Assessing Climatic and Technological Constraints to Agricultural Productivity in South Asia

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Declaration

I certify that the thesis presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work unless otherwise clearly indicated.

I warrant that this authorisation does not, to the best of my belief, infringe the rights of any third party.

I declare that my thesis consists of approximately 80,000 words.

Statement of Conjoint Work

Chapter 3 was co-authored with Francisco Fontes and Charles Palmer. My contribution amounted to 50% of the paper.

Chapter 5 was co-authored with Ali Dehlavi and Ben Groom. My contribution amounted to 70% of the paper.

Abstract

This thesis comprises of four essays that seek to advance understanding of the role that climatic constraints have on agricultural productivity in India and Pakistan. This work emphasises that the constraints posed to agricultural production must be understood within the context of an evolving set of environmental and technological conditions. The thesis employs empirical methods to understand these relationships, where particular emphasis is placed on methods suitable for learning about the challenges agriculture will face in the future. The first chapter studies the impact of climate change on rice yields in India by modelling the inter-annual distribution of yield conditional on projected temperature increases. The results suggest a decrease in average yield and a substantial increase in the probability of low yields. It is also shown that yields have become increasingly resilient to heat over time. The second chapter studies the effect of drought on cereal production in India by estimating thresholds of drought impact. By examining thresholds over time, evidence is found of decreasing average impacts, but with evidence of an abrupt increase in average drought impacts in more recent years. Thresholds of precipitation are also estimated, indicating substantial heterogeneity in resilience to drought across crop types and regions of India. The third chapter examines how changes in agricultural technology brought about by the Green Revolution affected the relative importance of agro-climatic factors in determining crop yields. Using a detailed measure of crop suitability it is found that yields increased relatively more in areas of higher suitability, indicating complementarity between agricultural technologies and favourable agro-climatic characteristics. The final chapter uses farm-level data from a specifically-designed survey to assess the impact and determinants of climate change adaptation strategies on crop productivity in Pakistan. Adaptation has a beneficial effect on rice yields, but not on wheat yields. This chapter also finds that a number of household and institutional factors are strongly related to whether households have adapted to climate change.

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List of Abbreviations and Acronyms

ATT - Average Treatment Effect on the Treated

ATU - Average Treatment Effect on the Untreated

CGIAR - Consultative Group for International Agricultural Research

CIMMYT - Centro Internacional de Mejoremiento de Maiz y Trigo

CO_2 - Carbon dioxide

°C - Degrees Celsius

°F - Degrees Fahrenheit

FAO - Food and Agriculture Organisation of the United Nations

GAEZ - Global Agro Ecological Zone

GDP - Gross Domestic Product

HYV - High Yielding Variety

ICRISAT - International Research Institute for the Semi-Arid Tropics

IIASA - International Institute for Applied Systems Analysis

IMD - Indian Meteorological Department

IPCC - Intergovernmental Panel on Climate Change

IRRI - International Rice Research Institute

NGO - Non Governmental Organisation

OLS - Ordinary Least Squares

PDSI - Palmer Drought Severity Index

R & D - Research and Development

TFP - Total Factor Productivity

UN - United Nations

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Chapter 1

Introduction

This introductory chapter aims to motivate the importance of understanding the evolving constraints to agricultural productivity to assess the challenges facing agriculture in the twenty-first century. Firstly, I outline the importance of understanding these constraints due to the need to meet a growing demand for food in the future. Secondly, I discuss a number of the evolving constraints to increasing production. In particular, I highlight the significance of understanding constraints related to agricultural productivity and the climate. After this, I provide an overview of these issues in the context of my study area, South Asia. Finally, I outline each of the thesis chapters by providing brief summaries of the aim, contribution, methodology and results of these chapters.

1.1 The growing demand for food

In the coming decades, the agricultural sector must produce enough food to meet the demands of an increasingly affluent and growing population. By the middle of the century, global population is expected to reach 9.7 billion, adding a further 2.4 billion people compared to the present day (UN, 2015). Economic growth, especially in developing economies, is also projected to continue to increase in the coming decades, boosting the incomes of many (Rodrik, 2014). Put together, these trends will have major implications for the global demand for food. The demand for staple cereal crops, such as rice, wheat, maize, and soybeans is likely to be of particular importance given the vital role that these crops play in the diets and expenditure of a large part of the global population. For example, these four crops made up 46 percent of all calories globally consumed in 2010, with this percentage significantly larger in many low income countries (Pingali, 2015). Although the contribution of these crops to total calories consumed tends to decline as income levels increase (Deaton and Dreze, 2009), the demand for staple cereal crops is still projected to increase by around 60 to 100 percent by 2050 compared with 2010 (Tilman et al., 2011; Fischer et al., 2014).

Failure to increase the supply of these crops is likely to result in higher prices for these agricultural goods, putting the food security of many consumers at risk. The vulnerability of the global food system was highlighted between the years 2007 and 2008, in which prices for agricultural commodities elevated rapidly. During this period, average prices of food commodities increased by over 50% (Tadesse et al., 2014). These price increases were particularly steep for a number of the aforementioned staple cereals, however. Rice, wheat, and maize saw respective prices increases of 225%, 81% and 87% during this period (Headey and Fan, 2008). It has become clear following this period that there may be winners and losers from price increases such as these. On the one hand, price increases could actually increase the incomes of many producers if higher consumer prices translate into higher farm gate prices. On the other hand, the distributional effect of price increases would likely disproportionately fall on many of the world's poor, particularly urban consumers and rural net buyers of food, who spend larger portions of their income on food (Dorward, 2012). For instance, in the majority of developing countries, the poorest 20 percent tend to be net buyers of food (FAO, 2011). The knock-on effects of rising food prices have also been linked to wider social impacts, such as the increased incidence of social unrest(Bellemare, 2015).

1.2 Assessing the constraints to agriculture

1.2.1 The role of productivity in the twenty-first century

Increasing amounts of scholarly attention has already been devoted to bringing attention to the evolving constraints that will be important for determining the production of food in the future (Naylor, 1996; Tilman et al., 2002). Although the exact nature of these constraints depends on the context in question and will later be explored in the main body of the thesis, a number of these constraints are common across much of the world's agricultural sector. For instance, one way to increase production in future will be to increase the amount of land that is cultivated. Historically, increases in area cultivated have been important for increasing the supply of agricultural goods. For example, between 1970 and 2005, cultivated area for the ten major global crops, which make up nearly 60% of cultivated area, increased by 26% (Rudel et al., 2009). The prospects for continuing to increase cultivated area appear to be very limited, however. A primary issue is that there is increasing international recognition of the threat posed by agricultural land expansion to biodiversity, such as the encroachment of agriculture into fragile ecosystems, including forests (Bulte and Engel, 2006). Similarly, increased land use competition from biofuels and other non-food crops is also predicted to restrict the amount of land that can be devoted to food crops (Lobell et al., 2014; Rueda and Lambin, 2014). Expanding cultivatable area is therefore unlikely to be the solution to increasing the supply of agricultural production in the future. This means that increases in yield will form the basis for increasing the supply of crops (Barbier, 2011).

Past experience has highlighted agriculture's ability to substantially increase the productivity of land. For instance, sustained rates of yield growth for a number of staple crops were characteristic of the sector in many parts of the world during the twentieth century (Ruttan, 2002; Federico, 2005). Key to this was the increased use of a range of modern agricultural technologies. These technologies transformed land previously farmed using more traditional methods, into land that delivered much greater output per acre in many areas of the world. The utilisation of improved crop varieties and the use of modern farm inputs, such as fertiliser and irrigation, were integral to increasing the productivity of land in most areas of the world. For example, across developing countries yields for wheat increased by over 200% and yields for rice increased by over 100% (Pingali, 2012). The increased supply of staple crops has had very substantial effects on the real price of food, which showed trend rates of decline in the latter part of the twentieth century (Rudel et al., 2009). Evenson and Rosegrant (2003) estimate that rice prices would have been 80-124% higher and wheat prices 29-61% higher without the productive gains spurred by crop genetic improvement programmes that occurred as part of the Green Revolution. Global food challenges in the present day are in many ways comparable to those fifty years ago. For example, between 1970 and 2005, total production of staple crops increased by 123%. Concerns about an impending Malthusian crisis due to rapid and concentrated population growth were thus successfully averted.

Despite previous success in increasing the productivity of agriculture, a crucial issue pertains to whether rates of productivity growth in agriculture will be sustained in the future. There is increasing evidence that the productivity gains made from switching to modern farming techniques are slowing. A number of studies have noted a slowdown and a even stagnation in the rate of yield growth for key staple crops in recent decades. Ray et al. (2012) estimate that globally, 24-39% of areas growing cereals such as rice, wheat, maize and soybeans display non-increasing trends in yield growth. In addition, Lin and Huybers (2012) show that 50% of major wheat growing areas show stagnant growth rates. Levels of public R&D in agriculture have also fallen over time, meaning that research into maintaining and improving the yield potential of cultivars has decreased (Piesse and Thirtle, 2010). In light of this, the primary challenge facing agriculture in the coming decades will be to maintain the productive success of the past and continue to increase the supply of these crops to meet future demand. In order to do this, agriculture will have to increasingly confront constraints to productivity on existing cultivated land (Tilman et al., 2002; Hertel, 2011). How significant these constraints are for current productivity and whether these constraints are likely to evolve in future is thus a first order concern for research on food security in the twenty-first century.

1.2.2 The changing role of the climate in agriculture

Given the importance of continuing to increase the productivity of agriculture in the coming years, it is crucial to understand the evolving constraints the sector could be exposed to. In recent years, increasing amounts of research effort has been devoted to understanding the interaction between environmental features and economic production systems in general. Much of this research has been motivated by overwhelming evidence that human-induced emissions of greenhouse gases, such as carbon dioxide, are contributing to rising global temperatures. According to the IPCC (2014), average surface temperatures around the world have increased by 0.85°C between 1880-2012. For example, previous work has shown that since 1980 yields of major cereals across the world have already reduced due to temperature increases, offsetting some of the gains made by technological improvements over this period (Lobell et al., 2011). Projections of future warming, although suffering from significant uncertainties about the sensitivity of the climate system to changes in greenhouse gas emissions and the uncertain nature of future emissions trajectories, indicate substantial increases in global temperatures. Warming by the end of the century is likely to exceed 2°C and in extreme cases could amount to 5°C. These projected increases in temperature have been predicted to substantially lower the productivity of agriculture in the future owing to the harmful effect of heat on crop growth (Schlenker and Roberts, 2009; Challinor et al., 2014; Deryng et al., 2014).

Moreover, climate change is also likely to affect other climatic inputs integral to agriculture, such as rainfall patterns and extreme heat, which could influence the probability of events generally considered harmful for agriculture, like drought and floods (IPCC, 2012). How resilient the agricultural sector is to these shocks will be crucial to avoiding the adverse effect shocks to productivity for global markets and for producers and consumers more locally. The share of food traded internationally has risen steadily over time, and a range of government support schemes have been introduced aiming to stabilise the price of agricultural commodities so that local productivity shocks in agriculture tend to have less effect on local food prices (Anderson, 2010). However, the productivity of agriculture still remains crucial as a source of income for farmers and labourers.

Although these changes in climate present a challenge from a global food security perspective, a crucial point pertains to the expected geographical distribution of climate change impacts. For instance, growing areas in lower latitude regions (those nearer to the equator) have been identified as areas most vulnerable to the adverse effects of climate change (Mendelsohn et al., 2006; Auffhammer and Schlenker, 2014). This stems from the fact that already these areas tend to be hotter and thus prone to extreme weather (Nordhas, 2006). Output from climate models predicts that by the end of the this century, growing season temperatures in the majority of tropical and sub-tropical areas will exceed those historically recorded as hottest more often than not (Battisti and Naylor, 2009). Despite this, research examining the potential economic impacts of climate change on agriculture has largely taken place in the United States and other developed countries (Burke et al., 2015). Increased amounts of research are thus needed to assess exactly how agricultural production could be affected in areas of the world that may be particularly vulnerable to these changes and to understand the opportunities for reducing the adverse impacts of future changes borne by climate change.

1.3 Research location: South Asia

To contribute to understanding the evolving constraints to agriculture, the work contained in this thesis examines these issues in the context of two countries in South Asia: India and Pakistan.

The challenges to agriculture at the global level are readily reflected in South Asia. Growing domestic demand for staple crops like wheat and rice will to continue to grow. The current population of India numbers 1.25 billion and 182 million in Pakistan. In India, the population is expected to reach 1.66 billion by 2050 and in Pakistan will likely reach 300 million by 2050 (UN, 2015). To meet the demands of these increasing populations, the role of domestic agricultural production will remain integral for the food security of these countries.

To further reflect trends at the global level, constraints to future production growth in

South Asia are pressing. The inability of agriculture to expand onto more land is a critical constraint in most agricultural areas of India and Pakistan. While rates of urbanisation will continue to increase, and burgeoning modern sectors of the economy will continue to reduce the relative share of agriculture in national income, these changes are likely to place additional competition on land currently used for agriculture, placing the onus on agricultural productivity growth to meet future demand.

Previously, India and Pakistan were able to benefit immensely from technological innovation during the Green Revolution, which began in the mid-1960s. Following colonial independence in 1947, agriculture in both countries was in a state of low productivity with stagnant growth rates (Chaudhry and Chaudhry, 1997; Roy, 2007). In a relatively short amount of time however, the increased production of key staple crops, especially rice and wheat, meant that agricultural sectors of these economies produced enough food to consistently cater to the increasing internal demand from rapidly growing populations. In both countries, average wheat yields at the end of twentieth century were roughly three times those in 1960, and had increased by more than double for rice (Evenson, 2005).

The initial gains in productivity from the Green Revolution and the subsequent diffusion of these technologies to wider areas delivered sustained productivity growth for a number of decades. However, more recent analyses have highlighted that the rate of increase in yields is not increasing and even declining in many areas. This is particularly notable in India, where wheat yields have stagnated or actually declined in 70% of areas in the previous decade. For rice, trends suggest that yields are not increasing in 35% of rice areas (Ray et al., 2012).

Importantly, the sustainability of the Green Revolution model of development which forms the basis for the agricultural production systems of both countries is being called into question. Overexploitation of groundwater and land degradation are particular concerns in high productivity areas of both India and Pakistan (Murgai, 2001). Indeed, recent satellite estimates show that groundwater depletion is particularly acute in many areas (Rodell et al., 2012). Additionally, claims that increases in average productivity masked regional inequalities in agricultural development by consolidating the productivity of the most favourable growing areas casts further doubt on the suitability of this model in the coming years (Pingali, 2012).

The constraints to agricultural production are also compounded by projections of future climate change. Models suggest that average temperature increases across the region are likely to amount to increases in average surface temperature of between 1 and 2°C by 2050, and between 3-4.5°C by the end of century relative to observed temperatures in the middle of the twentieth century (Ahmed and Suphachalasai, 2014). Moreover, changes in the climate may also manifest themselves by affecting a particularly salient feature of the South Asian agricultural sector, the monsoon. The probability of extreme rainfall events, which can lead to drought and floods, has significantly increased over the last fifty years (Singh et al., 2014). Although there is no scientific consensus about whether levels of rainfall will change in the future, there is more agreement that climate change is likely to increase the variability of monsoon patterns, leading to more extreme precipitation events (Turner and Annamalai, 2012).

Finally, assessing the performance of agriculture in these two countries is motivated by the crucial role agriculture continues to play in the economic lives of millions in the region. The proportion of people living below the internationally-determined extreme poverty line of $1.90 a day amounts to 21.3% of the population in India and 8.3% in Pakistan (World Bank, 2016). These numbers are more startling given the absolute number of people that these statistics refer to. In India, this represents one-quarter of a billion falling below this line. Symptomatic of these poverty rates is that agriculture remains the dominant form of employment throughout the region. According to the International Labour Organisation, 50% of those employed work in agriculture in India, with this figure at 45% in Pakistan in 2010. Although absolute levels of urbanisation will continue to increase, rural populations who primarily rely on income from agriculture will remain very large and roughly constant in absolute terms by the middle of this century in both countries (United Nations, 2014). As such, the role of agriculture as a source of income and employment will remain an important factor for the living standards of many in these areas (Datt and Ravallion, 1998; de Janvry and Sadoulet, 2010). Higher levels of productivity have increased the incomes of rural farmers and agricultural labourers. Similarly, greater food availability can also reduce the price of food for rural and urban consumers alike, with some estimates suggesting that rates of growth in the agricultural sector can reduce poverty by three times more than growth in other sectors of the economy (Christiaensen et al., 2011).

In assessing the future of food security in these areas, it is crucial to consider the evolving nature of the constraints to agriculture and how these could affect prospects for the future. Research assessing the constraints borne by climate change is crucial for assessing implications for productivity of the sector. On top of this, understanding possibilities to adapt and cope quickly enough so as not to compromise the livelihoods of the millions dependent the sector is of foremost importance. These themes are pursued in the rest of the thesis.

1.4 Data and methodological approach

The chapters that follow employ a number of different empirical methods in order to assess a number of constraints to agricultural productivity. The data used and the empirical methodology are described in detail in each chapter. Before describing each separate paper that makes up the thesis, however, it is important to note the different types of data used throughout this thesis.

The first three chapters exploit a lengthy set of panel data pertaining to district-level agricultural outcomes in India. The use of panel data in this context is advantageous since it allows for the application of a number of empirical approaches to isolate the effect of various climatic constraints to agriculture. Over recent years, a burgeoning literature has sought to apply empirical methods to assess the role that various climatic variables play in affecting agricultural production (Auffhammer and Schlenker, 2014). A key development is the substantial increase in the availability of historical data relating to both physical variables, such as temperature and rainfall, and corresponding data on various economic outcomes that could be affected by variation in these physical variables (Auffhammer et al., 2013). The panel data on agricultural outcomes is also matched with a set of state-of-the-art weather data and agro-climatic suitability indices. Detailed descriptions of this data and construction of the variables used to undertake the analysis are discussed in depth in each paper.

The fourth chapter takes a slightly different approach by utilising a set of data from Pakistan. This data differs from data used in the previous chapters in two ways. Firstly, the data is measured at the household level as opposed to the district-level. Second, the data is cross-sectional since it resulted from an agricultural survey undertaken in 2013. The relative benefits and costs of examining data at this level are discussed in the chapter.

1.5 Thesis outline

Given the issues previously outlined, the aim of this thesis is to assess the role that a number of different climatic constraints have on agricultural production in South Asia. In doing so, empirical methods will be used to understand these relationships in order to learn about the challenges South Asian agriculture will face in the future. A key point made throughout this thesis is that the role of climatic constraints should be understood within the context of a changing agricultural sector. As such, a particular emphasis is placed on understanding how the effect of relevant climate variables may have changed over time and whether we can use knowledge of the past to more accurately provide policy makers with information about how to better plan for the future. The individual chapters of this thesis proceed as follows.

In Chapter 2, I assess the effect of climate change on rice yields in India. An important contribution of this paper is the assessment of the impact that temperature increases have on the year-to-year distribution of rice yields as well on average productivity. Given that low productivity outcomes can lead to significant welfare costs to producers and consumers, an assessment of whether climate change has the potential to significantly alter the likelihood of these occurrences is of high importance. This is achieved by applying the moment-based maximum entropy technique, which is used to construct distributions of rice yield conditional on future temperature scenarios. A district-level database of rice yields in India is combined with records of daily weather data to empirically model the historic response that temperature has had on crop productivity. I first estimate that based on the relationship between temperature and rice productivity between 1970 and 2009, average yields decline by 4.4% for the period 2011-2040 and 9.9% by 2041-2070. Importantly, the effect of warming also leads to a large increase in the probability of particularly low yields. By the middle of the century, I predict that low yields that historically occurred with 25 percent probability increase to 38 percent. One important finding from this study is that rice yields have become more resilient to heat over time. Although absolute yield losses from heat have remained constant over time, there has been a significant reduction in the relative effect of heat on yields over time. These findings suggest that researchers should examine changes in heat tolerance of agriculture in order to provide more accurate predictions about future impacts and investigate the possible mechanisms behind these changes.

To further examine the vulnerability of the agricultural sector in India to climatic threats, in Chapter 3 I conduct an assessment of an enduring obstacle for agriculture: drought. This is conducted with co-authors Francisco Fontes and Charles Palmer. The consequences of drought continue to pose a substantial challenge for farmers and policy makers alike given the adverse effect drought tends to have on agricultural production. In order to assess the vulnerability of cereal production in India to drought, we adopt a threshold regression approach in order to identify data-driven ranges for which the magnitude of drought impacts on cereal production differs. This is first applied to understand whether the effect of cereal production has changed over time and to identify whether there are distinct periods of time between which average drought impacts vary. We find evidence of a non-linear pattern in average district cereal yields over time. While drought impacts have reduced over time, we find evidence of a sharp break in this trend towards the end of the sample period. A number of evolving issues are discussed to explain this pattern of impacts. In addition, we estimate precipitation thresholds for drought impacts. This allows us to determine levels of rainfall at which drought becomes particularly harmful for crop yields. An advantage of this approach is that we are able to compare estimated thresholds with official classifications of drought based on precipitation deficiency. Overall, we find significant and negative marginal impacts of drought for levels of rainfall below 70 to 80 percent of long-term rainfall, which corresponds with official drought definitions. These results suggest, however, that drought definitions that do not account for local differences in average climate and crop choice are likely to provide misleading policy guidance about the effects of drought on crop productivity.

Agricultural technologies are crucial for allowing farmers to grow crops effectively across a range of environments. The ability of agricultural technologies to grow effectively under harsher environments will be important for whether technologies will be effective in areas exposed to environmental changes, such as climate change, in the future. In Chapter 4, I examine whether technological change in agriculture changes the relative importance of environmental characteristics that determine crop productivity. To do this I study the changes in agricultural technology brought about by the Green Revolution. A common claim is that high yielding variety seeds, which facilitated yield increases over time, were complementary in the production process to areas better endowed with more favourable climates and fertile soil. Consequently, this complementarity could have led to yield growth that was land quality biased, increasing yields relatively more on better quality land following the Green Revolution. I test the validity of this hypothesis by examining whether yields for rice and wheat increased relatively more in areas most suited to crop growth after the Green Revolution in India. Particularly important for this chapter is the accurate measurement of agro-climatic conditions. Accordingly, I adopt a crop-specific measure of land quality from the FAO Global Agro-Ecological Zones project. The results of this analysis show that for both rice and wheat, yield gains after the Green Revolution significantly increased the productive advantages of districts with higher agro-climatic suitability for crop growth. This result is consistent across a number of subsets of geographical regions, over time, and does not seem to be driven by differences in the diffusion of technology across districts. This work highlights that developing agricultural technologies that work effectively under increasing environmental strain is important for maintaining agricultural productivity in the future.

Chapter 5 differs from the previous chapters in two ways. First, I turn my attention to Pakistan. Second, I use farm-level data taken from a specifically-designed agricultural household survey that collected data on farmers' observed adaptation strategies, farm production and household characteristics. While several studies have estimated that average crop yields may decline with climate change, no prior work has empirically examined the role that adaptation to climate change might play. A detailed understanding of the range of strategies available to farmers and the productive benefits of these strategies is therefore needed. The data from this study is employed to assess whether the use of climate change adaptation strategies has a positive effect on farm productivity. The empirical approach used in the paper addresses the issue of farmer self-selection into adaptation by utilising an endogenous switching regression framework. It is found that the impact of employing adaptation measures differs according to crop. We predict that the use of adaptation strategies for rice farmers has, on average, increased yields by 9%. In contrast, for wheat farmers, we predict positive but statistically insignificant productive gains from adaptation. We also estimate the counterfactual gains for non-adapting farmers had they adapted to climate change. We find these effects to be much larger, suggesting that policies aimed at relaxing the constraints to undertaking adaptation could have significant effects on food security. This chapter also finds that a number of household and institutional factors are strongly related with whether households have adapted to climate change. This indicates that in order to allow farmers to efficiently adapt to climate change in the future, policies are required to relax some of the persistent constraints that hamper agricultural development.

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Chapter 2

Worse than average? Assessing the impact of higher temperatures on the distribution of rice yields in India

Abstract

Empirical studies examining the impact of climate change in agriculture typically evaluate impacts using measures of average productivity. Assessing the effect that climate change could have on other economically relevant measures of productivity is important for a fuller assessment of any potential costs. In this paper, I examine the effect that increased exposure to higher temperatures has on the rice yields in India, predicting the effect on average yields and the probability of low productivity events, or downside risk. District-level data between 1970 and 2009 is used along with daily weather data to estimate the historical relationship between rice yield and temperature in India. The moment-based maximum entropy approach is then employed to estimate the effect of temperature on the higher order moments of yield and to construct probability distributions of yield conditional on future temperature scenarios. While I predict that average yields will decline by 4.4% for the period 2011-2040 and 9.9% by 2041-2070, I also predict that climate change leads to substantial increases in the probability of low yield events. Projected warming by the middle of the century implies that the likelihood of yields below those that occurred with a 5 percent probability under baseline temperatures increases to 15 percent. The likelihood of yields falling below the lowest 25th percentile of historic yield distribution increases to 38 percent by the middle of the century. There is substantial regional heterogeneity in estimated impacts, with districts in northern states likely to be most affected by increased heat exposure both in terms of reduced average yield and substantial increases in the probability of low yield events. This study also finds that rice yields have become more resilient to heat over time. These findings suggest that researchers should examine changes in heat tolerance of agriculture in order to provide more accurate predictions about future impacts and investigate the possible mechanisms behind these changes.

2.1 Introduction

Temperatures are projected to continue to rise around the globe due to increases in greenhouse gas emissions. Economic production in a number of sectors is expected to be negatively affected by higher temperatures, which have historically been shown to lead to reductions in economic activity (Dell et al., 2012; Burke et al., 2015b). The effects of temperature increases could be particularly significant in the agricultural sector, where average crop yields have been predicted to significantly decrease in many parts of the world owing to the harmful effect of heat on crop growth (Challinor et al., 2014; Deryng et al., 2014).

To evaluate the effect of climate change in the agricultural sector, the vast majority of previous studies have examined effects on average agricultural outcomes (Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009; Auffhammer and Schlenker, 2014). The economic effects of climate change, however, may not be well-summarised by restricting analysis to measures of average productivity. One possibility is that more exposure to hotter weather leads to the increased likelihood of extreme productivity outcomes (IPCC, 2012). These changes could be a concern if climate change substantially affects the probability of unfavourable outcomes, such as when crop yields fall to particularly low levels. As such, if modest changes in average productivity are accompanied by a significant change in the likelihood of particularly bad events, then previous studies may be underestimating the effects of increased temperature in the agricultural sector by not considering changes in tails of the distribution of crop yields.

Researchers and policymakers have generally been concerned about evaluating outcomes beyond averages in agriculture (Hardaker et al., 1997). While a number of studies have shown that farmers tend to be averse to the increased probability of unexpected outcomes (Binswanger, 1981; Chavas and Holt, 1996), an associated issue is the likelihood of unfavourable events, which refer to downside risk. Typically producers show preferences that imply a particular aversion to downside risk (Menezes et al., 1980; Hanemann et al., 2016). Exposure to downside risk is particularly relevant in many developing countries, where a large proportion of the population is dependent on income derived from agricultural production. A large literature has found a causal link between productivity shocks in agriculture and a range of factors relevant to welfare, such as declines in rural wage rates (Jayachandran, 2006), increases in morbidity and mortality (Burgess et al., 2014), and higher probability of conflict (Hsiang et al., 2013). The consequences of productivity shocks in agriculture are usually much larger in areas of the world where a significant fraction of the population is poor and not able to access income-smoothing mechanisms like credit markets (Jayachandran, 2006; Burgess et al., 2014), which owing to problems of enforcement, moral hazard, and adverse selection tend to be underprovided in many rural areas (Besley, 1994). Thus, understanding whether climate change could increase the occurrence of these productivity shocks is a crucial for further understanding the implications of higher temperatures in agriculture.

Given the importance of considering measures of agricultural productivity beyond the mean, only a small number of studies have examined the relationship between climate change and higher order moments of crop yield. These studies have primarily focused on estimating the effect that certain climatic variables have on measures of the variability of crop yields. Chen et al. (2004) and Isik and Devadoss (2006) study the effect that increases in average temperature and changes in precipitation could have on inter-annual crop yield variability using panels of county and state-level. Both papers use stochastic production function methods (Just and Pope, 1978, 1979), enabling them to estimate the variance of inter-annual yields conditional on changes in exogenous climate variables. Chen et al. (2004) find that higher temperatures reduce average corn yields and increase their variance. On the other hand, Isik and Devadoss (2006) predict that climate change will not have large effects on average yields and will reduce the variance of yields. More recent work by Urban et al. (2012) further explores the effect that temperature increases could have on the inter-annual variability of county maize yields in the U.S. They argue that an increase in the variability of yield can occur if climate change increases the probability of temperatures that are damaging for yields.[1] They confirm this by estimating the effect

[1] This pertains to the findings of numerous empirical studies that show that yield is a concave function of temperature, such that higher temperatures first increase yields until the optimum point is reached, after which yields then begin to decline (Schlenker and Roberts, 2009; Burke et al., 2015b). While average yields would fall owing to more exposure to hotter temperatures, the additional effect of greater exposure to harmful temperatures substantially increases the set of low yields that occur since the new climate implies

that higher temperatures have on coefficient of variation of maize yield, predicting this will increase by 47 percent nationally by 2030-2050. A key implication from these results is that the distribution of crop yields is unlikely to be stationary in the future, which means risk managers should be aware of factoring in extra risk to crop yields posed by climate change in the future (McCarl et al., 1998).

These works, however, only permit a limited understanding of the consequences of climate change on downside risk for a number of reasons. First, restricting interest to general measures of variability, such as the variance and coefficient of variation, does not allow for the possibility that changes in the yield distribution may be asymmetric. Incorporating the possibility that temperature increases affect the skewness of yields over time may be important, since increasing negative skewness leads to an increase in downside risk (Menezes et al., 1980). Second, although it is possible to extend previous work to study effects on higher moments of yield (Antle, 1983), these studies do not allow for the estimation of the probability distribution of yields, which is useful for quantifying the likelihood of yields in the lower tail of the crop yield distribution, which in turn are important for quantifying changes in downside risk due to climate change (Hanemann et al., 2016). Third, as with the vast majority of research on climate change impacts in agriculture, these studies have been undertaken in the U.S. (Burke et al., 2015a), which creates a need for a better understanding of impacts in developing country contexts, which may differ both in exposure to climate change and the technological capacity to deal with these changes (Mendelsohn et al., 2006).

In this paper, I predict the effect that changes in temperature will have on district-level rice yields in India by assessing the effect on average yields and on exposure to downside risks. Rice is the dominant crop grown across Asia and plays an integral role in the food security of the region. For India specifically, rice is grown in most parts of the country and makes up around one-third of cropped area. Its successful growth is thus integral to the welfare of millions of farmers and consumers.[2] To do this, I construct conditional probability distributions of inter-annual rice yields using data covering the period 1970-2009. Yield

that temperatures are on an increasingly downward sloping part of the yield-temperature curve.

[2]This is particularly true for the poorest households in India who spend around 20% of income on rice (Groom and Tak, 2015).

distributions are constructed using the moment-based maximum entropy approach (Wu, 2003; Tack et al., 2012).[3] The method is a two-step procedure that initially estimates the effect that temperature has on different raw moments of yield. Information from these estimations is then used to map moments of yield into a distribution of yields. This allows me to predict how changes in temperature for the periods 2011-2040 and 2041-2070 will affect the probability of low yields.[4] This is done by using a measure of downside risk that assesses the probability of yields falling below certain levels of interest.

The yield data is combined with gridded daily data on temperatures and rainfall over the entire period. Many earlier studies examining the effects of climate on crop yields have relied on simplistic measures of average temperatures over long periods, such as a growing season (Auffhammer et al., 2012). These studies have been criticised for poorly representing the agronomic impact that temperature has on crop yields. More recent work has emphasised the non-linear relationship between crop yields and daily temperature, where exposure to abnormally hot days significantly harms crop growth (Schlenker and Roberts, 2009; Lobell et al., 2012). To account for this, I specify each moment of yield as a semi-parametric function of daily temperature, which allows for potential non-linearities.

Previous studies that have examined the effect of climate change on average agricultural yields in India have found mixed results on the direction of impacts depending on methodological approach and modelling assumptions (Mall et al., 2006). Only a handful of papers have applied empirical methods to estimate the effect of temperature on observed yields (Guiteras, 2009; Burgess et al., 2014), although these studies focus on aggregate measures of agricultural productivity which are problematic for deciphering crop-specific relationships between temperature and yield which may differ significantly.[5] Statistical approaches have a key advantage over crop model simulation approaches since they allow for the estimation of yield-temperature relationships under actual conditions. As such, this paper

[3]This approach has also been applied by Tack and Ubilava (2013, 2015) to study the effect of the El Nino Southern Oscillation and its implications for the distribution of crop yields in the U.S.

[4]Future changes in precipitation are not considered since projections vary widely depending on climate model used. A better understanding of the physical processes governing monsoon patterns across India is still an ongoing area of research (Turner and Annamalai, 2012).

[5]Auffhammer et al. (2012) is a notable study on the impact of climate change on rice yields in relation to climate change. These authors focus on the implications of changing rainfall patterns. Additionally, Fishman (2012) considers the impact of the inter-annual distribution of rainfall and the role of irrigation.

builds on these existing approaches using detailed weather data to specifically study the implications of climate change for rice yields, examining both impacts on average yields and the likelihood of low yields.

The estimated historical relationship between temperature and yield suggests that heat has a highly significant effect on rice yields. For India as a whole, average yields are projected to decline by 4.4% for the period 2011-2040 and 9.9% by 2041-2070 relative to the baseline historic temperature scenario. Given the variety of conditions under which rice is grown in India, there is substantial heterogeneity in mean impacts at the regional level, with northern and central areas of the country expected to be most affected by increases in temperature. In contrast, districts in the south are shown to be less affected by increases in temperature, although these impacts are still projected to be negative. Rice yields in these areas show a weaker response to temperature fluctuations compared with other areas. This may be driven by lower average baseline temperatures in these areas or due to rice being grown over a number of different seasons.[6]

The rise in projected temperatures implies significant changes to the likelihood of very low yields. This is done by comparing the conditional yield distributions under historic temperatures with the distribution under projected future temperatures. I then compare likelihood of rice yields falling below the level of yield that was historically in the lowest 25th and 5th percentile. The results show that the projected temperature increase by 2050 increases the probability of achieving yields in the lowest 5th percentile to 15 percent. The likelihood of yields falling below the level that defined the 25th percentile in the baseline scenario increases to 38 percent by the middle of the century. The change in exposure to low levels of yield due to higher temperatures is driven by two factors. First, a decline in average yield shifts the yield distribution. Second, there is a significant fattening of the tails of the distribution due to an increase in the probability of extreme outcomes. The increase in variability is particularly pronounced in northern areas, which may reflect that exposure to downside risk will be highest to those areas already locating in the hottest areas of the country.

[6] Previous studies using a variety of methods have predicted that rice yields in the south may be less affected and even benefit from small temperature increases (Soora et al., 2013; Barnwal and Kotani, 2013).

One potential issue in using the historical response of heat on crop productivity to learn about future impacts is the degree to which this relationship has remained stable over time. If there has been a significant change in the response of yields to heat over time, the use of data over long time scales could lead to erroneous assessments of the impact of future warming. Thus, I compare the response of rice yields to temperature for data in early time periods (1970-1989) relative to later time periods (1990-2009). My findings indicate that heat exposure had roughly the same effect on absolute yields in both periods. However, since average yields have increased over time, the effect of heat exposure on relative yields has decreased substantially. By re-calculating distributions for future temperature scenarios by each period sub-sample, it is shown that future impacts are substantially lower using the later period as the baseline period. These results may be due to a number of possible factors, such as improvements in agricultural technology over time or policies have enabled farmers to react better to higher temperatures. There is also some evidence to suggest that irrigation is not driving the results. I estimate that results are broadly comparable for irrigated versus non-irrigated areas suggesting that these areas have similar reactions to fluctuations in heat. These findings suggest that researchers should examine the stability of effects over time in order to provide more accurate predictions about future impacts.

The rest of the paper is structured as follows. Section 2.2 reviews issues surrounding the impacts of climate change on the agricultural sector in India and details the importance of rice. The agricultural and climate data used in this study are then detailed in Section 2.3. In Section 2.4 the empirical methodology is described and results are presented in Section 2.5. The implications of these results are discussed in Section 2.6 and Section 2.7 concludes.

2.2 Climate change and rice in India

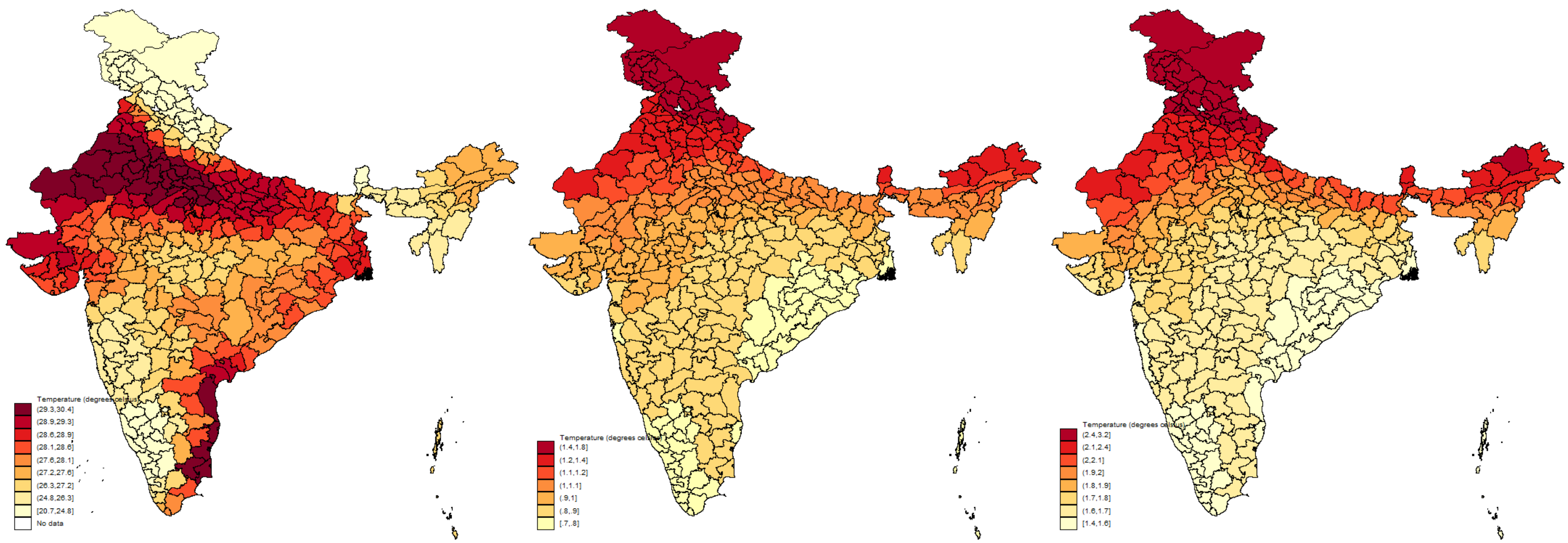
Temperature is likely to play an increasingly important role in Indian agriculture in the coming decades. Climate models predict that average temperatures will rise markedly by the middle of this century. Figure 2.1 shows predicted changes in annual mean temperature (relative to the 1961-90 average) across the country for the periods of 2011-2040 and 2041-2070 using an ensemble average across a range of climate models and emissions scenarios. The baseline average temperature over the 1961-1990 period is also shown for the months of June-October, the main growing season. For baseline temperatures, a clear spatial pattern can be seen, with northern areas, such as Punjab and Haryana, on average hotter, with daily temperatures averaging close to 30°C. In a number of southern areas, particularly those on the west coast, temperatures are much lower. The average of the model projections for future temperatures are shown in panels (b) and (c). These projections suggest that there will be significant increases in temperature across the country, with northern areas expected to experience absolute gains in temperature of over 2°C in the middle of the century. For the country as a whole, average temperature is expected to increase by 1.02°C in the years 2011-2040 and by 1.87°C in 2041-2070.

Research into the consequences of temperature increases on economic production has drawn particular attention to its effect on the agricultural sector owing to weather as a natural but uncontrollable input into the production process. In general, vulnerability to future warming is expected to be greater in regions or areas of the world, such as India, that are already prone to hot temperatures since crops in these areas are already nearer to the biological limits for plant growth (Auffhammer and Schlenker, 2014).

Future climate change is likely to be disruptive for many rice growing areas, which are mainly located in Asia, where the vast majority of the crop is both grown and consumed domestically. The success of rice production is highly significant in India where it is grown in almost all states of the country and is the largest single crop planted, with 36 percent of planted area devoted to its cultivation (Shreedhar et al., 2012). Future temperature increases are hypothesised as unlikely to benefit rice growth given that the majority of the crop is cultivated in areas where temperatures frequently exceed those shown to be optimal, with agronomic studies suggesting that temperatures in the range of 20-30°C are most conducive to rice growth (Krishnan et al., 2009). The increased likelihood of high temperatures due to climate change may have substantial impacts on heat stress-induced damage to rice growth during the growing season, since high temperatures disrupt a number of biological mechanisms that govern rice growth, such as grain filling and spikelet formation (Wassman et al., 2009).

Figure 2.1: Historical and projected future average daily temperatures for districts in India

(a) Average temp. 1961-1990 (b) Change 2011-2040 relative to 1961-1990 (c) Change 2041-2070 relative to 1961-1990



Note: Panel (a) shows the district average daily temperature in °C during main growing season for the reference period 1961-1990. The growing season is defined as the months of June-October. Panels (b) and (c) show average projected temperature changes in the two future periods relative to the 1961-1990 average. Future period projections are based on model averages from 9 climate models. Source: Author calculations based on temperature data from the Indian Meteorological Department.

Although high temperatures are generally known to be harmful for rice growth, determining the degree to which rice yields in India will be affected by future climate change is a pressing area of research. Modelling approaches used to quantify the impact of climate change on rice production in India can generally be divided into two. The first, crop model simulation studies, use more detailed scientific models to estimate temperature's effect on plant growth to estimate rice yields under different climatic conditions. Mall et al. (2006) review earlier studies using simulation models in India. They conclude that these models do not generally agree on the direction of yield changes due to climate change. For instance, an earlier result by Aggarwal and Mall (2002) found that future climate change would benefit yields in all areas of the country. However, more recent work by Soora et al. (2013), incorporating more detailed information such as temperature thresholds effects on growth, estimate that irrigated yields are projected to decline by 7% by 2050, and by 2.5% in rain-fed areas.

A criticism of simulation studies is that they do not reflect actual growing conditions in the field. To address this issue the 'statistical' approach is often applied using observational data on crop yields to understand the effect that weather variables, such as precipitation and temperature, have on crop yields in a number of parts of the world (Auffhammer and Schlenker, 2014). For instance, in India, Auffhammer et al. (2012) study the relationship between state-level rice yields and monsoon rainfall patterns under climate change. This work, however, does not study the contribution that future temperature rises could have on rice production.

Recently, the increased availability of high resolution weather data has allowed for the improved measurement of the historical relationship between crop output and temperature. A primary finding from this work, as noted by Auffhammer and Schlenker (2014), is that the relationship between yield and temperature is non-linear and that seasonal exposure to extreme heat is a good predictor of yields for many crops. Since average temperatures over a long period, such as a growing season, may poorly categorise the range of harmful temperatures, the effects of future increases in temperature on agricultural yields may be poorly estimated by earlier studies. A prominent study by Schlenker and Roberts (2009) uses yearly, county-level data on a range of crops including corn, soybeans and cotton in the U.S to show that exposure to daily temperatures beyond 29-32°C significantly harm yields.

Similar methods have been applied to understand the effects of climate change on agriculture in India, although these studies focus on the effect of temperature on aggregated measures of agricultural output rather than crop-specific relationships. Burgess et al. (2014) argue that rural areas are most vulnerable to the effects of heat since agricultural productivity, the primary means of rural employment, falls significantly with more exposure to heat. They specify a model of aggregate district agricultural productivity against daily temperatures. Their findings indicate that daily temperatures above 80°F (27°C) negatively affect district agricultural yields, and that an additional day above 85°F (29°C) reduces annual yield by 0.5%. Guiteras (2009) uses a similar model to study the effect of climate change on average district agricultural productivity. He estimates that increased warming could reduce average yields by 4.5-9 percent by 2010-2039 and by 25 percent by 2070-2099. These studies, however, are likely to be less informative for studying the impacts of climate change since, as shown by Schlenker and Roberts (2009), the yield response to temperature is likely to be crop-specific. Additionally, since crops such as rice are traditionally grown in the summer as opposed to wheat which is primarily grown in the winter, growing seasons should be defined separately for these crops. The only paper to apply detailed weather data to rice yields in India is Fishman (2012), who studies the effect that the distribution of rainfall has on rice and wheat yields at the district level. He uses numerous measures of weather, such as annual rainfall, the distribution of rainfall, and accumulated temperature over the growing season to study their relative influence in driving climate change impacts in 2080-2100. A key finding from this study is that climate change-induced temperature increases dominate any potential changes in rainfall in the future. This is for two reasons. First, a number of climate models predict increases in annual precipitation across India, which tend to increase average rice yields. Second, while it is estimated that the expansion of irrigation can reduce the impact of precipitation shocks, irrigation does not seem to be related to reducing the impact of temperature fluctuations.

One crucial aspect of quantifying the effect of climate change on rice yields in India is accounting for the regional heterogeneity in growing environments. As was shown in Figure

2.1, parts of the country differ substantially in their exposure to high average temperatures. Given the range of temperatures considered optimal for rice growth, which generally occur in the range of 20-30°C, warming will increase exposure to harmful temperatures most in areas already close to the top of this range. On the other hand, different rice varieties have been successfully grown in most agro-ecological regions of India suggesting that areas of the country may differ in their sensitivity to especially hot temperatures due to varieties being chosen to suit particular local growing conditions (Gollin et al., 2005). Investigating differences in spatial patterns of vulnerability is an important part of understanding whether there are likely to be distributional consequences of climate change across India.

Previous studies using simulation models have made an important contribution in highlighting that climate change impacts on rice production are likely to vary substantially across the country. For instance, Soora et al. (2013) use a model of rice growth to show that although average yields in India are predicted to be 4% lower between 2010-2039 due to climate change. States such as Punjab, Haryana, and Rajasthan will experience significantly larger impacts owing to their exposure to already hot temperatures. In comparison, some southern areas like the large rice-producing state of Andhra Pradesh, are predicted to benefit from increased warming. In order to investigate this question from an empirical perspective later in the paper, India is divided into four areas that have broadly similar growing conditions. These contain districts located in Northern, Western, Eastern, and Southern areas. Northern districts are all districts within the states of Punjab and Haryana. These states have historically been highly important in the food security of the country given the high levels of productivity of farms across these states. Rice production is also undertaken under fully irrigated conditions owing to the generally hot, semi-arid conditions that require supplemental water. Central districts are Gujarat, Madhya Pradesh and Maharashtra. Although not large producers of rice compared to other states, rice is grown in these districts under a variety of conditions including rain-fed lowland, rain-fed upland and irrigated conditions. The states of Bihar, Uttar Pradesh, Orissa and West Bengal make up the eastern region. Given the high levels of annual rainfall normally experienced in these areas, rice is often grown under rain-fed conditions, sometimes in flooded conditions. The southern rice areas are defined as Andhra Pradesh, Tamil Nadu, Karnataka and Kerala. These states are generally more temperate than others states with ample rainfall.

2.3 Data

Agricultural data used in this study are taken from an annual district-level dataset compiled by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT, 2012). I use data on annual rice production and area cropped to construct yield data for rice between 1970 and 2009. Only districts that contain non-missing data over this period are used in the study. Additionally, the states of Himachal Pradesh and Assam are excluded from the analysis. This leaves a total of 155 districts.[7]

Daily temperature and precipitation data are taken from two gridded databases collected by the Indian Meteorological Department. Data on daily average temperature are available at a 1°x1° resolution (Srivastava et al., 2009). Daily temperature is measured as the average of minimum and maximum temperature over a 24 hour period. Precipitation data at 0.25°x0.25° resolution are also used (Pai et al., 2014). The gridded weather data is mapped to districts by using a weighted average of the proportion of each grid cell falling within a district boundary. District boundaries correspond to those drawn in 1966.

To simulate the effect of climate change, I use projections of future temperatures contained in the Global Agro-ecological Zones (GAEZ) v3.0 database (IIASA/FAO, 2012). The database contains projected increases in annual mean temperatures. Data is available globally in gridded format and is mapped to district boundaries to calculate projected future temperature for each district.

Temperature projections are related to two future time periods which are used to reflect short and medium term changes in the temperatures over the periods 2011-2040 and 2041-2070 respectively. To deal with the inherent uncertainty of future climate projections I use two strategies. Firstly, annual temperature projections are taken from four general circulation models. The four climate models used are: HadCM3 (Hadley Centre, UK Meteorolog-

[7]Unfortunately, during the 2000s there is substantial missing data on rice production in Central and Eastern regions.

ical Office); ECHAM4 (Max Planck Institute for Meteorology, Germany); CSIRO (Commonwealth Scientific and Industrial Research Organisation, Australia); CGCM2 (Canadian General Circulation Model). These models differ both in magnitudes of average temperature increases across India and also in their projections about regional warming within India. Second, given uncertainties surrounding the trajectory of future greenhouse gas emissions, I use projections from these models under different emissions scenarios. These vary depending on assumed rates of demographic change, economic development, and technological advancement (IPCC, 2000). Four scenarios, A1, A2, B1 and B2 are used.

2.4 Methodology

The approach used to model the effect of climate change on the crop yield distribution is that of moment-based maximum entropy introduced by Wu (2003) to model income distributions and by Tack et al. (2012) who applied this to the study of crop yield distributions. This method allows for the calculation of yield probability distribution functions conditional on changes in relevant independent variables. The estimation proceeds in two parts. The first step is to model the effect that temperature has on each separate yield moment so that crop yield moments can be estimated conditional on changes in the relevant climate variables. The second step uses the information provided by the yield moments to construct yield distributions using maximum entropy techniques.

2.4.1 Modelling the effect of temperature on rice yield

This modelling approach is similar to that of Antle (1983, 2010) who specifies a flexible moment based approach in order to study the effect that explanatory variables have on higher order moments, which characterise the shape of the probability density function of output.[8]

A key distinction between these approaches relates to the dependent variable used in the

[8] This approach has been applied to a number of settings relevant to agriculture including the effect of crop diversity on farm productivity (Di Falco and Chavas, 2009), technological change on production risk (Wu and Wang, 2003), and drought management practices on farm profits (Groom et al., 2008).

higher order moment equations. The Antle approach uses *centred* moments, where the second and third order moment equations are specified as powers of the residuals from the mean (first moment) equation. The approach used in this paper is to specify the higher order moment equations using the uncentred or raw moments of yield, which are used to estimate conditional probability distributions of yield. This approach has previously been demonstrated by Tack et al. (2012) as a way to construct crop yield distributions conditional on a set of weather variables. The Antle approach uses *centred* moments, where the second and third order moment equations are specified as powers of the residuals from the mean (first moment) equation. As is noted by Zhang and Antle (2016), the uncentered and centered approaches are theoretically equivalent ways of modelling the mean and higher order effects of the independent variables on crop yield. One disadvantage of the uncentered approach relative to the centered approach is the assessment the behavioural effect that certain explanatory variables have on the higher moments of yield. The centered approach, for instance, would allow one to assess how marginal changes in weather variables affect the variance or skewness of crop yields. While this provides one way of assessing possible impacts of climate change on crop yields, this paper assesses climate change impacts by evaluating changes in the overall crop yield distribution by estimating uncentered moments of crop yield and using maximum entropy techniques to approximate conditional crop yield distributions.

To model the impact of temperature on the distribution of crop yields, it is necessary to consider how temperature affects moments of yield above and including the first moment. Crop yield in district i at time t is denoted as y_{it}, so that the jth raw moment of yield, y_{it}^j, is specified as yield to the power of $j = 1, 2, 3$. These three moments are sufficient to allow for yield distributions to vary in terms of the mean, spread around the mean and asymmetry about the mean.[9]

The vector of explanatory variables x_{it} can then be related to each crop yield moment by the following j regressions:

[9]More than the three moments could plausibly be estimated, although the economic relevance of these measures is not explored in this paper.

$$y_{it}^{j} = x_{it}'\beta_j + \epsilon_{jit} \tag{2.1}$$

where the coefficient vector β_j estimates the effect that independent variables x_{it}' have on the jth raw moment. The error term for each equation is denoted as ϵ_{jit}.

The population mean for each moment $j = 1, 2, 3$ can be represented by $\mu_j = E[Y_{it}^{j}]$, which is the expected value of the random variable denoting yield in area i at time t Y_{it}^{j}, calculated over a specified collection of individuals and/or time periods. Since we are interested in calculating each moment conditional on the state of a set of climate variables, conditional moments can be expressed as $\mu_j = E[Y_{it}^{j}|X = x]$. The sample counterpart for each moment is computed by taking a linear prediction of the estimated model, which is an estimate of the population mean given the law of large numbers. This makes it possible to compare the value of each moment under the observed set of covariates with moments estimated using predicted values of covariates under different climate change scenarios.

2.4.2 Empirical specification

To empirically model the effect of weather variables on yield moments, I specify the following reduced form equation for each moment:

$$y_{it}^{j} = \alpha_i + \sum_{1}^{k} \beta_{jk} TempDays_{it} + \delta_{1j} Rain_{it} + \delta_{2j} Rain_{it}^{2} + d_{1i}t + d_{2i}t^{2} + \epsilon_{jit} \tag{2.2}$$

where moments of crop yield, measured in tonnes per hectare, are represented by Y_{it}^{j} for district i at time t. The key variables of interest are those representing the effect of temperature. The semi-parametric temperature 'bins' approach is chosen to model the effect of daily temperatures on raw moments of the yield. By specifying k temperature bins, each of which contains the number of days spent within each temperature interval during a growing season, a separate coefficient is estimated for the effect of temperature within each interval. This allows for the measurement of the effect that one additional day spent in each bin has on rice yield. The width of each interval is 2°C, although for temperatures greater than 34°C, a single bin is specified owing to a lack of observations beyond this range. The strength of this specification is that it allows for temperature to affect yield moments in a non-linear fashion. This is consistent with findings of Schlenker and Roberts (2009), who identify the strongly negative impact of extreme temperatures on crop yields in a more flexible way than other agronomic temperature measures.[10]

The parameters that capture the effect of the daily temperature bins on yield, β_{jk}, are identified based on the assumption that temperature realisations in each year represent random deviations from average district-level conditions which are captured in the district fixed effect term, α_i. This controls any unobserved district-level characteristics that are constant over time. For instance, differences in soil quality or altitude across districts may affect the impact that weather variables have on crop yields.

Similarly, given that Indian agriculture has gone through a rapid process of modernisation since the 1960s, it is necessary to control for the effect of technology on yields. I include deterministic district-specific quadratic time trends, t and t^2 to account for the upward trend in yields that are likely to be due to technological innovations, such as new seed varieties. The inclusion of quadratic time trends is likely to be particularly important given that steady rates of yield increase since the 1960s have tended to slowdown in recent years (Pingali, 2012).[11]

The key identifying assumption of the coefficients β_{jk} is that variability in temperature in each bin over a growing season is orthogonal to omitted variables that determine crop yields (Deschenes and Greenstone, 2007; Schlenker et al., 2006), such that short-run temperature deviations are not correlated with unobserved decisions, such as inputs choices, that could condition the impact of temperature on crop yields. Inclusion of the district fixed effect term α_i means the coefficients are estimated by exploiting random year-to-year variation in number of days in each bin relative to the average number of days spent within each bin in a district.[12]

[10] Closely related to the temperature bins approach is the *growing degree days* approach. This is similar in that it measures the effect of accumulated heat over the growing season. However, as is noted by Schlenker et al. (2006) it relies on assumptions about the temperature ranges that are beneficial or harmful for crop growth. The bins approach is thus more flexible since it does not depend on defining these bounds.

[11] A cubic time trend was added but this did not improve the overall fit of the model.

[12] In addition to district fixed effects, another plausible strategy to deal with other potential confounding

Accurately defining crop growing seasons is an important aspect of deciphering the response of crop yield to temperature. The timing of sowing and harvesting of rice varies significantly across India owing to differences in climate. It is thus necessary to allow growing seasons to vary by location. To do this I utilise monthly data on crop calendars which are available at the Indian state level (Portmann et al., 2010). Only days falling within the main rice growing season in a state, usually between June and November, are used to construct the temperature variables.[13]

I control for the effect of rainfall on crop yield by including a regressor $Rain_{it}$ to measure the level of rainfall that fell over the monsoon period. Rainfall has a strong impact on rice yields owing to the rain-fed conditions under which much of the country grows rice. Also included is a squared regressor $Rain_{it}^2$ to capture the strong possibility that the relationship between rainfall and yield is non-linear. For instance, Auffhammer et al. (2012) find that both extremely high or low rainfall years have serious impacts on yield. In this paper I do not consider the impact that climate-induced changes in rainfall could have on crop yields. Regional climate models predict wide variations in the magnitude and spatial extent of changes in future rainfall due to an inadequate understanding of the physical forces driving the summer monsoon (Turner and Annamalai, 2012). As such, all estimates should be interpreted as holding levels of rainfall constant.

The error term ϵ_{it} contains unobserved determinants of district yield. As is noted by Burgess et al. (2014), it is plausible that the error terms for each district are correlated over time. To account for potential autocorrelation, error terms are clustered by district.

factors would be to include an additional set of fixed effects that vary over time. For instance, in India, state-by-year fixed effects are likely to account for a number of factors that commonly vary within a state in a year, such as prices or agricultural subsidies. However, a number of authors caution against the inclusion of too many fixed effect terms in estimating relationships between agricultural yields and short-run weather fluctuations (Fisher et al., 2012; Auffhammer and Schlenker, 2014). This is because using time-varying fixed effects clustered by geographically contiguous units, such as states, are likely to account for a substantial part of the variation in the weather variables. The likelihood of measurement error in the weather variables, owing to the need to interpolate observations from different weather stations to match grids or political boundaries, means that the resulting coefficient estimate of the effect of the weather variables is likely to be close to zero, since the much of the real variation in weather has been absorbed by the time-varying fixed effects and measurement error still remains.

[13]An empirical issue is that rice is sometimes grown over multiple seasons during the year. In this analysis I focus only on areas that that primarily crop rice during the wet Kharif season, which broadly takes place during the months of June to November. For India as a whole, 85 percent of annual rice is cropped during this season (Burney and Ramanathan, 2014).

Additionally, there exists substantial differences in rice area cropped between districts. For instance, some districts contain large urban areas or plant crops other than rice. I weight regressions by the square root of the proportion of area cropped within a district to give greater weight to districts that plant more of the crop. The same procedure is applied by (Deschenes and Greenstone, 2007).[14]

2.4.3 Deriving distributions

Using the estimated relationship between yield and temperature for each moment as specified in equation 2.2, I predict the value of each moment conditional on various climate change scenarios. For each scenario, a set of three moments is calculated. The estimated moments do not directly allow for the effect of climate change to be summarised in a useful way. The moments can, however, be used as information to construct the a yield distribution which can then be applied to characterise the probability density function of yield conditional on climate. Nonetheless, a problem remains that even with a well-estimated set of yield moments, μ_j, the overall density function of yield cannot be analytically determined since there are an infinite number of potential densities that could fit these conditions (Golan et al., 1996). A solution to this is to ascertain the shape of the distribution based on the information provided in the moment conditions. This can be achieved by employing maximum entropy techniques.[15] These methods have been applied in a number of settings where limited information is available, such as physics (Jaynes, 1982), linguistics (Berger et al., 1996), and finance (Zhou et al., 2013).

Formally, the method works by picking the yield distribution $f(y)$ that maximises the function

[14]This would likely lead to more precise estimates for two reasons. First, since annual weather is averaged over the whole district area, districts with larger proportionally cropped areas would more accurately reflect the effect of weather on district crop yields. Second, areas that only plant a small amount may be prone to fluctuations in area cropped and production which may lead to noisier district yield measures.

[15]This approach is succinctly stated by Jaynes (1982, p.940) as: "The MAXENT [maximum entropy] principle, stated most briefly, is: when we make inferences based on incomplete information, we should draw them from that probability distribution that has the maximum entropy permitted by the information that we have"

$$H(f) = -\int f(y) \ln f(y) dy \tag{2.3}$$

where $H(.)$ is the entropy function.[16]

The shape of the density function can be derived by maximising the entropy function subject to the information provided by the estimated moment conditions. This amounts to choosing the set of densities that are most consistent subject to known information (Golan et al., 1996). The moment conditions, μ_j, thus, act as constraints in a maximisation problem and are expressed as

$$\int y^j f(y) dy = \mu_j \text{ and } \int f(y) dy = 1, j = 1, 2, 3 \tag{2.4}$$

where the former expression denotes the moment-consistency constraints and the latter expression denotes the standard normalisation condition that the densities must sum to unity.

The problem is solved by constrained optimisation by forming the Lagrangian function

$$L = -\int f(y) \ln f(y) dy - \left[\gamma_0 \int f(y) dy - 1\right] - \sum_{j=1}^{J} \gamma_j \left[\int y^j f(y) dy - \mu_j\right] \tag{2.5}$$

in which the Lagrange multipliers are represented as $\gamma_0, ..., \gamma_j$ for the constraints shown in equation (2.4). Following Wu and Wang (2011), the necessary conditions for the solution to the constrained optimisation problem are given by:

$$\ln f(y) + 1 - \gamma_0^* - \sum_{j=1}^{J} \gamma_j^* y^j = 0 \tag{2.6}$$

in addition to the constraints from equation (2.4). The maximum entropy density function $f^*(y)$ can be written as

[16]The entropy function was derived by Shannon (1947) to describe the uncertainty of a set of values y.

$$f^*(y) = \exp\left[\sum_{j=1}^{J} \gamma_j^* y^j - 1 + \gamma_0^*\right] = \exp\left[\sum_{j=1}^{J} \gamma_j^* y^j - \Psi(\gamma^*)\right] \tag{2.7}$$

such that $\Psi(\gamma^*) = \ln\left[\int \exp(\sum_{j=1}^{J} \gamma_j^* y^j)dy\right]$ is a normalisation factor so that the integral of the density function is equal to one. The optimal values of the Lagrange multipliers found from the solutions to equation (2.5) are then used to characterise the function $f^*(y)$.

To practically estimate the maximum entropy technique, I use the sequential updating method described by Wu (2003). This method offers the most tractable way to solve the optimisation problem given that higher order moments are generally not independent of their lower order counterparts. Higher order moments can be more easily estimated with information provided by lower order moments.[17] An advantage of the maximum entropy approach is that it allows for a range of possible distributions in the generalised exponential family, which include exponential, normal, lognormal, and gamma distributions (Wu, 2003).

2.5 Results

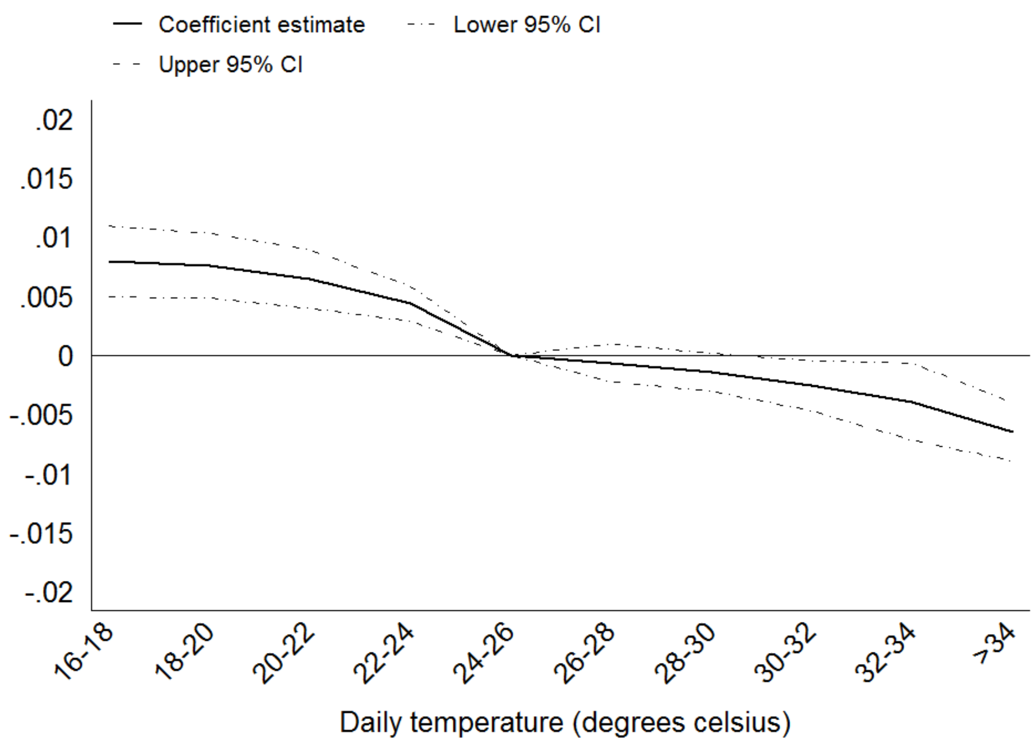
2.5.1 Moment regressions

This section begins by discussing the regression results used to estimate the effect of climate change on rice yields. Table 2.1 displays the estimated coefficients for each of the three raw moments of rice yield for all districts. The main variables of interest are the temperature variables, where each coefficient is interpreted as the effect of one additional day spent in each temperature interval on rice yield relative to a day spent in the temperature range 24-26°C which is used as the reference category. The 24-26°C temperature bin thus takes the value of zero. To easily visualise the effect that daily temperature has on the first moment of yield, Figure 2.2 plots these estimated coefficients along with their 95% confidence

[17] The superiority of the sequential updating approach was found during the empirical estimation. In a number of cases, an algorithm that was used to estimate maximum entropy densities that introduced the moment conditions simultaneously failed to achieve convergence. I am grateful to Jesse Tack for suggesting the use of the sequential algorithm and sharing Matlab code with which to apply the method.

interval. The effect of temperature on the first moment of yield, Y, can clearly be seen. Low temperatures are clearly beneficial for rice yields, as seen by the positive coefficient for days spent in average daily temperatures between 16-24°C. In contrast, the harmful effect of temperatures beyond 28-30°C is clear, consistent with previous statistical studies on the effect of daily temperatures on crop yields in countries such as the U.S (Schlenker and Roberts, 2009). At temperatures above 34°C these findings suggest that, on average, one *additional* day spent above this threshold reduces rice yield by 0.006 tonnes (6 kg) per hectare.

Figure 2.2: Marginal effect of daily temperature on yield in India 1970-2009



Note: The plot shows coefficient estimates for the effect of one day extra spent within each 2°C temperature bin on rice yield. Estimated coefficients are relative to that of a day in the 24-26°C interval. The solid line shows the estimated value of each coefficient at in each interval. The 95% confidence interval is indicated by dotted line either side of the solid line. Standard errors are clustered at the district level.

Reverting back to Table 2.1, temperature extremes are also particularly significant for the higher order moments of yield Y^2 and Y^3, indicating that exposure to temperature in these

Table 2.1: Regression results of temperature's impact on raw yield moments for the whole sample of Indian districts

Dependent variable:	Y	Y^2	Y^3
Temperature bins (°C)			
16-18	0.008***	0.026***	0.061
	(0.002)	(0.009)	(0.050)
18-20	0.008***	0.028***	0.085**
	(0.001)	(0.007)	(0.033)
20-22	0.006***	0.030***	0.124***
	(0.001)	(0.006)	(0.032)
22-24	0.004***	0.019***	0.071***
	(0.001)	(0.004)	(0.018)
26-28	-0.001	0.003	0.025*
	(0.001)	(0.004)	(0.015)
28-30	-0.001*	-0.001	0.013
	(0.001)	(0.004)	(0.019)
30-32	-0.003**	-0.004	0.012
	(0.001)	(0.005)	(0.028)
32-34	-0.004**	-0.010	-0.013
	(0.002)	(0.008)	(0.037)
>34	-0.006***	-0.032***	-0.135***
	(0.001)	(0.006)	(0.034)
Controls			
Time trend/1000	57.326***	168.645***	322.669***
	(4.200)	(21.201)	(106.706)
Time trend squared	-431.979***	-39.059	6475.648**
	(94.360)	(536.026)	(2912.904)
Monsoon rainfall (m)	0.128*	0.262	0.385
	(0.069)	(0.330)	(1.431)
Monsoon squared	-0.037**	-0.106	-0.289
	(0.017)	(0.076)	(0.318)
Constant	0.623***	-1.268**	-9.101***
	(0.100)	(0.500)	(2.330)
District fixed effect	Y	Y	Y
N	6,045	6,045	6,045
R^2	0.850	0.834	0.790

* p<0.10 ** p<0.05 *** p<0.01. Standard errors clustered by district. Estimated temperature coefficients are relative to the effect of an extra day in the 24-26°C temperature interval which is the omitted category.

ranges is key for driving the distribution of crop yields. This is consistent with the intuition that high temperatures are particularly damaging for yields, impacting the possible range of low outcomes that could occur. Low temperatures are also highly significant for higher moments, suggesting that these temperatures, since they are associated with better plant growth, increase the range of good yield outcomes that can occur.

The control variables also have the expected signs. The upward trend in district-specific yields over time is clear given that the coefficient on the time trend variable is positive and significant, with evidence of a slowdown in the average rate of yield growth over time as seen by the negative and significant squared time trend. Rainfall also shows a clear and expected effect, with higher levels of rainfall associated with higher yields, although this relationship is concave given the negative squared rainfall coefficient.

To examine the heterogeneity of temperature impacts across India, each set of moment equations is estimated separately for groupings of districts in certain geographical areas. Four separate regions are examined: North, Central, East, and South. Table 2.2 displays the coefficient estimates for each region. As before, the coefficients on the temperature variables for the first moment are plotted graphically to ease interpretability of the results. These are shown in Figure 2.3. The harmful effect of additional daily temperatures above 34°C on average yields can clearly be seen for Northern, Central and Southern areas, with all coefficients negative and statistically significant at least at the 10% level. Owing to non-exposure to temperatures greater than 34°C, this coefficient is not estimated for Southern districts. In these districts, additional days above 26°C have negative but statistically insignificant impacts on mean rice yields. The effect of extremely high temperatures on higher moments is also apparent in all regions except for the South, although in all regions exposure to relatively low temperatures has a clearly significant positive effect in all areas.

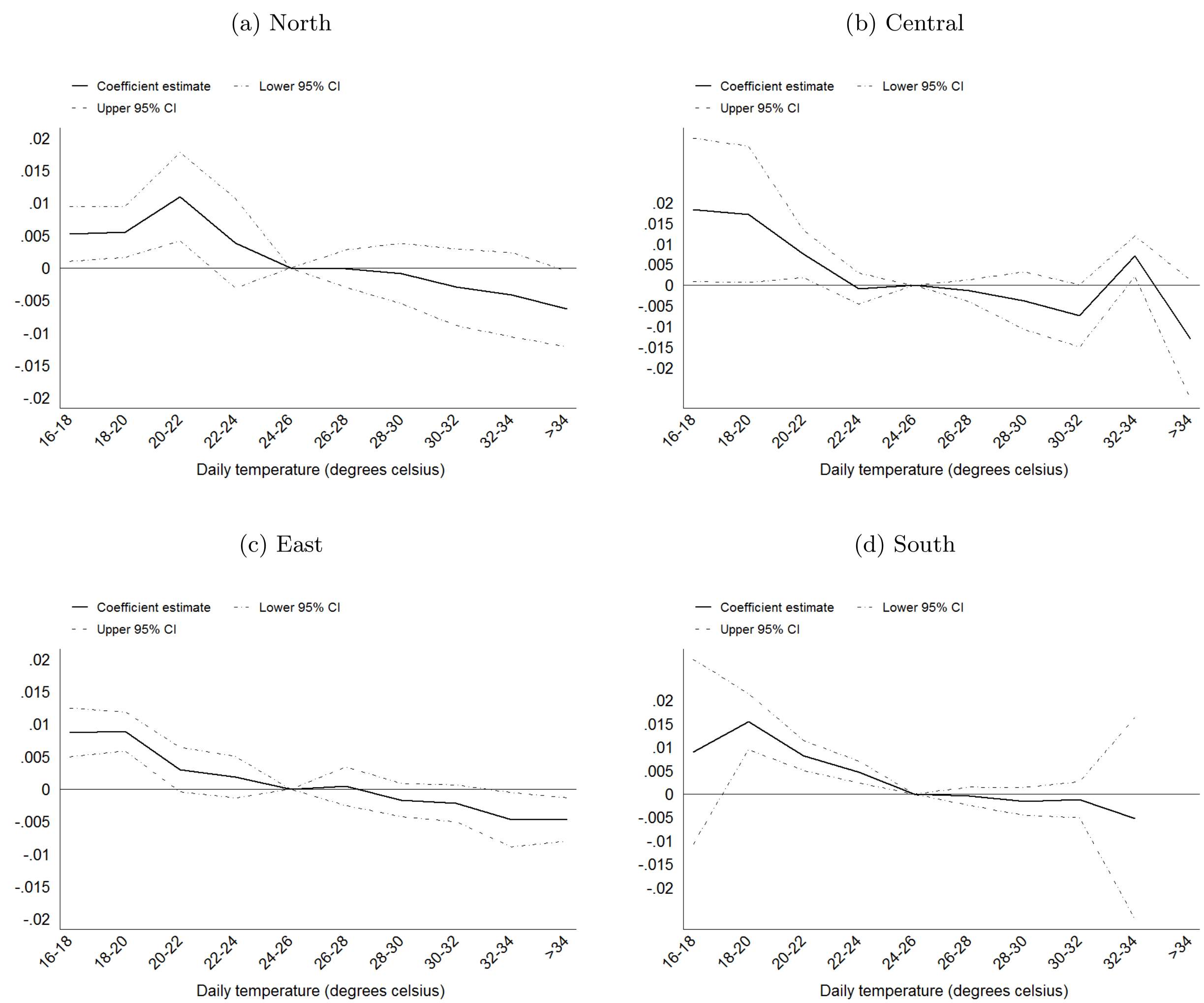
Interestingly, there is also significant heterogeneity in the effect of the control variables on yields. For instance, the beneficial effect of rainfall on average yields can be seen in all states apart from the two Northern states of Punjab and Haryana which likely explained by the fact that districts in these states were almost fully irrigated throughout the sample

Table 2.2: Moment regression results of temperature impact on yield for regions of India

	North			Central			East			South		
Dependent variable:	Y	Y^2	Y^3	Y	Y^2	Y^3	Y	Y^2	Y^3	Y	Y^2	Y^3
Temperature bins (°C)												
16-18	0.005**	0.026*	0.103	0.018**	0.079**	0.262**	0.009***	0.024***	0.058**	0.009	-0.101*	-0.937***
	(0.002)	(0.014)	(0.076)	(0.008)	(0.034)	(0.107)	(0.002)	(0.008)	(0.028)	(0.010)	(0.058)	(0.294)
18-20	0.006***	0.042***	0.245***	0.017**	0.060*	0.162*	0.009***	0.025***	0.063***	0.016***	0.075***	0.306***
	(0.002)	(0.011)	(0.065)	(0.008)	(0.030)	(0.087)	(0.002)	(0.006)	(0.020)	(0.003)	(0.017)	(0.079)
20-22	0.011***	0.081***	0.451***	0.008**	0.025**	0.065*	0.003*	0.008	0.018	0.008***	0.044***	0.188***
	(0.003)	(0.024)	(0.136)	(0.003)	(0.010)	(0.033)	(0.002)	(0.007)	(0.022)	(0.002)	(0.009)	(0.046)
22-24	0.004	0.029	0.176	-0.001	-0.006	-0.025	0.002	0.001	-0.015	0.005***	0.026***	0.108***
	(0.003)	(0.021)	(0.118)	(0.002)	(0.007)	(0.020)	(0.002)	(0.006)	(0.023)	(0.001)	(0.006)	(0.028)
26-28	-0.000	-0.002	-0.020	-0.001	-0.004	-0.010	0.000	0.002	0.003	-0.000	-0.001	-0.006
	(0.001)	(0.009)	(0.051)	(0.001)	(0.005)	(0.016)	(0.001)	(0.005)	(0.016)	(0.001)	(0.006)	(0.026)
28-30	-0.001	-0.002	-0.004	-0.004	-0.013	-0.039	-0.002	-0.006	-0.020	-0.002	-0.001	0.014
	(0.002)	(0.016)	(0.095)	(0.003)	(0.012)	(0.035)	(0.001)	(0.005)	(0.016)	(0.001)	(0.007)	(0.030)
30-32	-0.003	-0.008	0.014	-0.007*	-0.021*	-0.053	-0.002	-0.009	-0.029	-0.001	-0.000	0.013
	(0.003)	(0.018)	(0.093)	(0.004)	(0.012)	(0.032)	(0.001)	(0.005)	(0.020)	(0.002)	(0.011)	(0.050)
32-34	-0.004	-0.021	-0.089	0.007***	0.028***	0.082***	-0.005**	-0.011	-0.016	-0.005	-0.028	-0.119
	(0.003)	(0.020)	(0.106)	(0.002)	(0.007)	(0.022)	(0.002)	(0.009)	(0.034)	(0.011)	(0.052)	(0.202)
>34	-0.006**	-0.035*	-0.151	-0.013*	-0.057**	-0.170***	-0.005***	-0.018***	-0.056***			
	(0.003)	(0.017)	(0.093)	(0.007)	(0.022)	(0.058)	(0.002)	(0.006)	(0.019)			
Controls												
Time trend/1000	27.925**	29.357	-484.194	50.235***	149.294***	345.645***	69.391***	200.698***	454.800***	50.092***	202.157***	643.955***
	(10.317)	(67.076)	(393.109)	(7.320)	(26.745)	(79.438)	(6.151)	(23.683)	(75.814)	(6.604)	(37.841)	(168.643)
Time trend squared	158.852	4020.665**	32905.711***	-568.712***	-1184.234*	-1149.986	-654.969***	-1160.544**	-195.948	-302.607	-395.884	2237.264
	(216.554)	(1622.138)	(10312.751)	(154.674)	(568.998)	(1739.563)	(141.209)	(572.731)	(1946.858)	(182.494)	(1023.472)	(4503.326)
Monsoon rainfall (m)	-0.179	-1.313	-6.600	0.447***	1.198***	2.560**	0.385**	1.307**	3.852*	0.298*	1.112	3.309
	(0.214)	(1.480)	(8.152)	(0.102)	(0.385)	(1.188)	(0.150)	(0.579)	(1.992)	(0.161)	(0.830)	(3.484)
Monsoon rainfall squared	-0.085	-0.275	-0.382	-0.077***	-0.217***	-0.501**	-0.139**	-0.522**	-1.664**	-0.062*	-0.239	-0.750
	(0.107)	(0.699)	(3.766)	(0.015)	(0.060)	(0.192)	(0.061)	(0.237)	(0.817)	(0.034)	(0.168)	(0.692)
Constant	1.892***	3.389	4.766	0.799***	0.257	-1.031	0.466***	-0.539	-2.804	0.743***	-1.332	-10.294**
	(0.313)	(2.087)	(11.252)	(0.113)	(0.385)	(1.070)	(0.170)	(0.655)	(2.192)	(0.155)	(0.857)	(3.918)
District fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	615	615	615	979	979	979	2,131	2,131	2,131	2,320	2,320	2,320
R^2	0.835	0.832	0.811	0.632	0.630	0.607	0.802	0.765	0.694	0.722	0.669	0.598

* $p<0.1$, ** $p<0.05$, *** $p<0.01$. Standard errors are shown in parentheses and are clustered at the district level.
Omitted temperature bin is 24-26. Coefficients show the effect of one additional day spent in other bins relative to the omitted category.
All regressions are weighted by the proportion of district area devoted to rice.

Figure 2.3: Marginal effect of daily temperature on rice yield by region



Note: Each plot shows coefficient estimates for the effect of one extra day spent within each 2°C temperature bin on rice yield. Estimated coefficients are relative to that of a day in the 24-26°C interval. Regressions are estimated separately for districts in each region. The solid line shows the estimated value of each coefficient. The 95% confidence interval is indicated by dotted line either side of the solid line. Standard errors are clustered at the district level.

period.[18]

2.5.2 Baseline distributions

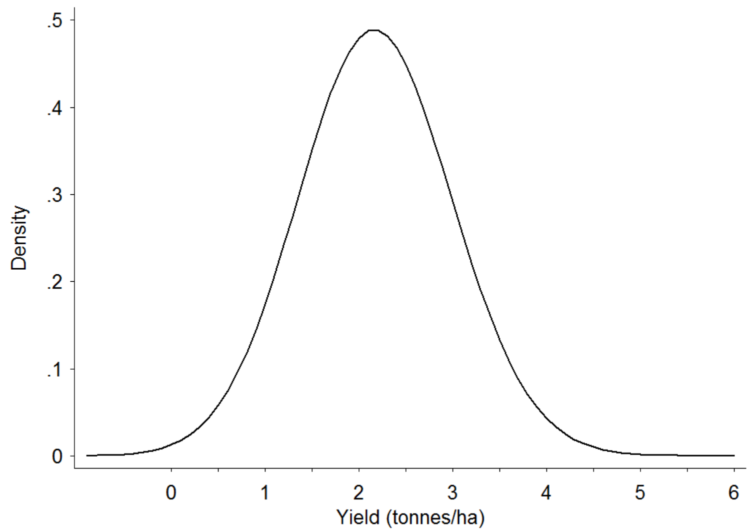
Using the maximum entropy approach described in the previous section, these moments can be used to estimate the baseline distribution of rice yields conditional on observed temperature over the sample period. To do this, the estimated coefficients from Tables 2.1 and 2.2 are used to calculate the value of each of the three moments of rice yield conditional on the baseline climate. These are predicted by using the values of each coefficient along with the corresponding sample average of each of the variables over the sample period.

The estimated moments are shown in Table 2.3. It is clear from the first moment, m_1, that average rice yields vary substantially across the country. The early Green Revolution states in the North are most productive, whereas districts in eastern states have on average the lowest productivity. Using the maximum entropy approach described in the previous section, these moments can be used to estimate the distribution of rice yields over the sample period. In Figure 2.4 these distributions are plotted. Panel (a) shows the distribution of rice yields in India. This distribution should be seen as one that characterises the average Indian district since it is derived from the estimated behaviour of all districts in the sample. The distribution is roughly symmetric with the mass of the distribution centred around yields of two tonnes per hectare. As seen from the estimated moments in Table 2.3, there is substantial regional heterogeneity in rice yields. This is reflected in the estimated distributions for the four regions in Figure 2.4. It can be seen that the distribution for Northern states is much further towards higher yields relative to other districts reflecting higher productivity in these areas, compared particularly with states in the East which have much lower productivity. The importance of considering the whole distribution of yields can also be seen from the varying shapes of the regional distributions, which may have a substantial bearing on the regional variation in the impact of temperature increases described in the following section.

[18]For instance, in 1970 around 85% of rice cultivated in these states was grown under irrigated conditions. By 1985, effectively all rice grown in these areas was done so using irrigation.

Figure 2.4: Baseline estimated rice yield distribution in India 1970-2009

(a) All India



(b) Regional

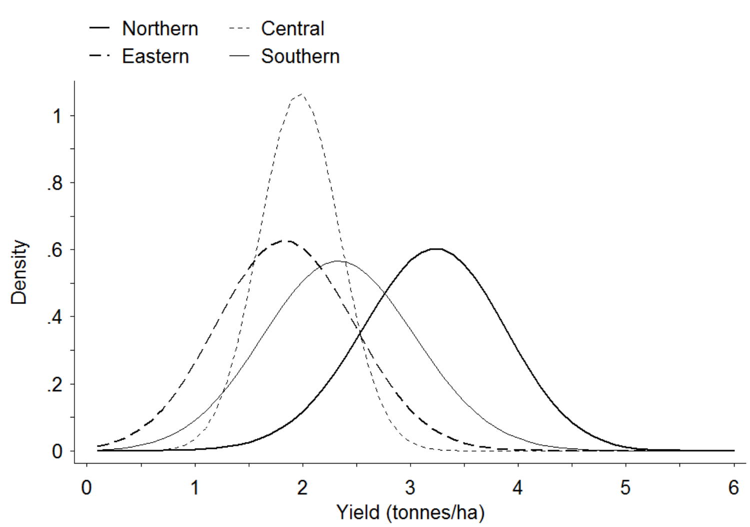


Table 2.3: Estimated moments of Indian rice yields 1970-2009

	Region				
Moment	*All*	*North*	*Central*	*East*	*South*
m_1	2.191	3.199	1.975	1.848	2.344
m_2	5.458	10.676	4.044	3.819	5.997
m_3	15.098	36.945	8.586	8.563	16.587

2.5.3 Climate change scenarios

To simulate the effect of climate change on the distribution of yields, I use temperature projections for the periods 2011-2040 and 2041-2070. In order to estimate this using the temperature bins approach, the number of days spent in each bin under each new temperature scenario is calculated. This is done by assuming that daily temperatures in each district uniformly increase by the amount projected in each model. The average number of days spent in each temperature bin is then re-calculated under each model scenario.[19]

To get a sense of the magnitude of the effect that increased temperatures are projected to have on the number of days spent in each temperature interval, Figure 2.7 shows the distribution of the change in the number of days spent in at each 1°C interval. On the top row is the historical frequency distribution of the number of days spent in each temperature bin per growing season across districts. The grey shaded boxes show the interquartile range of each scenario with the median number of days displayed by the horizontal line inside. Minimum and maximum adjacent values are also indicated by the black vertical lines. Between 1970 and 2009, the majority of days fall in the range of 24-30°C with days where average daily temperature exceeds 30°C a rare occurrence. The lower two graphs in Figure 2.7 show the *change* in the number of days spent in each temperature interval based on projected temperature increases for the periods 2011-2040 and 2041-2070. For both future

[19] Although climate here is not represented strictly as a distribution, it is assumed that the variability of climatic outcomes is the same, so that climate change represents a location shift in the distribution. Empirical support for this assumption comes from Donat and Alexander (2012) who find that a comparison of observed global temperatures between 1951-1980 and 1981-2010 shows a significant shift in the distribution but not an increase in the variance.

scenarios, the number of days above 28°C increases substantially, with the majority of this increase occurring in the 28-32°C range. There is also a substantial increase in the number of days above 34°C, which is likely to be significant for climate change impacts given that estimated exposure to these temperatures is associated with particularly harmful effects in yields.

2.5.4 Effect on average yields

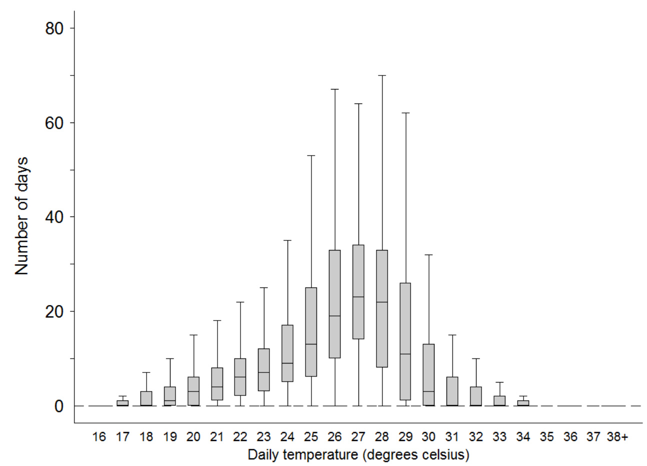
Before reporting the effect of climate change on the full distribution of rice yields, it is useful to quantify the effect on average yields by examining changes in the first moment only. This is done by comparing mean rice yields under future temperature scenarios with those estimated over the historic sample period. The estimated coefficients for the period of 1970-2009 are used to characterise the relationship between yield and temperature. Then, the number of days projected to be spent in each temperature interval under future temperature scenarios are used to predict the moment estimates. All other variables are held constant at their observed sample mean. It should be noted here that the relationship between historical yield and temperature is used to make these predictions. As such, assumptions about future adaptation options to climate change are not made. I discuss the implications of this later in the paper.

Table 2.4 shows the predicted change in mean yield. For an Indian district on average, rice yields are projected to decline by 4 percent between 2011 and 2040 and by 10 percent in the later period of 2041-2070. There is substantial regional variation in these estimates. The most heavily affected districts are those in the central states of Maharashtra and Madhya Pradesh where productivity is predicted to decline by over 11% by the 2050s. These results are highly consistent with the results of Soora et al. (2013) who use a regional crop simulation model to project that average yields will decline by 4-6% in the period 2010-2039 and by around 7% in 2040-2069. Similarly, districts in southern areas are projected to be the least affected by projected climate change, which reflects the weaker relationship between temperature fluctuations and yields in these districts.[20]

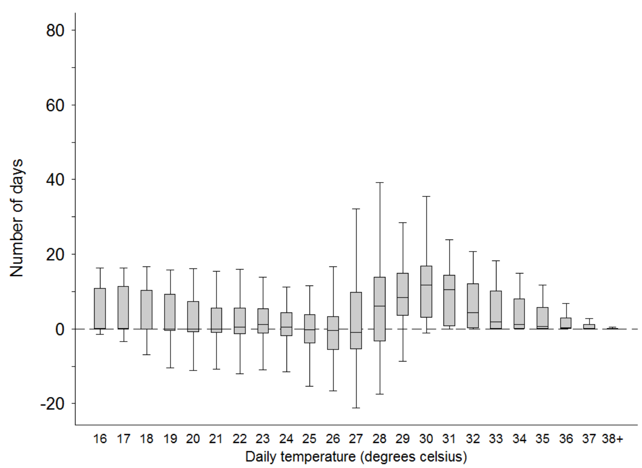
[20] A crucial difference between the results in this paper and those of Soora et al. (2013) is the latter's inclusion of projected changes in rainfall. For instance, Soora et al. (2013) project that rain-fed yields in

Figure 2.5: The frequency distribution of daily temperatures in India 1970-2009 compared with climate change simulations

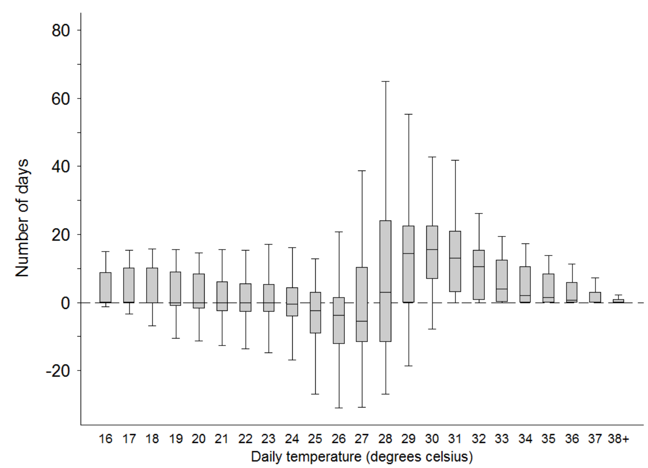
(a) Distribution of daily average temperature 1961-90



(b) Change 2011-2040 relative to 1961-90



(c) Change 2041-2070 relative to 1961-90



Note: The top row shows the frequency distribution of daily average temperature between the key growing season months of June-November for all districts for the historical period 1961-90. The bottom row shows the average *change* in the number of days spent at each degree temperature interval under projected climate change. These temperatures projections are based on those from the ECHAM4 climate model under the B2 emissions scenario.

Table 2.4: Predicted climate change impact on mean rice yields

Yield (tonnes/hectare)	Observed	Estimated average yield *% change from baseline*	
	1970-2009	2011-2040	2041-2070
All	2.191	2.094	1.973
		-4.4%	*-9.9%*
North	3.200	3.091	2.976
		-3.4%	*-7.0%*
Central	1.976	1.861	1.765
		-5.8%	*-10.7%*
East	1.849	1.791	1.705
		-3.1%	*-7.8%*
South	2.345	2.305	2.186
		-1.7%	*-6.8%*

Average yield for future scenarios 2011-2040 and 2041-2070 are calculated by taking the average of estimated yields under climate change for the nine different temperature scenarios.

2.5.5 Changes in distribution

To investigate the effect that projected temperature increases have on the distribution of rice yields, I re-estimate each yield moment under the set of new temperature scenarios. The distribution for each scenario is then calculated using the moment-based maximum entropy approach. The historical baseline distribution is shown as a solid line and projected distributions shown as dotted lines.

The results using the sample of all districts are shown in Figure 2.6. Qualitatively, the results for the period 2011-2040 suggest a modest leftward shift in the probability distribution of yields at the all-India level. There is, however, a clear flattening of the distribution that increases the weight of the lower tail, implying the possibility of low yields increases despite a relatively small effect on average yields. This pattern is compounded in the later 2041-2070 period. Interestingly, there does not appear to be a decrease in the probability of achieving yields in the upper tail of the distribution. This implies that climate change does not act as a limiting factor in achieving very good yields but does have a substantial impact on the likelihood of low yield outcomes. It is important to note that the increase

Tamil Nadu and Andhra Pradesh will benefit due to increased levels of rainfall.

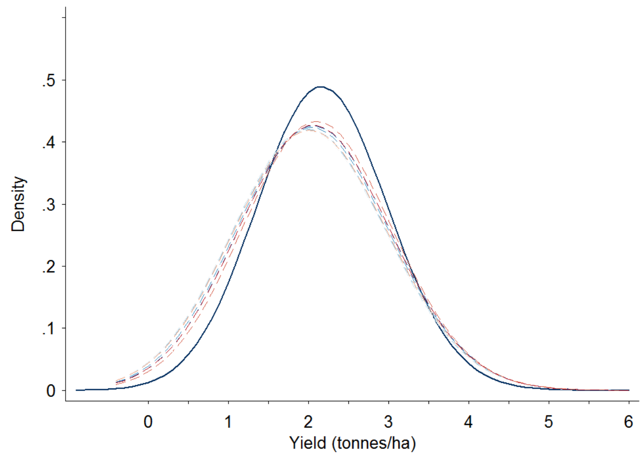
in the probability of very low yields is driven by the combination of both a shift in the distribution towards lower average yields and an increase in the spread of yields, similar to the effect predicted by Urban et al. (2012).

Figure 2.7 shows the distributions for each region. In the top row, the distributions for 2011-2040 are shown and the estimates for 2041-2070 on the bottom. There is a substantial change in the distribution for the Northern states of Punjab and Haryana. Although mean yield declines by around 4%, there is a large increase in mass around the tails of the distribution, implying a substantial increase in the variability of average yields around the mean. The probability of low yields increases along with the probability of higher than average yields, suggesting the increased variability of yields occurs. The effect of additional warming in the 2050s is to further shift the distribution towards lower yields. Despite these areas being highly irrigated, this finding suggests that higher temperatures substantially affect the yields in these states. This is again similar to the findings of Urban et al. (2012) who find that increases in variability under climate change are positively correlated with higher baseline temperatures for maize yields in the U.S. Since Northern states tend to have higher average growing season temperatures than many other rice growing areas in India, greater exposure to harmful temperature seems to substantially increase the likelihood of extremely low yields.

The distribution in Central areas, predicted to be the area with highest impacts on mean yields suggests both a substantial shift of this distribution towards lower yields and a flattening of the distribution. Temperature increases in the 2050s are in particular likely to increase exposure to very low yields. Interestingly, although there is a downward shift in average yield in Eastern districts, there seems to be no corresponding increase in the probability of low yield tail events even in the 2050 warming scenario. This implies that higher temperatures have the potential to decrease the variability of yields in eastern areas, which is in stark contrast to its effect in Northern and Central areas. In line with results from the mean productivity effect in the previous section, the yield distribution for Southern districts is only marginally affected, with little change in the distribution in the 2020s, although increased exposure to downside risk appears to be more substantial in the 2050s with both a shift and flattening of the distribution.

Figure 2.6: Impact of climate change on Indian crop yield distribution

(a) 2011-2040



(b) 2041-2070

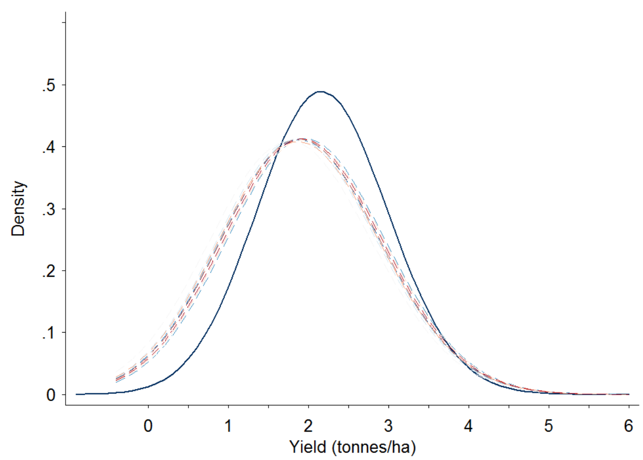
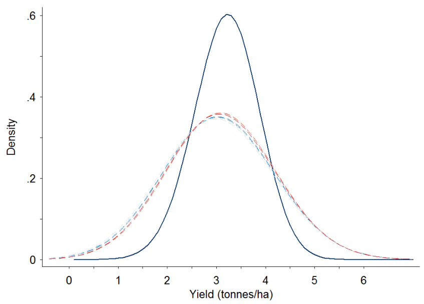
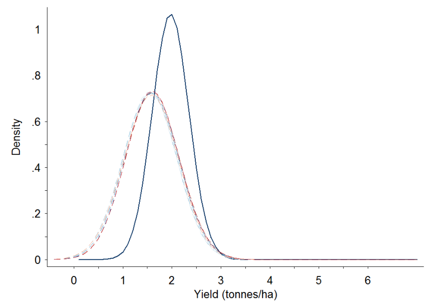


Figure 2.7: Impact of climate change on regional Indian crop yield distributions

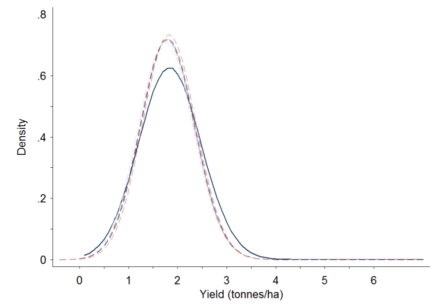
(a) North (2011-2040)



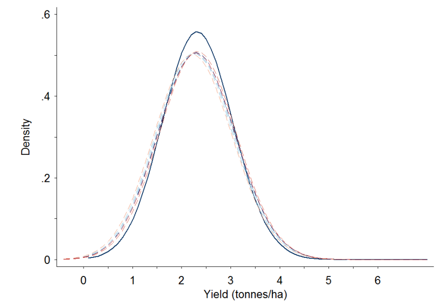
(b) Central (2011-2040)



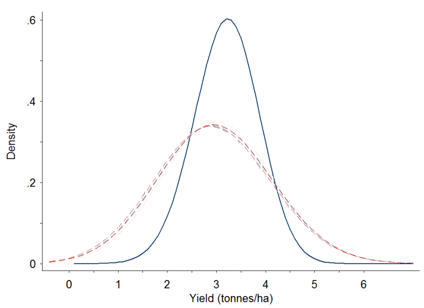
(c) East (2011-2040)



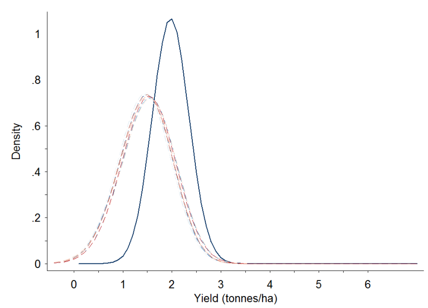
(d) South (2011-2040)



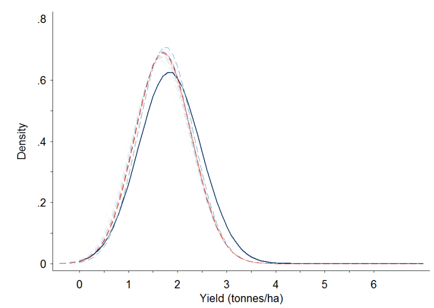
(e) North (2041-2070)



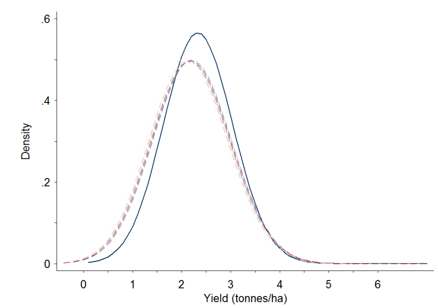
(f) Central (2041-2070)



(g) East (2041-2070)



(h) South (2041-2070)



Note: For each figure, the solid blue line shows the baseline historical yield distribution using observed data between 1970-2009. The dashed lines represent changes in the distribution based on different model temperature projections. Plots on the top row show the estimated change in the crop yield distributions for temperature scenarios in the 2011-2040 period. The bottom row shows the estimated change in distribution for projected temperatures in the 2041-2070 period.

2.5.6 Change in downside risk

The previous interpretation of the estimated change in rice yield distributions is highly qualitative. In order to quantify the estimated effect of climate change on the crop yield distribution, I calculate the change in probability of achieving yields in the lower tails of the distribution. This is a simple measure of downside risk that assesses the probability of achieving yields within a given yield percentile. This is done by first using the historical baseline distribution of crop yield to estimate the level of yield Y associated with the lowest 5th and 25th percentile of yield. If b^* is used to express the level of yield associated with the lowest zth percentile, then b^* is estimated by calculating the area under the yield probability density function $f_Y(y)$:

$$P[Y \leq b^*] = \int_0^{b^*} f_Y(y)dy = z \tag{2.8}$$

where z = $\{0.05,0.25\}$. Once the value of b^* is estimated from the historical distribution, then the yield density functions under future climate change scenarios are used to estimate the probability of yields below b^*.

The results of this exercise are shown in Table 2.5. For India as a whole, the consequences of climate change are to substantially increase the risk of previously rare tail events. Yields that were historically associated with the 5th percentile of yields are projected to increase to around 10 and 15 percent for the 2020s and 2050s respectively. Yields that historically occurred one-quarter of the time are projected to happen around one-third of the time with future climate change.

As seen by qualitatively examining changes in distributions in Figures 2.6 and 2.7, changes in exposure to yields in different areas of the yield distribution vary regionally. For instance, the substantial 'fattening' of the distribution in northern states implies much more exposure to downside risks, increasing the probability of 5% events to over 20% by the middle of the century, and 25% yields to over 40%. What is stark from these results is the large change in the distribution even under fairly modest amounts of warming, as temperatures increasingly occur in ranges that are hotter than is optimal for rice growth.

Table 2.5: Predicted changes in exposure to downside risk under climate change scenarios

	Yield	**Pr(Yield $< b^*$)**		
	b^*	1970-2009	2011-2040	2041-2070
All				
	1.0	5	10.9	15.0
	1.7	25	31.9	38.1
Northern				
	2.1	5	19.3	23.4
	2.8	25	40.6	45.1
Central				
	1.4	5	19.2	25.6
	1.7	25	30.4	38.1
Eastern				
	0.9	5	5.4	1.3
	1.4	25	24.2	12.7
Southern				
	1.3	5	10.2	13.7
	1.9	25	30.9	36.8

The consequences for downside risk are also very similar in magnitude for central states.

Southern regions which were estimated to be least affected in terms of mean yields do, however, show increased exposure to low yields, where yields in the historical 5th and 25th percentile to increase in probability to 14 and 37 percent respectively. In contrast to the rest of India, there actually seems to be a *decrease* in exposure to low yields in eastern states even though mean yields are projected to decline.

2.5.7 Comparing early and late sample periods

The previous results show the average relationship between temperature and yield moments over the entire sample period. It is, however, plausible that the effect of temperature on rice yields has not remained constant over time. For instance, agricultural technology, such as higher yielding seed varieties, fertilisers and pesticides, has diffused across the country since the Green Revolution beginning in the 1960s. As is argued by Mendelsohn et al. (2006), it is possible that as farmers increase levels of technology, the climate sensitivity of agriculture decreases. Although it is difficult to isolate the effect that such practices have on the heat tolerance of crops, it is possible to look for indirect evidence of improved heat tolerance over time that might indicate such changes. To examine whether this is the case, I split the sample period in two. The early period corresponds to the years 1970-1989 and the later period covers the more recent years 1990-2009.

The effect of temperature on the first moment of rice yields for each sample period is shown in Figure 2.8. Two different model specifications are included to study both the absolute and relative effects. The absolute impact on rice yields for the two time periods is shown in the top row. The curves are broadly similar in terms of the predicted effects of temperature on levels of yield. One additional day above 34 degrees significantly reduces rice yield by around the same amount in both periods, suggesting that extreme heat has roughly the same absolute impact on yields over time. There is also evidence of a smaller effect of moderately high temperatures in the latter period. Temperatures in the range 28-32°C only have a statistically significant negative impact on rice yields in the earlier sample period.

Given that yields have increased over time due to technological progress, measuring the effect that temperature has on the *absolute* level of rice yield may understate the degree to which the historical temperature relationship has changed over time. Accordingly, I specify a model with the logarithm of yield as the dependent variable for the first moment of rice yields. These estimates are shown in the bottom row of Figure 2.8. Here it can clearly be seen that the effect of temperature on relative yield has decreased substantially over time. For the period 1970-1989, an additional day at temperatures above 32°C was associated with a 0.5% decline in annual yield. In contrast, in the later sample period, the marginal effect of daily temperature on yield is largely statistically indistinguishable from zero. Temperatures above 30°C are estimated to adversely affect yield but this effect is small. For temperatures above 34 degrees, the point estimate is -0.002 (which implies that an additional day spent above 34°C decreases average yield by 0.2%) and significant at the 10% level, implying that very high temperatures continue to damage crop yields although this effect is roughly half the effect compared with the earlier period.

These results contrast with results from studies in other contexts. For instance, Schlenker

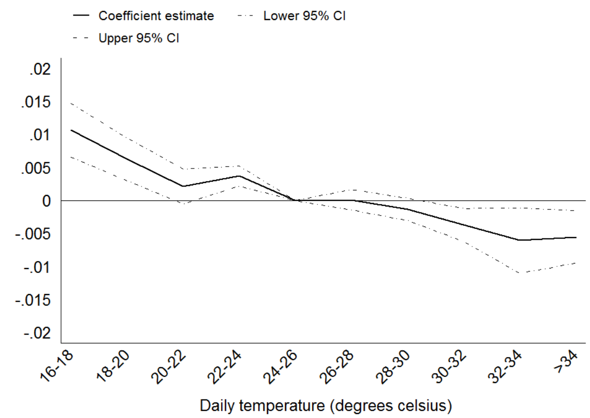
Table 2.6: Yield moment regression equations estimated using data from different time periods

	1970-1989			1990-2009		
Dependent variable:	Y	Y^2	Y^3	Y	Y^2	Y^3
Temperature bins (°C)						
16-18	0.011***	0.035***	0.100**	0.004*	0.012	-0.011
	(0.002)	(0.010)	(0.040)	(0.003)	(0.018)	(0.098)
18-20	0.006***	0.019***	0.059**	0.003*	0.013	0.042
	(0.002)	(0.007)	(0.030)	(0.002)	(0.010)	(0.053)
20-22	0.002	0.006	0.025	0.004**	0.021**	0.096**
	(0.001)	(0.006)	(0.024)	(0.002)	(0.009)	(0.042)
22-24	0.004***	0.013***	0.040***	0.002*	0.012*	0.063*
	(0.001)	(0.003)	(0.013)	(0.001)	(0.006)	(0.033)
26-28	0.000	0.005	0.029**	0.001	0.004	0.027
	(0.001)	(0.003)	(0.014)	(0.001)	(0.005)	(0.021)
28-30	-0.001	-0.000	0.009	-0.001	-0.003	-0.003
	(0.001)	(0.003)	(0.012)	(0.001)	(0.005)	(0.027)
30-32	-0.004***	-0.010*	-0.022	-0.001	-0.002	0.018
	(0.001)	(0.005)	(0.020)	(0.001)	(0.007)	(0.041)
32-34	-0.006**	-0.012	-0.011	-0.003	-0.013	-0.041
	(0.003)	(0.012)	(0.051)	(0.002)	(0.010)	(0.049)
>34	-0.006***	-0.021**	-0.077**	-0.006***	-0.033***	-0.136***
	(0.002)	(0.008)	(0.031)	(0.002)	(0.007)	(0.032)
Controls						
Time trend/1000	17.791***	23.791	-33.291	27.775	43.218	-312.344
	(6.816)	(28.355)	(101.338)	(19.223)	(112.482)	(580.107)
Time trend squared	1371.141***	6748.384***	25090.807***	-17.726	1792.114	16504.216
	(327.368)	(1393.656)	(5163.669)	(322.378)	(1980.298)	(10584.305)
Rainfall (m)	0.088	-0.194	-2.343	0.089	0.175	0.305
	(0.087)	(0.415)	(1.807)	(0.075)	(0.404)	(1.892)
Rainfall squared	-0.005	0.098	0.681*	-0.036**	-0.118	-0.341
	(0.019)	(0.089)	(0.389)	(0.016)	(0.087)	(0.406)
Constant	0.876***	0.297	-1.595	1.127***	0.872	0.144
	(0.091)	(0.406)	(1.621)	(0.289)	(1.518)	(7.014)
District fixed effect	Y	Y	Y	Y	Y	Y
N	3,026	3,026	3,026	3,019	3,019	3,019
R^2	0.846	0.835	0.798	0.835	0.836	0.814

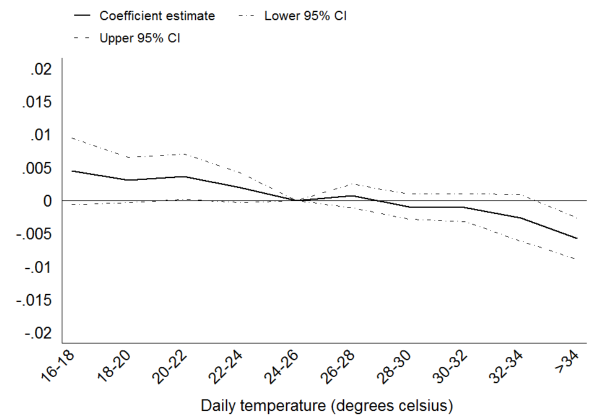
* p<0.1, ** p<0.05, *** p<0.01. Standard errors are shown in parentheses and are clustered at the district level.
Omitted temperature bin is 24-26. Coefficients show the effect of one additional day spent in other bins relative to the omitted category.
All regressions are weighted by the proportion of district area devoted to rice.

Figure 2.8: Marginal effect of daily temperature on rice yield by time period

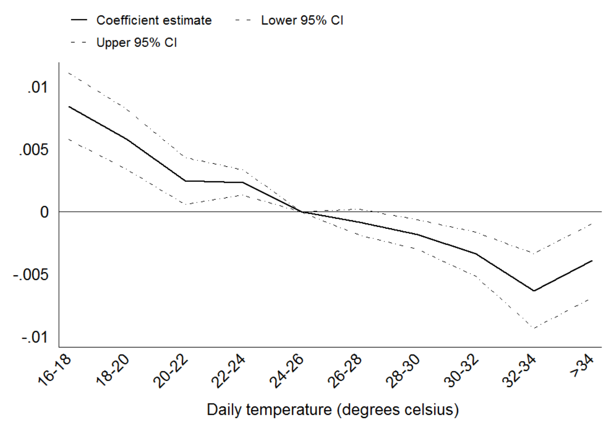
(a) 1970-1989 - Levels



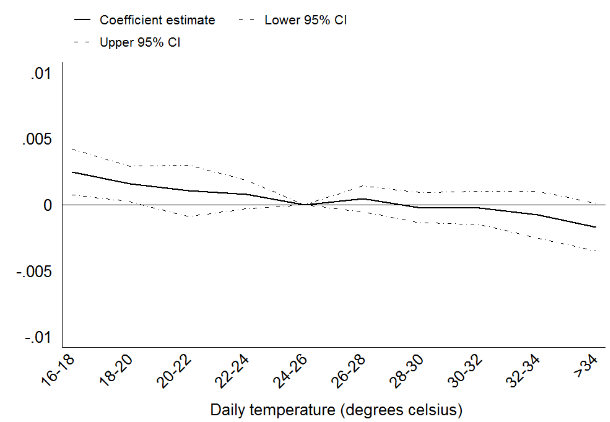
(b) 1990-2009 - Levels



(c) 1970-1989 - Logs



(d) 1990-2009 - Logs



Note: Each plot shows coefficient estimates for the effect of one extra day spent within each 2°C temperature bin on rice yield. Estimated coefficients are relative to that of a day in the 24-26°C interval. Regressions are estimated separately for districts in each region. The solid line shows the estimated value of each coefficient. The 95% confidence interval is indicated by dotted line either side of the solid line. Standard errors are clustered at the district level.

Table 2.7: Probability of yields falling below historic thresholds under climate change by different time periods

Yield (tonnes/hectare)	**Observed**	**Estimated average yield** *% change from baseline*		
Early period	1970-1989	2011-2040	2041-2070	
	1.719	1.579	1.458	
		-8.13%	*-15.7%*	
Late period	1990-2009	2011-2040	2041-2070	
	2.584	2.532	2.470	
		-1.9%	*-4.2%*	
	Yield		**Pr(Yield < b^*)**	
Early period				
	b^*	1970-1989	2011-2040	2041-2070
	0.8	5	15.1	15.0
	1.3	25	21.3	48.6
Late period				
	b^*	1990-2009	2011-2040	2041-2070
	1.4	5	6.2	7.0
	2.1	25	28.0	30.0

and Roberts (2009) estimate the extent of adaptation by considering the difference in the yield-temperature relationship at different time periods. They find that the relative heat tolerance of corn, soybean and cotton in 1950-1977 has remained very similar to that estimated between 1978 and 2005.[21]

In light of these findings, I re-estimate projections of future yield distribution for each sample period separately. These results are shown in Table 2.7. It can easily be seen that by using the estimated yield-temperature relationship over the period 1990-2009 dramatically reduces the projected impacts of future temperature increases. For instance, while average yield would be reduced by around 16% in the 2050s using the early sample period as representative, estimated average yield decline could be as small as 4% given the relationship between yield and temperature since 1990. Exposure to low yields also declines substantially. Whereas temperature rises were predicted to increase the risk of historically occurring 25th percentile events to roughly fifty percent by 2050 using the early sample period, the increased risk of these events only increases to 30% when the later period

[21] A related study by Burke and Emerick (2016) compares the difference in yield response between short run temperature fluctuations and long run changes (where adaptation is assumed to be possible) and find little difference between these estimates.

is used. Overall, these results imply that significant progress has been made over time in making Indian agriculture more resilient to heat stress which affects the arithmetic of projecting future climate change impacts.

2.5.8 Comparing irrigated areas with rain-fed areas

Identifying pathways through which the adverse impacts of temperature increases can be avoided is a crucial empirical question (Hertel and Lobell, 2014). In the previous section, it was shown that the relative effect of temperature on rice yields has reduced over time. One plausible pathway for mitigating the effect of heat on crop yields is through irrigation. This has previously been estimated by Birthal et al. (2015) to be the driving force behind the reduction in drought impacts on rice in India. To investigate whether temperature affects the behaviour of irrigated yields to rain-fed areas differently, the sample is split depending on the proportion of district area under irrigation.[22]

A district is defined as irrigated if more than 50 percent of rice area is irrigated over the sample period (Fan et al., 2000). The resulting relationship between yield and temperature for these sub-samples are shown in Figure 2.9 with the full set of estimated coefficients shown in Table 2.8. For both rain-fed and irrigated areas, daily temperatures above 34°C have clear negative effect on yields, which is statistically significant at the 1% level. Other coefficients in the table confirm the differences between irrigated and rain-fed areas. For instance, the coefficient estimating the effect of rainfall on yields is only significant for rain-fed districts, which highlights how successful many irrigated areas have been at utilising water from irrigation to substitute for rainfall. The effect of temperature on rice yields are similar for each sub-sample, with daily temperatures above 30 degrees associated negatively with yield. Interestingly, temperature has a more adverse impact on rice yields in irrigated areas than non-irrigated areas in terms of the absolute level of yields. This is perhaps expected however, since yields in irrigated areas tend to be higher than those in predominantly rain-fed areas. The relative effect of temperature on yields is shown in the

[22]Splitting the sample between irrigated versus rain-fed areas is analogous to the approach of Schlenker et al. (2005) who study the effect that irrigation has on hedonic estimates of climate change impacts in U.S. agriculture. They argue that omission of irrigation from the regression means that the estimated parameters on temperature are likely to reflect the impact of irrigation.

Table 2.8: Moment regression equations by irrigation group

	Rain-fed			Irrigated		
Dependent variable:	Y	Y^2	Y^3	Y	Y^2	Y^3
Temperature bins (°C)						
16-18	0.012***	0.038***	0.108***	0.008***	0.029***	0.083
	(0.002)	(0.008)	(0.030)	(0.002)	(0.011)	(0.056)
18-20	0.012***	0.036***	0.095***	0.007***	0.029***	0.107***
	(0.003)	(0.011)	(0.033)	(0.001)	(0.008)	(0.039)
20-22	0.006***	0.019***	0.054***	0.007***	0.040***	0.185***
	(0.001)	(0.005)	(0.017)	(0.002)	(0.010)	(0.051)
22-24	0.004***	0.015***	0.043***	0.005***	0.023***	0.093***
	(0.001)	(0.004)	(0.013)	(0.001)	(0.007)	(0.035)
26-28	-0.002***	-0.006*	-0.013	0.002	0.014**	0.072***
	(0.001)	(0.003)	(0.011)	(0.001)	(0.006)	(0.023)
28-30	-0.002*	-0.004	-0.008	-0.000	0.004	0.036
	(0.001)	(0.004)	(0.014)	(0.001)	(0.007)	(0.032)
30-32	-0.002	-0.006	-0.013	-0.002	0.001	0.034
	(0.002)	(0.008)	(0.030)	(0.001)	(0.007)	(0.037)
32-34	-0.006	-0.008	0.016	-0.003	-0.005	0.006
	(0.004)	(0.016)	(0.063)	(0.002)	(0.011)	(0.051)
>34	-0.004***	-0.013***	-0.040**	-0.007***	-0.032***	-0.129***
	(0.001)	(0.005)	(0.019)	(0.002)	(0.007)	(0.040)
Controls						
Time trend/1000	57.036***	155.612***	314.315***	57.203***	183.016***	364.333**
	(6.308)	(22.708)	(69.431)	(5.564)	(32.555)	(174.157)
Time trend squared	-378.498***	-47.213	3530.571**	-468.020***	-113.401	8114.479*
	(134.698)	(516.794)	(1744.353)	(132.410)	(844.947)	(4752.175)
Monsoon rainfall (m)	0.182**	0.489	1.026	0.162	0.392	1.167
	(0.076)	(0.299)	(1.012)	(0.131)	(0.673)	(3.088)
Monsoon rainfall squared	-0.043**	-0.132*	-0.341	-0.082**	-0.261	-0.884
	(0.017)	(0.067)	(0.220)	(0.041)	(0.207)	(0.953)
Constant	0.523***	-0.538	-3.007	0.480***	-2.480***	-15.588***
	(0.121)	(0.554)	(2.006)	(0.169)	(0.864)	(4.160)
District fixed effect	Y	Y	Y	Y	Y	Y
N	2,247	2,247	2,247	3,798	3,798	3,798
R^2	0.809	0.775	0.705	0.839	0.818	0.775

* $p<0.1$, ** $p<0.05$, *** $p<0.01$. Standard errors are shown in parentheses and are clustered at the district level.
Omitted temperature bin is 24-26. Coefficients show the effect of one additional day spent in other bins relative to the omitted category.
All regressions are weighted by the proportion of district area devoted to rice.

bottom row of Figure 2.9. In this case, we see that the effects are roughly comparable, although the estimation for high temperature days above 34 degrees Celsius is noisier for the non-irrigated sub-sample. In sum, it appears that although irrigation is an effective means of increasing average yields, it is not associated with a reduction in sensitivity to heat. For both rain-fed and irrigated areas, temperatures above 34°C have a clearly negative effect on yields which is statistically significant at the 1% level.

To see whether higher temperatures have heterogeneous effects on average yields and downside risk exposure between irrigated and rain-fed areas, I calculate the effects of climate change for these two groups. These results are shown in Table 2.9. Average yields are projected to decline most in areas without irrigation with losses of 7.4% by 2050. This compares with declines of 4.6% in irrigated areas. However, it should be noted that although average yields do not decline as substantially in irrigated areas, exposure to downside risk increases in a similar manner for both groups highlighting the importance of considering the effects of temperature on the wider distribution.

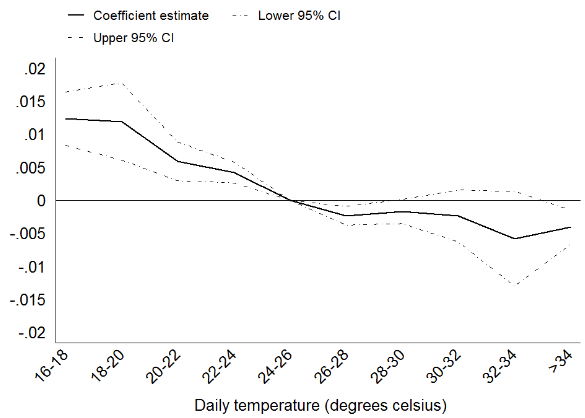
Table 2.9: Probability of yields falling below historic thresholds under climate change by irrigation group

Yield (tonnes/hectare)	**Observed**	**Estimated average yield** *% change from baseline*		
Rain-fed	1970-2009	2011-2040	2041-2070	
	1.873	1.827	1.734	
		-2.5%	*-7.4%*	
Irrigated	1970-2009	2011-2040	2041-2070	
	2.449	2.437	2.334	
		-0.4%	*-4.6%*	
	Yield		**Pr(Yield < b^*)**	
Rain-fed				
	b^*	1970-2009	2011-2040	2041-2070
	0.9	5	10.7	17.0
	1.5	25	29.1	36.9
Irrigated				
	b^*	1970-2009	2011-2040	2041-2070
	1.1	5	8.2	11.9
	1.8	25	27.8	33.5

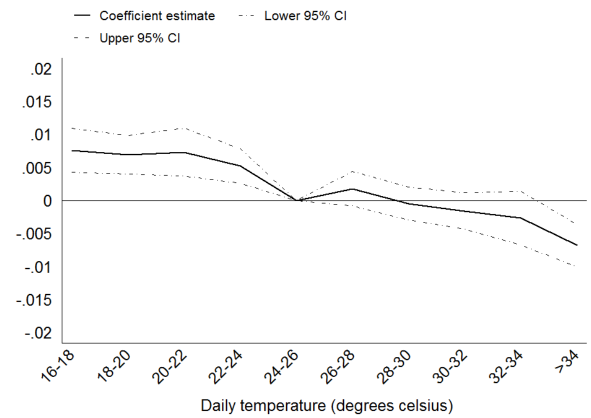
The finding that irrigation is an ineffective means of coping with increased heat exposure accords with that of a related study by Fishman (2012) who studies the relative impor-

Figure 2.9: Marginal effect of daily temperature on rice yield by irrigated area

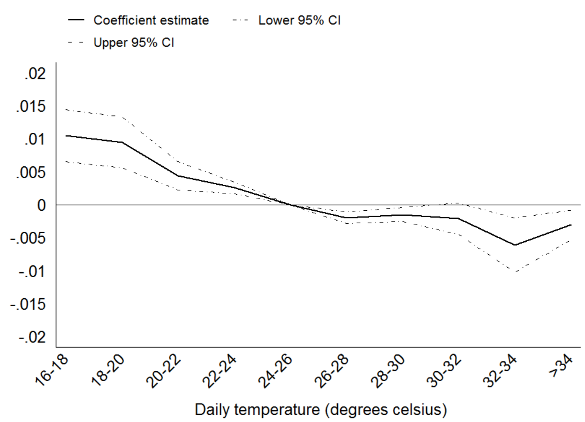
(a) Rain-fed - levels



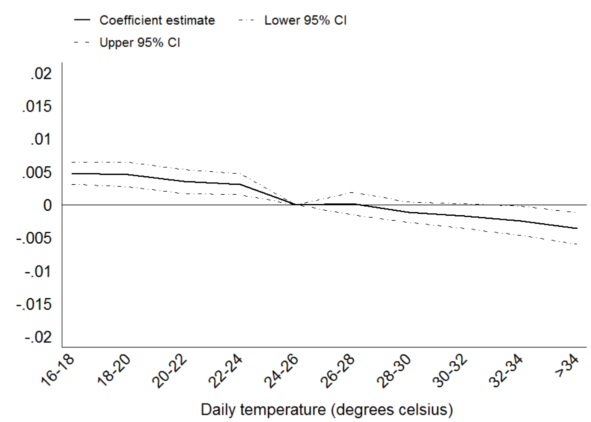
(b) Irrigated - levels



(c) Rain-fed - Logs



(d) Irrigated - Logs



Note: Each plot shows coefficient estimates for the effect of one extra day spent within each 2°C temperature bin on rice yield. Estimated coefficients are relative to that of a day in the 24-26°C interval. Regressions are estimated separately for districts in each region. The solid line shows the estimated value of each coefficient. The 95% confidence interval is indicated by dotted line either side of the solid line. Standard errors are clustered at the district level.

tance of irrigation in mitigating the effects of precipitation and temperature. He uses an interaction term between proportion of district area irrigated and accumulated growing season temperature to show irrigation has an insignificant effect on reducing the effects of heat exposure on rice yields. This is attributed to the idea that increased water use does not substitute for the physical damage that heat does to plants. In addition, rice is grown under irrigated conditions in hotter northern areas such as in Punjab. Regional results shown earlier in the paper confirm that these areas are likely to be those afflicted most by future increases in temperature. In these areas, since temperatures are already further away from optimal rice growing temperatures, it is plausible to expect that additional heat exposure will be harmful for rice growth even under highly irrigated conditions.

2.6 Discussion

In assessing the future effects of climate change on agricultural yields it is important to discuss the limitations of the statistical modelling approach used to generate these predictions and weigh up how important these limitations are likely to be for the validity of any research findings.

One issue is that using historical relationships between weather variables and measures of productivity to infer future relationships may not yield accurate predictions if substantial adaptation occurs (Auffhammer and Schlenker, 2014). Indeed, studies based on crop models have predicted significant opportunities for adaptation to offset some of these projected impacts (Soora et al., 2013; Challinor et al., 2014). Although it is impossible to predict the range of options that will be available to farmers in the future, there are a number of factors over the observed sample period that may inform us about the likelihood of this happening. On the one hand, the ability of farmers to mitigate crop yield losses due to short-run fluctuations in heat seems to have increased over time. The exact reason for this is unclear and is a downside of using the reduced-form estimation employed in this paper. Interestingly, a possible pathway for this, irrigation, does not seem to explain this relationship, since irrigated areas show similar relative response to short-term temperature fluctuations. Although it is often purported that rain-fed regions are likely to be most affected by climate change (Wassmann and Dobermann, 2007), these results imply that areas where rice is grown under irrigated conditions are likely to be affected as much, if not more, than rain-fed areas. Whereas previous studies have identified irrigation as a key factor in reducing the sensitivity of Indian agriculture to precipitation deficiencies (Fishman, 2012; Birthal et al., 2015), irrigation seems to be less effective at coping with heat stress.

Other explanations for a reduction in the relative importance of temperature fluctuations are less straightforward to quantify using the available data. The use of varieties better suited to growing under local temperatures could be a significant factor. The first adoption of Green Revolution technologies coincided with the period 1970-1989 when yields were shown to be more sensitive to temperatures. Understanding of how best to cultivate these new Green Revolution seed technologies could have improved over time. Similarly, given that earlier varieties have continued to be replaced by newer varieties, it is plausible to expect that this has led to local adaptation and less volatile production (Gollin et al., 2005). Understanding which mechanisms are responsible for driving reduced sensitivity of rice to temperature is an integral area of future research for reducing the effects of future warming in the agricultural sector. Although a number of studies have used crop yield data at aggregated levels such as district and state levels, the use of data at lower spatial scales such as the farm-level will be crucial to identifying the mechanisms behind these aggregate relationships.

An aspect previously mentioned as important for the distribution of crop yields is the preferences of farmers themselves regarding risk. This study finds that over time farmers have become increasingly resilient to fluctuations in temperature. One possible explanation for this is that farmers have become increasingly risk averse over time, deploying methods to reduce exposure to certain types of risk, in this case temperature, and settling for lower average yields. This hypothesis is not possible to verify in the current analysis for a number of reasons: First, the aggregate nature of the district level data used in this study makes it more difficult to model farm decisions. Second, the reduced form regression methods used in this study focus primarily on the role of weather variation on output. The inclusion of other input variables, which have previously been used in farm-level studies to study risk behaviour, is not possible in the current study.

Despite substantial yield gains over time and the estimated increase in heat tolerance found in this study, the ability to deal with the effect of future climate change may be more limited. Numerous studies have highlighted the unsustainable use of water in many key rice growing areas (Rodell et al., 2012; Panda and Wahr, 2016). This is especially apparent in areas that this study predicts to be most affected by future temperature increases, such as the northern states of Punjab and Haryana. Since water has been successfully used to construct growing environments more suited for rice production, the combination of even higher temperatures in these relatively arid areas and growing pressure on water resources highlights the challenges for agriculture in India.

As with all empirical studies of climate impacts, the possible beneficial effect of increased levels of CO_2 due to the carbon dioxide fertilisation effect are also not studied in this paper. For plants that grow using C_3 photosynthesis, such as rice and wheat, these effects could be significantly positive, with around a 5% increase relative to historical production for a 100 parts per million elevation in CO_2 for rice in South Asia (McGrath and Lobell, 2012).

In lieu of factors that reduce the impact of temperature on crop yield, institutions to help farmers deal with the consequences of low yields on welfare is a clear way to address these issues. One potential solution is crop insurance. For instance, the absolute number of farm households under some form of crop insurance scheme in India is already larger than anywhere else in the world, with 22 million households enrolled (Swain, 2014). Insured farmers remain a large minority, however, so that the continued development of schemes such as the National Agricultural Insurance Scheme will be vital to the future welfare of farmers. As well as the need to expand insurance services to cover a broader set of farmers due to more exposure to risk, this paper also highlights the increase in risk to insurers through climate change. Well-functioning markets for insurance depend on the correct valuation of risk that farmers are exposed to. Understanding the increased risk that climate change poses to agriculture by examining the effect of climate on the distribution of yields is important to understand the changes in future exposure to historically rare events.

While many studies have focused on estimating the correct shape of yield distributions to accurately assess the probability of low crop yields that are covered by crop insurance programs (Just and Weninger, 1999; Sherrick et al., 2004),[23] those involved in managing these risks, such as governments and private insurers, should work to design schemes that account for the potential increase in risk over time. For instance, as is noted by McCarl et al. (1998), the assumption of stationarity of the yield distribution may be a poor one as the climate changes.

Finally, future climate change-related losses in the agricultural sector may also increase due to a higher occurrence of extreme weather events. The modelling approach used in this paper to quantify future temperature increases assumes a shift in the distribution of mean temperature. This modelling approach does not allow me to model the effect that extreme events, such as the possibility of more droughts and floods, and the effect these may have on crop yields. Similarly, since I assume that the distribution of temperature within a year does not matter for annual crop yields, I cannot account for recent observed changes in the intra-seasonal distribution of heat. For instance, increasing trends in the number of heatwaves have been found across parts of India (Rohini et al., 2016). The effect that these patterns could have on crop yields is an important area of future research.

2.7 Conclusion

This paper examines the effect that temperature has on district-level rice yields in India. Detailed records of daily temperature are used to quantify the relationship between temperature and different moments of yield. The moment-based maximum entropy approach is then used to construct yield distributions. A key point from this study is that increases in average temperature have the potential to significantly damage crop yields and increase the probability of low rice yields that were historically rare. Based on projections of future temperature, I estimate that average district yield will decline by 4.4% in the period 2011-2040 and by 9.9% in 2041-2070. Temperature is shown to have a significant effect

[23] Other prominent studies include Goodwin and Ker (1998) Ramirez et al. (2003), and Harri et al. (2009) and Koundouri and Kourogenis (2011).

on higher moments of yield. Using predicted changes in the distribution of crop yields under climate change, I estimate that based on the historical relationship between yield and temperature between 1970 and 2009, exposure to yields that previously had a 25% likelihood of occurring increases to 38% while yields in the lowest 5th percentile increase to 15% by the middle of the century. A salient issue in estimating the impact of future climate change is the extent to which farmers may be able to cope with greater exposure to heat. To examine this issue, I examine the sensitivity of rice yields to heat for two distinct sample periods. These findings suggest that in more recent years, the relative effect of temperature on yield has reduced. Using more recent periods to predict the impact of future temperature increases suggests that average yields only decline by 4% and exposure to 25th percentile events increases to 30 percent. This has a number of implications for future research. Firstly, researchers who use historical data to predict future outcomes should be aware of changes over time that may affect the sensitivity of economic variables to environmental variables, such as weather. Secondly, this creates a need for researchers to understand potential mechanisms of increased resilience of the sector to heat to inform future adaptation choices.

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Chapter 3

Threshold effects of drought on agricultural production in India

Abstract

Understanding the impacts of drought on agricultural production is crucial for meeting food security needs during the twenty-first century. This is particularly the case in India, where the looming prospect of increased intensity and frequency of drought due to climate change threatens the wellbeing of hundreds of millions dependent on income from the sector. Using district-level agricultural data for six major cereals grown in India between 1966 and 2003, we adopt a threshold regression approach along with a flexible definition of drought in order to measure the full range of potential drought events. This approach enables us to identify data-driven ranges for which the magnitude of drought impacts on cereal production differs. First, we apply this model to identify whether there are distinct periods of time between which average drought impacts vary. We find evidence of a non-linear pattern in average district cereal yields over time. Although yields became more resilient to drought impacts in the middle of our sample period, average impacts increased markedly for droughts since 1998. This highlights the mounting challenges that farmers face in effectively mitigating drought impacts in the future. Second, we estimate precipitation thresholds for drought impacts. This allows us to determine levels of rainfall at which drought becomes particularly harmful for crop yields. An advantage of this approach is that we are able to compare estimated thresholds with official classifications of drought based on precipitation deficiency. Overall, we find significant and negative marginal impacts of drought for levels of rainfall below 70 to 80 percent of long-term rainfall, which corresponds with official drought definitions. Arid areas are resilient to small deviations of rainfall, but, due to low levels of absolute rainfall, are badly affected by severe droughts. Crop-level results suggest very different impacts by cereal, with rice being the worst affected cereal. These results suggest that drought definitions that do not account for local differences in average climate and crop choice are likely to provide misleading policy guidance about the effects of drought on crop productivity.

3.1 Introduction

DROUGHT has widespread and recurrent impacts on economic activity in many parts of the world. Periods of low rainfall and high temperature reduce the availability of moisture relative to normal conditions leading to the occurrence of drought. The resilience of the agricultural sector to drought is a pressing concern given that these conditions tend to adversely affect crop production, leading to significant welfare costs to producers through lost income and to consumers through higher food prices. In parts of the world where the reliance on agricultural income is high, drought can have particularly devastating effects on human welfare and pose a challenge to policymakers who manage the response to these events. Accurately assessing the vulnerability of agriculture to drought is also paramount given the growing threat from climate change. Although drought occurs as a natural part of climate variability, the combined effects of increasingly erratic precipitation and higher average temperatures mean that the likelihood of dry conditions conducive with drought will increase in many areas (IPCC, 2012).

A key challenge for researchers seeking to inform policymakers about future vulnerability to drought is how to use past climatic variation to learn about the resilience of the agricultural sector (Auffhammer and Schlenker, 2014). One approach to this is the use of past variation to understand the conditions under which drought has particularly negative effects on the productivity of agriculture. This may be particularly important if there are critical points that indicate conditions under which drought impacts are prone to increase. In general, this could refer to thresholds "beyond which the biophysical, socioeconomic, or institutional system in question is significantly affected by, or fundamentally changes (Naylor et al., 2007, p.7752)." If agricultural production systems are prone to threshold behaviour in drought impacts, then identifying where particular thresholds occur is an important way of assessing the vulnerability of the sector to drought.

In this paper we assess drought impacts on cereal productivity by adopting a threshold regression approach (Hansen, 1999, 2000). We apply this to a panel of district-level agricultural data from India spanning the years 1966-2003. This estimation approach allows us to identify data-driven ranges between which average impacts of drought significantly change for a variable of interest. The advantage of this empirical approach amounts to being able to estimate the location of thresholds of drought impact that can be used to determine cut-off points associated with increased vulnerability to drought.

We first evaluate drought impacts over time by using the threshold model to identify whether average impacts can be divided into specific periods. Previous research has indicated trends of reduced impact on crop yields in recent decades. Yu and Babcock (2010) use county-level data on corn and soybean yields in the U.S. between 1980 and 2008 and find that yields of these crops have become more tolerant to drought over time. Additionally, Birthal et al. (2015) study the drought tolerance of rice yields in India between 1970 and 2005 and find the same pattern. These studies, however, may provide a misleading reflection of the resilience of the agricultural sector over time if impacts are prone to abrupt changes that may be caused by periods of increased drought intensity or changes in the availability of resources to mitigate drought impacts. For instance, a number of studies have linked recent improvements in yield-improving technology with lower tolerance to drought (Lobell et al., 2014; Hornbeck and Keskin, 2014).[1] In recent years, studies have also indicated that the depletion of water resources is increasingly likely to act as a limiting factor on farmers' ability to respond to drought (Rodell et al., 2012; Panda and Wahr, 2016). The strength of the threshold approach in this context is that it can be used to identify sudden shifts in drought impacts that may signal periods of increased vulnerability to drought that cannot easily be determined by looking at slow-moving trends over time.

Second, assessing the effect that climatic variables have on production losses during drought is also crucial for furthering our understanding of the resilience of agriculture. Of particular interest is identifying critical levels of precipitation deficiency that are harmful to agricultural production. The threshold regression approach allows us to measure impacts of drought non-linearly by analysing critical levels of precipitation after which impacts of drought significantly change. While other studies have used methods to identify temperature thresholds that tend to be harmful for crop growth (e.g. Schlenker and Roberts (2009)), to our knowledge no studies have identified thresholds for precipitation.

[1] Another recent study by Lesk et al. (2016) finds that globally droughts between 1985 and 2007 had more severe impacts on production compared with droughts over the period 1964-1984.

The assessment of precipitation thresholds is of high policy relevance. Droughts are often declared by governments using simple measures of precipitation deficiency. In India, these indices are used to declare drought if precipitation falls below a given threshold (Ministry of Agriculture, 2009). Comparison of officially determined thresholds with those determined according to agricultural impacts is important for effective response to these events in the future. Often the management of drought events is dictated according to arbitrarily defined precipitation thresholds, which may have little relevance to the actual impact drought has on production (Wilhite and Glantz, 1985).

An important challenge in evaluating drought impacts is consideration of which climatic variables shape the severity of drought impacts. Researchers interested in evaluating drought impacts in agriculture tend to define drought differently to policymakers tasked with managing impacts. On the one hand, policymakers frequently base their evaluation of drought on simple indices of precipitation deficiency. A fundamental criticism of this approach is that important interactions between precipitation and temperature are omitted. Exposure to high temperatures has been shown to reduce the yield of major crops worldwide (Schlenker and Roberts, 2009; Lobell et al., 2012; Deryng et al., 2014). These effects are likely to exacerbate the effects of low rainfall, increasing the severity of a drought event and its impact on agricultural production. On the other hand, researchers estimating drought impacts on agriculture have developed indices to incorporate both precipitation and temperature (Yu and Babcock, 2010). However, these approaches often restrict the definition of drought to exclude events that are considered droughts by policymakers, sometimes omitting instances of serious drought leading to significant bias in the assessment of drought impacts in agriculture. As such, both of these approaches fail to account for drought events that have potentially disastrous impacts for farmers, thereby limiting the relevance of these research findings for policymakers. We address this shortcoming by utilising a drought index that includes both temperature and precipitation in a more flexible way than previous research has done, thus incorporating all potential droughts considered by policymakers and researchers alike.

We apply these techniques to study drought impacts in India, which remains one of the most drought-prone countries in the world (Mishra and Singh, 2010). Exposure to the welfare effects of drought are especially high in this context, since the agricultural sector still represents about 20% of gross domestic product (GDP), and employs half of the working population. Between 1951 and 2003, severe droughts were estimated to have lowered the country's annual GDP by 2 to 5 percent (Gadgil and Gadgil, 2006). More specifically, low rainfall events have also been linked to measures of welfare that are affected by shocks to crop productivity such as rural wages, poverty, conflict, and human capital accumulation (Jayachandran, 2006; Sarson, 2015; Shah and Steinberg, forthcoming). Identifying how vulnerable the agricultural sector is to drought is crucial for prioritising policies that reduce the impact of these events on crop production and provide effective relief in response to these events in the future. Climate models predict greater inter-annual variability of rainfall (Turner and Annamalai, 2012), suggesting that the need to understand climate extremes and their impact is of growing importance for the future of agriculture in a country that is widely expected to become the most populous in the world before the middle of the century (UN, 2015). Only a small number of studies have undertaken detailed analyses of drought on agriculture in the country, however. Birthal et al. (2015) and Auffhammer et al. (2012) examine its impact on rice yields at the district and state level respectively. Pandey et al. (2007b) similarly look at the impacts on rice production in eastern India. As well as limiting analysis to a single crop, these studies all suffer from restrictive definitions of drought which may reduce the validity of these findings leading to potential biased assessments of the effects of drought in India.

Previous studies have failed to consider heterogeneity across India in agro-climatic factors that may substantially affect crop losses from drought. For instance, arid areas of the country experience low average levels of rainfall and may respond differently to drought than humid areas that are characterised by high average rainfall. These differences may mean that precipitation thresholds differ substantially across regions, which would invalidate approaches that assume thresholds to be the same across the country. Accordingly, we separately estimate drought impacts by agro-climatic region to test for differences across these regions. Partly due to these agro-climatic differences, crop choices also differ markedly across districts. Since different crops have different sensitivity to heat and water stress, drought impacts are likely to vary across crops. Since previous research has highlighted that different crops have benefited unevenly in improving drought resistance over time in other contexts (Yu and Babcock, 2010), we estimate drought effects on the six main cereal crops in India: rice, wheat, maize, barley, millet, and sorghum.

Of considerable interest is how an area's resilience to drought is influenced by the availability of alternative water sources in the form of irrigation. In the case of India, area under irrigation varies substantially across the country. Previous studies on crop exposure to a range of weather events have highlighted the importance of irrigation in conditioning the impacts of adverse weather events (Schlenker et al., 2005; Duflo and Pande, 2007; Fishman, 2012; Birthal et al., 2015). We consider the differences in drought impacts for high irrigation areas versus low irrigation areas by separately estimating regressions across these two sub-samples.

The results of this study show that impacts of drought on cereal productivity have generally decreased over time since the 1960s, with particularly low impacts in the 1990s. However, contrary to previous literature, we identify significant thresholds of increased drought impact in the late 1990s and early 2000s. These impacts were comparable in terms of production losses with drought in the 1960s, suggesting that despite a period of relative stability in average impacts, the agricultural sector remains acutely vulnerable to drought in recent years. This pattern occurs for aggregate district cereal productivity but also for rice, the most water-intensive crop we study. Whereas the pattern of reduced impacts seems to align with previous studies that have found increased levels of irrigation important in mitigating drought (Birthal et al., 2015), increased vulnerability to drought in the late-1990s may correspond with the observed depletion of groundwater resources that constrain the ability of farmers to substitute rainfall with water from irrigated sources (Shah et al., 2009). This highlights the evolving challenges of achieving food security under drought in areas that have previously relied on abundant supplies of water from irrigation.

We also determine thresholds of precipitation. We find that for India as a whole, the marginal impacts of drought become negative and significant for levels of rainfall below 70%-80% of long-term rainfall. Impacts are more severe in areas with low irrigation. We also find that arid areas, probably as a result of long-run adaptation, tend to be more resilient to small deviations of rainfall. These areas are, however, acutely affected by severe droughts as a result of low levels of absolute rainfall. In addition to this, our results suggest that the impacts differ widely by cereal, with rice clearly being the most adversely affected cereal. These findings are of relevance to policymakers and researchers alike since they highlight that the sensitivity of production to deviations from average rainfall varies substantially according to the agro-climatic setting. This is crucial in order to understand the potential distributional impacts of climate change as well as challenging the idea of studying a large country like India as a single, homogeneous unit.

The rest of the paper proceeds as follows. Section 3.2 provides the background to drought in India and reviews related literature from other contexts. Section 3.3 outlines issues in measuring drought on agricultural production. Section 3.4 discusses the construction of the drought index used in this paper. The data used in the study is introduced in Section 3.5. In Section 3.6 we discuss the threshold regression technique. Section 3.7 presents the results and Sections 3.8 and 3.9 discuss and conclude to the paper.

3.2 Drought in India

India is particularly exposed to the consequences of drought since over two-thirds of the country is classed as vulnerable to drought (Ministry of Agriculture, 2009). This is compounded by the dependence of the majority of agricultural production on annual rainfall, given that 57% of cropped area is farmed under rain-fed conditions (Sharma, 2011). The production of crops in many areas during the wetter summer (*Kharif*) season relies directly on rainfall as their main source of water. Crops grown in the subsequent drier (*Rabi*) season also rely on rainfall from the previous season for soil moisture and water stored in sources such as tanks and canals.

Drought years in India generally occur because of deficient monsoon rainfall. For the country on average, 80% of rainfall falls between the monsoon months of June to September. Although the monsoon occurs annually, its intensity varies substantially from year-to-year. Studies have identified a decrease in average levels of annual rainfall over the past half century, while the probability of extreme rainfall events, which can lead to drought and floods, has significantly increased (Singh et al., 2014; Turner and Annamalai, 2012). For drought in particular, Pai et al. (2011) found that changes in exposure to precipitation drought significantly increased for approximately 10 percent of Indian districts over the last century. Kumar et al. (2013) additionally argue that the conditions for drought have been exacerbated by rising temperatures over time. They find evidence of increasing average drought intensity across the country, which they attribute to the increased air temperatures. Future projections of climate change-induced changes in rainfall patterns across India will result in increasingly erratic rainfall, although uncertainty over the physical mechanisms underpinning future monsoon dynamics are not yet understood well enough to yield discernible spatial patterns of future rainfall (Ghosh et al., 2012; Turner and Annamalai, 2012).

Of high policy relevance are the factors that affect how severely crop productivity is impacted in a given drought year. Identifying these features is crucial for evaluating how drought impacts vary across time and across space, which may indicate periods of time or regions that are particularly vulnerable to drought. The impacts of drought in India are likely to be conditioned by a number of factors that vary across the country. Given that India is a large country, it is debatable whether we are able to properly characterise drought impacts based on a country-wide average. As such, the rest of this section reviews sources of heterogeneity that may affect drought impacts.

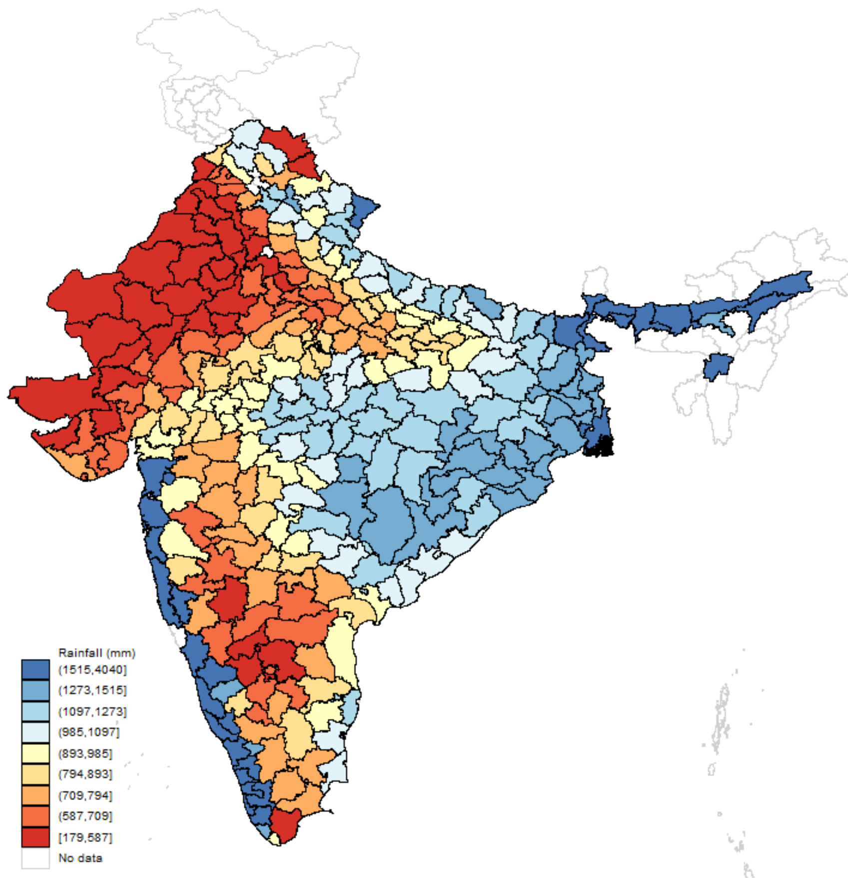
3.2.1 Agro-climatic differences

One important aspect is that average climatic conditions vary substantially across growing regions. This is illustrated in Figure 3.1. Panel (a) shows average levels of annual rainfall in each district across the country. Areas in the north-west of the country are characterised by extremely low average rainfall, in contrast with areas in the east and coastal-west that have much higher levels of average rainfall. These differences in mean rainfall are primary determinants of a permanent feature of regions: aridity.

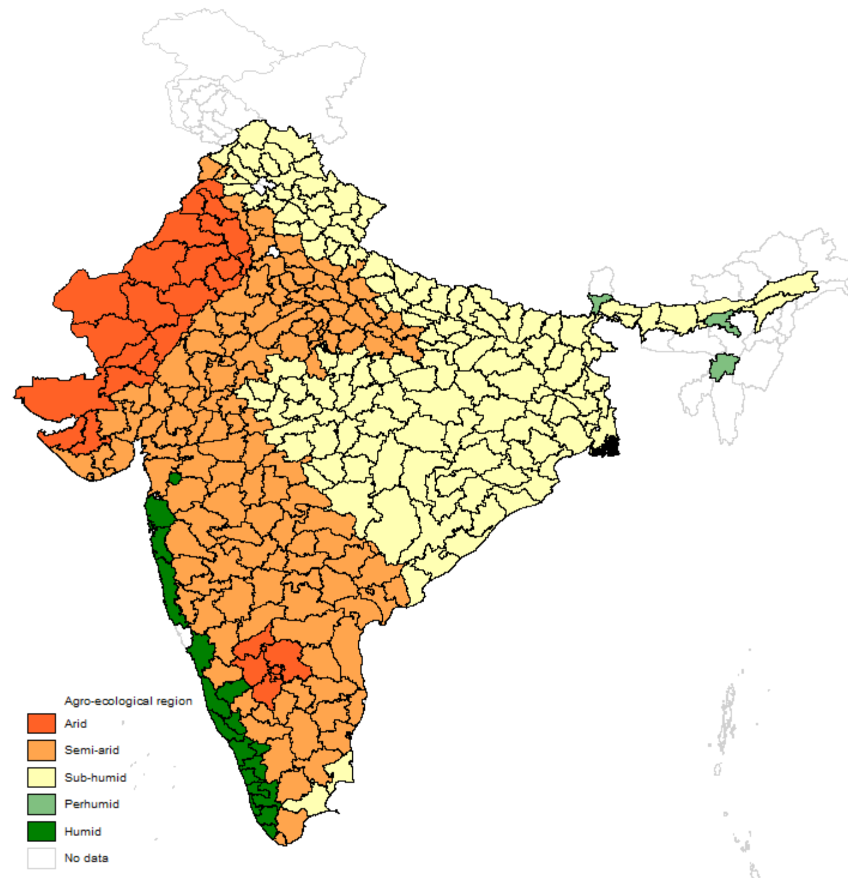
Estimating drought impacts separately for these different zones is important for a number

Figure 3.1: Average rainfall across agro-ecological regions in India

(a) Average rainfall



(b) Agro-ecological region



Note: Panel (a) shows district-wise average rainfall over the period 1957-2009. Panel (b) maps the agro-ecological grouping of districts using the methodology described in this section. For both maps, only districts with available agricultural data are shaded. Districts with no data are shown as white polygons. District boundaries refer to those drawn in 1966.

of reasons. Firstly, identifying areas of drought vulnerability based on climatic differences is important for informing policy about future vulnerability. For instance, if regions that are on average drier and hotter are most affected by drought, it is likely that future warming could exacerbate these already challenging growing conditions. Secondly, understanding the difference in sensitivity to rainfall deviations can help policymakers more accurately ascertain when a drought is likely to start harming agricultural productivity. Given that, for instance, arid areas experience generally low levels of absolute rainfall, it may be simplistic to assume that a given proportional deviation below average would have comparable effects on agricultural productivity than an area with very high absolute levels of rainfall. While a 20% deviation in rainfall from the long term average would amount to 30mm in arid areas, the same proportional deviation would be around 200mm in humid areas. This may have substantially different effects on crop growth between these areas.

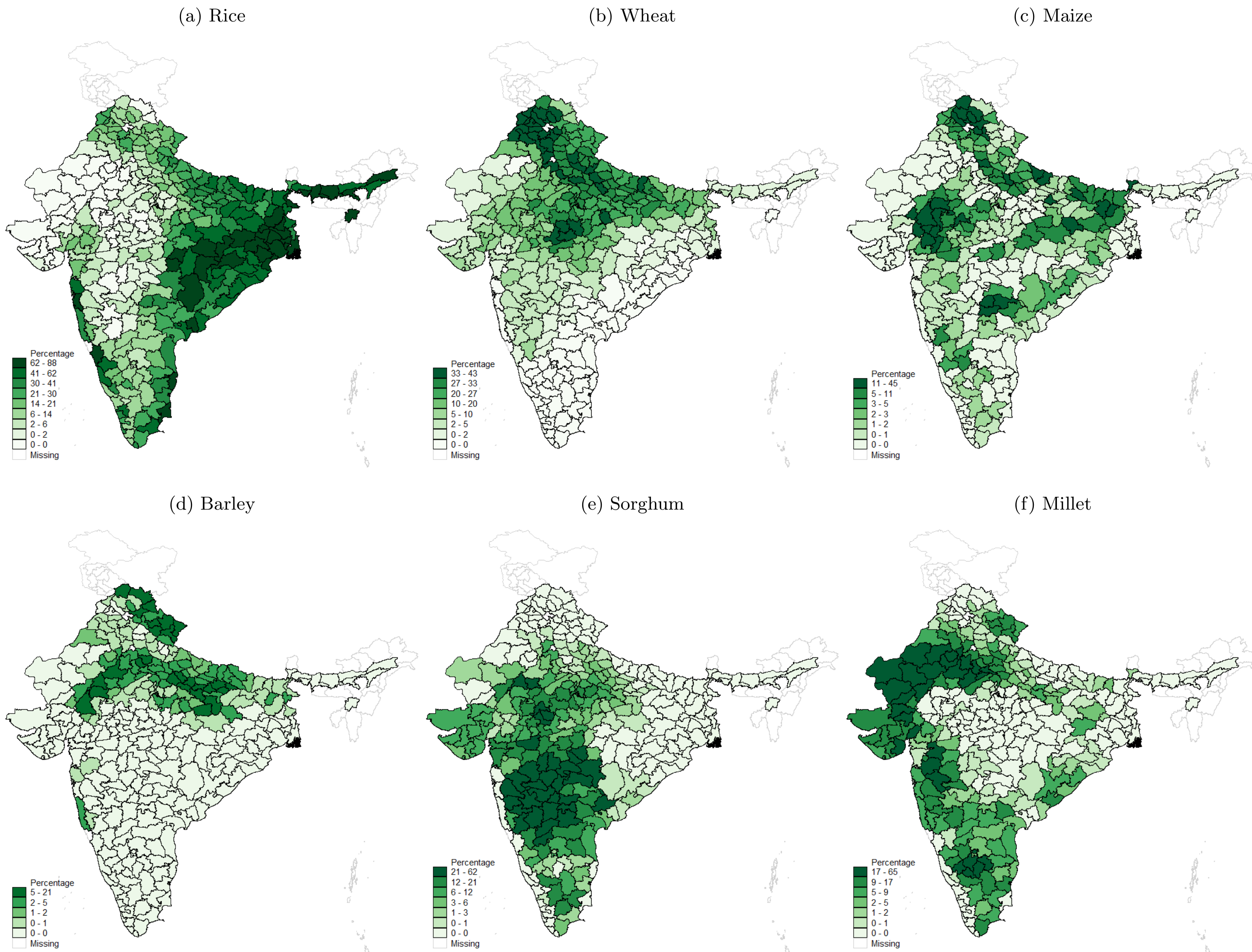
Given that physical exposure to drought may vary substantially across the country, we divide India into distinct regions based on their average agro-climatic characteristics. Panel (b) in Figure 3.1 displays a characterisation of Indian districts based on similar agro-climatic factors. Prior research has suggested that India can be split into twenty agro-climatic regions based on a number of climatic variables, such as rainfall, temperature, and soil characteristics (Gajbhiye and Mandal, 2010). We simplify this agro-climatic zones classification to group districts depending on whether they fall into arid, semi-arid, sub-humid, or humid zones. This allows us to maintain a relatively large number of districts in each zone to aid the empirical analysis. It can be seen by comparing panels (a) and (b) that this classification of zones corresponds very clearly with patterns of average rainfall, indicating that average rainfall is a key driving factor behind the variation in agro-climatic conditions across the country. The arid areas of the country are mainly located in the states of Gujarat and Rajasthan. Semi-arid districts span the majority of the Maharashtra, Madhya Pradesh, Karnataka, and Andhra Pradesh. Eastern states such as Bihar, Orissa, and West Bengal make up the wetter sub-humid states. Finally, western coastal districts in Kerala, Karnataka and Maharashtra fall into the humid district classification.

3.2.2 Crop type

Another crucial aspect that may be important in determining drought impacts is crop type. Consideration of the impacts of drought at the crop level may be important for two reasons. First, given the variation in average climatic conditions shown in Figure 3.1, crop choice in a district is likely to reflect these conditions. For instance, water-intensive crops, such as rice, are more likely to be grown in less arid areas. Figure 3.2 shows the spatial distribution of the proportion of area planted to the six crops examined in this study. Rice is planted most intensively in areas with high rainfall in the south and east of the country, under semi-humid and humid regions. In contrast, wheat is grown mainly in the more arid northern part of the country reflecting a lower dependence on rainfall. The crops most suited to growth in dry environments, sorghum and millet are both sown across arid and semi-arid regions in the north-west. These patterns place additional emphasis on possible variations in drought impacts within India if crops vary substantially in their resilience to water stress (FAO, 2012). Whether crops grown in areas used to lower absolute levels of rainfall, such as sorghum and millet, are better at coping with drought conditions is a question considered in the empirical analysis.

Examining drought impacts at the crop-level is also important since changes in the drought tolerance of crops over time may also be crop specific. One reason for this is that genetic advancement in some crops may have been more successful at improving drought resistance of certain crops. For instance, Yu and Babcock (2010) argue that past efforts to reduce pest damage to crops thus enabling them to survive better in drought conditions, has increased the drought tolerance of county-level corn and soybean yields in the U.S. Other authors have argued that increased drought resistance is not an inevitable outcome of agricultural modernisation, however. Lobell et al. (2014) use data at the field-level and find that soybean and corn yields in the U.S. between 1995-2012 have recently become more sensitive to drought due to cultivar improvements focused on maximising yields under optimal weather conditions. To add to this, other studies have argued that agricultural modernisation has not led to a decline in drought's impact on Indian agriculture. Since the adoption of new seed varieties has been very successful at increasing average yields across

Figure 3.2: District area planted for six main cereals in India



(a) Rice (b) Wheat (c) Maize

(d) Barley (e) Sorghum (f) Millet

Note: Panels (a)-(f) show the proportion of gross cropped area devoted to each of the six crops used in the analysis. For districts with no data, these areas are shown as white polygons. District boundaries refer to those in 1966.

the country, a measure of the success of the country's Green Revolution depends on how resilient the agricultural sector remains to drought. A number of studies have argued that the adoption of higher yielding seeds by farmers has increased the year-to-year variability of production since these varieties do not cope well when conditions deviate from those considered optimal for growth (Hazell, 1984; Larson et al., 2004).[2]

3.2.3 Irrigation

Irrigation is likely to be a highly significant factor that affects production losses during a drought. Since both a decrease in rainfall and an increase in temperature effectively imply lower moisture availability, irrigation often appears to be a panacea to drought. The rationale behind irrigation is simple in that moisture deficiencies can be replaced by water from irrigation. On the one hand, a number of studies have shown that irrigation is strongly associated with mitigating the impact of low rainfall. Duflo and Pande (2007) show that the construction of dams across India reduces the sensitivity of district crop yields to extreme rainfall in India. In a study on the resilience of district rice yields in India to drought over time, Birthal et al. (2015) argue that irrigation was the main driver in mitigating drought impacts on rice productivity at the district level given that irrigated area increased dramatically since the 1960s. Irrigation's impact is, however, limited to the availability of a water source, and half of total cropped area remains rain-fed.

Although it seems intuitive to link the expansion of irrigation to lower drought impacts, a number of recent studies have questioned the long-run effect of increasingly water-intensive farming practices on the drought sensitivity of production. Hornbeck and Keskin (2014) consider the dynamic impact of irrigation on the drought sensitivity of agriculture in the U.S., noting that although the utilisation of water from aquifers initially lowers drought sensitivity of production, sensitivity subsequently increases due to the adoption of more profitable, water-intensive crops over time. Another study by Fishman (2012) emphasises that although the effectiveness of irrigation in mitigating low seasonal rainfall in India is

[2] In related agronomic work by Prashant et al. (2015), the authors study the genetic traits of 'modern varieties' and argue the introduction of these varieties has increased the susceptibility of key Green Revolution crops, such as rice and wheat, to drought since genes associated with drought tolerance were lost in favour of higher yielding characteristics, such as semi-dwarf properties.

high, this has little impact in reducing the effect that high temperatures have on rice yields in India, which may limit the extent to which irrigation remains an effective strategy in the face of hotter droughts driven by increases in average temperatures.

Increasingly, the sustainability of the Green Revolution model of agricultural development, based on the use of irrigation often from groundwater sources, to large drought shocks has been called into question by a number of recent studies. Work by Rodell et al. (2012) and Panda and Wahr (2016) uses satellite-based methods to assess changes in stocks of groundwater over time in India. These studies conclude that sustained depletion of aquifers has occurred particularly in the Ganges Basin region, where groundwater is vital for sustaining the rice-wheat production systems in what is a primarily semi-arid climate. The slow recharge rate of aquifers in this region means that the consequences of previous levels of groundwater extraction are likely to be a pressing concern for farmers in the future, and of particular importance for farmers during drought years. Firstly, aquifer depletion over time lowers water tables, so that water becomes more costly and difficult to access since farmers must dig deeper wells and use more energy to pump water from the ground. This limits the ability of farmers to mitigate the adverse impacts of drought on crop growth. Secondly, as is shown by Chen et al. (2014) and Panda and Wahr (2016), rates of groundwater extraction increase substantially during drought years. This works to reduce groundwater stocks in the years following a drought which in turn limits the potential for farmers to use irrigation to mitigate the effects of droughts in future years. As such, it is plausible that although the increased use of irrigation is a useful strategy in mitigating drought when water is abundant, its diminishing availability may act as a source of increased vulnerability of Indian agriculture over time.

3.3 Measuring the physical severity of drought

In order to assess the impacts of drought, it is important to define the climatic conditions that cause drought. While there is no universal definition of the conditions that constitute a drought (Wilhite, 2000), drought is generally referred to as an extreme natural event associated with water deficiency over an extended period of time (Mishra and Singh, 2010). The severity of a drought and its impacts are however, determined by a number of other aspects, both physical and human, which may differ substantially across space and time. As such, given that drought is such a complex phenomenon and its impacts are highly dependent on a number of aspects, natural and man-made, it is unsurprising that a wide range of indices have been used in research and policy. These range from simple precipitation indices, which are highly favoured among policymakers, to very data-intensive multidimensional measures.

A number of studies have estimated impacts of drought on agricultural production using simple metrics of precipitation deficiency in India. These measures of drought have the advantage of being easily interpretable and capture the most obvious characteristic of drought, rainfall deficiency. For instance, a commonly used method to define drought is used by Pandey et al. (2007b) who define drought as annual rainfall 80 percent below normal levels. Moderate drought is defined if rainfall is 80-70 percent of normal, with severe drought 70 percent below normal. They use this definition to estimate drought impact in areas that grow rice in Asia at the aggregate and household level. They find that drought impacts vary markedly across countries. While drought is associated with a 36% loss in production value in rain-fed areas in Eastern India, production losses in Thailand and China are much lower at 10% and 3% loss of output respectively. A similar definition is also used by Auffhammer et al. (2012) to study the effect of monsoon rainfall on rice yields for states in India. They define drought if monsoon rainfall is 15% below normal and find that drought was associated with a 12 percent fall in state rice yield.

Studies such as those above that use simple definitions of drought are problematic for our understanding of the impacts for two reasons. Firstly, they impose arbitrary thresholds to define drought, evaluating drought impacts only after a given level of precipitation. It is not clear, however, whether such thresholds have any agronomic or empirical basis (Wilhite and Glantz, 1985). Secondly, variables in addition to precipitation may have important effects when determining the physical severity of a drought. Overall, the misspecification of the variables that cause drought could lead to substantial bias in the estimation of impacts since potentially destructive drought events may be overlooked.

One factor that undeniably affects the severity of a drought is temperature. A number of recent studies emphasise the detrimental effect that high temperatures have on crop yields. Schlenker and Roberts (2009) find that high temperatures reduce county-level yields for corn, soybeans, and cotton in the United States. In India, Guiteras (2009) and Burgess et al. (2014) both show that, on average, daily temperatures above 34°C tend to reduce agricultural productivity of a district. Lobell et al. (2012) identify the same threshold as harmful for wheat yields in the country.

High temperatures have particularly acute effects on crop growth during periods of low precipitation since the rate of evapotranspiration, the combined process of water evaporated from land surfaces and plants, increases as temperatures rise (Prasad et al., 2008; Lobell and Gourdji, 2012). In general, this increases a plant's demand for water at a time when water availability is already lowered due to deficient precipitation. The importance of temperature in determining the physical severity of drought is also of high importance given temperature increases driven by climate change (Hatfield et al., 2011). Recent research has documented that droughts over a range of settings have increased in severity as mean temperatures have increased. These studies have shown that higher temperatures, rather than the increased intensity of low rainfall events, have been responsible for these drying trends (Vicente-Serrano et al., 2014; Diffenbaugh et al., 2015). As such, not considering the effect that temperature could have on the severity of a drought event could lead to a serious underestimation of the severity of a drought and give misleading information about the likelihood of future production losses driven by climate change.

In order to improve the understanding of the impacts of drought in agriculture, recent literature has worked on the incorporation of both precipitation and temperature into the measurement of drought. Yu and Babcock (2010) study drought as a period over the growing season when precipitation is below its average level *as well as* temperature being higher than average. The findings of this study suggest that soybeans and corn have become increasingly drought-tolerant over time. Birthal et al. (2015) use the same index to study the resilience of rice yields to drought in India. Their results indicate that rice yields have become more resilient to drought over time. A key weakness of these studies however, is that the index used in these approaches restricts drought to be an event that only occurs if a period of low rainfall is accompanied by higher than average temperatures. For instance, a year when rainfall is very low but temperature was not above average would not be considered as a drought. Omission of potentially destructive droughts could lead to significant bias in estimates of drought impact. Since events that could be considered drought are included in the control group, the index suggested by Yu and Babcock (2010) is likely to underestimate the total impact of drought. In the following section, we detail a drought index that builds on this previous work that allows us to consider the whole range of potential drought events.

3.4 Drought index

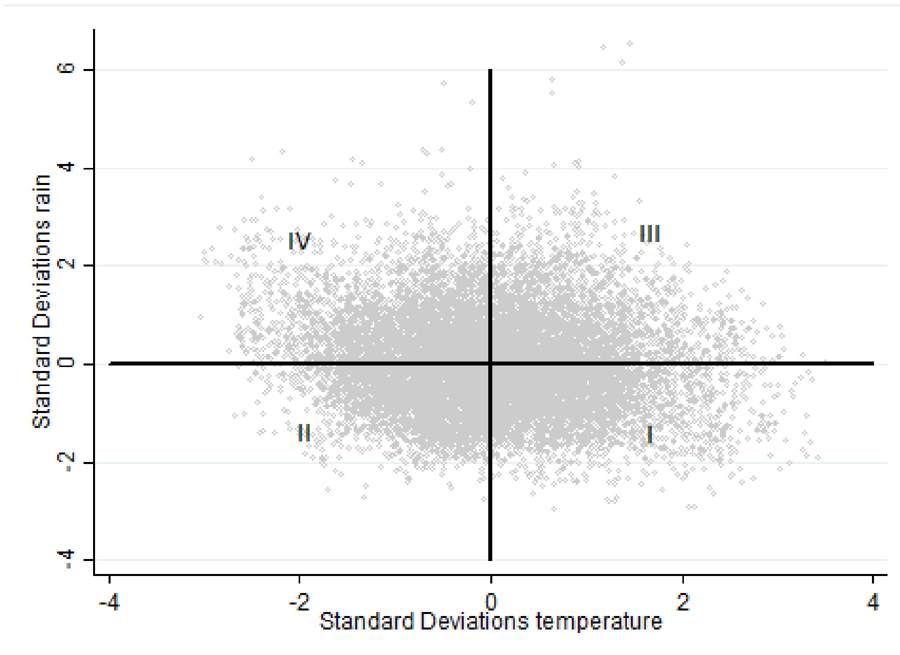
In this section, we build on the approach taken by Yu and Babcock (2010) to construct an index of drought incorporating both rainfall and temperature. According to their classification, a drought occurs in a year when *both* temperature is uncommonly high and precipitation low, relative to the long term average of these variables.[3] As such, the intensity of a drought increases with lower levels of precipitation and hotter temperatures. The strength of this index lies in its ability to capture the potential that high temperatures exacerbate the effects of low rainfall on crop production.

A crucial weakness of this index, however, is that drought is defined only in years when an area suffers both low rainfall *and* high temperatures. An important omission is that years when rainfall is low but temperature is not uncommonly high are not considered as potential droughts. This can be illustrated by considering Figure 3.3. Defining drought events according to both low rainfall and high temperature restricts the measure of drought to the lower right quadrant of events (I). However, events in the lower left quadrant (II), where area rainfall is low but temperatures are not unusually hot, are not considered droughts. It can be clearly seen that a large number of low precipitation events occur

[3]We limit our analysis to considering drought as a prolonged absence of rainfall over a year. As such, we do not analyse shorter or longer periods of drought. For instance, Fishman (2016) studies the intra-annual distribution of rainfall in India and concludes that this has important effects on productivity. To analyse the impacts of rare, multi-year droughts we would require a drought measure with 'memory' that takes into account soil moisture conditions. Since drought in India is mainly driven by variation in the annual monsoon, we argue that this annual measure is most relevant in this context.

in this quadrant which is likely to have serious implications for assessing the impact of drought.

Figure 3.3: Potential droughts events and their categorisation in the drought index



To address this, we use the logic of the Yu and Babcock (2010) index to consider a wider set of drought events. First, we calculate district-specific cumulative rainfall over the growing season, R_{it}, and then calculate its long term average $LTAR_{it}$ for the growing season (June-September) over the period 1956-2009. A standardised measure of rainfall is then estimated as $ZR_{it} = (R_{it} - LTAR_i)/sdR_i$, where sdR_i is the standard deviation of R_{it}.

Analogously, we calculate the district-specific cumulative growing season temperature, HDD_{it}, for the growing season (June-September) as the cumulative number of daily degree days above the mean daily growing season temperature over the period 1956-2009.[4] Similar to rainfall, this variable is standardised by estimating $ZHDD_{it} = (HDD_{it} - LTAHDD_i)/sdHDD_i$, where $LTAHDD_{it}$ is average cumulative daily degree

[4]The growing season daily degree days are calculated as follows. First, we obtain the average growing season temperature for each district. Second, for each day we subtract the average temperature from the observed temperature and obtain the number of degrees above the average temperature for each day. Finally, we sum all the positive temperature deviations for each day of the growing season and obtain the cumulative daily-degree days

days over the growing season and $sdHDD_i$ is the standard deviation of HDD_{it}.

We differ from Yu and Babcock (2010) in creating a normalised version of the rain and temperature variables such that they vary strictly between 0 and 1. Normalising the negative of rainfall, rather than rainfall directly, allows us to generate a variable bounded between 0 and 1, with higher values signalling a more severe precipitation deficiency. We construct a variable, R_{it}, which is simply the negative of R_{it} (i.e. $R_{it} = -R_{it}$). The following is estimated to obtain NR_{it} and $NHDD_{it}$:

$$NR_{it} = (R_{it} - R_i^{min})/(R_i^{max} - R_i^{min}) \tag{3.1}$$

where R_i^{min} denotes the minimum observed value for district i (i.e. the maximum rainfall observed), and R_i^{max} denotes its maximum observed value (i.e. lowest rainfall). The same normalisation procedure is then applied to the temperature variables:

$$NHDD_{it} = (HDD_{it} - HDD_i^{min})/(HDD_i^{max} - HDD_i^{min}) \tag{3.2}$$

where HDD_i^{min} denotes the minimum observed value for district i (i.e. the maximum number of degree days observed), and HDD_i^{max} denotes its maximum observed value (i.e. lowest number of degree days observed).

From these two variables, we then create a normalised rainfall-temperature index $NRTI_{it}$, which is simply a product of these variables:

$$NRTI_{it} = NR_{it} * NHDD_{it} \tag{3.3}$$

We illustrate these events in equation (3.4). Potential droughts can be classified as $D1$ which corresponds with that of Yu and Babcock (2010) where rainfall is below normal and temperature above normal. $D2$ then corresponds with low rainfall in the absence of abnormally high temperatures. The value of both of these indexes is increasing in temperature but decreasing in precipitation. The multiplicative relationship generated between the two normalised variables, is used to illustrate the comparison between different types of drought event. Formally, we have:

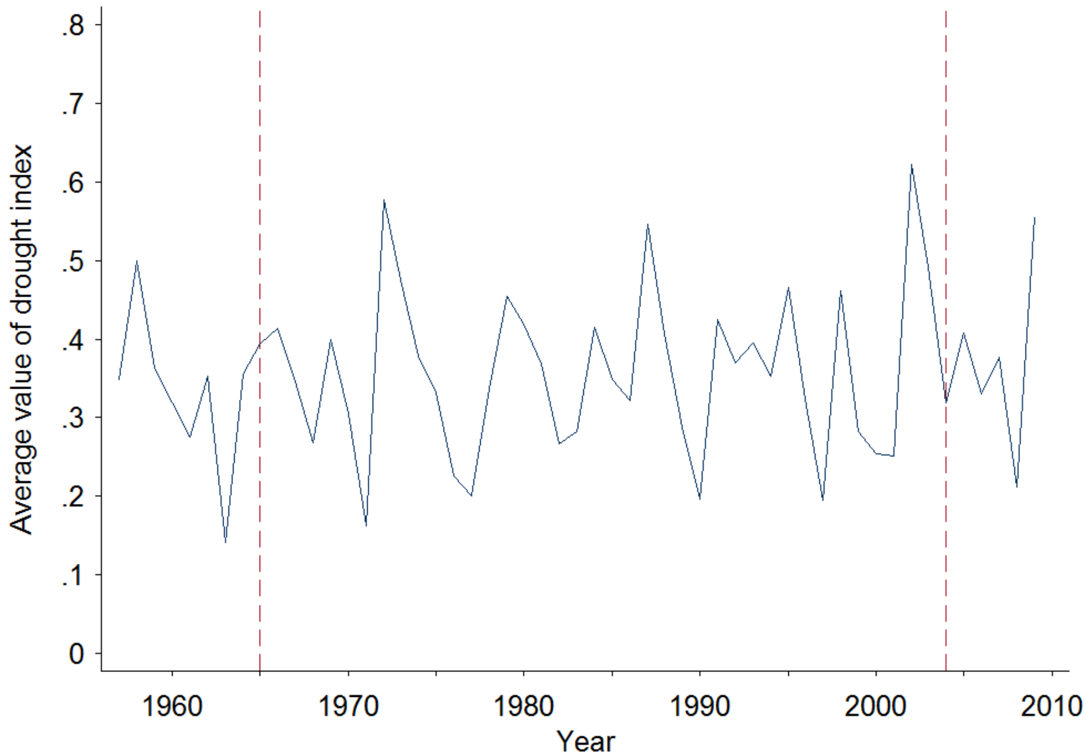
$$Drought = \begin{cases} D1_{it} = NR_{it} * NHDD_{it} & \text{if} \quad ZR_{it} < 0 \,\&\, ZHDD_{it} > 0, 0 \text{ otherwise} \\ D2_{it} = NR_{it} * NHDD_{it} & \text{if} \quad ZR_{it} < 0 \,\&\, ZHDD_{it} < 0, 0 \text{ otherwise} \\ D12_{it} = NR_{it} * NHDD_{it} & \text{if} \quad ZR_{it} < 0, 0 \text{ otherwise} \end{cases} \tag{3.4}$$

As such, $D1_{it}$ can be interpreted as a normalised version of Yu and Babcock's (2010) index. It captures all events in the lower right quadrant (quadrant 1) of Figure 3.3, taking a strictly positive value for all events characterised by below-average precipitation and above-average temperatures. The second index, $D2_{it}$, only takes non-zero values for events with below-average rainfall and below-average temperature, the category Yu and Babcock omit. Finally, a third index, $D12_{it}$, simply combines $D1_{it}$ and $D2_{it}$ and hence, captures all the events in the lower half of Figure 3.3.

To illustrate the efficacy of the drought index, Figure 3.4 plots the average value of the index over time for all districts included in our sample. The particular sample period that we examine (explained in the next section) is shown between the red vertical lines. There is substantial variation in the average severity of drought over time. In particular, we note that the index takes particularly high values in years historically identified as serious droughts across wide areas of the country. For instance, the years 1972, 1979, 1987, and 2002 were particularly serious droughts across the country (Wang, 2006) and subsequently are the years when our drought index takes the highest values.

In order to study precipitation thresholds it is necessary to make a small innovation to this index. In particular, we need a precipitation index that is continuous in proportion of rain. As such, for the case of the precipitation index, we give a non-zero value to the cases where rain is above average but temperatures are also high. In terms of the events shown in Figure 3.3, this refers to quadrant III. Although these events should not be considered as potential droughts, their inclusion is necessary in the index so that rainfall can be

Figure 3.4: Average severity of drought in India 1956-2010



treated as a fully continuous variable so that we can test for where structural breaks for precipitation deficiency are located.[5]

This approach has the advantage of allowing us to remain agnostic in terms of the relationship between precipitation and the drought impacts. However, it also has a slight disadvantage, in that our index is not easily interpretable at regions of precipitation above 1 since a higher value of the index could both mean a value of rain closer to normal rain (in which case we would expect a positive relationship) or a very high temperature irrespective of the precipitation level (in which case we may expect a negative relationship). But since our goal is to focus on the analysis of drought, we are more concerned about the parts of the index for proportions of rain below one and, as such, we believe that the flexibility that the index confers outweighs the difficulty of interpretability for regions above normal

[5]It is unnecessary to include events in quadrant IV since by any definition these do not constitute drought.

rainfall.

The rationale for utilising this index relates to practical issues concerning data ideally needed to measure variables that affect crop growth. An ideal measure of drought would measure soil moisture in a particular area at a given time. Comprehensive measurements of observed soil moisture do not, however, exist over the time period studied in this paper or for the spatial extent needed to study drought across India. The unavailability of this type of data has led researchers to construct indices that proxy for variables affecting soil moisture. The specific index chosen in this paper has been chosen over other indices due to the nature of the data available. Although drought indices have been constructed to try to attempt to accurately model soil moisture conditions, variables needed to construct these are unavailable in the context of this study. For instance, the Palmer Drought Severity Index (PDSI) is frequently used to monitor drought in the U.S. Its applicability elsewhere is more limited, however, due to its computational intensity and data needs, which include evaporation measurements and water runoff. Additionally, it has been criticised for the arbitrariness of some of its modelling assumptions. See Alley (1984) for an overview of issues surrounding the use of the PDSI. Thus, in order to construct an index over the whole sample period, the drought index used throughout the rest of this paper is constrained by the availability of data over this period.

3.5 Data

The agricultural data is taken from the ICRISAT Meso-level Database, which contains information on a range of agricultural and socioeconomic variables at the district-level (ICRISAT, 2012).[6] We use data for the years 1966-2003 to conduct the analysis. Although the panel extends to 2009 for most districts, a number of missing observations occur in the 2000s. Given that the empirical analysis requires a balanced panel data set, districts with missing observations are dropped from the analysis. Since it is impractical to exclude all of these districts from the analysis, we choose to compromise by only using years up until

[6]Since 1966 a number of districts have split into smaller districts. To maintain spatial consistency over time, district splits are dealt with by returning split districts to their parent districts in 1966.

2003 which allows us to keep the largest number of districts. Consequently, out of the 311 available in the database, 240 districts that have non-missing data for all years are used in the main analysis.

Data are available on annual crop production and area, which are used to construct crop yield variables. Rice, wheat, maize, barley, sorghum, and millet production statistics are used.[7] We investigate drought impacts on an aggregate cereal productivity index and separately for each crop. The aggregate cereal index is constructed by taking a weighted average of district cereal yield for each of these six cereals weighted by the proportion of each crop's area planted in a district. Data on the area irrigated and fertiliser use in a district are also used. These variables are available as district-level aggregates and are not crop-specific. In addition, socioeconomic census data is available on district population.

To construct the drought index, we use weather data on daily rainfall and daily average temperatures from the Indian Meteorological Department. The rainfall data is available in gridded format at a resolution of 0.25°x 0.25°(Pai et al., 2014). Gridded temperature data is at a resolution of 1°x1°(Srivastava et al., 2009). District-wise weather data is then obtained by taking a weighted average of gridded weather observations from grid cells that fall within a district's boundary based on the proportion of the grid cell that falls in each district.

3.6 Empirical methodology: Threshold regression

To estimate the impact of drought on Indian agriculture, we employ a threshold regression estimation strategy with fixed effects (Hansen, 1999).[8] This model augments the standard linear fixed effects model by estimating how the effect of the drought variable on crop yield differs between thresholds of a variable of interest.

The equation below illustrates the model in the case of a single threshold, γ. D_{it} is the drought index variable and $\ln y_{it}$ is the natural logarithm of crop yield.[9] Since the

[7]For millet we add data on quantities of pearl millet and finger millet to create an aggregate quantity of millet.

[8]To estimate the fixed effects threshold model we utilise Stata code which is described in Wang (2015).

[9]We use the log transformation of yield because we are interested in the relative impact of drought. This

threshold regression approach precludes the use of trended data and integrated processes, prior to running the regression we detrend crop yield, Y_{it}, by fitting a district-specific quadratic time trend which gives us a detrended logarithm of yields, which we denote by y_{it}. Detrending in this way removes trends in yields that are associated with technological progress over time. To check if the yield variable is stationary in all model specifications after the detrending procedure, we apply a number of panel unit root tests.[10] For all specifications we reject the null hypothesis of the dependent variable having a unit root at a 1% significance level. A set of control variables are also included in $\mathbf{X}_{it}$ and the error term, which is clustered at the district level to account for potential autocorrelation in the error term, is represented by e_{it}.

$$\ln y_{it} = \alpha_i + D^j_{it}(q_{it} < \gamma)\beta_1 + D^j_{it}(q_{it} \geq \gamma)\beta_2 + \mathbf{X}_{it}\delta + e_{it} \tag{3.5}$$

which can be written more compactly as

$$\ln y_{it} = \alpha_i + D^j_{it}(q_{it}, \gamma)\beta + \mathbf{X}_{it}\delta + e_{it} \tag{3.6}$$

where

$$\ln y_{it} = \begin{cases} \alpha_i + D^j_{it}\beta_1 + \mathbf{X}_{it}\delta + e_{it} & \text{if } q_{it} < \gamma \\ \alpha_i + D^j_{it}\beta_2 + \mathbf{X}_{it}\delta + e_{it} & \text{if } q_{it} \geq \gamma \end{cases}$$

Rather than the effect of drought being identical across all values of the threshold variable q_{it}, the threshold model estimates the value $q_{it} = \gamma$, at which the effect of drought on cereal productivity changes in a statistically significant way. This means that the average effect of drought before $q_{it} = \gamma$ is different from the effect after $q_{it} = \gamma$. In this case, β_1 and β_2 represent the impacts of drought for members of the sample either side of the threshold, γ. This method allows us to test, firstly, whether such a threshold exists and,

specification also allows for better comparison of drought impacts across areas where absolute differences in productivity may be large.

[10]The Levin-Lin-Chu, Harris-Tzavalis, Breitung, and Im-Pesaran-Shin unit roots tests are deployed.

secondly, how the effects of drought vary across values of a specified variable of interest q_{it}.

The threshold value is estimated by least squares and involves picking the value of γ that minimises the residual sum of squares of the model (Hansen, 2000). Even if a threshold is estimated, it may not be statistically significant. Accordingly, a likelihood ratio test of whether $H_0 : \beta_1 = \beta_2$ is implemented. However, as is noted by Hansen (2000), asymptotic sampling distributions of Wald statistics are known to behave poorly when these distributions depend on unknown parameters, as is the case for threshold regressions. Accordingly, inference in the model relies on a bootstrap procedure where individual sample observations are drawn with replacement, holding the values of regressors and the threshold variable fixed. For each bootstrap sample, the model is then estimated to calculate the likelihood ratio. This procedure is repeated 300 times to calculate the proportion of simulated sample draws that yield likelihood ratio statistics greater than the observed sample. This gives the asymptotic p-value at which the null hypothesis of no threshold can be rejected. If we fail to reject H_0, the model is equivalent to the linear model where the effect of the regressors included in the model are not significantly different across values of the proposed threshold variable.

It may be possible that more than one threshold of drought impact exists. We thus test for the existence of multiple thresholds. The number of thresholds tested for is sequential in the sense that if we first predict a model with a significant single threshold, we then test for the existence of a second threshold. This procedure is continued by allowing for a maximum of three threshold values.[11]

We estimate separate models for two threshold variables, namely for time and the proportion of rainfall below normal (from long-term district average rainfall). For the set of regressions using time as a threshold variable, the model works by testing whether there are years that demarcate periods when drought has distinctly different impacts on cereal yields. This is analogous to a multiple-point Chow test for structural instability in drought

[11]We are constrained in estimating a maximum of three thresholds by the code described in Wang (2015). However, we posit that this does not pose a problem for the analysis since, as will be seen in the following section, the number of times that we fail to reject a three threshold model is very rare. This implies that the likelihood of the number of thresholds beyond three is very low.

impacts where the break points are *a priori* unknown.[12] The second threshold variable we use is rainfall. This is to test for the values of proportion of rainfall below average between which drought impacts are different.

A benefit of using panel data to measure drought impacts is that it allows us to credibly identify the effect of drought on agricultural productivity. This comes from a number of characteristics of the statistical model. Inclusion of district fixed effects terms control for the influence of time-invariant district factors, such as soil types or institutional differences, that may affect the impact of drought. Inclusion of the district fixed effect also means that identification of the impact of drought relies on plausibly random variability in the severity of drought *within*-districts over time.

We also estimate our results with and without a set of time-varying control variables $\mathbf{X}_{it}$. These control variables are detrended at the district-level using the same procedure as for crop yields. This is to account for the likelihood that the level of these variables may be trending over time. Although identification using the reduced form approach assumes that drought is a random, exogenous shock to agricultural productivity, it is plausible that drought may be correlated with a number of time-varying district factors that may condition drought's impact. A key factor could be that input decisions change as drought unfolds over time, which would mean that our estimate of drought impact on productivity is picking up the influence of various factors that condition drought impact. In order to test whether this affects our estimates of the impact of drought, we control for a number of factors that drought may be correlated with, which may provide a more precise estimate of the drought impacts.

We include census data on rural population density to try to control for the effect that labour availability could have on productivity during drought years. A period of drought could induce temporary or permanent migration away from a rural area, reducing the availability of labour.

[12] A number of papers have used similar techniques to identify points of structural change using time series data. A prominent example of this approach is Bai and Perron (1998) who suggest a method for identifying multiple potential breakpoints in a data series over time. Interestingly, this method has been applied by Chand and Parappurathu (2012) to understand distinct periods of productivity growth in Indian agriculture.

Annual cereal area cultivated is also included as a control. This is motivated by the finding of Siderius et al. (2016) who find that farmers in the Ganges Basin make dynamic adjustments to land use in response to rainfall variability. For instance, farmers tend to decrease cropped area of rice and wheat in rain-fed areas in response to water stress. These adjustments could lead to an underestimate of the impact of drought on productivity if, for instance, lower productivity land is taken out of production during a drought year in order to conserve water resources for higher productivity land.

It is also plausible that farmers' input decisions vary in response to a drought. One possibility is that farmers respond to drought by increasing the area under irrigation. This could lead us to underestimate the impact of drought on productivity. Use of other inputs may also be affected. Another possibility is that fertiliser use may decline during a drought year. For instance, Pandey et al. (2007a) find that fertiliser use decreases during drought years, although they observe that most input decisions do not change substantially during drought years since many input decisions are made before the extent of drought is known. In the following results section, we test whether these control variables affect the drought impact estimates by reporting results with and without the set of controls.

3.7 Results

In this section we present the results from the threshold regressions of drought impact. Each table is split into three parts and should be read as follows. The top section of each table displays the p-values from the likelihood ratio test for the existence of the number of thresholds of drought impact. The selection rule used is to select the highest number of thresholds that are accepted at a p-value of less than 0.1 (10% significance level). The section below displays the location of the estimated thresholds ($\gamma_1, \gamma_2, \gamma_3$) and their associated confidence intervals in square brackets. The thresholds are listed from smallest to largest. The third section shows the estimated coefficients. The first coefficient in the variable list shows the coefficient on a dummy variable included to measure the average effect of drought over the sample period. This captures the intercept change (in terms of yield) of having less than normal rainfall. This variable takes the value of one if precipitation is below normal and zero otherwise.[13] Omitting this variable would mean that the estimated coefficients of marginal drought impact would capture both the intercept change and the marginal effect of the drought index on yield. The next set of coefficients display the marginal effects of the drought index each side of the estimated threshold value along with coefficients of the included control variables.

3.7.1 Time thresholds of drought impact

Table 3.1 displays the threshold regression results using time as a threshold variable. The dependent variable is the natural logarithm of district cereal yield. The first two columns show results for the whole sample, while the following four columns display results for non-irrigated and irrigated districts respectively. For India as a whole, the model estimates that average drought impacts can be divided into three distinct periods given that two thresholds have been estimated. The first threshold occurs in 1987. Here, the marginal effect of drought on cereal yield is statistically significant at -0.271. Recall that the drought index takes values from one to zero, with the worst drought in a district over the sample period taking the value of one. As such, for a drought which takes the value 0.5, this is estimated to lead to a negative deviation in yields from trend of 13.5%. Consistent with findings in Birthal et al. (2015), we also see that average impacts decreased substantially for the 1987-1998 period, as opposed to the pre-1987 period. This could potentially be explained by the increased use of irrigation technologies which spread across the country following the Green Revolution. While initially confined to a small number of areas such as the northern 'grain belt' states such as Punjab and Haryana, technologies became more readily available to farmers across the country. Chand and Parappurathu (2012) argue that beginning in the late 1970s, a period of 'wider technology dissemination' saw the increased adoption of new seed varieties and complementary inputs, such as groundwater irrigation, across the country. One advantage of our approach is that it does not impose linearity to the evolution of the impacts over time and allows us to identify sharp breaks in average drought impact. As a result, we also find that in the later periods of the sample,

[13] In terms of the the distribution of potential drought events shown in Figure 3.3, this corresponds to all events in quadrants I and II.

more specifically after 1999, we find very large coefficients for average drought impact, with these magnitudes broadly comparable to those of the pre-1987 period. This suggests that, despite extensive technological progress, the Indian agricultural sector is not immune to large shocks, such as the droughts that characterised the early 2000s. The severity of drought in this period can clearly be seen in Figure 3.4, which previously displayed average drought severity over time. The value of the drought index over the sample period is, on average, highest for the years 2001/02. Additionally, other authors have argued that high impacts in these later years may also reflect water scarcity over the medium term. As is argued by Shah et al. (2009), while 1998 was a moderate drought for much of India, this was followed by subdued rainfall in the 1999-2001 time period, which aggravated the impacts of the drought in 2002, when the negative rainfall deviations were very high. The inclusion of control variables does not substantially change the results. For the full sample we do see a change in one of the estimated threshold locations from 1987 to 1992, although the new threshold estimated includes the old threshold in the confidence interval. The included control variables also take the expected signs, although the likelihood that these variables are endogenous means that no causal interpretation is attached to these estimated coefficients. The marginal effect of cereal area on yield is negative, implying possible diminishing returns to yield from increasing cereal area. The marginal effect of fertiliser and irrigation is positive during the sample. The effect that rural population density has on yield is not clear.

The results by irrigation category suggest drought impacts over time have differed substantially between the two groups. The third column, which looks at low irrigation districts highlights that, with the exception of the period between 1985 and 1987 (when many areas of the country were hit by particularly severe droughts), there has been a general trend of decreasing impacts. Conversely, for high irrigation districts, we reject the threshold model against the conventional fixed effects model which implies that we could not reject the hypothesis that impacts were not significantly different over two sub-periods.

Table 3.2 shows the results for whether there have been significant thresholds of drought impact over time when the sample is split into four agro-ecological zones (AEZ). The existence of significant thresholds only occurs in one AEZ, where the years 1984-1987 were

Table 3.1: Time threshold regressions of drought in India

Existence of thresholds	**Full sample**		**Low irrigation**		**High irrigation**	
P-value						
Single	0.027	0.010	0.017	0.027	0.840	0.723
Double	0.000	0.010	0.000	0.000	0.147	0.320
Triple	0.210	0.810	0.260	0.327	0.810	0.590
Threshold location						
γ_1	1987	1992	1984	1984		
CI	[1986,1988]	[1987,1993]	[1983,1985]	[1983,1985]		
γ_2	1998	1998	1987	1987		
CI	[1997,1999]	[1997,1999]	[1986,1988]	[1986,1988]		
γ_3						
CI						
Variables						
Drought dummy	-0.046***	-0.025*	-0.025	-0.026	-0.016	-0.010
	(0.015)	(0.013)	(0.025)	(0.023)	(0.011)	(0.011)
Period$< \gamma_1$	-0.271***	-0.278***	-0.380***	-0.351***	-0.149***	-0.135***
	(0.044)	(0.042)	(0.060)	(0.060)	(0.028)	(0.027)
$\gamma_1 \leq$ Period $< \gamma_2$	0.013	-0.005	-0.791***	-0.824***		
	(0.039)	(0.030)	(0.133)	(0.135)		
Period$> \gamma_2$	-0.278***	-0.300***	-0.235***	-0.254***		
	(0.039)	(0.035)	(0.058)	(0.047)		
Controls						
Cereal area (log)		-0.099***		-0.167***		-0.003
		(0.036)		(0.047)		(0.055)
Fertiliser (log)		0.082***		0.051**		0.126***
		(0.016)		(0.022)		(0.015)
Irrigation (log)		0.137***		0.074**		0.180***
		(0.025)		(0.032)		(0.037)
Rural population (log)		0.040		0.119***		-0.120**
		(0.032)		(0.042)		(0.053)
Constant	0.064***	0.061***	0.089***	0.091***	0.038***	0.032***
	(0.006)	(0.006)	(0.010)	(0.010)	(0.005)	(0.005)
N	8,917	8,436	4,477	4,218	4,440	4,218
No. of districts	241	228	121	114	120	114
R-squared	0.073	0.209	0.105	0.168	0.047	0.21

* p<0.1, ** p<0.05, *** p<0.01. Standard errors are shown in parentheses and are clustered at the district level. The top part of the table shows the results for the testing procedure for the number of thresholds estimated. Below this the threshold locations are shown corresponding with the number of thresholds estimated. The final part of the table shows the regression estimates for the impact of drought between each of the thresholds and also the a set of control variables included in the regression.

Table 3.2: Time threshold regressions of drought in India across agro-ecological zones

Existence of thresholds	**Arid**		**Semi-arid**		**Sub-humid**		**Humid**	
P-value								
Single	0.053	0.000	0.270	0.240	0.293	0.560	0.343	0.330
Double	0.070	0.030	0.040	0.010	0.467	0.000	0.027	0.073
Triple	0.223	0.190	0.787	0.673	0.567	0.813	0.480	0.670
Threshold location								
γ_1	1984	1984						
CI	[1982,1990]	[1982,1989]						
γ_2	1987	1987						
CI	[1986,1989]	[1981,1989]						
γ_3								
CI								
Variables								
Drought dummy	-0.188**	-0.127*	-0.027*	-0.004	-0.029*	-0.018	0.017	-0.006
	(0.072)	(0.063)	(0.014)	(0.013)	(0.016)	(0.017)	(0.014)	(0.026)
Period$< \gamma_1$	-0.476*	-0.565**	-0.206***	-0.212***	-0.161***	-0.158***	-0.234***	-0.280*
	(0.242)	(0.233)	(0.043)	(0.039)	(0.038)	(0.038)	(0.054)	(0.115)
$\gamma_1 \leq$ Period $< \gamma_2$	-1.142**	-1.188***						
	(0.438)	(0.378)						
Period $> \gamma_2$	-0.184	-0.267**						
	(0.163)	(0.113)						
Controls								
Cereal area (log)		0.022		-0.070		0.105*		-0.276**
		(0.114)		(0.046)		(0.057)		(0.087)
Fertiliser (log)		0.138**		0.044***		0.081***		0.035
		(0.059)		(0.016)		(0.026)		(0.026)
Irrigation (log)		0.273**		0.256***		0.098***		0.003
		(0.126)		(0.026)		(0.024)		(0.024)
Rural population (log)		-0.002		-0.020		-0.204***		0.074
		(0.116)		(0.039)		(0.073)		(0.08)
Constant	0.184***	0.164***	0.058***	0.047***	0.047***	0.041***	0.025***	0.052***
	(0.033)	(0.034)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.009)
N	851	777	4,551	4,551	2,886	2,849	629	259
No. of districts	23	21	123	123	78	77	17	7
R-squared	0.166	0.361	0.055	0.24	0.054	0.185	0.067	0.196

* p<0.1, ** p<0.05, *** p<0.01. Standard errors are shown in parentheses and are clustered at the district level. The top part of the table shows the results for the testing procedure for the number of thresholds estimated. Below this the threshold locations are shown corresponding with the number of thresholds estimated. The final part of the table shows the regression estimates for the impact of drought between each of the thresholds and also the a set of control variables included in the regression.

Table 3.3: Time threshold regressions by crop (I)

Existence of thresholds	**Rice**		**Wheat**		**Maize**	
P-value						
Single	0.010	0.013	0.030	0.010	0.607	0.063
Double	0.060	0.820	1.000	1.000	0.460	0.960
Triple	0.750	0.637	0.540	0.900	0.163	0.803
Threshold location						
γ_1	1987	1986	1967	1967		1967
CI	[1986,1988]	[1979,1987]				
γ_2	1999					
CI						
γ_3						
CI						
Variables						
Drought dummy	-0.050***	-0.031**	-0.036***	-0.018*	0.146***	0.147***
	(0.016)	(0.015)	(0.011)	(0.010)	(0.019)	(0.019)
Period$< \gamma_1$	-0.355***	-0.372***	-0.517***	-0.484***	-0.336***	-0.046
	(0.037)	(0.041)	(0.086)	(0.083)	(0.041)	(0.085)
$\gamma_1 \leq$ Period $< \gamma_2$	-0.015	-0.168***	-0.079***	-0.100***		-0.335***
	(0.044)	(0.033)	(0.023)	(0.023)		(0.040)
Period $> \gamma_2$	-0.301***					
	(0.044)					
Controls						
Cereal area (log)		0.026		-0.023		0.138***
		(0.060)		(0.047)		(0.051)
Fertiliser (log)		0.120***		-0.025		0.026
		(0.022)		(0.021)		(0.022)
Irrigation (log)		0.117***		0.254***		0.026
		(0.031)		(0.025)		(0.027)
Rural population (log)		-0.161***		-0.078**		-0.090**
		(0.055)		(0.039)		(0.044)
Constant	0.076***	0.073***	0.042***	0.036***	-0.009	-0.014**
	(0.006)	(0.006)	(0.004)	(0.004)	(0.007)	(0.007)
N	6,882	6,475	6,586	6,549	5,402	5,365
No. of districts	186	175	178	177	146	145
R-squared	0.093	0.159	0.04	0.18	0.015	0.027

* p<0.1, ** p<0.05, *** p<0.01. Standard errors are shown in parentheses and are clustered at the district level. The top part of the table shows the results for the testing procedure for the number of thresholds estimated. Below this the threshold locations are shown corresponding with the number of thresholds estimated. Confidence intervals are not given if the interval overlaps with the first or last year of the sample period. The final part of the table shows the regression estimates for the impact of drought between each of the thresholds and also the a set of control variables included in the regression.

Table 3.4: Time threshold regressions by crop (II)

Existence of thresholds	**Barley**		**Sorghum**		**Millet**	
P-value						
Single	0.037	0.023	0.577	0.593	0.363	0.270
Double	0.577	0.557	0.107	0.090	0.780	0.470
Triple	0.797	0.687	0.740	0.767	0.277	0.360
Threshold location						
γ_1	1984	1984				
CI	[1983,1985]	[1982,1985]				
γ_2						
CI						
γ_3						
CI						
Variables						
Drought dummy	-0.019	-0.024**	0.021	0.02	0.008	0.02
	(0.012)	(0.012)	(0.018)	(0.019)	(0.018)	(0.017)
Period$< \gamma_1$	-0.197***	-0.199***	-0.131***	-0.137***	-0.211***	-0.241***
	(0.040)	(0.041)	(0.043)	(0.043)	(0.041)	(0.041)
Period $> \gamma_1$	-0.017	-0.014				
	(0.024)	(0.022)				
Controls						
Cereal area (log)		-0.022		-0.067		-0.033
		(0.051)		(0.051)		(0.047)
Fertiliser (log)		-0.058***		-0.018		0.019
		(0.018)		(0.018)		(0.022)
Irrigation (log)		0.045		0.037		0.114***
		(0.032)		(0.023)		(0.043)
Rural population (log)		0.014		0.004		0.102**
		(0.043)		(0.041)		(0.051)
Constant	0.030***	0.033***	0.016**	0.017***	0.037***	0.037***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
N	2,997	2,997	5,069	5,069	4,699	4,662
No. of districts	81	81	137	137	127	126
R-squared	0.034	0.044	0.05	0.045	0.017	0.049

* p<0.1, ** p<0.05, *** p<0.01. Standard errors are shown in parentheses and are clustered at the district level. The top part of the table shows the results for the testing procedure for the number of thresholds estimated. Below this the threshold locations are shown corresponding with the number of thresholds estimated. The final part of the table shows the regression estimates for the impact of drought between each of the thresholds and also the a set of control variables included in the regression.

associated with very large impacts. It should be noted that the confidence intervals of these threshold locations are fairly large, so much so that these two thresholds cannot be statistically distinguished from one another. Despite this, we estimate that drought impacts have substantially reduced over time where drought impacts in the most recent period were around half those in the earliest period.

Tables 3.3 and 3.4 look at the crop-specific impacts of drought on yields over time. For rice, we notice the same pattern as for district cereal yields as a whole. Drought impacts were significantly negative for the years before 1987, but were insignificant in the years following until 1999. After this period, however, drought impacts were large and comparable to those before 1987. For wheat and maize, the threshold model picks the first year as a threshold value which reflects the fact that a very large drought occurred at this time. After this, however, average drought impacts are estimated to have remained constant. Evidence of increased drought tolerance over time is clearly visible for barley where the mid-1980s are estimated as the threshold. For the two most drought tolerant crops, sorghum and millet, the existence of significant thresholds are rejected. It is important to note at this point that the rejection of significant thresholds over time does not necessarily imply that average impacts have not changed over time. While the threshold model is useful for picking up sharp changes in average impacts, it is less useful for assessing slow moving trends over time. Thus, we are cautious about stating that impacts have not changed over time in the case where a threshold is not estimated.

3.7.2 Precipitation thresholds of drought impact

Table 3.5 shows estimates of precipitation thresholds for district cereal yields. Units of precipitation of the threshold variable relate to the proportion of annual rainfall relative to a district's long term average. To begin with, we separately estimate regressions using two different drought indices to investigate the importance of considering the full range of drought events. For instance, earlier in the paper we discussed that previous studies had neglected to consider a wide set of drought events that are potentially harmful for agriculture (Yu and Babcock, 2010; Birthal et al., 2015). The first relevant factor is that the two drought dummy variables are large, negative and significant, indicating that on average low rainfall is bad for crop growth. For both indices, two thresholds are estimated. In terms of the marginal effect, we observe the same pattern across all specifications with very large, significant and negative impacts for very large (first threshold) and large (second threshold) negative deviations from long-term rainfall.

We see that the marginal effect of an increase in the drought index for precipitation levels below 0.597 of normal rain is strongly negative, suggesting that this threshold is associated with particularly severe droughts. Drought impacts are considerably lower (about half) between the two thresholds. Above the second threshold, which ranges from 0.738 to 0.808 across model specifications, the drought index is not significant. However, this does not mean that there are no impacts of drought at this level of rainfall, since the large coefficients on the dummy variables suggests that even at low deviations of rainfall, the average impacts are negative. These results indicate that marginal impacts of drought start to turn negative, on average, when rainfall falls below 0.738-0.808 of normal rainfall. The inclusion of a set of control variables does not change the results considerably. Interestingly, we also note that, for the whole of India, the estimated thresholds are not very different from the drought thresholds used by the Indian government to denote droughts (0.75 and 0.5).

Given that previous approaches to measuring drought impact have confined interest to what we denote as Type 1 droughts (Yu and Babcock, 2010; Birthal et al., 2015), it can clearly be seen that this leads to the omission of a whole set of events that have highly significant negative effects on crop yields. The first two columns of Table 3.5 clearly show that both Type 1 and Type 2 droughts seriously harm crop yields. The results for the drought index used in this paper, which considers the whole range of potential drought events, shown in the next two columns illustrate that this index captures the effect of both these types of drought in a single index.

Results for low and high irrigation districts are shown in Table 3.6.[14] The first threshold is close to 0.6 for both groups and below this value of rainfall the coefficient on the impacts

[14]In this paper we define high- and low-irrigation as districts with average levels of irrigation over the sample period above and below the median, respectively.

of drought for the low irrigated districts is over three times larger than for irrigated areas below this threshold. This indicates that severe droughts have very serious impacts in low irrigated areas. This is also suggestive of the role that irrigation has in substantially mitigating severe droughts. Between the two thresholds, as we would expect, we find lower impacts for highly irrigated areas but the differences between drought impacts between the two groups are less stark.

Estimates of drought threshold effects for districts within different AEZs are shown in Table 3.7. A clear pattern is present for the location of the thresholds for each of the AEZs. The more arid the climate, the lower the threshold for precipitation. Compared with the marginal impacts estimated for other AEZs, we find that arid areas are more resilient to smaller negative deviations in rainfall. However, at larger deviations from the average levels of rainfall (more specifically below 0.64) the impacts are extremely severe. This is most likely explained by the fact that crops require a minimum amount of water with which to grow. Although areas with low rainfall are better at coping with smaller precipitation deviations away from the average, beyond a certain threshold of rainfall deficiency achieving crop growth is very difficult. In semi-arid areas, we notice the same pattern, even if it is less pronounced. We find very large impacts below 0.59 and large impacts between 0.59 and 0.79, but no significant negative marginal impacts for rainfall levels above 0.79. In semi-humid areas, the impacts are, on average lower but, in the case of semi-humid areas, the thresholds occur much earlier. In AEZ5, which represents humid regions, we see significant drought effects below the estimated threshold, although the magnitudes are fairly similar to those in sub-humid areas for similar rainfall deficiencies. In the specification where control variables are included, a second threshold is estimated at 0.72. Here the marginal effect of drought on district cereal yield is comparable to very severe droughts in semi-arid areas, where the threshold is estimated at 0.59. This is probably indicative of the fact that humid areas are used to very high absolute levels of rainfall, and a relatively small proportional deviation away from normal rainfall reduces water availability substantially.

Precipitation thresholds estimated separately by crop are shown in Tables 3.8 and 3.9. It is interesting that for the two main crops grown in India, rice and wheat, the location of precipitation thresholds are similar. There is a negative and significant marginal effect of the drought index on yields at proportions of rainfall of 0.85 for rice and 0.86-0.93 for wheat. The second threshold is located between 0.68-0.75 for both crops. However, we note that marginal impacts of the drought index on rice yields are much higher for comparable levels of rainfall. Since rice is more water-intensive than wheat, water deficiency has more serious implications for rice yields. Similarly, since rice is mainly grown during the main monsoon period, rainfall deficiency plausibly has a larger direct effect on crop yield. For maize, three thresholds are identified, although only the lowest two thresholds are relevant for drought. Compared with rice and wheat, these thresholds are lower and, interestingly, the coefficients for the marginal effects of maize for rainfall deviations between 0.61 and 0.75 are similar to those of wheat for rainfall deviations below 0.75. A clear pattern of threshold impacts is also present for barley, sorghum and millet. The first threshold is estimated at between 0.81 and 0.86 for all of these crops, suggesting the rainfall deficiency first becomes problematic for crop yields below this level. Additional thresholds at 0.62 are also estimated for sorghum and millet, indicating severe damage to yields below this proportion of normal rainfall. It is interesting to note that for millet, known as one of the most drought-tolerant cereals, drought impacts do not become significantly negative until a precipitation threshold of 0.73 is passed, confirming its ability to grow under even moderate drought conditions.

Table 3.5: Precipitation threshold regressions and comparision of drought indices

Existence of thresholds	**Two indices**			**Single index**	
P-value					
Single	0.000	0.000		0.000	0.000
Double	0.000	0.000		0.000	0.000
Triple	0.163	0.157		0.790	0.740
Threshold location					
γ_1	0.587	0.586		0.587	0.586
CI	.				
γ_2	0.738	0.745		0.791	0.808
CI	[0.731,0.747]	[0.732,0.751]		[0.785,0.798]	[0.788,0.815]
γ_3					
CI					
Variables					
Drought dummy (type 1)	-0.067***	-0.067***	Drought dummy (two types)	-0.073***	-0.064***
	(0.010)	(0.010)		(0.008)	(0.008)
Drought index (type 1)			**Drought index (two types)**		
Rain< γ_1	-0.496***	-0.500***	Rain< γ_1	-0.560***	-0.585***
	(0.073)	(0.074)		(0.068)	(0.070)
$\gamma_1 \leq$ Rain < γ_2	-0.140***	-0.131***	$\gamma_1 \leq$ Rain < γ_2	-0.164***	-0.176***
	(0.035)	(0.029)		(0.025)	(0.020)
Rain > γ_2	0.065**	0.075***	Rain> γ_2	0.092***	0.070***
	(0.029)	(0.023)		(0.022)	(0.017)
Drought dummy (type 2)	-0.072***	-0.071***			
	(0.010)	(0.009)			
Drought index (type 2)					
Rain< γ_1	-0.943***	-0.862***			
	(0.123)	(0.115)			
$\gamma_1 \leq$ Rain < γ_2	-0.424***	-0.345***			
	(0.064)	(0.060)			
Rain > γ_2	0.169***	0.240***			
	(0.058)	(0.046)			
Controls					
Cereal area (log)		-0.132***			-0.134***
		(0.035)			(0.035)
Fertiliser (log)		0.076***			0.074***
		(0.015)			(0.015)
Irrigation (log)		0.133***			0.133***
		(0.023)			(0.023)
Rural population (log)		0.063**			0.064**
		(0.030)			(0.031)
Constant	0.041***	0.033***		0.049***	0.052***
	(0.010)	(0.008)		(0.006)	(0.005)
N	8,917	8,436		8,917	8,436
No. of districts	241	228		241	228
R-squared	0.127	0.272		0.116	0.260

* p<0.1, ** p<0.05, *** p<0.01. Standard errors are shown in parentheses and are clustered at the district level. The top part of the table shows the results for the testing procedure for the number of thresholds estimated. Below this the threshold locations are shown corresponding with the number of thresholds estimated. Confidence intervals are not given if the interval overlaps with the first or last year of the sample period. The final part of the table shows the regression estimates for the impact of drought between each of the thresholds and also the a set of control variables included in the regression.

Table 3.6: Precipitation threshold regressions by irrigated area

Existence of thresholds	Low irrigation		High irrigation	
P-value				
Single	0.000	0.000	0.000	0.000
Double	1.000	1.000	0.003	0.007
Triple	0.877	0.917	0.237	0.307
Threshold location				
γ_1	0.601	0.602	0.793	0.791
CI	.		[0.784,0.798]	[0.781,0.797]
γ_2			0.998	1.004
CI			[0.989,1.004]	[0.990,1.010]
γ_3				
CI				
Variables				
Drought dummy	-0.105***	-0.117***	-0.079***	-0.066***
	(0.013)	(0.013)	(0.013)	(0.012)
Rain$< \gamma_1$	-1.001***	-1.068***	-0.155***	-0.143***
	(0.123)	(0.124)	(0.028)	(0.026)
$\gamma_1 \leq$ Rain $< \gamma_2$	-0.022	-0.004	0.087***	0.086***
	(0.033)	(0.023)	(0.032)	(0.029)
Rain$> \gamma_2$			-0.090***	-0.062**
			(0.027)	(0.024)
Controls				
Cereal area (log)		-0.218***		-0.008
		(0.044)		(0.052)
Fertiliser (log)		0.049**		0.125***
		(0.019)		(0.014)
Irrigation (log)		0.065**		0.176***
		(0.029)		(0.036)
Rural population (log)		0.166***		-0.107**
		(0.040)		(0.051)
Constant	0.083***	0.089***	0.059***	0.049***
	(0.009)	(0.007)	(0.007)	(0.007)
N	4,477	4,218	4,440	4,218
No. of districts	121	114	120	114
R-squared	0.174	0.262	0.081	0.24

* p<0.1, ** p<0.05, *** p<0.01. Standard errors are shown in parentheses and are clustered at the district level. The top part of the table shows the results for the testing procedure for the number of thresholds estimated. Below this the threshold locations are shown corresponding with the number of thresholds estimated. Confidence intervals are not given if the interval overlaps with the first or last year of the sample period. The final part of the table shows the regression estimates for the impact of drought between each of the thresholds and also the a set of control variables included in the regression.

Table 3.7: Precipitation threshold regressions across agro-ecological zones

Existence of thresholds	**Arid**		**Semi-arid**		**Sub-humid**		**Humid**	
P-value								
Single	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.010
Double	0.103	0.410	0.000	0.000	0.043	0.013	0.933	0.030
Triple	0.487	0.413	0.733	0.050	0.807	0.780	0.910	0.580
Threshold location								
γ_1	0.638	0.669	0.585	0.585	0.793	0.744	0.882	0.718
CI	[0.610,0.672]	[0.619,0.707]			[0.785,0.807]	[0.728,0.751]	[0.842,0.895]	
γ_2			0.792	0.786	1.026	0.874		0.884
CI			[0.783,0.799]	[0.777,0.792]	[1.005,1.030]	[0.796,0.880]		[0.832,0.894]
γ_3								
CI								
Variables								
Drought dummy	-0.146***	-0.121***	-0.072***	-0.055***	-0.098***	-0.047***	-0.014	-0.044***
	(0.034)	(0.034)	(0.010)	(0.009)	(0.016)	(0.011)	(0.013)	(0.009)
Rain$< \gamma_1$	-0.690***	-0.725***	-0.552***	-0.530***	-0.183***	-0.015	-0.218***	-0.555***
	(0.232)	(0.193)	(0.076)	(0.076)	(0.038)	(0.010)	(0.045)	(0.125)
$\gamma_1 \leq$ Rain $< \gamma_2$	0.116	0.014	-0.140***	-0.173***	0.104***	-0.232***	-0.031	-0.254**
	(0.117)	(0.077)	(0.029)	(0.025)	(0.034)	(0.038)	(0.060)	(0.070)
$\gamma_2 \leq$ Rain $< \gamma_3$			0.103***	0.080***	-0.073*	-0.091***		-0.024
			(0.023)	(0.019)	(0.038)	(0.032)		(0.083)
Rain$> \gamma_3$						0.031		
						(0.025)		
Controls								
Cereal area (log)		0.022		-0.110**		0.088		-0.278**
		(0.103)		(0.045)		(0.054)		(0.092)
Fertiliser (log)		0.129**		0.045***		0.073***		0.033
		(0.059)		(0.015)		(0.026)		(0.025)
Irrigation (log)		0.271**		0.238***		0.097***		0.001
		(0.128)		(0.025)		(0.024)		(0.024)
Rural population (log)		0.002		0.015		-0.181**		0.074
		(0.090)		(0.039)		(0.072)		(0.094)
Constant	0.079**	0.105***	0.050***	0.047***	0.063***	0.045***	0.032***	0.061***
	(0.037)	(0.026)	(0.008)	(0.007)	(0.007)	(0.006)	(0.010)	(0.014)
N	851	777	4,551	4,551	2,886	2,849	629	259
No. of districts	23	21	123	123	78	77	17	7
R-squared	0.193	0.376	0.138	0.312	0.094	0.211	0.082	0.273

* p<0.1, ** p<0.05, *** p<0.01. Standard errors are shown in parentheses and are clustered at the district level. The top part of the table shows the results for the testing procedure for the number of thresholds estimated. Below this the threshold locations are shown corresponding with the number of thresholds estimated. Confidence intervals are not given if the interval overlaps with the first or last year of the sample period. The final part of the table shows the regression estimates for the impact of drought between each of the thresholds and also the a set of control variables included in the regression.

Table 3.8: Precipitation threshold regressions by crop (I)

Existence of thresholds	**Rice**		**Wheat**		**Maize**	
P-value						
Single	0.000	0.000	0.000	0.000	0.000	0.000
Double	0.000	0.000	0.027	0.080	0.000	0.000
Triple	0.677	0.663	0.810	0.927	0.100	0.030
Threshold location						
γ_1	0.731	0.745	0.678	0.715	0.608	0.607
CI	[0.713,0.815]	[0.718,0.824]	[0.631,0.698]	[0.677,0.731]		
γ_2	0.841	0.850	0.859	0.926	0.756	0.755
CI	[0.821,0.853]	[0.819,0.861]	[0.846,0.871]	[0.860,0.936]	[0.732,0.772]	[0.723,0.772]
γ_3						1.089
CI						[1.057,1.104]
Variables						
Drought dummy	-0.082***	-0.079***	-0.049***	-0.027***	0.006	0.046***
	(0.012)	(0.011)	(0.009)	(0.009)	(0.013)	(0.016)
Rain< γ_1	-0.411***	-0.366***	-0.158***	-0.157***	-0.482***	-0.494***
	(0.036)	(0.036)	(0.024)	(0.023)	(0.063)	(0.066)
$\gamma_1 \leq$ Rain $< \gamma_2$	-0.184***	-0.137***	-0.030	-0.056**	-0.203***	-0.241***
	(0.037)	(0.034)	(0.024)	(0.022)	(0.032)	(0.036)
$\gamma_2 \leq$ Rain $< \gamma_3$	0.028	0.048*	0.058***	0.025	0.012	-0.075**
	(0.027)	(0.026)	(0.020)	(0.022)	(0.032)	(0.035)
Rain $> \gamma_3$						0.214***
						(0.053)
Controls						
Cereal area (log)		-0.001		-0.033		0.112**
		(0.058)		(0.049)		(0.050)
Fertiliser (log)		0.122***		-0.02		0.022
		(0.021)		(0.021)		(0.021)
Prop irrigated (log)		0.111***		0.251***		0.015
		(0.030)		(0.025)		(0.027)
Rural population (log)		-0.146***		-0.080**		-0.063
		(0.054)		(0.038)		(0.044)
Constant	0.078***	0.071***	0.028***	0.027***	0.041***	0.029***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.010)	(0.010)
N	6,882	6,475	6,586	6,549	5,402	5,365
No. of districts	186	175	178	177	146	145
R-squared	0.108	0.182	0.035	0.175	0.043	0.052

* p<0.1, ** p<0.05, *** p<0.01. Standard errors are shown in parentheses and are clustered at the district level. The top part of the table shows the results for the testing procedure for the number of thresholds estimated. Below this the threshold locations are shown corresponding with the number of thresholds estimated. Confidence intervals are not given if the interval overlaps with the first or last year of the sample period. The final part of the table shows the regression estimates for the impact of drought between each of the thresholds and also the a set of control variables included in the regression.

Table 3.9: Precipitation threshold regressions by crop (II)

Existence of thresholds	**Barley**		**Sorghum**		**Millet**	
P-value						
Single	0.080	0.037	0.000	0.000	0.000	0.000
Double	0.223	0.340	0.000	0.000	0.013	0.023
Triple	0.593	0.697	0.667	0.670	0.053	0.083
Threshold location						
γ_1	0.831	0.831	0.623	0.623	0.616	0.615
CI	[0.793,0.848]	[0.793,0.848]			[0.585,0.646]	[0.585,0.645]
γ_2			0.812	0.812	0.728	0.727
CI			[0.787,0.824]	[0.787,0.824]	[0.709,0.745]	[0.689,0.745]
γ_3					0.855	0.856
CI					[0.810,0.868]	[0.809,0.868]
Variables						
Drought dummy	-0.016	-0.021*	-0.023**	-0.027**	-0.057***	-0.053***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.013)	(0.012)
Rain$< \gamma_1$	-0.094***	-0.096***	-0.548***	-0.572***	-0.393***	-0.439***
	(0.021)	(0.022)	(0.065)	(0.067)	(0.058)	(0.060)
$\gamma_1 \leq$ Rain $< \gamma_2$	0.001	0.002	-0.091**	-0.110***	-0.217***	-0.255***
	(0.026)	(0.024)	(0.039)	(0.038)	(0.045)	(0.046)
$\gamma_2 \leq$ Rain $< \gamma_3$			0.139***	0.136***	0.028	0.001
			(0.029)	(0.027)	(0.042)	(0.041)
$\gamma_3 \leq$ Rain					0.175***	0.158***
					(0.031)	(0.029)
Controls						
Cereal area (log)		-0.036		-0.115**		-0.064
		(0.049)		(0.050)		(0.050)
Fertiliser (log)		-0.055***		-0.013		0.02
		(0.019)		(0.017)		(0.022)
Irrigation (log)		0.043		0.012		0.106**
		(0.034)		(0.022)		(0.041)
Rural population (log)		0.005		0.052		0.128**
		(0.044)		(0.039)		(0.050)
Constant	0.013	0.015*	0.021**	0.026***	0.039***	0.044***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
N	2,997	2,997	5,069	5,069	4,699	4,662
No. of districts	81	81	137	137	127	126
R-squared	0.026	0.036	0.059	0.064	0.059	0.095

* p<0.1, ** p<0.05, *** p<0.01. Standard errors are shown in parentheses and are clustered at the district level. The top part of the table shows the results for the testing procedure for the number of thresholds estimated. Below this the threshold locations are shown corresponding with the number of thresholds estimated. Confidence intervals are not given if the interval overlaps with the first or last year of the sample period. The final part of the table shows the regression estimates for the impact of drought between each of the thresholds and also the a set of control variables included in the regression.

3.8 Discussion

The fact that agricultural production in India as a whole became more resilient to drought after the mid-1980s highlights the role that intensive production techniques can have in allowing a large number of farmers to avoid crop losses due to drought. Indeed, the substantial reduction in drought impact on cereal productivity after this time coincides with the wider diffusion of Green Revolution technologies across growing region beyond the first adopters of these technologies. Perhaps the most significant move was the increased use of irrigation from groundwater sources, which became increasingly available due to improvements in low-cost pumping technology (Sekhri, 2014). Groundwater irrigation is particularly effective at mitigating drought since its application can be timed to match periods of rainfall deficiency. However, the pattern of drought impacts that we observe in this paper highlights potential challenges that India faces in mitigating drought in the future. Given that we identify drought years in the early 2000s as having the same relative impact on production losses as drought thirty years earlier, we show that large drought events continue to pose a considerable problem for Indian agriculture. Tellingly, although we find this pattern holds for our measure of district cereal yield, the pattern is also identified for rice, the most commercially important cereal. This has two main implications. Firstly, it challenges the finding of Birthal et al. (2015) which posits that rice yields have become more drought tolerant over time. Second, it also highlights possible vulnerability of rice production systems to drought in India in the future. Given that many high productivity rice areas, such as in Punjab, have historically benefitted from abundant irrigation primarily from groundwater, the ability of these areas to deal with drought in the future is increasingly being called into question. Indeed, one of the leading explanations for this upswing in drought impacts in recent years is the increasing pressure on water resources, especially those from groundwater sources. For instance, as is noted by Shah et al. (2009, p.12), a heavy reliance of groundwater can be problematic since, "During a drought, groundwater aquifers are doubly hit: there is less rainfall and little recharge to aquifers but there is also additional demand pressure on the resource as farmers struggle to save their crops and livelihoods." Since unchecked exploitation has led to depletion of key aquifers over time, farmers have in recent years, lacked the ability to mitigate drought losses effectively by exploiting water that previously allowed them to deal with periods of deficient rainfall. This was particularly the case for drought years in the early-2000s when a series of consecutive droughts in many areas led to high levels of groundwater use which lowered water tables, making it more difficult to extract water from these sources in successive drought years.[15] While it would be premature to conclude that the severity of impacts in the latter part of our sample constitutes a new trend of increasing impacts of drought on agriculture in India, these findings suggest that there is no room for policymakers to be complacent about resilience to drought in the future. Further work into investigating drought impacts up until the present day are vital for understanding the evolving vulnerability to drought.[16]

A key advantage of the method we use to evaluate drought impacts is that it allows us to evaluate the suitability of definitions used by policymakers to define droughts. The definition used to declare drought in India is whether rainfall falls below 75% of long-run average seasonal rainfall. Additionally, a drought is classified as severe if rainfall falls below 50% of the average. The definition of drought is crucial for the declaration of drought in an area and thus how quickly resources can be diverted into managing the consequences of this event. The declaration is decided at state-level generally by the end of the monsoon rains in October. Funds can then be requested from the central government to provide relief (Ministry of Agriculture, 2009). While our results find empirical support for these thresholds for the country on average, we also find substantial heterogeneity in terms of agro-climatic characteristics and crop choice. For instance, in arid areas, probably as a result of the need to grow relatively drought tolerant crops to cope with persistently low levels of rainfall, we find that officially imposed thresholds misspecify the conditions necessary for a drought to significantly harm agricultural productivity. This may lead to the inefficient allocation of resources. The findings from this work suggest that

[15] Hornbeck and Keskin (2014) also find that in the context of U.S agriculture, increasing exploitation of groundwater irrigation does not necessarily lead to the reduced sensitivity of crop productivity to drought in the long term. However, in contrast to explanations offered in India which emphasise growing depletion of these resources as the primary limiting factor in mitigating drought, they suggest that the adoption of more profitable but more water-intensive crops increases the sensitivity of production to drought.

[16] At the time of writing in 2016, India was undergoing one of its most severe droughts in decades.

policymakers should account for such heterogeneity when designing policies for effective drought declaration and response to these events in the future.

3.9 Conclusion

This paper has studied the impacts of drought on cereal production in India. To address some of the shortcomings of previous studies, we assess these impacts using an index of drought intensity that does not omit drought events that are commonly overlooked by alternative definitions. This allows us to provide a full assessment of drought impact regardless of how drought is defined. When combined with the threshold regression model we are able to estimate ranges of a given threshold variable for which drought impacts differ significantly from each other. A crucial strength of the empirical modelling approach used in this paper is that we are able estimate the *locations* of thresholds of drought impact. The advantage of this can clearly be seen when applied to drought impacts over time. Rather than assuming that trends in drought impact are smooth over time, we have been able to identify a period of abrupt increase in average drought impacts in recent years. This contrasts with previous research that has suggested that drought impacts have steadily decreased over time. The recent period of increased drought impact corresponds with a series of particularly severe droughts. However, evidence from work done elsewhere highlights the increasing scarcity of water resources that may have led to a reduced ability on behalf of farmers to access sufficient water during drought. This underscores the potential vulnerability of water-intensive production systems that have previously been able to effectively cope during periods of drought. Future work is needed to ascertain the interaction between water availability and drought years in order to understand whether the agricultural sector in India will be able to cope with the threat of more frequent and intense droughts due to climate change.

This paper also investigates the ranges of proportion of rainfall for which the impacts are negative. The estimation approach we use enables us to examine the validity of drought definitions frequently used to declare drought by the Indian government by identifying thresholds of precipitation that indicate increased drought impact. We find that the rainfall thresholds previously used by policymakers to measure drought severity by the Indian government are not very far from the thresholds beyond which we estimate negative marginal effects for drought for the whole of India. However, it is important to notice that our estimated thresholds differ substantially according to agro-ecological zones and the particular cereal under consideration. This suggests that a criteria that takes into account the agro-ecological heterogeneity of a large country like India would provide more effective indicators of drought. The fact that we perform the analysis for the six major cereals in India highlights that impacts differ substantially and that rice seems to be the least drought tolerant of the crops in our sample. Similarly, the fact that the crop-specific impacts are so heterogeneous seems to highlight that crop choice may be an important aspect of coping with droughts in the future.

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Chapter 4

The growing importance of nature: Did the Green Revolution consolidate agro-climatic productive advantages in India?

Abstract

This paper examines the extent to which modernisation in agriculture consolidates productivity gains in the most naturally suited areas. A common contention is that characteristics of higher-yielding variety (HYV) seeds developed during the Green Revolution made them complementary to higher quality land attributes such as soil quality, climate, and terrain. As such, yield increases achieved since the Green Revolution may have been biased towards areas of higher land quality. I investigate this claim by empirically estimating whether yields for rice and wheat increased relatively more in relatively favourable environments following the onset of the Green Revolution in India. To do this I use half a century of district-level data combined with continuous and crop-specific measures of land suitability from the FAO Global Agro-Ecological Zones project. I attempt to identify the bias of Green Revolution technologies by exploiting the differential timing of district-level adoption of new seed varieties, comparing variation in yields and agro-climatic suitability for districts within the same state. I find evidence that for both rice and wheat, yield gains after the Green Revolution significantly increased the productive advantages of districts with higher agro-climatic suitability for crop growth. This result is consistent across subsets of geographical regions, over time, and does not seem to be driven by differences in the diffusion of HYVs across districts. I also estimate that gains to land quality were highest in irrigated areas, suggesting that the availability of controllable water was key for determining whether more suitable area could take advantage of favourable land characteristics. Overall, this work suggests that increased effort should be put into designing agricultural technologies that grow more effectively in less favourable areas in order to maintain agricultural productivity under increased environmental stress.

4.1 Introduction

Agro-ecological characteristics, such as climate and soil quality, are amongst the most fundamental factors determining the production possibilities of agriculture. Understanding the role that these factors play in the production process is now a burgeoning area of research owing to concerns that future environmental problems, such as climate change and land degradation, may make growing conditions more challenging in coming years (Naylor, 1996). A crucial consideration is the role that certain types of technology play in potentially relaxing these environmental constraints. The ability of agricultural technologies to effectively increase crop yields under a wide range of agro-ecological conditions will be of high importance in continuing to increase the productivity of the sector (Hornbeck, 2012).

The extent to which agricultural technologies allow farmers to achieve higher crop yields across different agro-ecological environments depends on the interaction of technology and environmental features in the production process (Mendelsohn et al., 2006). On the one hand, a new technology could act as a substitute for certain agro-ecological factors. For instance, fertiliser could substitute for soil nutrients, allowing farmers to achieve high yields in areas of low soil quality. On the other hand, technology may require a set of suitable conditions in which to be effective, such as a stable and temperate climate. In this case, technology is complementary to agriculturally favourable aspects of land. The extent to which either of these interactions is true will determine how reliant production systems are on underlying environmental quality as technology becomes more advanced.

Previous evidence shows that agricultural technologies have helped to markedly increase the average productivity of land in many areas of the world (Ruttan, 2002; Federico, 2005). These production practices, broadly characterised as intensification, typically involve the replacement of traditional seed varieties with improved varieties that are more responsive to the application of inputs, such as inorganic fertilisers, pesticides, and irrigation. These intensive practices now form the dominant model for crop production across the world (Tilman et al., 2002). A leading example of this was the Green Revolution. With this came the adaptation of improved varieties of widely grown staple crops, such as rice and wheat, to new growing conditions which enabled farmers to achieve higher yields in many parts of Asia in the latter half of the twentieth century (Evenson and Gollin, 2003; Hazell, 2009). For India in particular, the aggregate increase in productivity allowed the country to become self-sufficient in major food grains a decade or so following the introduction of new technology in the mid-1960s (Shreedhar et al., 2012).

Despite impressive increases in average yields, however, the Green Revolution model of agricultural development continues to attract a number of critics. A common contention is that Green Revolution technologies failed to evenly spread yield benefits across growing areas (Pingali, 2012). Specifically, areas where soil was of high quality, had good supplies of water, and flat terrain are perceived to have experienced yield gains that were greater compared with areas less well endowed with these features. The basis for these claims rests on the idea that technological change during the Green Revolution led to the development of technologies that were complementary in the production process to better quality land (Evenson and Gollin, 2003; Barbier, 2010). A centralised agricultural innovation process during this period focused on developing a small number of varieties that would deliver yields gains under 'optimal' growing conditions (Anderson et al., 1982; Baranski, 2015). The consequence of this environment-technology complementarity would plausibly mean that yield growth was biased towards land of higher quality, increasing the productive advantage of areas that were already most naturally favourable for agricultural production.

The aim of this paper is to empirically test the validity of this hypothesis. Two previous studies have examined this question by studying differences in regional agricultural productivity growth in India following the Green Revolution (Fan et al., 2000a; Palmer-Jones and Sen, 2003). These papers find that regions defined as 'more favourable' for agriculture saw yields increase by more than in 'less favourable' areas. These studies, however, suffer from a number of shortcomings that could lead to a misunderstanding of the role Green Revolution technology played in increasing the returns to land quality. First, favourability for agriculture is arbitrarily defined according to groupings of areas sharing similar agro-ecological characteristics. This leads to potential problems in isolating the effect of natural suitability on productivity due to confounding factors that also influence agricultural productivity, such as political institutions, that may be common across agro-ecological regions. The discrete classification of regions also precludes estimating the magnitude of any possible land quality bias, since agro-ecological conditions between regions are not quantitatively comparable. Second, the agronomic conditions required to grow specific crop types, such as rice and wheat, vary substantially. Thus, a measure of aggregate favourability for agriculture is likely to lead to a misleading measure of the conditions that make an area suitable for growing specific crops. Therefore, measures of crop-specific suitability should ideally be used to study this question.

To address the shortcomings of previous studies, I use district-level agricultural data between 1957 and 2009, covering years before, during, and after the Green Revolution in India. This allows me to study whether the arrival of new technology increased productive gains in more naturally suited areas relative to less suitable areas. I study rice and wheat, which were both the focus of international and national research efforts to increase yields of crops crucial to Indian food security. While both crops are cultivated across a range of different growing conditions, individual crop needs in terms of climate, soil, and terrain differ. Accordingly, I separately test whether productivity growth for each crop was highest in districts most naturally suited for growing that crop. To do this, I exploit a crop-specific measure of agricultural suitability, which integrates natural characteristics such as climate, soil quality, and terrain to assess the potential suitability for growing each crop.

I model the onset of the Green Revolution as a productivity shock to agriculture within a differences-in-differences framework. To implement this strategy, I exploit the staggered timing in the diffusion of technology across districts, indicated by high yielding seed varieties (HYVs). This allows me to examine whether the arrival of new technology led to higher yield growth in more suitable districts relative to less suitable districts. This strategy rests on the assumption that technological innovation embodied in seed varieties was largely a result of external, international research efforts that led to the development of HYVs (Foster and Rosenzweig, 1996). One issue with implementing this strategy is that a range of institutional factors may have affected a district's exposure to this productivity shock. To account for this, I exploit *within*-state variation by accounting for a set of state-by-year fixed effects. Since expenditure on rural education, infrastructure, and agricultural support policies, such as public research and extension services, are largely budgeted at the state-level (Fan et al., 2000b; McKinsey and Evenson, 2003), this minimises concerns that regional institutions drove differences in productivity over time. This empirical strategy thus enables me to model differences in yield gains across areas of varying agro-ecological suitability within areas that share similar institutional characteristics and exposure to new technologies.

The results of this study show that the arrival of Green Revolution technology, on average, increased the relative productive advantage of areas more naturally suited to crop growth. This is common for both rice and wheat. I estimate that a one-standard deviation increase in district land quality led to a 4% increase in the relative yield advantage to more suitable areas for rice growing districts. For wheat, this effect is larger. A standard deviation increase in land quality increased relative yield advantage by 8%. These results remain robust to the inclusion of a set of time-varying controls, such as rural population density, farm size and literacy, which could explain variation in agricultural productivity between districts. These results are also apparent for different sub-sets of geographical regions, suggesting that technology had similar effects across different types of land and institutional settings. The results also show that these effects have remained similar in magnitude over time. One possibility is that these results reflect the uneven diffusion of Green Revolution technology over time. To investigate this, I test whether HYV seeds were more intensely adopted in more suitable areas. I find that there is no significant correlation between proportion of cropped area devoted to HYVs and the higher district land suitability, which provides some evidence that differences in yield gains were not driven by unequal diffusion of HYVs across districts.

In addition to agro-climatic suitability, irrigation has been posited as important in determining how favourable an area is for the use of modern seed varieties (Hazell, 2009). Previous studies have shown that the availability of supplementary water from sources such as dams and groundwater, markedly improved agricultural productivity (Duflo and Pande, 2007; Sekhri, 2014). Accordingly, I estimate separate regressions for high and low irrigation areas. The results suggest that for both crops, irrigated areas saw increased yield gains to land quality. This effect was not significant for low irrigation areas. These results support the view that irrigation was a key facilitating factor in allowing farmers to achieve higher yields during the Green Revolution, although its availability was particularly important for allowing farmers to consolidate advantageous environmental characteristics.

Overall, these findings support the hypothesis that, although achieving impressive increases in aggregate production, the type of agricultural modernisation seen during the Green Revolution in India increased the relative importance of favourable agro-ecological factors in achieving higher yields. These findings have a number of implications. First, given that the marginal productivity of technology increases with land quality, deterioration in factors that determine land quality, such as climate and soil quality, means that these technologies become less effective as the resource base declines. This suggests that the adaptation challenge to declining environmental quality with current technology is likely to be greater compared with a counterfactual scenario where technology effectively substitutes for high quality environmental characteristics and reduces agriculture's relative dependence in these factors. Indeed, a growing research area uses historical data to assess whether agricultural technology has substantially changed the relative importance of natural factors, such as climate and soil, in determining agricultural outcomes. Whether land as a resource has declined in its importance for agriculture has been debated by Schultz (1951) and Johnson (2002). Both authors argue that the relative importance of land has reduced due to modernisation. Empirical support for this is, however, not found by Hornbeck (2012) who shows that land characteristics have maintained their dominance in terms of land values on farms in the United States. He groups farm land in the U.S. into discrete categories based on average temperature, precipitation, and soil group to examine whether agricultural modernisation has changed the relative influence of these characteristics on farm values over time. He finds that there is no evidence of a change in the influence of these characteristics on farm values between 1920 and 2002. This suggests that, on average, improvements in agricultural technology preserve relative environmental advantages.[1] My findings suggest a stronger result than this: the relative importance of agro-ecological

[1]The degree to which improvements in agricultural technology have enabled farmers to adjust to new environments is also studied by Olmstead and Rhode (2010) who examine the spatial distribution of wheat growing areas between 1939-2009. They find evidence of very substantial adaptation of wheat to harsher growing environments over time and attribute this to biological innovation, which led to improvements in wheat cultivars that could be grown in previously unsuitable growing areas.

characteristics can increase with higher levels of technology.

Second, these findings also relate to works that examine reasons for variation in regional agricultural growth in India. Previous work has highlighted that higher agricultural productivity is associated with substantial reductions in rural poverty, since farm incomes and wages increase as a result (Datt and Ravallion, 1998). Determining whether one of the explanations for differences in regional productivity is due to the inadequacy of technology to work effectively across agro-climatic regions is important for prioritising resources that address these inequalities. For instance, a failure of technology to work effectively across growing areas places precedence on diverting resources into improvements to make technologies more applicable to work under diverse agro-ecological contexts rather than on policies that support technology uptake. One lesson that can be learned from this is that while centralised research into agricultural technologies may be an effective strategy for delivering productivity increases on average, more emphasis on tailoring technology to suit local conditions is needed to address crop growing constraints to lower quality land.

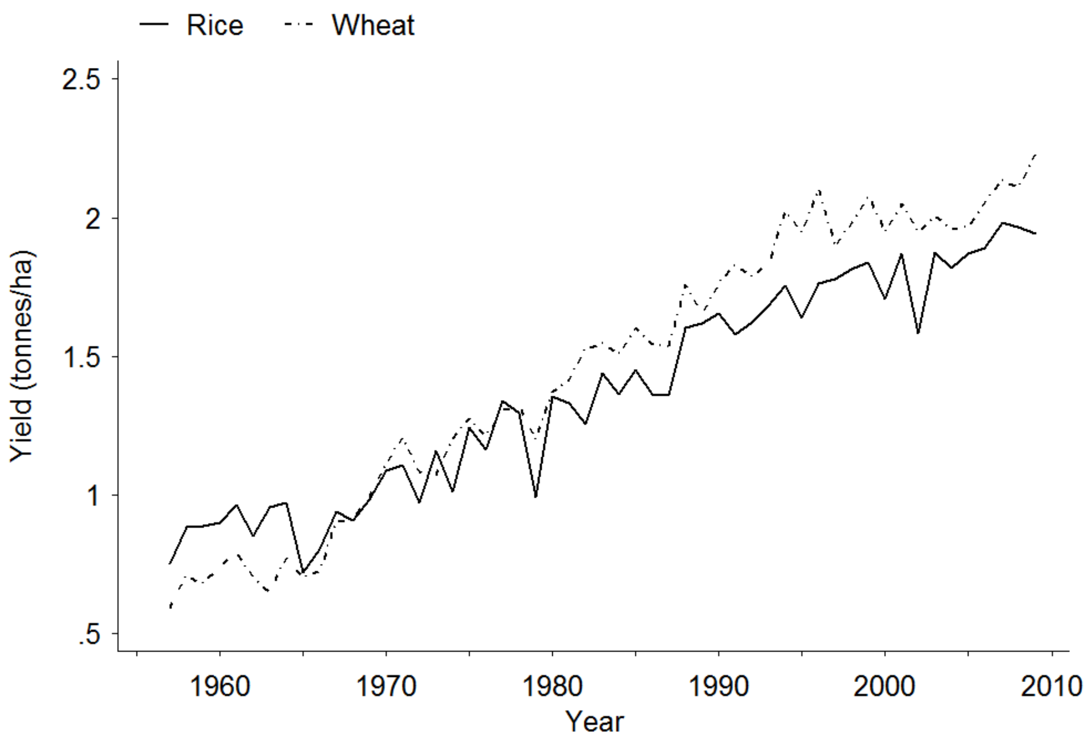
The rest of this paper is structured as follows. Section 4.2 provides background on the Indian Green Revolution and describes the basis for the claim that areas already most suitable for production benefitted the most from the introduction of new technology. The empirical approach is outlined in Section 4.3. The data used in the study are described in Section 4.4 with particular attention paid to the construction of the land suitability index. Results and discussion follow in Sections 4.5 and 4.6, with Section 4.7 concluding.

4.2 Green Revolution in India

4.2.1 Background

The rapid intensification of the agricultural sector in India, known as the Green Revolution, began in the mid-1960s after a period of relative stagnation in the productivity of staple crops following colonial independence in 1947. The productive gains brought about by the Green Revolution are credited with allowing India, and a number of other countries across Asia, to become self-sufficient in the production of key foodgrains, such as rice

Figure 4.1: Average rice and wheat yields in India (1957-2009)



and wheat, for domestic consumption in the decades following its onset (Shreedhar et al., 2012). These two crops were the principal beneficiaries of productivity gains over this period. This is illustrated in Figure 4.1, which shows the increase in average yields for rice and wheat for this period. A steady upward trend can be seen for both crops in the late 1960s, with average productivity increasing by 212% and 290% for rice and wheat respectively between 1957-1966 and 2000-2009. These two crops continue to make up a highly significant proportion of India's agricultural sector, with 36 percent of current cropped area planted to rice and 22 percent devoted to wheat (Shreedhar et al., 2012).

This growth in land productivity over time was primarily facilitated by the development and use of new varieties of seeds that embodied characteristics that allowed for higher yields. These improved crop varieties, known as 'High Yielding Varieties', were first released to Indian farmers in 1966 as the result of international collaboration to develop new varieties better suited to growth in many Asian countries.[2] These seed varieties were integral to the success of the Green Revolution since, when combined with other modern inputs, like fertiliser and pesticide, much higher yields could theoretically be achieved. The most significant development common to these new varieties was the incorporation of 'semi-dwarf' characteristics which had previously been used successfully in a number of countries, such as Mexico. The significance of dwarf features was that they allowed for substantial increases in the amount of fertiliser that could be applied to these new varieties, in contrast to traditional varieties which, due to their long stems, were prone to falling over when heavily fertilised (Dalrymple, 1979).[3]

4.2.2 The importance of irrigation

Even in areas where climate and soil are deemed amenable for crop production, HYVs generally required the steady supply of water to realise their yield potential. As is argued by (Hazell, 2009), the Green Revolution involved a package of inputs. Although HYV seeds allowed for higher yield growth, this occured when combined primarily with fertiliser and irrigation. This meant a premium was placed on abundant and stable supplies of water, since HYV seeds were more responsive to higher water application. Indeed, previous work by Fan et al. (2000a) has shown that rates of productivity growth following the Green Revolution were highest in irrigated areas of India. Additionally, Sekhri (2014) shows that the availability of more abundant groundwater irrigation was associated with higher levels of fertiliser use. Furthermore, Duflo and Pande (2007) find that districts benefitting from irrigation as a result of large dams planted more HYVs. Given that irrigation was a crucial part of the Green Revolution package, evaluating how the availability or non-availability of irrigation affected the ability of farmers to grow crops under varying agro-ecological conditions is of high importance.

[2]Institutions such as the Consultative Group on International Agricultural Research (CGIAR), the International Maize and Wheat Improvement Centre (CIMMYT) and the International Rice Research Institute (IRRI) were amongst the most important of a number of institutions that played a role in the development of new technologies (Pingali, 2012).

[3]This point was succinctly summarised by Norman Borlaug in his Nobel Peace Prize acceptance speech: "If the high-yielding dwarf wheat and rice varieties are the catalysts that have ignited the Green Revolution, then chemical fertilizer is the fuel that has powered its forward thrust (Borlaug, 1970)."

4.2.3 Land and technology complementarity

Despite impressive yield increases on average, a common criticism of agricultural productivity growth since the Green Revolution has been its inequality in achieving growth across the country (Evenson and Gollin, 2003).[4] One explanation for this inequality is related to the contention that the characteristics of newly developed seed varieties made them most effective on land closest to optimal conditions. Although agricultural technologies can act as substitutes for various features of the environment (Sunding and Zilberman, 2001; Hornbeck, 2012), a number of authors have emphasised that the nature of technological change during the Green Revolution was to develop technologies that were complementary to higher quality land attributes (Evenson and Gollin, 2003; Barbier, 2010). As is written by Barbier (2010, p.569), "the application of the Green Revolution agronomic technologies, such as fertilizers, pesticides, irrigation and mechanization, mainly boosted the productivity of arable lands suitable to agricultural intensification and located in favorable environments with good quality soils, plentiful rainfall and freshwater supplies, and low or moderate slopes."[5]

A key reason for these claims stems from the nature of technological innovation during the Green Revolution. Particularly important is the reliance on externally-driven biological innovation to improve crop yields (Anderson et al., 1982). For instance, as is argued in recent work by Baranski (2015) on the history of Green Revolution breeding programmes, the focus of plant breeding programmes by international organisations and later by Indian scientists underwent a structural change in the years leading up to the Green Revolution. This influenced the degree to which new biological innovations were successful at spreading productivity gains across different growing environments. The reasons for this were twofold. First, in order to avert future crises in food availability, breeding efforts were focused on areas of existing high productivity that could be counted on to yield substantial increases in aggregate domestic supply. Hence, breeding efforts were focused on areas of high productivity, such as Punjab, owing to the impact that increasing productivity in

[4]See Pingali (2012) for a discussion of some of the other potential limitations of the Green Revolution, including soil and water degradation, reduced dietary diversity, and gender inequality.

[5]For instance, Pingali (1989) argues that soil that can hold a greater amount of water and nutrients can yield higher gains from intensification.

these areas would have on aggregate production. Second, it was assumed by agricultural scientists at the time that it was possible to breed a small set of crop varieties that had wide application by assuring these varieties worked best on high quality land.[6] These varieties would then be assumed to work under more marginal conditions. Thus, breeding efforts focused on this idea of 'wide adaptation' meant that research efforts went into development of varieties under optimal conditions, which lead to a "systemic bias against marginal agriculture" (Baranski, 2015).[7]

4.2.4 Crop-specific differences

It is also of policy relevance to determine whether the pattern of productivity gains with respect to land quality has been homogenous across crop types since the Green Revolution. Information about the relative success or failure to transform crop breeding improvements into yield gains across environments is crucial to prioritising future investments with respect to particular crop types. Rice and wheat, the two crops studied in this paper, were the prime beneficiaries of these improvements.

Rice is largely grown under flooded conditions during the warm summer season in India. These growing conditions mean that water is a key determinant of how successfully rice can be grown. Water requirements for rice are substantially higher when compared with many other crops, including wheat (Dalrymple, 1979).[8] The highest yields are, thus, achieved where average rainfall is high and predictable, or where irrigation facilities are available (FAO, 2012). For early HYV varieties in India, water was indeed a crucial requirement. This meant that productivity gains were largely confined to fertile land with very good supplies of water (Estudillo and Otsuka, 2013). Wheat is grown globally across of range of agro-climatic regimes, including extreme conditions in arctic, humid, and highland areas. In India, wheat is generally grown in drier parts of the country and over winter or spring

[6]For instance, as is noted by Anderson et al. (1982, p.7) "The conception of scientific research as embodied in IRRI was exogenous, simple, and centralist."

[7]Baranski (2015) additionally goes on to argue that a biased focus on producing varieties suited to the best environments was due to a combination of the research goals of international organisations and the centralised power of scientists based primarily in north-western states which led to biased focus on fertile areas as opposed to more marginal growing areas.

[8]For instance, globally, rice is estimated to receive 24-30 percent of available freshwater supplies (Bouman et al., 2006).

seasons. The amount of irrigation needed depends on exposure to high temperature, variety type and soil (FAO, 2012), although the amount of water needed is significantly less than the amount needed to grow rice. Thus, access to irrigation is less important for wheat compared to rice.

On top of the general adaptability of these crop types across agro-ecological conditions, progress in developing new varieties to grow under a range of conditions may also be crop-specific. For instance, rice growing areas in India tend to be more heterogeneous in growing conditions which may have made it more difficult to develop rice varieties suited specially to each area (Evenson and Gollin, 2003; Estudillo and Otsuka, 2013). In contrast, wheat varieties released at the onset of the Green Revolution were better suited to cope with application across wider growing areas. This has led to a small number of 'multi-zonal' varieties maintaining their dominance as primary cultivars since early on in the Green Revolution (Munshi, 2004). In addition, Lantican et al. (2003) provide evidence using yield trial data that, globally, the Green Revolution has been successful in pushing forward the production possibility frontier of marginal wheat environments. Similarly, Olmstead and Rhode (2008, 2010) chronicle the impact of cultivar improvements in allowing wheat production in North America to spread to areas that were previously thought unsuitable for cultivation.[9]

4.2.5 Biased technological change

The focus of this paper is to investigate how the arrival of new agricultural technology affects the relative importance of land quality characteristics such as soil and climate in determining agricultural productivity. In particular, I am interested in whether technological progress increases the returns to higher quality land. Conceptually this refers to the potential complementarity between technology and the land quality in the agricul-

[9]This view of agricultural development places emphasis on the role of technological innovation in spurring agricultural productivity growth over time. This accords with the view of Olmstead and Rhode (1993) who argue that the success of public research efforts in developing improved crop varieties suited to different growing environments were the primary ingredient affecting regional success in U.S. agriculture. This contrasts with other prominent theories used to explain development, such as the induced innovation hypothesis, which posits that technological change takes place due to changes in factor prices, so that technologies will be developed that are factor-saving in the most scarce factor (Hayami and Ruttan, 1971).

tural production function. Two inputs will be complementary in the production process if an increase in the level of one input increases the marginal product of the other input. In the case of the Green Revolution, the hypothesis that new technology that was geared towards achieving high yields under optimal growing conditions would mean that the marginal product of land quality increases with technology.

In order to illustrate this relationship, I outline a simple agricultural production function that maps inputs used in the production process to output. This particular specification makes explicit the role that new technology has on certain inputs and borrows from work by Ackerman et al. (2015) and Berman (2000) who study the role technological change has on the productivity of workers of varying skill levels. This can be illustrated using a Cobb-Douglas production function, which takes the form:

$$Y_{it} = e^{\alpha_0 + D_{it}\alpha_1} K_{it}^{\beta_{k0} + D_{it}\beta_{k1}} L_{it}^{\beta_{l0} + D_{it}\beta_{l1}} e^{\epsilon_{it}} \tag{4.1}$$

Y_{it} is the yield of a particular crop (production per unit land) in a district i and at time t. Output is produced using a combination of district-level inputs which are given by per unit of land. K_{it} could embody various inputs, such as the stock labour or capital, that are available in a district. The term L_{it} refers to land quality. I model land quality as an input into the production process, which is a composite measure of the relative suitability of factors such as climate, soil and terrain. For each district this is represented as a scalar for which higher values indicate more favourable conditions for crop growth. The term e captures average total factor productivity (TFP), which refers to how much output can be explained by factors not due to the inputs used in the production process. For example, this could relate to the efficiency with which inputs are combined to produce output (Comin, 2008). The error term will capture the district-specific variations from average TFP over time.

An important innovation of this model is the incorporation of technological change in the exponent terms, which describes the effect that technology has on the output elasticity of each factor of production. New technology is modelled by the dummy variable D_{it}, which reflects a shift in technology used in production. This takes the value of one in the period that new technology is utilised (and thereafter) and zero in the period before. An advantage of this specification is that it allows for various possibilities concerning the nature of technological change. For instance, if technological change leads to an increase in the marginal product of a particular input, then the coefficients β_{k1} and β_{l1} would take positive values. The focus of this paper is to test the hypothesis that returns to land quality increased following the introduction of Green Revolution technology. This amounts to testing whether $\beta_{l1} > 0$. [10]

A convenient feature of the Cobb-Douglas formulation is that it can easily be transformed into an empirically tractable equation. By taking the natural logarithm of equation 4.1, we get:

$$y_{it} = \alpha_0 + D_{it}\alpha_1 + \beta_{k0}k_{it} + D_{it}\beta_{k1}k_{it} + \beta_{l0}l_{it} + D_{it}\beta_{l1}l_{it} + \epsilon_{it} \tag{4.2}$$

As such, a change in the returns to land quality will be seen by sign and significance of the coefficient β_{l1}. In the next section I describe how I empirically estimate this parameter.

4.3 Empirical strategy

4.3.1 Baseline specification

As a baseline estimation strategy, I choose a generalised differences-in-differences approach. This allows me to test whether district crop yield following the introduction of HYV seeds increased by more on higher quality land. The benefits of this approach are that I am able to implement a number of strategies in order to reduce the influence of possible confounding factors that could explain differences in productivity across districts.

The strategy rests on the assumption that the Green Revolution was a 'shock' to agricultural productivity. A key identifying assumption is that this shock was common across

[10] If, in contrast, the shift in technology is not biased towards any of these factors, then it is the case that α_1 is non-zero, so that technology works primarily through increasing total factor productivity and not through its effect of increasing the returns to particular inputs.

districts with differing land quality. In one regard, this is likely to be the case since early research into HYVs was primarily as a result of external, international research that led to the development of new seed varieties (Foster and Rosenzweig, 1996). On the other hand, however, it is possible that exposure to this shock was conditioned by a set of other factors that led to heterogeneity in how exposed certain areas were to this shock. If areas of higher land quality were more exposed to Green Revolution technology, this would likely overestimate land quality bias caused by the complementarity of new technology and land quality. In this section I outline my strategy to account for potential heterogeneity.

To do this I estimate the following baseline equation:

$$y_{ijt} = \beta_0 GR_{it} + \beta_1 SUIT_i + \beta_2 SUIT_i \times GR_{it} + \delta X_{it} + \alpha_i + \gamma_{jt} + \epsilon_{ijt} \tag{4.3}$$

The dependent variable y_{ijt} measures the natural logarithm of crop yield for district i in state j at time t.[11]

The crop-specific measure of district land suitability, $SUIT_i$, enters the model as an exogenous, time invariant variable. The construction of this variable is described in the next section. This variable is continuously ordered so that areas most naturally suited to crop growth take a higher value in the index. Since the constituent components of suitability are average climate, soil and terrain characteristics, these are set as fixed over time.[12]

Technology is included in the model by the inclusion of the variable GR_{it}, a dummy variable indicating the beginning of the Green Revolution, and zero in years before. Importantly, I allow the onset of the Green Revolution to vary across districts, since some districts began the process of technology adoption earlier than others. This allows for a more accurate

[11] The log transformation is preferred for two reasons. First, it generally makes strictly positive variables like yield behave more in accordance with the normal distribution (Wooldridge, 2015). Secondly, since district productivity may differ substantially between regions, it is more informative to investigate the relationship between differences in land quality and relative changes in yield rather than absolute changes in yield.

[12] Two arguments could potentially be made about land quality not being fixed over time. Firstly, climate change may have altered the suitability over the sample period. However, since average climate is calculated between 1961-90, this matches most of this period of study. Secondly, it could be argued that land degradation is a relevant factor since intensive methods have reduced the natural fertility of soil over time. Quality data on land degradation is not available to evaluate the possible effect of this claim, however. The implications of this for agricultural productivity in India are left to future work.

measurement of the effect of technological change on yields, since it allows me to capture upward trends in yields associated with Green Revolution technology. I proxy the use of Green Revolution technology with the adoption of high yielding variety seeds in a district. These new seeds represent a good indicator of Green Revolution technology since these allowed for yield increases when combined with other modern, complementary inputs, such as fertiliser. Thus, the adoption of seeds represents a suite of farming practices adopted under the Green Revolution umbrella.

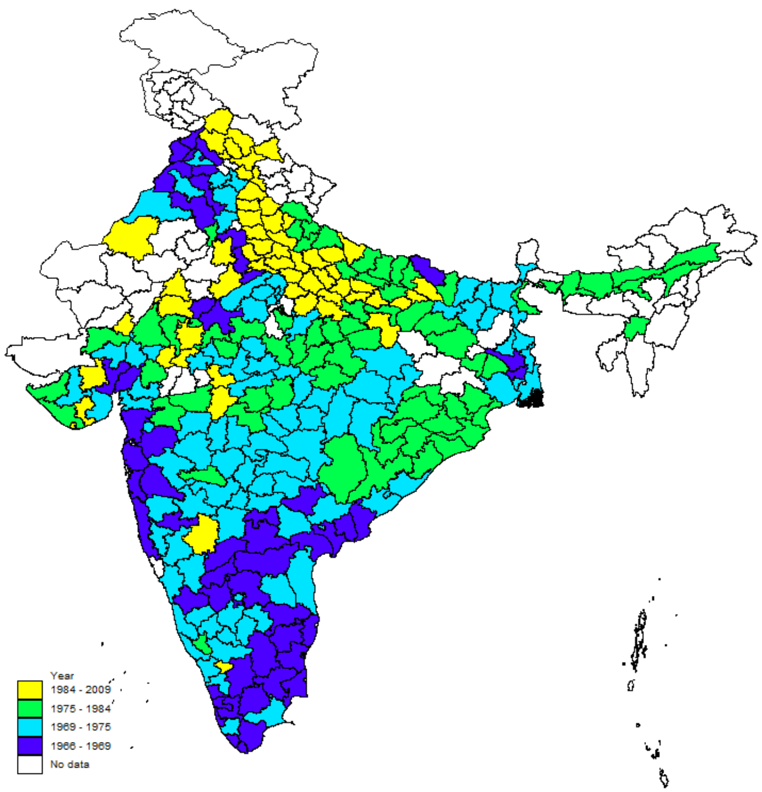
Figure 4.2 illustrates the varying times of adoption across the country. The threshold of ten percent of crop area planted to HYVs is chosen to indicate the onset of the Green Revolution in each district. This threshold is found by Griliches (1957) to represent "acceptance" of a technology (in his case hybrid corn) and is motivated by the common assumption in the technology diffusion literature that cumulative adoption of a technology tends to conform to a logistic relationship. For rice, the earliest adopters in the late-1960s were mainly in the northern states of Punjab and Haryana, as well as in the southern states of Andhra Pradesh and Tamil Nadu. For wheat, early adoption is also seen for the northern states and western areas like Gujarat. Areas in the east also adopted early, although these areas only plant small amounts of wheat. For both crops, most districts in Uttar Pradesh and Madhya Pradesh adopted later. Interestingly, adoption dates for non-typical wheat growing areas such as West Bengal are early, although these areas only produce a small amount of wheat.

The main variable of interest in the model is represented by the interaction term $SUIT_i \times GR_{it}$. The coefficient of this variable, β_2, shows the effect of land suitability has on yields in the post-GR period relative to earlier periods. A positive estimate of this coefficient would indicate that districts with land more suitable for crop production grew faster relative to less suitable districts after the introduction of modern agricultural technology.

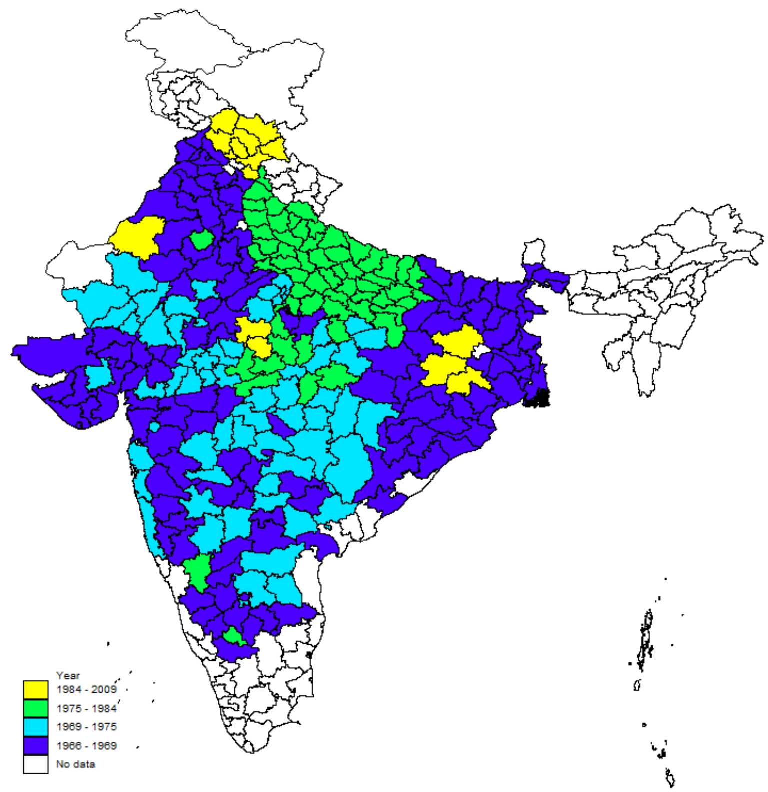
The central empirical aim is to identify whether the application of modern technologies are biased towards land of higher quality. A key empirical concern is that productivity of agriculture is likely to be affected by a range of other factors not due to natural constraints imposed on production, but due to other factors that are omitted from the regression. For

Figure 4.2: Date of high yielding varieties adoption across Indian districts

(a) Rice



(b) Wheat



Note: Maps show the date of adoption of HYVs in a district. Date of adoption corresponds to the condition that 10% of district rice and wheat area is sown using HYV seeds. Districts that either do not plant any of the crop or do not adopt HYVs over the sample period are indicated in white.

instance, Fan et al. (2000a) and Binswanger et al. (1993) argue that more 'favourable' areas i.e. those with better land quality, received higher levels of investment in productivity-enhancing factors. As such, higher productivity growth in more suitable areas may be due to factors that relate to the political economy of agricultural development rather than due to technology-land quality complementarity. This may lead to an overestimate of the effect of technological bias. To deal with these concerns, I pursue a number of empirical strategies.

Omitted time-invariant factors at the district-level could explain differences in productivity. For instance, locational factors like the distance to coastal areas, altitude, and major cities could be systematically related to crop yield in the post-Green Revolution period. The district fixed effects could also capture variables like culture or the persistence of institutions, which themselves might have important influences on productivity. The district fixed effect would also wipe out any unmeasured aspects of land quality that are not included in the GAEZ measure. To address this, I include the district fixed effect term, α_i, which absorbs the influence of such variables. The inclusion of district fixed effects means that I am exploiting within-district variation in returns to land quality. As such, I am comparing returns to land quality following the Green Revolution *relative* to the returns to land quality prior to its onset.

Additionally, I include a set of state-by-year fixed effects, indicated by γ_{jt}. The inclusion of these variables is used to account for omitted variables that vary annually in each state. Accounting for these factors are very important for the empirical strategy for a number of reasons. Firstly, state policies were a crucial factor in enabling farmers to take advantage of Green Revolution technologies. Owing to India's federal structure, a large amount of public investment happens at the state level. For instance, expenditure on rural education and agricultural policies, such as public research and extension services, are largely budgeted at the state level (McKinsey and Evenson, 2003). Importantly, state seed corporations were a primary means of distributing new varieties of seeds (Singh et al., 2008). Other important productive factors such as electricity provision are also determined at the state level (Gulati and Narayanan, 2003). Indeed, substantial inequalities in levels of state investment have been shown by Fan et al. (2000b), who find that state level spending on agricultural research and building roads has had important effects in explaining variations in productivity growth. If state investments over time were significantly higher in areas of better land quality, this would create a bias in the estimate of the technological effect on land quality upwards. Controlling for state-by-year effects enables me to wipe out the influence that differences in annual state policies have on yields. Secondly, the inclusion of state-by-year fixed effects influences the type of variation in land quality and yields that I am exploiting, since state-by-year fixed effects means that I am comparing within-state differences in land quality and yields. As such, I am not comparing the effect of technology between districts in humid areas with districts in arid areas, which are likely to differ significantly in terms of institutions, technology, and land quality. By confining interest to areas that are similar both institutionally and geographically, it is likely that I am capturing the areas exposed to a similar technological shock. For instance, I am not comparing tropical wet areas, such as Kerala, with arid areas like Rajasthan.

Despite addressing a range of omitted variable concerns that can be addressed by the inclusion of district and state-by-year fixed effects, it is still possible that inter-district variation within states could explain the relationship between yield and land quality after the Green Revolution. To explore this, I control for a set of covariates that vary over time at the district-level. Rural population density is included to proxy for the availability of labour. Since Green Revolution technologies were typically more labour-intensive than traditional varieties (Headey et al., 2010), areas with higher population densities may have been better able to supply labour to make effective use of these varieties. Investments in public infrastructure projects, such as roads, could lower the costs of marketing agricultural commodities and buying key inputs. This would allow farmers better access to yield improving technologies available since the Green Revolution (Antle, 1984; Binswanger et al., 1993). Controls for road length are thus included. Related to this, average farm size may be related to crop yields (Chand et al., 2011). Farm size is also a factor that could explain the productive returns to technology. Although Green Revolution technology was in theory scale-neutral, a number of authors have shown that smaller farmers may have been less able to take advantage of these technologies (Feder and O'Mara, 1981).[13] Accordingly, I

[13] A good review of these issues in India is provided by Verma and Bromley (1987) who conclude, however,

control for the proportion of large (>10 hectares) and medium (4-10 hectares) sized farms in a district.

Regressions are also weighted to account for the differential size of rice and wheat areas in each district. This is important since the variable $SUIT_i$ measures *average* land suitability in a district. It could be the case that a district that has, on average, low suitability may have small pockets particularly suitable for growing rice or wheat. This may lead us to wrongly conclude that for this district, high yield growth occurred on less suitable land. To minimise this possibility, each regression is weighted according to the proportion of area devoted to rice or wheat relative to the total area of a district. Areas that only grow a small proportion of that crop will receive less weight in the estimation.[14]

4.3.2 Extension: Technology time trend

The specification shown in equation 4.3 does not allow me to investigate whether the value of β_1 is equal over time. To examine this I interact the suitability measure with dummy variables indicating each year:

$$y_{ijt} = \lambda_t + \beta_1 SUIT_i + \beta_k \sum_{k=-m}^{q} SUIT_i \times \lambda_{it} + \delta X_{it} + \alpha_i + \gamma_{jt} + \epsilon_{ijt} \tag{4.4}$$

where m is the number of time periods after Green Revolution technology was released and q the years before. This approach has two advantages. First, it is possible that returns to land quality were not constant over time. Gains could have been higher at earlier stages of technology than later. This specification, thus, lets the effect of land quality vary over time. This approach is similar to that of Baltagi and Griffin (1988) who show that this variable represents a general technology index that can be interacted with input variables in the production function to identify factor bias in technology. Second, it allows me to assess the validity of the *parallel trends* assumption. This assumption would be violated

that the relationship is not conceptually clear.

[14]Unweighted regressions were also run to check consistency. These results were similar to the weighted regression.

if β_k was significant for m years before the Green Revolution. Since I am interested in measuring the effect that Green Revolution technologies have on changing the relationship with land quality, a significant relationship between land quality and changes in yield before the Green Revolution would suggest other factors not related to the introduction of new technology were responsible for driving changes in the importance of land quality over time.

4.3.3 Extension: Unequal diffusion

A weakness of the above strategy is that it imposes certain restrictions on the nature of technological change during the Green Revolution. Specifically, it assumes that the Green Revolution is a common shock to agricultural productivity across districts, conditional on a set of fixed effects and controls. One criticism of this strategy is that the diffusion of technology is not accounted for. A number of studies have pointed to the complex patterns with which the Green Revolution spread over space and time, that led to differential rates in the diffusion of technology. Explanations for heterogeneous diffusion in India includes social learning (Munshi, 2004), farm size (Feder and O'Mara, 1981), and irrigation (Sekhri, 2014).

Another explanation may be that the diffusion of HYV technology was unequal across districts with varying land quality. For instance, areas with higher than average land quality adopted technologies with more intensity than areas of lower land quality. These differences could be driving any possible positive relationship yield gains following the Green Revolution. In order to test this competing hypothesis, I regress a measure of diffusion on a time trend interacted with the district land suitability measure for rice and wheat:

$$HYV_{ijt} = \lambda_t + \beta_j \sum_{k}^{q} SUIT_i \times \lambda_t + X_{it} + \alpha_i + \gamma_{jt} + \epsilon_{ijt} \tag{4.5}$$

The measure of diffusion is the proportion of area planted to HYVs in a district relative to the total area planted to that crop. The term λ_t is specified as a dummy variable equal to one for each year after the diffusion of HYVs. This measures the average intensity of diffusion across the country. The additional term $SUIT_i \times \lambda_t$ measures whether there was an additional effect of land quality on diffusion. A positive estimate of this coefficient would imply that HYVs were, on average, more prevalent in districts with higher land quality. The regression is estimated by also including the full set of district and state-year fixed effects as well as control variables.

4.4 Data

4.4.1 Land suitability data

To measure the natural suitability of districts for agricultural production, this paper exploits a land suitability index from the FAO's Global Agro-Ecological Zones (GAEZ) database (IIASA/FAO, 2012). The GAEZ database has recently been used to study a number of aspects of agriculture, including climate change (Costinot et al., 2015) and the link between agricultural productivity and structural transformation (Bustos et al., 2016). The database contains detailed maps of agricultural suitability for 19 major crops grown across the globe, which are ranked from most suitable to least suitable for crop growth. The data are available at a very fine resolution enabling measures of agricultural suitability to be calculated at the district-level.[15]

The GAEZ methodology aggregates a rich set of data on climate[16], soil, and terrain to create a composite measure of suitability based on agronomic models of crop growth. Since this measure is calculated using models of agronomic growth according to a range of natural characteristics, and not based on observations of past yields, it can be classified as exogenous. A key advantage of the methodological approach used to construct the GAEZ suitability indices is that it allows for *crop-specific* measures of suitability that improve on basic classifications of agricultural suitability according to broadly defined

[15]The GAEZ estimates of agricultural suitability are available as gridded data at the scale of 5 arc minutes. At the equator, 5 arc minutes are roughly equal to 10 kilometres.

[16]Climate data pertains to rainfall, temperature, wind, sunshine and relative humidity. A detailed explanation of the modelling methodology can be found in IIASA/FAO (2012).

agro-ecological zones. For instance, Palmer-Jones and Sen (2003) divides India into 19 areas of similar agro-ecological characteristics. A key advantage of using the GAEZ index is that it is a continuous measure of suitability, where each grid cell is rated according to a scale from 'most suitable' to 'unsuitable'. This allows me to estimate the *extent* to which suitability matters rather than comparing areas in one distinct agro-ecological category with another. This also improves on papers that use an 'aggregate suitability index' that orders land based on various natural endowments. This would be problematic since different land characteristics can make an area suitable for varied types of crop. Even within a class of crops like cereals, different agro-climatic conditions would create conditions differentially suited for growing different crops. For example, drier areas would be more suitable for growing wheat, and wetter areas more naturally suited to rice. Thus, an aggregate suitability index of cereal production would mean that most areas would be classed as 'suitable' for a given crop. This would make it hard to derive an ordering comparing more and less suitable areas.

The GAEZ data are available in raster form and grid cells are matched to district boundaries using GIS technology.[17] Where grid cells overlap district boundaries, a grid cell is given to a district if more than half of the cell falls in that district. The GAEZ database contains data on crop-specific suitability at varying levels of inputs. Low, medium, and high input scenarios are available. In this study, the medium intensity input scenario is chosen.[18] The construction of a suitability measure for rice is, however, complicated by the disaggregation of GAEZ data. The database contains separate measures for rain-fed and wetland rice. Since the production data available does not report separate data for these two types of rice, I follow Costinot et al. (2015) in allowing the type of rice with the highest level of suitability. In each grid cell k within a district i, rice suitability is chosen such that:

$$SUIT_{ki}^{RICE} = \max\left\{SUIT_{ki}^{RF}, SUIT_{ki}^{WL}\right\}$$

[17] A shapefile of district boundaries for the census year 1961 was obtained from ML Infomap: https://www.mlinfomap.com/.

[18] There is, however, little variation in district suitability at different crop-specific GAEZ input intensity levels.

The values of the index of agricultural suitability are then summed across the districts in order to gain a district-specific measure of suitability. The aggregate sum of suitability is then divided by the total area of the district. Agricultural suitability for each district across India is then standardised to yield a variable with a mean of zero and standard deviation of one.

The suitability indices for rice and wheat mapped to district boundaries are shown in Figure 4.3. Panel (a) shows the geographical distribution for rice. Districts in the east and south of the country are clearly most suitable for rice production owing to their wetter, more temperate climates. In Panel (b), it can be seen that areas most suitable for wheat production are located on the stretch of land running from the state of Punjab along to West Bengal which forms much of the Ganges basin. In contrast to rice, which has a fairly wide geographical spread of particularly suitable growing areas, districts amenable for wheat production are mainly located in the north and east. most areas in the southern part of the country are very unsuitable for wheat growth.

4.4.2 Agricultural data

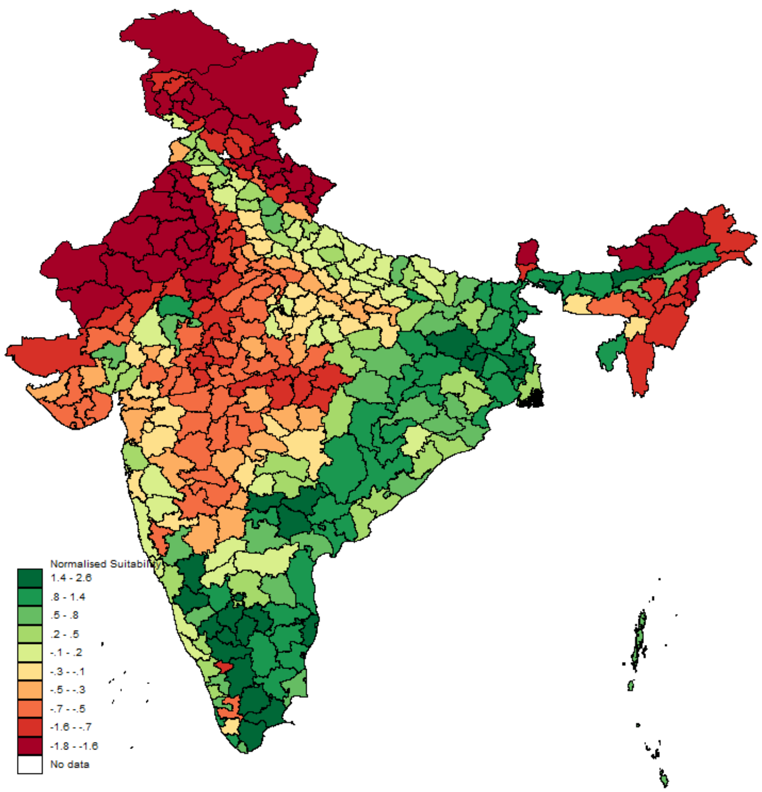
The agricultural data used in this study are primarily taken from a district-level database complied by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT). The dataset includes a range of key variables relating to agricultural outputs and inputs, infrastructure, and demographics, with data available on an annual basis for the years 1966-2009. Data on rice and wheat production and area are used, as well as data on the area of HYVs planted and area irrigated.

A total of 305 districts are available over time.[19] One criticism of the ICRISAT data, however, is that its starting year of 1966 roughly coincides with the beginning of Green Revolution policies in India and does not allow for a sufficient 'before and after' study. To address this, I add production data for the years 1957-1965 to the ICRISAT panel. The

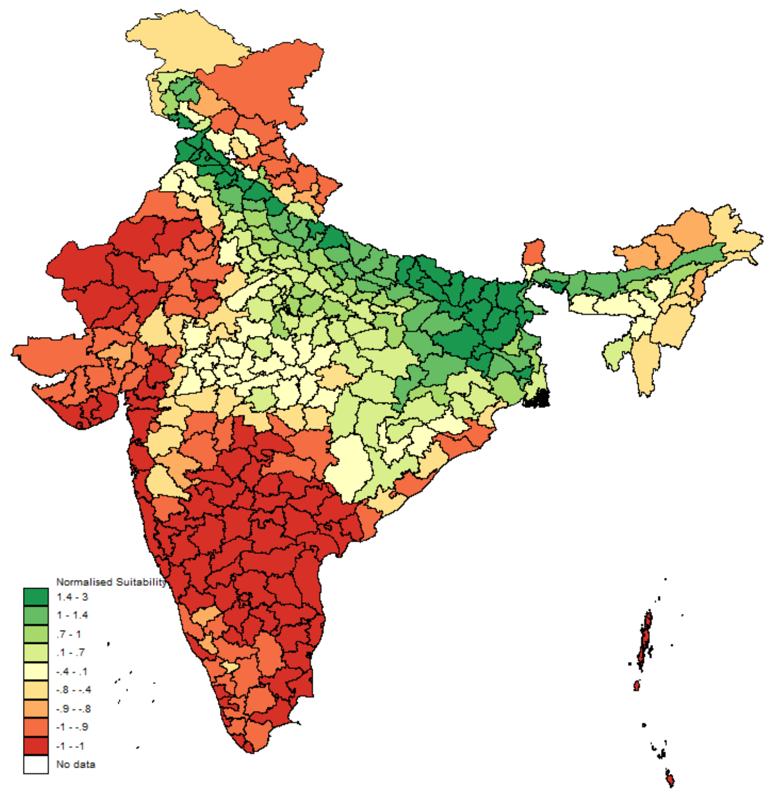
[19]The analysis at district-level presents a potential empirical challenge in India due to the division of districts over the period of study. For instance, the number of districts rose by 67% between 1971-2001, from 356 to 593 (Kumar and Somanathan, 2009). In the ICRISAT data, boundary splits are dealt with by returning separated districts to their parent districts according to boundaries in 1966 (ICRISAT, 2012). All analysis is thus carried out according to these historically-defined boundaries.

Figure 4.3: District rice and wheat suitability index in India

(a) Rice



(b) Wheat



Note: Maps show district-wise suitability computed from the FAO GAEZ database. Green areas denote districts ranked as most suitable and red indicates districts least suitable for crop production. The GAEZ measure of suitability has been standardised so that the district with average suitability is equal to zero.

pre-Green Revolution data are taken from the Indian Agriculture and Climate (IAC) Data Set (Sanghi et al., 1998), a precursor data set to the more recent ICRISAT data. Both data sets use the same district boundaries so that merging the data is straightforward. The result of merging agricultural outcomes from these two data sets is a panel of agricultural outcomes for the years 1957-2009. It is improtant to note, however, that the number of available districts is less in the IAC data, since districts in the states of Assam and Kerala, and also less agriculturally important states of Himachal Pradesh and Jammu and Kashmir are not included. Assam, Kerala, and Himachal Pradesh are thus only included for years succeeding 1966. In total, 297 districts are used for rice and 277 for wheat.

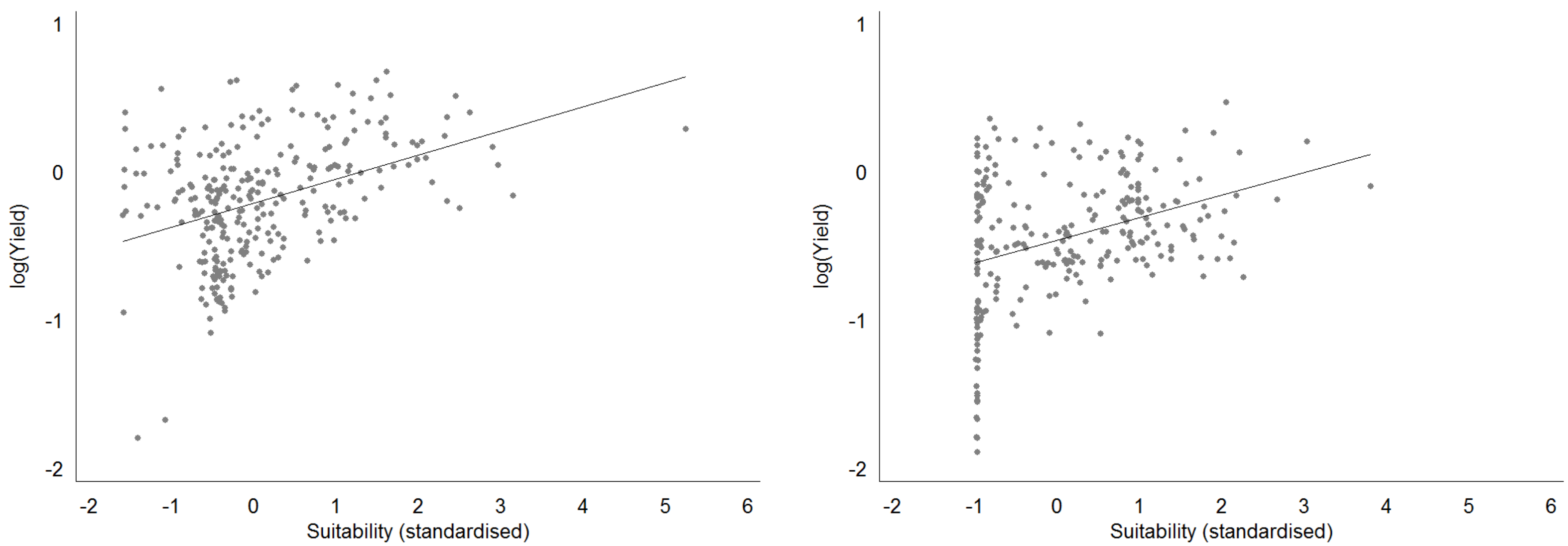
4.5 Results

4.5.1 Crop yields and land quality pre-Green Revolution

To begin studying the role that land quality plays in Indian agriculture, I examine the association between crop productivity and the land quality index described in the previous section. Specifically, I examine the correlation between crop productivity and crop-specific suitability in the period before the onset of the Green Revolution. Figure 4.4 graphs the linear correlation between the logarithm of average crop yield in a district before the onset of Green Revolution technology and the value of suitability index. As is the case throughout the paper, the suitability measure is standardised so that the district with mean suitability takes the index value zero. This relationship is plotted separately for rice and wheat.

A positive linear relationship between crop yield and suitability can clearly be seen for both crops, such that areas where agro-climatic features make land more amenable for crop growth seem to have an important bearing on variation in crop yields. To get a better sense of the magnitude and statistical significance of this relationship, I run a pooled ordinary least squares regression of yield on agro-climatic suitability using each district-year observation before the Green Revolution. I also include a set of control variables to account for potential factors that could explain differences in crop yields between districts

Figure 4.4: Suitability index and productivity pre-Green Revolution



that could also be correlated with land quality. Table 4.1 displays these results. The clear positive relationship between land quality and crop yield can be seen across each of these specifications. For rice, it is estimated that a one standard deviation increase in land quality increases yields by around 7.5 percent on average. For wheat, the magnitude of the association between land quality and yield is larger, with estimates suggesting that a one standard deviation in land quality increases yield by around 12 percent. Inclusion of control variables in columns (2) and (4) does not substantially alter the size of the effect in both cases, suggesting that these factors were not systematically correlated with crop-specific suitability over this period. Overall, these results give an indication of the important role that underlying agro-climatic factors play during a period of relatively low agricultural development. In the next section, I study how the relative dependence on these underlying characteristics changes as increased levels of technology are deployed.

4.5.2 Crop yield, land suitability, and the Green Revolution

The effect that the onset of the Green Revolution had on the returns to land quality is estimated in Table 4.2. The first two columns display coefficient estimates for districts that grow rice. The latter two columns are for those that grow wheat. The coefficient of interest is for the interaction term $Suitability \times GR$. This coefficient shows, on average, how much yields increased on more suitable land following the onset of the Green Revolution relative to before the Green Revolution. Since the suitability measure is standardised with mean zero and standard deviation of one, the estimated coefficient $Suitability \times GR$ is interpreted as the change in the logarithm of yield given a one standard deviation increase in land suitability. All regressions are run by including fixed effects at the district level. Additionally, state-by-year fixed effects are included to control for the effect of omitted variables that vary annually at the state-level.

In columns (1) and (2) the estimates for rice are shown. The results show that an increase in land quality was associated with higher yields following the onset of the Green Revolution. Specifically, a one deviation increase in suitability for rice was, on average, associated with yields that were 3.7% following the uptake of HYV seeds in a district. This estimate

Table 4.1: District crop yield and suitability pre-Green Revolution

Dependent variable: ln(Yield)	Rice		Wheat	
	(1)	(2)	(3)	(4)
Suitability	0.074***	0.085***	0.127***	0.114***
	(0.008)	(0.009)	(0.009)	(0.012)
Controls				
Population/km^2		0.026***		0.035***
		(0.006)		(0.009)
Percentage urban		0.250***		-0.041
		(0.059)		(0.069)
Literate percentage rural		0.665***		0.867***
		(0.057)		(0.075)
Proportion of large farms		0.000		-0.000
		(0.002)		(0.002)
Road length/km^2		0.044***		0.005
		(0.005)		(0.007)
Cropped area		0.000**		0.002***
		(0.000)		(0.000)
Constant	-0.217***	-0.517***	-0.324***	-0.522***
	(0.007)	(0.017)	(0.009)	(0.020)
N	5,409	5,338	3,780	3,750
R^2	0.016	0.098	0.054	0.110

* $p<0.1$, ** $p<0.05$, *** $p<0.01$. Standard errors are shown in parentheses and are clustered at the district level. All regressions are weighted by the proportion of district area devoted to rice or wheat.

is statistically significant at the 5% level. The inclusion of control variables increases this estimate slightly. A similar result is seen in columns (3) and (4), which shows the change in returns to land suitability in wheat growing areas. Here we can see that a one standard deviation increase in land suitability for wheat is associated with yields that were 8% higher, which is significant at the 1% level. Including a set of time varying control variables in this regression increases the magnitude of the coefficient $Suitability \times GR$ slightly, suggesting there may be some correlation between the control variables and land suitability.

Although this estimation exploits within-state variation, it is plausible that the estimated coefficients at the national level may be hiding considerable differences in the effects of Green Revolution technology across different regions. To investigate whether the relationship averaged over districts at the national level holds for subsets of regions, Tables 4.3 and 4.4 show these split into four different regions, Northern, Western, Eastern, and Southern areas. Northern districts are all districts within the states of Punjab and Haryana. These states have historically been highly important in the food security of the country given the high levels of productivity of farms across these states. Central districts are Gujarat, Madhya Pradesh and Maharashtra. The states of Bihar, Uttar Pradesh, Orissa and West Bengal make up the eastern region. The southern rice areas are defined as Andhra Pradesh, Tamil Nadu, Karnataka and Kerala.

At this level, the relationship between within-state differences in land quality and yields after the Green Revolution shows some heterogeneity. For rice, the Green Revolution is estimated to only have had a statistically significant effect on the relative importance of land quality in southern districts, where this coefficient implies a standard deviation increase in suitability led to a 8% relative increase. This may reflect the transformation that areas such as Tamil Nadu underwent during the Green Revolution, since these areas are often considered as 'model' Green Revolution states. For the rest of the regions, this effect is not statistically significant, although it is positive for all areas apart from central districts (although this effect is very close to zero). There is a large estimated point estimate for the northern states of Punjab and Haryana, although this is not significant not significant. This presents some evidence that in states that were considered as fundamental

Table 4.2: Yield and land suitability post-Green Revolution

Dependent variable: ln(Yield)	Rice		Wheat	
	(1)	(2)	(3)	(4)
Suitability x GR	0.037**	0.039**	0.081***	0.091***
	(0.018)	(0.020)	(0.020)	(0.020)
GR	0.023	0.017	-0.045	-0.046
	(0.029)	(0.027)	(0.032)	(0.032)
Controls				
Population/km^2		0.041**		-0.010
		(0.020)		(0.012)
Percentage urban		0.162		-0.370
		(0.148)		(0.235)
Literate percentage rural		0.148		-0.448**
		(0.146)		(0.210)
Proportion of large farms		0.000		-0.001
		(0.001)		(0.002)
Road length/km^2		0.002		-0.004
		(0.003)		(0.005)
Cropped area		0.000		0.000
		(0.000)		(0.000)
Constant	0.556***	0.190	0.878***	1.241***
	(0.033)	(0.133)	(0.038)	(0.154)
District FE	Y	Y	Y	Y
State-year FE	Y	Y	Y	Y
N	12,063	11,987	11,065	10,975
R^2	0.887	0.888	0.939	0.940

* $p<0.1$, ** $p<0.05$, *** $p<0.01$. Standard errors are shown in parentheses and are clustered at the district level. All regressions are weighted by the proportion of district area devoted to rice or wheat.

Table 4.3: Yield and land suitability post-Green Revolution by region: Rice

Dependent variable: ln(Yield)	Rice			
	North	Central	East	South
	(1)	(2)	(3)	(4)
Suitability x GR	0.081	-0.005	0.022	0.082***
	(0.064)	(0.141)	(0.026)	(0.025)
GR	0.151**	0.023	0.019	-0.053
	(0.064)	(0.071)	(0.031)	(0.043)
Controls				
Population/km^2	-0.021	-0.009	0.051**	0.021
	(0.051)	(0.064)	(0.025)	(0.028)
Percentage urban	-1.400*	0.253	-0.140	1.211***
	(0.688)	(0.537)	(0.157)	(0.273)
Literate percentage rural	-1.668**	0.720	-0.196	1.124***
	(0.690)	(0.902)	(0.129)	(0.420)
Proportion of large farms	-0.224	0.264	0.000	-0.073
	(0.250)	(0.228)	(0.001)	(0.073)
Road length/km^2	0.007	0.004	0.002	-0.004
	(0.007)	(0.020)	(0.004)	(0.005)
Cropped area	-0.000	0.001	0.000	0.001**
	(0.000)	(0.001)	(0.000)	(0.000)
Constant	2.804***	-0.490	0.239	-0.300
	(0.655)	(0.612)	(0.175)	(0.266)
District FE	Y	Y	Y	Y
State-year FE	Y	Y	Y	Y
N	706	2,402	5,961	2,647
R^2	0.932	0.797	0.829	0.823

* p<0.1, ** p<0.05, *** p<0.01. Standard errors are shown in parentheses and are clustered at the district level.
All regressions are weighted by the proportion of district area devoted to rice or wheat.

Table 4.4: Yield and land suitability post-Green Revolution by region: Wheat

Dependent variable: ln(Yield)		Wheat	
	North	Central	East
	(1)	(2)	(3)
Suitability x GR	0.069***	0.024	0.118***
	(0.023)	(0.061)	(0.041)
GR	-0.038	-0.015	-0.082*
	(0.054)	(0.065)	(0.042)
Controls			
Population/km^2	0.042	0.070	-0.017
	(0.034)	(0.045)	(0.013)
Percentage urban	-0.852**	1.436**	-0.306
	(0.295)	(0.688)	(0.312)
Literate percentage rural	-0.386	0.503	-0.750**
	(0.397)	(0.360)	(0.305)
Proportion of large farms	0.029	-0.050	-0.001
	(0.176)	(0.101)	(0.002)
Road length/km^2	-0.005	-0.032*	0.000
	(0.005)	(0.018)	(0.006)
Cropped area	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
Constant	1.756***	0.198	1.334***
	(0.390)	(0.304)	(0.191)
District FE	Y	Y	Y
State-year FE	Y	Y	Y
N	749	2,974	5,978
R^2	0.969	0.903	0.914

* $p<0.1$, ** $p<0.05$, *** $p<0.01$. Standard errors are shown in parentheses and are clustered at the district level.
All regressions are weighted by the proportion of district area devoted to rice or wheat.
Districts in Southern region are excluded due to unsuitable wheat growing conditions

to driving production increases for the country as a whole, the consolidation of favourable land quality was highest.

For wheat, a stronger regional pattern emerges. Both for northern and eastern states, there was on average a consolidation of productive advantages, implying gains to a standard deviation increase in land quality of around 6-10%. For both of these areas, estimates are significant below the 1%. In central areas, this coefficient is still estimated to be positive but is not statistically significant. It should be noted that the effect of wheat is not estimated for southern districts owing to the fact that there is little variation in land suitability, owing to the general unsuitability for wheat growth in these areas. Overall, these regional regressions indicate that the consolidation of favourable land following the onset of the Green Revolution followed a fairly widespread regional pattern.

4.5.3 Dependence on land suitability over time

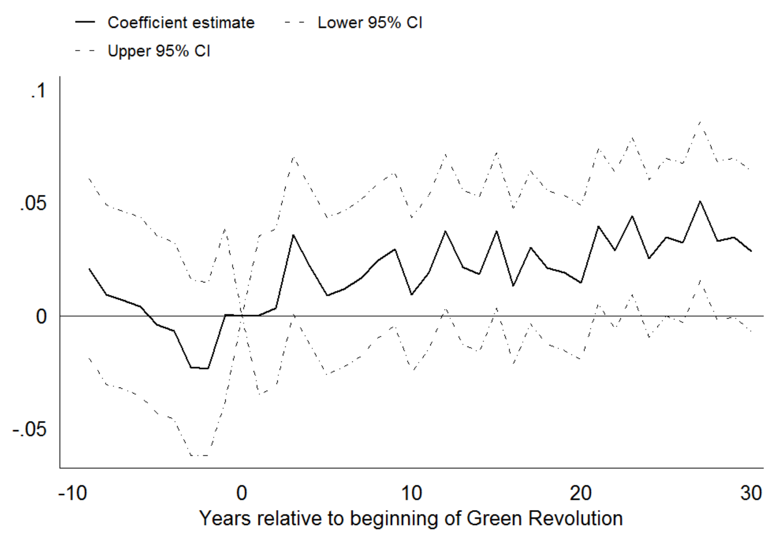
In the previous results, the effect of Green Revolution technology is modelled using a single dummy variable to indicate years after onset of the Green Revolution in a district. This captures the average gains to land quality for all periods following the Green Revolution's onset. To investigate the extent to which this effect may have varied over time, Figure 4.5 displays the coefficient estimates when district land suitability is interacted with a dummy variable for each year. The magnitude of each coefficient is reported relative to the year of adoption of HYV seeds.

In panel (a) the coefficient estimates for rice are shown. There is a clear, steady upward trend seen over time, suggesting that the returns to land quality become more important as technology matured. Encouragingly, for the years before the onset of the Green Revolution, it can clearly be seen that there is a generally very noisy relationship between land suitability and yield. This adds support to the theory that the introduction of Green Revolution technology was the driving force behind the consolidation of yield gains on more naturally suited land.

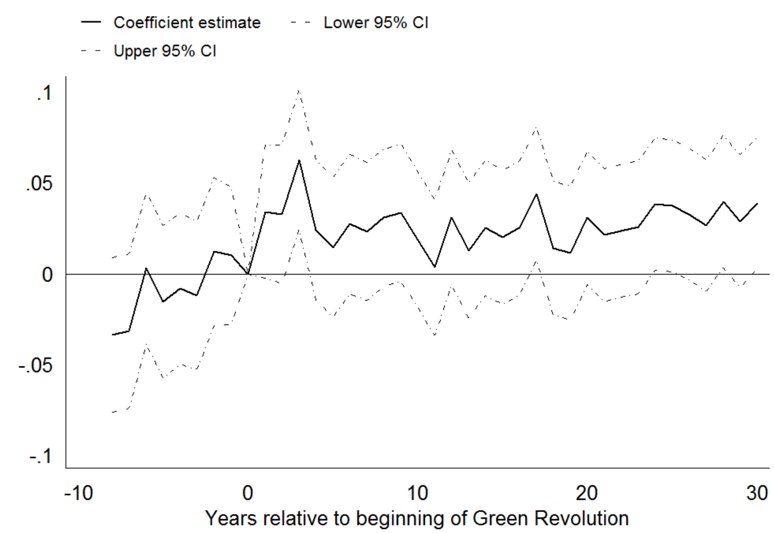
For wheat, in panel (b), a similar pattern emerges. It does, however, seem that gains to land quality were particularly large for a short period after the adoption of technology.

Figure 4.5: Relative effect of land suitability on yield over time in India

(a) Rice



(b) Wheat



Note: Graphs show the value of the coefficient on the interaction term $SUIT_i \times \lambda_t$ which is the district suitability measure for each time period t. This coefficient is estimated relative to the district-specific year of adoption which is normalised to zero. The regression includes both district and state-by-year fixed effects terms and control variables.

This effect was tempered somewhat in the years after, although the value of this coefficient is consistently positive following the onset of the Green Revolution.

4.5.4 Heterogenous adoption of HYVs

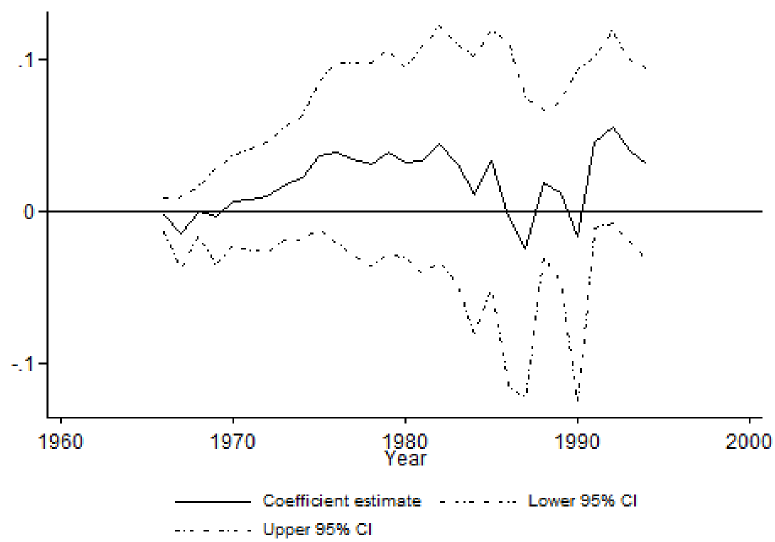
Evidence presented in the previous sections shows that there is a clear positive relationship between increases in yield and higher quality land following the Green Revolution. To get a better understanding of why this might be, I investigate whether higher yield gains due to land quality were driven by heterogeneous adoption of seeds succeeding the Green Revolution. If higher levels of adoption were seen on better quality land, then this would provide some evidence to suggest that gains in yield were not realised due to lower adoption on different types of land. To investigate this, I estimate equation 4.5. The only difference between this equation and my main estimating equations is the dependent variable used. In this case, I specify proportion of crop area devoted to HYVs. This is specified separately for rice and wheat. One shortcoming of the ICRISAT data used in this study is that the data covering the use of HYV seeds becomes very patchy in the 1990s, with around half of all districts showing missing data for area under HYVs after 1994.[20] Accordingly, I only study the relationship between HYVs and land suitability up until this year, in order to maintain the vast majority of districts in my sample.

These estimates are shown in Figure 4.6. In both cases, there does not appear to be a clearly discernible pattern in differences in the proportion of crop area planted to HYVs on varying land suitability over time. For rice, there is a small amount of evidence suggesting that proportion of cropped area was higher on better land, although the confidence intervals for this estimate are very wide. For wheat, the estimation is statistically more significant although the coefficients are estimated very close to zero for the vast majority of the sample.

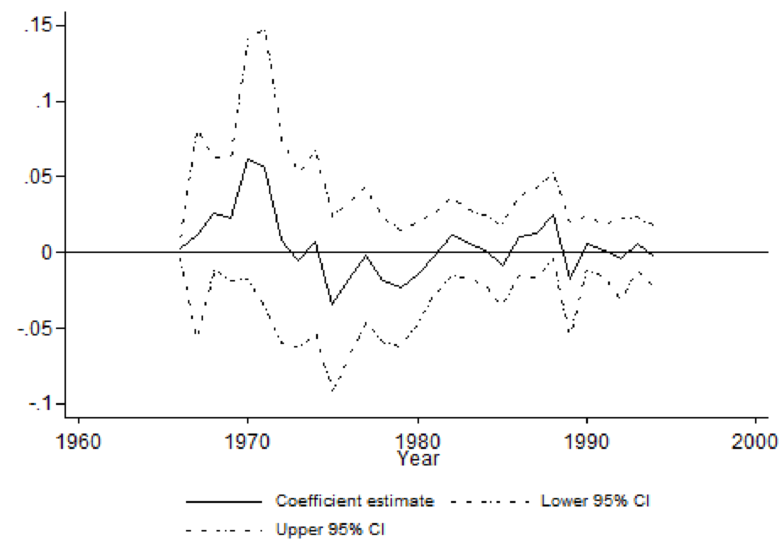
[20]This may reflect that by 1994, 67% of rice area was cropped using HYVs and 80% of wheat area was planted with HYVs. As such, interest in collected data on HYVs may have waned because their use became so widespread.

Figure 4.6: Relationship between HYV area planted and land suitability over time

(a) Rice



(b) Wheat



Note: Graphs show the value of the coefficient on the interaction term $SUIT_i \times \lambda_t$ which is the district suitability measure for each time period t. The dependent variable is proportion of crop area under HYVs. The regression includes both district and state-by-year fixed effects terms and control variables.

4.5.5 Access to irrigation

To test whether the relative gains to land quality were consistent across irrigated and rain-fed areas, I divide the sample according to the amount of irrigated area in a district. I follow Fan et al. (2000a) in classifying a district as irrigated if more than 50 percent of crop-specific area is irrigated. The results show a clear pattern. The relative importance of land suitability following the Green Revolution increases significantly in irrigated districts. For rice, a standard deviation increase in the index of land suitability increases yields by 4% (significant at the 5% level) following the Green Revolution. For wheat, this effect amounts to gains of 9 percent and is highly significant at the 1% level. In contrast to rain-fed areas, the relative gains to land suitability are not statistically significant from zero. These results suggest that irrigation played an important role in facilitating the growth of HYVs on higher quality land. Indeed, the availability of water may itself have been a key factor in enabling farmers in more productive areas to exploit the complementarity between HYVs and higher quality land. This supports the view that although aspects of natural suitability such as climate and soil quality were important determinants of the suitability of an area for successful growth of HYVs, the availability of irrigation was crucial to whether these areas could take advantage of these beneficial natural characteristics.

Table 4.5: Yield and land suitability post-Green Revolution: Irrigation

Dependent variable: ln(Yield)	Rice		Wheat	
	Rainfed	Irrigated	Rainfed	Irrigated
	(1)	(2)	(3)	(4)
Suitability x GR	0.026	0.043**	-0.009	0.091***
	(0.027)	(0.024)	(0.091)	(0.020)
GR	0.021	0.049	-0.047	-0.039
	(0.031)	(0.043)	(0.041)	(0.040)
Controls				
Population/km^2	0.033	0.049	0.113**	-0.010
	(0.025)	(0.041)	(0.056)	(0.014)
Percentage urban	0.055	0.660	-0.896	-0.324
	(0.140)	(0.413)	(0.816)	(0.242)
Literate percentage rural	0.126	0.013	-0.527	-0.485**
	(0.184)	(0.281)	(0.523)	(0.237)
Proportion of large farms	-0.000	0.001	-0.002**	0.002***
	(0.001)	(0.002)	(0.001)	(0.000)
Road length/km^2	0.002	0.001	-0.019	-0.005
	(0.005)	(0.006)	(0.020)	(0.005)
Cropped Area	0.000	0.000	0.001	0.000
	(0.000)	(0.000)	(0.001)	(0.000)
Constant	-0.120	0.451	0.479	1.487***
	(0.160)	(0.325)	(0.441)	(0.160)
District FE	Y	Y	Y	Y
State-year FE	Y	Y	Y	Y
N	7,224	4,763	4,185	6,790
R^2	0.820	0.912	0.858	0.942

* $p<0.1$, ** $p<0.05$, *** $p<0.01$. Standard errors are shown in parentheses and are clustered at the district level. All regressions are weighted by the proportion of district area devoted to rice or wheat.

4.6 Discussion

Innovations in agricultural technology during the Green Revolution allowed farmers across India to achieve higher crop yields and increase the supply of food. Whilst this was highly successful from an aggregate production perspective, evaluating the shortcomings of the Green Revolution is an important part of a balanced assessment. In particular, if these shortcomings are relevant for understanding the future of agriculture in the country, assessing their importance is integral to learning about the vulnerability of the agricultural sector in the future. Over recent years, a growing number of studies have focused on estimating the role that environmental factors, such as climate, have on agricultural outcomes (see Mendelsohn et al. (1994)and Deschenes and Greenstone (2007) for examples of prominent approaches used). However, a smaller amount of evidence exists about how changes in production techniques over the long-run have changed the importance of natural constraints. Recent work by Hornbeck (2012) and Olmstead and Rhode (2008, 2010) has argued that historical evidence of the relationship between agricultural outcomes and environmental quality is important for learning about the extent to which technological innovation has altered agriculture's dependence on the environment. Such evidence is important for evaluating the long-run persistence of environmental features that are integral for agriculture. For instance, the costs of climate change, which could make many areas hotter and rainfall more erratic, will be larger if technologies have primarily exploited more beneficial environments, such as those with moderate temperatures. This is because a farmers' ability to utilise technologies under harsher conditions will be more limited if technologies require a set of increasingly favourable agro-climatic conditions with which to grow. The results of this paper indicate that this was the case for the Green Revolution in India. This paper does, however, only provide a partial understanding of how agriculture becomes relatively more dependent on agro-climatic factors over time. One limitation of the way in which agro-climatic conditions are assessed in this study is that it is not possible to disentangle the relative contribution of the various factors that determine the index of suitability. This lays out the possibility for future work to help further our understanding of specific agro-climatic characteristics have been most important for the complementary relationship between technology and agro-climatic factors over time.

Furthermore, broader criticisms of the Green Revolution also point to its reliance on other types of resources that may be subject to degradation in future. For instance, the role of water was integral to successful growth in many areas (Fan et al., 2000a). Increasing scarcity of water, especially from groundwater sources, may make growing conditions even more challenging in the future. This presents an additional challenge for policymakers, since the set of 'optimal' conditions under which the Green Revolution thrived may be subject to substantial stress in the near future. This suggests that policy should shift focus to future agricultural development that puts these constraints at the forefront of developing new technologies to help continue and bolster the productivity of Indian agriculture. The arguments put forth in this paper maintain that the reason for the patterns of productivity growth since the Green Revolution were likely to have been driven by biological innovations in seed technology. It is perhaps not a surprise therefore, that technologies tended to favour areas that would deliver the highest yield increases, since a primary policy objective of researchers and policymakers before the onset of the Green Revolution was to increase aggregate food production (Baranski, 2015). In this objective they were undeniably successful. However, in order to continue to increase productivity in the future, this model of development is likely to be less suitable and not sustainable. Given that climate change is projected to increase the challenges to crop growth differently in many areas of India, the model of centralised research based on developing a small set of technologies that grow successfully under a wide range of conditions will be of less use. Localised, targeted approaches to technological development may be of more use for generating new technologies that can be tailored to specific growing areas or certain environmental stresses, such as drought tolerance.

4.7 Conclusion

This paper studies how technological change in agriculture affects the relative importance of environmental characteristics, such as climate and soil quality, in determining agricultural productivity. The use of high resolution land suitability data is a key part of this paper, since it allows for an accurate measurement of agro-climatic factors important for crop growth. In addition to this, variation in crop suitability within areas that share similar institutional characteristics allows for the comparison of crop yield growth between districts exposed to a similar set of policies over the period studied. The findings of this study suggest that the gains in yield witnessed since the Green Revolution have placed a greater emphasis on exploiting characteristics of the environment that make an area more naturally advantageous for agriculture. Specifically, relative yield differences due to variation in these characteristics have increased in magnitude as agriculture moves from a state of low technology into an increasingly productive state. Overall, these results reinforce claims that the Green Revolution model of development, which relied on centralised technological innovation processes to increase aggregate production, increased inequalities with regards to differences in land quality. The consequence of the increased exploitation of favourable land characteristics to generate productivity gains signals a challenge for future of Indian agriculture. Whereas these efforts to increase the production of agricultural goods in the twentieth century relied on the complementarity between technology and environmental characteristics to meet food security needs, the onus will increasingly fall on technologies that can successfully substitute for less favourable characteristics. These technologies will be important both for increasing the productivity of less favourable areas and for ensuring technologies maintain their effectiveness under future environmental stress due to climate change.

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Chapter 5

Crop productivity and adaptation to climate change in Pakistan

Abstract

The effectiveness of adaptation strategies is crucial for reducing the costs of climate change in agriculture. Using plot-level data from a specifically designed survey conducted in Pakistan, we investigate the productive benefits for farmers who adapt to climate change. The impact of implementing on-farm adaptation strategies is estimated separately for two staple crops grown across Sindh and Punjab provinces: wheat and rice. We employ an endogenous switching regression model to account for the possibility that farmers self-select into adapting to climate change. Estimated productivity gains are 9 percent for rice farmers who adapted but negligible for wheat. Counterfactual gains for non-adapters were significantly larger. We found evidence of unobserved selection into adaptation, with more productive farmers more likely to adapt. Other factors associated with adaptation were formal credit mechanisms and extension services, underscoring the importance of addressing institutional and informational constraints that inhibit farmers from improving their farming practices.

5.1 Introduction

Climate change is likely to be problematic for the food security of farmers in Pakistan. Annual average mean temperatures in the country have increased by 0.47°C since 1960, with current projections from regional climate models predicting that temperatures in the last quarter of this century will increase by around 3°C relative to 1961-90 (Chaudhry et al., 2009; Islam et al., 2009). Observed rainfall has also become more erratic with extreme precipitation events now increasingly common (Hijioka et al., 2014; Turner and Annamalai, 2012). As a largely arid country, future climate change is likely to exacerbate already challenging growing conditions. With 45% of the labour force employed in agriculture and 24% of gross domestic product derived from the sector (Government of Pakistan, 2010), the resilience of agricultural production to climate change is of high importance to the continued development of Pakistan's economy.

Many studies predict that climate change will have a negative effect on average crop yields (Auffhammer and Schlenker, 2014). Economic studies typically estimate the cost of climate change using cross-sectional (Mendelsohn et al., 1994) or panel estimation techniques (Deschenes and Greenstone, 2007). Similar methods applied in Pakistan have estimated significant negative effects due to climate change for widely grown staple crops like rice and wheat (Siddiqui et al., 2012). What is less clear from these approaches, however, is the impact that adaptation might have in offsetting the effects of climate change. Whether effective means of adaptation can be identified is a key part of reducing the uncertainty of climate impacts and informing policy about how best to reduce these costs in the future (Fankhauser et al., 1999; Auffhammer and Schlenker, 2014).

To estimate the impact of adaptation, we study its role in explaining the crop productivity of farmers who have already altered their agricultural activities in response to perceived changes in climate. We focus our interest on autonomous adaptations, which are those undertaken by individual farmers.[1] These adaptations are key to altering agricultural systems in the future given that they are likely to be implemented most efficiently based

[1] While planned adaptations carried out by governments or other institutions may also be important at ameliorating the costs of climate change (Lobell and Burke, 2010), we constrain our interest to autonomous adaptation.

on farmers' private interests (Mendelsohn, 2000). Identifying the impact that adaptation measures have on current yields is important to understanding whether already available technologies or practices could ameliorate projected adverse impacts of climate change. In addition, by measuring the impact of adaptation on current farm yields, we consider whether there are gains to food security in the short-term. If such gains exist, identifying barriers to adaptation and encouraging use of these practices should be a primary consideration for policymakers interested in immediate economic development goals.

This paper is the first to study the impact of climate change adaptation strategies in Pakistan.[2] We use a new cross-sectional data set collected in 2013 from a specifically designed survey of 1,422 farm households of Sindh and Punjab provinces. The study was conducted to understand how agricultural households in the major agricultural areas of the country produce and how a range of household and institutional features affect production. The survey also collected detailed information on the range of adaptation strategies that farmers use to adapt to climate change. The various strategies employed include switching crop types or varieties, changing farm inputs, as well as soil and water conservation practices.

We apply an endogenous switching regression first used by Di Falco et al. (2011) to estimate the productive effect of adaptation in agriculture. Since the decision to employ adaptation practices may be the result of unobservable differences between farmers, standard regression techniques such as ordinary least squares may result in biased impact estimates. The endogenous switching framework allows us the estimate the impact of adaptation by comparing observed productivity with counterfactual productivity. Thus, it is possible to estimate the gains from adaptation for groups of farmers who actually adapted and for farmers that did not adapt.

To build on earlier studies, we estimate the impact that adaptation has on the productivity of two of the most widely grown crops in Pakistan: wheat and rice. Since climate change may affect the productivity of these crops unevenly (Siddiqui et al., 2012) and that agronomic constraints and farm management options differ across these crops, it is

[2] Most of the literature on the microdeterminants and impact of adaptation strategies has been conducted in the context of African agriculture. A useful review of these studies can be found in Di Falco (2014).

important to understand whether adaptation has heterogeneous effects for different crops. Additionally, consideration of the institutional determinants and constraints to adaptation is of high interest in a country with a complex mix of formal and informal institutions. Identifying relevant characteristics that determine whether or not farmers adapt to climate change is crucial to providing policymakers with information about what constrains farmers from undertaking adaptation.

The results of this study show that the productive benefits of adaptation are heterogeneous across crops in the sample. For wheat, we estimate a positive but not statistically significant impact of adaptation. For rice, however, the estimated impact implies productive gains of 9 percent. Estimated potential gains from adaptation for non-adapting farmers are significantly larger, indicating barriers to employing measures to adapt to changes in climate. For both crops there is evidence of selection into adaptation suggesting that farmers who have adapted to climate change in Pakistan are more productive than the average farmer. There is also suggestive evidence about characteristics that drive the decision to adapt. Credit seems to be important for adaptation. However, households that received credit from informal sources such as middlemen, were significantly less likely to adapt. This underscores the importance of a well-functioning credit market for funding changes in farm practices. There also seems to be significant scope to expand the reach of extension services to encourage adaptations since these services are only utilised by a small proportion of the sample.

The remainder of the paper is structured as follows. Section 5.2 reviews issues the surrounding climate change impact and agriculture. Section 5.3 describes the survey and the variables used in the paper. Section 5.4 outlines the empirical specification of the study with Section 5.5 presenting the results. Finally, Section 5.6 discusses implications of the results and concludes.

5.2 Adapting agriculture to climate change

While the literature investigating impacts of climate change in agriculture has grown substantially, work on possible adaptative responses is smaller in comparison (Auffhammer and Schlenker, 2014). Modelling approaches have focused more on identifying the effects of weather and climate variables on agricultural production. For instance, Mendelsohn et al. (1994) use a hedonic approach where cross-sectional variation in climate conditions and land use enables them to estimate the costs of climate change on farm values. The strength of this approach is its ability to implicitly model the range of adaptation available to farmers (Schlenker et al., 2006). With ample data, panel approaches to measuring economic impacts concentrate on estimating the reduced form relationship between weather variables and economic activity while accounting for potential bias induced by locational time invariant factors (see (Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009)). An extension of this approach by Burke and Emerick (2016) uses long term climate trends to identify the degree to which adaptation has occurred. A key limitation of these approaches is that they do not provide policymakers and researchers with an idea of specific strategies available to farmers to adapt to climate change and the efficacy of these measures. While extensions of the Ricardian approach have worked on incorporating explicit types of adaptation strategies, such as irrigation and crop switching (Kurukulasuriya and Mendelsohn, 2007, 2008), detailed information on the range of strategies available and their direct impact is lacking.

Additionally, many studies do not consider the factors that drive the decision to adapt to climate change. As is argued by Hertel and Lobell (2014), many technologies currently available to farmers could have significant positive benefits. These could embody a range of agronomic strategies or investments that could enhance productivity in the face of environmental change. The role of autonomous adaptation, where farmers decide on their own course of action, is of high importance in agriculture given the atomistic nature of production which is often undertaken by a large number farmers operating on small plots of land (Mendelsohn, 2000). Di Falco (2014) argues that it is crucial to account for a range of ecological, social, and institutional characteristics that affect the farm-level adaptation decision. Studies by Maddison (2007) and Deressa et al. (2009) estimate these factors in the context of African agriculture. Maddison (2007) finds that the majority of farmers in Africa perceive temperatures to have increased and precipitation to have decreased. Farmers, however, cite poor access to credit and poverty as barriers to adaptation. Similarly, Deressa et al. (2009) find that over 50 percent of farmers in Ethiopia think that temperatures have increased or rainfall has decreased in the last 20 years. Barriers to adaptation are found to be access to information related to climate change as well as a lack of financial resources. Many of the identified factors that influence the probability of adaptation taking place are similar to those identified in the more general literature on technology adoption in agriculture (Foster and Rosenzweig, 2010). Often, switching farming practices or adopting new technology involves significant upfront costs which are hard to bear for resource-constrained farmers. Additionally, adoption may be affected by risk or uncertainty in relation to returns from adopting. As such, the ability of farmers to adapt may be affected by inefficiencies in a number of markets (Jack, 2011). For instance, poor access to credit would hinder many farmers from undertaking practices that bear a significant up-front cost. As such, this literature highlights the importance of studying the determinants of adaptation both in terms of farmer characteristics and also the broader institutional environment in which farmers operate.

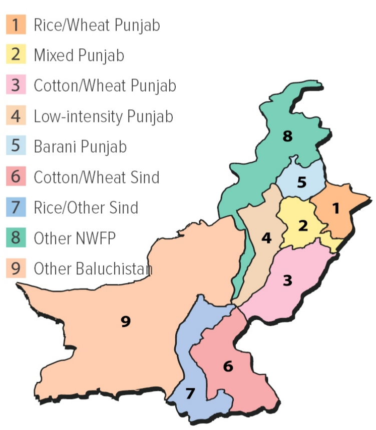
A method of both estimating the impact of adaptation and investigating its various determinants has been applied by Di Falco et al. (2011) and Di Falco and Veronesi (2013). This method rests on the idea that farmers have already used measures to adapt to climate change. Modelling the effect these adaptive measures have on farm productivity is an important way of identifying how effective adaptation might be. Findings from this approach indicate that households that adapted to climate change saw productivity benefits of around 20% in terms of yield gains. Access to credit and extension services were shown to be important determinants of adaptation among Ethiopian farmers. Whether these results can be extrapolated outside of this context and expanded to other parts of the world is an open question.

In the next section we detail the context of our study and discuss the variables we use to assess the determinants and impact of adaptation. We also discuss the set of adaptations that we observed farmers using to adapt to climate change in Pakistan.

5.3 Data

We use data collected during April-June 2013 from a detailed household survey designed to specifically address the determinants and impact of climate change adaptation for agricultural households in Pakistan. The survey collected data on agricultural practices, households characteristics, as well as a range of institutional characteristics. In total, 1,422 households were surveyed in the provinces of Sindh and Punjab, the two most commercially important agricultural areas. Within these provinces, survey sites were then chosen to reflect a range of different agro-climatic conditions and cropping patterns. Figure 5.1 plots the location in which each survey site falls and the agro-climatic zone each falls into. The sampling of our survey covers four areas: Barani (rainfed) agriculture in Punjab; cotton and wheat in Punjab; cotton and wheat in Sindh; and rice growing in Sindh. In Punjab, the survey sites were located in the districts of Chakwal, Rawalpindi, Rahim Yar Khan, and Jhang. In Sindh, responses to the survey were gathered across the districts of Sangar, Sukkur, and Larkana.

Figure 5.1: Map of Survey Sites and Agro-climatic Zones in Sindh and Punjab



Agroclimatic Zones				
Map reference no (see left panel)	Name of zone	Sites Sampled	Numbers of household sampled	District population
5	Barani Punjab	Chakwal	219	1,951,728
		Rawalpindi	209	6,058,214
3	Cotton/wheat Punjab	Rahim Yar Khan	194	5,656,859
6	Cotton/wheat Sindh	Sanghar	181	2,616,821
		Sukkur	219	1,635,928
7	Rice/other Sindh	Larkana	200	3,470,537

Map source: adapted from International Food Policy Research Institute's Research Report No. 77 (IFPRI, 1989) based on an agro-climatic zone division proposed originally in Pakistan Agricultural Research Council's Collaborative Project Paper 86/7 (PARC/CIMMYT, 1986).

As a preliminary to the survey, a reconnaissance study was carried out in December 2012. 18 focus group meetings were held in 3 different villages to identify key areas of interest. Using information obtained from these meetings, a detailed household survey was designed. The total sample of farmers were then surveyed by a team of trained enumerators. Survey modules on household characteristics, farm production and inputs, institutional features, and adaptation practices were collected as part of the survey.

Table 5.2 summarises variables used in the present study and their sample mean for sample households.

5.3.1 Definition of adaptation

In this paper, we are careful to focus only on actions taken by farmers in response or anticipation of factors attributed to climate change. Since farmers may undertake some of these strategies as part of more general processes of agricultural technology adoption, we require that these strategies are undertaken because of climate change for it to constitute adaptation. Accordingly, in one section of the survey, farmers were asked: *"How has your household adapted to cope with climatic changes?"* For the present study, our interest is on the impact of autonomous, on-farm adaptation measures on productivity. In the survey, some farmers identified off-farm work as their adaptation strategy. We do not include this strategy in our definition of adaptation since its impact on farm productivity is ambiguous, although we include this variable in the set of controls to study.[3] Similarly, we further exclude public infrastructure investments, such as large irrigation schemes, since these are not part of the farmers adaptation choice set.

The adaptation variable was then constructed as a binary variable equal to one if farmers were classed as adapters and zero otherwise. To define adapters, we used a simple rule that identified adapting farmers as those that had responded that they had used at least one of the on-farm adaptations listed. Non-adapters were then defined as those that that

[3] On the one hand, income earned off-farm could alleviate household liquidity constraints allowing investment into productivity improving agricultural technologies. For example, Kousar and Abdulai (2016) find that households that had a member working off-farm were more likely to invest in soil conservation methods in Punjab. On the other, lost household labour could plausibly reduce productivity by reducing the amount of household labour input available.

had either responded that they had not adapted or did not carry out any of the on-farm adaptations listed. To ensure that these made up mutually exclusive categories, a check was done to test for discrepancies in these definitions. This was done by identifying whether there were any farmers who had been classed as adapters but had also answered that they had not adapted. This check revealed that a total nine farmers had erroneously been categorised as adapters but had responded negatively to the adaptation question. Since it was not possible to tell whether the farmers or enumerators had incorrectly responded with a false positive or false negative to the adaptation question, a decision was made to exclude these farmers from the sample.

On-farm adaptation strategies can be grouped into the following categories. These were alterations in crop timing, crop switching, agricultural inputs, or the adoption of soil or water conservation technologies. These are listed and described in detail in Table 5.1. The survey revealed that the majority of farmers use a combination of these strategies. The average number of strategies undertaken by farmers was 2.14.[4]

Changing crop timing is a strategy to avoid planting or harvesting during adverse seasonal climatic conditions. For instance, higher average temperatures may mean that the planting of summer crops needs to be brought forward to reduce exposure to high temperatures in early growing stages. Survey responses showed that 25% of farmers who adapted used this strategy. Of those who changed crop timings, the majority had reverted to later sowing or earlier harvesting of crops. For wheat, farmers have switched to planting in November rather than October. Harvesting has also taken place earlier in April or in late-May. For rice, some farmers have switched to planting in April to May.

Changing variety or type of crop could be beneficial if certain crops grow better in more adverse conditions. For instance, a farmer facing an increased likelihood of drought may switch to faster maturing varieties of the same crop or switch into a different crop that is more tolerant to lower water availability (Lobell and Burke, 2010). A study by Kuruku-

[4] Here we acknowledge the alternative approach taken by Di Falco and Veronesi (2013) who use a multinomial endogenous switching regression model to study the importance of *separate* adaptation strategies. They find that a combination of strategies is superior to strategies used in isolation in terms of their impact on farm revenue. Strategies used in isolation do not have a statistically significant impact on household revenue. We do not employ this method due to the problem of estimating a relevant baseline for impact since the number of potential combinations of adaptation strategies is large.

lasuriya and Mendelsohn (2008) found that incorporating crop switching into calculations using the Ricardian framework significantly lowers the cost of climate change across African farms. One-third of adapting farmers had done so by switching crops. One concern is that by including crop switching (which includes both switching types and/or varieties) in the definition of adaptation at the household level, we may not pick up the productivity effects since farmers may be switching out of the measured crop type. However, the survey revealed that of households that *only* adapted by using crop switching, only 9 households switched crop variety into something other than rice or wheat. The vast majority of these households (45) switched into new varieties of wheat or rice, which in over two-thirds of these cases meant the adoption of two recently released wheat varieties, Sehar-2006 and Shafaq-2006.

Farmers may also change the input mix they apply to crops in response to past or expected climate change. Perhaps the most obvious strategy is increasing the amount of water applied to crops to counter extreme heat and/or low precipitation. Along with this, the survey also showed that a substantial number of farmers increased the amount of fertiliser used. This is the dominant adaptation type with over half of adapters changing inputs in some way.

Increased temperatures and more erratic rainfall may have significant impacts on the state of both soil and water resources, meaning that investments to conserve these resources help farmers adapt to climate change. Higher temperatures are likely to increase the rate at which water is lost from the soil, meaning that they will have to exert more effort into maintaining soil moisture. In addition, heavy rainfall would increase the amount of soil erosion, placing greater emphasis on the need to invest in techniques to reduce these impacts. Investments to counter these effects in Pakistan include contour planting, use of shelterbelts, or manure application. Overall, soil conservation was used by half of adapters.

Given the aridity of the climate, more efficient use of water is paramount to adaptation strategies in Pakistan (Baig et al., 2013). These strategies are clearly important since 47 percent of adapters use them. Farmers could utilise rainwater harvesting methods or the construction of bunds around fields to reduce run-off. Water conservation used by farmers

Table 5.1: Types of on-farm adaptation

Category	Description	Used by x% of adapters
Crop timing	Changed the timing of cropping activities e.g. sowing and/or harvesting dates have been changed	25
Crop type/variety	Household has either changed the crop variety (e.g. switched to a different type of wheat) or changed the crop grown	34
Input alteration	Change in the amount of a variable input used. This could relate to increased water use on irrigated farms, higher rate of seed, fertiliser, and/or pesticide use	55
Soil conservation	Adoption of measures to maintain the fertility of soil or reduce erosion. Includes the application of organic matter (manure, crop residue), zero tillage methods, shelterbelts, or contour farming	52
Water conservation	Adoption of measures to use water more efficiently on-farm. Rainwater harvesting, construction of bunds, land levelling, furrow irrigation techniques	47

in our sample show a distinct pattern. In areas where irrigation is scarce, bunding is the primary strategy used. In areas where irrigation is available, more emphasis is put on more water-efficient methods such as furrow irrigation.

5.3.2 Crop types

In this analysis we study farmers who grow either wheat or rice. The average productivity of farmers for each crop is shown in Table 5.2. In contrast to Di Falco et al. (2011), who estimate a model using an aggregation of five major crop types, we study each crop separately. Aggregation of different crops into a single production function, however, may have significant disadvantages for studying adaptation's effect on productivity.[5] Primarily, aggregation may confuse analysis when growing conditions differ significantly or inputs are used differently. Similarly, the seasonal nature of production in Pakistan over the Rabi (harvested in spring) and Kharif (harvested in autumn) seasons may also complicate the interpretation of an aggregated production function. To account for this, we estimate separate regressions for each crop and test whether the impacts of adaptation differ between crops.

The primary crop grown in our sample is wheat. According to FAO (2013), 80% of farmers in Pakistan grow wheat and the crop makes up around 37% of energy intake of the population. Wheat production takes place over the Rabi season when temperatures and rainfall are lower than the summer. Yields of wheat, however, are low based on the agro-ecological potential of the growing environment.[6] A lack of suitable irrigation infrastructure and access to productive inputs are argued to be behind persistent low yields (FAO, 2013). The implications for wheat yields in the face of climate change are important to whether farmers adapt. Sultana et al. (2009) use agronomic crop models to predict the impacts of climate change on wheat yields across different climatic zones in Pakistan. They conclude that increases in temperature will decrease wheat yields in arid, semi-arid and sub-humid zones, although increases in temperature could increase yields in humid areas. The authors also explore the possibility of adaptation by shifting growing to cooler months and conclude that this might be an effective adaptation to mitigate the effects of increases in temperature. Siddiqui et al. (2012) estimate the yield response of district-level wheat to temperature and precipitation changes in Punjab. They conclude that projected climate change would have a non-negative impact on the production of wheat.

Rice is one of the most important Kharif (summer) crops grown in Sindh and Punjab. It is important as both a food crop and cash crop. Its growth requires access to a good water

[5] To a certain degree, aggregation across different types of crop is hard to avoid. For instance, aggregation is done even within the same crop type. In our sample, 19 different wheat varieties are grown. It is plausible that factors such as input requirements may substantially differ even within crop types.

[6] There is a significant amount of variation in the varieties of wheat grown across Sindh and Punjab. Different varieties may be more suited to location-specific agronomic factors. Smale et al. (1998) use district-level data from Pakistan's Punjab to show that the diversity of wheat varieties grown is synonymous with higher yields and lower variance of yields in rainfed areas.

Table 5.2: Variable summary

Variable name	Description	Mean	SD
Adaptation			
Adapt	1 if adapted to climate change, 0 otherwise	0.47	0.49
Productivity			
Yield (Wheat)	Wheat output (maunds/acre)	18.22	10.38
Yield (Rice)	Rice output (maunds/acre)	31.39	18.10
Explanatory variables			
Plot size (acres)	Crop area (acres)	4.07	4.39
Total land (acres)	Household land (acres)	8.49	11.03
Seed (kg/acre)	Seed used (kg/acre)	36.33	46.13
Fertiliser (kg/acre)	Fertiliser used (kg/acre)	2.84	2.38
Labour	Adult labourers (number)	4.12	4.19
Irrigated	1 if plot is irrigation, 0 otherwise	0.76	0.42
Maximum education	Maximum household education (1-7)	1.12	2.03
Females in household	Percentage of females in household	0.45	0.14
Work off-farm	1 if household member has off-farm job, 0 otherwise	0.59	0.49
Owns livestock	1 if owns cattle or buffalo	0.73	0.44
Bank credit	1 if credit from formal finance institution, 0 otherwise	0.08	0.27
Informal credit	1 if credit from informal lender, 0 otherwise	0.19	0.40
Owns land	1 if land is owned, 0 otherwise	0.74	0.43
Formal extension	1 if receives formal extension services, 0 otherwise	0.07	0.24
Affected by flooding	1 if affected by flooding (2010-2012), 0 otherwise	0.62	0.48
Village school	1 if village has a school, 0 otherwise	0.87	0.33
Ave. temp increase	Perceives average temperature increased	0.79	0.40
Change in rain amount	Perceives amount of rain changed	0.88	0.31
Change in rain timing	Perceives timing of rainy season changed	0.08	0.27
Extreme events inc e	Perceives extreme events (drought, flood) increased	0.55	0.49

supply mostly supplied by irrigating the crop during the hot summer months, although it is sometimes grown under rainfed conditions. Given that high summer temperatures are already present across rice growing areas in Pakistan, increased temperatures driven by climate change have been projected to negatively affect rice productivity (Siddiqui et al., 2012).

Table 5.3: Characteristics of adapters and nonadapters: Differences

	Adapters	Non-adapters	Difference
Productivity			
Yield (Wheat)	19.58	17.20	2.38***
Yield (Rice)	33.94	28.37	5.56***
Explanatory variables			
Plot Size	4.60	4.24	0.36
Total land (acres)	9.82	7.68	2.13***
Seed	56.97	44.33	12.64***
Fertiliser	3.00	2.51	0.48***
Labour	4.05	4.32	-0.26
Irrigated	0.82	0.62	0.19***
Maximum education	0.78	1.17	-0.39***
Females in household	0.46	0.43	0.03***
Work off-farm	0.54	0.68	-0.13***
Owns livestock	0.78	0.69	0.09***
Bank credit	0.10	0.04	0.06***
Informal credit	0.16	0.22	-0.05**
Owns land	0.72	0.77	-0.05**
Formal extension	0.08	0.04	0.04***
Affected by flooding	0.69	0.52	0.17***
Village school	0.88	0.86	0.02
Ave. temp increase	0.82	0.76	0.06***
Change in amount of rain	0.89	0.88	0.01
Change in timing of rainy season	0.09	0.06	0.03
Extreme events increase	0.56	0.51	0.04
Chakwal	0.07	0.19	-0.11***
Jhang	0.13	0.12	0.01
Rahim Yar Khan	0.13	0.06	0.07***
Rawalpindi	0.01	0.10	-0.09***
Sanghar	0.17	0.14	0.03
Sukkur	0.24	0.17	0.07***
Observations	746	916	1662

*p<0.1, **p<0.05, ***p<0.01

5.3.3 Variables

The variables shown in Table 5.2 are used to conduct the empirical analysis described in the next section. Table 5.3 additionally displays the difference in the sample mean of these characteristics between adapters and non-adapters. As defined previously, adaptation is a dummy variable indicating whether or not the household has adapted to climate change. In our sample, just under half the households have undertaken on-farm measures to adapt to climate change.

Agricultural input data was collected at the plot level to account for the fact that households often grow more than a single crop.[7] We also include the total landholdings of a household to examine the relationship between farm size and adaptation. On average, households in our sample are two acres larger than the national average which stands at 6.4 acres (Government of Pakistan, 2010). Adapters tend to be households that farm more land. Plot-level inputs include seed, fertiliser, and labour. The labour input was computed as the number of adult labourers working each plot of land. Differences between adapters and non-adapters suggest that adapters are more input intensive.

We include a dummy variable indicating whether a plot is irrigated to account for the likelihood that irrigated yields are higher than rainfed yields. It can be seen that a high proportion of farms (76%) are irrigated, underscoring the importance of irrigation for farms across Punjab and Sindh.

As well as production input variables, we also include a set of variables to control for observable differences between households that could influence their productivity and likelihood of adapting. To control for the education status of households, we include a variable indicating the maximum education of a household member. This variable takes values from one if the highest level of education is that someone in the household can read and write and seven if somebody has an advanced degree. On average, levels of education are low although most households are equipped with basic reading and writing skills.

We include a variable to measure the gender composition of the household. Women play

[7] On average, households crop three different crops.

an important part in farming activities, supplying a large amount of labour. Their role in farming activities is often constrained, however, since they are excluded from many of the most productive activities such as operating machinery (Samee et al., 2015).[8]

A crucial aspect in the decision to conduct on-farm adaptation may be the existence of off-farm employment. To study this, we include a dummy variable indicating whether a household member is engaged in off-farm labour. Nearly sixty percent of households have at least one member off-farm. Interestingly, non-adapters are significantly more likely to have at least one member that works off-farm.

As well as the decision to supplement income off-farm, the ability to generate other forms of agricultural income may affect whether farmers engage in adaptation involving their cropping activities. The variable *Livestock* was included to indicate whether the household owned cattle or buffalo which can be used for dairy farming. The majority of households in our sample own livestock, although adapters are more likely to do so.

Numerous studies have cited the difficulty of obtaining credit as a crucial factor in determining the ability of farmers to adapt to climate change in other settings (Deressa et al., 2009; Maddison, 2007). Credit markets are an important feature of Pakistan's rural agricultural economy owing to the range of different types of lenders that offer credit (Aleem, 1990). They may be an important part of the adaptation decision because some adaptations require significant up-front investment that may have to be leveraged with credit. We distinguish between two types of credit. Formal credit is provided by established institutions like banks and microfinance organisations. Chandler and Faruqee (2003) find that formal credit only accounts for 7% of households who are in receipt of credit, but makes up 22% of the volume of loans since formal loans are larger than informal loans. Informal credit is provided by a range of actors, such as family members or landlords. Most salient in Pakistan is the role of the middleman who often supplies credit in exchange for providing farmers with marketing services. There is a common perception that middlemen charge high rates of interest on loans (Haq et al., 2013), although it is argued by Aleem (1990) that higher rates of interest reflect high screening costs and the riskiness of lending

[8] A related paper by Udry (1996) documents that plots farmed by women in Burkino Faso have yields 30% lower than those controlled by men due to unequal access to farm inputs.

to farmers. We test for the role that different types of credit play by including dummy variables for farmers in receipt of both formal and informal lines of credit. Only a small proportion of households in our sample have access to formal credit, while a fifth of households are reliant on informal credit. More adapters use formal credit whereas non-adapters use more informal credit.

A variable to indicate whether the household owns their land is included to test whether property rights are an important institutional determinant of adaptation. Different land rights may affect the decision to adapt. For instance, Jacoby and Mansuri (2008) link higher investments in land-improving practices with the security of tenure in Pakistan. Similarly, Ali et al. (2012) show that investments in land and farm productivity are lower for leased relative to owned land in Punjab. Of the farmers sampled here, three quarters own their land.

Formal extension services, those provided by government and NGOs, may be one way in which farmers learn about new farming information. Those that are best informed about suitable adaptation practices may be more likely to adopt these practices. For instance, work by Hussain et al. (1994) concludes that the Training and Visit extension programme in Punjab in the late 1980's was successful at encouraging the adoption of new agricultural technologies. A surprisingly low proportion (7%) of farmers are in receipt of these services in our sample, although adapters are more likely to be in receipt.

Given the heavy losses endured due to flooding between 2010-2012 in areas of Sindh and Punjab, the experience of extreme events may condition whether farmers adapt to climate change. On the one hand, experience of extreme events may prime the farmer to the possibility of such events in future. On the other, extreme events may have prolonged effects that constrain a farmer's ability to invest in costly adaptive measures. We thus include a dummy variable to indicate whether households have experienced income losses due to flooding in the last three years. Over sixty percent of farmers experienced losses due to flooding in the years prior to the survey, with more adapters experiencing flooding than non-adapters.

Factors at the village-level could reflect the relative development of some areas over others.

To proxy for these factors we indicate whether a school is present in the village. Schools are present in the vast majority of villages sampled.

The final four variables in the table relate to farmers' subjective opinions about whether the climate is changing. Since a necessary condition for adapting is the perception that the climate is changing, we investigate which aspects of the climate farmers think are changing. The first variable in this set shows that the majority of farmers, 79 percent, perceive average temperatures to have increased, although this proportion is greater for adapters. An even larger proportion felt that the amount of rain was changing, reflecting the observation that the South Asian summer monsoon has become more erratic (Singh et al., 2014). Only a low proportion of farmers perceive the timing of this phenomenon to have changed, however. Given the experience of extreme events previously mentioned, we also include a variable that relates to whether extreme events, defined as droughts and floods, have increased in frequency. Over half the sample perceives this to be the case.

5.4 Empirical framework

5.4.1 Theoretical model

To model the impact of adaptation on farmer productivity an endogenous switching framework is employed. This has previously been applied to the study of climate adaptation and crop productivity by Di Falco et al. (2011).

We begin by assuming that farmers are risk neutral and therefore evaluate the benefits of adaptation based on their productive benefits.[9] Farmers will choose to adapt to climate change if the expected benefit is greater than not adapting. We assume that the necessary condition for adaptation is that productivity under adaptation is higher than under no adaptation. This can be represented by an unobserved variable A_i^* which represents a farmer's productive benefits from adaptation. We can express the decision to adapt based on a set of observed Z_i and unobserved ω_i factors. The observed factors could include

[9]In assuming risk neutrality, we do not consider the role risk aversion may play in the adaptation decision.

household characteristics and other variables that affect the benefits from adapting to climate change. This decision can be expressed as:

$$A_i^* = \boldsymbol{Z}_i \boldsymbol{\pi} + \omega_i \tag{5.1}$$

where

$A_i = 1$ if $A_i^* = \boldsymbol{Z}_i \boldsymbol{\pi} + \omega_i > 0$

or

$A_i = 0$ if $A_i^* = \boldsymbol{Z}_i \boldsymbol{\pi} + \omega_i \leq 0$

where the variable A_i represents the observed decision to adapt or not.

An important empirical concern in impact evaluation is the possibility that unobservable farmer characteristics affect both the decision to undertake adaptation and the productivity of farmers. As such, farmers self-select into adaptation in ways that do not mimic an idealised experiment where adaptation is the result of a random allocation process. Simple approaches to estimating the impact of adaptation by including a dummy variable in single production function, such as by ordinary least squares, could result in inconsistent estimates of the impact of adaptation on productivity. An example could be that households that have better farm management skills are likely to be more productive and also have a higher propensity to adapt their farming activity to climate change. In this case, the influence of such an unmeasured characteristic could lead us to over-estimate adaptation's impact on crop productivity.

To address concerns about selection bias in estimating the impact of adaptation, we use an endogenous switching regression model. This method is based on that of Heckman (1979) who treats selection bias as an omitted variable that can be estimated.

To empirically estimate this relationship, the sample is split in two based on whether the household has adapted or not:

$$y_{1i} = \boldsymbol{X}_{1i}\boldsymbol{\beta}_1 + \epsilon_{1i} \text{ if } A_i = 1 \tag{5.2}$$

$$y_{2i} = \boldsymbol{X}_{2i}\boldsymbol{\beta}_2 + \epsilon_{2i} \text{ if } A_i = 0 \tag{5.3}$$

The variables y_{1i} and y_{2i} represent crop yields for adapters and non-adapters respectively. The vectors $\boldsymbol{X}_{1i}$ and $\boldsymbol{X}_{2i}$ contain explanatory variables and $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ are vectors of estimated coefficients. The errors for each equation are contained in ϵ_{1i} and ϵ_{2i}.

As mentioned previously, the possibility that farmers self-select into adaptation may lead to correlation between the error terms in the production equations and the error in the selection into adaptation equation. The correlation between these terms represented in the covariance matrix $\boldsymbol{\Sigma}$ containing the three error terms ϵ_{1i}, ϵ_{2i} and ω_i. These are assumed to be distributed with trivariate zero mean and take the form:

$$\boldsymbol{\Sigma} = \begin{vmatrix} \sigma_\omega^2 & \sigma_{\omega 1} & \sigma_{\omega 2} \\ \sigma_{\omega 1} & \sigma_1^2 & . \\ \sigma_{\omega 2} & . & \sigma_2^2 \end{vmatrix}$$

where σ_ω^2 represents the variance of the error term in the selection equation. Similarly, the variances of the production equations are represented by σ_1^2 and σ_2^2. $\sigma_{1\omega}$ and $\sigma_{2\omega}$ are the covariances between the errors in the selection and production regimes 1 and 2 respectively. Since the outcomes of regimes 1 and 2 are not simultaneously observed for each household, the covariance between the two production equations are not specified and are represented simply with a dot (.).

In the presence of selection bias, the expectations of the error terms for the two production regimes will be non-zero depending on whether farmers have adapted or not. Thus, conditional on sample selection, the expected error terms can be expressed as follows:

$$
\begin{aligned}
E[\epsilon_{1i}|A_i = 1] &= \sigma_{\omega 1} \frac{\phi(\boldsymbol{Z}_i \boldsymbol{\pi})}{\Phi(\boldsymbol{Z}_i \boldsymbol{\pi})} \\
&= \sigma_{\omega 1} \lambda_{1i}
\end{aligned}
\tag{5.4}
$$

and

$$
\begin{aligned}
E[\epsilon_{2i}|A_i = 0] &= -\sigma_{\omega 2} \frac{\phi(\boldsymbol{Z}_i \boldsymbol{\pi})}{1 - \Phi(Z_i \pi)} \\
&= \sigma_{\omega 2} \lambda_{2i}
\end{aligned}
\tag{5.5}
$$

where ϕ and Φ are standard normal probability distributions and standard normal cumulative distributions respectively. The terms λ_{1i} and λ_{2i} are interpreted as inverse Mills ratios (Heckman, 1979) which are included in the productivity equations as explanatory variables to account for any selection bias.

Of empirical interest is the direction of correlation between the decision to adapt and productivity. This relationship can be written as:

$$
\rho_1 = \sigma_{\omega 1}^2 / \sigma_\omega \sigma_1 \tag{5.6}
$$

and

$$
\rho_2 = \sigma_{\omega 2}^2 / \sigma_\omega \sigma_2 \tag{5.7}
$$

were the terms ρ_1 and ρ_2 are correlation coefficients between the error term in the selection equation ω_i and the errors from the productivity equations ϵ_{1i} and ϵ_{2i} respectively. The sign and significance of the estimated correlation coefficients ρ_1 or ρ_2 indicate the presence of selection bias since unobservable factors associated with productivity are correlated with unobserved characteristics that determine whether farmers adapt to climate change. If either of these coefficients is significantly different from zero, it can be concluded that there is evidence of unobserved selection into adaptation which would likely bias estimates of the impact of adaptation on crop productivity using straightforward techniques such as

OLS.

The estimation of the parameters of the model are estimated using the full information maximum likelihood procedure. This involves the simultaneous estimation of both the selection and production equations and is superior to two-step estimators which are inefficient in deriving standard errors of the parameters (Lokshin and Sajaia, 2004).

5.4.2 Treatment effects

The aim of this study is to identify whether the use climate change adaptation strategies have increased the productivity of farmers measured in terms of yields, expressed in maunds per acre. To estimate this impact, we use the standard treatment effects framework to estimate yields of farmers in a counterfactual adaptation scenario. Adaptation is defined as the treatment variable which can take discrete values 0 or 1, where $D = \{0, 1\}$. Following Heckman et al. (2003), the expected value of the crop productivity Y_{i1} for farmers that adapted can be written as:

$$E(Y_{i1}|D = 1) = \boldsymbol{X}_{1i}\boldsymbol{\beta}_1 + \sigma_{\omega 1}\lambda_{1i} \tag{5.8}$$

where the last term adjusts for unmeasured characteristics of the adapters in the sample. In the same way, the outcome Y_{i2} for non-adapters is expressed as:

$$E(Y_{i2}|D = 0) = \boldsymbol{X}_{2i}\boldsymbol{\beta}_2 + \sigma_{\omega 2}\lambda_{2i} \tag{5.9}$$

These equations represent the observed outcomes for the adapters and non-adapters. The switching regression framework can also be used to estimate counterfactual outcomes for adapters and non-adapters. For the adapters, the counterfactual is the scenario where they do not adapt, represented by:

$$E(Y_{i2}|D = 1) = \boldsymbol{X}_{1i}\boldsymbol{\beta}_2 + \sigma_{\omega 2}\lambda_{1i} \tag{5.10}$$

The case where non-adapters do adapt can be represented similarly as:

$$E(Y_{i1}|D=0) = \boldsymbol{X}_{2i}\boldsymbol{\beta}_1 + \sigma_{\omega 1}\lambda_{2i} \tag{5.11}$$

Using a generalised treatment effects framework, the impact of adaptation can be estimated for adapters and non-adapters. The average predicted effect of adaptation on those that adapted is calculated as the average treatment effect on the treated (ATT),

$$\begin{aligned} ATT &= E(Y_{i1}|D=1) - E(Y_{i2}|D=1) \\ &= \boldsymbol{X}_{1i}(\boldsymbol{\beta}_1 - \boldsymbol{\beta}_2) + (\sigma_{1\omega} - \sigma_{2\omega})\lambda_{1i} \end{aligned} \tag{5.12}$$

The predicted impact of adaptation on those that did not adapt can be calculated as the average treatment effect on the untreated (ATU), defined as

$$\begin{aligned} ATU &= E(Y_{i1}|D=0) - E(Y_{i2}|D=0) \\ &= \boldsymbol{X}_{2i}(\boldsymbol{\beta}_1 - \boldsymbol{\beta}_2) + (\sigma_{1\omega} - \sigma_{2\omega})\lambda_{2i} \end{aligned} \tag{5.13}$$

Estimating the ATU is useful for assessing whether any potential productive gains from adaptation could be extended to those who have not yet adapted. If this effect is positive, this could provide motivation for policies to further the reach of existing adaptation practices.

5.4.3 Selection instrument

Estimation and identification using the endogenous switching approach requires the inclusion in the selection equation of at least one variable that affects the probability of adapting but not the productivity of farmers.[10] Di Falco et al. (2011) use climate information sources as selection instruments. We argue against the use of these instruments in the context of this study given that our survey identified that farmers gathered advice

[10] It is theoretically possible to identify this model without the inclusion of additional instruments since λ_{1i} and λ_{2i} are non-linear functions of the included variables in the selection equation. However, problems of multicollinearity can make this type of identification weak in practice (Huber and Mellance, 2014).

on farming practices and associated climate information from a range of sources including landlords and middlemen. Since these agents may have important implications for farmers' productivity, other than through adaptation, we choose not to follow in the use of these instruments.

The variables we include relate to farmer perceptions about climate change. We argue that farmers who perceive certain changes in the climate are more likely to adapt. Although we would expect that the perception of climate change in general is a prerequisite for farmers adapting, perceiving different types of change may be important predictors of adaptation. For instance, farmers perceiving increases in average temperatures may be more likely to adapt than farmers who perceive other types of climate change.

In order for these selection instruments to appropriately identify the impact of adaptation on farmer productivity, two conditions are required. First, the instruments should not be correlated with any unobserved determinants on the productivity of farmers (instrument validity). Second, in order for the instruments have sufficient predictive power in explaining adaptation, they must significantly correlate with the observed adaptation decision (instrument relevance).

Although instrument validity cannot be directly tested, a way of providing support for this assumption is to test whether the included selection instruments drive the productivity of farmers who do not adapt. If perceptions are both informative and valid as instruments, they should impact productivity only indirectly *through* the adaptation variable. Hence, these instruments should not correlate with the productivity of farmers who have not adapted. A test for this is carried out by Di Falco et al. (2011). They conduct an auxiliary regression of selection instruments on productivity using the subset of non-adapting farmers. Only non-adapting farmers are included in this regression since if these instruments were valid predictors of adaptation, they would likely be significant determinants of productivity for farmers that had adapted.[11] Thus, non-significance of the perception variables in the productivity equation would signal that these variables were not significantly

[11]Since adaptation would be included in the residual of the productivity equation for farmers that adapted, if adaptation had a significant impact on productivity, the perceptions selection instruments would likely be significant for the adapters.

correlated with unobserved determinants of productivity.

To test the second condition, referred to as instrument relevance, it is possible to add empirical justification to this assumption by testing the correlation between the decision to adapt and the selection instruments. Evidence that these instruments did not correlate with the adaptation decision would signal the presence of weak instruments. To test this assumption, the joint significance of the perception variables is tested. Evidence that the instruments have sufficient explanatory power is done through a Wald test. A rejection of then null hypothesis that these variables are jointly insignificant when included in a probit regression modelling the decision to adapt would signal that these instruments were not weak predictors of adaptation.

Table 5.4 shows how strongly the selection instruments perform in a) predicting the probability of adaptation and b) predicting productivity of non-adapters. The inclusion of four climate perception variables in probit regressions predicting the probability of adaptation are both jointly significant at the 5% level for wheat and at the 10% level for rice. This provides evidence that the included instruments do not fail at providing sufficient predictive power and are not classed as weak instruments. It is the case, however, that the strength of the instruments appears to be stronger for rice than wheat. An F-test of joint linear significance of these variables in the productivity for non-adapters finds no evidence of a statistically significant linear association for both wheat and rice, providing evidence that these variables are not correlated with the productivity of farmers. While this test does not mean that the selection are valid (since this assumption is untestable), but it does add credence to the validity of the instruments since if these variables were not valid and correlated with unobserved determinants of productivity, it is likely that the selection variables would fail this test.

Table 5.4: Test of the validity of selection instruments

	Wheat		Rice	
	Probit	OLS	Probit	OLS
	Adaptation 1/0	Yield (nonadapters)	Adaptation 1/0	Yield (nonadapters)
Perceptions				
Ave. temp increase	0.239**	-2.047	0.404*	2.395
	(0.095)	(1.274)	(0.215)	(3.944)
Change in amount of rain	0.054	0.304	-0.276	1.831
	(0.125)	(2.483)	(0.253)	(5.600)
Change in timing of rainy season	0.262*	-0.666	-0.323	4.292
	(0.144)	(2.005)	(0.284)	(5.239)
Extreme events increase	-0.107	-1.979	-0.398	-3.358
	(0.090)	(1.571)	(0.237)	(5.972)
Wald Statistic $\chi^2(4)$	12.41**		8.57*	
F test		$F_{(4,751)} = 0.88$		$F_{(4,109)} = 0.33$
R^2	0.138	0.330	0.176	0.352

Standard errors are heteroskedasticity robust
*p<0.1, **p<0.05, ***p<0.01
In this table we omit the other covariates used in the regressions and only report the perception variables

5.5 Results

5.5.1 Household determinants of adaptation

We start by looking at the determinants of adaptation for each household with simple logit regression in Table 5.5. Only households that crop either wheat or rice are included. A binary variable indicating whether a household has adapted or not is the dependent variable. Each explanatory variable is measured at the household level. We do not include variables measured at the plot level, such as production inputs, in this regression. A set of district fixed effect terms are included in the regression to control for average regional characteristics such as climate and farming practices which vary across the country.[12] Although the estimated coefficients cannot be interpreted causally, we investigate the correlation between adaptation and these variables to see if they have the expected relationship on the probability of adaptation.

The results show some support for the role that gender could play in the adaptation decision since households with a higher proportion of women are more likely to undertake adaptation. There is also some support for the hypothesis that adaptation on-farm is

[12] We initially experimented with the inclusion of weather and climate variables but found these to be highly collinear with the regional dummy variables.

Table 5.5: Household determinants of adaptation: logit regression

Logit regression	
Dependent variable: Adapt (0/1)	Coef./se
Irrigated	0.001
	(0.258)
Max educ.	-0.001
	(.038)
Females in household	1.092**
	(0.449)
Work off-farm	-0.347**
	(0.146)
Bank credit	0.586**
	(0.266)
Informal credit	-0.460**
	(0.182)
Owns land	0.076
	(0.175)
Formal extension	0.590**
	(0.277)
Affected by flooding	0.906***
	(0.281)
Village school	0.586***
	(0.215)
Owns livestock	0.320**
	(0.159)
Total land (acres)	0.007
	(0.006)
Ave. temp increase	0.368**
	(0.179)
Change in amount of rain	0.195
	(0.234)
Change in timing of rainy season	0.360
	(0.257)
Extreme event increase	-0.448***
	(0.171)
Constant	-1.831***
	(0.549)
Pseudo-R^2	0.129
N	1065

Regression includes regional dummy variables
Standard errors are heteroskedasticity robust
*$p<0.1$, **$p<0.05$, ***$p<0.01$

substitutable for working off-farm, as those households with a member off-farm are significantly less likely to adapt. Interestingly, formal credit is positively related to the propensity to adapt, whereas informal credit is negatively related, providing suggestive evidence that credit channels affect the costs and benefits of investing in new technologies.

As expected, households who receive extension from the government or NGOs are more likely to adapt. Surprisingly, previous exposure to floods is positively related to adaptation, perhaps supporting the view that experience of extreme events primes households to adapt. Perhaps counterintuitively, households who also own livestock are positively associated with adaptation, not supporting the hypothesis that livestock rearing is a substitute for adaptation.

Subjective opinions of climate change are also interestingly related to whether households have adapted. It seems that those who adapted are more likely to perceive that average temperatures are increasing. However, adapters are significantly less likely to perceive extreme events, such as droughts or floods to have increased.

5.5.2 Endogenous switching regressions

In Tables 5.6 - 5.7 we present results for the crop-specific yield and determinants of adaptation. In column (1) of each table, coefficients are estimated by OLS where production functions are pooled across adapters and non-adapters. Columns (2) and (3) then present separate production functions for non-adapters and adapters. Column (4) shows the estimated determinants of adaptation which are read as probit estimates.

Wheat

Table 5.6 displays the coefficient estimates for farmers who crop wheat. Column (1) first displays coefficient estimates using OLS estimation, when adapting and non-adapters are pooled together in the same production function. The preliminary estimate of the impact of adaptation is shown by the the variable *Adapt*, a dummy equal to one if farmers have adapted and zero if not. This coefficient is significantly positive at the 10% level providing preliminary evidence that adaptation is associated with higher wheat yields. Given average wheat yields of 18.39 maunds/acre, this suggests a gain in productivity of approximately 8%.

The productive effect of plot-level inputs on productivity can also be seen for the pooled sample and in separate productivity equations for non-adapters and adapters in columns (2) and (3). Fertiliser and labour intensity both show expected positive coefficients, while there is evidence of diminishing returns to scale in plot size due to the negative sign of this coefficient. There is also some evidence to indicate the importance of household characteristics on farm production. Households who earn income off-farm seem to be less productive. Interestingly, households who use credit from formal sources are also less productive.[13]

The determinants of adaptation for wheat producers are shown in column (4). Here we see that households with a higher proportion of females are more likely to adapt, whereas those with a member working off-farm are less likely to adapt. This suggests that adaptation on-farm may be substitutable to earning income off-farm. Similarly, there is a lower probability of adapting for households that use informal credit. As is noted by Chandler and Faruqee (2003), this may be because informal loans are typically granted to fund consumption over short durations and are not sufficient to fund productive investments on-farm.

The significance of the extension service variable highlights the important role extension services play in facilitating farm adaptation. This accords with previous evidence that generally finds that extension services have positive effects on the adoption of productivity-enhancing technologies (Birkhauser et al., 1991; Hussain et al., 1994). Previous experience of flooding and ownership of livestock are also shown to be positively related to adaptation. The significance of the selection instruments can also be seen from coefficients on the climate change perception variables. These variables are included on the assumption that

[13]One explanation may be the finding of Chandler and Faruqee (2003) who document that households with very large landholding (>25 acres) account for 41.6% the receipt of formal credit. They argue that larger households are less productive than smaller households. This is the case for wheat farmers in the sample. Total land area was 14.7 acres for farmers using formal credit, compared with 8.5 acres for those without. Similarly, wheat plot size was on average 2 acres larger for formal credit farmers. As such, diminishing marginal returns to land may be driving this result.

Table 5.6: OLS and endogenous switching regressions: Wheat

	(1) OLS	(2) Yield Non-Adapters	(3) Yield Adapters	(4) Adapt(0/1)
	Coef./se	Coef./se	Coef./se	Coef./se
Adapt	1.473*			
	(0.857)			
Plot size (acres)	-0.530***	-0.858***	-0.250	-0.011
	(0.137)	(0.175)	(0.155)	(0.009)
Fertiliser (kg/acre)	0.316**	0.236**	0.279	-0.006
	(0.125)	(0.106)	(0.258)	(0.009)
Pesticide (kg/acre)	0.668	-0.090	1.915***	0.045*
	(0.712)	(0.509)	(0.412)	(0.026)
Labour intensity (no. of adults/acre)	1.219***	1.345***	1.037***	-0.020*
	(0.227)	(0.312)	(0.264)	(0.011)
Seed (kg/acre)	0.010	0.060***	-0.011**	0.002***
	(0.007)	(0.020)	(0.005)	(0.001)
Irrigated	0.696	2.903*	-1.705	0.081
	(1.210)	(1.568)	(1.787)	(0.135)
Max educuation	0.072	-0.022	0.225	0.001
	(0.210)	(0.273)	(0.307)	(0.022)
Females in household	-1.459	-0.622	-6.443*	0.594**
	(3.017)	(4.520)	(3.556)	(0.243)
Work off-farm	-1.858**	-1.137	-1.719	-0.174**
	(0.880)	(1.184)	(1.245)	(0.080)
Bank credit	-5.616***	-6.963***	-4.424***	0.216
	(1.282)	(2.362)	(1.431)	(0.150)
Informal credit	-0.328	-1.503	0.928	-0.306***
	(1.109)	(1.461)	(1.513)	(0.099)
Owns land	1.311	2.444	0.578	-0.033
	(1.168)	(1.837)	(1.461)	(0.095)
Formal extension	-0.435	-0.480	-0.116	0.524***
	(1.709)	(2.385)	(2.147)	(0.155)
Affected by flooding	0.871	2.348	-2.126	0.518***
	(1.580)	(2.295)	(2.180)	(0.157)
Village school	0.987	1.782	-1.208	0.291**
	(1.531)	(2.163)	(1.856)	(0.118)
Owns livestock	-0.314	-1.223	-0.087	0.192**
	(0.942)	(1.188)	(1.374)	(0.086)
Total land (acres)	0.031	0.175**	-0.090**	0.005
	(0.043)	(0.082)	(0.043)	(0.004)
Ave. temp increase				0.224**
				(0.102)
Change in amount of rain				0.100
				(0.134)
Change in timing of rainy season				0.322**
				(0.161)
Extreme event increase				-0.114
				(0.097)
Constant	16.049***	9.299**	30.015***	-1.504***
	(3.327)	(4.645)	(4.939)	(0.309)
Region dummies	Yes	Yes	Yes	Yes
lnσ		2.673***	2.527***	
		(0.110)	(0.061)	
ρ		0.033	-0.243***	
		(0.109)	(0.123)	
Log psuedolikelihood				-6288.513
Wald test of indep. eq. ($\chi^2(2)$)				0.128
N	1364	779	585	

Regression includes regional dummy variables
Standard errors are heteroskedasticity robust
*p<0.1, **p<0.05, ***p<0.01

they influence the probability of adaptation but do not affect realised productivity. It can be seen that farmers who perceived temperatures to be increasing and also those who thought that the timing of the rainy season had changed were more likely to have adapted.

To validate the importance of accounting for selection bias using endogenous switching regression approach, the results also show that the term ρ is negative and statistically significant for the adapters in the sample, indicating the presence of positive selection bias in the adaptation decision (Lokshin and Sajaia, 2004). Intuitively, this implies that those households with higher than average productivity are more likely to have adapted to climate change. This finding is similar to that of Abdulai and Huffman (2014) in the case of adoption of soil and water conservation technologies in Ghana.

Rice

The results for rice farmers are shown in Table 5.7. Immediately it can be seen from column (1) that the OLS estimate for adaptation's impact is positive and significant at the 5% level. The magnitude of this coefficient implies that gains from adaptation could be as high as 21% given average rice yield of 22.67 maunds per acre.

As expected, fertiliser intensity and farm labour has a positive effect on yields given their positive coefficients. Irrigation is also associated with strong productive benefits highlighting the importance of water use for a water-intensive crop like rice. Interestingly, household characteristics that are associated with labour availability have a negative effect on productivity. In particular, a higher proportion of females and off-farm work is associated with lower productivity. Reasons for the lower productivity of households with a high number of females may relate to the fact that in some cases, despite the availability of farm equipment, women's access to this is undermined, thus reducing the productivity of their labour supplied (Samee et al., 2015).[14] The lower productivity of households who engage in off-farm labour likely reflects the opportunity cost of using labour to produce income on-farm versus off-farm. This finding is in line with Fafchamps and Quisumbing

[14] Although women contribute heavily to crop production, they play an integral role in non-crop agriculture such as livestock rearing and in household chores such as food preparation, water collection, and care of children and the elderly (Samee et al., 2015).

Table 5.7: OLS and endogenous switching regressions: Rice

	(1) OLS	(2) Yield Non-Adapters	(3) Yield Adapters	(4) Adapt(0/1)
	Coef./se	Coef./se	Coef./se	Coef./se
Adapt	4.744**			
	(2.085)			
Plot size (acres)	0.029	0.550*	-1.547*	-0.037
	(0.476)	(0.294)	(0.835)	(0.033)
Fertiliser (kg/acre)	1.388**	1.963*	0.326	0.093*
	(0.603)	(1.036)	(0.754)	(0.053)
Pesticide (kg/acre)	0.857	-0.470	0.792	0.111**
	(0.530)	(0.577)	(0.740)	(0.053)
Labour intensity (no. of adults/acre)	0.507**	0.357	0.895**	-0.024
	(0.233)	(0.247)	(0.361)	(0.019)
Seed (kg/acre)	-0.026	-0.085	-0.062	0.009
	(0.061)	(0.086)	(0.084)	(0.006)
Irrigated	5.924**	4.173	2.863	0.454*
	(2.578)	(2.733)	(5.014)	(0.252)
Max educ	-0.397	-0.519	-0.693	0.025
	(0.578)	(0.811)	(1.010)	(0.064)
Females in household	-14.285**	-16.302*	-14.939	1.171**
	(7.061)	(8.736)	(9.928)	(0.555)
Work off-farm	-4.192*	-3.451	-6.954**	-0.132
	(2.319)	(2.989)	(3.446)	(0.188)
Bank credit	0.756	1.330	-1.779	0.458
	(3.394)	(4.272)	(4.506)	(0.337)
Informal credit	0.757	1.654	0.133	-0.321
	(2.574)	(3.523)	(3.663)	(0.220)
Owns land	2.518	6.000*	1.860	-0.530***
	(2.401)	(3.221)	(3.493)	(0.192)
Formal extension	0.204	-1.435	1.647	-0.631
	(3.001)	(2.788)	(5.834)	(0.454)
Affected by flooding	7.720**	13.332***	4.146	1.305***
	(3.570)	(3.983)	(4.810)	(0.338)
Village school	-4.308	-3.003	-11.718**	0.346
	(2.999)	(3.073)	(5.149)	(0.263)
Owns livestock	-0.007	-2.723	4.228	0.597***
	(2.940)	(3.345)	(4.130)	(0.215)
Total land (acres)	0.097	0.155	0.006	0.018
	(0.147)	(0.203)	(0.217)	(0.012)
Ave. temp increase				0.508**
				(0.203)
Change in amount of rain				-0.263
				(0.234)
Change in timing of rainy season				-0.333
				(0.263)
Extreme events increase				-0.525*
				(0.272)
Constant	7.653	9.617	40.858***	-2.099***
	(6.260)	(7.084)	(14.536)	(0.603)
Region dummies	Yes	Yes	Yes	Yes
lnσ		2.619	2.832	
		(0.070)	(0.101)	
ρ		0.153	-0.651*	
		(0.226)	(0.357)	
Log psuedolikelihood				-1384.125
Wald test of indep. eq. ($\chi^2(2)$)				0.128
N	297	161	136	

Regression includes regional dummy variables
Standard errors are heteroskedasticity robust
*p<0.1, **p<0.05, ***p<0.01

(1999) who find that male household members earn higher incomes off-farm, thus diverting their labour allocation away from farming.

Interestingly, households with experience of flooding are shown to be more productive. The magnitude of this effect is large for both groups, although only significant for the non-adapters. Although we must be cautious in interpreting this effect causally, there are two plausible reasons for this. Firstly, flooding can lead to the transportation and deposit of organic matter that increases soil fertility. Secondly, flooding could increase the amount of irrigation available, most likely from canal irrigation.[15]

The selection equation in column (4) shows that households that have access to modern inputs such as fertiliser and pesticide, as well as irrigation are more likely to adapt. This may be indicative of adaptation as a decision that, in line with many studies of technology adoption, is more likely to be undertaken by households that engage in more advanced cropping activities. As with wheat, households with more women are more likely to adapt. Contrary to studies that predict that land ownership increases incentives to invest in productivity-improving measures on-farm, ownership of land is negatively associated with adaptation (Jacoby and Mansuri, 2008; Ali et al., 2012). Similarly, exposure to past natural hazards as evidenced by previous flooding has a positive effect on adaptation as with wheat farmers. The need to address unobserved selection into adaptation can be seen by the significance the parameter, ρ, for the adapters in the sample. As with wheat, farmers with higher unobserved productivity are more likely to undertake adaptation.

5.5.3 Impact of adaptation

Adapters

A simple estimation of the impact of adaptation using a dummy variable to indicate adaptation in the crop productivity equations estimated by OLS showed that this variable was positive and significant for both wheat and rice. However, the above regressions

[15]Since rice is a water intensive crop, increased availability of water from irrigation could increase productivity. The most recent floods in 2011 and 2012 occurred in Sindh province. In our survey, a large proportion of households in Sangar and Sukkur districts were affected in both floods. Households from these districts form nearly half of rice producers in the sample.

Table 5.8: Impact of adaptation on yields of adapters

	Mean Outcome (units: maunds/acre)			
	Adapt	Not Adapt	Difference (ATT)	% Change
Wheat	19.573	19.274	0.299	1.6
	(0.345)	(0.460)	(0.367)	
Rice	33.926	31.175	2.751***	8.8
	(0.844)	(0.636)	(0.742)	

Table 5.9: Impact of adaptation on yields of non-adapters

	Mean Outcome (units: maunds/acre)			
	Adapt	Not Adapt	Difference (ATU)	% Change
Wheat	23.398	17.193	6.204***	36.1
	(0.351)	(0.361)	(0.231)	
Rice	47.245	28.376	18.869***	66.4
	(1.186)	(0.836)	(1.020)	

indicated the presence of positive selection bias for farmers that adapted to climate change. As such, more productive households were those that were more likely to have adapted. To estimate the impact of adaptation to account for this, we estimate the average treatment effect on the treated (ATT) derived in equation (5.12).

Table 5.9 shows the estimated change in crop productivity for those that actually adapted. For rice, compared to the OLS estimate of 1.473 maunds per acre increase in yield for adapters, the selection bias corrected estimate of adaptation is estimated at 0.299 maunds per acre and not statistically significant from zero. For rice, the treatment effect estimated by the endogenous switching approach is also less than that when estimated by OLS, falling from 4.744 to 2.751 maunds per acre. In contrast to the impact estimate for wheat, this is significantly positive, indicating productivity benefits of around 9 percent for farmers that adapted. The results for rice compare in magnitude to those in a recent meta-analysis of the effect of temperature and adaptation on crop yields at the regional-scale using crop simulation models. For instance, Challinor et al. (2014) find that adaptations at crop-level for both rice and wheat increase yields by 7-15% on average.[16] The benefits of adaptation are also studied by Soora et al. (2013) for rice yields in India using a simulation model. They find that in irrigated rice areas, agronomic improvements, such as shifting cropping dates and switching rice varieties, offset expected climate change damages of around 5% up until 2040.

Non-Adapters

Using the treatment effects framework we are also able to estimate the change in productivity for non-adapters had they adapted. The average treatment effect on the untreated (ATU) for these farmers is shown in Table 5.9. It is noticable that the estimated gains from adapting for this group of farmers are much larger than for adapters. For wheat farmers, we estimate that the adoption of adaptation strategies could lead to yield gains of around 36%. The gains for rice are even larger at over 60%.[17] These results are large, and indeed, suprising given the relatively smaller gains estimated for adapters. The explanation may lie in the counterfactual that is being estimated. As is noted by Shiferaw et al. (2014), the ATU reflects the difference in outcomes if non-adapters had similar characteristics to adapters. As such, these differences could reflect the effect of relaxing the constraints on non-adapters and the associated benefits that this would have on productivity.

5.6 Discussion and Conclusion

This study investigates whether strategies used by farmers to adapt to climate change lead to higher crop productivity for farmers in Punjab and Sindh provinces of Pakistan. We also study factors that affect whether farmers have adapted to climate change or not.

We estimate that farmers who have previously adapted to climate change have benefited in terms of productivity improvements for rice. The results for wheat farmers suggest that

[16] In accord with our study, Challinor et al. (2014) consider only ‘incremental’ changes to current crop production practices such as changes in cropping dates or switching varieties.

[17] A similar result was found by Di Falco et al. (2011) in Ethiopia who estimate much larger gains for non-adapting farmers.

there are positive gains to adaptation but these are not statistically different from zero. This highlights the importance of considering differences in crop responses to adaptation. While gains from adaptation for rice estimated here at the farm-level in Pakistan add credence to results at more aggregated scales from crop simulation models, it is interesting that we do not see very significant gains for wheat. One possible explanation could be that adaptations are not effective at increasing average yields. As is noted by Sultana et al. (2009), shifting planting dates of wheat to later in the year is a key adaptation strategy. Indeed, one-quarter of farmers in our sample use this strategy. Since this effectively reduces the length of the growing season, it is possible that farmers are trading-off the potential benefits of a longer growing season for the security of growing wheat during more temperate months. For instance, Semenov et al. (2014) study adaptation of wheat to climate change in Europe and find that although the use of quicker maturing varieties are a useful adaptation for avoiding months where temperatures are hottest, use of these varieties is associated with lower yields due to the shorter growing durations. As such, avoiding yield losses due to risk averse preferences may be a primary factor in farmers' adaptation decision. This highlights an interesting area for future work that examines whether risk preferences of farmers are significant in explaining their adaptation and the benefits of these decisions in terms of productivity.

The regression results showed the importance of accounting for unobservable differences between adapting farmers and non-adapters. Specifically, it was shown that unobservable factors associated with higher crop productivity were present among adapters in our sample. This appears to explain why estimates obtained by OLS were larger than those when accounting for selection bias. Positive selection was present for both wheat and rice. These findings suggest that it is important to account for factors that drive the decision for farmers to adaptation.

Estimated productivity gains for non-adapters are found to be large. Given that adaptation is practiced by more productive farmers on average, we interpret this finding to indicate that there are significant opportunities to increase the food security of farmers. Unobserved differences between farmers may indicate the existence of high transaction costs that inhibit current non-adapters from adapting. Given that many farmers perceive the climate to have changed to some degree, the reason for not adapting could reflect differences in the cost of adapting or other constraints that hinder non-adapting farmers from make potentially yield improving adaptations.

Observable determinants of adaptation also provide evidence that institutional factors play an important part in allowing farmers to adapt. We find that access to credit is important. However, it appears that the *type* of credit crucially affects the propensity to adapt. Whereas informal credit reduces the probability of adapting, formal credit increases the probability of adaptation. This underlines the need for a greater expansion of the reach of formal credit, which is currently used by only a minority of farmers. The heterogeneity of institutions providing credit to farmers in rural Pakistan is large. This study underlines that variation in the specific form of these institutions has important effects on agricultural development. Similarly, it is also the case that access to extension services provided by governmental and non-governmental organisations is associated with a higher probability of adaptation. An obvious policy response to this would be to increase access to these services.

Growth in the wider economy may provide opportunities and incentives for household members to earn income off-farm. We find evidence that households engaging in these alternative income generating activities are less likely to engage in on-farm adaptation. Given that the off-farm labour variable is associated with lower productivity also, it appears that there is some substitutability between investing in productivity-enhancing measures on-farm versus allocating time and effort off-farm. What this pattern implies for the incentives to conduct adaptation on-farm over a longer time horizon is a very relevant question that also warrants further examination. Overall, these results imply that farmers can potentially increase crop productivity in the short term whilst also undertaking measures that could prepare themselves for climate change. Policymakers thus should focus on encouraging the adoption of these practices as a strategy for addressing future food security in Pakistan.

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Chapter 6

Conclusion

This thesis comprised four essays that sought to assess the role that environmental constraints to production, in particular those related to the climate, have on agricultural productivity in India and Pakistan. In employing empirical methods to understand these relationships, special emphasis was placed on how these methods can be used to learn more about the challenges that agriculture will face in the future. In addition, understanding how farmers have previously reacted to these constraints is also vital for discerning whether or not attempts to alleviate these constraints have been successful at reducing the future costs of climate change. What is identified in this thesis is that the constraints posed to agricultural production must be understood within the context of an evolving set of environmental and technological conditions. If both of these factors are not considered, it is likely that future assessments of food security in South Asia will provide a misleading account regarding the future of the region's agricultural production. This concluding chapter summarises the results of each of the preceding chapters as well as discussing the implications of the findings of this research for policy and directions for future research.

The degree to which climate change could affect agricultural productivity is examined in Chapter 2 by assessing how projected temperature increases could affect rice production in India. The findings of this paper predict that, in addition to a decline in average yields, higher temperatures also have important effects on the overall probability distribution of rice yields. Rather than an increase in temperature entailing a simple shift in average yields, greater exposure to heat was shown to increase the likelihood of yields at the extreme ends of the distribution. This effect increases the exposure to downside risk. These findings have implications for both researchers and policy makers. Firstly, future climate change impact studies would benefit from considering changes in the shape of the crop yield distribution, which may be substantial. Although this chapter highlights this empirically, there is room for future work to theoretically understand these mechanisms. Mapping how changes in temperatures could theoretically alter the shape of crop yield distributions would be an important step to a more detailed understanding of the effects of climate change in agriculture. Secondly, policy makers should also be aware of the extra risk that may be posed to agriculture by increases in temperature. This may entail greater emphasis put on dealing with *ex post* risk, such as crop insurance.

A key finding from this study is the relative decline in the effect that short-run temperature deviations have on agricultural productivity over time. This underscores the importance of considering climate change within the context of a changing agricultural sector. There are two main implications that stem from this. Firstly, it emphasises the need for future work to understand the drivers behind increased resilience of crop yields to heat. Given that higher temperatures are predicted to adversely affect rice production in India both in terms of affected average yields and downside risk, understanding exactly how these negative impacts can be avoided is a first order concern for policy makers in India. Secondly, in predicting the impacts of future climate change on agriculture, this work highlights that researchers should pay attention to how the resilience of the sector has changed over time in order to accurately assess these impacts. Since many empirical studies rely on variation between weather outcomes and measures of productivity over time, it should not simply be assumed that conditions in the past necessarily reflect those of the present.

In line with the findings of the previous chapter, Chapter 3 also presents evidence that crop production in India has become more resilient to drought. By examining drought impacts over time, this chapter was able to identify a reduction in average yield losses owing to drought conditions. As with the previous study, the reasons for these trends are not studied in this chapter. The decline in drought impacts does, however, accord with the wider diffusion and maturing of a suite of yield-increasing technologies by farmers in

India that began during the Green Revolution. Judging by this evidence alone, it might be tempting to conclude that the threat to agricultural productivity from drought in the future is not a pressing concern.

What is made clear in this study, however, is that there is evidence that these trends may be prone to significant changes in the future. By employing an empirical approach able to identify critical points between which drought impacts have significantly changed, we notice a substantial increase in average impacts towards the end of our sample period. While this period corresponded with the significant period of increased drought intensity, this result highlighted that policy makers should certainly not be complacent about previous trends in increased resilience of the sector. Indeed, this result may bring some credence to concerns about the unsustainability of a number of aspects of India's agricultural sector. One aspect of this is likely to be the availability of water. Previous studies have highlighted the key role this resource has played in constructing production environments suitable for modern agriculture and to increase resilience of crop yields during drought (Duflo and Pande, 2007; Birthal et al., 2015). The unchecked exploitation of the resource, however, has led to observations of severe depletion of water sources (Rodell et al., 2012). This is unlikely to be helpful for farmers during periods of drought and casts a shadow over the findings of increased resilience of the India agricultural sector to climatic stress over time. This highlights the need for future work that integrates information on the resources available to farmers and how changes in the availability of these resources may constrain future adaptation strategies to cope with climatic stresses.

The results in Chapters 2 and 3 also place emphasis on understanding the regional distribution of food security challenges. The policy relevance of considering regional exposure to drought impacts is underlined in Chapter 3. Given the variety of growing environments in which agriculture takes place in India, it is hardly surprising that these areas differ in vulnerability to drought. However, what is clear from this analysis is that failing to account for the regional heterogeneity in exposure to drought impacts would lead to an inefficient way for policy makers to prioritise resources to deal with the adverse consequences of drought for agricultural production.

The importance of considering regional heterogeneity is also explored in Chapter 2. Here it was shown that the impacts of future temperature increases are likely to be larger in areas already more exposed to higher baseline temperatures. In addition to this, these areas could see significant changes in the likelihood of yields that were historically relatively rare events. In particular, the vulnerability of India's most productive regions in the north of the country may increase relative to other areas, such as areas in the south, which will likely be subject to smaller increases in absolute temperature. The regional heterogeneity of impacts presents some interesting challenges to policy makers. Given that higher temperatures will make hotter areas in India increasingly less suitable for rice production, it will fall on policy makers to decide whether resources would be better aimed at areas projected to be less affected by climate change. Given that the sustainability of Green Revolution production systems are also facing constraints due to water scarcity, the added effect of rising temperatures could add to the unsustainability of the rice-wheat production systems in areas such as Punjab, which have historically been important for the food security of India. The political feasibility in reality may, however, be more limited. Given the political clout of some of the most productive areas in India that benefitted substantially from the Green Revolution, a significant diversion of resources away from these areas may be hard to achieve.

The long-term consequences of India's Green Revolution and its relationship with the environment are further investigated in Chapter 4. While the productive success of these technologies over the past fifty years is well documented, evaluating potential weaknesses of this model is important for understanding the long-term consequences of these technologies. This paper studies whether agricultural technologies employed during this period were more effective at increasing yields on land more agro-climatically suitable for crop growth. This has historically been a criticism of the Green Revolution owing to the contention that Green Revolution technologies had an uneven effect across regions and subsequently led to divergent productivity growth in agriculture across India. What is emphasised in Chapter 4, however, is the importance of understanding this question in the context of developing technologies that work effectively across different environments. This study finds that yield growth was highest in areas that were agro-climatically most suitable. In one respect, these findings point to a weakness in the Green Revolution model of centralised technological innovation and infrastructure development. On the other hand, the productive success of this model should not be wholly overlooked for addressing the challenges of the future. A hard-headed approach by policy makers may be needed in the coming years to ensure these productive gains continue. One strategy may be to target resources into developing technologies at growing areas that may be less affected by future climate change to maintain levels of total production.

Assessing the cost of the future impacts of climate change is limited by the inherent uncertainty about the range of options that will be available to farmers in the future. Although this uncertainty is ever present, learning about the range of options available to farmers to mitigate potential climate change in the future is important. Chapter 5 sought to provide a greater understanding of the impact that climate change adaptation strategies could have on productivity. This is undertaken within the context of two major agricultural areas in Pakistan. Crucial to this study was the use of farm-level data from a specifically designed survey on farmers' climate change adaptation strategies. While previous studies have examined the impact of climate change adaptation strategies in other parts of the world, providing information to policy makers in other contexts about the nature of these strategies and their productive impact is needed. This study found some evidence that adapting to climate change can have short-term productive benefits. This provides evidence that by using technologies and practices that are currently available, farmers can productively benefit. While we should be cautious not to necessarily attribute these findings to how successful these techniques will be at dealing with future climate change, it does provide some evidence that these technologies work better under current climatic conditions.

A particularly relevant finding for policy from this study pertains to the importance of the set of constraints that farmers face in effectively adapting to climate change. Indeed, a counterfactual analysis undertaken in this paper found that gains from adapting to climate change could be very substantial. This highlights a crucial lesson to policy makers for enabling farmers to autonomously react to changes in the climate. If farmers will be able to act to undertake suitable adaptations in the future, it is necessary for policy makers to make it easier for them to do so. What is apparent from this study is that a number of the determinants concerning whether or not farmers have adapted correspond to constraints to technology adoption identified in many other developing country contexts (Sunding and Zilberman, 2001; Foster and Rosenzweig, 2010). While relaxing these adoption constraints is likely to increase the welfare of individual farmers, policy makers should also be aware of the importance of allowing farmers to efficiently undertake adaptation in order to maintain aggregate food security under the stress of climate change. In short, it is important not just to consider the constraints of that are posed by climate change. It is also vital to consider the opportunities that exist to increase agricultural productivity in the future and make sure that these are utilised.

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Appendix A

Survey Evaluation: The Determinants, Impact and Cost Effectiveness of Climate Change Adaptation in the Indus Ecoregion: A Micro Econometric Study

A.1 Survey context

The survey was conducted with the aim of increasing understanding of the resilience of Pakistan's agricultural sector to climate change and was supported by the International Development Research Centre (IDRC Project Number 106857-001). The survey was jointly undertaken by partners from the WWF-Pakistan, Lahore University of Management Sciences, and the London School of Economics and Political Science.

The main data collection part of the survey took place between the 20th April 2013 and the 29 June 2013. In total, 1,422 households were surveyed.

The final survey comprised of six separate sections that gathered information on household characteristics; agricultural outputs and inputs; labour use; institutional arrangements; climate change adaptation measures; and household income. The detailed nature of the survey was intended to understand a range of characteristics that may affect agriculture and resilience to climate change in Pakistan. A copy of the survey is included at the end of this thesis.

A.2 Sampling frame

The survey took place in the two provinces of Punjab and Sindh, and was sampled in four of the nine key agro-climatic zones in Pakistan. Barani (rainfed) agriculture in Punjab; cotton and wheat in Punjab; cotton and wheat in Sindh; and rice growing in Sindh. Although it was initially considered to survey households in Baluchistan, security concerns at the time of scoping the survey meant it was not possible to study this area.

To further narrow down the sampling frame in these two provinces, seven different districts were chosen across the chosen agro-ecological zones. These districts were thus selected non-randomly based on whether they fell in the chosen growing areas. In Punjab, the survey sites were located in the districts of Chakwal, Rawalpindi, Rahim Yar Khan, and Jhang. In Sindh, responses to the survey were gathered across the districts of Sangar, Sukkur, and Larkana.

A.3 Sample selection

To select sample sites within agro-climatic zones a two-stage cluster sampling strategy was applied to the seven districts. This meant that a set of random villages or 'clusters' were selected in each district. Within the selected clusters, a set of randomly chosen households were then surveyed.This approach allowed us to offset the prohibitive financial, time, and informational constraints required to elicit a simple random sample.

A.4 Design and pre-testing

Prior to the design of the full survey, a reconnaissance survey was conducted during 15-18th December 2012. This survey had a number of objectives. First, it was essential to establish relationships and gain trust of key village informants who would provide local knowledge and ensure that survey teams could freely travel around survey sites. Second, focus group sessions were held with local farmers in order to gain a preliminary understanding of local agricultural issues. A copy of this survey is also included at the end of the thesis.

Focus groups comprised groups of roughly eight to ten farmers, who were interviewed by enumerators from WWF-Pakistan. The focus groups were asked a total of 84 questions on their farming activities (types of inputs and outputs used; prices; water use; cropping dates; harvesting methods), institutional arrangements (types of credit, subsidies), and farmers' perceptions and reactions to climate change. The focus groups questions on climate change were integral for designing an effective set of questions concerning farmers climate change adaptation strategies. Accordingly, the focus group asked farmers whether their farming practices had changed in the past five years and their motivations for this change. Responses ranged from changing practices due to the availability of new technologies to utilising a series of strategies to cope with changes in climate patterns, such as increased heat earlier in the growing season and unseasonal rains. What was clear from the survey was that farmers were concerned about a range of climatic phenomena that they felt had changed over time, more specifically in the last 5 to 10 years. Audio recordings of the focus groups were also made for use in designing the main survey.

A key finding from the focus group concerned the complexity of institutional arrangements governing farm production in Punjab and Sindh. This identified two key aspects that had previously not been given due consideration. The first concerned the role of that credit played in allowing farmers to buy inputs and generally smooth consumption. The most important aspect of this related to the providers of credit. In particular, the role of informal moneylenders or 'middlemen' was identified as a crucial. This enabled for a more thorough set of questions on sources of credit and the role of middlemen to be incorporating into the survey. Second, the role of tenure arrangements was specified by farmers as having a bearing on their ability to conduct on-farm decisions. This often related to farmers often receiving instructions from landowners about farming decisions, which could act as a constraint to changing farming practices. These findings were used to inform a set of questions on institutional arrangements in the main survey.

In addition, the focus groups allowed for a greater understanding of the various strategies used by farmers in response to climate change and their perceptions about how the climate was changing. Accordingly, farmers were asked about whether they had used any strategies in response to climate change, and to explain what these strategies were. These responses were then used to group adaptation strategies by type for the main survey. It was also made clear from the focus groups that farmers perceived that various aspects of the climate had changed over time, including higher average temperatures and changing patterns of rainfall. The responses from the focus group were used to design survey questions that allowed farmers to pick from a number of possible types of adaptation measures and aspects of the climate that they perceived to have changed.

Using the results of from the focus groups, a survey was then drafted to collect data on the areas of interest for research. A first draft of this survey was then sent to experts specialising in agronomy and rural economics in Pakistan for feedback. Comments from these experts were then incorporated into the final draft of the survey.

A.5 Training of enumerators and field conduct

In order to train enumerators in how to conduct the survey in the field, a one-day workshop was held in Karachi to ensure that enumerators followed the same collection procedures across survey sites. Senior members of the team who had played a part in the survey design took enumerators through the survey. This included explaining the purpose of each of the questions and specifying the way that each question should be asked and how each response should be filled in on the questionnaire. After this, the enumerators were then split into pairs to mimic asking and responding to questions in the field.

The survey was designed and recorded in English. The decision was taken for enumerators to translate the questions in the field. During the training session, senior members of the survey team discussed and trained the enumerators in how to translate each question and what would be possible terminology used by the local people/farmers. The decision to administer the survey through enumerator translation was taken for two reasons. First, the primary languages spoken across Punjab and Sindh differed, so that translating the surveys into different languages would lead to additional costs and time. Second, since it was expected that a number of surveyed farmers would not be literate, enumerators skilled in the local language would have to ask these questions nonetheless. Therefore, this method of translating the survey was chosen as the most practical means of eliciting survey responses.

Senior enumerators undertook pre-testing of the survey in order to test the length of time needed for each survey to be undertaken. This allowed for the identification of possible translation issues. Senior enumerators then accompanied hired enumerators into the field to ensure that issues identified in pre-testing were corrected during the main survey. Senior enumerators accompanied the hired enumerators to at least three surveys before these enumerators were left to survey in their specified teams, although senior members of staff were available by phone to answer queries brought up in the field. On average, the survey took 30 to 40 minutes to complete and were completed on paper. In the main, surveys took place on respondents' farms or in their houses. The household head responsible for farming activities was asked for their responses to the survey. In a number of cases, household heads were not found on farm but in local communal areas, such as teahouses. Surveys were then conducted in these areas if the respondent agreed to be surveyed.

Once all of the surveys were completed, the responses were entered into a single Excel table by WWF-Pakistan staff in Karachi. This raw data was then sent to London for analysis.

A.6 Possible sources of bias

A.6.1 Length, complexity, and inaccuracy of survey responses

The survey aimed to gather a comprehensive set of data on farm household behaviour and characteristics in Pakistan. One downside of this approach was that the survey was lengthy and required considerable concentration from the enumerators and survey participants. Although it is not clear whether the length of the survey led to biased responses from participants, some evidence of errors in the reporting of responses was clear. This manifested itself in some repeated responses to questions (e.g. the amount of fertiliser used on separate plots of land). Without follow up questions to assess the suitability and length of the survey, it is not possible to understand whether this was a significant factor in the survey.

Two strategies were undertaken at the data cleaning stage to improve the accuracy of survey responses that may have been prone to error in recording. First, the data was viewed by eye in Excel tables to check for inconsistencies. Obvious data entry errors, such as data clearly being entered in the wrong columns, was corrected. Second, incoherent responses were dropped from the analysis if these occurred in data that was used to construct variables used in the analysis.

Since farmers were asked a variety of complex questions related to quantities and timings, it is perhaps understandable that some error would have occurred in the collection of survey responses. In particular, inaccurate assessments of land holdings would clearly lead to error in the recording of acreage and, hence, farm yield estimates. It was discussed prior to the data collection phase whether it would be possible to accurately collect data on plot sizes through independent verification by enumerators during the survey. This method, however, was deemed not suitable since it placed additional costs and need for expertise from the enumerators. It would also have meant additional intrusion on farm households. Thus, future surveys could build extra resources and technology into more accurately recording these variables and taking some of the onus off farmers. Despite this, it is the case that most of the responses in the survey require accurate recollection from the farmers. Eliminating any recall bias that could have occurred in the survey would require a more thorough, timely, and resource-intensive data collection procedure. Future surveys would benefit from explicitly assessing the time and resource trade-offs that exist between the number of households surveyed and the amount of time ensuring data is collected to the highest possible accuracy.

A.6.2 Measuring farm input and output prices

It was the aim of the survey to gather detailed data on the price of farm outputs sold and inputs bought so that it would be possible to construct net revenue functions. It was, however, apparent during the data cleaning stage that significant problems had occurring in correctly ascertaining farm prices. There was significant variation in prices across farmers for the prices that were paid for farm outputs. Enumerators questioned about this following the data collection responded that many farmers had problems identifying the prices certain crops were sold for since often these were sold as part of interlinked transaction with moneylenders or landlords. This made it difficult to accurately assess output prices and it was decided that the primary variable of interest would be crop yield (amount produced divided by area). Another problem encountered was for input price data. Prices were missing for many inputs used. There are two main reasons this may have happened. Firstly, as with farm outputs, many farmers used inputs in tandem with complex interlinked arrangements, meaning that they were not fully aware of prices paid. Second, a number of inputs, such as water, did not have a clear price since institutional arrangements covering water usage and pricing are complicated. These variables showed significant amounts of missing data and it was not clear whether this was due to prices being zero or whether farmers were unable to answer this question.

A.6.3 Measuring adaptation practices

An important and novel aspect of the survey pertained to the collection of data concerning whether or not farmers had adapted to climate change. Significant effort was put into ensuring that information on adaptation was as accurate as possible.

A key concern during the survey design stage was that farmers would attribute general changes in farming methods, such as the adoption of higher yielding seeds, to adaptation even if these were not adopted to cope with changes in climate. To minimise this possibility, enumerators were instructed to directly ask farmers, 'How has your household adapted to cope with climatic changes?'. A concern was that farmers might be prompted by enumerators to answer that they had adapted when they had not. To minimise this risk, the farmers response to the question was recorded rather than a series of options being read out to the farmer. Farmer responses were then grouped according to the type of adaptation by the enumerator. This was recorded in question E6 in the survey.

In addition, to minimise the possibility that farmers were giving vague answers to adaptation survey questions, a series of follow up questions specifically related to adaptation strategies were asked. These are shown in sections E8 to E12 in the survey. For instance, farmers who answered that they had changed their planting or harvesting dates were asked for new planting dates and previous planting dates.

Given the large amount of information collected on adaptation practices, the analysis reported in Chapter 5 of this thesis serves to answer only a direct question about the nature of climate change adaptation in Pakistan. Further analyses using this data could interrogate particular types of adaptation, their determinants and impact.

Reconnaissance Survey - Schedule (15 - 18 Dec 2012)

15 Dec 2012 - Day 1	
Meeting with WWF- P staff and key informants	- Arrival in Sanghar by 12 pm - Meetings with key informants to: • To finalise itinerary for the field visit, and decide meeting point and date/ time for focus group meeting at all clusters. • To establish 3 groups of enumerators (3-4 each) and assign deliverables for next days' focus group meeting respectively. • Collate data from WWF- P staff and key informants for sampling excel sheet containing villages' names, number of households, average household size, etc for output 4. • Collect information to complete output 1, 2, and 3. • Input on logistical concerns, e.g. CBO Rep or guide availability for the main survey.
16 Dec 2012 - Day 2	
Focus Group Meeting in Cluster 1 (Union Council: Mian) **Villages include _____**	- Reach the village at 10 am. - Conduct meeting with 3 focus groups (of preferably of 8-10 wheat growers) which are to be interviewed by 3 groups of enumerators respectively. - Enumerators to administer the given questionnaire with each group. - Further, each enumerator group to assign a specific output based on the above mentioned deliverables. - Record the complete interview and take notes. - Finish the meetings by 5 pm. - Compile and streamline collected data in the required format.
17 Dec 2012 - Day 3	
Focus Group Meeting in Cluster 2 **(UC: Shah Sikandarabad)** **Villages include _____**	- As above
18 Dec 2012 - Day 4	
Focus Group Meeting in Cluster 3 **(UC: Mian)** **Villages include _____**	- As above.

Survey Output:

	Task	Description	Output	Responsibility
1	Homogenous Sample	• Establish homogeneity of farmers based on types of crops grown, Land size holding, rain fed vs. irrigation, fixed capital.	Work Sheet	IA and AS
2	Stratification and Sub-groups	• Deliberate sampling of certain characteristics for treated, untreated and control group: a) Treatment type 1: Farmer field school participants (WWF or others) for adapter vs. non adapters grouping. b) Treatment type 2: Flood affectees with in last 3 years and within last 10 years. • Evaluate feasibility of sampling such as possibility through CBO Rep, cost of the sample, etc.	Listed by total numbers on work sheet	IA and AS
3	Target No of Questionnaire	• Identification of zones at each site, and sub-division of zone into clusters to achieve a sample size of 250 at each site. • Identification of villages within each cluster respectively. • Setting target number of respondents per zone, by cluster, by hour of the day, etc.	Representation of zones with villages marked on a Map	IA and AS
4	Excel sheet for random sampling procedure	• Work sheet with column on a) Village name, b) average household family size, c) number of households in each village, d) village population. • Work sheet for treated groups type 1 and 2	Excel Sheet, (format attached).	AS
5	Questionnaire Design	• Details on farming activities, processes and naturally occurring payment vehicle. • Phrasing of the questions • Terms in the local language • Input on unit of measurement (acre, maund) • Information on Adaptation practices	Audio recording of focus group meetings, and detailed notes	Enumerators
6	Logistic arrangement	• Distance between clusters, and other logistical aspects that would finalise the total number of enumerators and vehicles needed. • Identify/ meet 1-2 CBO representatives for each zone who could assist in gathering respondents for the survey. Set meeting point and date/ time for each settlement, or possible zone.	Excel Sheet.	AS

Questions for Focus Group meeting:

Details on farming activities, Input, Output

1. What crops are grown in past 12 months? Name and duration in months?
2. Date of sowing and harvesting for all crop grown in a year.
3. Are these typical for the past 10 years? What other crops do you grow?
4. What is the yield of each crop this year (in maund)? What was it last year?
5. What is the selling price of each crop this year? (in maund) What was it last year?
6. What is the area of your farm? (In acres)
7. Are you the owner or is it on lease? What are the terms of lease?
8. Are terms affecting by owner offloading cost of crop loss onto you? Is this because of climate change or other reasons?
9. Have you cultivated wheat as yet? Date of sowing?
10. What was the crop immediately before, and immediately after wheat?
11. Is this cropping order strictly observed each year?
12. What is the support price of wheat in 2011 and 2012?

Water Source:

13. Is this a Barani area or Katcha?
14. Do you receive water through Canal system?
15. Does it lower cost of your irrigation? First, second or which one? By how much does it reduce unit cost of the concerned irrigation?
16. Is the canal water available throughout the season? If not, which month is it available and for how long? Reasons?
17. What are its charges per season in PKR?
18. Who collects the money for canal system? Extension officer or do you deposit yourself in Bank? What month of the season?
19. Do you also use tubewell for water? For which crop?
20. Is it owned or rented?
21. Where do you rent from? What is this year rent (in PKR)? Are the terms of rent in days or for No of hours used?
22. Do you rent the tubewell for the complete season or for each application?
23. What is the method of irrigation? e.g. flood, drip, furrow etc.
24. How many hours in a day do you receive electricity for tubewell?
25. If not, electricity, how do you power your tubewell?
26. How many times do you normally irrigate for a wheat crop? And for other crops grown in a year? How many hours each time?

Land Preparation:

27. How many days are needed for land preparation for wheat and the other crops grown? Explain the steps?
28. What equipment are needed for land preparation? Names in Sindhi, Urdu and English as well.
29. Are the equipment rented or owned?
30. Cost of equipment and rent in PKR? Is the rent inclusive of fuel charges?
31. How many household people are involved in land preparation activity?
32. How many days by each household member? How many hours do they work in a day?
33. Do you involve household female and children in this activity? How many hours in a day?
34. Do you hire labor for this particular activity? Is the hiring by number of days, or for the complete season?
35. Do you pay wages daily, monthly or for season? Do you also pay in kind or money?
36. What is the wage rate/day?
37. How much water is required for this activity? (In hours)
38. Do you apply pesticides, weedicides, UREA or DAP as this stage?
39. How many Kgs of each item for 1 acre land?
40. What is the cost of one bag of each item?
41. Do you receive information from any source on when to cultivate? Name the source?
42. Do you pay for this service? And Is it reliable?

Planting Activity

43. How many Kg of seed is required for one acre of land?
44. Where do you buy the seed from? Is it your own?
45. Do you receive advice from any source on which variety of seed to use? Name the source?
46. How do you sow seed? Method?
47. Do you broadcast the seed yourself, household member or hire labour?
48. How many people do you hire for one acre of land? For how many days?
49. What do you do for planking? Name the equipment and its rent?
50. Do you water the field as well? Name the source used?
51. How many hours do you water at this stage?
52. Do you also use fertilizers and Weedicides at this stage? How many kgs?
53. Which input among all your input is the most critical for the success of wheat crop? Cotton? And any other grown crop?
54. Does wind lower wheat or other crops' yield (via dust gathering on leaves)? Do you ever do an additional irrigation or use labor to wipe leaves?
55. Have higher night time temperature caused a decline in yield?
56. Has the yield been affected by extreme heat stress? How much does it affect irrigation cost? Give example.

Harvesting:

57. Which equipment do you use at this stage? Name the equipment and its rent?
58. What is the fuel cost of this machinery for one acre of land?
59. Do you hire labor for threshing? Or is it done by household members?
60. How many people are required for one acre of land? And for how many days?

Post-Harvest Activity:

61. Where do you sell your produce? Local market or middle men?
62. Is this a government middleman?
63. What is the commission of the middleman? (% per mound)
64. Do you store your produce or sell immediately? Where? (Underground or Silo)
65. What is the cost of storage per year?
66. How do you transport your produce to the market?
67. Is it a rented vehicle? What is the rent in PKR?
68. Typically what is the share of home consumption of wheat or rice? Is it used for feeding cattle or given to any other relative or neighbor? Free or charged?

Institutional Arrangements:

69. Have you asked for a loan in the last five year? Source?
70. What are the terms of the loan? Interest? Duration?
71. Do you receive any government subsidy? On seed, fertilizers, etc.?
72. Is it provided annually or for each season?
73. Any other subsidy from other sources like NGO etc?

Adaptation Practices and other information:

74. Were you affected by flood in 2010 or flash rains in 2011 and 12?
75. Did you suffer any loss in these events?
76. Were you affected in floods in the past 10 years?
77. Have you changed your agricultural practices or cropping pattern in the past 5 years?
78. What was the motivation for this change? Provide an example.
79. Have you brought any changes in your agricultural practices due to delay in rain?
80. What cost did you incur? Give concrete example.
81. Have you done any measures to cope with unseasonal rain?
82. What are typical economically motivated adjustments in farming activities? Provide example
83. Have you participated in any farmer field school programme by WWF?
84. Or any other Farmer field school participation (Govt or other NGO)?

Questionnaire No. |__|__|__|

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LUMS

"The Determinants, Impact and Cost Effectiveness of Climate Change Adaptation in the Indus Ecoregion"
Micro Econometric Study

HOUSEHOLD SURVEY (1,600 households)
(Household is defined as group of people living under the same roof and sharing a budget for food)

IDRC CRDI
International Development Research Centre
Centre de recherches pour le développement international

Complete address:________________ village name: ________________ Union Council: _____________

Village GPS Code:_________ HH GPS code___________

Name of Respondent with Father's/Husband's Name:_______________________________________

Age of the respondent:

National Identification Number (NIC) of the respondent _____________________________________

Cell Number of the respondent (optional) ____

Relationship of the Respondent with the Head of Household:

Relation with head of the household:

1. Self;
2. Wife/husband;
3. Son/daughter;
4. Son-in-law/daughter-in-law;
5. Grand son/grand daughter;
6. Mother/Father;
7. Brother/sister;
8. Other relatives;
9. Other non-relatives

Date of interview:

1st visit __/__/__

Interviewer's name : ____

Supervisor's name : ____

Checked by : ____.____
(Checker's Name & Signature)

Edited by : ____.___________
(Editor's Name & Signature)

Relevant Codes:

NA: Not Applicable
DK: Don't Know
Zero: O
P: Protest

SECTION A: HOUSEHOLD CHARACTERISTICS

A1. Basic structure and livelihood source

A11. How many persons usually live in this household? (Exclude guests and those currently residing elsewhere even for 2-3 months of the year) [ ][ ]

Table A12: Family structure, and livelihood source

Person Code		Relation with head of family *1		Gender 1.Male 2.Female		Age (years)		Education status *2		Principal Means of livelihood *3		Secondary means of livelihood *3		State if primary occupation is: 1. Outside village 2. In urban area		Marital Status *4	
A121		A121a		A121b		A121c		A121d		A121e		A121f		A121g		A121h	
A122		A122a		A122b		A122c		A122d		A122e		A122f		A122g		A122h	
A123		A123a		A123b		A123c		A123d		A123e		A123f		A123g		A123h	
A124		A124a		A124b		A124c		A124d		A124e		A124f		A124g		A124h	
A125		A125a		A125b		A125c		A125d		A125e		A125f		A125g		A125h	
A126		A126a		A126b		A126c		A126d		A126e		A126f		A126g		A126h	
A127		A127a		A127b		A127c		A127d		A127e		A127f		A127g		A127h	
A128		A128a		A128b		A128c		A128d		A128e		A128f		A128g		A128h	
A129		A129a		A129b		A129c		A129d		A129e		A129f		A129g		A129h	
A1210		A1210a		A1210b		A1210c		A1210d		A1210e		A1210f		A1210g		A1210h	
A1211		A1211a		A1211b		A1211c		A1211d		A1211e		A1211f		A1211g		A1211h	

*1 Self [1]; Wife/husband [2]; son/daughter [3]; son/daughter in law [4]; Grandson/daughter [5]; Mother/father [6]; Brother/sister [7]; other relatives [8]; other non-relatives [9]
*2 Read & write [1]; primary [2]; middle [3]; Matriculation [4]; intermediate [5]; graduate [6]; masters [7]; illiterate [8]
*3 Farming [1]; private employee (e.g. small business/ shop) [2]; Government employee (e.g. teacher, peon) [3]; (daily) wage earner [4]; Fishing [5]; Other _________ [6]
*4 Married [1]; Single [2]; Divorced [3]; Widow/er [4]

Table A13: Tenure Arrangements: [seasons: Kharif (May - September); Rabi (Oct - April)]

Separate land	Size of the total parcel (acres)	Distance from field to home (1-way km)	Rate quality of soil of this parcel?*1	Season	Cultivated crop (incl. fallow land) in 2012? *2	Total areas under cultivation? (acres)	Tenure Arrangement *3	How many years have you continuously used this plot?	Shared cropping: What is the sharing arrangement? (In %)	Shared cropping: Other payment e.g. inputs (PKR/ yr)	Rent paid/ received if plot is leased? (PKR/yr)	Duration of tenancy contract (years)?	Tenancy changed in past 5 years? *4	Distance of plot to landlord? (tenants only) (Km)	Frequency of landlord's visit? (tenant/ landlord)
Parcel 1	A131	A131a		Rabi	A1311b	A1311d	A1311f	A1311h	A1311j	A1311l	A1311n	A1311p	A1311r	A1311t	A1311v
					A1312b	A1312d	A1312f	A1312h	A1312j	A1312l	A1312n	A1312p	A1312r	A1312t	A1312v
					A1313b	A1313d	A1313f	A1313h	A1313j	A1313l	A1313n	A1313p	A1313r	A1313t	A1313v
				Karif	A1311c	A1311e	A1311g	A1311i	A1311k	A1311m	A1311o	A1311q	A1311s	A1311u	A1311w
					A1312c	A1312e	A1312g	A1312i	A1312k	A1312m	A1312o	A1312q	A1312s	A1312u	A1312w
					A1313c	A1313e	A1313g	A1313i	A1313k	A1313m	A1313o	A1313q	A1313s	A1313u	A1313w
Parcel 2	A132	A132a		Rabi	A1321b	A1321d	A1321f	A1321h	A1321j	A1321l	A1321n	A1321p	A1321r	A1321t	A1321v
					A1322b	A1322d	A1322f	A1322h	A1322j	A1322l	A1322n	A1322p	A1322r	A1322t	A1322v
					A1323b	A1323d	A1323f	A1323h	A1323j	A1323l	A1323n	A1323p	A1323r	A1323t	A1323v
				Karif	A1321c	A1321e	A1321g	A1321i	A1321k	A1321m	A1321o	A1321q	A1321s	A1321u	A1321w
					A1322c	A1322e	A1322g	A1322i	A1322k	A1322m	A1322o	A1322q	A1322s	A1322u	A1322w
					A1323c	A1323e	A1323g	A1323i	A1323k	A1323m	A1323o	A1323q	A1323s	A1323u	A1323w
Parcel 3	A313	A133a		Rabi	A1331b	A1331d	A1331f	A1331h	A1331j	A1331l	A1331n	A1331p	A1331r	A1331t	A1331v
					A1332b	A1332d	A1332f	A1332h	A1332j	A1332l	A1332n	A1332p	A1332r	A1332t	A1332v
					A1333b	A1333d	A1333f	A1333h	A1333j	A1333l	A1333n	A1333p	A1333r	A1333t	A1333v
				Karif	A1331c	A1331e	A1331g	A1331i	A1331k	A1331m	A1331o	A1331q	A1331s	A1331u	A1331w
					A1332c	A1332e	A1332g	A1332i	A1332k	A1332m	A1332o	A1332q	A1332s	A1332u	A1332w
					A1333c	A1333e	A1333g	A1333i	A1333k	A1333m	A1333o	A1333q	A1333s	A1333u	A1333w

*1. (1) Low; (2) Medium; (3) High
*2: (1) Fallow; (2) Fodder; Wheat - Sahar (1); wheat - Shafaq (2); wheat - Faisalabad 10 (3); wheat - Punjab 90 (4); wheat – Lasani (5); wheat – Bhakkar (6); Kapas(cotton) - Neelum 121 (7); Kapas(cotton) - Neelum 3700 (8); Kapas(cotton) - CIM-142 (9); Kapas(cotton) - CIM-886 (10); Kapas(cotton) - AA-703 (11); Kapas(cotton) - AA-802; Chawal (Paddy Rice) - IRRI-6; Chawal (Paddy Rice)- Basmati 382, Chawal (Paddy Rice) - Bastmati 386; Chawal (Paddy Rice) – Kernal (3)Kado Loki (Bottle Gourd);(4)Tuori (Ribbed Guord);(5)Bengan (Egg plant);(6)Bhendi (Lady Finger);(7) Hari Mirch (Green Chilies);(8)Tematar (Tomatoes);(9)Khira (Cucumber);(10)Kerela (Bitter Guord);(11)Gidra (Musk Melon);(12)Pan (Piper Bettle);(13)Kela (Pan);(14); Narial (Coconut);(15)Cheekoo (Mud Apple);(17)Ganna (Sugar Cane);(18)Aam (Mango);(20)Aloo (Potato);(21)Other (Specify here_______________)
*3: Own land and cultivated (1); own land and rent to others (2); share cropped land (3); Land rented in (pay fixed rate to landlord) (4); Use of fructuary right (5); Other (specify)______ (6)
*4: Rented extra land out (1); rented extra land in (2); Gone from sharecrop to fixed rent (3); Fixed rent to share crop (4) purchase land.

A14: If you were able to buy all of your owned/ cultivated land today (2012), what is the maximum you would pay for it? Specify total acres _________________ and A14 a: Specify PKR per acre ___________

A15: How often are the terms of tenancy reviewed? ___________________________
Every year (1); every 2 years (2); every 4 years (3); at discretion of the landlord (4)

A16: Are rights to farm the land you're using? ____________________________________
Inherited (1); Purchased (2); Designated by national government; (3) Designated by local government (4)

A17: Since you have been a farmer, have you been evicted from any previous land? Yes/No

A18: Have you experienced other farmers in your village being evicted from their land? Often/Occasionally/Never

A19: Crop Choice

Who decides crop choice?		Circle as appropriate	If selected FARMER in the previous question, what are the primary reasons for the crop choices you make?		Rate 3 options		
A191	Farmer	1	Highest profit, high risk	1	1-Most Important	A191a	
A192	Landlord	2	Lower profit, lower risk	2	2-Most Important	A192a	
A193	Middleman	3	Past experience with these crops	3	3-Most Important	A193a	
A194	Credit supplier	4	Recommended by the landlord	4			
A195	Other (specify)	5	Recommended by the middleman	5			
			Preferred for home consumption	6			
			Low water use	7			
			Other (specify ____________________)	8			

Section B. Agricultural products: Inputs, outputs, and prices

B1. Agricultural products: outputs, and prices

Separate land	Season	Crop code as above	Planting Date	Harvesting date	Production in 2012 (Maunds)	Average Production in 2011 (Maunds)	Home Consumption (Maund)	Quantity consumed by Livestock (Maund)	Quantity stored (Maund)	Post - Harvest losses (Maund)	Quantity Sold (Maund)	Farmer Price (PKR/ Maund)	Market Price (PKR/ Maund)	Govt. price (PKR/ Maund)
Parcel 1	Rabi	B111b	B111d	B111f	B111h	B111j	B111l	B111n	B111p	B111r	B111t	B111v	B111x	B111z
		B112b	B112d	B112f	B112h	B112j	B112l	B112n	B112p	B112r	B112t	B112v	B112x	B112z
		B113b	B113d	B113f	B113h	B113j	B113l	B113n	B113p	B113r	B113t	B113v	B113x	B113z
	Karif	B111c	B111e	B111g	B111i	B111k	B111m	B111o	B111q	B111s	B111u	B111w	B111y	B111a
		B112c	B112e	B112g	B112i	B112k	B112m	B112o	B112q	B112s	B112u	B11w	B112y	B112a
		B113c	B113e	B113g	B113i	B113k	B113m	B113o	B113q	B113s	B113u	B113w	B113y	B113a
Parcel 2	Rabi	B121b	B121d	B121f	B121h	B121j	B121l	B121n	B121p	B121r	B121t	B121v	B121x	B121z
		B122b	B122d	B122f	B122h	B122j	B122l	B122n	B122p	B122r	B122t	B122v	B122x	B122z
		B123b	B123d	B123f	B123h	B123j	B123l	B123n	B123p	B123r	B123t	B123v	B123x	B123z
	Karif	B121c	B121e	B121g	B121i	B121k	B121m	B121o	B121q	B121s	B121u	B121w	B121y	B121a
		B122c	B122e	B122g	B122i	B122k	B122m	B122o	B122q	B122s	B122u	B122w	B122y	B122a
		B123c	B123e	B123g	B123i	B123k	B123m	B123o	B123q	B123s	B123u	B123w	B123y	B123a
Parcel 3	Rabi	B131b	B131d	B131f	B131h	B131j	B131	B131n	B131p	B131r	B131t	B131v	B131x	B131z
		B132b	B132d	B132f	B132h	B132j	B132l	B132n	B132p	B132r	B132t	B132v	B132x	B132z
		B133b	B133d	B133f	B133h	B133j	B133l	B133n	B133p	B133r	B133t	B133v	B133x	B133z
	Karif	B131c	B131e	B131g	B131i	B131k	B131m	B131o	B131q	B131s	B131u	B131w	B131y	B131a
		B132c	B132e	B132g	B132i	B132k	B132m	B132o	B132q	B132s	B132u	B132w	B132y	B132a
		B133c	B133e	B133g	B133i	B133k	B133m	B133o	B133q	B133s	B133u	B133w	B133y	B133a

B12. For total production (column d), what is the % upward or downward revision? ______________ (%) (Consider average of past 5 years (2007-2011))

B13. For farmer price (column j), what is the % upward or downward revision? ______________ (%) (Consider average past 5 years (2007-2011))

B14. For market price (column k), what is the % upward or downward revision? ______________ (%) (Consider average past 5 years (2007-2011))

B2: Agricultural Inputs

B21. How far is it to the market where you purchase your inputs? One way distance _______ (km)

B22. What kind of transport do you mostly use to bring input from the market? ____ (walk, local bus, personal vehicle, rented vehicle, donkey/ camel cart);
B22a. One way cost for a visit _______(PKR) (Not to be filled if farmer receives delivery of inputs by a middleman etc. Only relevant if farmer actually goes to the market to pick up goods)

B23: Fertilizers and Weedicides/ Pesticides

Separate land	Season	Enter Plot code as above	Weedicides/ Pesticides				UREA				D.A.P/ S.O.P				Manure			
			Quantity (Kgs)	Total Cost (PKR)	Source*	% of cost paid by the farmer?	Quantity (Kgs)	Total Cost (PKR)	Source*	% of cost paid by the farmer?	Quantity (Kgs)	Total Cost (PKR)	Source*	% of cost paid by the farmer?	Quantity (Kgs)	Total Cost (PKR)	Source*	% of cost paid by the farmer
Parcel 1	Rabi	B2311b	B2311d	B2311f	B2311h	B2311j	B2311l	B2311n	B2311p	B2311r	B2311t	B2311v	B2311x	B2311z	B2311bb	B2311dd	B2311ff	
		B2312b	B2312d	B2312f	B2312h	B2312j	B2312l	B2312n	B2312p	B2312r	B2312t	B2312v	B2312x	B2312z	B2311bb	B2312dd	B2312ff	
		B2313b	B2313d	B2313f	B2313h	B2313j	B2313l	B2313n	B2313p	B2313r	B2313t	B2313v	B2313x	B2313z	B2313bb	B2313dd	B2313ff	
	Kharif	B2311c	B2311e	B2311g	B2311i	B2311k	B2311m	B2311o	B2311q	B2311s	B2311u	B2311w	B2311y	B2311a	B2311cc	B2311ee	B2311gg	
		B2312c	B2312e	B2312g	B2312i	B2312k	B2312m	B2312o	B2312q	B2312s	B2312u	B2312w	B2312y	B2312a	B2312cc	B2312ee	B2312gg	
		B2313c	B2313e	B2313g	B2313i	B2313k	B2313m	B2313o	B2313q	B2313s	B2313u	B2313w	B2313y	B2313a	B2313cc	B2313ee	B2313gg	
Parcel 2	Rabi	B2321b	B2321d	B2321f	B2321h	B2321j	B2321l	B2321n	B2321p	B2321r	B2321t	B2321v	B2321x	B2321z	B2321bb	B2321dd	B2321ff	
		B2322b	B2322d	B2322f	B2322h	B2322j	B2322l	B2322n	B2322p	B2322r	B2322t	B2322v	B2322x	B2322z	B2322bb	B2322dd	B2322ff	
		B2323b	B2323d	B2323f	B2323h	B2323j	B2323l	B2323n	B2323p	B2323r	B2323t	B2323v	B2323x	B2323z	B2323bb	B2323dd	B2323ff	
	Kharif	B2321c	B2321e	B2321g	B2321i	B2321k	B2321m	B2321o	B2321q	B2321s	B2321u	B2321w	B2321y	B2321a	B2321cc	B2321ee	B2321gg	
		B2322c	B2322e	B2322g	B2322i	B2322k	B2322m	B2322o	B2322q	B2322s	B2322u	B2322w	B2322y	B2322a	B2322cc	B2322ee	B2322gg	
		B2323c	B2323e	B2323g	B2323i	B2323k	B2323m	B2323o	B2323q	B2323s	B2323u	B2323w	B2323y	B2323a	B2323cc	B2323ee	B2323gg	

Parcel 3	Rabi	B2331b		B2331d		B2331f		B2331h		B2331j		B2331l		B2331n		B2331p		B2331r		B2331t		B2331v		B2331x		B2331z		B2331bb		B2331dd		B2331ff			
		B2332b		B2332d		B2332f		B2332h		B2332j		B2332l		B2332n		B2332p		B2332r		B2332t		B2332v		B2332x		B2332z		B2332bb		B2332dd		B2332ff			
		B2333b		B2333d		B2333f		B2333h		B2333j		B2333l		B2333n		B2333p		B2333r		B2333t		B2333v		B2333x		B2333z		B2333bb		B2333dd		B2333ff			
	Kharif	B2331c		B2331e		B2331g		B2331i		B2331k		B2331m		B2331o		B2331q		B2331s		B2331u		B2331w		B2331y		B2331a		B2331cc		B2331ee		B2331gg			
		B2332c		B2332e		B2332g		B2332i		B2332k		B2332m		B2332o		B2332q		B2332s		B2332u		B2332w		B2332y		B2332a		B2332cc		B2332ee		B2332gg			
		B2333c		B2333e		B2333g		B2333i		B2333k		B2333m		B2333o		B2333q		B2333s		B2333u		B2333w		B2333y		B2333a		B2333cc		B2333ee		B2333gg			

*1: On cash payment from market/ local dealer (1); on credit from market/ local dealer (2); on cash from Middleman (3); On credit from Middleman (4); free from middleman (5); free from Landlord (6); on credit from land owner (7); Government (8); NGO/agricultural extension (9); other, pls. specify ________ (10)

B24: Seed

Farm land	Season	Enter Plot code as above		Seed							
				Quantity (Kg)		Total Cost (PKR)		Source*		% of cost paid by the farmer?	
Parcel 1	Rabi	B2311b		B2311bb		B2311dd		B2311ff			
		B2312b		B2311bb		B2312dd		B2312ff			
		B2313b		B2313bb		B2313dd		B2313ff			
	Kharif	B2311c		B2311cc		B2311ee		B2311gg			
		B2312c		B2312cc		B2312ee		B2312gg			
		B2313c		B2313cc		B2313ee		B2313gg			
Parcel 2	Rabi	B2321b		B2321bb		B2321dd		B2321ff			
		B2322b		B2322bb		B2322dd		B2322ff			
		B2323b		B2323bb		B2323dd		B2323ff			
	Kharif	B2321c		B2321cc		B2321ee		B2321gg			
		B2322c		B2322cc		B2322ee		B2322gg			
		B2323c		B2323cc		B2323ee		B2323gg			
arcel	Rabi	B2331b		B2331bb		B2331dd		B2331ff			

		B2332b		B2332bb		B2332dd		B2332ff			
		B2333b		B2333bb		B2333dd		B2333ff			
	Kharif	B2331c		B2331cc		B2331ee		B2331gg			
		B2332c		B2332cc		B2332ee		B2332gg			
		B2333c		B2333cc		B2333ee		B2333gg			

*1: On cash payment from market/ local dealer (1); on credit from market/ local dealer (2); on cash from Middleman (3); On credit from Middleman (4); free from middleman (5); free from Landlord (6); on credit from land owner (7); Government (8); NGO/agricultural extension (9); other, pls. specify _______ (10)

25: Usage of Water

Farmland	Season	Crop code as above		What is your source of water?*1		Total No of water application per cropping cycle?		How many canal water applications?				How many tubewell applications?				If you use tubewell, who owns it? *1		If selected 2, 3 or 4, what was the rent of the tubewell per application? (PKR)		What is fuel expense for the tubewell per application for this crop? (PKR)		Which method do you use to water your farm?	
								No of applications		Hours per application		No of applications		Hours per application									
Parcel 1	Rabi	B2611b		B2611d				B2611f		B2611h		B2611j		B2611l		B2611n		B2611p					
		B2612b		B2612d				B2612f		B2612h		B2612j		B2612l		B2612n		B2612p					
		B2613b		B2613d				B2613f		B2613h		B2613j		B2613l		B2613n		B2613p					
	Kharif	B2611c		B2611e				B2611g		B2611i		B2611k		B2611m		B2611o		B2611q					
		B2612c		B2612e				B2612g		B2612i		B2612k		B2612m		B2612o		B2612q					
		B2613c		B2613e				B2613g		B2613i		B2613k		B2613m		B2613o		B2613q					
Parcel 2	Rabi	B2621b		B2621d				B2621f		B2621h		B2621j		B2621l		B2621n		B2621p					
		B2622b		B2622d				B2622f		B2622h		B2622j		B2622l		B2622n		B2622p					
		B2623b		B2623d				B2623f		B2623h		B2623j		B2623l		B2623n		B2623p					
	Kharif	B2621c		B2621e				B2621g		B2621i		B2621k		B2621m		B2621o		B2621q					
		B2622c		B2622e				B2622g		B2622i		B2622k		B2622m		B2622o		B2622q					
		B2623c		B2623e				B2623g		B2623i		B2623k		B2623m		B2623o		B2623q					
Parcel 3	Rabi	B2631b		B2631d				B2631f		B2631h		B2631j		B2631l		B2631n		B2631p					
		B2632b		B2632d				B2632f		B2632h		B2632j		B2632l		B2632n		B2632p					
		B2633b		B2633d				B2633f		B2633h		B2633j		B2633l		B2633n		B2633p					
	Kharif	B2631c		B2631e				B2631g		B2631i		B2631k		B2631m		B2631o		B2631q					
		B2632c		B2632e				B2632g		B2632i		B2632k		B2632m		B2632o		B2632q					
		B2633c		B2633e				B2633g		B2633i		B2633k		B2633m		B2633o		B2633q					

*1. Canal Irrigation (1); Rain fed (2); Tubewell (3); Other (specify_____________) (6)
*2. Personal (1); rented from neighbor (2); rented commercially (3); free/ subsidized rate from landlord (4)
*3. Drip Irrigation (1); Flood irrigation (2); Sprinkler irrigation (3); Furrow irrigation (4); other (specify _____________) (4)

B28: During which month (s) did you face water scarcity in the past 12 months? ________________

B7: Machinery Expense – Parcel 1

Light Equipment (Tick appropriate one)	Use of equipment/machinery (Enter crop code as above)																Who owns the equipment/ animal? *1		If equipment is shared, what % of costs does farmer pay?		Who are these costs shared with*2?		Year of Purchase		Value at year of Purchase (PKR)	
	Parcel 1																									
	Rabi								Kharif																	
	Crop 1		Crop 2		Crop 3		Crop 4		Crop 1		Crop 2		Crop 3		Crop 4											
Hand Hoe	B71a		B71b		B71c		B71d		B71e		B71f		B71g		B71h		B71i		B71j		B71k					
Axe	B72a		B72b		B72c		B72d		B72e		B72f		B72g		B72h		B72i		B72j		B72k					
Scythe (Drati)	B73a		B73b		B73c		B73d		B73e		B73f		B73g		B73h		B73i		B73j		B73k					
Rake (kilna)	B74a		B74b		B74c		B74d		B74e		B74f		B74g		B74h		B74i		B74j		B74k					
Other	B75		B75b		B75c		B75d		B75e		B75f		B75g		B75h		B75i		B75j		B75k					
Heavy Machinery (Enter rental cost in PKR)																										
Draft animal power																										
Rotor weigh	B76a		B76b		B76c		B76d		B76e		B76f		B76g		B76h		B76i		B76j		B76k					
Plough (Gobal)	B77a		B77b		B77c		B77d		B77e		B77f		B77g		B77h		B77i		B77j		B77k					
Leveler (Dhallai)	B78a		B78b		B78c		B78d		B78e		B78f		B78g		B78h		B78i		B78j		B78k					
Khiria	B79a		B79b		B79c		B79d		B79e		B79f		B79g		B79h		B79i		B79j		B79k					
Loader	B710a		B710b		B710c		B710d		B710e		B710f		B710g		B710h		B710i		B710j		B710k					
Cultivator	B711a		B711b		B711c		B711d		B711e		B711f		B711g		B711h		B711i		B711j		B711k					
Reaper	B712a		B712b		B712c		B712d		B712e		B712f		B712g		B712h		B712i		B712j		B712k					
Thresher	B713a		B713b		B713c		B713d		B713e		B713f		B713g		B713h		B713i		B713j		B713k					
Tractor	B714a		B714b		B714c		B714d		B714e		B714f		B714g		B714h		B714i		B714j		B714k					
Generator	B715a		B715b		B715c		B715d		B715e		B715f		B715g		B715h		B715i		B715j		B715k					
Tubewell	B716a		B716b		B716c		B716d		B716e		B716f		B716g		B716h		B716i		B716j		B716k					

*1 & 2: Personal (1); landlord (free) (2), land lord rented (3), middleman/trader free (4), middleman rented (5) Rented from market (6)

B7: Machinery Expense – Parcel 2

Light Equipment (Tick appropriate one)	Use of equipment/machinery (Enter crop code as above)								Who owns the equipment/ animal? *1	If equipment is shared, what % of costs does farmer pay?	Who are these costs shared with*2?	Year of Purchase	Value at year of Purchase (PKR)
	Parcel 2												
	Rabi				Kharif								
	Crop 1	Crop 2	Crop 3	Crop 4	Crop 1	Crop 2	Crop 3	Crop 4					
Hand Hoe	B71a	B71b	B71c	B71d	B71e	B71f	B71g	B71h	B71i	B71j	B71k		
Axe	B72a	B72b	B72c	B72d	B72e	B72f	B72g	B72h	B72i	B72j	B72k		
Scythe (Drati)	B73a	B73b	B73c	B73d	B73e	B73f	B73g	B73h	B73i	B73j	B73k		
Rake (kilna)	B74a	B74b	B74c	B74d	B74e	B74f	B74g	B74h	B74i	B74j	B74k		
Other	B75	B75b	B75c	B75d	B75e	B75f	B75g	B75h	B75i	B75j	B75k		
Heavy Machinery (Enter rental cost in PKR)													
Draft animal power													
Rotor weigh	B76a	B76b	B76c	B76d	B76e	B76f	B76g	B76h	B76i	B76j	B76k		
Plough (Gobal)	B77a	B77b	B77c	B77d	B77e	B77f	B77g	B77h	B77i	B77j	B77k		
Leveler (Dhallai)	B78a	B78b	B78c	B78d	B78e	B78f	B78g	B78h	B78i	B78j	B78k		
Khiria	B79a	B79b	B79c	B79d	B79e	B79f	B79g	B79h	B79i	B79j	B79k		
Loader	B710a	B710b	B710c	B710d	B710e	B710f	B710g	B710h	B710i	B710j	B710k		
Cultivator	B711a	B711b	B711c	B711d	B711e	B711f	B711g	B711h	B711i	B711j	B711k		
Reaper	B712a	B712b	B712c	B712d	B712e	B712f	B712g	B712h	B712i	B712j	B712k		
Thresher	B713a	B713b	B713c	B713d	B713e	B713f	B713g	B713h	B713i	B713j	B713k		
Tractor	B714a	B714b	B714c	B714d	B714e	B714f	B714g	B714h	B714i	B714j	B714k		
Generator	B715a	B715b	B715c	B715d	B715e	B715f	B715g	B715h	B715i	B715j	B715k		
Tubewell	B716a	B716b	B716c	B716d	B716e	B716f	B716g	B716h	B716i	B716j	B716k		

*1 & 2: Personal (1); landlord (free) (2), land lord rented (3), middleman/trader free (4), middleman rented (5) Rented from market (6)

B7: Machinery Expense – Parcel 3

Light Equipment (Tick appropriate one)	Use of equipment/machinery (Enter crop code as above)								Who owns the equipment/ animal? *1	If equipment is shared, what % of costs does farmer pay?	Who are these costs shared with*2?	Year of Purchase	Value at year of Purchase (PKR)
	Parcel 3												
	Rabi				Kharif								
	Crop 1	Crop 2	Crop 3	Crop 4	Crop 1	Crop 2	Crop 3	Crop 4					
Hand Hoe	B71a	B71b	B71c	B71d	B71e	B71f	B71g	B71h	B71i	B71j	B71k		
Axe	B72a	B72b	B72c	B72d	B72e	B72f	B72g	B72h	B72i	B72j	B72k		
Scythe (Drati)	B73a	B73b	B73c	B73d	B73e	B73f	B73g	B73h	B73i	B73j	B73k		
Rake (kilna)	B74a	B74b	B74c	B74d	B74e	B74f	B74g	B74h	B74i	B74j	B74k		
Other	B75	B75b	B75c	B75d	B75e	B75f	B75g	B75h	B75i	B75j	B75k		
Heavy Machinery (Enter rental cost in PKR)													
Draft animal power													
Rotor weigh	B76a	B76b	B76c	B76d	B76e	B76f	B76g	B76h	B76i	B76j	B76k		
Plough (Gobal)	B77a	B77b	B77c	B77d	B77e	B77f	B77g	B77h	B77i	B77j	B77k		
Leveler (Dhallai)	B78a	B78b	B78c	B78d	B78e	B78f	B78g	B78h	B78i	B78j	B78k		
Khiria	B79a	B79b	B79c	B79d	B79e	B79f	B79g	B79h	B79i	B79j	B79k		
Loader	B710a	B710b	B710c	B710d	B710e	B710f	B710g	B710h	B710i	B710j	B710k		
Cultivator	B711a	B711b	B711c	B711d	B711e	B711f	B711g	B711h	B711i	B711j	B711k		
Reaper	B712a	B712b	B712c	B712d	B712e	B712f	B712g	B712h	B712i	B712j	B712k		
Thresher	B713a	B713b	B713c	B713d	B713e	B713f	B713g	B713h	B713i	B713j	B713k		
Tractor	B714a	B714b	B714c	B714d	B714e	B714f	B714g	B714h	B714i	B714j	B714k		
Generator	B715a	B715b	B715c	B715d	B715e	B715f	B715g	B715h	B715i	B715j	B715k		
Tubewell	B716a	B716b	B716c	B716d	B716e	B716f	B716g	B716h	B716i	B716j	B716k		

*1 & 2: Personal (1); landlord (free) (2), land lord rented (3), middleman/trader free (4), middleman rented (5) Rented from market (6)

C1: Labor Composition – Parcel 1

Season	Enter Crop Code	Activities	Household labor (please enter person code in no column) 1 day= 6-8 hours of work completed by 1 individual						Hired Labor 1 day= 6-8 hours of work completed by 1 individual.							
			Male		Female		Child (<16)		Male			Female			Child (<16)	
			No	days	No	Days	No	Days	Days	Days	Daily wage rate	No	Days	Daily wage rate	No	Days
Rabi	Crop 1	Land Preparation	c11a	c11b	c11c	c11d	c11e	c11f	c11g	c11h	c11i	c11j	c11k	c11l		
		Planting	c12a	c12b	c12c	c12d	c12e	c12f	c12g	c12h	c12i	c12j	c12k	c12l		
		Watering	c13a	c13b	c13c	c13d	c13e	c13f	c13g	c13h	c13i	c13j	c13k	c13l		
		Weeding/ pesticides	c14a	c14b	c14c	c14d	c14e	c14f	c14g	c14h	c14i	c14j	c14k	c14l		
		Harvesting	c15a	c15b	c15c	c15d	c15e	c15f	c15g	c15h	c15i	c15j	c15k	c15l		
		Post harvesting	c16a	c16b	c16c	c16d	c16e	c16f	c16g	c16h	c16i	c16j	c16k	c16l		
	Crop 2	Land Preparation	c17a	c17b	c17c	c17d	c17e	c17f	c17g	c17h	c17i	c17j	c17k	c17l		
		Planting	c18a	c18b	c18c	c18d	c18e	c18f	c18g	c18h	c18i	c18j	c18k	c18l		
		Watering	c19a	c19b	c19c	c19d	c19e	c19f	c19g	c19h	c19i	c19j	c19k	c19l		
		Weeding/ pesticides	c110a	c110b	c110c	c110d	c110e	c110f	c110g	c110h	c110i	c110j	c110k	c110l		
		Harvesting	c111a	c111b	c111c	c111d	c111e	c111f	c111g	c111h	c111i	c111j	c111k	c111l		
		Post harvesting	c112a	c112b	c112c	c112d	c112e	c112f	c112g	c112h	c112i	c112j	c112k	c112l		
	Crop 3	Land Preparation	c113a	c113b	c113c	c113d	c113e	c113f	c113g	c113h	c113i	c113j	c113k	c113l		
		Planting	c114a	c114b	c114c	c114d	c114e	c114f	c114g	c114h	c114i	c114j	c114k	c114l		
		Watering	c115a	c115b	c115c	c115d	c115e	c115f	c115g	c115h	c115i	c115j	c115k	c115l		
		Weeding/ pesticides	c116a	c116b	c116c	c116d	c116e	c116f	c116g	c116h	c116i	c116j	c116k	c116l		
		Harvesting	c117a	c117b	c117c	c117d	c117e	c117f	c117g	c117h	c117i	c117j	c117k	c117l		
		Post harvesting	c118a	c118b	c118c	c118d	c118e	c118f	c118g	c118h	c118i	c118j	c118k	c118l		
	Crop 4	Land Preparation	c119a	c119b	c119c	c119d	c119e	c119f	c119g	c119h	c119i	c119j	c119k	c119l		
		Planting	c120a	c120b	c120c	c120d	c120e	c120f	c120g	c120h	c120i	c120j	c120k	c120l		
		watering	c121a	c121b	c121c	c121d	c121e	c121f	c121g	c121h	c121i	c121j	c121k	c121l		
		Weeding/ pesticides	c122a	c122b	c122c	c122d	c122e	c122f	c122g	c122h	c122i	c122j	c122k	c122l		
		Harvesting	c123a	c123b	c123c	c123d	c123e	c123f	c123g	c123h	c123i	c123j		c123k	c123l	
		Post harvesting	c124a	c124b	c124c	c124d	c124e	c124f	c124g	c124h	c124i	c124j		c124k	c124l	
Kharif	Crop 1	Land Preparation	c125a	c125b	c125c	c125d	c125e	c125f	c125g	c125h	c125i	c125j		c125k	c125l	
		Planting	c126a	c126b	c126c	c126d	c126e	c126f	c126g	c126h	c126i	c126j		c126k	c126l	
		Watering	c127a	C127b	c127c	c127d	c127e	c127f	c127g	c127h	c127i	c127j		c127k	c127l	
		Weeding/ pesticides	c128a	c128b	c128c	c128d	c128e	c128f	c128g	c128h	c128i	c128j		c128k	c128l	

		Harvesting	c129a		c129b		c129c		c129d		c129e		c129f		c129g		c129h		c129i		c129j				c129k		c129l			
		Post harvesting	c130a		c130b		c130c		c130d		c130e		c130f		c130g		c130h		c130i		c130j				c130k		c130l			
	Crop 2	Land Preparation	c125a		c125b		c125c		c125d		c125e		c125f		c125g		c125h		c125i		c125j				c125k		c125l			
		Planting	c126a		c126b		c126c		c126d		c126e		c126f		c126g		c126h		c126i		c126j				c126k		c126l			
		Watering	c127a		C127b		c127c		c127d		c127e		c127f		c127g		c127h		c127i		c127j				c127k		c127l			
		Weeding/ pesticides	c128a		c128b		c128c		c128d		c128e		c128f		c128g		c128h		c128i		c128j				c128k		c128l			
		Harvesting	c129a		c129b		c129c		c129d		c129e		c129f		c129g		c129h		c129i		c129j				c129k		c129l			
		Post harvesting	c130a		c130b		c130c		c130d		c130e		c130f		c130g		c130h		c130i		c130j				c130k		c130l			
	Crop 3	Land Preparation	c125a		c125b		c125c		c125d		c125e		c125f		c125g		c125h		c125i		c125j				c125k		c125l			
		Planting	c126a		c126b		c126c		c126d		c126e		c126f		c126g		c126h		c126i		c126j				c126k		c126l			
		Watering	c127a		C127b		c127c		c127d		c127e		c127f		c127g		c127h		c127i		c127j				c127k		c127l			
		Weeding/ pesticides	c128a		c128b		c128c		c128d		c128e		c128f		c128g		c128h		c128i		c128j				c128k		c128l			
		Harvesting	c129a		c129b		c129c		c129d		c129e		c129f		c129g		c129h		c129i		c129j				c129k		c129l			
		Post harvesting	c130a		c130b		c130c		c130d		c130e		c130f		c130g		c130h		c130i		c130j				c130k		c130l			
	Crop 4	Land Preparation	c125a		c125b		c125c		c125d		c125e		c125f		c125g		c125h		c125i		c125j				c125k		c125l			
		Planting	c126a		c126b		c126c		c126d		c126e		c126f		c126g		c126h		c126i		c126j				c126k		c126l			
		Watering	c127a		C127b		c127c		c127d		c127e		c127f		c127g		c127h		c127i		c127j				c127k		c127l			
		Weeding/ pesticides	c128a		c128b		c128c		c128d		c128e		c128f		c128g		c128h		c128i		c128j				c128k		c128l			
		Harvesting	c129a		c129b		c129c		c129d		c129e		c129f		c129g		c129h		c129i		c129j				c129k		c129l			
		Post harvesting	c130a		c130b		c130c		c130d		c130e		c130f		c130g		c130h		c130i		c130j				c130k		c130l			

C1: Labor Composition – Parcel 2

Season	Enter Crop Code	Activities	Household labor (please enter person code in no column) 1 day= 6-8 hours of work completed by 1 individual						Hired Labor 1 day= 6-8 hours of work completed by 1 individual.							
			Male		Female		Child (<16)		Male			Female			Child (<16)	
			No	days	No	Days	No	Days	Days	Days	Daily wage rate	No	Days	Daily wage rate	No	Days
Rabi	Crop 1	Land Preparation	c11a	c11b	c11c	c11d	c11e	c11f	c11g	c11h	c11i	c11j	c11k	c11l		
		Planting	c12a	c12b	c12c	c12d	c12e	c12f	c12g	c12h	c12i	c12j	c12k	c12l		
		Watering	c13a	c13b	c13c	c13d	c13e	c13f	c13g	c13h	c13i	c13j	c13k	c13l		
		Weeding/ pesticides	c14a	c14b	c14c	c14d	c14e	c14f	c14g	c14h	c14i	c14j	c14k	c14l		
		Harvesting	c15a	c15b	c15c	c15d	c15e	c15f	c15g	c15h	c15i	c15j	c15k	c15l		
		Post harvesting	c16a	c16b	c16c	c16d	c16e	c16f	c16g	c16h	c16i	c16j	c16k	c16l		
	Crop 2	Land Preparation	c17a	c17b	c17c	c17d	c17e	c17f	c17g	c17h	c17i	c17j	c17k	c17l		
		Planting	c18a	c18b	c18c	c18d	c18e	c18f	c18g	c18h	c18i	c18j	c18k	c18l		
		Watering	c19a	c19b	c19c	c19d	c19e	c19f	c19g	c19h	c19i	c19j	c19k	c19l		
		Weeding/ pesticides	c110a	c110b	c110c	c110d	c110e	c110f	c110g	c110h	c110i	c110j	c110k	c110l		
		Harvesting	c111a	c111b	c111c	c111d	c111e	c111f	c111g	c111h	c111i	c111j	c111k	c111l		
		Post harvesting	c112a	c112b	c112c	c112d	c112e	c112f	c112g	c112h	c112i	c112j	c112k	c112l		
	Crop 3	Land Preparation	c113a	c113b	c113c	c113d	c113e	c113f	c113g	c113h	c113i	c113j	c113k	c113l		
		Planting	c114a	c114b	c114c	c114d	c114e	c114f	c114g	c114h	c114i	c114j	c114k	c114l		
		Watering	c115a	c115b	c115c	c115d	c115e	c115f	c115g	c115h	c115i	c115j	c115k	c115l		
		Weeding/ pesticides	c116a	c116b	c116c	c116d	c116e	c116f	c116g	c116h	c116i	c116j	c116k	c116l		
		Harvesting	c117a	c117b	c117c	c117d	c117e	c117f	c117g	c117h	c117i	c117j	c117k	c117l		
		Post harvesting	c118a	c118b	c118c	c118d	c118e	c118f	c118g	c118h	c118i	c118j	c118k	c118l		
	Crop 4	Land Preparation	c119a	c119b	c119c	c119d	c119e	c119f	c119g	c119h	c119i	c119j	c119k	c119l		
		Planting	c120a	c120b	c120c	c120d	c120e	c120f	c120g	c120h	c120i	c120j	c120k	c120l		
		watering	c121a	c121b	c121c	c121d	c121e	c121f	c121g	c121h	c121i	c121j	c121k	c121l		
		Weeding/ pesticides	c122a	c122b	c122c	c122d	c122e	c122f	c122g	c122h	c122i	c122j	c122k	c122l		
		Harvesting	c123a	c123b	c123c	c123d	c123e	c123f	c123g	c123h	c123i	c123j		c123k	c123l	
		Post harvesting	c124a	c124b	c124c	c124d	c124e	c124f	c124g	c124h	c124i	c124j		c124k	c124l	
Kharif	Crop 1	Land Preparation	c125a	c125b	c125c	c125d	c125e	c125f	c125g	c125h	c125i	c125j		c125k	c125l	
		Planting	c126a	c126b	c126c	c126d	c126e	c126f	c126g	c126h	c126i	c126j		c126k	c126l	
		Watering	c127a	C127b	c127c	c127d	c127e	c127f	c127g	c127h	c127i	c127j		c127k	c127l	
		Weeding/ pesticides	c128a	c128b	c128c	c128d	c128e	c128f	c128g	c128h	c128i	c128j		c128k	c128l	

		Harvesting	c129a	c129b	c129c	c129d	c129e	c129f	c129g	c129h	c129i	c129j		c129k	c129l	
		Post harvesting	c130a	c130b	c130c	c130d	c130e	c130f	c130g	c130h	c130i	c130j		c130k	c130l	
	Crop 2	Land Preparation	c125a	c125b	c125c	c125d	c125e	c125f	c125g	c125h	c125i	c125j		c125k	c125l	
		Planting	c126a	c126b	c126c	c126d	c126e	c126f	c126g	c126h	c126i	c126j		c126k	c126l	
		Watering	c127a	C127b	c127c	c127d	c127e	c127f	c127g	c127h	c127i	c127j		c127k	c127l	
		Weeding/ pesticides	c128a	c128b	c128c	c128d	c128e	c128f	c128g	c128h	c128i	c128j		c128k	c128l	
		Harvesting	c129a	c129b	c129c	c129d	c129e	c129f	c129g	c129h	c129i	c129j		c129k	c129l	
		Post harvesting	c130a	c130b	c130c	c130d	c130e	c130f	c130g	c130h	c130i	c130j		c130k	c130l	
	Crop 3	Land Preparation	c125a	c125b	c125c	c125d	c125e	c125f	c125g	c125h	c125i	c125j		c125k	c125l	
		Planting	c126a	c126b	c126c	c126d	c126e	c126f	c126g	c126h	c126i	c126j		c126k	c126l	
		Watering	c127a	C127b	c127c	c127d	c127e	c127f	c127g	c127h	c127i	c127j		c127k	c127l	
		Weeding/ pesticides	c128a	c128b	c128c	c128d	c128e	c128f	c128g	c128h	c128i	c128j		c128k	c128l	
		Harvesting	c129a	c129b	c129c	c129d	c129e	c129f	c129g	c129h	c129i	c129j		c129k	c129l	
		Post harvesting	c130a	c130b	c130c	c130d	c130e	c130f	c130g	c130h	c130i	c130j		c130k	c130l	
	Crop 4	Land Preparation	c125a	c125b	c125c	c125d	c125e	c125f	c125g	c125h	c125i	c125j		c125k	c125l	
		Planting	c126a	c126b	c126c	c126d	c126e	c126f	c126g	c126h	c126i	c126j		c126k	c126l	
		Watering	c127a	C127b	c127c	c127d	c127e	c127f	c127g	c127h	c127i	c127j		c127k	c127l	
		Weeding/ pesticides	c128a	c128b	c128c	c128d	c128e	c128f	c128g	c128h	c128i	c128j		c128k	c128l	
		Harvesting	c129a	c129b	c129c	c129d	c129e	c129f	c129g	c129h	c129i	c129j		c129k	c129l	
		Post harvesting	c130a	c130b	c130c	c130d	c130e	c130f	c130g	c130h	c130i	c130j		c130k	c130l	

C1: Labor Composition – Parcel 3

Season	Enter Crop Code	Activities	Household labor (please enter person code in no column) 1 day= 6-8 hours of work completed by 1 individual						Hired Labor 1 day= 6-8 hours of work completed by 1 individual.							
			Male		Female		Child (<16)		Male			Female			Child (<16)	
			No	days	No	Days	No	Days	Days	Days	Daily wage rate	No	Days	Daily wage rate	No	Days
Rabi	Crop 1	Land Preparation	c11a	c11b	c11c	c11d	c11e	c11f	c11g	c11h	c11i	c11j	c11k	c11l		
		Planting	c12a	c12b	c12c	c12d	c12e	c12f	c12g	c12h	c12i	c12j	c12k	c12l		
		Watering	c13a	c13b	c13c	c13d	c13e	c13f	c13g	c13h	c13i	c13j	c13k	c13l		
		Weeding/ pesticides	c14a	c14b	c14c	c14d	c14e	c14f	c14g	c14h	c14i	c14j	c14k	c14l		
		Harvesting	c15a	c15b	c15c	c15d	c15e	c15f	c15g	c15h	c15i	c15j	c15k	c15l		
		Post harvesting	c16a	c16b	c16c	c16d	c16e	c16f	c16g	c16h	c16i	c16j	c16k	c16l		
	Cr	Land Preparation	c17a	c17b	c17c	c17d	c17e	c17f	c17g	c17h	c17i	c17j	c17k	c17l		

		Planting	c18a		c18b		c18c		c18d		c18e		c18f		c18g		c18h		c18i		c18j		c18k		c18l					
		Watering	c19a		c19b		c19c		c19d		c19e		c19f		c19g		c19h		c19i		c19j		c19k		c19l					
		Weeding/ pesticides	c110a		c110b		c110c		c110d		c110e		c110f		c110g		c110h		c110i		c110j		c110k		c110l					
		Harvesting	c111a		c111b		c111c		c111d		c111e		c111f		c111g		c111h		c111i		c111j		c111k		c111l					
		Post harvesting	c112a		c112b		c112c		c112d		c112e		c112f		c112g		c112h		c112i		c112j		c112k		c112l					
	Crop 3	Land Preparation	c113a		c113b		c113c		c113d		c113e		c113f		c113g		c113h		c113i		c113j		c113k		c113l					
		Planting	c114a		c114b		c114c		c114d		c114e		c114f		c114g		c114h		c114i		c114j		c114k		c114l					
		Watering	c115a		c115b		c115c		c115d		c115e		c115f		c115g		c115h		c115i		c115j		c115k		c115l					
		Weeding/ pesticides	c116a		c116b		c116c		c116d		c116e		c116f		c116g		c116h		c116i		c116j		c116k		c116l					
		Harvesting	c117a		c117b		c117c		c117d		c117e		c117f		c117g		c117h		c117i		c117j		c117k		c117l					
		Post harvesting	c118a		c118b		c118c		c118d		c118e		c118f		c118g		c118h		c118i		c118j		c118k		c118l					
	Crop 4	Land Preparation	c119a		c119b		c119c		c119d		c119e		c119f		c119g		c119h		c119i		c119j		c119k		c119l					
		Planting	c120a		c120b		c120c		c120d		c120e		c120f		c120g		c120h		c120i		c120j		c120k		c120l					
		watering	c121a		c121b		c121c		c121d		c121e		c121f		c121g		c121h		c121i		c121j		c121k		c121l					
		Weeding/ pesticides	c122a		c122b		c122c		c122d		c122e		c122f		c122g		c122h		c122i		c122j		c122k		c122l					
		Harvesting	c123a		c123b		c123c		c123d		c123e		c123f		c123g		c123h		c123i		c123j				c123k		c123l			
		Post harvesting	c124a		c124b		c124c		c124d		c124e		c124f		c124g		c124h		c124i		c124j				c124k		c124l			
Kharif	Crop 1	Land Preparation	c125a		c125b		c125c		c125d		c125e		c125f		c125g		c125h		c125i		c125j				c125k		c125l			
		Planting	c126a		c126b		c126c		c126d		c126e		c126f		c126g		c126h		c126i		c126j				c126k		c126l			
		Watering	c127a		C127b		c127c		c127d		c127e		c127f		c127g		c127h		c127i		c127j				c127k		c127l			
		Weeding/ pesticides	c128a		c128b		c128c		c128d		c128e		c128f		c128g		c128h		c128i		c128j				c128k		c128l			
		Harvesting	c129a		c129b		c129c		c129d		c129e		c129f		c129g		c129h		c129i		c129j				c129k		c129l			
		Post harvesting	c130a		c130b		c130c		c130d		c130e		c130f		c130g		c130h		c130i		c130j				c130k		c130l			
	Crop 2	Land Preparation	c125a		c125b		c125c		c125d		c125e		c125f		c125g		c125h		c125i		c125j				c125k		c125l			
		Planting	c126a		c126b		c126c		c126d		c126e		c126f		c126g		c126h		c126i		c126j				c126k		c126l			
		Watering	c127a		C127b		c127c		c127d		c127e		c127f		c127g		c127h		c127i		c127j				c127k		c127l			
		Weeding/ pesticides	c128a		c128b		c128c		c128d		c128e		c128f		c128g		c128h		c128i		c128j				c128k		c128l			
		Harvesting	c129a		c129b		c129c		c129d		c129e		c129f		c129g		c129h		c129i		c129j				c129k		c129l			
		Post harvesting	c130a		c130b		c130c		c130d		c130e		c130f		c130g		c130h		c130i		c130j				c130k		c130l			
	Crop 3	Land Preparation	c125a		c125b		c125c		c125d		c125e		c125f		c125g		c125h		c125i		c125j				c125k		c125l			
		Planting	c126a		c126b		c126c		c126d		c126e		c126f		c126g		c126h		c126i		c126j				c126k		c126l			
		Watering	c127a		C127b		c127c		c127d		c127e		c127f		c127g		c127h		c127i		c127j				c127k		c127l			
		Weeding/ pesticides	c128a		c128b		c128c		c128d		c128e		c128f		c128g		c128h		c128i		c128j				c128k		c128l			

		Harvesting	c129a		c129b		c129c		c129d		c129e		c129f		c129g		c129h		c129i		c129j				c129k		c129l			
		Post harvesting	c130a		c130b		c130c		c130d		c130e		c130f		c130g		c130h		c130i		c130j				c130k		c130l			
	Crop 4	Land Preparation	c125a		c125b		c125c		c125d		c125e		c125f		c125g		c125h		c125i		c125j				c125k		c125l			
		Planting	c126a		c126b		c126c		c126d		c126e		c126f		c126g		c126h		c126i		c126j				c126k		c126l			
		Watering	c127a		C127b		c127c		c127d		c127e		c127f		c127g		c127h		c127i		c127j				c127k		c127l			
		Weeding/ pesticides	c128a		c128b		c128c		c128d		c128e		c128f		c128g		c128h		c128i		c128j				c128k		c128l			
		Harvesting	c129a		c129b		c129c		c129d		c129e		c129f		c129g		c129h		c129i		c129j				c129k		c129l			
		Post harvesting	c130a		c130b		c130c		c130d		c130e		c130f		c130g		c130h		c130i		c130j				c130k		c130l			

C3: Off-farm employment for members of household

Person Code		No. of days (6-8 hours) worked off-farm		Daily wage paid (in PKR)	
C31a		C31b		C31c	
C32a		C32b		C32c	
C33a		C33b		C33c	
C34a		C34b		C34c	
C35a		C35b		C35c	
C36a		C36b		C36c	
C37a		C37b		C37c	
C38a		C38b		C38c	

C4: Marketing and Transport Channel:

Where do you sell your produce *		What is middleman's commission? In %		Is there a metaled road to the market (Yes/No)		Cost for transport (In PKR) (Rent + fuel) (Conditional on farmer marketing own produce)		Cost of packaging (PKR) (Conditional on farmer marketing own produce)		How long have you sold produce through this marketing channel (years)?		How far is it to the market where you sell your harvest? (km)	
C41a		C41b		C41c		C41d		C41e		C41f		C41g	

*Local Market (1); Urban Market (2); Middle man (3); Govt. Agents (4); Landlord (5)

Table B15. Livestock production, consumption, prices etc. (2012)

Type of Animal *1	No. of Animals	No of animals born or bought in 2012	Ownership		Home consumption [Nos./Yr] *2	No. of animal sold [2012]			Who did you sell it to? *3	Monthly earning from animal produce (PKR) *4	Total feeding and veterinary cost (PKR/ yr)	Grazing cost (PKR/ yr)	Own Labour (Hours/ yr)	Hired Labour (PKR/ yr)	No of cultivable land from parcels tha is instead used as enclosure for animals
			Own	Shared		Nos. Sold	Farmer's Price (PKR)	Market Price (PKR)							
B151	B151a	B151b	B151c	B151d	B151e	B151f	B151g	B151h	B151i						
B152	B152a	B152b	B152c	B152d	B152e	B152f	B152g	B152h	B152i						
B153	B153a	B153b	B153c	B153d	B153e	B153f	B153g	B153h	B153i						
B154	B154a	B154b	B154c	B154d	B154e	B154f	B154g	B154h	B154i						
B155	B155a	B155b	B155c	B155d	B155e	B155f	B155g	B155h	B155i						
B156	B156a	B156b	B156c	B156d	B156e	B156f	B156g	B156h	B156i						
B157	B157a	B157b	B157c	B157d	B157e	B157f	B157g	B157h	B157i						

*1 (1) Cows (2) Buffalo (3) Goats (4) Sheep (5) Camels (6) Horses (7) Asses (8) Mules (9) Others
*2 including for sacrifice, gifting, marriages, religious and other festivals
*3 neighbor, local market, urban market, middleman, other ______
*4 Includes milk, butter, and leftovers sold for preparation

Section D: Institutional Arrangements

D1: Type and source of household credit

Credit Source		Loan in past year (In PKR)		Interest rate/ year		What is the repayment time? (In months)		Any collateral for the loan? *1		Where did you primarily spend this loan?*2		How long have you dealt with this loan provider (in years)		If applied but not received the loan, what are the reasons for your ineligibility? *3	
D11	Bank	D11a		D11b		D11c		D11d		D11e		D11f		D11g	
D12	Micro finance institutes	D12a		D12b		D12c		D12d		D12e		D12f		D12g	
D13	Farmer associations	D13a		D13b		D13c		D13d		D13e		D13f		D13g	
D14	Land lord	D14a		D14b		D14c		D14d		D14e		D14f		D14g	
D15	Relative or Friend	D15a		D15b		D15c		D15d		D15e		D15f		D15g	
D16	Local Lender	D16a		D16b		D16c		D16d		D16e		D16f		D16g	
D17	Middleman	D17a		D17b		D17c		D17d		D17e		D17f		D17g	

*1 Land (1); share of output (2); use of farmers labour (3); other (specify) (4)

*2 Buy inputs (seeds, fertilizer, machinery) (1); invest in irrigation (2); buy food/clothing/medical care (3); education/training (4)

*3 incomplete identification documents (1), lack of collateral (2), insufficient income/ employment for repayment (3), default on previous loans (4).

D2: Have you received any other loans in the past 5 years? _________________________ in PKR

D3: Village characteristics

How any people live in your village?		How far are you from the centre of the village?		No. of relatives in village	
D3a		D3b		D3c	

D4: Village Profile

Facilities		Tick as appropriate
D41	School	
D42	Dispensary/ hospital	
D43	Shop/market	
D44	Public Transport	
D45	Telephone network	
D46	Internet access	
D47	Electricity supply	
D49	Farmer association	
D410	Agricultural extension office	
D411	Agricultural NGO/ CBO	

Next 3 questions only to be answered by those farmers who trade through a middleman

D5: When did you agree to trade through a middleman?		Tick as appropriate	: Would it be a problem for you to switch to a different middleman if you felt the terms of your contract were not satisfactory? (Yes/No)		Have you switched middleman before? (Yes/no)	
D51	Just before harvest		D6		D7	
D52	Just after harvest					
D53	During crop preparation					

D8: Have you received any of the following types of subsidies during last 12 months (give amount (PKR) per year)

Source		Seed Subsidy		Fertilizer Subsidy		Other	
D81	Government	D81a		D81b		D81c	
D82	NGO	D82a		D82b		D82c	
D84	Private sector sources	D84a		D84b		D84c	
D85	Other (Pls. specify)	D85a		D85b		D85c	

D9: Do you get information or advice from agricultural extension workers or other sources on crop production technology?

Source		How many visit each season	How much do you pay annually for this service?			Did you implement any of the advice received on production techniques/ equipment? (Yes/ No)		If yes, was it useful? (Yes/ No)		If not, what was the reason for not implementing their advice*
D51	Govt. agricultural extension services	D51a		D51b		D51c		D51d		D51e
D52	Local farmer associations	D52a		D52b		D52c		D52d		D52e
D53	NGOs/ CBOs	D53a		D53b		D53c		D53d		D53e
D54	Research institute	D54a		D54b		D54c		D54d		D54e
D55	Neighbor or Relative	D55a		D55b		D55c		D55d		D55e
D56	print Media	D56a		D56b		D56c		D56d		D56e
	Radio/ TV									
D57	Landlord	D57a		D57b		D57c		D57d		D57e
D58	Middleman	D58a		D58b		D58c		D58d		D58e

*Too expensive (1); want to stick with known methods (2); unsure about how to use new technologies (3); Unable to use new technologies without landlords permission (4); lack of infrastructure to support new technologies (e.g. inadequate irrigation) (5); Other (6)

Section E: ADAPTATION

E1: How long have you been a farmer? _______ (in number of years)

E2: Changes in Rainfall and Temperature:

Change in Rainfall		Have you noticed any change over the last 15 years? Tick as appropriate		Change in Temperature		Have you noticed any change over the last 15 years? Tick as appropriate	
E21	No change in the rain	E21a		E21b	No change in temperature	E21c	
E22	Less rain	E22a		E22b	More Hot days	E22c	
E23	More rain	E23a		E23b	less Hot days	E23c	
E24	Change in the onset rainy seasons	E24a		E24b	Change in night time temperature	E24c	
				E25b	Increase in cold spells	E25c	
					Change in onset of hot season		

E4 Extreme Events

Events		Have you experienced any of the following events in the past 15 years? Yes/ No		How would you rate the frequency of this event over the last 15 years?*1		How would you rate the severity of the of this event over the past 20 years?*1		Loss of asset, property, income, food shortage, decline in consumption? (Y/N)	
E41	Floods/ flash floods	E41a		E41b		E41c		E41d	
E42	Wind/ Dust storm	E42a		E42b		E42c		E42d	
E43	Drought	E43a		E43b		E43c		E43d	
E45	Hail storm	E45a		E45b		E45c		E45d	

* 1: Increasing (1); Same (2); Decreasing (3)

E3: Rainfall

Which month did the rainy season begin in the past 15 years?		In which month did the rainy season begin this year?		How would you characterize the amount of rain relative to past 15 years? *1		In which month in this year's rainy season did you get the most rain?	
E31		E31a		E31b		E31c	

*1 more (1); same (2); less(3)

E5: Past Flood Experience

Were you affected by flooding in any of the following years? Yes=1, No=2			Did this affect your harvest? Yes=1, No=2		What % of harvest across all crops was lost?		Any other loss? *1		How did you cope with losses?*2	
E51	2012		E51a		E51b		E51c		E51d	
E52	2011		E52a		E52b		E52c		E52d	
E53	2010		E53a		E53b		E53c		E53d	

*1 Loss of livestock (1), loss of housing/ storage/ animal shed (2), loss of family member (3), loss of any other asset (machinery, vehicle, etc) (4)

*2 Took out a loan to cover expenses (1); Sold off farm assets (machinery, livestock) (2); Relied on savings (3); Worked as a labourer/other work away own farm (4); Financial support from relatives/local villagers (5); Government/NGO assistance (6); Other (specify) (7)

E6: Adaptation actually undertaken

Adaptation Measures		How has your household adapted to cope with climatic changes?		Go to Question:
E61	Altering the timing of "cropping activity" (e.g. harvest date)	E61a		E7
E62	Shift in cropping pattern (e.g. crop portfolio)	E62a		E8
E63	Altering agricultural input	E63a		E9
E64	Investment in soil conservation	E64a		E10
E65	Investment in water conservation	E65a		E11
E66	Diversification of Income	E66a		E12
E67	Public/ Household infrastructure incl. water defenses			E13
E68	No Adaptation	E67a		-
	Other, specify_________________________	E68a		-

E7: Altering the timing of cropping activity:

Which activities have you shifted		Which plot/crop?		Previous time of the activity (month)		Current time of the activity (Month)		If you do not plan to continues this? Please explain your reason for discontinuation? *1	
E71	Delayed Sowing	E71a		E71b		E71c		E71d	
E72	Early Harvesting	E72a		E72b		E72c		E72d	
E73	Late Harvesting	E73a		E73b		E73c		E73d	

* 1 lack of money (1), lack of information (2); shortage of labor (3); Has little/no effect on crop outputs (4) Lower returns (5) Other (specify) (6) …

E8: Shift in cropping patterns

What crop did you swap?				When did you start to change (Year)		What is the change in the income?		Did you incur any additional cost of change? In PKR		If you do not plan to continues this? Please explain your reason for discontinuation *1	
Previous		New									
		E81		E81a		E81b		E81c		E81d	

* 1 lack of money (1), lack of information (2); shortage of labor (3); Has little/no effect on crop outputs (4) Lower returns (5) Other (specify) (6) …

E9: Change in Agricultural Input due to climate change:

Which agricultural input did you change?		When did you start to change (Year)?		How did you change?*1		Did you incur cost of change? (In Rs.)		If you do not plan to continues this? Please explain your reason for discontinuation *1	
E91	Fertilizers	E91a		E91b		E91c		E91d	
E92	Seed	E92a		E92b		E92c		E92d	
E93	Pesticides	E93a		E93b		E93c		E93d	
E94	Labor	E94a		E94b		E94c		E94d	
E95	Water	E95a		E95b		E95c		E95d	

*1. Increase (1); Reduce (3); Different variety of input (seed, fertilizer etc.)

2. lack of money (1), lack of information (2); shortage of labor (3); Has little/no effect on crop outputs (4) Lower returns (5) Other (specify) (6)

E10 Soil Conservation Management

Have you used crop residue (Mulching), green manure, or cover crop before this season to provide organic matter to the soil? Y/ N		Did you use zero tillage, and direct sowing for soil preparation? Y/ N		Have you implemented contour planting to reduce soil erosion? Y/ N		Have you used shelter belts for improved soil–water retention and to reduce erosion? Y/ N	
E101		E101a		E101b		E101c	

E11: Water Management/ conservation:

Alteration of irrigation use, including amount, timing to conserve water? Y/ N		Adoption of supplementary water sources such as rainwater harvesting? Y/ N		Construction of flood defense infrastructure? Y/ N		Construction of bunds around fields, or land leveling to preserve water and maximize water uptake of the crops? Y/ N		Adoption of water-efficient methods to conserve soil moisture (e.g. Furrow irrigation)? Y/ N	
E111		E111a		E111b		E111c			

E12: Diversification of Income of household members:

Shift source of Income		Change in Income		How many household members shifted to this livelihood			
E121	Livestock, fishing, etc	E121a		E121b		E121c	
E122	Off farm job	E122a		E122b		E122c	
E123	Private business (store)	E123a		E123b		E123c	
E124	Share Crop/ Lease your land	E124a		E124b		E124c	
E125	Move to urban area	E125a		E125b		E125c	
E126	Other (specify)	E126a		E126b		E126c	

E30: Recent infrastructure developments in past 15 years

Has your village witnessed public infrastructure construction with bearing to agriculture? (Y/N)		What infrastructure was built? *1	
E281		E281a	

*1: Dam/ Canal (1); Electricity lines (3); Roads (4); Tubewell (5); Rain water harvest tanks/ ponds (6); Flood defense infrastructure (7); other, specify______________________

E6: Adaptation actually undertaken

Adaptation Measures		Kindly list 3 most important reasons other than climate change for applying these measures	
E61	Altering the timing of "cropping activity" (e.g. harvest date)	E61a	
E62	Shift in cropping pattern (e.g. crop portfolio)	E62a	
E63	Altering agricultural input	E63a	
E64	Investment in soil conservation	E64a	
E65	Investment in water conservation	E65a	
E66	Diversification of Income	E66a	
E67	Public/ Household infrastructure incl. water defenses		
E68	No Adaptation	E67a	
	Other, specify_________________________	E68a	

*1. Change in price or availability of input such as seed, fertilizer, water (1); Household factors: food and fodder self-sufficiency (2); Market Price of output/ higher expected return (3); Change in agricultural contract/ terms (4); Other________ (5)

F3: Household assets owned: quantity and value (2012)

Type of assets		Quantity		Approx. Value (Rs.)	
Electronic Appliance	TV	F31a		F31b	
	Radio	F32a		F32b	
	Other: ______	F33a		F33b	
Communication	Telephone	F34a		F34b	
	Internet	F35a		F35b	
	Mobile Phone	F36a		F36b	
Motorized Transportation: (Truck, car, etc.)		F37a		F37b	
Generator		F38a		F38b	

Section F. HOUSEHOLD INCOME:

F1 Kindly provide information on all kinds of income to this households during the last one year (in Rs.)

		Annual Income
F1a.	Wages (kind, yearly) approximate value in Rs.	[ ][ ][ ][ ][ ][ ][ ]
F1b.	Farm income	
F1c.	From business (shops, factory etc.)	[ ][ ][ ][ ][ ][ ][ ]
F1d.	From handicrafts	[ ][ ][ ][ ][ ][ ][ ]
F1e.	Remittances from other household members & relatives	[ ][ ][ ][ ][ ][ ][ ]
F1f.	Sale of property/ other asset	[ ][ ][ ][ ][ ][ ][ ]
F1g.	Land rental	[ ][ ][ ][ ][ ][ ][ ]
F1h.	Livestock	[ ][ ][ ][ ][ ][ ][ ]
F1i.	Other sources (gift, zakat, charity etc.)	[ ][ ][ ][ ][ ][ ][ ]
F1j TOTAL YEARLY INCOME: (in Rs.)		[ ][ ][ ][ ][ ][ ][ ][ ][ ][ ]

F2. Kindly provide information on monthly expenditure (in Rs.) of this household

F2a.	on food items bought / consumed	[ ][ ][ ][ ][ ][ ]
	Wheat	[ ][ ][ ][ ][ ][ ]
	Fodder	[ ][ ][ ][ ][ ][ ]
	Vegetable	[ ][ ][ ][ ][ ][ ]
	Rice	[ ][ ][ ][ ][ ][ ]
	Pulses	[ ][ ][ ][ ][ ][ ]
	Meat	[ ][ ][ ][ ][ ][ ]
	Other nutritional items _______	[ ][ ][ ][ ][ ][ ]
F2b.	on purchase of clothing and other items	[ ][ ][ ][ ][ ][ ]
F2c.	on health care (doctors/provider's fees and purchase of medicines)	[ ][ ][ ][ ][ ][ ]
F2d.	Miscellaneous	[ ][ ][ ][ ][ ][ ]

F2e TOTAL MONTHLY EXPENDITURE: (in Rs.) [ ][ ][ ][ ][ ][ ][ ]