at 20, 40, 60 and 80% quantile of temperature and e) three knots placed at 5 degree Celsius interval which show lowest Residual Sum of Square (RSS) (largest goodness of fit). Plot (f) shows histogram of hourly temperature data for wheat growing season. Knot locations are specified by dotted vertical lines. 95% confidence bands are derived from 1000 block-bootstrapping, with observations blocked by year and district (to account for spatial dependence within a year). The dark line in the middle show median response function.

Regional sub-sampling

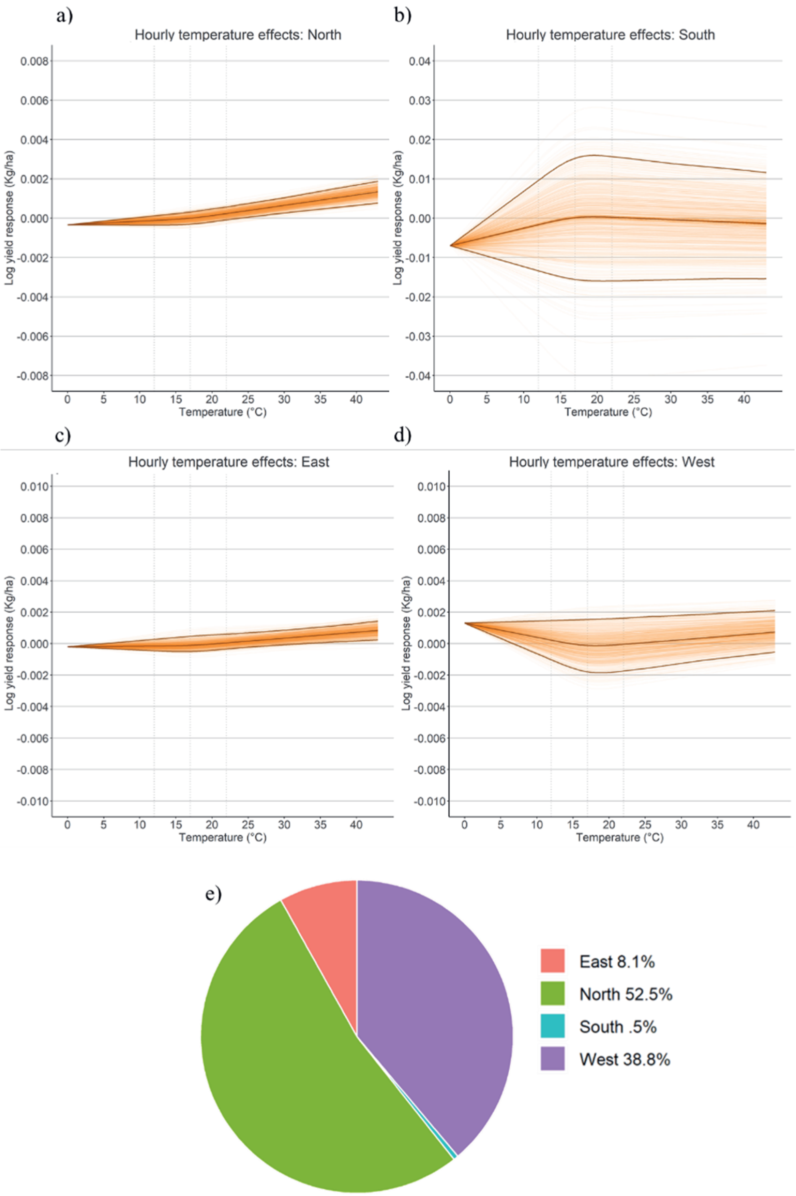
For soybean district analysis, we also repeated the analysis on different geographical sub-samples to understand the impact of heat exposure on different regions in India (Supplementary figure S4.15) Negative effect of heat exposure is observed for all the regions except the Southern region. It is also important to note that majority of soybean growing areas in India are in the western region, which also shows a negative effect of heat exposure.



Supplementary figure S4.15 Hourly temperature effects on regional sub-samples of soybean district yields based on ECMWF Reanalysis version 5 (ERA5) and Climate Hazards Group InfraRed Precipitation with Station

(CHIRPS) weather data: Panel shows geographical sub-sampling based on different regions-north, south, east, and west. Knot locations are specified by dotted vertical lines and based on the best-fit model. 95% confidence bands are derived from 1000 block-bootstrapping, with observations blocked by year and district (to account for spatial dependence within a year). The dark line in the middle shows the median response function. The pie chart shows the soybean area under cultivation in each region.

Similarly for wheat, analysis by different geographical sub-samples (Supplementary figure S4.16), positive effect of heat exposure is observed for all the regions except the Southern region. It is also important to note that the southern region, accounts for only .5% of total area under cultivation.



Supplementary figure S4.16 Hourly temperature effects on regional sub-samples of wheat district yields based on ECMWF Reanalysis version 5 (ERA5) and Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) weather data: Panel shows geographical sub-sampling based on different regions-north, south, east, and west. Knot locations ae specified by dotted vertical lines and based on the best-fit model. 95% confidence bands are derived from 1000 block-bootstrapping, with observations blocked by year and district (to account for spatial dependence within a year). The dark line in the middle shows the median response function. The pie chart shows the wheat area under cultivation in each region.

Chapter 5

How do production systems recover from production shocks? A global recovery analysis

Adapted from Vyas, S., Meuwissen, M.P.M., Ramirez-Villegas, V., Kropff, M., Dalhaus, T., 2024. Will be submitted to a journal.

Abstract

Farm production across the world is affected by sudden losses from weather extremes, geopolitical and socio-economic events, with increasing fragility from climate change as an additional risk multiplier across many regions. To quantify the resilience of national food production, we conducted a global analysis of maize and milk production systems spanning over six decades, using statistical shock detection and survival analysis. Our results show that maize production systems recover faster than milk production systems at a global scale (likelihood of recovery in one year is 58% for maize, compared to 45% for milk production), despite maize production systems having greater shock exposure and intensity. Latin America and Sub-Saharan Africa are hotspots of high shock exposure, intensity, and likelihoods of longer recovery time across both maize and milk production systems. The findings further reveal distinct sub-regional recovery features in high-income regions including longer recovery likelihoods in Southern Europe for maize and Western Europe for milk production. Our results remain consistent across robustness checks and largely suggest that resilience to production shocks at the global scale requires highly differentiated approaches to address region-specific shock types, vulnerabilities, and adaptive capacities, as well as to account for unique system-specific production system characteristics.

Keywords: Recovery, resilience, maize, dairy milk, production systems

5.1 Introduction

Food supply chain disrupting events such as extreme weather, violent conflicts, geopolitical crises, or global pandemics can cause substantial production shocks within food producing countries (W. B. Anderson et al., 2019; Laborde et al., 2021; Mishra et al., 2021; Osendarp et al., 2021). Productivity losses aside, these events influence food security (Hasegawa et al., 2021), disrupt the stability of food supply chains and markets (Janssens et al., 2020; Kent et al., 2017). The resilience of farm production critically underpins positive food systems' outcomes including food and nutritional security (Cottrell et al., 2019). Depending on the magnitude or extent of the shock, production systems' resilience can be achieved through robustness (ability to withstand), adaptability (ability to partially change), and/or transformability (ability to change the entire structure) as a response to stress or external shocks (Meuwissen et al., 2019). Resilience of farm production systems has been researched (Cottrell et al., 2019; Lesk et al., 2016; Slijper et al., 2022; Zampieri et al., 2020) at multiple scales and for several types of shocks, with a substantial focus on understanding and assessing (synchronous) shocks. Whereas assessing shocks and their impact is important to understand risks to trade systems and global food security, evidence on after-shock recovery is generally lacking. Such data can be vital for policy planning, international aid, and resilience and recovery programming.

In this chapter, we focus on the recovery of maize and livestock milk production systems across the world. Maize and milk production systems are critical for food, income, and nutrition for over 4.5 billion people globally; together, they contribute to nearly 50% of the daily caloric intake, especially in low- and middle-income countries (LMICs). Notably, mixed maize-livestock production systems feature in substantial parts of many agricultural landscapes in LMICs, especially in Africa (Sekaran et al., 2021; Thornton & Herrero, 2015). In this study, we add to the previous literature on farm resilience by quantifying the recovery likelihood (i.e., the likelihood of reaching pre-shock production levels) in the years after a production shock for both maize and milk production (see Table 5.1 for a list of key concepts). The analysis covers substantial production drops without explicitly attributing this to a causal event, which allows us to understand the robustness of food production for food security planning and to identify hotspots that require particular attention regardless of shock type and effect. The analysis seeks to (i) identify production shocks, recovery time, and recovery likelihood functions (after production shocks) for maize and milk production systems across the globe; (ii) assess differences in recovery likelihood functions for different sub-regions (in addition, we also highlight specific countries as case-studies) for both maize and milk production systems; and (iii) identify sub-regional hotspots based on co-occurrence of low recovery likelihoods in both maize and milk production systems. Based on survival analysis (Clark et al., 2003), therefore, we produce the first global analysis of maize and milk resilience (i.e., shock recovery) to date.

5.2 Data and methods

Key concepts

We focus on recovery likelihood functions of maize and milk production globally. We define each concept used in this analysis (including production shock, shock intensity, recovery time and recovery likelihood) in Table 5.1.

Table 5.1 Key concepts used in this analysis and their description.

Key concepts	Definition
Baseline production	A rolling median of previous 3 years' production value, excluding the current year
Expected production trend	Expected production trend is based on local polynomial fit of production values, to corresponding year
Cook's distance	A statistical measure that helps in identifying the influential data points in a time series
Production shock	A significant negative deviation from the expected production trend. The production shock should have a value less than the baseline production value and have a Cook's distance value of > 0.1 (indicating significant deviation from the expected production trend)
Shock size	Magnitude of drop in production, relative to the baseline production. The magnitude of loss in production is normalized relative to the baseline production value
Recovery time	In the years following a production shock, the time taken (in years) to reach at least 95% of baseline production (before the shock). In the case of consecutive shocks, where an additional shock occurs before the recovery from the preceding shock, the recovery time is extended to account for the compounded impact from both shocks
Recovery likelihood	At any given time (t), it is the probability that the production system will recover to at least 95% of its baseline production value within time t (for example, for t=1 the recovery likelihood is the probability that the production system will recover to 95% of the baseline in 1 year). The recovery likelihood starts from 0 and approaches 1 subsequently over time (indicating a full recovery). For cases where full recovery is not observed, the curve ends at the last observed t and the subsequent time steps are not calculated

Data

We gathered global datasets on maize and livestock (dairy milk) production per country from 1961 to 2021 from the United Nations Food and Agriculture Organization (FAO) statistical database (FAOSTAT)[15]. After collecting production data on maize and milk production systems, country identifiers are checked (country names and ISO codes) for any discrepancies (due to political factors such as change in country boundaries or names) (summary statistics by sub-regions are provided in Supplementary table S5.1 and S5.2). For some identified countries, the names/ISO codes are merged and for all the data, additional variables of region and sub-region names are added. The sub-regions are identified using the UN Geoscheme[16]. Using the data, we then detect production outliers and flag these as shocks. Finally, we estimate reverse Kaplan-Meier recovery functions at the global and sub-regional level, which provide the likelihood of recovering from a shock per year.

Production shock identification

We follow Cottrell et al. (2019) to identify production shocks based on a regression approach that flags influential outliers. For each country, we estimate a local polynomial regression (LOESS) model of the total production against years and thereby obtain a very flexible smoothed trend line (Cottrell et al., 2019). LOESS is a commonly used non-parametric regression technique, without strong assumptions on the distributional form of data. It locally fits (to a subset of data) a weighted least square regression, with a window of data points around each point being smoothed (the length of this window is often denoted as α, or the span). The weighted least square is fit within this window and reiterated for each data point, allowing the fitted curve to adapt with variations in the data points. Mathematically, LOESS can be represented as (Equation 5.1):

$$y_i = f(t_i) + e_i \qquad (5.1)$$

Where y_i is the production value, t_i is the year, $f()$ is the smooth function and e_i is the residual error between observed and predicted value for the i-th observation(Mehrabi & Ramankutty, 2019).

[15] http://faostat3.fao.org/download/Q/QC/E
[16] https://en.wikipedia.org/wiki/United_Nations_geoscheme

The weighted least square function is fitted locally around a subset of the data, with a window centered around y_i. The distance from y_i determines the weight assigned to each data point (in the window). The weights are assigned based on the "tricube" method. Using a tricubic weighting function, the weights decrease as the distance from y_i increases. This process is applied to all data points, until a smooth curve is obtained that covers all the local variations in the data.

We use a value of α=0.6 (i.e., 60% of data points are used to fit each local polynomial). This parameter controls the degree of smoothening with a larger value leading to a smoother curve which is less sensitive to local variations or outliers. The residuals are then regressed against the lag-1 residuals, to calculate Cook's distance. Mathematically, Cook's distance measure D_i is an aggregated influence measure, calculated using Equation 5.2.

$$D_i = \frac{\sum_{j=1}^{n}(\hat{Y}_j - \hat{Y}_{j(i)})^2}{p.MSE} \tag{5.2}$$

Where D_i is the Cook's distance for the i-th observation, n is the total number of observations, $\hat{Y}_j$ is the predicted value for the j-th observation including all the data points, $\hat{Y}_{j(i)}$ is the predicted value for j-th observation from the model calculated without the i-th observation, p is the total number of predictors (in this case only 1-for lagged residuals) and MSE is the mean square error of the model (Kutner et al., 2005).

Using this method, the observations with Cook's distance value above 0.1 and production values less than the baseline median production (highlighting losses in the production time series) are identified as production shocks (Altman & Krzywinski, 2016; Elrys et al., 2023). This is undertaken for each country and production system (maize, milk production) separately. The Cook's distance threshold of 0.1 is chosen after conducting a sensitivity analysis of change in the Cook's threshold value and number of production shocks identified. Similar to Cottrell et al. (2019), we chose the value of Cook's distance when the curve between Cook's distance and number of shocks begins to flatten out (asymptote). For each data point in the time series the following variables were thus estimated: LOESS fitted production, residuals and their lag, Cook's distance value, shock point (identifier variable with binary values as True or False).

After identifying the production shocks, we also calculate the shock size (Cottrell et al., 2019). This is performed by calculating the magnitude of loss in the shock year (as identified above), normalized by the baseline production value (Equation 5.3). Mathematically, it can be shown as (Equation 5.3):

$$S = (P_b - P_t)/P_b \tag{5.3}$$

Where S is the normalized shock size, P_b is the baseline production value (previous 3-year median at time t) and P_t is the production value at time t.

For selected shocks and countries, we identify coincidental natural or socio-political events that occurred in the same year of the shocks. We consult three global databases to identify events which co-occur with production shocks—the first is a global database on observed disaster events[17], the second is global data for armed conflicts and crisis events[18] and finally, we used the database of events already identified by Cottrell et al. (2019). We randomly select countries from different sub-regions for both maize and milk and identify the (likely) associated event, from these three sources. We do this to illustrate how selected events can possibly be associated (among other factors) with production shocks. However, we do not imply any causality; exploring attribution or causality is outside the scope of this study.

Calculating recovery time

After identifying production shocks in a country's time series data, we calculate recovery time for each shock point (see Table 5.1 for definitions). A rolling median over a window of 3 years is calculated as the baseline, and recovery time is defined as the time taken in years (duration) from the occurrence of shock, until the production reaches at least 95% of the rolling median baseline (Cottrell et al., 2019) (Equation 5.4).

$$RT = min\{t > 0 \mid P_t \geq 0.95 \times median(P_{t-5:\,t-1})\} \tag{5.4}$$

Where RT is the recovery time for each production shock and P_t is the production value at time t.

This results in calculation of recovery time for each production shock. However, there are instances where consecutive production shocks are identified with overlapping recovery time (a second shock resulting in an even lower production value than the first shock). Since our

[17] https://public.emdat.be/data
[18] https://acleddata.com/

analysis is based on the likelihoods of recovery time (recovery probabilities), these 'nested' or consecutive shocks can lead to erroneous results, as any shock identified after the first would be considered less significant than they are, given that the country is still recovering from the initial shock. For such instances, we calculate the combined recovery time for consecutive shock years to a single value and treat it as a single shock event, akin to previous studies (Lesk et al., 2016). Each data point in the time series where a shock is identified is assigned a rolling median baseline, a shock size, a recovery time (in years), and a modified recovery time (after dealing with consecutive shock years). It is important to note that for some production shocks, recovery time is not observed in the study time-period. This can be due to many factors—significant area and/or land-use changes (for example, a country systemically stops producing maize), observed shock events near the end of the study period (for example, a shock identified in 2020), and the country still undergoing recovery (right censoring of the data-beyond the time-period of this study). For each country, we show the actual production values, the residual fit against the lag and the Cook's distance value for each observation (Supplementary information S5.4).

Recovery likelihood

The final step in the analysis is the computation of recovery likelihoods. We use reverse Kaplan-Meier analysis to estimate functions that show recovery likelihoods after production shocks in subsequent years. The recovery likelihood at time *t* is defined as the probability that the production recovers to 95% of the pre-shock baseline value within time *t* (also see Table 5.1 for definitions). In practical terms, this can also be seen as the probability of the shock's effects until time *t*.

Survival analysis (the methodology used here) is a specialized time series analysis in which the main outcome of focus is the event of interest (Bland & Altman, 1998; Garcia et al., 2024; Key & Roberts, 2006). In our model, we use recovery (production reaching 95% of the baseline (Cottrell et al., 2019), which is the rolling median) as an event of interest, and the time variable as recovery time. The Kaplan-Meier function is a step function which computes survival likelihood at each year after the shock (Equation 5.5)

$$SL_t = \prod_{t_i \leq t}\left(1 - \frac{d_i}{n_i}\right) \tag{5.5}$$

Where, SL_t is the survival likelihood until time t (probability that the recovery time from the production shock is equal to or longer than t), t_i are the distinct time steps at which recovery occurs, d_i is the number of recoveries that happen at time t_i, and n_i is the number of observations just before time t_i.

Using this estimator, the recovery likelihood is calculated at each time step (year 1, 2, …, n); the overall recovery probability is calculated by multiplying the probabilities of recovery at each time step up to time t. The Kaplan-Meier method is non-parametric (i.e., it does not assume a specific distribution) and considers data censoring (in this case, for instance, a country where no shock is observed within the study period). It is widely used to estimate the survival probabilities. The result from this estimator can be represented by a stepwise graphical function of survival probability over time, represented as a Kaplan-Meier graph. However, in our study, survival probability is counterintuitive, as our focus is on the recovery likelihood (the probability that the production recovers *within* time t). Therefore, we compute recovery likelihood RL_t simply as 1- SL_t. We therefore produce reverse Kaplan-Meier graphs, where the graph shows time at the X-axis and the recovery likelihood at the Y-axis, with each time step representing the observed time-period. Therefore, the curve increases over time, approaching one (i.e., full recovery) as the time increases. This fundamentally means that the longer the recovery likelihood curve is, the more difficult (i.e., less likely) it is for the country to recover. It thus follows that longer recovery times would typically be associated with larger, more impactful shocks, and less capacity to respond (lower resilience levels).

We calculate the reverse Kaplan-Meier curves at global scale for maize and milk production separately, pooling recovery time and event data (production shock) for each country across the globe, to compare the recovery probabilities of maize with those of livestock milk production. To highlight sub-regional differences and/or vulnerabilities, the reverse Kaplan-Meier estimates are also stratified based on sub-regions. This pools the data together for countries belonging to a specific sub-region. Sub-region definition follows the United Nations Geoscheme.

Robustness and sensitivity checks

We explored the sensitivity of the results from the analysis to the choice of model parameters and thresholds used. To make sure our results are robust to these assumptions, we employ a series of robustness checks by changing different parameters at each step of the methods described above. We vary the rolling median window for baseline production (we use 3, 5 and 7 years) and the LOESS span (0.4, 0.6, 0.8) and re-compute the analyses. We assess the variability in shock detection, recovery times, and recovery likelihoods resulting from varying these parameters.

5.3 Results

Shock exposure

Our results show that most countries (68% for maize, 54% for milk production) have experienced at least one shock during the study period (Figure 5.1). For maize, high exposure to production shocks is seen in Sub-Saharan Africa, followed by Latin America and the Caribbean. A high number of shocks (3 or more) is seen in Central and Eastern African countries including Malawi, Zambia and Kenya and Western African countries such as Gabon, Ghana. In Asia, Afghanistan, Nepal, and Japan also show a high number of production shocks. Selected production shocks (shown as an example) coincide with weather extremes such as droughts, heat stress and floods, while others are concurrent with armed conflict events (text insets in Figure 5.1A). Milk production is less exposed to shocks as compared to maize systems (Figure 5.1B), but it shows similar regional features compared to maize production, with the highest number of shocks occurring in Sub-Saharan Africa and Latin America. Countries with a greater number of shocks (more than 2) include Somalia, Angola, Argentina, Colombia, Germany. Some of these production shocks happen together with weather-related disasters, livestock epidemic outbreaks and conflict events (see text insets in Figure 5.1B).

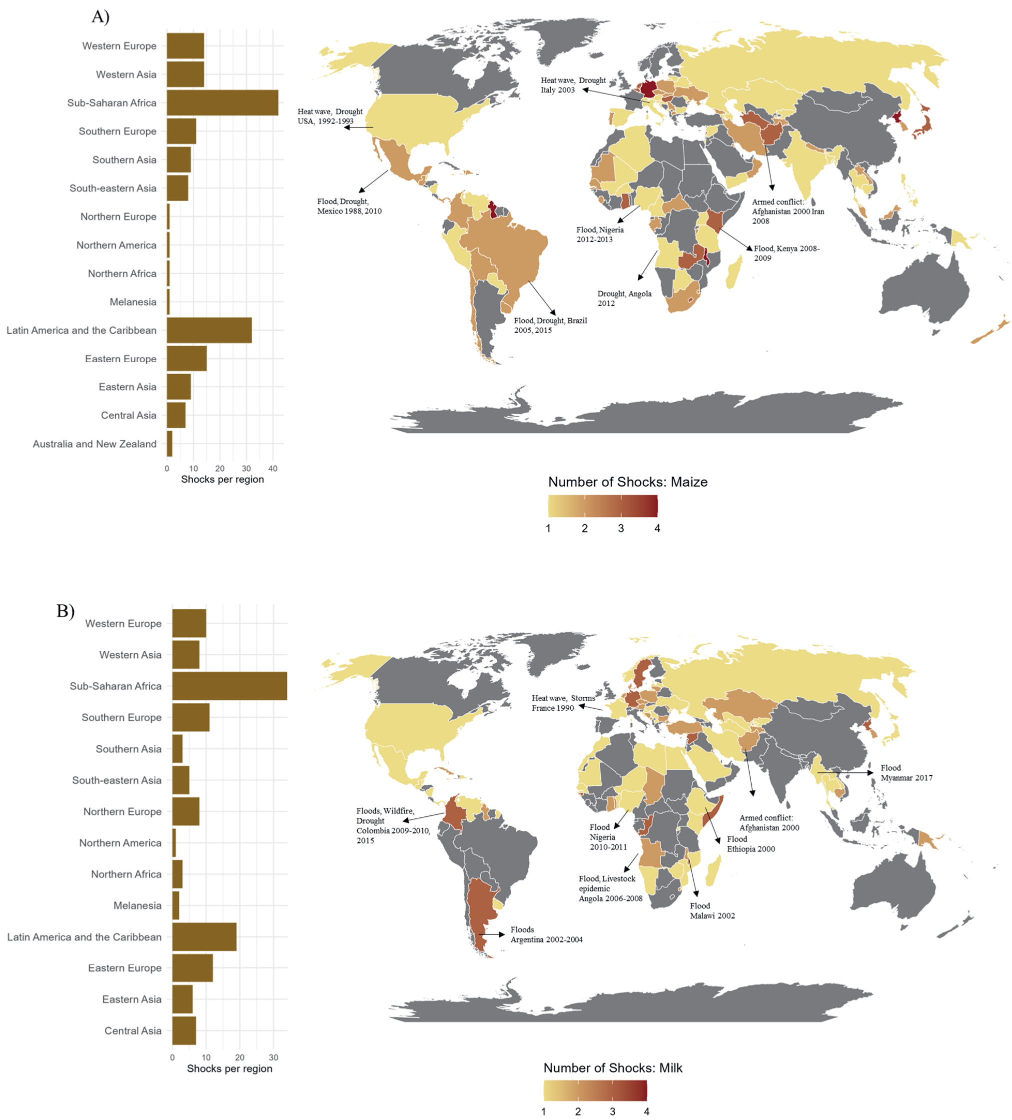


Figure 5.1 Map showing exposure to national production shocks in A) Maize and B) Milk production systems. The left inset shows cumulative shock frequency in the study time-period (1961–2021) aggregated at sub-regional level. Gray color indicates no shock occurrence. The text insets on the maps show co-occurrence of observed events like weather-related disasters, armed conflicts, and livestock epidemics with a production shock in the same year. Please note that this is only shown for some countries as an illustration.

Shock size and recovery time

On average, the shock size observed in maize production systems is significantly more intense than milk production (Figure 5.2A). For maize, the highest magnitude of losses (up to 40% relative to the baseline production) is observed in Northern and parts of Southern Africa (Algeria, Angola, Botswana, South Africa, Zambia,), Central Asia (Kazakhstan). For milk production, the shock size is highest in Northern Africa (Chad, Libya, Mauritania) and Central Asia countries (Afghanistan, Iran) (up to 25% relative to the baseline production) (Figure 5.2B).

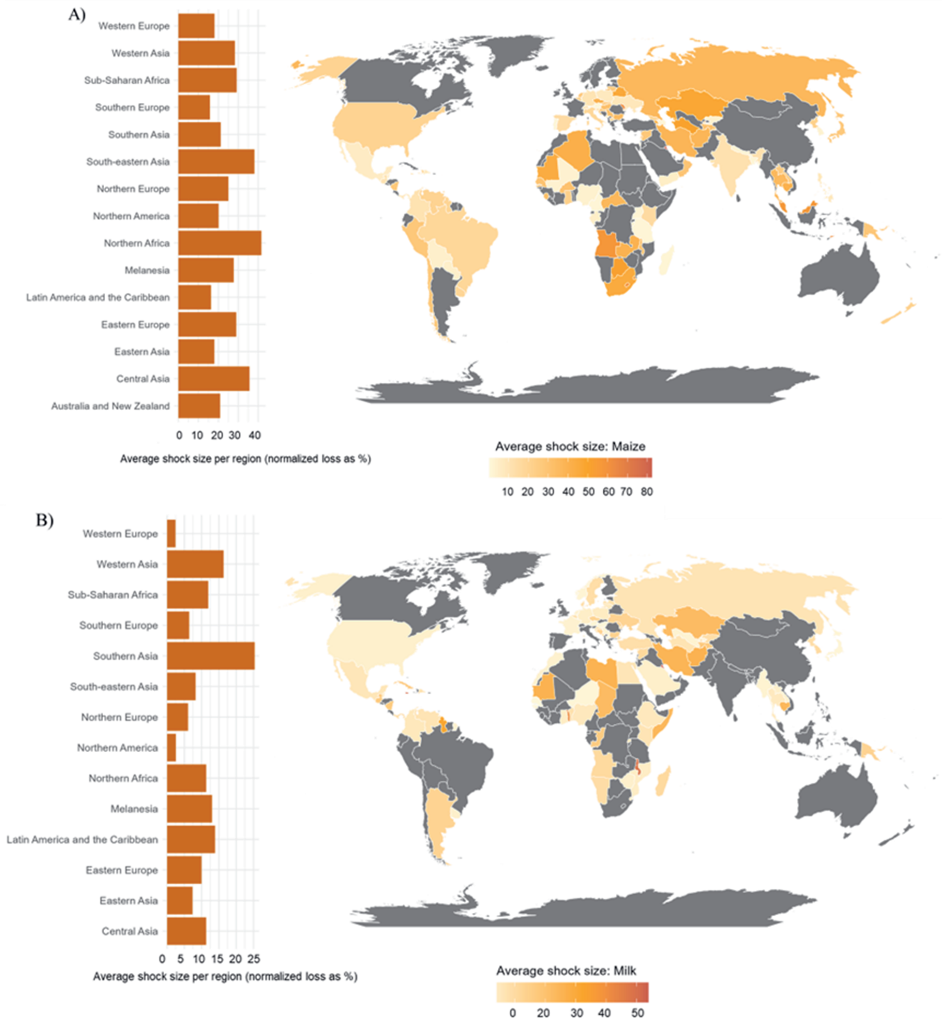


Figure 5.2 Map showing average shock size observed in the study time-period in A) Maize and B) Milk production systems at national level. The left inset shows average shock size observed in the study time-period (1961–2021) aggregated at sub-regional level. The shock size is normalized relative to the baseline production level and expressed as percentage. Gray color indicates no shock occurrence.

Figure 5.3 shows average recovery time (in years) from shocks for maize and milk production. On average, recovery time for maize production is faster than for milk production systems, even when the shock intensity is observed to be higher for maize systems. This is probably due to the nature of production systems—maize is a short season crop, with a new growing cycle every year. By contrast, a shock in milk production that affects the function of animals or their ecosystems (e.g., rangeland) can lead to a disturbance for many years. Thus, the recovery is generally prolonged for milk production because it can take many years to stabilize the herd size, health, or the ecosystem productivity after a disturbance (floods, drought, or epidemics). Livestock is also costlier than maize to replace in case of death, which can happen under extreme consecutive drought years, flood events, or epidemics. The average recovery time for most countries for milk production is almost double than that of maize production (less than four years for maize and upto 10 years for milk production) (Figure 5.3).

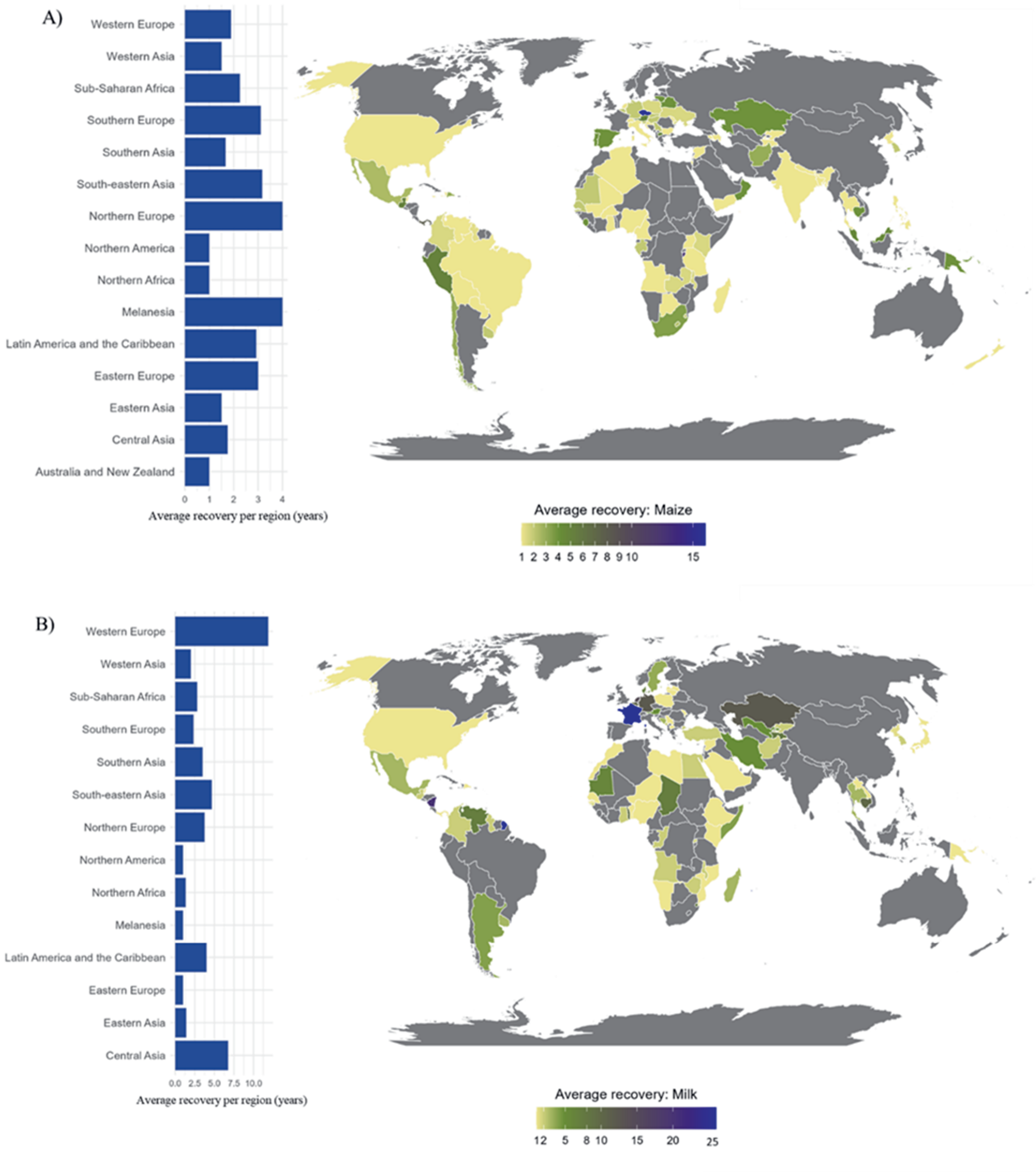


Figure 5.3 Map showing average recovery time (in years) from national production shocks in A) Maize and B) Milk production systems. The left inset shows average recovery time in the study time-period (1961–2021) aggregated at the sub-regional level. Gray color indicates no shock occurrence.

Global and sub-regional estimates of recovery likelihood

Globally, maize production appears to be more resilient than milk production (Figure 5.4). The results show that maize production systems recover faster than milk production systems. This is also seen previously in the results for recovery time (Figure 5.3). Recovery likelihood at t=1 (i.e., the probability of recovery in one year), for example, is 58% for maize, compared to 45% for milk. Recovery likelihood at year t=2 is 76% for maize, and 64% for milk (Figure 5.4). This is due to the systemic differences in the nature of the two production systems (as described previously). The statistics for the recovery likelihoods and confidence intervals are provided in Supplementary information (Supplementary table S5.3 and S5.4).

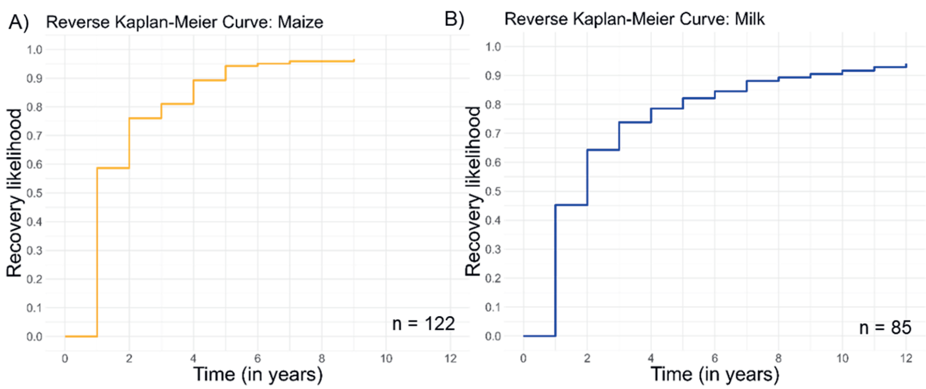


Figure 5.4 Global functions of recovery likelihoods for maize (A) and dairy milk (B) production, shown as reverse Kaplan-Meier curves, n is the number of shocks observed. The X-axis is limited to 12 years (as most of the recovery happens within this time-period, for full recovery likelihood graphs and statistics please refer to the Supplementary figure S5.3).

Expectedly, large differences are observed in the recovery likelihood between world sub-regions (Figure 5.5) and different recovery features become apparent. First, the recovery likelihood at each year across sub-regions and commodities is indicative of their level of resilience to the production shocks. Secondly, the total length of time for the production system to reach a recovery likelihood of 100% (time to full recovery) is another important recovery feature. Finally, a steeper curve indicates a faster ascent and hence quicker recovery. The reduction in recovery likelihood between immediately subsequent years also suggests changing levels of resilience to shocks and possibly shock intensities. A plateau in the curve suggests that after a given point of time (t), it is highly unlikely that production system will ever recover.

These features become apparent (Figure 5.5) across different sub-regions for both maize and milk production. Across all regions (except Europe), the maize curve is to the left of the milk production curve, indicating quicker recovery of the first (in regions with sufficient sample size, i.e., n=4 or above). For maize production, the recovery likelihood at t=1 is highest for Southern and Western Asia at 83%. This can be due to low exposure and lower shock intensity observed in these two sub-regions as also shown in Figures 5.1 and 5.2. The curve reaches full recovery within 6 years in both regions. Southeast Asia, on the other hand, shows a very low recovery likelihood at t=1 (33%). However, a sharp ascent is observed in subsequent years, reaching 100% recovery likelihood by t=4, which indicates that most of the recovery happens between this time-period (t=1 and t=4). This might be related to the fact that a higher shock intensity is observed in this region, as compared to Southern and Western Asia.

Latin America and Caribbean show a recovery likelihood of 57% at t=1. After this time, the curve is stable and rises gradually until t=6, again highlighting longer recovery times in this sub-region. It also has lower shock intensity on average, but very high shock exposure. This indicates that the sub-region experiences very frequent shocks, affecting the recovery and overall resilience of maize systems. A similar curve is observed for Sub-Saharan Africa, although the recovery likelihood at t=1 is slightly higher (62%), and it takes even longer to fully recover (beyond t=9). This sub-region faces a considerably higher degree of shock intensity, along with high shock exposure. Consequently, the resilience of these two regions to maize production shocks appears to be very low.

For Southern Europe there is a 44% recovery likelihood at t=1. However, a steep ascent is observed at t=2 (66%), showing that some shocks recover within this time window. The curve ends at t=9, indicating that maize production can fully recover within this time-period. The shock intensity is observed to be comparatively lower (18%) in this sub-region, and the overall recovery curve is long, with long recovery time specifically observed in two countries—Portugal and North Macedonia. The production shocks co-occur with the years of extreme weather events such as drought, wildfire, extreme cold and floods in these two countries, which could be the cause of the long recovery times observed. For Western Europe, the curve starts lower at 55% at t=1, showing overall higher resilience as compared to Southern Europe in year 1. The curve subsequently approaches 0 by t=5, suggesting full recovery takes roughly half the time than in Southern Europe. For all the sub-regions, except in Southern Europe, Latin America and Caribbean, and Sub-Saharan Africa, the likelihood curve tends towards 0 within 5 years.

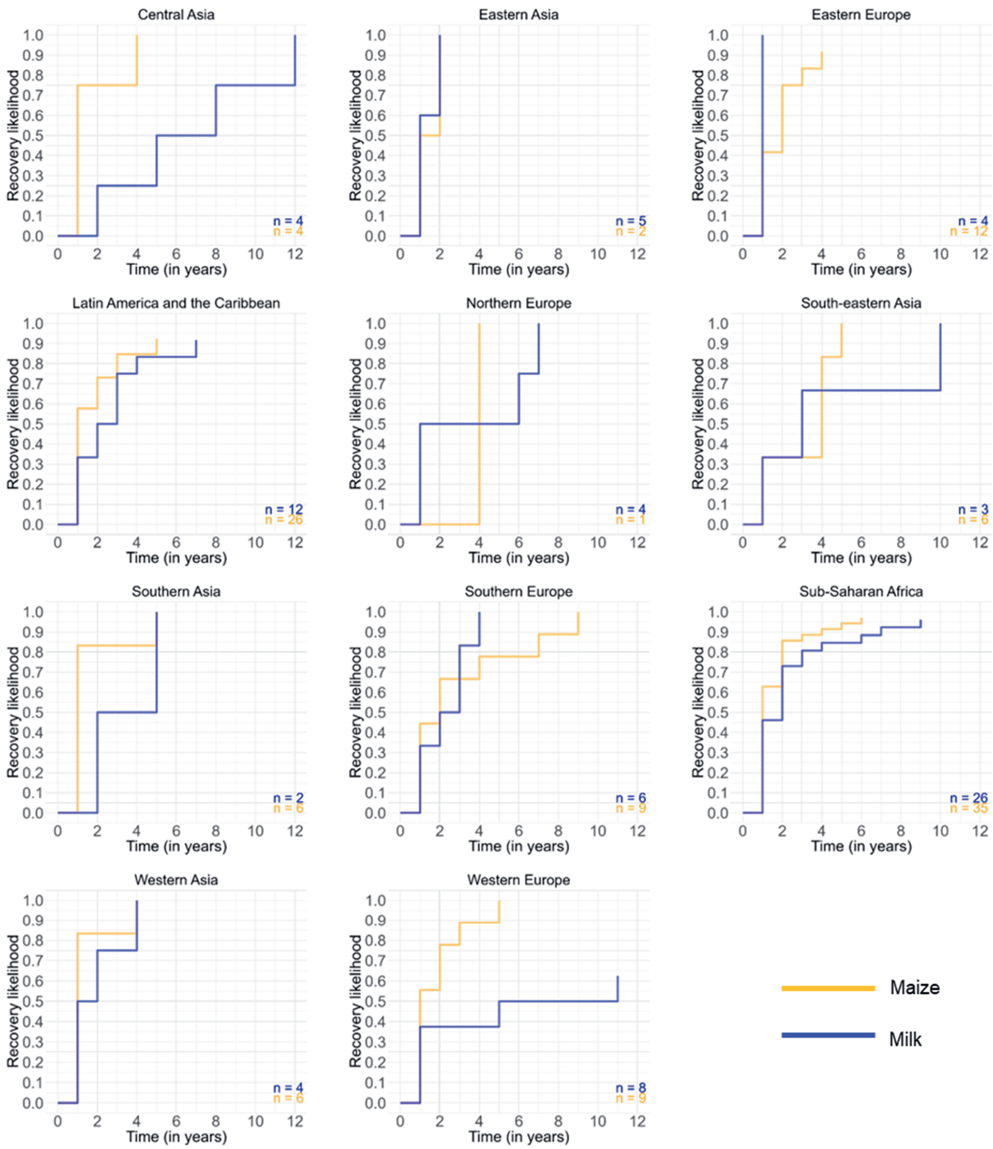


Figure 5.5 Sub-regional reverse Kaplan-Meier functions showing recovery likelihoods for maize (orange) and milk (blue) production, n is the number of shocks observed.

For dairy milk production, the recovery likelihood curves are (in general) much longer as compared to maize production. The recovery likelihood at t=1 is generally lower across all the sub-regions (less than 50%), showing that most sub-regions take longer to recover. Across all the sub-regions, this value at t=1 is highest for Northern Europe (50%) and Western Asia (50%). Shock frequency for both these sub-regions is lower when compared to others. However, Northern Europe experiences high shock intensity over other sub-regions. This implies that this sub-region has high adaptive capacity to recover even from intense shocks (Thiault et al., 2019; Varis et al., 2019). For Northern Europe, the curve is constant after t=1 and until t=6, and then rises rapidly showing complete recovery within 7 years. Western Asia has a very steep curve which rises rapidly and approaches 1 by t=4, showing complete recovery in the sub-region. Similarly, Southern Europe also has a very steep curve which rises rapidly and approaches one by t= 4, indicating complete recovery within this time frame. The curve for Southern Europe however starts at a value of 33% at t=1, highlighting that most of the recovery happens in the later years (t=3 to 4). Incidentally, the shock size for Southern Europe is very low (5%) (Figure 5.2).

For Central Asia, the curve indicates that recovery starts very late in this sub-region, with the value of 25% at t=2. The curve is equally spaced with gradual ascent, and even at t=10, the recovery likelihood value is 75%, showing recovery extends beyond this time frame (or do not fully recover at all). The shock size in Central Asia is high at 10%, and some of the shocks observed in the sub-region also co-occur with geopolitical events such as armed conflict and wars, which likely explains the long recovery. Latin America and Caribbean experiences a high number of shocks and has an elongated curve, with no drastic ascent. The curve starts at the value of 33% at t=1, and starts gradually rising after t=3, ultimately reaching 91% at t=10—this shows that most of the recovery in the sub-region happens within this time frame. It also has high shock intensity at the average value of 10%. Sub-Saharan Africa shows a similarly featured curve. However, for this sub-region, steep ascents are observed between t=1 and t=2, showing that a lot of countries recover within this time frame (73% by t=2), with full recovery beyond t=9. The average shock size is 12%, which could explain the overall longer recovery curve observed for the sub-region due to repeated shocks and moderate shock intensity.

The recovery curve for Western Europe for milk production is very distinct, commencing with the value of 37% at t=1. The curve shows very little change and even at t=11, the recovery likelihood is 62%, highlighting that the sub-region only makes complete recovery beyond 10 years. Surprisingly, the shock size and shock exposure in this sub-region are low. The observed data shows very long recovery years (more than 20 years) for 3 shock instances—Germany and France in 1990 and Netherlands in 1986. These are related to structural changes in dairy economy and the mandatory quota imposed by the European Commission on milk supply since 1986, to control existing costs of dairy products (Beck et al., 1991a; Van Berkum et al., 2006) (see Discussion section 5.4). The change in milk production trends for these countries can also be seen in the production data (please refer to Supplementary information S5.4). Our results remain robust for several sensitivity checks. The global estimates of recovery likelihoods do not show a significant change, even after varying several model parameters (Supplementary information S5.3).

5.4 Discussion and conclusion

Our analysis shows that over 50% of maize and milk producing countries experience production shocks at the national level. Some shocks co-occur with extreme weather events, such as floods (Brazil, Mexico, Nigeria, Kenya), drought and heat stress (US, Angola, Colombia), and livestock epidemics affecting milk production (Angola), while some co-occur with geopolitical tensions including armed conflict (Afghanistan) and market and economic changes (EU milk supply restrictions and quotas).

At a global scale, if a country does not recover within the first few years after a production shock, it is highly unlikely for it to recover in the following years—this is particularly true for milk production as compared to maize. This is likely related to the nature of these two production systems. Maize is an annual crop, which can facilitate faster recovery for farmers. In milk production systems, severe shocks such as droughts or livestock epidemics can lead to impacts on animal wellbeing, ecosystem (e.g., rangeland) functions, distress sales, or even animal death (Acosta et al., 2021; Bogale & Erena, 2022; Musyoka et al., 2021). Very long recovery times are thus likely needed for the herd size and ecosystem function to stabilize and the production levels to return to normal (Aragie & Thurlow, 2022; Vroege et al., 2023).

High shock intensity that occurs at various frequencies combined with varying adaptive capacity in many sub-regions leads to a wide range of recovery likelihoods. Our recovery likelihood estimates show distinct features for different sub-regions, with highly time-variable recovery probabilities. We contextualize these specific sub-regional features with shock exposure and shock intensities, localized adaptive capacity and vulnerabilities (and possible related events). Results show that Sub-Saharan Africa and Latin America and Caribbean are hotspots of slow recovery, high shock exposure and medium to high shock intensity, in both maize and milk production systems. These two sub-regions include large maize and milk production areas (Gilbert et al., 2018; Grogan et al., 2022). Adoption of improved and stress-tolerant maize varieties, along with other adaptation measures such as climate information services, nutrient and water management, and enabling policy measures to support these adaptations, could contribute to build resilience (Gilbert et al., 2018; Grogan et al., 2022). Maize yield gaps are high in Sub-Saharan Africa and Latin America[19], with low to moderate yield growth rates (Grassini et al., 2013; Ray et al., 2013). Socio-economic and infrastructural constraints can lead to slow adoption and scaling of these technologies and farm adaptations in regions like Sub-Saharan Africa (Ogisi & Begho, 2023; Prasanna et al., 2021). For instance, limited irrigation infrastructure and/or irrigation potential severely constrain productivity of maize and further adaptation to drought (Higginbottom et al., 2021; Schmitt et al., 2022). Extreme weather events and climate change also undermine the suitability of many such farm adaptations in the region (Lobell et al., 2011; Rahimi et al., 2021).

Our results have important policy and research implications. Concerted efforts must be made at a global scale to increase the resilience of both maize and milk production systems, focusing on both short and long-term recovery. On average, it is 50% likely that these two systems take more than one year to recover. This highlights the time-sensitivity and importance of resilience building policies. Importantly, livestock and maize are highly interconnected at global, regional, and local scales across the value chain—from the production stage (maize being used as fodder for cattle) to trade (where changes in maize policies have a significant effect on milk prices) (Bai et al., 2021; Wu et al., 2022). Recovery efforts are often narrow or short-term focused, addressing the specific season or year when the shocks occur, ignoring the effort needed for the food system to stabilize after a large shock (Kahiluoto, 2020; Pingali et al., 2005; Tendall et al., 2015). In addition, policies often fail to consider the interlinkages between the two systems as mentioned above, and generally

[19] https://www.yieldgap.org/gygaviewer/index.html

lack an integrated approach (Farrukh et al., 2020; Moore et al., 2023; Pemsl et al., 2022). This general trend in recovery efforts, combined with the lack of preemptive planning (Mathijs & Wauters, 2020; Mdee et al., 2021; Tadesse et al., 2008), may also explain why recovery after the first few years is challenging. Most of the recovery efforts in the short term are reactive and tactical, focusing on the Immediate need to minimize losses and restore baseline production. These may include aid and pay-outs to protect food security from sudden food production shocks; for example, due to an armed conflict like the Russia-Ukraine war or a sudden shock like the COVID-19 pandemic (Lioutas & Charatsari, 2021; Mottaleb et al., 2022).

Further interventions that may help respond to shocks include, for maize, for instance, life-saving irrigation to address drought, and for milk production, temporary shelters to protect animals from sudden heat waves. Long-term recovery efforts are more strategic and proactive, and focus on building long-term resilience to such shocks, remove inefficiencies in production systems and introduce transformative changes, wherever possible. For maize, these efforts may include strategic scaling-up of drought tolerant varieties, and for livestock, sustained insemination efforts towards more high-yielding, hardy livestock breeds, and improved livestock feeding interventions (Baltenweck et al., 2020; Jennings et al., 2024; Nakweya, 2022; Parodi et al., 2022).

Widespread shocks can have a diverse range of responses based on the diverse nature of these production systems and different adaptive capacities. For example, the introduction of milk quotas in the European Union (EU) led to structural and systemic changes in milk production systems—these quotas were imposed by restricting the amount of milk delivered to the dairies and limiting the level of direct sales at farm level. Farms with diversified income sources could cope with such shocks in a better way than intensive farms solely relying on milk sales (Thorsøe et al., 2020). There is evidence on how the milk production levels in some of the EU-10 countries[20]—countries where these changes were implemented in 1983, of which France, Germany, and the Netherlands formed the bulk of milk production before 1983—never reached 1980s level again until the end of 2020s (this is also evident from the milk production data for these countries in the Supplementary information S5.4) (Beck et al., 1991b). However, some countries like Ireland were able to again expand the production after

[20] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Archive:Milk_and_milk_products_-_30_years_of_quotas

the quota abolition (Kelly et al., 2020). This is an example of how a production shock caused by a similar event, can have diverse effects on farm production, based on different national policy priorities, farm conditions, enabling factors and vulnerabilities (Bouamra-Mechemache et al., 2008; Klopčič et al., 2019). In our study, at a regional scale, this implies longer recovery time as observed for Western Europe, but this might not necessarily mean low overall resilience (as a function of long recovery period) because the market policies aimed at restricting milk production.

It is also important to note that while this study focuses on significant production shocks at national and regional level, localized or sub-national shocks (such as local extreme weather events) can also have a significant effect on food security (Marmai et al., 2022; Ramsey et al., 2021), especially for low food production nations. We do not seek to minimize the importance of such localized and region-specific production shocks; however, such local shocks are inevitably less detectable from national production data (utilized in our study). The methodology used here can further be used to design more in-depth, contextually driven research using higher resolution data, and focusing on local production and likely associated casual factors and events to bring more nuance to the farm resilience research and discussion.

Investment in climate adaptation processes will be needed to enhance production system resilience. Although our analysis does not explicitly link the detected production shocks to any specific cause, Figure 5.1 shows examples where a production shock co-occurs with an extreme weather event including drought, heat stress and floods. Severe impacts of weather-related events on production have been reported in major production systems (Lesk et al., 2016). As the climate continues to warm during the 21st century, the frequency and intensity of climate extremes is projected to intensify (Fischer et al., 2021; Fowler et al., 2021), further slowing recovery from climate-related shocks. A multitude of adaptation options exist (Klein et al., 2015), but their benefits may take time to be realized due to adoption constraints including accessibility, cost, knowledge, labor, and land tenure (Karimi et al., 2021; Owen, 2020). One crucial way to adapt maize production to drought is the use of drought tolerant varieties (Prasanna et al., 2021).

However, in Sub-Saharan Africa, which shows great exposure and slow recovery in this study, the development and adoption of drought tolerant maize varieties (Cacho et al., 2020) may take several years due to policy and farm-level adoption constraints (Challinor et al., 2016; Rippke et al., 2016). Similarly, weather, and seasonal climate forecasts have substantial potential for helping small-scale farmers manage climate risk (Benami et al., 2021), but their benefits are yet to be fully realized across many LMICs especially for the livestock sector (Faisal et al., 2021; Mujeyi et al., 2022). Additionally, we argue that while a priority, climate adaptation efforts cannot happen in isolation from other resilience-building efforts. For livestock, resilience-building efforts should also consider mitigation as an important research and policy agenda (Cheng et al., 2022; Horton et al., 2017; Rahimi et al., 2022; Uwizeye et al., 2020). Climate change is expected to act as a risk multiplier, amplifying the existing vulnerabilities from geo-political and economic events (Hsiang et al., 2013; Mach et al., 2019). Thus, faster, and more coordinated resilience-building actions will be paramount (Masuka et al., 2017). We underscore the need for greater alignment between peacebuilding, humanitarian, and climate actions for resilience in farming and food systems to be achieved (Läderach, Pacillo, et al., 2021; Läderach, Ramirez-Villegas, et al., 2021).

Longer-term transformational change is also warranted to reduce shock effect and ensure rapid recovery and stabilization of production after a shock. Production systems may undergo fundamental transformative changes towards more resilient pathways, likely resulting in improved recovery times. Some countries and sub-regions may undergo substantial changes in land-use and may switch to alternative crops, as crop or milk production becomes either economically or biophysically unfeasible. On the other hand, recovery strategies need to consider potential long-term outcomes, as they may also exacerbate vulnerability to future events of similar or greater magnitude. For instance, excessive use of irrigation can lead to groundwater depletion (Devineni et al., 2022; Mukherjee & Mukherjee, 2018) and create greater long-term vulnerability to drought. Likewise, pesticide use (Möhring et al., 2020) can reduce pest damage over the short term, but it can have detrimental impacts on pollinators and other ecosystem services which contribute to resilient agricultural landscapes (Wuepper et al., 2020). Recovery programmes may also be directed for immediate post-conflict relief, failing to address the root causes of conflict, and their relationship with other factors such as climate hazards or natural resources. There is evidence of observed and projected impacts of armed conflict on food production, possibly triggering food security crises and exacerbating losses from weather events (W. Anderson et al., 2021; Jagermeyr et al., 2020). Future research thus needs to address all production system resilience capacities (robustness, adaptability, and transformability) (Meuwissen et al., 2019), and how these can enhance shock recovery.

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Supplementary information

S5.1 Supplementary summary statistics

Supplementary table S5.1 Summary statistics for global milk production data (in tons) for the study time-period by sub-region (1961–2021).

Sub-region	Count	Mean	Median	Minimum	Maximum	First quartile	Third quartile
Australia and New Zealand	122	9,494,494	7,813,500	5,217,000	21,947,466	6,456,721	10,117,500
Central Asia	211	2,104,517	1,020,900	170,000	11,242,745	332,795	3,492,600
Eastern Asia	244	4,914,523	2,030,369	1,543	37,276,274	91,500	7,066,100
Eastern Europe	515	11,461,820	3,458,100	224,900	108,378,600	1,399,660	11,992,647
Latin America and the Caribbean	1,464	2,021,564	470,716	1,076	36,508,411	95,353	1,494,720
Melanesia	61	510	175	130	1,703	160	780
Northern Africa	376	1,204,478	760,500	10,396	5,494,000	289,775	1,900,000
Northern America	122	39,343,903	30,904,824	7,104,747	102,629,025	7,964,108	67,002,313
Northern Europe	273	3,046,889	2,933,000	1,473,280	5,666,000	1,868,000	3,713,968
Southeastern Asia	488	217,988	26,869	1,900	2,319,280	13,605	222,001
Southern Asia	473	5,802,949	780,000	16,191	108,306,664	210,690	3,523,000
Southern Europe	518	2,419,499	683,920	14,139	13,202,450	370,985	1,997,941
Sub-Saharan Africa	2,379	328,185	85,750	78	4,692,994	22,146	304,448
Western Asia	761	1,133,172	209,894	1,600	21,749,342	46,000	712,100
Western Europe	510	11,371,056	5,602,335	264,480	34,538,496	3,673,595	15,958,750

Source: FAO production data

Supplementary table S5.2 Summary statistics for global maize production data (in tons) for the study time-period by sub-region (1961–2021).

Sub-region	Count	Mean	Median	Minimum	Maximum	First quartile	Third quartile
Australia and New Zealand	122	209,630	190,939	10,262	506,725	152,641	238,074
Central Asia	150	273,633	199,060	2,600	1,129,508	98,940	436,781
Eastern Asia	244	27,910,898	489,536	144	272,762,124	53,350	7,221,566
Eastern Europe	485	4,595,760	2,135,210	1,000	42,109,850	808,360	7,182,200
Latin America and the Caribbean	1,464	3,240,492	342,495	680	103,963,620	71,916	979,214
Melanesia	61	4,737	3,000	39	13,000	167	8,300
Northern Africa	305	1,013,619	37,000	185	8,542,635	2,456	356,500
Northern America	122	113,845,197	51,347,350	741,912	412,262,180	6,981,125	208,262,756
Northern Europe	30	42,243	17,330	2,700	141,690	8,542	77,075
Southeastern Asia	549	2,262,221	433,500	8,000	30,253,938	61,877	3,448,538
Southern Asia	488	2,183,793	571,455	925	31,650,000	50,750	1,563,029
Southern Europe	457	2,068,973	863,410	1,110	11,368,007	333,456	2,529,100
Sub-Saharan Africa	2,379	943,567	179,999	4	17,551,000	33,030	936,273
Western Asia	630	319,536	28,150	-	6,750,000	4,873	149,850
Western Europe	388	2,444,163	265,208	179	18,343,320	58,117	2,146,483

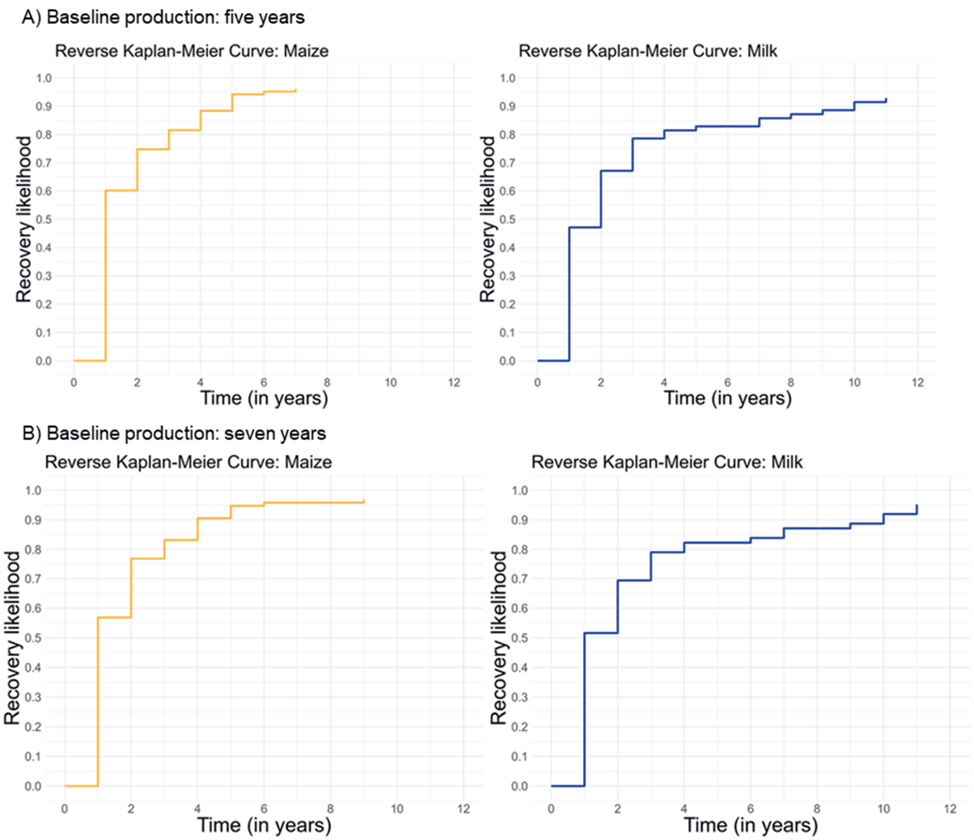
Source: FAO production data

S5.2 Supplementary data and methods

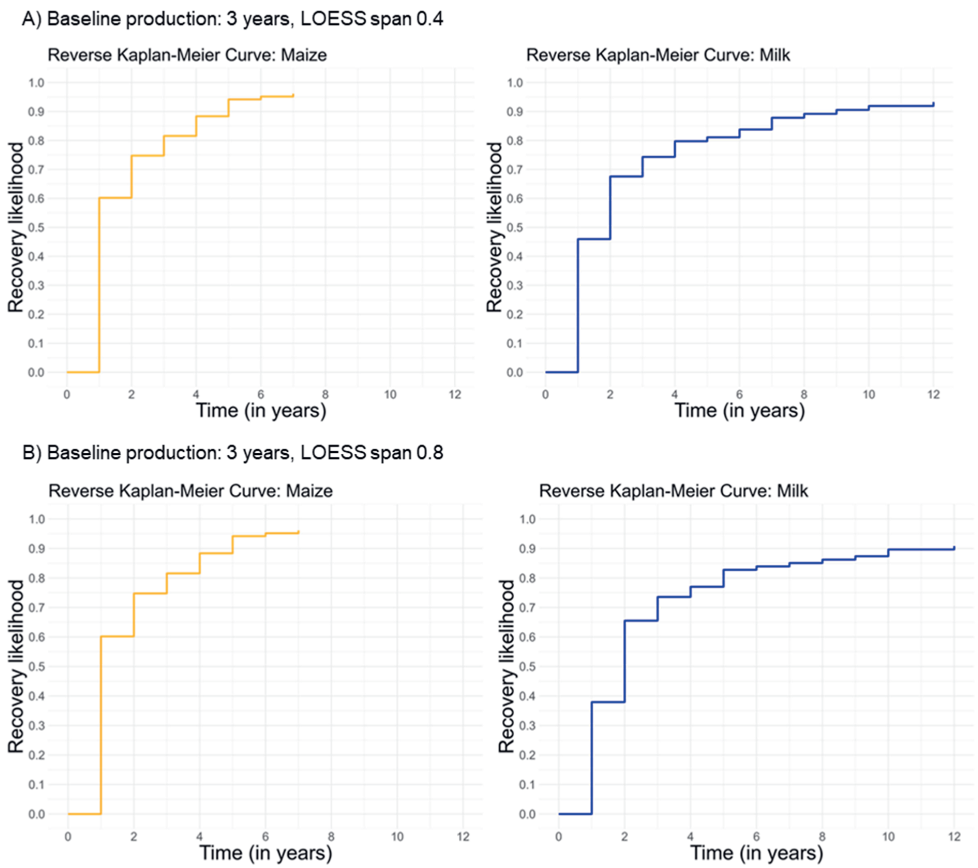
We identify limitations in our analysis—especially regarding the data and methods. First, our analysis is based on FAO data and with different levels of data quality in some countries due to a range of factors (especially when the data at national scale is imputed or collected during a national emergency like armed conflict). Second, our shock detection methodology is driven by a statistical method (albeit well established in the literature) and may not always correspond with a causal event (like an extreme weather event, market disturbances etc.). However, we argue that the causality of production shocks is beyond the scope of this study, which is focused on recovery likelihoods irrespective of the nature of event. Future research may look at how these recovery functions respond to different types of events (for example, production shocks caused due to drought as compared to floods). In addition, we employ a series of robustness checks and sensitivity analysis to ensure that the results are robust to model parameter changes. We show detailed shock detection statistics for each country and production system in the Supplementary information to show in which year a shock was detected (and why). Further, the shock detection method used in this study has been previously used to identify production shocks and causally link them to different socio-economic and climatic changes (although at an aggregated sectoral scale) (Cottrell et al., 2019). Further, it is important to note that not all long recovery periods are necessarily bad; some production systems may take a long time to adapt and fundamentally transform towards a more resilient pathway—structural changes like these may take a long time to recover but can be more resilient than quickly recovering to status-quo production levels. Therefore, future research should also focus on the transformability dimension of farm resilience and look at how production systems change (Meuwissen et al., 2019).

S5.3 Robustness checks and sensitivity analysis

The analysis was replicated with different sensitivity and robustness checks. These include changing the number of years in the baseline production (three and seven years) and changing the span of the LOESS function (0.4 and 0.8). The results are shown below for both:



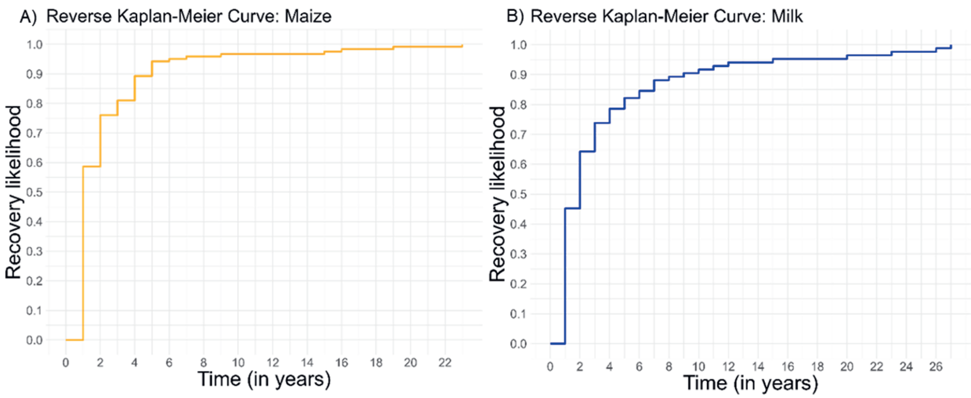
Supplementary figure S5.1 Sensitivity analysis of global functions of recovery likelihoods for maize and milk production by changing the baseline production years to (A) five years (B) seven years, shown as reverse Kaplan-Meier curves.



Supplementary figure S5.2 Sensitivity analysis of global functions of recovery likelihoods for maize and milk production by changing the LOESS span to (A) 0.4 (B) 0.8, shown as reverse Kaplan-Meier curves.

S5.4 Supplementary results

We show LOESS fitted curve over actual production data, residuals vs lag-residuals and Cook's distance value over the years for each country (symbolized by its ISO3 code) for both farming systems maize and dairy milk farming systems. These files are available, along with codes in the online repository at https://github.com/Shalika-WUR/Recovery-analysis.



Supplementary figure S5.3 Global functions of recovery likelihoods for maize (A) and dairy milk (B) production, shown as reverse Kaplan-Meier curves, the X-axis shows the full recovery time observed (beyond 12 years as shown in the main results).

Supplementary table S5.3 Descriptive statistics for recovery likelihood functions (at global scale) for maize production.

Recovery time (t)	Recovery likelihood	Lower confidence interval	Upper confidence interval
1	0.587	0.489	0.666
2	0.760	0.671	0.826
3	0.810	0.725	0.868
4	0.893	0.820	0.936
5	0.942	0.881	0.972
6	0.950	0.892	0.977
7	0.959	0.903	0.982
9	0.967	0.913	0.987
15	0.975	0.924	0.992
16	0.983	0.935	0.996
19	0.992	0.942	0.999
23	1	NA	NA

Supplementary table S5.4 Descriptive statistics for recovery likelihood functions (at global scale) for milk production.

Recovery time (t)	Recovery likelihood	Lower confidence interval	Upper confidence interval
1	0.452	0.335	0.549
2	0.643	0.524	0.732
3	0.738	0.625	0.817
4	0.786	0.677	0.858
5	0.821	0.718	0.887
6	0.845	0.745	0.906
7	0.881	0.787	0.933
8	0.893	0.801	0.942
9	0.905	0.816	0.951
10	0.917	0.831	0.959
11	0.929	0.846	0.967
12	0.940	0.861	0.975
15	0.952	0.876	0.982
20	0.964	0.892	0.988
23	0.976	0.906	0.994
26	0.988	0.916	0.998
27	1.000	NA	NA

Supplementary table S5.5 Descriptive statistics for recovery likelihood functions (at sub-regional scale) for maize production.

Sub-region	Recovery time (t)	Recovery likelihood	Lower confidence interval	Upper confidence interval
Australia and New Zealand	1	1.000	NA	NA
Central Asia	1	0.750	0.000	0.954
Central Asia	4	1.000	NA	NA
Eastern Asia	1	0.500	0.000	0.875
Eastern Asia	2	1.000	NA	NA
Eastern Europe	1	0.417	0.059	0.638
Eastern Europe	2	0.750	0.334	0.906
Eastern Europe	3	0.833	0.409	0.953
Eastern Europe	4	0.917	0.456	0.987
Eastern Europe	16	1.000	NA	NA
Latin America and the Caribbean	1	0.577	0.337	0.730
Latin America and the Caribbean	2	0.731	0.493	0.857
Latin America and the Caribbean	3	0.846	0.621	0.938
Latin America and the Caribbean	5	0.923	0.709	0.980

Sub-region	Recovery time (t)	Recovery likelihood	Lower confidence interval	Upper confidence interval
Latin America and the Caribbean	15	0.962	0.737	0.994
Latin America and the Caribbean	19	1.000	NA	NA
Melanesia	4	1.000	NA	NA
Northern Africa	1	1.000	NA	NA
Northern America	1	1.000	NA	NA
Northern Europe	4	1.000	NA	NA
Southeastern Asia	1	0.333	0.000	0.621
Southeastern Asia	4	0.833	0.003	0.972
Southeastern Asia	5	1.000	NA	NA
Southern Asia	1	0.833	0.003	0.972
Southern Asia	5	1.000	NA	NA
Southern Europe	1	0.444	0.003	0.690
Southern Europe	2	0.667	0.160	0.868
Southern Europe	4	0.778	0.246	0.935
Southern Europe	7	0.889	0.295	0.982
Southern Europe	9	1.000	NA	NA
Sub-Saharan Africa	1	0.629	0.428	0.759
Sub-Saharan Africa	2	0.857	0.678	0.937
Sub-Saharan Africa	3	0.886	0.713	0.955
Sub-Saharan Africa	4	0.914	0.747	0.971
Sub-Saharan Africa	5	0.943	0.781	0.985
Sub-Saharan Africa	6	0.971	0.803	0.996
Sub-Saharan Africa	23	1.000	NA	NA
Western Asia	1	0.833	0.003	0.972
Western Asia	4	1.000	NA	NA
Western Europe	1	0.556	0.077	0.786
Western Europe	2	0.778	0.246	0.935
Western Europe	3	0.889	0.295	0.982
Western Europe	5	1.000	NA	NA

Supplementary table S5.6 Descriptive statistics for recovery likelihood functions (at sub-regional scale) for milk production.

Sub-region	Recovery time (t)	Recovery likelihood	Lower confidence interval	Upper confidence interval
Southern Asia	2	0.500	0.000	0.875
Southern Asia	5	1.000	NA	NA
Sub-Saharan Africa	1	0.462	0.231	0.623
Sub-Saharan Africa	2	0.731	0.493	0.857
Sub-Saharan Africa	3	0.808	0.577	0.913
Sub-Saharan Africa	4	0.846	0.621	0.938
Sub-Saharan Africa	6	0.885	0.666	0.960
Sub-Saharan Africa	7	0.923	0.709	0.980
Sub-Saharan Africa	9	0.962	0.737	0.994
Sub-Saharan Africa	15	1.000	NA	NA
Southern Europe	1	0.333	0.000	0.621
Southern Europe	2	0.500	0.000	0.775
Southern Europe	3	0.833	0.003	0.972
Southern Europe	4	1.000	NA	NA
Western Asia	1	0.500	0.000	0.812
Western Asia	2	0.750	0.000	0.954
Western Asia	4	1.000	NA	NA
Latin America and the Caribbean	1	0.333	0.005	0.553
Latin America and the Caribbean	2	0.500	0.120	0.716
Latin America and the Caribbean	3	0.750	0.334	0.906
Latin America and the Caribbean	4	0.833	0.409	0.953
Latin America and the Caribbean	7	0.917	0.456	0.987
Latin America and the Caribbean	20	1.000	NA	NA
Western Europe	1	0.375	0.000	0.635
Western Europe	5	0.500	0.000	0.750
Western Europe	11	0.625	0.083	0.847
Western Europe	23	0.750	0.170	0.925
Western Europe	26	0.875	0.218	0.980
Western Europe	27	1.000	NA	NA
Eastern Europe	1	1.000	NA	NA
Northern America	1	1.000	NA	NA
Eastern Asia	1	0.600	0.000	0.863
Eastern Asia	2	1.000	NA	NA
Northern Europe	1	0.500	0.000	0.812
Northern Europe	6	0.750	0.000	0.954
Northern Europe	7	1.000	NA	NA
Northern Africa	1	0.667	0.000	0.933
Northern Africa	2	1.000	NA	NA
Southeastern Asia	1	0.333	0.000	0.700

Sub-region	Recovery time (t)	Recovery likelihood	Lower confidence interval	Upper confidence interval
Southeastern Asia	3	0.667	0.000	0.933
Southeastern Asia	10	1.000	NA	NA
Central Asia	2	0.250	0.000	0.574
Central Asia	5	0.500	0.000	0.812
Central Asia	8	0.750	0.000	0.954
Central Asia	12	1.000	NA	NA
Melanesia	1	1.000	NA	NA

Chapter 6

General discussion

6.1 Introduction

Food systems face risks from an increasing incidence of extreme weather events which are projected to further intensify due to climate change (Eckstein et al., 2019; Lesk et al., 2016). Pre-existing socio-economic vulnerabilities coupled with biological limits to increasing food production in many areas compound this challenge. In addition, many farming systems are rendered fragile when confronted by a depletion of natural resources and exposure to risks. In many regions, it is vital for farming systems to adapt to such scenarios (Tebaldi et al., 2021). In fact, farmers across the world are continuously trying to adopt practices to improve and de-risk their production (Phillipo, 2015). A comprehensive understanding of risks faced by farming systems, the processes in response to these risks (like adaptation), and resilience of the farming systems is thus significant area of interest in farming system research. This allows for a better nuanced understanding of the multi-dimensional challenges faced by the farming systems (Darnhofer et al., 2016; Doherty et al., 2019; Horton et al., 2017). Such research in LMICs (Low- and Middle-Income Countries) is often constrained by data scarcity. There is a clear research gap between the current state of adaptations (including adaptation policies) and resilience in farming systems, and how they align with risk—especially at the global scale. This thesis addressed this gap by providing global evidence on how adaptation and resilience strategies of different farming systems are aligned with current and projected risks. Specifically, the study focused on the following four research objectives:

I. Assess the alignment of global climate action policies with projected risks, readiness to scale adaptation based on economic, governance and social capacities of nations, and biophysical scope for adaptation. (Chapter 2)
II. Map global research on agricultural insurance across agricultural sectors, geographies, insurance product types, and research themes. In addition, analyze the geographical alignment of research intensity on agricultural insurance with historical and projected risk hotspots. (Chapter 3)
III. Identify the impacts of heat extremes on crop production under climate-smart agriculture. (Chapter 4)
IV. Assess how farming systems recover from production shocks. (Chapter 5)

Section 6.2 brings forth the overall synthesis from the research across cross-cutting themes of resilience, and insights from the global perspective of this thesis. Section 6.3 discusses the limitations of this work and opportunities for future research. The scientific contribution of the thesis is discussed in Section 6.4. Subsequently, the policy and business recommendations are discussed in Section 6.5, and the main conclusions are described in Section 6.6.

6.2 Synthesis

The research chapters in the thesis were framed based on framework on coping, adaptation, and transformation framework (Figure 1.1). In addition, different issues from multiple dimensions of different types of risk, the sector, the geographical and temporal scope were focused across different chapters (Section 1.5). The findings and implications from the four research chapters in this thesis, have common overall synergies and emergent themes, which I classify into—a) resilience of farming systems, and b) insights from a global perspective.

Resilience of farming systems

First, I discuss different risks that this thesis addressed. Next, I revisit the different resilience strategies analyzed in this thesis followed by reflections on the framing and quantifying of the resilience attributes across different chapters.

Farming system risks

This thesis analyzed several types of risks faced by farming systems—long-term climate change (Chapter 2 and 3), biological risks like livestock epidemics (Chapter 3), extreme weather events (Chapter 3 and 4), and production shocks due to multiple climatic, geo-political and market/economic fluctuations (Chapter 5). Further, while risk exposure was the focus across all the Chapters, risk intensity was also duly considered in Chapter 2, 4 and 5. Each of these risks are described individually below.

Risks from projected climate change and extreme weather events remained central to all the chapters in the thesis. Based on long-term projected impacts from climate change, observations from Chapter 2 revealed most of Africa, Eastern Asia, Latin America, and Northern Europe to be risk hotspots of high impacts of climate change on cereal productivity, in line with previous findings (Aggarwal et al., 2019a; Hasegawa et al., 2022). However, the results were different in Chapter 3, where Northern America, and Northern Asia were found as hotspots of global warming. This may be explained by the fact that Chapter 2 looked at projected climate change impacts on cereal yields by 2050s (from meta-analysis of crop modelling studies), while Chapter 3 focused on annual temperature change for every country.

Although both these indicators measure future risks from projected climate change, they are fundamentally different and cannot be directly compared. Annual temperature change is a broad risk indicator for projected global warming in Chapter 3, having impact across different sectors and in multiple ways. Crop modelling studies in comparison, use daily (observed or projected) weather data as inputs, and capture crop growth phenology, soil-water-atmosphere dynamics through different modelling components. Therefore, the risks identified through both these indicators may be correlated but are not comparable as they estimate different things.

Biological risks like livestock epidemics were focused on in Chapter 3[21] and found East Asia, Southern Europe, and a few African countries to be at high risk from repeated exposure to transboundary livestock epidemics. This, however, could also be related to poor monitoring and surveillance of these epidemics in LMICs (Abubakar et al., 2022). There is thus a need to strengthen efforts to develop robust monitoring systems for biological risks in both livestock (Van Boeckel et al., 2019) and crop systems, and put in place suitable adaptation strategies for the same, especially when global trade and climate change can play a critical role in disease transmission across different geographies, and the fragility of food systems was already shown during the COVID-19 pandemic (Fones et al., 2020; Herrero and Thornton, 2020; Laborde et al., 2021).

Risks from extreme weather events were the focus across all the chapters except Chapter 2. South Asia, North America and Latin America were underscored to be hotspots of extreme weather disasters (especially drought, Chapter 3), while central India was the focus of Chapter 4.

Chapter 5 evaluated all types of production shocks observed (irrespective of the underlying causal event). This is likely the reason why Sub-Saharan Africa—consistently emerging as a hotspot for both maize and dairy milk systems based on shock intensity and frequency (Chapter 5)—was not a risk hotspot in Chapter 3. While market and geo-political risks were not the key focus in this thesis, Chapter 5 did evaluate significant production shocks at national scale, some of which were likely caused by widescale market and geo-political disruptions. The results highlight that some of these events can cause significant changes in

[21] https://empres-i.apps.fao.org/

production systems (like the EU milk quotas introduced in the 1980s; armed conflicts in the Middle East) and are potentially transformative (Beck et al., 1991; Läderach et al., 2021).

Resilience strategies

The central theme of this thesis was based on the risks faced by farming systems, the processes in response to these risks (like adaptation), and resilience of the farming systems as an outcome of these processes. The theoretical framework placed three response pathways as cope, adapt and transform, across different timings of risk—before, during after the event (Chapter 1, Figure 1.1). Resilience was thus defined as an outcome of these responses, each of which are discussed below.

Coping strategies aim at restoring the baseline function of a system after a sudden shock or gradual risk. In farming systems, these strategies may include a series of agronomic, farm risk management and broader policy measures ranging from change in planting dates, irrigation management at micro-level, crop species/variety, insurance and income diversification for risk management and aid, and subsidies after a disaster at macro-level. Chapter 3 highlights insurance as a frequent coping strategy to mitigate farm risks, commonly used in high income countries. Various insurance impact evaluation studies reviewed in the chapter underscore the pay-outs from insurance used in cropping cycles next year to stabilize farm production. Chapter 5 looked at these coping strategies at a much broader level, by focusing on recovery after a production shock. It also highlighted the distinct impact of different recovery building strategies (both short- and long-term) on recovery likelihoods across different regions. For instance, while Chapter 3 revealed the need for more insurance research in the LMICs—particularly Africa and Latin America as under-researched areas, Chapter 5 delineated these two regions as hotspots of high shock frequency and moderate to high shock intensity. This calls for a more nuanced approach towards coping strategies, and in particular, more research on the viability of such coping mechanisms (like insurance), given the nature of risk, and consequently the need for adaptation and transformation.

Next, adaptation was described in three chapters. A key highlight of the analysis of agricultural insurance literature (Chapter 3) was the new research theme on the adaptive aspect of insurance—particularly insurance as adaptation to climate change. This chapter also highlighted various adaptation pathways of insurance—either through bundling with other adaptations (such as climate-smart agriculture), or as a feedback mechanism into other adaptive actions (insurance pay-outs being deployed for the purchase of drought-resistant seeds) (Falco et al., 2014; Muchuru and Nhamo, 2019)—in addition to spillover effects of a well-designed insurance on other farm adaptations (Beckie et al., 2019; Foltz et al., 2013; Kron et al., 2016). Climate-smart agriculture (CSA) is another important farm adaptation and Chapter 4 highlighted how CSA wheat and soybean farms in India were observed to be resilient to heat stress—even across different CSA bundles. While previous literature discusses the negative effects of heat stress on the general farm population and the role of farm adaptation in reducing these risks (Lobell and Tebaldi, 2014; Tack et al., 2017), most of the evidence comes from temperate regions. The findings from Chapter 4 contradict previous studies and demonstrate how the general farm population in the study region was also resilient to heat stress—possibly due to already ongoing farm adaptations like improved cultivars, widespread irrigation, and nutrient-use. Incidentally, this finding was also supported by the result from Chapter 5, which found very low frequency of shocks and consequently better recovery likelihoods in maize systems of India (showing overall resilience of the general farming systems). While some of these farm adaptations can augment risk reduction, they also have negative effects on the environment, especially in the context of environmental sustainability and resource depletion issues in the region (Mukherjee and Mukherjee, 2018; Wuepper et al., 2019).

The farm adaptations discussed above—insurance and CSA are also important components of climate adaptation policies globally. Chapter 2 took a policy approach towards the role of adaptation in building resilience to climate change—by focusing on planned national adaptation actions (in the form of Nationally Determined Contributions-NDCs) and showed that the intent for adaptation was likely to be futile if not accompanied by necessary actions to improve the readiness for scaling and uptake of adaptation. The key finding, that most of the countries have restricted scope or readiness to implement adaptation (42% of the countries reviewed in the chapter, had low scope for adaptation), is in line with the existing literature on the urgent need to ratchet climate action pledges and bolster the enabling environment for climate adaptation (Zhang et al., 2020). This finding also highlighted important cues for transformative action, which can help in building long-term resilience. In many regions, there is already a need for transformative action and innovations in the way food is produced. For instance, regions restricted by land-use expansion and limited productivity potential will have to inevitably implement significant changes and potentially redesign their existing food systems (Herrero et al., 2020a; Meadu et al., 2023). Chapter 2 explicitly showed this need for transformation—especially in countries with limited scope, which is also supported by existing literature (Rippke et al., 2016). The results from Chapter 5 also reinforce this need for transformative action, although the analysis solely focused on farm coping strategies—the low recovery likelihoods coupled with more intense and frequent shocks, make a strong case for future transformations (Herrero et al., 2020b; Webb et al., 2020).

Quantification of resilience

Another important highlight from this thesis was how resilience was framed and quantified across different chapters. Previous literature on resilience quantification in farming systems draws on the ecological definitions of resilience, in addition to resilience as framed in risk management (Meuwissen et al., 2019; Zampieri, 2021; Zampieri et al., 2020). These include resilience attributes like resistance (to external shocks) through adaptive capacity, efficiency, stability (or volatility), independence (from shocks in other farming systems, sectors), transformation and recovery (Arani et al., 2021; Galappaththi et al., 2022). Using an interdisciplinary approach and drawing lessons from diverse fields, this thesis looked at multiple dimensions of resilience quantification—through policy and research intensity focus, resistance, and recovery attributes. Chapter 2 took a policy lens and approached resilience quantification based on adaptive capacity—by developing a quantifiable framework to monitor and track climate adaptation policies at a global scale. Previous literature on adaptive capacity has often focused on individual farmer and/or farm characteristics or at a broader scale based on macro-economic indicators (Headey and Barrett, 2015; Knippenberg et al., 2019). Based on this research, Chapter 2 developed upon this finding and evaluated resilience quantification from a policy lens. Apart from the policy focus, quantifying research intensity on resilience building strategies (like agricultural insurance) as a possible indicator was also explored (Chapter 3).

Resistance to an external shock (like extreme weather events) has been explored previously in the literature. This thesis also focused on the productivity impact of an important extreme weather event, heat stress in climate adapted farms in India (Chapter 4). Post-shock recovery was the focus of Chapter 5, which specifically looked at maize and dairy milk production systems. The findings differed from existing literature on shocks, where high frequency of shocks was found for crops and livestock production in Asia and many countries in Africa (Cottrell et al., 2019), whereas Chapter 5 found highest frequency of shocks in Sub-Saharan

Africa and Latin America. This is likely because different crops (cereals, coarse grains, fruits and vegetables, roots, and tubers), and animal products (meat, milk, and egg from different animal sources) were combined in the analysis, compared to Chapter 5 which focused solely on individual farming systems, and the difference in study period, by extending the analysis from 1961 to 2021 in Chapter 5, compared to 2013 in Cottrell et al. (2019). While virtually no studies exist on recovery likelihoods (cogitated upon in chapter 5), previous literature also found low shock intensities in maize systems in Latin America and Caribbean, and Africa (as Chapter 5). However, it disagreed with findings on shock intensity in other regions compared to Chapter 5 (Lesk et al., 2016). This is likely because the analysis in Lesk et al. (2016) was limited to shocks from extreme weather events such as droughts and heat stress, and Chapter 5 looked at all production shocks.

Insights from a global perspective

A key theme in this thesis was the research conducted at global scale (except Chapter 4). Without undermining the need for more localized studies in food system research (as carried out in Chapter 4), I discuss the unique insights derived from having a global perspective—a) hotspot and priority action areas, b) macro-level trends, and c) synergies and opportunities for cross-learnings.

The global scale allows for easier comparison across different geographies, identification of highly vulnerable areas, and in defining priorities in research and policy. For example, Figure 6.1 shows the hotspots found across different research chapters. These hotspots are identified using multiple dimensions across risks and resilience—based on projected climate impacts and adaptation needs (Chapter 2), risk exposure and insurance research intensity (Chapter 3) and production shock exposure and low recovery likelihoods (Chapter 5). When analyzed together, regions Middle-east and Northern Africa, Sub-Saharan Africa and Southeast Asia emerge as hotspots across multiple dimensions of adaptation, resilience, and risk exposure. Such insights are difficult to derive from localized studies, especially due to data scarcity and high-cost of replicating research across different regions.

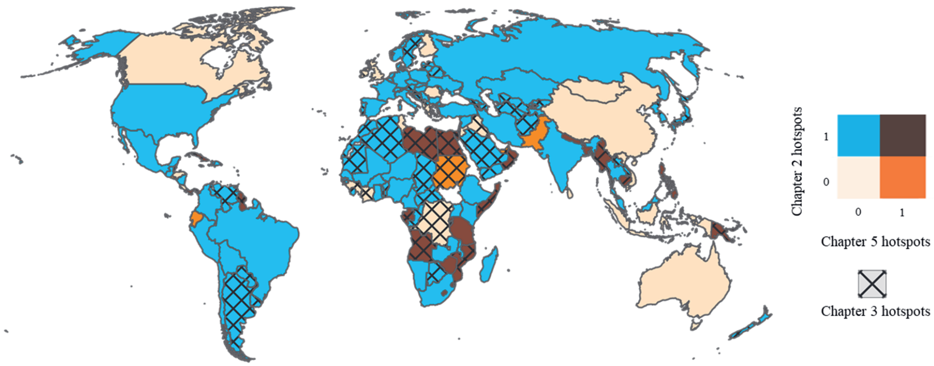


Figure 6.1 The global priority areas identified in this thesis. The bivariate choropleth map shows different combinations of hotspots identified in different chapters (the binary classification into 0 and 1 shows absence/presence of hotspots in the respective research chapter). The hotspots are based on medium to high adaptation need, and low readiness or scope for adaptation (Chapter 2), production shock exposure and low recovery likelihoods in maize and dairy milk systems (Chapter 5). The hatched areas show low research intensity of agricultural insurance (Chapter 3).

Apart from identifying hotspots, a global overview also helps in identifying macro-level trends across different regions and resilience dimensions (Debonne et al., 2022). Chapter 3 offered an overview of different risks faced by global food systems, the frequency of disasters (on an average, major disaster every year since 2000, in major breadbaskets of USA, China, India, France and Brazil) and livestock epidemics (China, France, Italy, the Netherlands, Germany) and low research on agricultural risk management in many areas of the world. Despite this risk exposure, Chapter 5 showed that overall, maize, and dairy milk production systems are resilient at macro-scale and can recover from observed production shocks within the first two years with high likelihood (more than 50%). However, given the fragility of the food systems and worsening impacts from climate change, the adaptation actions in these countries are not on track to sufficiently meet food demand by 2050s, as shown in Chapter 2.

Additionally, farming systems in every country and region have their own set of diverse challenges and lessons. A global approach helps in identifying these and prioritizing different regions wherever necessary. For instance, Chapter 3 showed very high insurance research intensity in the USA, along with a high degree of risk exposure in the form of extreme weather events. However, Chapter 5 demonstrates that these events do not translate into production shocks and overall high recovery likelihood in the region. This can mean that in general, farmers are better able to cope with extreme events in this region through large scale implementation of risk management strategies like agricultural insurance (proxied by high research intensity Chapter 3) and the enabling policy environment and readiness (social and economic capacities) to scale adaptations (Chapter 2). While overall this is a promising trend (also in part due to the nature of high production intensive farming), it does not necessarily mean that this will hold true in the future as well. Factors of note are the projected increase in frequency and intensity of events and major sustainability challenges in the region (including minimizing emissions from agriculture).

This allows for drawing lessons in both ways—by identifying pathways which might not be the most suitable/sustainable in the future as well as opportunities for synergies. An example of such synergy is CSA, Chapter 4 provided evidence on climate resilience of CSA farms in India, possibly having lessons for other countries confronted by similar risks (like heat stress) in Sub-Saharan Africa, Latin America, and Southern Europe. The resilience built via on-farm adaptations like irrigation, improved cultivars, reduced tillage, precision nutrient and pesticide management, climate information services (as implemented in the study) can be potentially beneficial innovations for other countries as well. However, excessive irrigation might not be sustainable in the long run and can give rise to major sustainability issues. Scaling out sustainable irrigation practices in regions where its role is still limited in food production, like many countries in Sub-Saharan Africa (Burney et al., 2013; Dorothea Beier et al., 2023), can help in increasing crop yields and protect crops from risks like heat stress. Similarly, climate information services can help farmers in Latin America to adjust their crop calendar and plan better (Born et al., 2021). Resource conservation strategies like precision nutrient management techniques which optimize nitrogen application, sustainable irrigation practices and conservation agriculture, can help in addressing various sustainability issues across the world. Many of these adaptations would require institutional reforms and improving the readiness of farmers to adopt such technologies in the future (Ishtiaque et al., 2024).

Global analysis allows a bird’s-eye view and helps in need assessment and problem identification at a larger scale, especially considering advances in modelling, remote sensing technology and data science, which can provide many opportunities to enable such analysis in (hitherto) data scarce regions like LMICs (Benami et al., 2021; Jain et al., 2019). This thesis provides scientific evidence on risks, adaptation and resilience building actions on a global scale from multiple perspectives. It provides a structured approach and methodologies which can help in problem diagnosis and provide entry points for resilience research for food systems. This is useful for policy makers and the private sector, for prioritizing investments, and for setting larger research agenda in food systems research and provide strategic directions for the same.

6.3 Limitations and opportunities for future research

In line with the research framework, used for this thesis (Figure 1.1, Chapter 1), I discuss the limitations of this work and avenues for future research along the themes of risks, resilience, and adaptation.

More dedicated studies are needed to fully understand the complexities of risks faced by the livestock sector, for instance, this thesis briefly looks at the biological risks (livestock epidemics) and drought risk for the livestock sector (Chapter 3). This is important for two reasons, first, very limited evidence exist on the nature of risks faced by the livestock sector especially in the LMICs, and secondly, Chapter 5 showed how the livestock sector is already vulnerable in terms of longer recovery and lower recovery likelihoods from the production shocks. This sector is important not only because of its role in the smallholder economy (1. 3 billion people depend on it for livelihood security)[22] but also due to its significant contribution towards agricultural emissions—around 31% of global (Greenhouse Gas) GHG emissions from food systems are from livestock and fisheries sector[23] (Mehrabi et al., 2020). Incidentally mitigation was also not focused upon in this thesis but remains an important area for food system research (Richards et al., 2018). The need to expand research beyond major food production systems (mainly cereals like maize, rice, wheat), also extends to other underutilized and neglected crops (Manners and van Etten, 2018). While this thesis tries to partly address this gap by focusing on livestock sector and soybean crop, concerted efforts are needed to increase the research intensity across different sectors (including livestock, fisheries) (FAO, 2019; Lam et al., 2020) and non-cereal crops, especially when many pulses, roots and tuber crops remain vital for achieving future livelihood and nutritional security (Herrero et al., 2017; The Eat-Lancet Commission, 2019). Similarly, food systems face a

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[22] https://www.worldbank.org/en/topic/agriculture/brief/moving-towards-sustainability-the-livestock-sector-and-the-world-bank

[23] https://ourworldindata.org/food-ghg-emissions

diverse range of risks, often occurring at the same time. Future research should thus also focus on the risk from potentially severe impacts from concurrent shocks (Toreti et al., 2019), especially when many cropping systems are highly interconnected through global trade and making cropping system unstable in many regions (Anderson et al., 2019; Mehrabi and Ramankutty, 2019). Possible follow-up studies directly resulting from this thesis include understanding the impact of drought exposure in CSA farms in India (Chapter 4) and understanding impact of specific weather events like drought and heat stress on recovery patterns across different crops (Chapter 5).

For adaptation, future research can focus on more dedicated policy analysis to understand the barriers and solutions to increasing readiness to scale-out agricultural technologies (limiting factor found in Chapter 2 across many nations) (Acevedo et al., 2020). With the next update of NDCs due in a few years[24], it is important to periodically track and monitor NDC progress and highlight gaps and course correct wherever possible. Comprehensive adaptation tracking in agriculture thus becomes an important area of future research. Although the need for adaptation is difficult to estimate objectively due to high uncertainty and context-specific future scenarios, future modelling studies can help in quantifying this need, create scenario-specific targets and design a mechanism to track adaptation policy objectives. Further, such policy analysis is equally important for the livestock sector (which was not included in Chapter 2), and more efforts are needed to measure and track climate action in livestock[25]. This also extends to risk management research in the livestock sector, Chapter 3 showed limited focus of agricultural insurance research and policies in the livestock sector in LMICs. Similarly, to design and better understand the impacts of risk management practices like CSA, more evidence from the field is required with replication studies across different geographies. A major limitation of Chapter 4 was the lack of comparable non-CSA farms and using district-level yields as proxy for control. Future impact studies can be specifically designed to compare the effects of CSA with non-CSA farms (perhaps with randomized controlled trials), and specifically isolating the role of irrigation for wheat. Similarly, further refining the study by using observed weather data from weather stations instead of using satellite data (which can underestimate weather extremes) can also be useful.

[24] https://unfccc.int/process-and-meetings/the-paris-agreement/nationally-determined-contributions-ndcs
[25] https://ccafs.cgiar.org/resources/tools/agriculture-in-the-ndcs-data-maps-2021

Finally, resilience in this thesis was looked at from multiple dimensions, by focusing on a particular subset of interest. For instance, Chapter 5 looked only at the recovery aspect of resilience, future research can focus on a broader, large-scale study looking at different aspects of farm production resilience across different regions (maybe a single resilience indicator with global scope). This can help to bring out more nuanced findings on complexities of resilience—how shocks, adaptive capacity, and different resilience attributes interact and affect each other in different ways. Data on these is however scarce, but a case study approach could prove extremely informative. Finally, this thesis had very limited focus on transformational research (only Chapter 2, from a policy angle), future research should also aim at looking at more transformative actions and innovations required at different scale, especially when scope for current adaptations is already limited in many countries (as shown in Chapter 2) (Jaacks, 2021).

At a broader scale, the findings from this thesis also have implications for setting research and investment priorities—for donors and research institutions. Firstly, hotspot analysis across all the chapters underscores important priority action areas and investment planning. The research from this thesis has highlighted many regions in the LMICs to be a "hotspot" for future research and policy action (Middle-east and North Africa, Eastern and Southern Africa and South America)—these geographical areas show high vulnerabilities consistently across different themes of this thesis (risk exposure, data gaps, risk research intensity, low resilience, and misaligned adaptation priorities). International development and donors can focus on these regions and research themes and channel investments to strengthen the farming systems. Some studies in the past have done such investment planning exercises based on risk exposure and production priorities[26,27]. The methods shown in this thesis (like Chapter 5) can help in further refining such efforts in the future. It can also feed into existing efforts to understand mega-trends across food production and anticipate future risks and embed these insights into resilience planning[28]. Such research projects will have significant impact on designing/informing resilience policies which are forward-looking and have been designed to anticipate both current and future (projected) risks.

[26] https://cgspace.cgiar.org/items/99580f69-0f9f-41b5-b8e4-e366ba751aa4
[27] https://cgspace.cgiar.org/items/d108fbb5-ede8-44b3-b7cc-95a422f4251f
[28] https://www.cgiar.org/initiative/foresight/

While these efforts are important, it is also important to focus on food system transformations—a monumental task which requires investments upto 1.3 trillion USD through this decade, annually (Steiner et al., 2020). In this thesis, transformation was only focused upon Chapter 2, the results still showed a need for more research into transformative actions, especially in areas where existing adaptations are already reaching their limits. These transformations can stem from radical innovations which are already changing the food systems at various scales like CRISPR technology (Clustered Regularly Interspaced Short Palindromic Repeats) to increase crop yield (Zhu et al., 2020), build pest and disease resistance and environmental stress tolerance (among others) and the development of plant-based meat alternatives having implications for the livestock sector (Kozicka et al., 2023). WUR, CGIAR (Consultative Group on International Agricultural Research) and other science-based and policy institutions like the local NARS (National Agricultural Research Systems) and other universities, have a significant role to bridge this gap; this can be achieved by scaling existing solutions by creating incubators for innovation, fostering partnerships and networks[29], and linking science with industry[30] and public sector to achieve the same. Finally, generating new evidence based on farm observations in (hitherto) data-scarce regions (Chapter 4) not only significantly advances current evidence, but also helps in refining the research and investment agenda (for instance, scaling out climate-smart interventions without sustainability consequences). CGIAR initiatives which target data gaps[31], especially in the LMICs[32], are not only highly encouraged but can have potentially rewarding outcomes in generating key evidence on how to contextualize and scale relevant agricultural adaptation to mitigate farm risks.

[29] https://cgspace.cgiar.org/items/82c78ef3-4a4c-4747-824f-030a07f8a001
[30] https://www.wur.nl/en/value-creation-cooperation/collaborating-with-wur-1/entrepreneurship-at-wur.htm
[31] https://www.cgiar.org/initiative/excellence-in-agronomy/
[32] https://adaptationatlas.cgiar.org/

6.4 Scientific contribution

The contribution of this thesis is structured around three themes—a) insights from interdisciplinary research, b) methodological and research contributions and c) implications.

Insights from interdisciplinary research

This thesis used an interdisciplinary and integrated approach to study risks, adaptation, and resilience in farming systems. By framing the research questions across different disciplines, policy analysis (Chapter 2), risk management (Chapter 3), agronomy and climate econometrics (Chapter 4) and agroecology and risk management (Chapter 5), it offers insights across risks and coping/adaptation pathways to improve farm resilience. Further, by moving across time, scale and farming systems, the findings help in comparison across different geographies from multiple dimensions. While the insights derived across space and time have been discussed above, the comparison across different farming systems also offer new insights. For instance, the findings indicate that the livestock sector is not merely exposed to more risks but is also often under-researched in the context of risk management (Chapter 3), with limited policy focus (Chapter 2). Furthermore, it has low resilience in the context of long recovery times and generally low recovery likelihoods (Chapter 5), when compared to other sectors like maize farming. For instance, only 5.7% of the papers reviewed in Chapter 3, focused on the livestock sector. The findings from maize systems are consistent with available literature in terms of urgency of adaptation and scope (Chapter 2) (Challinor et al., 2016), while the climate resilience of soybean towards heat stress (Chapter 4) adds to the very limited evidence available for this cropping system (Chaudhary et al., 2019; Dutta et al., 2022).

Methodological and research contributions

The next theme is the research and methodological contributions of this thesis. This includes data, methods and the novelty of research questions framed around the data/methods. In terms of data, the biggest contribution of this thesis comes from novel evidence on climate adaptation from farm level data with 5,175 wheat and soybean farms in from India from 2015–2020 (Chapter 4). To the best of my knowledge, no previous study has used observed farm level data from climate-smart farms to provide empirical evidence on climate resilience towards heat stress (especially from LMICs). The chapter significantly contributes to existing literature on heat stress in wheat and soybean farms. Hitherto, most of the existing studies on heat stress effects stem from either process-based models (Asseng et al., 2015, 2013) or farm observations in temperate countries (Tack et al., 2017, 2015), where there is general agreement on significant yield penalty from heat stress, especially in tropical regions (Akter and Rafiqul Islam, 2017; R. Dubey et al., 2020; Pequeno et al., 2021), although irrigation is shown to offset such effects. By using farm observation data, Chapter 4 shows no significant effect of heat stress on climate adapted farms, showing the need for more farm evidence on risk reducing effects of CSA in tropical countries (de Pinto et al., 2020; Kakraliya et al., 2018; Sun et al., 2018). This is important to complement the findings from modelling studies, which may be unable to capture the adaptation effects fully (Aggarwal et al., 2019b; Pequeno et al., 2021).

While large-scale use of irrigation (likely explaining the findings in Chapter 5) to offset heat impacts is not encouraged, as it raises important socio-economic and sustainability issues, the study nevertheless makes significant contribution towards climate resilience of farm adaptation in the tropics. This thesis further adds to the existing evidence on risk management by providing a comprehensive database on agricultural insurance literature globally (Chapter 3), and classifying it along different research themes, products insured, sectors and hazards covered. This database is the first of its kind in terms of its global coverage and the breadth of factors analyzed on agricultural insurance; it significantly contributes to the existing knowledge base on agricultural insurance. Several meta-analytical and review studies have shown the benefits of a growing knowledge and data base on a variety of topics such as conservation agriculture (Knapp and van der Heijden, 2018), climate services (Born et al., 2021), farmer adoption of agricultural technology (Ruzzante et al., 2021), climate-adaptive agronomic practices (Dubey et al., 2020), amongst several others.

Implications

Several implications can be drawn from this thesis. The framework developed in this thesis to monitor, track, and compare climate action in agriculture (Chapter 2), is one of the very few available frameworks to operationalize climate policy research, by globally quantifying NDCs and their mismatch with country-specific context realities. Similarly, while other studies have used existing risk/disaster data in agricultural science (Brás et al., 2021; El Hadri et al., 2019), Chapter 3 utilized different types of risk data to illustrate the spatial mismatch between research intensity with observed and projected risks, across all the agricultural sectors (including livestock and cropping systems)—thus creating unique evidence on the alignment of risk management priorities with observed risk exposure. Further, Chapter 5 used commonly researched FAO (Food and Agriculture Organization) data with survival analysis to offer novel evidence on recovery and resilience of production systems. It is the first global estimation of recovery likelihoods across maize and milk production systems, as a measure of coping resilience capacity. Using diverse methods and concepts across different disciplines, the research chapters address a wide scope of research objectives on risks and resilience.

6.5 Policy and business recommendations

Climate change is often described as a "wicked problem" in the policy literature, with uncertainties, complexities, and circularities cutting across different sectors beyond agriculture, making it difficult to communicate clear research, policy, and business priorities for the future (Rossa-Roccor et al., 2021). This thesis takes a broader, interdisciplinary view of the risks faced by farming systems today, different adaptation pathways and their role in building farming system resilience. The interdisciplinary and global scope of this thesis facilitates the articulation of clear policy, business, and donor recommendations. The policy recommendations are for policymakers across sub-national, national, and global scale. Businesses involved in risk management (agricultural insurance companies, credit providers and microfinance institutions), companies which provide farm inputs for adaptation (like providers of improved seeds, drip irrigation technologies) can also gain insights from the findings of this thesis. The recommendations for these different actors are described below.

Policy recommendations

At a global scale, the foremost recommendation from this thesis comes from the policy analysis of the Paris Agreement, where different nations periodically submit their pledges for climate action (Chand, 2020; Lesnikowski et al., 2017; Schleussner et al., 2016). From a policy perspective, Chapter 2 illustrates that nations need to realign their NDCs with existing scope and readiness to scale adaptation (in many cases, even ratchet up their adaptation ambitions). Policymakers at national and global scale—mainly Conference of the Parties (COP) which periodically meet to review and reshape NDCs can use the findings from this study to better design adaptation policies in the future. Further, the mismatch found between adaptation need (risk hotspots), policy focus, scope and readiness of adaptation also shows that the policymakers can also gain from formally adopting a comprehensive adaptation monitoring system, to systematically track climate action in agriculture at a global scale and course correct, where needed, like other global development goals[33]. This can help in assessing the progress in implementation and effectiveness of current adaptation policies, it also allows for continuous evaluation and adjustment of policies where needed, while at the same time also supporting climate action at national, sub-national and regional level like National Adaptation Plans (NAPs).

The national climate policies like NAPs can be improved in multiple ways—by identifying synergies across different adaptation options, and minimizing the negative consequences ex-ante (like excessive use of irrigation and fertilizers), improving adaptation tracking and ownership (by operationalizing the framework presented in Chapter 2), integrating indigenous and local knowledge from local communities, improving institutional efficiencies across scale, sustained efforts needed for adaptation financing included blended finance routes (Höhne et al., 2017; Pauw et al., 2016; Singh et al., 2020). Additionally, local, regional, and national policies need to be in-sync and coherent to achieve common adaptation objectives—for e.g., Chapter 2 brings to light the significant need for adaptation in agriculture for the United States; although it has only recently rejoined the Paris agreement, a lot its of sub-national, regional action plans have already had significant focus on climate action, highlighting the importance of policy action at multiple scales (Gurney et al., 2021; Hsu et al., 2021).

For policymakers at local and regional scale, more specific policy recommendations follow from this thesis, across risk management and climate adaptation. For instance, the evidence from Chapter 4 on resilience of CSA farms is of deep importance to many ongoing agricultural policies in India (Barooah et al., 2023; Patra and Babu, 2023). The recently launched National Mission on Natural Farming by Government of India, plans to massively scale-out chemical-free farming and reduce dependence on pesticides. The precision nutrient and pesticide management technologies followed by CSA farms in Chapter 4, can help in prioritizing and scaling-out such technologies across different geographies. Zero tillage and residue management technologies adopted by CSA farms in the study can help in restoring soil health and controlling emissions from stubble burning—already an important policy agenda for northern states in India (Balwinder-Singh et al., 2020; McDonald et al., 2020).

[33] https://ourworldindata.org/sdgs

Finally, while irrigation likely offsets heat stress effects in wheat and soybean (Chapter 4), this cannot be a blatant recommendation due to existing excessive groundwater use in the region, likely to get worse due to climate change (Mali et al., 2021)—alternative solutions like increasing water and energy efficiency through scaling-out micro and solar irrigation, reducing peak groundwater demand by adjusting planting dates and using conservation agriculture can be possible policy pathways in such cases (Mukherji, 2022). Policies promoting CSA should also be cognizant of the sustainability issues surrounding some of the risk reducing strategies like irrigation; instead, sustainable irrigation practices like drop irrigation systems can help in mitigating risks from extreme events, while also conserving natural resources.

Business recommendations

The findings from this thesis also helps in drawing recommendations for different businesses involved in agricultural risk management. Globally, agricultural insurance is a 30 billion USD industry, mainly operating in major food producing countries and regions like the US, China, India, and the European Union. Chapter 3 showed how smallholder agriculture (mainly in Sub-Saharan Africa and Latin America) is generally underserved by the insurance industry, while also being a major risk hotspot. The spatial mismatch between risk exposure and insurance research intensity calls for a scoping study on insurance feasibility (in terms of providing adequate risk coverage) of these regions when other farm risk management strategies fail to work or are too expensive. Comprehensive risk management recommendations from Chapter 3 which can possibly increase efficiency and adoption of insurance include—risk pooling financial instruments at regional scale, bundling insurance with other farm adaptations to reduce overall risk as well as packaging insurance with microfinance options like credit, and leverage data and technology for better service delivery (Awondo et al., 2020; Baum et al., 2018; Carter et al., 2018). Using these insights, insurance companies should focus on expanding their reach to underserved regions, by initially conducting a comprehensive scoping analysis to assess the feasibility of insurance products in these regions. Not all regions are insurable, and such scoping exercise can help in identifying opportunities for future growth, while also recognizing the implementation barriers in others. Further, insurance and reinsurance companies can explore risk financing through risk pooling at a larger scale, to overcome some of the challenges mentioned above. A few such institutions already operate in the region, like ARC (African Risk Capacity), and can focus on scoping studies in underserved geographies and sectors as highlighted by Chapter 3.

Another important business recommendation is combing different risk management strategies like insurance, credit, microfinance, and farm adaptations (like improved seeds). Chapter 3 and 4 both highlighted the risk reducing effects of some such farm strategies like insurance, drought-tolerant seeds, and CSA. Key businesses like seed companies, credit providers and microfinance institutions should work together to design effective bundled products, improving risk coverage, enhancing the adoption and profitability of their products. Further, they should capitalize on digital innovations to improve bottlenecks in service delivery and better target their products.

Given the broad scope of this work, direct recommendations for farmers cannot be directly drawn from this work. However, the scale and potential impact of lessons and recommendations from this thesis can have a significant impact in safeguarding the livelihood security of farmers, by identifying hotspots (especially in LMICs) and creating evidence for different resilience strategies at a global scale. The findings from this thesis shows the need to adopt a "systems approach" by both policymakers and businesses and design policies and products for food systems by considering technical, social, environmental implications too.

6.6 Main conclusions

I end this thesis by presenting the main conclusions below:

1. At the global scale, the intent for climate action (from adaption pledges in NDCs) is not aligned with adaptation need (arising from projected climate impacts), scope for adaptation including the biophysical limits (cereal productivity gains and arable land expansion), and the readiness based on economic, governance, and social capacities to scale adaptation. (Chapter 2)
2. Agricultural insurance research should target research gaps across selected product types (indemnity insurance), geographies (low-income countries), and sectors (non-cereal crops). An emerging research theme is the role of agricultural insurance in adaptation to climate change. (Chapter 3)

3. Spatial correlation between agricultural insurance research intensity and risk hotspots is negative, i.e., for climate change induced temperature increases in the future and current research on crop insurance, this is -0.04, and for livestock insurance papers with the observed occurrence of livestock epidemics, the correlation is -0.06. (Chapter 3)
4. No significant impact of heat stress is observed on wheat and soybean productivity of climate-smart farms in India, even across different levels (bundles) of CSA technologies and practices. Heat stress also has no impact on general farm production, likely due to high adoption of improved varieties and irrigation, giving rise to sustainability issues in the region. (Chapter 4)
5. Maize production systems at a global scale recover faster than milk production systems (likelihood of recovery during the first year after a shock is 58% for maize, compared to 45% for milk production)—despite the former having greater shock exposure and intensity. (Chapter 5)
6. Latin America and Sub-Saharan Africa are hotspots of high shock exposure, intensity, and likelihoods of longer recovery times of up to eight and 10 years for both regions (and farming systems), respectively. Distinct sub-regional recovery likelihoods are also observed in high-income regions, i.e., longer recovery likelihoods in Southern Europe for maize and Western Europe for milk production. This is likely due to maize systems exposed to extreme weather events and policy driven changes in dairy milk production in these regions. (Chapter 5)
7. Resilience-enhancing strategies need to be contextualized to local conditions, consider multiple dimensions of risk mitigation, scalability, and environmental sustainability. These strategies also need to focus on the regional hotspots identified in this thesis (in terms of misalignment between risk exposure and research and policy action): Eastern and Southern Africa, Middle-east and Northern Africa and South America. (Chapter 2, 3, 4, 5 and 6)

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English summary

Farming systems are facing many challenges magnified by increasing intensity and frequency of weather extremes. At the same time, rising food demand and rapid depletion of natural resources add to the complexity of these challenges. These include (but are certainly not limited to) biodiversity loss, groundwater depletion, nitrogen and pesticide pollution, and soil health deterioration crises. These stressors are compounded by rapid urbanization and geopolitical tensions; climate change often acts as risk amplifier across these myriad issues. To counteract such challenges, de-risking food production systems is vital. Insights on the state of resilience of farming systems and identification of hotspots is crucial for development of any de-risking strategy. A systematic analysis of how farming systems are exposed to and respond to different risks is thus necessary. The risk reducing pathways include a range of mechanisms to cope with and adapt to risks, ultimately contributing to farming systems resilience. Together, these three umbrella concepts of risk, resilience, and adaptation are the focus of this thesis.

Various studies have focused on risks, resilience, and adaptation in food systems. However, there are critical gaps in literature, including a lack of a global overview on how farming systems respond to risks, fragmented evidence on this response, a lack of focus on the interconnectedness of these components and a reductionist approach to risk and resilience in farming systems. This thesis addressed this gap by looking at risks, adaptation, and resilience of farming systems at a global scale, from multiple perspectives, by focusing on the following research objectives:

I. Assess the alignment of global climate action policies with projected risks, readiness to scale adaptation based on economic, governance and social capacities of nations, and biophysical scope for adaptation. (Chapter 2)
II. Map global research on agricultural insurance across agricultural sectors, geographies, insurance product types, and research themes. In addition, analyze the geographical alignment of research intensity on agricultural insurance with historical and projected risk hotspots. (Chapter 3)
III. Identify the impacts of heat extremes on crop production under climate-smart agriculture. (Chapter 4)
IV. Assess how farming systems recover from production shocks. (Chapter 5)

Chapter 2 illustrates a new framework for monitoring global climate action based on four dimensions—intent, need, scope and readiness for implementing adaptation in agriculture. While "intent" reflects intended climate action through national NDC (Nationally Determined Contributions) pledges, "need" highlights projected impacts from climate change. The third dimension, "scope", is related to the biophysical opportunities and limits to adaptation. Finally, the "readiness" dimension considers a country's current ability to implement various adaptation actions and policies. The framework is illustrated with a global analysis, using macro-level indicators for each of these dimensions, sourced from published literature. Results indicate that 61 countries (52% of the total reviewed) have high need for adaptation but a mismatch between scope, intent and/or readiness. The proposed framework provides a holistic way to monitor and track climate adaptation, contextualize, and align climate change strategies with existing conditions, and to help identify future trajectories.

Chapter 3 focuses on agricultural insurance, by mapping global research based on 796 peer-reviewed papers, and categorizing literature across agricultural sectors, geographies, insurance product types, and research themes. Additionally, by spatially correlating exposure to different types of physical and biological risks across livestock and cropping systems, the review shows (mis)alignment of research intensity across sectors—poor correlation between climate change induced temperature increases in the future and current research on crop insurance and that of livestock insurance papers with observed livestock epidemics. The review also shows how agricultural insurance contributes to adaptation—either through bundling with other adaptations like climate-smart agriculture (CSA), or as a feedback mechanism into other adaptive actions (pay-offs for insurance being used to buy drought-resistant seeds), having important implications for developing future risk management strategies.

Chapter 4 identifies the impact of heat stress on CSA farms, based on panel data from 5,175 farm-level wheat and soybean yield observations in India (2015–2020). By using fixed effects regression with restricted cubic splines, the results find no significant impact of heat exposure during the growing season for both crops, even for sub-samples based on different CSA bundles. The findings also remain constant for all district-level wheat and soybean yield statistics across India for the same time-period. This is likely due to policies and mechanisms stimulating broad uptake of improved varieties and irrigation practices aiding resilience to heat stress—although with severe environmental footprints. The results show the importance of shaping farm adaptations in the larger context of resilience and sustainability issues.

Chapter 5 assesses how maize and dairy milk systems recover from production shocks at a global scale, using national production data from FAOSTAT spanning 60 years across all the countries. The study uses statistical shock detection and survival analysis to show that maize production systems recover faster than milk production systems at a global scale (likelihood of recovery in the first year after the shock is 58% for maize, compared to 45% for milk production)—despite maize production systems having greater shock exposure and intensity. Latin America and Sub-Saharan Africa are hotspots of high shock exposure, intensity, and likelihoods of longer recovery time across both maize and milk production systems. The results show that resilience to production shocks at the global scale requires highly differentiated approaches that address region-specific shock types, vulnerabilities, adaptive capacities, and take account of unique system-specific production system characteristics.

Chapter 6 synthesizes the results and identifies common themes: a) resilience of farming systems including the types of risk faced and resilience strategies examined, and how resilience is conceptualized and quantified across different chapters and b) insights from a global perspective—hotspots identified, macro-trends detected, and synergies observed across the research chapters. Middle-east and Northern Africa, Sub-Saharan Africa and Southeast Asia emerge as hotspots across multiple dimensions of adaptation, resilience, and risk exposure. Finally, the policy, business, and donor recommendations are discussed. For policymakers, these include streamlining the global climate policy in the form of NDCs based on adaptation needs, scope and bolstering efforts to improve readiness and enabling environment to scale-out adaptation policies and ensure their adoption by farmers on the field. Another recommendation is designing policy instruments with both resilience and sustainability considerations; since some farm adaptations to reduce risk (like irrigation) may not be sustainable in the long run. For businesses, designing bundled risk management products (like agricultural insurance with farm adaptations or credit), and leveraging data and technology for better service and last mile delivery are key. For donors, recommendations include to invest in the identified “hotspots” (Middle-east and North Africa, Eastern and Southern Africa and South America). These areas show high vulnerabilities consistently across different themes (risk exposure, data gaps, risk and insurance research intensity, low resilience, and misaligned adaptation priorities); international development and donors may channel investments here to strengthen the farming systems.

The main conclusions of this thesis are:

1. At the global scale, the intent for climate action (from adaption pledges in NDCs) is not aligned with adaptation need (arising from projected climate impacts), scope for adaptation including the biophysical limits (cereal productivity gains and arable land expansion), and the readiness based on economic, governance, and social capacities to scale adaptation. (Chapter 2)
2. Agricultural insurance research should target research gaps across selected product types (indemnity insurance), geographies (low-income countries), and sectors (non-cereal crops). An emerging research theme is the role of agricultural insurance in adaptation to climate change. (Chapter 3)
3. Spatial correlation between agricultural insurance research intensity and risk hotspots is negative, i.e., for climate change induced temperature increases in the future and current research on crop insurance, this is -0.04, and for livestock insurance papers with the observed occurrence of livestock epidemics, the correlation is -0.06. (Chapter 3)
4. No significant impact of heat stress is observed on wheat and soybean productivity of climate-smart farms in India, even across different levels (bundles) of CSA technologies and practices. Heat stress also has no impact on general farm production, likely due to high adoption of improved varieties and irrigation, giving rise to sustainability issues in the region. (Chapter 4)
5. Maize production systems at a global scale recover faster than milk production systems (likelihood of recovery during the first year after a shock is 58% for maize, compared to 45% for milk production)—despite the former having greater shock exposure and intensity. (Chapter 5)
6. Latin America and Sub-Saharan Africa are hotspots of high shock exposure, intensity, and likelihoods of longer recovery times of up to eight and 10 years for both regions (and farming systems), respectively. Distinct sub-regional recovery likelihoods are also observed in high-income regions, i.e., longer recovery likelihoods in Southern Europe for maize and Western Europe for milk production. This is likely due to maize systems exposed to extreme weather events and policy driven changes in dairy milk production in these regions. (Chapter 5)

7. Resilience-enhancing strategies need to be contextualized to local conditions, consider multiple dimensions of risk mitigation, scalability, and environmental sustainability. These strategies also need to focus on the regional hotspots identified in this thesis (in terms of misalignment between risk exposure and research and policy action): Eastern and Southern Africa, Middle-east and Northern Africa and South America. (Chapter 2, 3, 4, 5 and 6)

About the author

I was born on September 28, 1987 in Meerut, Uttar Pradesh, India. Immediately after birth, I was raised and spent my childhood years in New Delhi (which I consider my home city). I obtained my undergraduate degree in *Agricultural Sciences* from University of Agricultural Sciences, Bangalore, India. In 2011, I graduated from Institute of Rural Management Anand, Gujarat, India (IRMA) with a post-graduation in Rural Management.

Since then, I have worked across different agricultural development stakeholders including government agencies, international NGOs and research institutes. I joined CGIAR in 2012, starting my journey with International Water Management Institute (IWMI). I spent eight years working for CGIAR research program on climate change (CCAFS-CIMMYT), where I discovered my interest and developed my skills in climate sciences. I started my Ph.D. in 2019 as an external candidate, while continuing to work for CGIAR research institutes, under the common research interest area of climate risk management (for the Business Economic group and CGIAR). In between my Ph.D. I changed jobs from CIMMYT to CIAT and relocated from New Delhi to Nairobi, Kenya.

Apart from climate risk management, I am also interested in research on food systems resilience and climate adaptation. I enjoy applying econometric methods for climate change attribution and impact studies, apart from learning new skills and methods from other disciplines and working across different scientific disciplines. I will continue to pursue these interest areas in future through my engagement across different international research institutes. In my free time, I enjoy hiking, learning new dance forms, cooking and travelling.

Shalika Vyas

Wageningen School of Social Sciences (WASS)

Completed Training and Supervision Plan

Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
A1 Managing a research project			
WASS Introduction Course	WASS	2020	1
Writing research proposal	WUR	2020	6
'The gap between intent and climate action in agriculture'	Global Climate Smart Agriculture Conference. Bali, Indonesia.	2019	1
'Where We Need to Drive Food-System Action'	CCAFS Science meeting. Barcelona, Spain and online.	2021	1
'Response of climate-smart agriculture to weather shocks'	AAEA (Agricultural and Applied Economics Association) Annual meeting. Anaheim, USA	2022	1
'Limited Impact of Heat Stress in Indian Wheat and Soy Under Climate-Smart Agriculture'	EAAE (European Association of Agricultural Economists) XVII Congress. Rennes, France.	2023	1
Attending BEC PhD meetings	WUR	2021	1
A2 Integrating research in the corresponding discipline			
Critical Perspectives on Social Theory	WASS	2020	4
Academic Publication and Presentation in the Social Sciences	WASS	2021	4
Summer school: Risk Analysis and Risk Management in Agriculture: Updates on Modelling and Applications	WASS	2021	3
B) General research related competences			
B1 Placing research in a broader scientific context			
Scientific Integrity	WGS	2020	0.6
WASS Economic Seminars and online seminars	WASS	2021	2
Working on INREF pre-proposal.	WUR	2020	2
Working on INSPIRE challenge	WUR	2020	2
B2 Placing research in a societal context			

Organizing INREF workshop on agricultural insurance in India related to published agricultural insurance review paper (Thesis Chapter 3)	CCAFS-BISA	2020	2
Writing blogs Blog on Thesis Chapter 2 on WUR Economics website. Blog on Thesis Chapter 3 on WUR Economics and CCAFS website. Blog on international INREF workshop on agricultural insurance Blog on data collection and field visit to Climate-smart Villages in India	WASS, CCAFS-BISA, CIAT	2019-2024	0.5
C) Career related competences/personal development			
C1 Employing transferable skills in different domains/careers			
Supervising research internship	CCAFS-BISA	2019	0.7
Writing review	Nature masterclass	2019	0.3
PhD competence assessment	WGS	2020	0.3
Total			**33.3**

*One credit according to ECTS is on average equivalent to 28 hours of study load

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Martin, thank you for your valuable policy and action-oriented thinking, you always made me think about the value of our research in terms of real-world impact, making sure the research is grounded in CGIAR's science-for-policy agenda. It is thanks to you that this PhD journey started long back in CIMMYT, and I will always remember our initial discussions in the BISA-CIMMYT office, my excitement and happiness that I could have your support going forward. Your encouragement towards excellence (grounded in reality) really helped in framing this research in a more holistic way. I also thank Pramod Aggarwal and Paresh Shirsath in supporting this Ph.D. during the initial years, during my time at CIMMYT.

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Last but not the least, Julian, this PhD would not have finished without your support. I changed jobs in the last leg of my PhD journey (from CIMMYT to CIAT), and the transition was so easy, thanks to you and your support. You helped in balancing both work and PhD, in a manner that was not overwhelming and created opportunity for me to feel more comfortable, relaxed and created space for me to achieve my targets in both. I will truly value this emotional support, apart from the technical skills and scientific reasoning I have learnt from you—your brilliant logical and scientific reasoning, is something I deeply admire and aspire to emulate. I am grateful our collaboration will continue beyond this journey, and I will have more time to learn from you, as I continue my journey in CIAT.

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This journey would not have been possible without the enormous support from my family and friends. My parents have seen the ups and downs, the breakdowns and euphoria as part of this journey, and stood by me throughout, they continued to support me when times were tough, and always encouraged and filled me with their positive enthusiasm. My brother Shikhar, who acted like an in-house therapist over the last five years; without him I don’t know where I will be. I dedicate this thesis foremost to them. My friends—Nitya, Shehnab, Sindhura, Chirag, Anna, Casey, Prakhar your support meant everything to me. A PhD can often lead to social isolation and heartbreaks, but you not only understood the stress and pressure I was in, but also gave me the space and time when needed (apart from supporting me in different stages of this emotional roller coaster). At last, I look back to the five-year younger Shalika, who had dreams of doing a PhD, and the growth she has had over these past years—you gave your best.

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