Climate and rainfed rice cultivation in India

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In memory of my father,

Barmeshwar Nath Singh

(11 January 1957 – 17 March 2007)

Abstract

Enabling food production to keep pace with population growth in the face of global climate change is a significant challenge. Drought is predicted to occur more frequently under climate change, which is likely to reduce rainfed crop yields and thereby put at risk the agriculture communities in rainfed regions. Rice is a major crop that is cultivated by rainfed farmers and is therefore, vulnerable to increased variability in rainfall. The main aim of my thesis is to understand the climatic risks to rainfed rice cultivation, focusing on rainfed regions in India. I analysed historical data on monsoon and rice yield and found that more locations showed a drying trend than a wetting trend, and that within-season distribution of rainfall were a more important driver of yield than the total rainfall, or timing of monsoon. I used a climate envelope modelling approach to show that the distribution of rainfed rice can be modelled using climate variables, and that variables measuring water availability were more important predictors of rice distribution than temperature. Using climate projections from multiple general circulation models and representative concentration pathways, I concluded that by 2050, between 14% - 40% of current rainfed areas might become climatically less suitable for cultivating rice. Using rice yield trials data, I examined the yield performance of locally and widely-grown rice cultivars under water- and heat-stress. I found that cultivars showed greater yield decline under heat-stress than under water-stress. In addition, I found greater decline in yield under heat-stress in cultivars that were more drought-tolerant, suggesting potential trade-offs in continued improvement of drought-tolerant rice. I conclude that rainfed regions are at risk from climate change, and that rice yields are particularly vulnerable to short-term variability in monsoon rainfall. Trade-offs between water- and heat-stress tolerances suggest that the development of new rice cultivars needs to consider multiple plant traits and drivers of yield, in addition to drought-tolerance. Therefore, improving irrigation infrastructure for timely availability of water, and access by farmers to the most resilient crop varieties will reduce future climate risks for farmers.

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“Tvadiyam vastu hey deva tubhyamaeva samarpayae

(I am offering you, O Lord, only a fraction of that I have received from you!)

Author's Declaration

I declare that this thesis is a presentation of original work and I am the sole author. This work has not previously been presented for an award at this, or any other, University. All sources are acknowledged as References.

Chapter 2

This chapter is currently in preparation for submission to Plos One:

Singh, K., McClean, C. J., Büker, P., Hartley, S. E. and Hill, J. K. Short-term daily reductions in monsoon rainfall reduce yield of rainfed rice.

The draft manuscript is reproduced in full in this thesis, with minor formatting alterations. The analysis and the initial draft manuscript was written by me with inputs from all the co-authors. C.J.M. and P.B provided statistical advice whilst S.E.H. provided plant physiological information. The study was supervised by J.K.H.

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Chapter 4

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The draft manuscript is reproduced in full in this thesis, with minor formatting alterations. The text was written by myself with input from all co-authors. P.S. and S.K.D. provided the data on rice breeding trials. The study was supervised by J.K.H.

Chapter 1 General Introduction

Grains of rice (Oryza Sativa) (photo courtesy: Patrick Büker)

1.1. Thesis Overview

Food security is one of the biggest challenges of the 21st century that has been aptly summarised by the following quote:

> *"Imagine all the food mankind has produced over the past 8,000 years. Now consider that we need to produce that same amount again — but in just the next 40 years if we are to feed our growing and hungry world."* - Paul Polman and Daniel Servitje, 2012.

The above quote highlights an important aspect of food security; producing enough food for the rapidly increasing human population, which is predicted to be ~9 billion people by 2035. However, this is a huge challenge that is made more complex by changing climate. Therefore, new studies are required to assess how key crops will be affected by climate change, especially under projected increased temperature and rainfall variability. Rice is a major food grain consumed and traded globally, and India is one of the leading producers of rice. As a water-intensive crop, rice plants are vulnerable to climatic stresses especially if cultivated under rainfed systems where the water supply primarily depends on seasonal monsoon rainfall. Given that rainfed rice is cultivated by millions of subsistence farmers, it is important to understand climatic risks to rainfed rice cultivation in order to inform adaptation and mitigation decisions.

The main aim of my thesis is to examine relationships between rainfed rice cultivation and yield and climate. I do this by analysing historical datasets at three different spatial resolutions: district-level (~5900 km^2; Chapter 2), grid-level (18 km X 18 km; Chapter 3) and plot-level (15 m X 15 m; Chapter 4). Across the three Chapters, I analyse historical data on yield and extent of rice cultivation in relation to climate variables derived from measures of monsoon temperature and rainfall, and I highlight the risks to rainfed rice cultivation from climate change. This General Introduction Chapter provides an overview of the research topics examined in my thesis, where I discuss important aspects of climate – crop relationships and highlight current knowledge gaps that are addressed in my thesis. I outline the thesis rationale and main hypotheses that I address in subsequent Chapters, which I then discuss in the final General Discussion Chapter and present the general conclusions arising from my study.

1.2. Food Security

Food security was formally defined at the World Food Summit of 1996 in relation to recognition of widespread malnutrition and concern about the capacity of the current food production system to meet future demands. The formal definition states:

> "*Food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life*" (World Food Summit, 1996)

This definition points to four essential aspects of food security: production, accessibility, stability and utilisation of food (Pinstrup-Andersen, 2009; Misselhorn *et al.*, 2012). Failing to address any one of these inter-linked aspects could undermine the objective of zero hunger by 2030, which is a UN Sustainable Development Goal (Colglazier, 2015). For example, sufficient production does not guarantee the accessibility of food to people if the food is too expensive. In the presence of high price volatility, food could become inaccessible to people living below a threshold level of income (Gilbert & Morgan, 2010; Naylor & Falcon, 2010). Similarly, stability of food supply chains is a crucial element of food security; food supply chains are severely disrupted by natural disasters such as drought or flooding, and hence lead to inter-annual fluctuation in the supply of food grains (Haile, 2005; De Haen & Hemrich, 2007; Lesk *et al.*, 2016). Lastly, utilisation is a key element of food security that captures the dietary requirements and food preferences of the population.

Often it is found that sufficient production, easy accessibility and a stable supply does not guarantee that the food is sufficiently nutritious and providing the appropriate micro and macro nutrients to the population (Barrett, 2010). Therefore, achieving complete food security is a complex and challenging task and all the aspects outlined above have to be sufficiently addressed to achieve the target of zero hunger. Ensuring sufficient production of food is the first pillar of food security and in this thesis, I will focus on aspects of crop production (yield and area) because these are significantly affected by climate (more discussion on this in section 1.4).

According to the latest estimates, ~795 million people are undernourished globally, although the prevalence of undernourishment has dropped from 18.6% in 1990 to 10.9% in 2014 (FAO *et al.*, 2015). This reduction in undernourished people reflects improvements to food security, but it may overestimate the achievements of reducing hunger globally. Current estimates of the prevalence of hunger are calculated by expressing the number of undernourished people as a percentage of the total population and, therefore, these percentage estimates could potentially mask the absolute number of people that are hungry. Hence, it has been suggested that reductions in the absolute numbers of undernourished people should be a criterion for assessing food security (Pingali, 2016). The world population is projected to reach ~9 billion people by 2035 (United Nations, Department of Economic and Social Affairs, 2015), which will require an increase of ~60% more food from existing agriculture land, or by bringing new areas under agriculture (Alexandratos & Bruinsma, 2012). However, it is unclear whether increasing crop production through land intensification and bringing additional land into cultivation are plausible in the presence of increased climate variability and other non-climatic stresses and other requirements for land that will add additional complexity to the task of achieving zero hunger.

1.2.1. Challenges to Food Security

Current agricultural systems face challenges of meeting the rising demand for food grains to feed an increasing global population. However, there are multiple climatic and non-climatic factors that could hinder the target of sufficient food production (Tendall *et al.*, 2015). For example, increased climate variability is considered to be the biggest risk to meeting crop demands, because climate change affects almost every crop and geographical region (Gregory *et al.*, 2005; Schmidhuber & Tubiello, 2007; Lal, 2013; Hertel, 2016; Lesk *et al.*, 2016) (see section 1.4). Similarly, changing dietary preferences such as increased demand for more meat-based products, leading to an increase in cattle and poultry, could divert food grains away from human consumption to animal feed (Godfray et al. 2012). In addition, competition for land from increasing biofuel cultivation (Rathmann *et al.*, 2010; Harvey & Pilgrim, 2011; Havlík *et al.*, 2011) and urbanisation (Seto *et al.*, 2012; Pandey & Seto, 2015) could divert agricultural land away from crop cultivation to other uses. Historically, increases in food production took place by bringing additional areas into cultivation; however, given the increasing competition from other sectors for land, there is a need to increase food production on existing agricultural land through intensification, which could lead to land degradation and unsustainable practices (Garnett *et al.*, 2013; Godfray & Garnett, 2014). Across these different factors, increased climate variability is likely to affect both crop yields and the extent of agricultural land, as well as accentuate the effects of other factors. Therefore, adaptation options that seek to increase the climate resilience of the existing agricultural system should be explored (Foley *et al.*, 2011; Vermeulen *et al.*, 2012; Odegard & van der Voet, 2014). For example, using modern breeding tools and exploiting the genetic diversity of wild ancestral crop varieties to develop more resilient crop cultivars could help increase crop yields and help crops adapt to a more variable climate (Tester & Langridge, 2010; McCouch, 2013). Similarly, reducing yield gaps in locations that have not yet reached their maximum potential yield could also contribute to increasing crop yields, for example by deploying irrigation infrastructure and high yielding cultivars in rainfed regions (Evenson & Gollin, 2003; Pingali, 2012; Anderson *et al.*, 2016). Other options such as improved management practises (Stoop *et al.*, 2002; Powlson *et al.*, 2014; McDermid *et al.*, 2016) and promotion of insects as an alternate protein food source (van Huis, 2011) may also help reduce undernutrition in future. However, in order to understand the climatic risks to food production, more understanding is required of how the climate is changing and the relationships between climate and crop production, especially with respect to rainfall patterns that are vital for supplying the necessary water for crop cultivation in rainfed regions.

1.3. Climate Change

The global climate is changing, with profound impacts across multiple sectors and geographical regions. Emissions of greenhouse gases are largely responsible for the observed increase in global mean surface temperature, which is causing melting ice, sea-level rise and increased climate variability (IPCC, 2013). The global averaged combined land and ocean surface temperature has risen by 0.85°C during the period 1880 to 2012 (IPCC, 2013) and, in the absence of any mitigation, the global average temperature is projected to increase by 2°C by 2050 (Joshi *et al.*, 2011; IPCC, 2013). The observed increase in temperature to date, has been associated with an increase in the frequency and intensity of temperature extremes (Perkins *et al.*, 2012; Horton *et al.*, 2016), and a greater increase in night-time than day-time temperatures (Easterling *et al.*, 1997; Meehl *et al.*, 2009; Donat & Alexander, 2012; Donat *et al.*, 2013). In contrast to temperature changes, changes in global precipitation show greater spatial heterogeneity and intensification, with projections of wet areas getting more wet and dry areas getting drier in the future (Donat et al. 2013; Donat et al. 2016).

In order to examine the impacts of climate change, future projections are made under different assumptions of greenhouse gas emissions and the resulting net radiative forcing of the planet brought about by different emissions trajectories ('Representative Concentration Pathways', RCPs) (Meinshausen *et al.*, 2011; van Vuuren *et al.*, 2011). The RCPs are used to drive climate simulations across multiple General Circulation Models (GCMs) as part of the Fifth Coupled Model Inter-comparison Project (CMIP5) (Taylor *et al.*, 2012). Simulations across multiple GCMs indicate more pronounced temperature extremes and heavy precipitation events globally in future (Fischer *et al.*, 2013; Cai *et al.*, 2014). Under the highest emissions scenario of

RCP 8.5, precipitation is projected to decrease in subtropical dry regions and mid-latitudes, whereas mid-latitude wet regions are projected to experience increased precipitation (IPCC, 2013). However, compared to temperature projections, there is relatively less confidence in these precipitation projections (Knutti & Sedláček, 2012) and therefore, any studies examining future climate change impacts on agriculture are recommended to use climate projections from multiple GCMs to account for model uncertainties (Lobell & Burke, 2008; Knutti, 2010; Knutti *et al.*, 2017). Using multiple GCMs (for example, BCC-CSM1-1, HadGEM2-ES and MIROC-ESM-CHEM that are used in this study) allows studies to capture the uncertainties associated with climate projections, and using multiple RCPs allows studies to examine 'worst-case' (RCP 8.5) through to 'best –case' (RCP 2.6) scenarios of climate impacts on rainfed rice cultivation, as carried out in this thesis.

Extreme climatic events, such as droughts, have increased globally and many regions, including parts of India that cultivate rainfed rice, have experienced drying trends (Dai, 2013; Carrão *et al.*, 2016; Das *et al.*, 2016; Tietjen *et al.*, 2017). Globally, droughts are triggered by anomalous sea surface temperatures and by global events such as El Niño Southern Oscillation (ENSO) events that are associated with droughts in Asia and South-America (Dai, 2011). The projections from future global climate change scenarios suggests an increase rate of drying leading to quicker establishment of ENSO droughts, which are likely to have greater intensity in the future (Prudhomme *et al.*, 2014; Trenberth *et al.*, 2014). However, contrasting studies have failed to fine significant increases in drought incidences globally (Sheffield *et al.*, 2012; Greve *et al.*, 2014), and this lack of consensus may be due to the specific methods used to calculate evapotranspiration and plant water-stress (Trenberth *et al.*, 2014). Therefore, in order to understand the risks of drought to crop cultivation, a measure of water-stress should be used that captures the net availability of water to plants, and that accounts for the loss of water through evapotranspiration.

1.4. Climate Change and Food Production

Climate change affects biological and human systems in many ways (Thornton *et al.*, 2014). The literature examining the impacts of climate change on food security has focused mainly on the production aspects of agriculture (Lobell *et al.*, 2008; Wheeler & von Braun, 2013). Overlooking the other key aspects, such as food availability, accessibility and utilisation, could underestimate the climate risks to overall food security (Harrison *et al.*, 2016), although including these additional aspects could add additional complexity to analyses (Wheeler & von Braun, 2013; Hertel, 2016). Nonetheless, providing sufficient food production is the first pillar towards ensuring food security, and therefore it is vital that there is a robust understanding of climate-yield relationships in order to make more informed decisions on adaptation (Lobell *et al.*, 2008).

The majority of studies use crop yield (production per unit area) as a response variable in analyses to assess climate change impacts on production. Such analyses are either statistical (Lobell *et al.*, 2011; Leng *et al.*, 2016; Ramankutty & Iizumi, 2016) or process-based (Challinor *et al.*, 2005; Estes *et al.*, 2013; Jones *et al.*, 2017). In spite of differences in the modelling approaches used, there are two key conclusions about the role of climate on yield from the published literature. Firstly, climate explains significant variation in yields of major crops (Schlenker & Roberts, 2009; Ray *et al.*, 2015; Potgieter *et al.*, 2016; Hochman *et al.*, 2017) with some evidence of a stronger climate signal post-1980 (Liang *et al.*, 2017). The majority of studies found that temperature (or some measure of heat availability) (Lobell & Field, 2007; Schlenker & Roberts, 2009; Teixeira *et al.*, 2013; Mondal *et al.*, 2014; Cammarano *et al.*, 2016) and rainfall (or some measure of water availability) (Pathak *et al.*, 2003; Holzkämper *et al.*, 2013; Osborne & Wheeler, 2013; Lobell *et al.*, 2014; Akossou *et al.*, 2016) are key drivers of yield. The effects of rainfall and temperature are often interrelated i.e. water deficit increases the negative impacts of high temperatures, and high temperatures accentuate the effects of water-stress (Barnabás *et al.*, 2008; Cho & Oki, 2012; Lobell *et al.*, 2014).

Secondly, the impact of climate change is projected to vary across different crops, for example, wheat and maize may show greater declines compared with rice (Knox *et al.*, 2012; Estes *et al.*, 2013; Osborne *et al.*, 2013). Climate impacts are also projected to vary across geographical regions, with more negative impacts on crop yields projected in mid latitudes than upper latitudes (Rosenzweig & Parry, 1994; Jones & Thornton, 2003; Parry *et al.*, 2004; Akossou *et al.*, 2016; Levis *et al.*, 2016), and in relation to crop management practises (Lobell & Asner, 2003; Bhatta *et al.*, 2016; Cobon *et al.*, 2016) and assumptions about future greenhouse gas emissions (Levis *et al.*, 2016). Similarly, the climate risks to crop production may also vary across different types of agriculture environment; for example, rainfed systems are projected to show more declines in crop productivity compared with irrigated systems (Osborne *et al.*, 2013; Lobell *et al.*, 2014; Leng *et al.*, 2016).

Hence, there is consensus across studies that the net impacts of climate change on crop yields will be negative, but that there will be significant spatial variation in projected crop yield declines (Knox et al. 2012). However, studies examining climate-yield relationships often contain methodological issues that could introduce uncertainties in projections. For example, failure to account for the effect of CO_2 fertilisation on plant growth (Caubel *et al.*, 2017), or changing agricultural technology and take-up of new crop cultivars (Challinor *et al.*, 2007; Xiong *et al.*, 2014) could overestimate the detrimental impacts of climate change. Similarly, analysing yield information in isolation, for example by not considering the effect of climate change on availability of land for cultivation (Ray & Foley, 2013; Cohn *et al.*, 2016), could underestimate the impact of climate change on food security. Therefore, any study examining crop yield-climate relationships should address these methodological issues in order to provide more robust assessments of climate change impacts. In addition, analysis of pooled yield data at coarse spatial resolution (e.g. at an administrative or country-level) is likely to overlook the sensitivities of individual cultivars to climate, which will be evident in more fine-scale data. Therefore, examining responses of different cultivars to climate change from finer-scale datasets can help reveal any inter-cultivar differences in sensitivities to climate variation (Lobell *et al.*, 2011). Among common crops, rice is a semi-aquatic crop with high water demand; given projected trends of increasing incidence of drought and climate extremes, it is important to understand climatic risks to rice cultivation, especially in a rainfed environment.

1.5. Rice

Rice (*Oryza sativa*) was domesticated ~9000 years ago from its wild relative (*Oryza rufipogon*) (Cheng *et al.*, 2003; Londo *et al.*, 2006; Fuller *et al.*, 2010) as a result of continuous selection for desirable features such as less grain shattering, absence of red pigmentation and reduced apical dominance (Kovach et al. 2007). Rice domestication resulted in two species that are cultivated across the globe: *Oryza glaberrima*, which is mostly cultivated in Africa, and *Oryza sativa* cultivated in Asia. Within *O. sativa*, there are two subspecies: *indica* and *japonica. Oryza sativa japonica* type is cultivated in temperate regions (e.g. China, Japan, Korea) and produces grains that are low in amylose content (hence making them 'sticky'). The *indica* type is predominantly grown in subtropical regions (e.g. India, Bangladesh, Pakistan) and has grains with relatively high amylose content (Garris *et al.*, 2005; Kovach *et al.*, 2007). As a result of cultivation across different geographical regions and environment, cultivated rice (*O. sativa)* has become one of the most diversified and important cereals for human consumption, and has a major contribution to global food security. Globally, rice is harvested across ~162 million ha and supplies ~20% of daily calories for the world population. Rice is of particular importance in south Asian countries which, as of 2010, account for more than 90% of world rice production (GRiSP, 2013).

Figure 1.1 Domesticated rice (O. sativa) plants (a) and grains (b) from the indica sub-species (Photo courtesy: Patrick Büker)

Rice is a C_3 crop i.e. it fixes atmospheric CO_2 using the Calvin-Benson cycle to form carbohydrates that are later used in the grain filling stage. In the Calvin cycle, the enzyme Ribulose Bisphosphate Carboxylase/Oxygenase (Rubisco) plays a critical role in catalysing the conversion of CO_2 to carbohydrates through carboxylation of ribulose1,5-bisphosphate using ATP and NADPH (Raines, 2003). However, Rubisco is a bifunctional enzyme and also catalyses the oxygenation of ribulose1,5-bisphosphate in order to remove some of the toxic compounds created during the Calvin cycle through a process called photorespiration. Photorespiration causes loss of ~40% of the fixed carbohydrates and therefore reduces the efficiency of the Calvin cycle (Jordan & Ogren, 1984; Sage *et al.*, 2012; Walker *et al.*, 2016). However, given the strong affinity of Rubisco to CO_2, increases in CO_2 concentrations such as those expected under future climate scenarios (IPCC, 2013) may increase photosynthesis and stomatal conductance leading to subsequent increases in yield and biomass (Long *et al.*, 2004; Ainsworth & Long, 2005; Erda *et al.*, 2005; Ainsworth & Rogers, 2007; van der Kooi *et al.*, 2016). In spite of such a fertilization effect of increased CO_2, studies suggest that simultaneous increases in temperature under climate change could overturn any gains from increased CO_2 concentrations, and therefore the net effect of climate change is projected to be overall declines in rice yields (Matsui *et al.*, 1997; Prasad *et al.*, 2002; Long *et al.*, 2006; Cai *et al.*, 2016; Wang *et al.*, 2016). There is currently research underway to examine whether a more efficient C_4 photosynthesis pathway in rice could lead to improved water-use and nitrogen-use efficiency (Brown *et al.*, 2005; Hibberd *et al.*, 2008; Gowik & Westhoff, 2011; Covshoff & Hibberd, 2012), and hence improve food security. However, transferring to a C_4 pathway in rice is still at an early stage of development and alternative methods, such as breeding cultivars that are more resilient or improved cultivation management practices, deserve higher priority for maintaining rice yields in the future. Moreover, it is not clear whether resilient cultivars with improved water-use efficiency are also tolerant to other climatic factors such as heat-stress. Part of the reasons for this lack of information is because yield data from multiple cultivars with different tolerance levels and phenotypic properties are often pooled together in climate-yield studies masking the true sensitivities of different rice cultivars to a range of climatic stresses. In this thesis, I analyse data from different cultivar types in order to address this issue.

1.5.1. Rice cultivation environment

Rice is grown in many different environments, which can be classified according to their hydrological characteristics as either irrigated, rainfed upland, rainfed lowland, or deep-water environments. While irrigated areas offer more control of water and hence, can support multiple rice cropping per year, the other three systems are dependent on seasonal rainfall to meet their water requirements, and therefore support only a single rice crop per year. This single cropping system applies to countries such as India, which has a defined monsoon season responsible for delivering the necessary water supply to rainfed areas. Irrigated areas contribute more than ~75% of the global rice production (Seck *et al.*, 2012), primarily due to higher yields from high-yielding dwarf rice cultivars developed during the Green Revolution that respond well to irrigation and fertilizer application (Evenson & Gollin, 2003; Pingali, 2012). Rainfed areas, on the other hand, experience erratic rainfall, low fertilizer use, and greater incidence of weeds, pests and diseases that have kept yields historically low (Singh & Singh, 2000). Therefore, there is a substantial yield gap in rainfed areas that could be filled to help meet future demands for rice (Sharma, 2011; Anderson *et al.*, 2016). Addressing this yield gap in rainfed areas is important because current yield trends are not sufficient to meet the projected demands in 2050 (Ray *et al.*, 2013), and there is yield stagnation in irrigated areas (Ray *et al.*, 2012; Grassini *et al.*, 2013). According to one study, average yields in rainfed areas are 23% to 42% lower than their yield potential (Stuart *et al.*, 2016), while another study puts this value at 50% (Lobell *et al.*, 2009). Therefore, initiatives, such as *Bringing Green Revolution in Eastern India* (BGREI), have been launched that aim to address constraints limiting the productivity of rice in rainfed regions. Such efforts to increase yields in rainfed areas will also benefit marginal and small-landholder famers that depend extensively on rainfed rice cultivation for their livelihoods (Joshi, 2015).

1.5.2. Drought and heat-stress damage to rice

In general, impacts of abiotic stresses such as drought and heat-stress vary across different cultivars and growth stages of rice (Yoshida, 1981). Usually a rice plant takes between 3 – 6 months from germination to maturity, depending on the cultivar and the environment it is grown in. Rice growth stages comprise vegetative, reproductive and ripening phases, with each phase further sub-divided into sub-phases. The vegetative phase comprises germination, active tillering, increase in plant height and gradual emergence of leaves. The reproductive phase primarily consists of flowering followed by the ripening phase, which involves filling of grains from fixed carbohydrates (Fig 1.2). The length of the reproductive and ripening phases are similar across different rice cultivars, and differences among cultivars in time to maturity is primarily driven by differences in the duration of the vegetative stage (Yoshida, 1981).

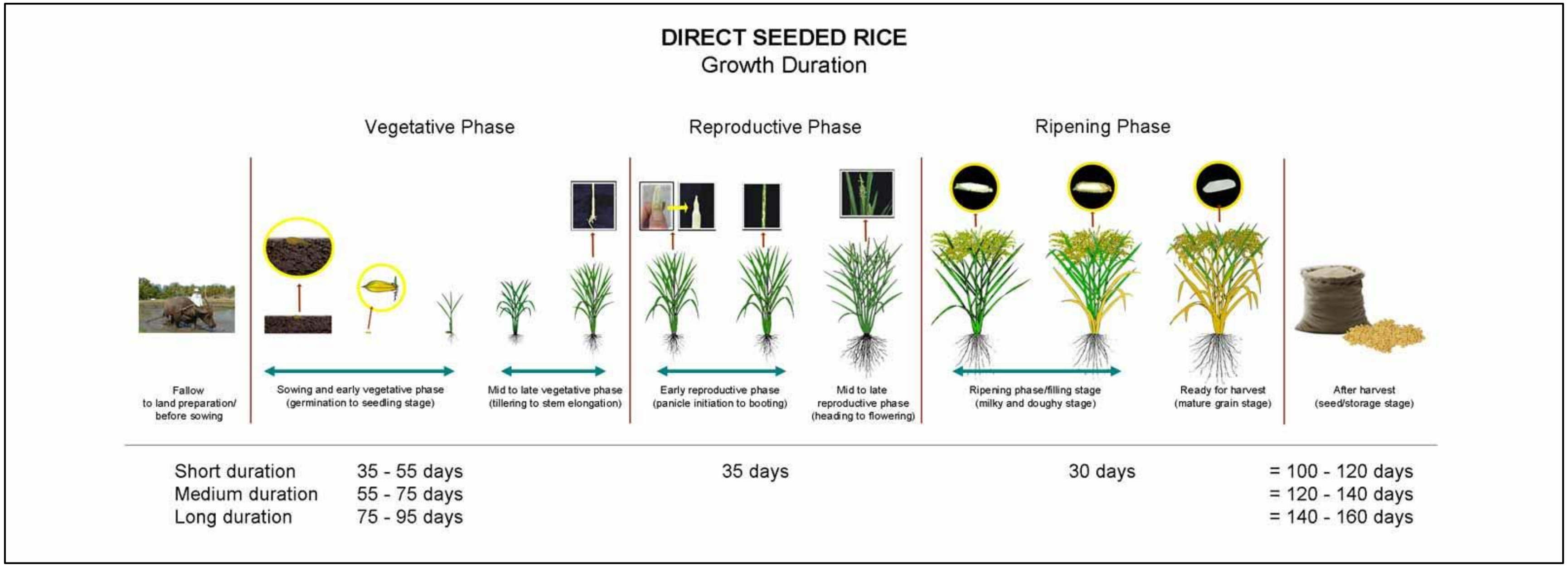

Figure 1.2 Schematic to show timing of different growth stages of three rice cultivars (representing short, medium and long growth durations) (Source: IRRI)

The final yield is a result of the cumulative interactions of environment, crop management and cultivar genotype (Rakshit *et al.*, 2012, 2016), together with any impacts of drought and heat-stress on different growths stages. Irrigated areas buffer plants from heat and drought effects, and so in this thesis I focus on rainfed environments. Rice is a semiaquatic plant and so rice production relies on ample and timely availability of water, especially in rainfed areas where erratic rainfall patterns could hinder rice growth and development. Drought stress is the most important constraint on rainfed rice production, affecting more than 10 million ha of upland and lowland rice globally (Wassmann *et al.*, 2009). Drought affects the net availability of water for plants, which is a consequence of total rainfall, evaporation, soil water-holding capacity, and temporal availability of water (Van Wesemael *et al.*, 2003; Mishra & Singh, 2010; Geng *et al.*, 2015; Fishman, 2016). Drought has detrimental effects on all growth stages, especially if it occurs during the flowering stage (Kazan & Lyons, 2016). Drought inhibits key plant reproductive processes such as development of ovaries, anther dehiscence, pollen germination and fertilization, all of which lead to sterile grains and hence low yields (Wassmann *et al.*, 2009).

Similar to drought impacts, heat-stress can adversely affect rice yields if high temperatures occur during reproductive and ripening growth stages. There are different impacts of high day-time (T_{max}) and night-time (T_{min}) temperatures on rice plants (Lobell & Ortiz-Monasterio, 2007; Welch *et al.*, 2010; Jagadish *et al.*, 2015); T_{max} has a greater impact during vegetative and reproductive stages while T_{min} plays a more crucial role during the ripening stage. Generally, a high T_{max} (generally above >35°C; Prasad et al. 2006) during the vegetative and reproductive stages causes stunted height, low tiller numbers, spikelet sterility, non-viable pollen and shortening of the growth stages, all of which are detrimental for flowering and hence yield (Prasad *et al.*, 2006; Craufurd & Wheeler, 2009; Shah *et al.*, 2011; Nguyen *et al.*, 2014; Sathishraj *et al.*, 2016). Higher T_{min} increases respiration and thus, uses up fixed carbohydrates, resulting in fewer carbohydrates available to fill the grains (Peng *et al.*, 2004; Mohammed & Tarpley, 2010; Shi *et al.*, 2013; Laza *et al.*, 2015). Higher T_{min} also results in increased rates of grain filling but also reduces the duration of grain filling, resulting in empty grains and/or grains with low weight and poor nutritional quality (Ambardekar *et al.*, 2011; Kim *et al.*, 2011; Ahmed *et al.*, 2015). Higher temperatures enhance stomatal conductance and plant transpiration (which has important cooling effects to avoid heat-stress damage to leaves), which could potentially interact with other factors (e.g. uptake of metals or salts; Gregorio et al. 2002) or could accentuate the damaging effects of drought if both heat-stress and drought co-occur (Mittler, 2006; Mittler & Blumwald, 2010). It has been projected that the occurrence of heat-stress could become more frequent in future (Gourdji *et al.*, 2013), with severe consequences for crop productivity.

The co-occurrence of drought and heat-stress is more damaging to a plant than either drought or heat-stress individually (Rizhsky *et al.*, 2002, 2004). The simultaneous exposure of plants to heat-stress and drought can result in co-activation of antagonistic stress-response plant physiological pathways. For example, under heat-stress, plants enhance mitochondrial respiration to avoid build-up of reactive oxygen species (Wahid *et al.*, 2007), but under drought conditions, plants synthesize osmoprotectants which reduce mitochondrial respiration (Rizhsky *et al.*, 2004). Similarly, at a whole-plant level, heat-stress enhances stomatal conductance for transpiration cooling (Mittler & Blumwald, 2010) whereas drought causes reduced stomatal opening to conserve water (Tombesi *et al.*, 2015). Given these conflicting responses, it is important to understand the yield responses of rice in the presence of both drought as well as heat-stress, and I address this topic in more depth in Chapter 4.

1.6. Rainfed agriculture in India

India's population is ~1.3 billion, with a decadal rate of growth of ~17% (Registrar General & Census Commissioner, 2011). Around ~54% of India's workforce is involved in the agricultural sector, making agriculture a key economic activity (Directorate of Economics and Statistics, 2016). In addition, India is also a leading exporter of major food grains, such as rice, wheat and maize and therefore, any declines in crop productivity will not only affect the

Indian population, but also countries dependent on food imports from India. The regions in Northern India are mostly irrigated and farmers are usually large land-holders, whereas areas in central and eastern India are mainly rainfed where farmers are small-landholders (Joshi, 2015) (Fig. 1.3)

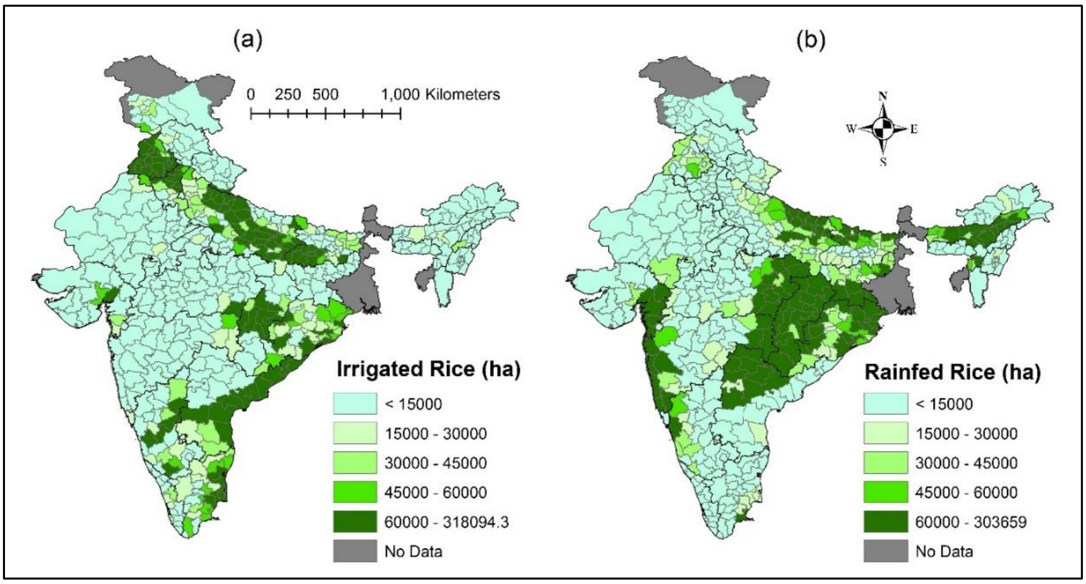

Figure 1.3. Rice growing areas in India. Maps show (a) irrigated rice cultivation and (b) rainfed rice cultivation. The data are average areas under cultivation (in ha) by district, for the period 1998 – 2010. I compiled the data from the India Directorate of Economics and Statistics, Ministry of Agriculture. The solid black lines represent State boundaries, grey lines represents district boundaries. States in grey have no data on rainfed or irrigated rice cultivation.

1.6.1. Monsoon and rice cultivation

There are two monsoon systems in India that operate annually; the south-west or summer monsoon and the north-east or the winter monsoon. The summer monsoon contributes > 75% of total annual rainfall and is the main growing season for crops across India. Historically, India's agriculture and economic well-being has been tied to the timing and length of the summer monsoon (Directorate of Economics and Statistics, 2016), which provides water for crop cultivation in rainfed regions between June to September (Revadekar & Preethi 2012; Gadgil 2003) (Fig 1.4).

A unique characteristic of a 'typical' Indian summer monsoon season (defined as when cumulative rainfall during June – September is between 96 % to 104% of the long-term average), is the phases of 'active spells' when there is good rainfall, and 'break spells' with little or no rainfall (Gadgil & Joseph, 2003; Rajeevan *et al.*, 2006, 2010). A monsoon which has long break spells indicates that rainfall is intense and confined to only a few heavy rainy days, and if the break spells correspond with critical rice growth periods where water demand is high, it is likely that the crop will fail (Fishman, 2016). Hence, two different monsoon seasons could be similar in terms of cumulative rainfall but could have different distributions of active and break phases, which would affect the timely availability of water to crops and hence crop yields. There are many uncertainties in rainfall projections, but future projections for the southwest monsoon predict an increase in all-India mean rainfall during the monsoon season (Fig 1.5).

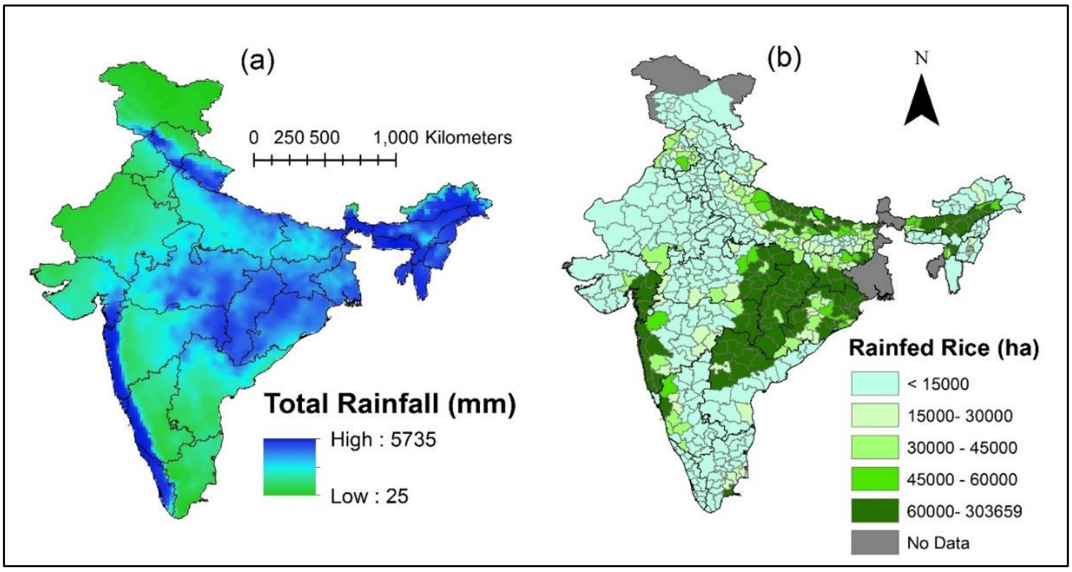

Figure 1.4. The maps show (a) the total rainfall for the south-west summer monsoon (June – September; 18 x 18 km grid resolution); and (b) average area under rainfed rice cultivation (district-level resolution). The rainfall data are total rainfall from June – September, averaged over 1970 – 2010 (Fick & Hijmans 2017).

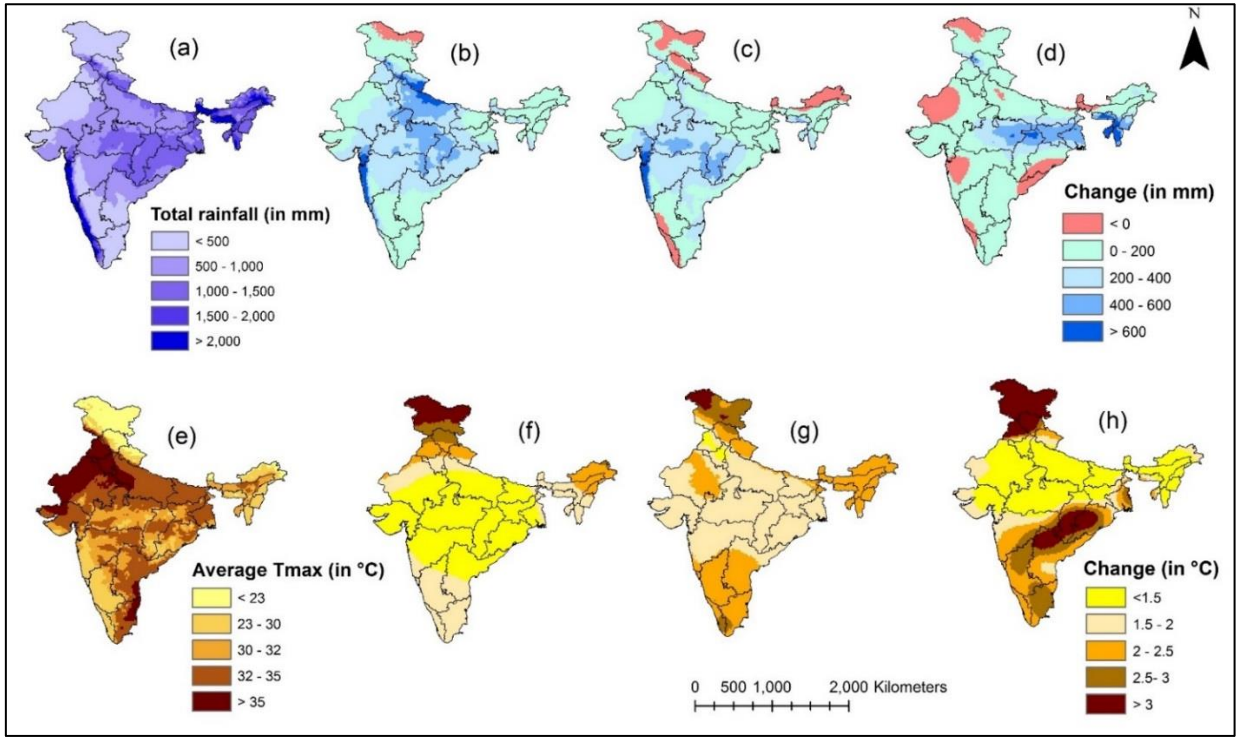

Figure 1.5 Total rainfall (a) and average maximum temperature (e) for current period (1970 -2000). Change in total rainfall (b) – (d) and average maximum temperature (f) – (h) for the summer monsoon season (June – September). Changes in temperature and rainfall were calculated by subtracting current rainfall and temperature from future rainfall and temperature (2050, RCP 8.5 scenarios). Future projections for rainfall and temperature are from three GCMs: (b) and (f) BCC-CSM1-1; (c) and (g) HadGEM2-ES; (d) and (h) MIROC-ESM-CHEM. The data are plotted at 18 x 18 km grid square resolution (Fick & Hijmans, 2017).

However, this overall increase in rainfall may mask temporal variability of rainfall, which many studies have shown is likely to increase in future i.e. monsoon rainfall is likely to become intense, with greater numbers of extreme dry and wet days expected by the end of century (Chaturvedi *et al.*, 2012; Mittal *et al.*, 2014; Rao *et al.*, 2014; Sharmila *et al.*, 2015). In spite of the importance of intra-seasonal patterns in rainfall, the majority of studies examining the impacts of the monsoon on rice yield have focused on cumulative rainfall throughout the entire growing season and have not considered the role of intra-seasonal rainfall patterns (phases of 'active' and 'break' days) in driving crop yields (Fishman, 2016; Lobell & Asseng, 2017); this is a focus of my analyses in Chapter 2.

Another important factor in understanding the impacts of summer monsoon is the spatial scale at which rainfall data are analysed. Analyses examining spatial and temporal variability of the summer monsoon have been carried out at coarse resolution (Sontakke *et al.*, 2008; Pal & Al-Tabbaa, 2011; Naidu *et al.*, 2015), and at finer resolution (Ramesh & Goswami, 2007; Lacombe & McCartney, 2014), using data covering different time periods which has resulted in some degree of disagreement regarding historical trends in monsoon patterns. Generally, as the spatial scale of analysis goes from coarser to finer resolution, regions emerge that show significant trends in total rainfall and frequency of extreme rainfall events (Guhathakurta & Rajeevan, 2008; Ghosh *et al.*, 2009). One probable reason for not detecting any significant trends at coarse resolution could be that rainfall variability is more prominent over local scales than when averaged over larger areas. At coarse scales, deficits in rainfall in one location may be compensated by excess rainfall nearby (Goswami *et al.*, 2006). Therefore, from an agricultural perspective, rainfall analyses should be carried out at fine resolution in order to reveal spatial and temporal heterogeneity in rainfall patterns, and relationships with crop yields. However, rainfall projections are made using GCMs that operate at coarse spatial scales, and are inadequate for modelling detailed climate – crop relationships, especially in India where there is considerable heterogeneity in the spatial distribution of rainfall (Tabor & Williams, 2010). Therefore, downscaling of rainfall data to finer resolution is performed, for example, by using regional climate models (Platts *et al.*, 2015), and these finer-scale data allow analyses that are more relevant to the spatial and temporal scales at which policies and adaption decisions are made. However, downscaling rainfall data from GCMs to finer resolution is more error prone and therefore care should be taken in deciding the most appropriate resolution for analyses, such that properties of GCMs are retained whilst providing meaningful results for policymakers and the scientific community (Ramirez-Villegas & Challinor, 2012).

The summer monsoon is a complex phenomenon to model, and hence to project future changes. The primary driving force of the summer monsoon is the seasonal imbalance in temperature between land and sea caused by annual cycles of solar radiation (Patil *et al.*, 2013). This temperature imbalance, combined with seasonal shifts in air pressure and the formation of tropical jet streams, gives rise to the summer monsoon in India. During the pre-monsoon season (March-May), the Indian landmass and the Indian Ocean warm up by absorbing heat (Nayagam *et al.*, 2013). However, because of its larger heat capacity, the ocean undergoes less increase in sea surface temperature compared with the land, resulting in a pressure gradient that creates the south-west trade winds (hence the name 'south-west' monsoon). These winds carry moisture from the ocean and hit the southern coast of India around the first week of June. The winds then split into two branches; the Arabian Sea branch which brings rainfall to the western coast, and the Bay of Bengal branch which brings rainfall to northern, central, and eastern areas (Ramesh & Goswami, 2007). However, the summer monsoon is a complex system and depends on many factors, resulting in considerable variability. For example, coupled ocean-atmosphere phenomena such as ENSO events cause monsoon variability (Allan *et al.*, 2003; Ummenhofer *et al.*, 2011). During an ENSO event, the southeast trade winds weaken and the warm water accumulated over the western Pacific returns to the eastern Pacific, causing heavy rainfall in South America and droughts in India, Indonesia and Australia. However, some studies have shown a weakening relationship between ENSO and monsoon characteristics in recent decades (Kumar *et al.*, 1999; Pai, 2004; Sarkar *et al.*, 2004), which may be due to increased surface temperatures resulting in enhanced land-ocean thermal gradients undermining the effects of ENSO events. Given such a complex monsoon system, it is not surprising that the scientific community faces a significant challenge in simulating future rainfall patterns in India (Menon *et al.*, 2013a). This challenge is reflected in the latest *"Coupled Model Inter-comparison Project Phase 5"* of the IPCC where there is wide uncertainty in monsoon rainfall projections for 2050, with some GCMs projecting increased variability while others project decreased variability (Jayasankar *et al.*, 2015). Given this wide uncertainty in future rainfall projections from different GCMs, it is important that any climate change impact studies on crop yields take into consideration these uncertainties and model output disagreements. Hence, in Chapter 3, my analyses take account of outputs from three GCMs, in assessing changes in the extent of rainfed rice cultivation in future.

1.7. Thesis Aims and Rationale

The main aim of my thesis is examine the relationship between climate and rainfed rice productivity in India. I examine the risks to rainfed rice from climate change, focusing on rainfed areas in India, which are dependent on the summer monsoon for growing rainfed rice. I carry out three main analyses. Firstly, I examine the main climate drivers of rainfed rice productivity by studying the relationships between rice yield and monsoon rainfall in India, based on historical data sets from 1998 to 2007. Secondly, I examine whether the current extent of rainfed rice cultivation can be modelled using climate variables derived from temperature and rainfall, and I identify where existing rainfed rice growing areas might become climatically less suitable in future (i.e. by 2050). Thirdly, I analyse yields of local and widely cultivated rice cultivars to examine their drought and heat-stress tolerance. The main hypotheses for these three analyses are outlined in more detail below:

Chapter 2 – Short-term daily reductions in monsoon rainfall reduce yield of rainfed rice.

The summer monsoon plays an important role in determining yield of rainfed rice, but the relative importance of quantity, distribution and timing of monsoon rainfall on rice yield is not well understood. I test the hypothesis that monsoon patterns have changed across the rainfed regions and that the within-season distribution of rainfall during the monsoon is more important for yield than the overall quantity and timing (onset and withdrawal) of the summer monsoon. I collate gridded rainfall data (~55 km resolution) and rice yield data (at district-level; ~5900 km^2) to examine: (1) historical changes in monsoon rainfall over the period 1951 – 2007, and (2) associations between yield data and monsoon total rainfall, number of wet and dry days, and monsoon onset and withdrawal dates. I conclude that more regions In India show a drying trend (26% as opposed to 15% showing a trend towards getting wetter), and that the number of wet and dry days is a more important driver of yield than total monsoon rainfall or timing of the monsoon.

This chapter considers the effect of rainfall variables on rice yield, yet we know that temperature variables and the extent of cropland are also important drivers of total agriculture output. Hence, in the next chapter I examine the role of temperature and rainfall variables in determining the extent of areas under rainfed rice cultivation.

Chapter 3 – Mapping regional risks from climate change for rainfed rice cultivation in India.

The main objective of this analysis is to map climate risks to areas under rainfed rice production. Yield is a function of production per unit area, as well as the extent of area under production. In this chapter, I test the hypothesis that the current extent of rainfed rice cultivation in India can be modelled with 'Species-distribution models' (SDMs) using climate variables derived from rainfall and temperature. I test whether rainfall is a more important predictor than temperature in predicting the current distribution of rainfed rice in India, and use the statistical SDMs to examine whether the climatic suitability of locations where rainfed rice is currently grown might decline in the future, given the future projections of increased temperature and variability in rainfall. I conclude that the current distribution of rainfed rice can be modelled with good accuracy using climate data, and that rainfall is more important in predicting the extent of rice cultivation than temperature. Incorporating future climate projections into SDMs shows that between 14% - 40% of current rainfed rice areas may become climatically less suitable for rainfed rice cultivation by 2050.

In these first two Chapters, I analyse rice yield and area data compiled at a district-level. These data usually pool information from multiple cultivars, which obscures the sensitivities of individual rice cultivars to climate factors. Hence, in the next Chapter I address this issue by analysing yield data from individual rice cultivars, allowing me to examine the relative importance of rainfall and temperature in more depth.

Chapter 4 – Selecting for drought-tolerance may increase the sensitivity of rainfed rice to heat-stress.

The main objective of this analysis is examine yield of popular rice cultivars to water-stress and heat-stress. Historically, breeding efforts have focused on developing rice cultivars that are tolerant to drought under the assumption that drought is the main abiotic stress in rainfed areas. However, there is little information on whether rice cultivars developed for improved drought-tolerance are also resistant to other stresses such as heat-stress, or if there are yield trade-offs. I examine yield trade-offs between drought and heat-stress, and I test the hypothesis that cultivars adapted to drought are more sensitive to heat-stress. I collate breeding trial data, from sites where the management practises are standardised, for two groups of cultivars; locally grown cultivars and widely- grown national cultivars. I examine if locally grown rice cultivars have higher yields and drought-tolerance than widely grown cultivars. I also examine the relative sensitivities of cultivars to drought- and heat-stress and conclude that local cultivars had higher yields and are more drought-tolerant, but that local cultivars are also more sensitive to heat-stress. Thus, breeders must focus on traits that confer tolerance to multiple stresses.

Chapter 5 – General conclusion.

In this section, I discuss the overall results and their robustness and future directions of this research.

Chapter 2 Short-term daily reductions in monsoon rainfall reduce yield of rainfed rice

Farmers plough their rice fields during the initial days of summer monsoon in central India

2.1. Abstract

Global climate change is likely to affect rainfall patterns, threatening crop yields in regions dependent on rainfed agriculture. In India, ~55% of rice is cultivated under rainfed conditions and most of this crop is dependent on the southwest monsoon and thus, potentially vulnerable to altered patterns of monsoon rainfall. I examined changes in monsoon rainfall patterns in relation to five monsoon variables important for rainfed rice cultivation: total monsoon rainfall, number of wet and dry days (i.e. days within the monsoon season with unusually high or low rainfall compared with the average), and timing of monsoon onset and withdrawal. Over the past six decades, there was considerable variation across India, but more areas showed a drying trend (i.e. reduced rainfall, reduced number of wet days, or increased number of dry days); 26% of the grids analysed showed a trend towards getting drier compared to 15% of grids showing trend towards getting wetter. I examined relationships between monsoon rainfall and reported yields of rainfed rice over a 10-year period (1998 to 2007) across 180 districts in India, and found that the frequencies of dry days and wet days had significant but opposite impacts on rice yield. Dry days reduced rice yields, particularly when they occurred during early plant growth, and outweighed the positive impacts of wet days. Each additional dry day resulted in ~16 kg/ha reduction in yield, corresponding to annual rice yields declining by ~1% to ~15% across my study region. The vulnerability of rainfed rice to short-term daily reductions in monsoon rainfall highlights the sensitivity of rainfed rice to within-season variation in rainfall and the need to develop strategies to improve food security in rainfed agricultural regions, such as the development of drought-resistant rice varieties and irrigation infrastructure.

2.1. Introduction

The global human population reached 7.3 billion by mid-2015 and is expected to reach 8.5 billion by 2030 (United Nations, Department of Economic and Social Affairs, 2015). Food production needs to increase significantly to keep pace with this increased demand, and to also cope with an increasingly variable climate (Tripathi *et al.* 2016). Future climate change is predicted to reduce the yields of major crops such as maize, wheat and rice (Challinor *et al.* 2014), with some evidence that recent climatic changes have already been sufficient to reduce yields (Lobell *et al.*, 2011; Ramankutty & Iizumi, 2016), despite potential benefits to plant growth from increased atmospheric CO_2 (Ainsworth, 2008; Lobell & Gourdji, 2012). Thus, there is a need for a better understanding of the rate and extent to which changes in climate will affect crop yields in order to identify areas at particular risk and to make informed decisions about securing future food production. Previous studies investigating climate-yield relationships have found rainfall to be an important driver of crop yields (Auffhammer *et al.*, 2012; Valverde *et al.*, 2015). Rainfed crops, which are not under irrigation, are particularly vulnerable to variation in rainfall, especially in those parts of the world, such as India, where farmers depend almost entirely on monsoons for meeting crop water requirements (Rao *et al.*, 2016). Crop productivity is known to be affected by the total amount of rainfall (Akossou *et al.*, 2016) and there is some evidence that the distribution of rainfall within the growing season is also an important influence (Fishman, 2016), although the impacts of short-term variation in rainfall on crop yield have received relatively little attention as yet.

In India, approximately half of all agricultural areas are under rainfed cultivation and over half of the total rice-growing area is rainfed. Most rainfed rice in India is grown during the *Kharif* or summer (southwest) monsoon, and so changes to the timing and intensity of the monsoon could lead to lower rice yields (Krishna Kumar *et al.* 2004, Subash and Ram Mohan 2011). For example, the timing of the monsoon end-date and number of days with no rainfall have significant impacts on crop phenology (Mondal *et al.*, 2015), and increased daily variability in monsoon rainfall has been shown to overturn the yield benefits from increased overall rainfall (Fishman, 2016). In addition, total rainfall during the summer monsoon had positive impacts on rainfed rice yields for some States but not others (Auffhammer *et al.*, 2012; Subash & Gangwar, 2014). These results imply that rainfed rice yields are dependent on several aspects of the summer monsoon, including timing of the monsoon, variation in daily rainfall, and total amount of monsoon rainfall.

The summer monsoon contributes more than 80% of the annual rainfall in India and there is some evidence for a recent trend of reduced monsoon rainfall (Ramanathan *et al.* 2005), a change which is detectable despite the considerable spatial variability in rainfall trends across India (Dash *et al.* 2007). The summer monsoon in India is characterised by very high rainfall overall, as well as within-season variation in precipitation patterns (Taraphdar *et al.* 2010), comprising phases of 'wet' and 'dry' days. This variation in daily monsoon rainfall has led to the identification of 'active' and 'break' days during the monsoon (Gadgil and Joseph 2003, Rajeevan *et al.* 2006), and analysis of days exceeding pre-defined rainfall thresholds (May, 2004; Ramesh & Goswami, 2007; Lacombe & McCartney, 2014). Short-term variation in rainfall and phases of wet and dry days could potentially affect crop yields, for example if they coincide with critical stages of plant development (Farooq *et al.*, 2009; Fishman, 2016). Moreover, some studies have shown a significant increase in the frequency of extreme precipitation events (Goswami *et al.*, 2006; Rajeevan *et al.*, 2008), which could compound any detrimental impacts of short-term rainfall variation on crop yields. Although rice yields are affected by a range of biotic (e.g. pests; Newbery *et al.* 2016) and abiotic (e.g. soil nutrients; Mondal *et al.* 2016) factors, in this study I focus on one of the most significant climatic variables for small scale farmers in India practising rainfed agriculture, namely the impacts of monsoon rainfall.

Statistical analysis of historical data can be a powerful technique for studying relationships between climate and yield on crops. Here, I analyse historical yield data to examine the impacts of monsoon rainfall on rainfed rice yields in India. Firstly, I examine variation in total monsoon rainfall, number of wet and dry days, and timing of monsoon onset and withdrawal. Secondly, I analyse published rainfed rice yield data and examine the effects of these monsoon rainfall variables on yield, and whether different rice development periods (plant growth versus grain ripening) vary in their sensitivity to monsoon rainfall patterns.

2.2. Methods

2.2.1. Sources of data for climate and rainfed rice yield

Summer monsoon rice yield data (tonne/ha/year) were downloaded from the website of the Directorate of Rice Development, Ministry of Agriculture, Government of India (http://drd.dacnet.nic.in/) and covered the 10-year period from 1998-2007 for 180 districts (~5900 km^2) within important rainfed rice growing states in India, which predominantly grow rainfed rice during the summer monsoon season: Assam, Bihar, West Bengal, Orissa, Madhya Pradesh, Maharashtra, and Chattisgarh (Fig. 2.1a). I obtained summer monsoon (1 June – 30 September) rainfall data from the APHRODITE (Asian Precipitation - Highly - Resolved Observational Data Integration Towards Evaluation of Water Resources) project (http://www.chikyu.ac.jp/precip/research/index.html). APHRODITE rainfall data are available at 0.5° lat/long (~55 km) grid square resolution and cover the period from 1951-2007, and are derived from interpolating rainfall data from rain gauge stations distributed at relatively high densities across the rainfed regions in India (Yatagai *et al.*, 2012). Information on monsoon onset and withdrawal were extracted from Indian Institute of Tropical Meteorological data (Singh and Ranade 2010), comprising monsoon onset and withdrawal dates as recorded by the Indian Meteorological Department for 19 sub-regions of India.

2.2.2. Calculating monsoon rainfall variables

I used APHRODITE data to derive three monsoon variables for each year: total monsoon rainfall (mm), and number of monsoon dry days and wet days. Total monsoon rainfall was computed as the arithmetic sum of daily rainfall from 1 June to 30 September each year for each 0.5° lat/long (~ 55 by 55 km) grid square for the period 1951-2007. I examined monsoon rainfall patterns over a

57-year period in order to investigate long-term trends, and I confirmed that all grid squares providing rainfall data contained cropland, based on the MODIS (Moderate Resolution Imaging Spectroradiometer) landcover map (2001-10) (Broxton *et al.*, 2014) (Fig. A1.1). I followed published methods (Rajeevan *et al.* 2006, 2010) for calculating the number of wet and dry days each year, as follows. For each 0.5° lat/long grid square and each year, I calculated the standard precipitation anomaly (SPA) for each day of the monsoon season, based on long-term precipitation data for that grid square from 1951-2007:

$$SPA_n = \frac{r_n - \bar{r}_n}{s_n} \qquad \text{Eqn. 1}$$

where:

r_n is rainfall on the n^{th} day of the monsoon (1 June -30 September);

$\bar{r}_n$ is the long term average daily rainfall on the n^{th} day of the monsoon for the period 1951-2007;

s_n is the standard deviation of daily rainfall for the n^{th} day of the monsoon for the period 1951-2007.

If, for any grid square, the value of SPA_n for the n^{th} day was greater than 1, that day was identified as a wet day, and if the SPA_n was less than -1, that day was a dry day. For each year, the number of days between 1 June – 30 September with SPA > 1 and < -1 were summed to obtain the number of wet and dry days per year per grid square. I used data on monsoon onset and withdrawal dates for the period 1975-2007 from 9 sub-regions in India that overlapped with the 180 districts analysed in this study (Fig. A1.2 maps the location of these sub-regions).

2.2.3. Long-term changes in monsoon variables

I examined long-term (1951-2007) changes in total monsoon rainfall, number of wet and dry days using gridded data at ~55 km grid-square resolution, and monsoon onset and withdrawal dates (1975-2007) using sub-regional data (Fig. 1). Rainfall data typically violate assumptions of normality and non-independence, which could result in over- or underestimation of statistical significance. To overcome these issues, I determined the magnitude of trends in total rainfall, and onset and withdrawal dates (and their statistical significance) using Sen's estimator (Sen, 1968) and Mann-Kendall (MK) tests of significance, using the package *zyp* (Bronaugh & Werner, 2013) in R (R Core Team, 2016). This method is a distribution free test (i.e. not affected by non-normality of data) and has been used previously for analysing trends in the Indian monsoon (Kumar *et al.* 2010, Pal and Al-Tabbaa 2011, Lacombe and McCartney 2014). I used Poisson regressions to calculate trends in the frequency of wet and dry days over time (and their significance), with a quasi-Poisson error to account for over-dispersion.

2.2.4. Examining relationships between monsoon rainfall and rice yield

To examine the relationship between monsoon rainfall and rice yield, I regressed rice yield for each year (1998-2007) and district (i.e. 1800 year by district values) against the five summer monsoon variables (total monsoon rainfall, number of wet and dry days, and monsoon onset and withdrawal). Since planting and harvesting periods differ across districts depending on monsoon onset, I defined the growing season separately for each district, and calculated the five monsoon predictor variables for each district's growing season each year (for the period 1998-2007). I defined the growing season for each district as spanning the period from the monsoon onset date (a proxy of planting day) to 30 days after the monsoon withdrawal date (a proxy of harvesting day). The harvesting date was considered to be 30 days after the withdrawal date to account for any damage to rice yields due to unexpected rainfall after the monsoon when the crop is being harvested (Auffhammer *et al.*, 2012). I took this approach, rather than using planting and harvesting dates provided by Sacks *et al.*, (2010) which are based on extrapolating data from southern states (Fig. A1.3), because information based on local monsoon timing is likely to provide a better proxy of local planting and harvesting dates.

I also wished to minimise the influence of potentially confounding spatially-varying factors (e.g. changing crop management practices, soil type) and temporally-varying factors (e.g. change in cultivars, irrigation infrastructure) on crop yields (Lobell & Field, 2007). In order to do this, I used linear mixed effect models (LMMs) with 'district' and 'year' as random factors, using the *lme4* package in R (Bates *et al.* 2015). I used an information theoretic approach to select the best models and to determine the relative importance of the five monsoon predictor variables on rice yield (Burnham & Anderson, 2002). I first fitted a global model with all five monsoon variables and I standardised these input variables by subtracting the mean and dividing by twice the standard deviation (Grueber *et al.* 2011). This standardisation allowed me to compare directly the effect sizes of the five monsoon variables on rice yield. After standardising, I generated model sub-sets using the *dredge* function in *MuMIn* package in R (Barton, 2016), using all possible combinations of the five monsoon variables, including the null model. From these models, I selected the best set of models based on AICc values, where the model with the lowest AICc value was deemed the 'best model'. Model averaging was used for models with ΔAICc <2 of the best model. I calculated the effect sizes and 95% confidence intervals for each monsoon variable, and variables had a significant effects if the confidence intervals did not span zero (Nakagawa & Cuthill, 2007). To assess the overall goodness-of-fit of models, I calculated conditional R^2 values (variance explained by the full model that includes the effect of monsoon variables, and random effects of district and year, on the yield) (Nakagawa & Schielzeth, 2013).

2.2.5. Sensitivity of rice growth stages to variation in rainfall

I examined if different growth stages of rice differed in their sensitivity to the timing of wet and dry days during different periods of rice plant development, by dividing the growing season into two broad rice growing periods: vegetative-reproductive stage (period from monsoon onset to monsoon withdrawal) and ripening-harvesting (period of 30 days after withdrawal). The precise timing of these periods differs across India depending on rice variety and rice planting dates (see above), but these periods correspond with the main rice growing periods (Auffhammer *et al.*, 2012). I focussed this analysis on wet and dry days and computed the number of wet and dry days per year for the two growth stages to examine the effects on yield. I built models with rice yield as the dependent variable and wet and dry days in the two growth stages as fixed effects, with 'district' and 'year' as random effects. A global model was constructed using all combinations of variables for the two growth stages. The best set of models was selected (based on ΔAICc <2) followed by model averaging to determine the effect of wet and dry days on the two rice growth stages.

2.3. Results

2.3.1. Long-term changes in summer monsoon rainfall

Over the past 57 years, there has been a tendency towards reduced rainfall across the predominantly rainfed areas of India, although there was considerable spatial variation in rainfall patterns. A total of 24% (27/110) of grid squares showed declining total rainfall (ranging from -1.74 mm/year to -9.5 mm/year in total monsoon rainfall) and only 3% (4/110) of grid squares showed increased total rainfall (from +1.26 mm/year to +4.4 mm/year; Fig. 2.1a). Over this 57-year period, there were more wet days (average 12 to 17 wet days per year per grid) than dry days (average 0 to 10 dry days per year per grid). However, an almost equal number of grids (~16% of grid squares) showed a trend of either decline in wet days (and increase in dry days) or an increase in wet days (and reduced number of dry days) (Fig. 2.1b and 2.1c). However, the frequency of dry days showed a greater rate of increase per year (increase of 1.74% to 3% per year) compared with wet days (0.5% to 1% increase per year), indicating an increasing drying trend. Overall, 26% of grids showed a drying trend (i.e. either reduced total rainfall, an increase in dry days or a reduction in wet days) as opposed to 15% of grids showing an increased wetting trend. There was little change in the timing of monsoon onset (except in eastern India which showed a significantly earlier onset of 9 days advance over time), whereas four regions showed significant delay in monsoon withdrawal, thereby lengthening the monsoon season by ~4 to ~8 days during the 1975-2007 period (Fig. 2.2).

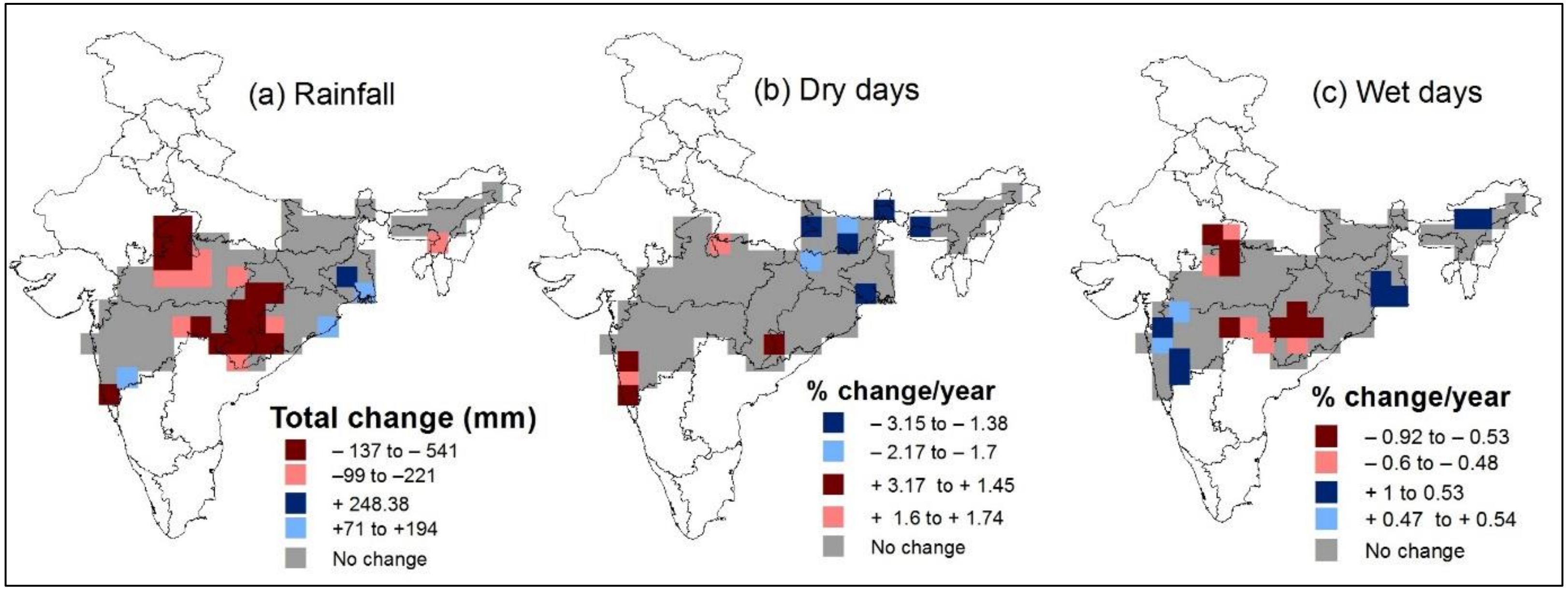

Figure 2.1. The maps shows changes in monsoon rainfall (1st June – 30th September) over a 57-year period (1951-2007) in relation to changes in (a) total rainfall, frequency of (b) dry days, (c) wet days. The monsoon data are analysed for only those states that cultivate rainfed rice. Grids getting drier (i.e. reduced rainfall, increased dry days or reduced wet days) are shown in dark red (P<0.05) and light red (P<0.1). Grids getting wetter (i.e. increased rainfall, reduced dry days or increased wet days) are shown in dark blue (P<0.05) and light blue (P<0.1). Each grid is ~55 km grid square resolution. Time-series plots are shown in Fig. A1.4. to Fig A1.15.

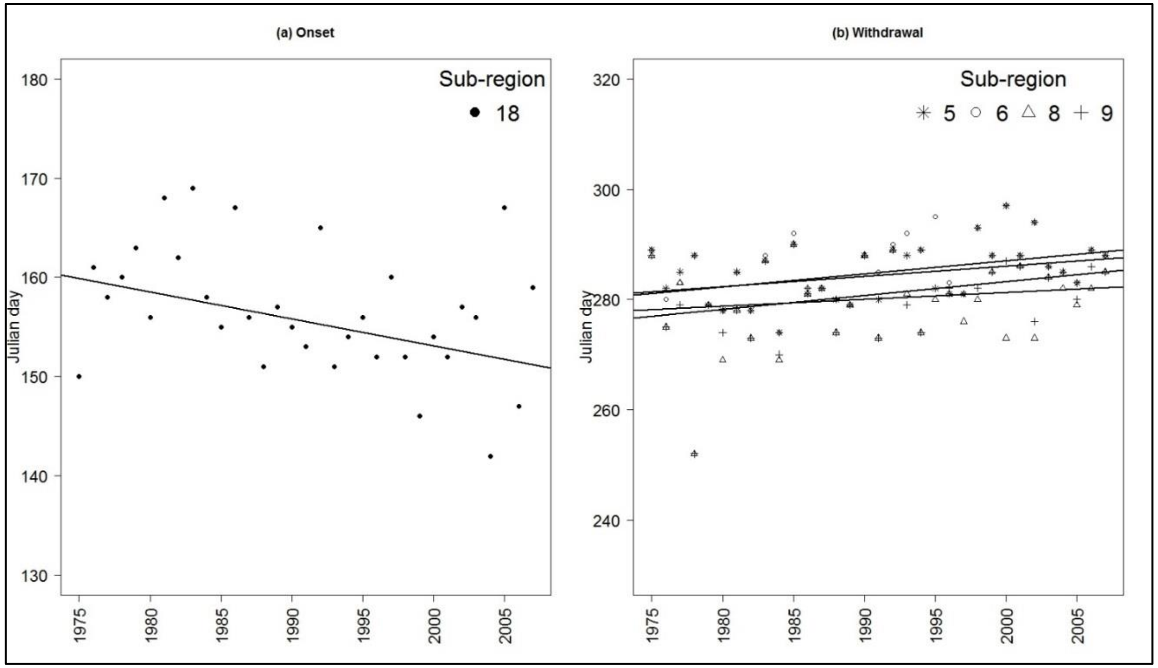

Figure 2.2. The plots shows changes in monsoon onset and withdrawal (refer to Singh and Ranade (2010) and Fig. A1.2. for the location of the 9 sub-regions providing data) across rainfed regions in India for the period 1975-2007. Data for only those regions are shown which showed a significant trend in onset and withdrawal. (a) Change in monsoon onset over time. The solid line shows a significant early onset of monsoon (9 days in region 18 overlapping districts in Assam); (b) change in monsoon withdrawal over time. The solid line shows a significant delay in monsoon withdrawal (4 to 8 days).

2.3.2. Examining relationships between monsoon rainfall and rice yield

Among the five monsoon rainfall variables that I examined, the number of dry days had the greatest negative impact on rice yield (standardised effect size = -133.26, CIs: -88.51, -78.02), followed by the number of wet days (positive impact; standardised effect size = 106.42, CIs: 67.09, 145.74) and withdrawal date (positive impact of later date; standardised effect size = 106.42, CIs: 20.79, 128.07), but there was no significant effect of the other two monsoon variables (total rainfall and onset dates) (Fig 2.3a). These standardised effect sizes should be interpreted as change in yield associated with two standard deviation change in the predictor. For example, an increase of two standard deviations above the mean value of the number of dry days per year will reduce rice yield by 133.26 kg/ha. In order to estimate the mean unstandardised effect sizes of best models, I ran my models again without standardising the predictor variables. My results showed that for every additional dry day per year, there was an associated reduction in rice yield of 16 kg/ha, as opposed to an increase of 7 kg/ha in yield for every additional wet day. In order to further explore the effect of the three important monsoon variables (dry days, wet days, monsoon withdrawl date), I used the average model derived from the 4 top models (Table 2.1) to predict rice yield for a given monsoon variable while keeping the other variables at their historical mean value (Fig 2.3b to 2.3d show the linear response functions of yield in relation to: dry days (negative), wet days (positive) and withdrawal (positive)). These results suggest that the detrimental effects of dry days could potentially outweigh the positive impacts of wet days on yield.

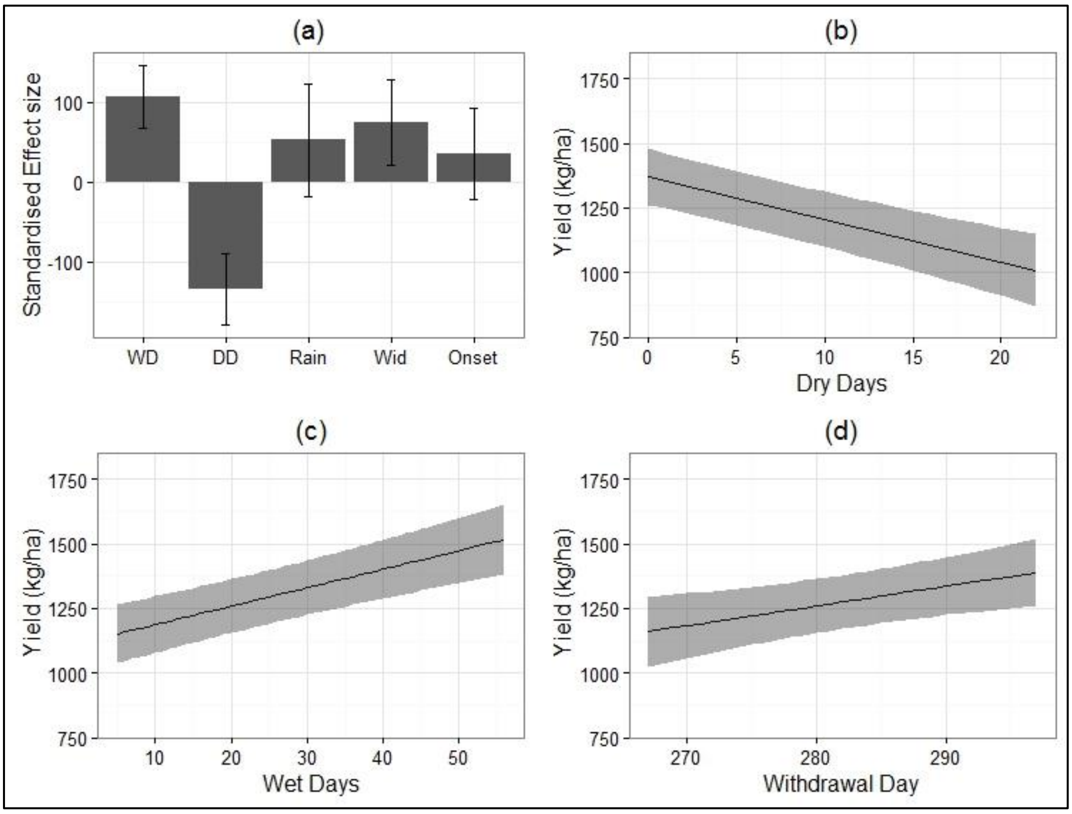

Figure 2.3.: The impacts of monsoon rainfall on rice yield. Histogram bars show: (a) the model averaged standardised effect sizes of five monsoon variables: wet days (WD), dry days (DD), total rainfall (Rain), withdrawal (Wid) and monsoon onset (Onset) on rainfed rice yield. Effect sizes are averaged over the 4 best models in Table 2.1 and errors bars represent model-averaged 95% CIs. Correlation matrices of the five monsoon variables are in Table A1.1. Regression plots show modelled rice yield (kg/ha) in relation to (b) dry days, (c) wet days and (d) withdrawal day when all other climate variables in the model were held constant at their historical mean value.

I estimate that average loss in yield per year due to dry days ranged from 1.4% to 15% of the average rainfed rice yields per year (depending upon the location; see Appendix 1.1 for calculations). Overall, the goodness-of-fit of the best models relating rice yield to monsoon variables (conditional R^2) was good, with the best model explaining 73% of overall variation (conditional R^2 ranged from 73.5% to 73.7%; Table 2.1). However, a model based only on monsoon variables (i.e. excluding the effect of other spatial and temporally-varying abiotic and biotic factors factors) has a low explanatory power (marginal-R^2). Thus, I conclude that although monsoon variables apparently have significant effects on rice yields, other abiotic and biotic factors contribute to yield variation over the 10 years of our study.

Table 2.1. Results of analyses of rice yield and five summer monsoon variables: total monsoon rainfall ('rain'), number of wet days ('WD'), number of dry days ('DD'), and date of monsoon onset and withdrawal. The table shows the list of best linear mixed models (LMMs) selected from the candidate set of models based on ΔAICc<2. Analyses are for the period 1998-2007 for 180 districts in India. Conditional and marginal R^2 values represent variance explained by the overall model and fixed effects respectively. Delta = difference in AICc values of each model and the best model (WD + DD + withdrawal); Weight = probability that a model is the best model for the given data.

Model	df	logLik	AICc	Delta	Weight	R^2	
						Conditional	Marginal
WD + DD + withdrawal	7	-13332.57	26679.2	0.00	0.29	73.6 %	2.2%
WD + DD + rain + withdrawal	8	-13331.60	26679.3	0.08	0.28	73.5%	2.4%
WD + DD + onset + rain + withdrawal	9	-13330.77	26679.6	0.43	0.24	73.6%	2.4%
WD + DD + onset + withdrawal	8	-13332.00	26680	0.87	0.19	73.7%	2.2%

2.3.3. Sensitivity of rice growth stages to variation in rainfall

Our analysis showed that both dry days and wet days had significant impacts on rice yield during the vegetative and reproductive stage (Fig. 2.4). Dry days reduced rice yields (standardised effect size = -139.711, CIs: -182.62, -96.8) demonstrating that interruptions in rainfall during the initial growing period are detrimental for subsequent crop yield. Wet days during the vegetative stage had a positive effect on yield (standardised effect size = 114.537, CI: 79.03, 150.04). Dry days were more common during the vegetative and reproduction stage than during the ripening stage (Kruskal-Wallis: chi-sq = 5789.8, df = 3, $p < 0.05$; Fig. A1.16).

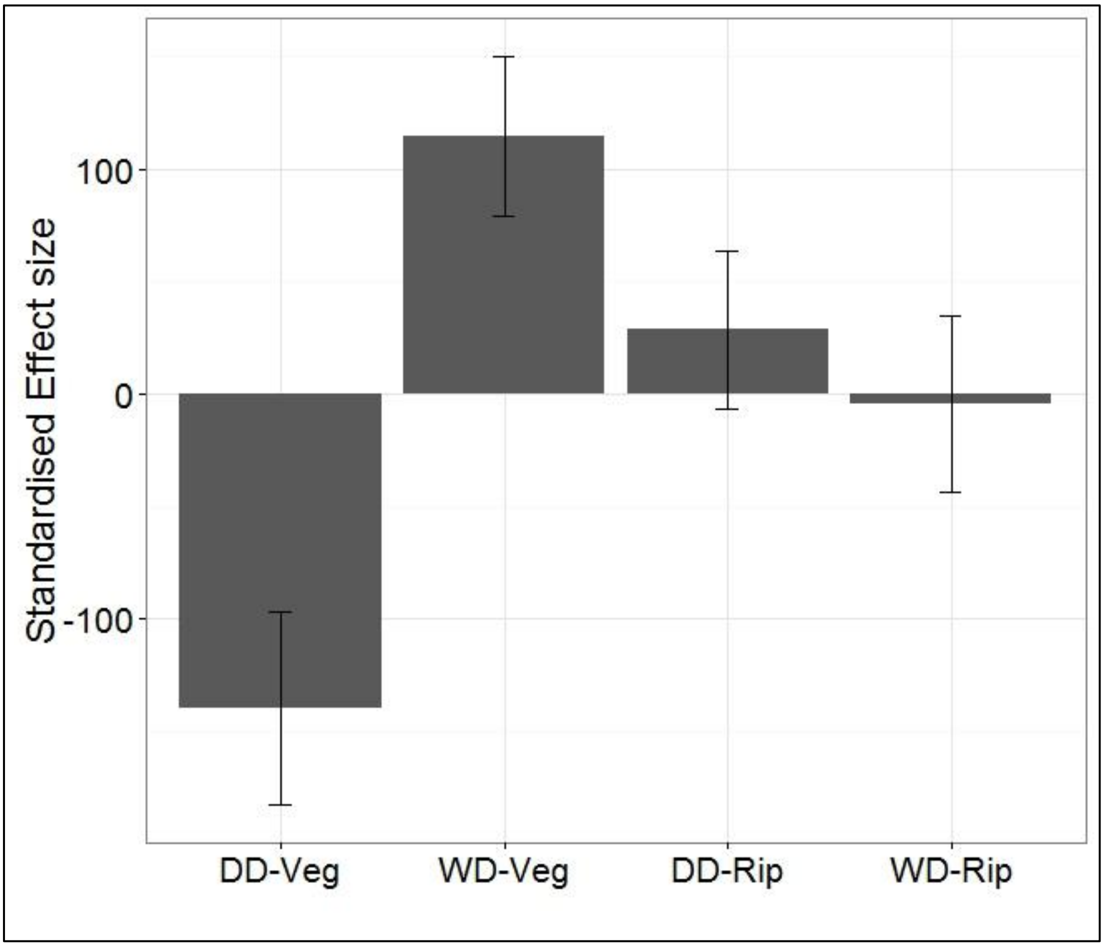

Figure 2.4. Standardised effect sizes of dry and wet days on rice yield for two rice growth stages – vegetative and ripening stages (DD-Veg = effect size of dry days on vegetative stage, WD-Veg = effect size of wet days on vegetative stage, DD-Rip = effect size of dry days on ripening stage, WD-Rip = effect size of wet days on ripening period. Effect sizes are slopes (standardised) and error bars show model-averaged 95% CIs.

2.4. Discussion

Extreme precipitation events during critical phases of crop growth affect crop yields (Revadekar & Preethi, 2012), and this study examined the effects of variation in monsoon rainfall variables (total rainfall, wet days, dry days, date of monsoon onset and withdrawal) on rainfed rice yields at district-level (~5900 km^2) in India. I derive two main conclusions from this study. Firstly, there has been a tendency towards reduced rainfall over the past 57 years, but there is considerable spatial variation in these changes in rainfall patterns. Secondly, rainfed rice yield is significantly reduced by short-term daily drought (dry days), which outweigh the positive effects of short-term high rainfall (wet days) on rice yield.

2.4.1. Long-term changes in monsoon rainfall

There are contrasting conclusions in the published literature in terms of trends in the Indian monsoon, which may be due to different spatial scales of analysis in different studies (Jain & Kumar, 2012). Generally, studies conducted at coarser-spatial scale (e.g. country-level, divisional-level) find few significant changes in monsoon rainfall (Goswami *et al.*, 2006; Rajeevan *et al.*, 2006), whilst studies conducted at finer resolution (grid-level or meteorological sub-division level) have detected some areas with significant changes in regional rainfall, with more locations showing declines over time than increases (Singh, 2013; Naidu *et al.*, 2015). The lack of any significant trends in rainfall being detected at coarser-spatial scales could be explained by the fact that declines in rainfall at one location are compensated by increased rainfall at other locations, resulting in little overall change in rainfall when averaged over a large area (Goswami *et al.*, 2006). Analyses at finer spatial scale, such as the ~55 km grid cell resolution in this study, are less likely to suffer from this "averaging out", and so are more likely to detect rainfall variation (Lacombe & McCartney, 2014).

Our analyses revealed reductions in rainfall over the past 57 years, as well as spatial variation in these long-term trends. For example, more areas witnessed declines in total monsoon rainfall as opposed to increases (24% vs.

3% of all grid squares). These results are in broad agreement with a declining rainfall trend reported by Ghosh *et al.* (2009) and support concerns about risks to rainfed agriculture in the future (Soora *et al.* 2013). More grids showed a decrease in wet days than grids showing increase in dry days which suggests that decline in heavy precipitation events contribute more to historical drying that an increases in dry days. However, the frequency of dry days has increased at a slightly faster rate than for wet days, supporting my conclusion of an overall drying trend over time. My results also imply greater variation in rainfall overtime, and more extreme rainfall patterns within the growing season, as reported in other studies (Sushama *et al.* 2014, Singh *et al.* 2014).

Despite evidence of drying trends, I found considerable spatial variation in rainfall patterns over the past 57 years, including increasing and decreasing rainfall trends. Scenarios of future climate change project an increase in precipitation in India in future (IPCC, 2013), due to increased atmospheric moisture content under higher temperatures, although there is only medium confidence in these rainfall projections. Future projections also indicate that precipitation extremes (rainfall intensity and length of dry spells) may become more frequent (Sharmila *et al.* 2015), with more dry spells likely to reduce rainfed rice yields, even when those spells are very short as in this study.

2.4.2. Rainfed rice yield is significantly reduced by dry days

Of the five monsoon variables I examined, the frequency of dry days had the greatest effect on rice yield, demonstrating that even short-term daily reductions in rainfall within the monsoon season could significantly impact rainfed rice harvests. The negative impacts of dry days on yield were greater than the positive effects of wet days, and dry days were detrimental for subsequent yield even if they occurred early during crop growth, suggesting rice plants cannot compensate for interruptions in rainfall which occur in the vegetative stage. However, this observation could be an artefact of the greater frequency of dry days during the initial rice growth stages compared with later stages. Even though dry days represent very short-term droughts, they apparently create soil moisture stress for rice plants at a critical stage of their growth. Plants respond to even relatively minor changes in soil moisture by altering their leaf water potential and stomatal conductance, leaf relative extension rates and net CO_2 assimilation rates (Henson *et al.* 1989), and these responses are evident in most soil types and occur even at levels of soil drying where water is still available to plants (Davies and Gowing, 1998). These processes potentially explain why reduced rice growth prior to flowering translates into reduced yield (Sikuku & Onyango, 2012) and why I detected these adverse impacts of dry days in analyses which did not incorporate direct information about soil types or soil drying levels. Our analyses also did not include information on the types of rice cultivars being grown, and different varieties vary in their sensitivity to drought (Lafitte *et al.* 2006). In addition, effects of varying planting dates (Zhao *et al.* 2016) and management practises could also significantly interact with climate in determining final harvest yields. Future analyses, therefore, examining impacts of rainfall on yield of different cultivars grown in areas with different patterns of rainfall will help to better understand potential yield gaps and highlight areas most at risk from future climate change.

By contrast with the effects of dry days, the occurrence of wet days (i.e. days of exceptionally high rainfall) had positive impacts of plant growth and reproduction reflecting the importance of regular abundant rainfall for crop yields (Revadekar & Preethi, 2012). However, these positive effects of wet days do not imply that severe drought stress in the initial stages can be compensated for completely by more rainfall during the later stages of plant development. In addition, some studies have found that high rainfall during the later stages of plant development causes physical damage to crops, especially in areas with particularly high rainfall (e.g. eastern India; Pattanaik and Rajeevan 2010), although this was not evident in our analyses. I may not have detected negative effects of wet days because my discrete binary measurement of wet and dry days (i.e. whether a day is wet, or dry, or neither), gives equal weight to all the extreme rainfall events irrespective of their absolute values. I examined the number of wet days that were heavy precipitation events based on definitions from the literature (i.e. heavy precipitation events = rainfall > district-specific 95th percentile thresholds for June–September daily rainfall, using pooled

1998–2007 data; (Auffhammer *et al.*, 2012) and found that for the period 1998 - 2007, only 5% - 22% of wet days were heavy precipitation events, which could explain why the number of wet days during the later stages of plant growth apparently had no negative impacts on yield in our study. In addition, unlike dry days, which are an indicator of 'drought' and over which the famers in rainfed areas have relatively little control, excess water as a result of more wet days can be managed on fields through diversion of excess water. In summary, my analyses revealed significant relationships between yield and short-term periods of reduced rainfall (dry days) and high rainfall (wet days) with the negative effects of dry days outweighing the positive effects of wet days. These findings also suggests that the effects of monsoon rainfall on rice yield is primarily through variation in the frequencies of wet and dry days rather than total rainfall *per se*. However, the absence of a significant relationship between total monsoon rainfall and rice yield could be an artefact of the relatively short time series analysed in our study (10 years) compared with other studies which report that total monsoon rainfall is an important driver of yield.

In conclusion, I have demonstrated the sensitivity of rice yield to short periods of interruptions in monsoon rainfall in rainfed areas in India. Farmers in rainfed regions generally do not have access to irrigation and these communities that are dependent on rainfed agriculture are likely to become more vulnerable to future changes in monsoon patterns if the summer monsoon becomes more erratic. In addition, improving food production and rice yields in these rainfed regions will require adaptation to anticipate more variable monsoons in future, such as better centrally subsidised irrigation infrastructure and/or introducing more resilient rice cultivars capable of maintaining yield in the face of unpredictable rainfall.

2.5. Acknowledgements

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Chapter 3 Mapping regional risks from climate change for rainfed rice cultivation in India

A farmer sowing rice plants using system of rice intensification in central India

3.1. Abstract

Global warming is predicted to increase in the future, with detrimental consequences for rainfed crops that are dependent on natural rainfall (i.e. non-irrigated). Given that many crops grown under rainfed conditions support the livelihoods of low-income farmers, it is important to highlight the vulnerability of rainfed areas to climate change in order to anticipate potential risks to food security. In this chapter, I focus on India, where ~50% of rice is grown under rainfed conditions, and I employ statistical models (climate envelope models (CEMs) and boosted regression trees (BRTs)) to map changes in climate suitability for rainfed rice cultivation at a regional level (~18 x 18 km cell resolution) under projected future (2050) climate change (IPCC RCPs 2.6 and 8.5, using three GCMs: BCC-CSM1.1, MIROC-ESM-CHEM, and HadGEM2- ES). I quantify the occurrence of rice (whether or not rainfed rice is commonly grown, using CEMs) and rice extent (area under cultivation, using BRTs) during the summer monsoon in relation to four climate variables that affect rice growth and yield: ratio of precipitation to evapotranspiration (PER), maximum and minimum temperatures (T_{max} and T_{min}), and total rainfall during harvesting. My models described the occurrence and extent of rice very well (CEMs for occurrence, ensemble AUC = 0.92; BRTs for extent, Pearson's r = 0.87). PER was the most important predictor of rainfed rice occurrence, and it was positively related to rainfed rice area, but all four climate variables were important for determining the extent of rice cultivation. My models project that 15% - 40% of current rainfed rice growing areas will be at risk (i.e. decline in climate suitability or become completely unsuitable). However, my models project considerable variation across India in the impact of future climate change: eastern and northern India are the locations most at risk, but parts of central and western India may benefit from increased precipitation. Hence, CEM and BRT models agree on the locations most at risk, but there is less consensus about the degree of risk at these locations. My results help to identify locations where livelihoods of low-income farmers and regional food security may be threatened in the next few decades by climate change. The use of more drought-resilient rice varieties and better irrigation infrastructure in these regions may

help to reduce these impacts and reduce the vulnerability of farmers dependent on rainfed cropping.

3.2. Introduction

Global temperatures rose above pre-industrial levels by +0.85°C in the last century, and are predicted to exceed +2°C this century (RCP 8.5 scenario; IPCC, 2013). There are aspirations to limit this temperature rise by reducing anthropogenic greenhouse gas emissions (Hulme, 2016), but current global warming trends are expected to lead to a greater intensity, frequency and severity of droughts (Prudhomme *et al.*, 2014; Diffenbaugh *et al.*, 2015). Higher temperature and increased rainfall variability will reduce yields of major crops such as maize, wheat and rice (Lobell *et al.*, 2011; Sage *et al.*, 2015) (there is evidence that climate change has already begun to reduce yields (Lesk *et al.*, 2016) in spite of the benefits for plants from increased atmospheric CO_2 (Hasegawa *et al.*, 2013).

Rainfed areas supply ca. 58% of global food production and play an important role in food security (Seck *et al.*, 2012). Rice is one of the major crops grown and consumed in rainfed areas, and rainfed cultivation accounts for about 25% of global rice production. Due to its dependence on climate, rainfed rice cultivation is vulnerable to changes in temperature and rainfall. Warm temperature (optimal range 20°C – 30°C) and high rainfall (optimal range 1500 mm - 2000 mm) (http://ecocrop.fao.org/) generally increase growth rates of rice plants, and hence yield (Yoshida, 1981). By contrast, very high temperatures (>35°C) induce heat stress and affect plant physiological processes, leading to spikelet sterility, non-viable pollen and reduced grain quality (Welch *et al.*, 2010; Nguyen *et al.*, 2014). Drought, on the other hand, reduces plant transpiration rates and may result in leaf rolling and drying, reduction in leaf expansion rates and plant biomass, immobilisation of solutes and increased heat stress of leaves (Jagadish *et al.*, 2010; Van Oort *et al.*, 2011).

Climate is the primary factor driving locations for rainfed rice cultivation and rice yields. Hence changes in climate, such as those projected to occur in the future, particularly those related to increased variability in rainfall (Meinshausen *et al.*, 2011), could result in some areas becoming climatically unsuitable for cultivating rainfed rice, or at least reduce crop yields. Statistical models have been used to map crop production in relation to climate, and to project changes in the suitability of cultivation for a wide variety of crops including cereals (Jones & Thornton, 2003; Fischer *et al.*, 2005), spices (Vlok & Olivier, 2003), biofuel crops (Tuck *et al.*, 2006), and fruit (White *et al.*, 2006; Machovina & Feeley, 2013). Climate envelope models (CEMs) have been used at regional scales to map distributions of crops in relation to climate variables and, by incorporating outputs from future climate change scenarios, to make projections about changes in the suitability of cropping areas (Estes *et al.*, 2013; Liu *et al.*, 2015). Generally, outputs of CEMs are expressed in terms of spatial (usually gridded) maps of probabilities of occurrence of the crop under study, with declines in probability under future climate change implying decreasing suitability for growing crops. CEM outputs can be used to identify regions that may become climatically unsuitable in the future, and highlight vulnerable areas where crops are most at risk from the detrimental impacts of climate change (Liu *et al.*, 2015). This mapping approach can be used at regional scales to guide policy makers in their choice of adaptation strategies, such as breeding new cultivars that can cope with the predicted climate change, developing irrigation infrastructure or shifting to new cropping systems.

In this study, I examine changes in climate suitability of rainfed rice cultivation in India, to highlight areas at risk from future climate changes. It is important to study rainfed rice cultivation here because India is the world's second largest producer of rice, of which a substantial amount is grown under rainfed conditions during the *Kharif* (i.e. summer monsoon season). Any detrimental impacts of climate would have major consequences for food security from local to global levels. Moreover, the majority of Indian farmers cultivating rainfed rice are smallholders, whose local livelihoods are highly vulnerable to climate changes and since 1980, the number of smallholder farmers in India increased by ~77% in 2010-11 (Joshi, 2015). In addition, the agricultural sector in India employs almost half of the labour force of the country, so any changes in rice cultivation are likely to have considerable social impacts.

I use multiple CEMs and BRTs (see Methods) to model the occurrence (presence/absence) and extent (area under cultivation) of rainfed rice cultivation in relation to four climate variables during the main summer monsoon growing season (precipitation-evapotranspiration ratio, total rainfall, average minimum and maximum temperatures). Modelling continuous data, i.e. extent of rainfed rice using boosted regression trees (BRTs), as well as categorical occurrence data using CEMs, allowed us to map changes in the suitability of rainfed rice growing areas (from CEM outputs), as well as to quantify changes in the absolute area available for rainfed rice cultivation (from BRT outputs). My study has three main aims. First, I examine whether the occurrence and extent of current-day rainfed rice cultivation can be modelled successfully using climatic variables derived from temperature and precipitation during the summer monsoon, and whether CEM and BRT model outputs agree in terms of which areas are climatically most suitable for growing rainfed rice. Second, I assess whether the models agree on which climate variables are important predictors of rainfed rice cultivation; I hypothesise here that rainfall-derived variables will be more important than temperature in this respect. Finally, I map future changes in the climate suitability of areas where rainfed rice is currently cultivated, and identify risk areas that my models project to possibly become climatically unsuitable for rainfed rice cultivation by 2050.

3.3. Materials and Methods

3.3.1. Sources of rice data

I modelled the occurrence (presence versus absence, categorical variable) and extent (area under cultivation, continuous variable) of rainfed rice cultivation in India. In order to generate these occurrence and extent data, I compiled existing data on the total area of rice cultivation (ha; combining irrigated and rainfed rice) and net irrigated rice area (ha) at district level (mean area of 519 districts = 5857 km^2) in India. These data are for the period 1998-2013, and are from the Ministry of Agriculture, Government of India (http://eands.dacnet.nic.in/) for the *Kharif* season (summer monsoon season, June - September). For each district in India, I calculated the area of rainfed rice cultivation, by subtracting the net irrigated rice area from the total rice area for each year for the period 1998-2013, and then averaged the annual rainfed rice area over 16 years to produce a single mean value for the area of rainfed rice cultivation for each district. There were changes to district boundaries over time, and new districts created during 1998-2013 were merged with parent districts before computing rainfed rice areas in order to analyse 519 districts over time. Thus, the final computed district-level data comprised the average area under rainfed rice cultivation (in ha) for 519 districts in India (Fig. A2.1a; excluding West Bengal, Tripura and the Island territories of Andaman, Nicobar and Lakshadweep where data were unavailable). These coarse district-level data were downscaled and converted into a gridded dataset (10 arc-minute resolution, which is ~18 km cell spatial resolution at the equator; Fig. A2.1b) to match the resolution of the climate datasets used in this study (see below). My downscaling methods are described in Appendix A2.1. This downscaling resulted in a total of 9674 cells from which I excluded cells without any rainfed rice cultivation (n=1700 cells) to eliminate locations where rice cannot be grown (e.g. Thar Desert).

From the remaining 7974 cells, I produced two datasets for inclusion into models; my first dataset mapped observed occurrence of rainfed rice per 18 km cell (binary variable; 1 = high occurrence of rainfed rice areas, 0 = low occurrence of rainfed rice area, subsequently termed 'presence' and 'absence'). All 18 km cells where rainfed rice occupied ≥ 15% of the cells were classified as presences (n = 1171 cells) and remaining cells were classified as absences (n = 6803 cells; Fig. 3.1a). Models have been generally shown to perform best when the harvested area is above 10%-15% of the gridded area being modelled (Watson *et al.*, 2015). I tested the sensitivity of my findings to different thresholds at 10% and 20%, and I found that my main conclusions were not largely affected by my choice of threshold value (Fig A2.2). My second dataset quantified the area of rainfed rice cultivation per 18 km cell (continuous variable (ha), subsequently termed observed 'extent'; Fig 3.1b).

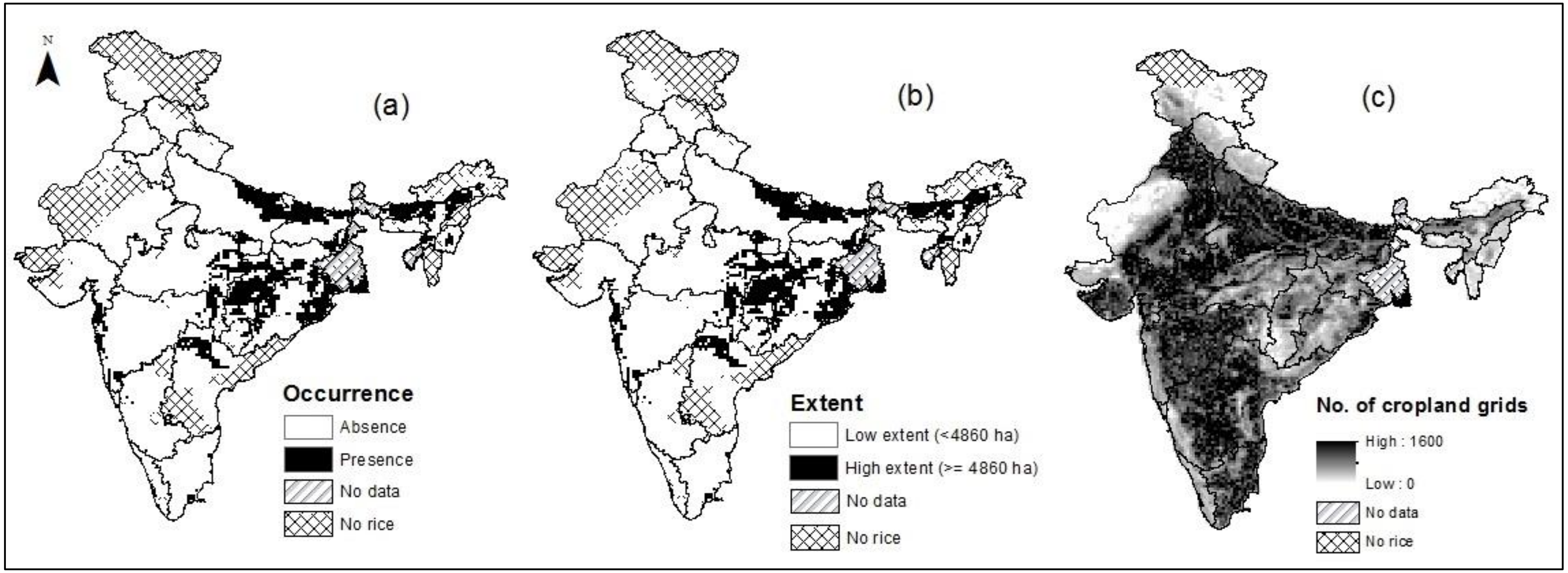

Figure 3.1. Observed (a) occurrence and (b) extent of rainfed rice. Data are plotted at 18 km cell resolution, black = presence/high extent; white = absence/low extent. (c) Number of cropland cells (0.5 km cell) per 18 km cell (Broxton *et al.*, 2014). State boundaries are plotted. Some areas were excluded from analysis due to unavailability of rice data (e.g. West Bengal) or because regions do not grow rice (e.g. western India.).

3.3.2. Sources of climate data

I examined the impact of four climate variables known to have important effects on rice growth, development and ripening (Table 3.1). Rice plant sensitivity to temperature and moisture varies during the different plant growth stages, and so I split the growing season into two periods: June – September (plant growth and reproductive stage) and October – November (grain ripening and harvesting) (Auffhammer *et al.*, 2012). The exact timing of these periods differs across India depending on monsoon onset and rice planting dates, but these periods broadly correspond with the main rice growing periods during the summer monsoon. There are >400 rice cultivars grown in rainfed regions in India (http://drdpat.bih.nic.in/Downloads/Rice-Varieties-1996-2012.pdf), but there is little information on how many of these varieties are actually adopted and cultivated by farmers. Thus, we split the growing season in two stages, to cover the likely growth and ripening periods of the most common rice cultivars. My four climate variables were (Table 3.1): the precipitation-evapotranspiration ratio (ratio of total rainfall to total potential evapotranspiration during plant growth, June – September; *PER*), average monthly maximum temperature during plant growth (further averaged over June – September; T_{max}), average monthly minimum temperature during ripening (further averaged over October – November; T_{min}), and total rainfall during harvesting (October – November; *Rain*). Potential evapotranspiration was calculated using Hamon's equation and *PER* was expressed as the ratio of total rainfall (mm) to potential evapotranspiration (mm). Detailed methods for computing *PER* are outlined in Appendix 2.2.

Table 3.1. List of predictor variables used for modelling current and future spatial distribution of rainfed rice. The correlation coefficient (Pearson's r for correlations between these variables) is shown in Table A2.1. The same set of predictor variables was used in both occurrence (CEM) and extent (BRT) models.

Variable	Abbreviation and unit	Importance for rainfed rice
PER (June - September)	PER	The ratio of total rainfall (June – September; mm) to total potential evapotranspiration (June – September; mm). Reduced moisture leads to stomata closure, reduced transpiration, reduced photosynthesis rate, immobilisation of solutes and heat stress on leaves in the absence of transpiration cooling(Van Oort *et al.*, 2011; Cho & Oki, 2012)
Mean maximum monthly temperature (June – September)	T_{max} (°C)	Higher T_{max} during the vegetative and reproductive stage leads to reduction in plant height, reduced tiller number, sterile spikelets and non-viable pollen (Kim *et al.*, 2011; Shah *et al.*, 2011; Nguyen *et al.*, 2014)
Mean minimum monthly temperature (October - November)	T_{min} (°C)	Higher T_{min} increases night-time respiration which increases maintenance respiration and uses up carbon fixed through photosynthesis. This leads to empty grains, or lower grain weight, as a result of less carbohydrate available for grain-filling during ripening (Peng *et al.*, 2004; Mohammed & Tarpley, 2010; Shi *et al.*, 2013).
Total precipitation (October – November)	Rain (mm)	An indicator of physical damage to the standing crop during ripening and harvest via excessive rainfall (Auffhammer *et al.*, 2012)

Correlations among all four climatic variables were less than 0.6; *Rain* and T_{min} were most strongly correlated (r =+0.47, P<0.05), whereas *PER* and T_{min} were not correlated (r =+0.04, P>0.05; Table A2.1). Monthly data for *Rain,* T_{max} *and* T_{min} were downloaded from WorldClim (http://www.worldclim.org/) for the present (1950-2000) and future scenarios at 10 arc-minute (~18 km) cell resolution (Hijmans *et al.*, 2005). There is considerable variation in future projections from different GCMs (Jayasankar *et al.*, 2015), and so I examined projections for 2050 for two scenarios, spanning the highest and lowest severity of future climate change, from three GCMs. IPCC RCP 8.5 represents the most severe ('business-as-usual') scenario, and RCP 2.6 represents the least severe ('mitigation') scenario (IPCC 2013). I obtained RCP 2.6 and 8.5 climate data from three different GCMs (BCC-CSM1.1, MIROC-ESM-CHEM, and HadGEM2-ES), selected to encompass a range of different modelling approaches and projections. These GCMs have been shown to be largely independent from each other (Knutti *et al.*, 2013) and encompass a range of different modelling approaches. In addition, these GCMs project a range of different trajectories for the Indian monsoon in the future: HadGEM2-ES predicts decreased variability in the Indian monsoon, MIROC-ESM-CHEM predicts little change from the present day whereas BCC-CSM1.1 predicts increased variability in future (Jayasankar *et al.*, 2015). Finally, all three GCMs have been shown to reproduce the current regional rainfall across India, albeit with low confidence (Menon *et al.*, 2013b). Therefore, using climate projections from multiple GCMs and RCPs allowed me to incorporate uncertainties associated with rainfall in our mapping of risk.

3.3.3. Modelling relationships between rainfed rice cultivation and current climate

I modelled the occurrence (presence/absence) of rainfed rice with the *biomod2* package in R using five CEMs (MAXENT, GBM, ANN, SRE and MARS) (Thuiller *et al.*, 2009). All five models were trained on 75% of these occurrence data and tested on the remaining 25% (repeated three times per model), and model performances were assessed by AUC values from the Receiver Operating Characteristic (ROC) curve (Marzban, 2004). For models displaying AUC >0.85, the CEM outputs reported the mean probability (averaged across the five models) of rainfed rice occurrence (0 = unsuitable, to 1= suitable) for each of the 7974 study cells. In order to quantify the impacts of future climate changes (see 2.4 below), these continuous probability values were transformed into categorical data (modelled presence/absence data) using a threshold probability value derived from the ROC curve (Marzban, 2004). The threshold value (0.17) was selected as the probability value at which sensitivity (number of observed presences predicted correctly) and specificity (number of observed absences predicted correctly) were maximised using the pROC package in R (Robin *et al.*, 2011). Transforming probability values from CEMs into categorical presence/absence data allowed me to compare modelled and observed occurrence data, and to facilitate comparisons of outputs from CEMs and Boosted Regression Trees (BRTs, see below) in order to assess spatial agreement between the two methods.

I modelled the extent of rainfed rice cultivation using BRTs (Elith *et al.*, 2008). My initial data exploration indicated that the gridded extent data had a negatively skewed distribution (i.e. most cells had little rainfed rice whereas a few cells had very large amounts of rainfed rice). Therefore, I ln-transformed these data (using the transformation ln(extent +1)) before running the BRTs (see Appendix 2.2 for BRTs details). I then back-transformed the BRT model outputs (which were on a natural logarithmic (ln) scale) and converted this continuous extent variable into a categorical variable (i.e. modelled 'high' and 'low' rainfed rice extent) using the same thresholding approach used for CEM outputs, derived from the ROC curve (see above; a threshold of 1517.93 ha of rainfed rice cultivation per cell was used for separating high extent from low extent cells).

I assessed the spatial agreement in modelled occurrence (CEMs) and extent (BRTs) of rainfed rice by mapping cells where CEM and BRT model outputs agreed/disagreed (i.e. modelled presences were in agreement with modelled high extent, and modelled absences agreed with modelled low extent). I also assessed the relative importance of the four climate variables using the inbuilt functions for CEMs and BRTs (Friedman & Meulman, 2003; Elith *et al.*, 2008). For CEMs, the relative importance of each climate variable was determined by making predictions based on including only a single climate variable into models and computing the correlation (Pearson's r) between these model outputs and models that include all four climate variables. The highest value of Pearson's r is obtained for the climate variable that has the most influence (Thuiller *et al.*, 2016). For BRTs, the importance of a climate variable in a single regression tree was determined from improvements at each split in the tree, and the relative importance of each climate variable is the averaged improvement over all the trees where the climate variable was used for splitting (Friedman & Meulman, 2003).

3.3.4. Projecting impacts of future climate change on rainfed rice cultivation

I incorporated outputs for 2050 from two IPCC RCPs scenarios (2.6. and 8.5, representing the lowest and highest radiative forcing) and from three climate models: BCC-CSM1.1, HadGEM2-ES and MIROC-ESM-CHEM. For each GCM x RCP combination, I quantified changes in climate suitability for rainfed rice cultivation by subtracting outputs based on current climate from those based on future climate projections. A change in probability values (CEMs) or change in extent (BRTs) was taken to indicate change (either increase or decrease) in climate suitability for rainfed rice cultivation in the future. I focussed specifically on cells where rainfed rice cultivation is recorded in the present-day (n = 1171 cells, see 3.3.1 above), because changes in climate suitability in these cells will have greatest impacts on rainfed rice production. I classified changes in the climate suitability of these cells into three suitability categories: improved (increased probability of occurrence/extent in future), less suitable (decreased probability of occurrence/extent) and unsuitable (decreased probability of occurrence/extent below current climate thresholds for cultivation; see 3.3.3). I combined results from the three GCMs to produce an ensemble result for each cell for each RCP. If all three GCMs were in agreement (e.g. all GCMs projected the cell to become unsuitable), then I deemed the result for the cell to be 'high confidence', if two GCMs agreed it was 'medium confidence' and if all three GCMs differed, this was 'uncertain' (i.e. the three

GCMs projected the same cell to be more suitable, less suitable and unsuitable). Cells which became less suitable or unsuitable, and for which there was high confidence in their projections, are henceforth referred to as cells ‘at risk’. All analyses were carried out in R 3.1.2 (R Core Team, 2013).

3.4. Results

3.4.1. Current distribution of rainfed rice in relation to climate

Overall, the CEMs were very good at modelling the occurrence of rainfed rice in relation to the four selected climate variables (ensemble AUC = 0.92). Rainfed rice was predicted to occur in 2435 cells and be absent from 5539 cells (Fig 3.2a; based on the CEM threshold probability of 0.17 to convert probability values into modelled presences and absences). My model sensitivity was 91% (i.e. 91% of modelled presences were in agreement with observed presences) and my model specificity was 79% (79% of absences were modelled correctly). CEMs tended to predict rainfed rice in more cells than those where there were observed presences (Fig. 3.2a) in India, implying that rainfed rice cultivation is also restricted by non-climatic factors not included in CEMs. For example, when I overlaid modelled presences from CEMs (n = 2435 cells) on the landcover map (Fig. 3.1c), and found that about a third of modelled presences were in locations with low availability of cropland. Thus, my subsequent focus on examining future changes in climate suitability only in those cells where rainfed rice is present in high extent (‘presence’ cells in Fig. 3.1a) means that I avoided studying locations where there was little available cropland.

The BRTs were also very good at predicting the observed extent of rainfed rice (Pearson’s r = 0.87 between observed and modelled extent; Fig. A2.3). The extent of rainfed rice was predicted to be high in 2408 cells and low in 5566 cells (AUC = 0.89, sensitivity = 84%, specificity = 79%, based on a threshold extent of 1517.93 ha; Fig. 3.2b). Comparing CEM and BRT outputs showed that 73% (5819/7974) of cells were in agreement (Fig. 3.2c), such that 55% of CEM rainfed rice presences were predicted by BRTs to have high extent of rice, and 80% of CEM absences were predicted to have low extent.

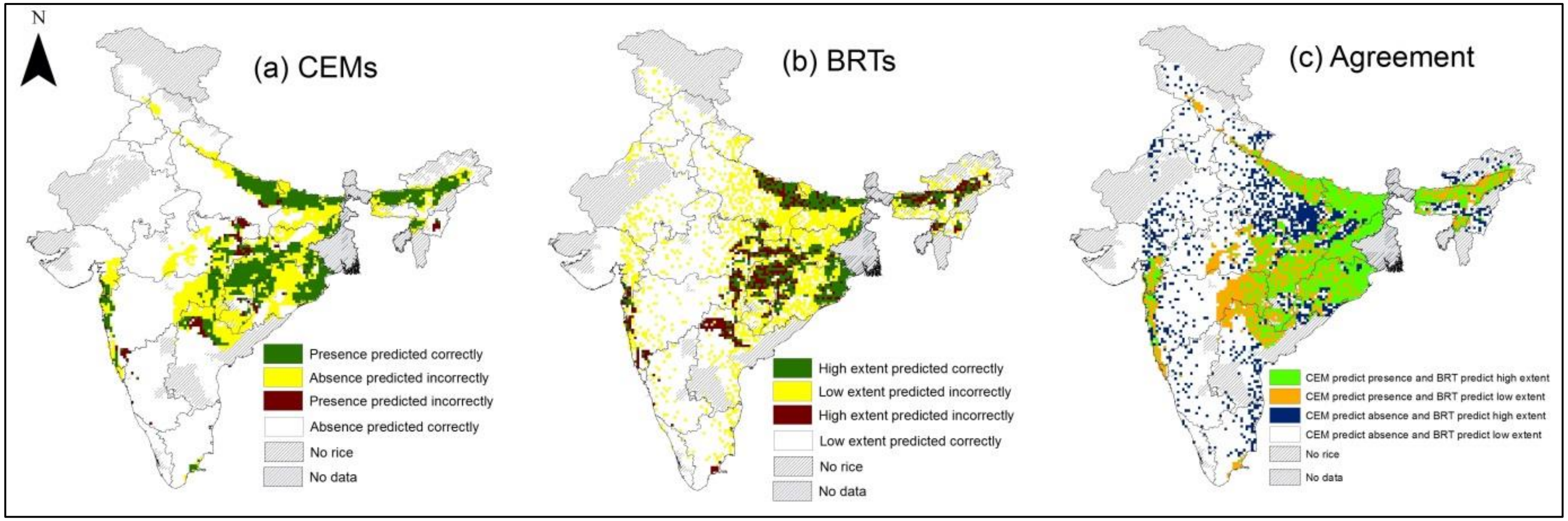

Figure 3.2. Modelled rainfed rice (a) presence/absence (from CEMs) and (b) high/low extent (from BRTs). Green and white areas show where model outputs agree with observed rainfed rice cultivation data, whereas yellow and brown areas are where models disagree with observed data. (c) Spatial agreement in CEM and BRT outputs, where green areas show agreed presences, and white areas are agreed absences. Disagreements are shown in orange (CEMs predict presence but BRTs predict low extent) and blue (CEMs predict absence but BRTs predict high extent). Data are plotted at 18 km cell resolution.

Thus, the CEMs and BRTs were in broad agreement in terms of the locations of climatically suitable cells for rainfed rice, but the models differed in terms of which climate variables were the most important predictors of rainfed rice cultivation. In the CEMs, *PER* was the most influential variable and it was almost 1.5 times more important than *Rain* and 2.5 times more important than T_{min} and T_{max} (Fig 3.3a). For BRTs, *Rain* was the most important variable, but was only marginally more influential than *PER* and only 1.5 times more important than the two temperature-derived variables (Fig. 3.3b).

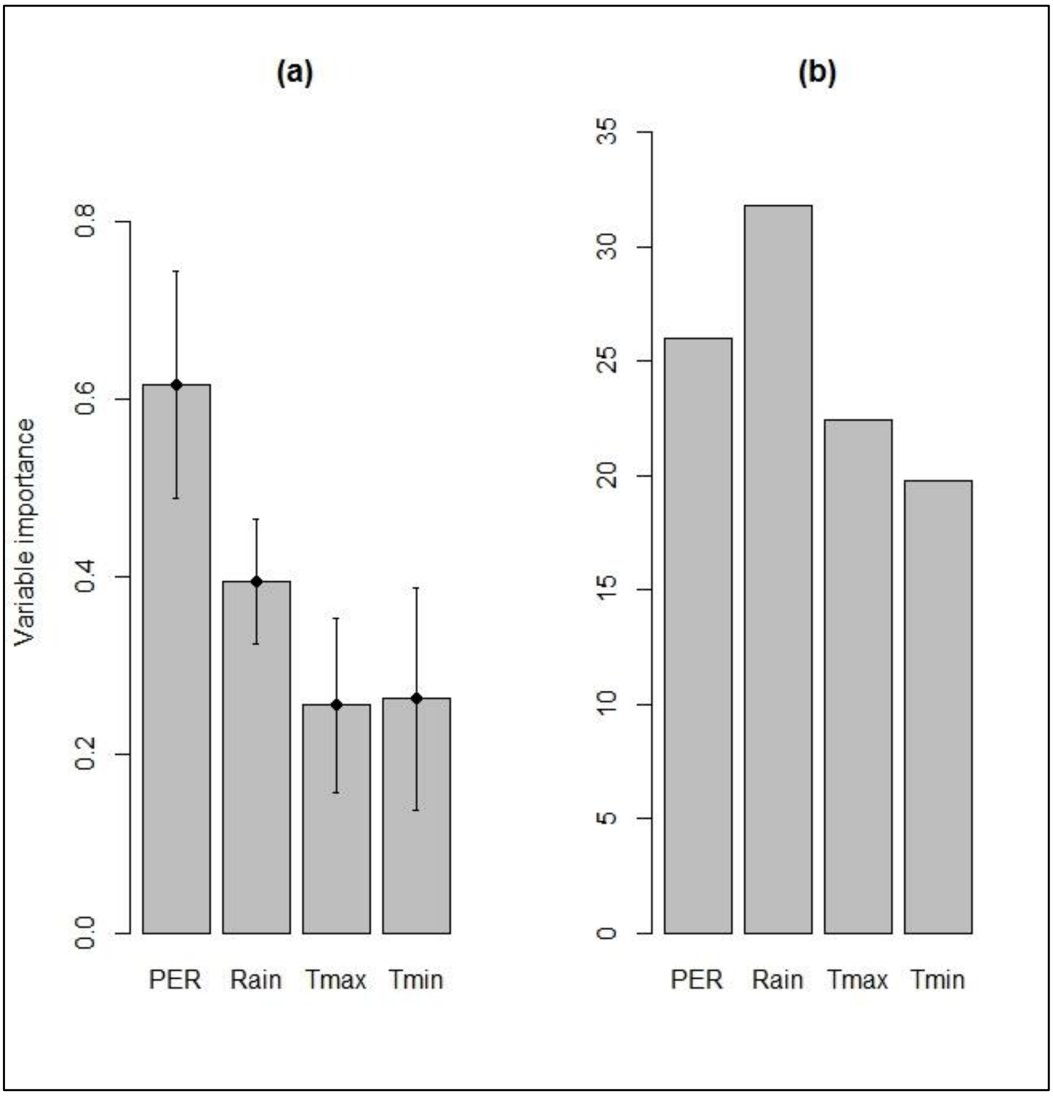

Figure 3.3. (a) Importance of four climate variables in (a) CEMs and (b) BRTs for modelling rainfed rice cultivation. In (a) the y-axis is the mean correlation coefficient (Pearson's r) (and SE) from model projections made with a single climate variable against predictions made by using all four variables. In (b) the y-axis plots the relative influence of each variable (higher numbers indicate stronger influence). Refer to section 3.3 for a brief description and Friedman & Meulman (2003) for full details.

3.4.2. Future spatial distribution of rainfed rice

By 2050, all the GCMs and RCPs generally predict hotter temperatures (T_{max} increase ranges from +0.3 to +1.9 °C; T_{min} increase ranges from +1.3 °C to + 3.1°C) and increased rainfall (*Rain* increase ranges from +3% to +68%) during the summer monsoon in India (Fig. A2.4.).

Focussing on the cells where rice cultivation is recorded in the present-day (n = 1171 cells; see Fig. 3.1a for the location of these cells), CEMs projected the average probability of rainfed rice occurrence to increase slightly under the RCP 2.6 scenario but decrease under RCP 8.5 (Fig. A2.5.), whereas BRTs generally projected decreases in extent in most RCPs and GCMs (Fig. A2.6.). There was variation in the projections for changes in climate suitability according to the different GCMs and CEM/BRT models. Overall, there was more agreement in the number of cells improving in climate suitability and less agreement in cells becoming less suitable or unsuitable between CEMs and BRTs. The percentage of cells becoming less suitable or unsuitable varied across the two modelling approaches: CEMs projected 39% to 57% of cells to become less suitable (depending on GCM), and 1% to 8% of cells to become unsuitable (Fig. 3.4a), whereas BRTs projected 29% to 42% of cells to become unsuitable and 20% to 29% of cells to become less suitable (Fig 3.4b; for spatial locations of these cells, refer to Fig. A2.7 and A2.8).

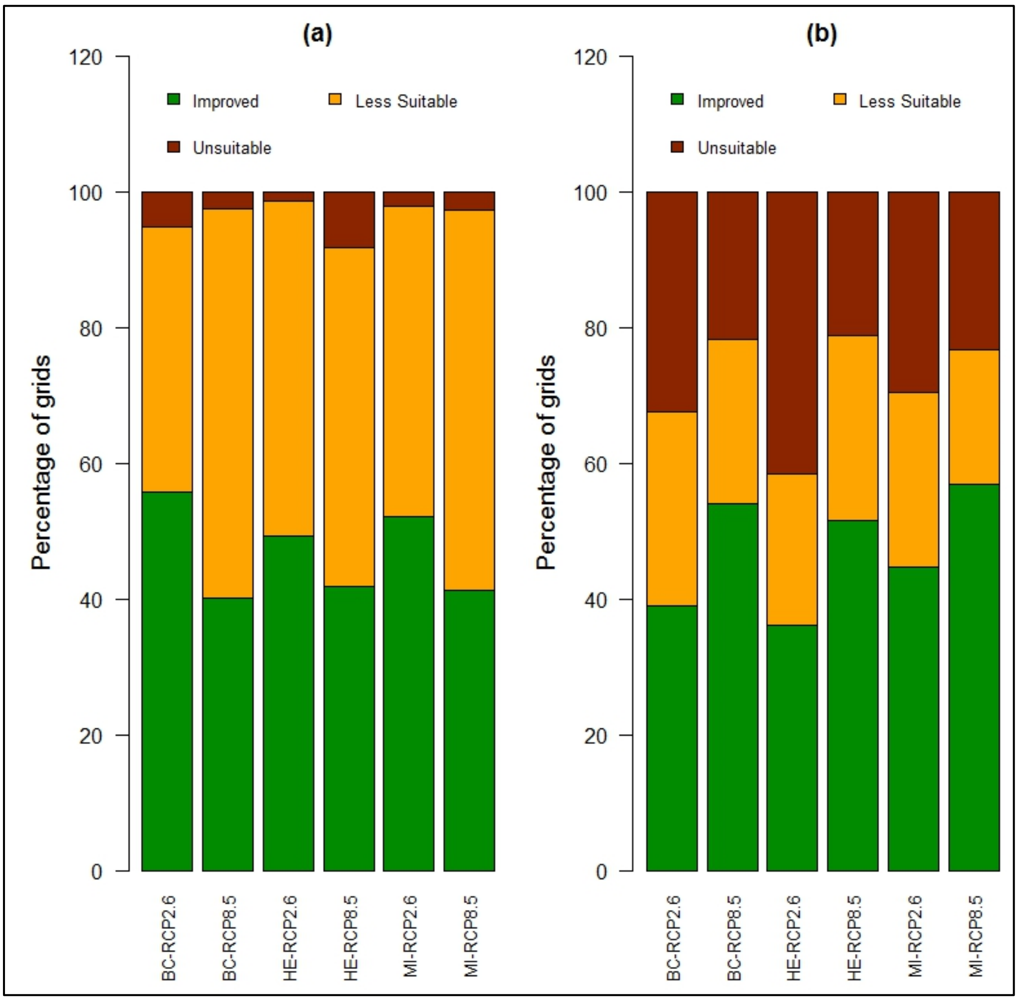

Figure 3.4. Future projected changes in the climate suitability of cells where rainfed rice is currently grown (n=1171 cells) for (a) CEMs and (b) BRTs. Cells are projected to become either climatically unsuitable (brown) or less suitable (yellow), or have improved suitability (green). The bars show all combinations of RCP (2.6 and 8.5) and GCMs (BC = BCC-CSM1-1, HE = HadGEM2-ES, MI = MIROC-ESM-CHEM). These data are plotted as maps in Figure A2.7 (CEMs) and A2.8 (BRTs) in Appendix 2.

However, all three GCMs reached a consensus on whether a cell was climatically improved, less suitable or unsuitable in future in 40% (BRTs) - 60% (CEMs) of cells for RCP 2.6, and between 40% (BRTs) - 70% (CEMs) of cells for RCP 8.5. I focussed on those cells that were projected to become less suitable or unsuitable in future, and where there was high confidence across the GCMs (i.e. all three GCM outputs were in agreement). These data suggest that by 2050, between 15% and 40% of locations where rainfed rice is currently cultivated could be at risk of adverse impacts of climate change, i.e. our models predict with high confidence that these locations will become either less suitable or unsuitable for rainfed rice cultivation by 2050 (Fig. 3.5). Both CEMs and BRTs project that cells at risk are mostly located in eastern states of Chattisgarh and Odisha, although the severity of that risk, i.e. whether the location becomes unsuitable or less suitable for rainfed rice cultivation, differs between the two modelling approaches.

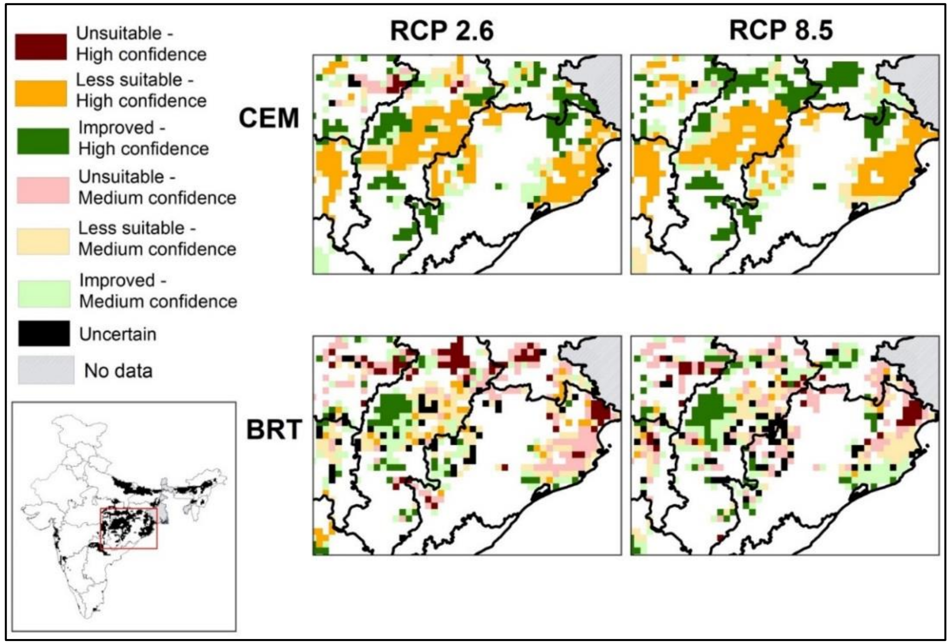

Figure 3.5. Maps showing spatial agreement in future changes in climate suitability of cells (cells becoming climatically unsuitable, less suitable or improved suitability by 2050) under RCP 2.6 and RCP 8.5 for CEMs and BRTs. Three GCMs (BCC-CSM1-1, HadGEM2-ES and MIROC-ESM-CHEM) were used. For a given scenario (RCP 2.6 or 8.5) and method (CEM or BRT), if outputs from the three GCMs agreed, then confidence is high. If any two GCMs agree, confidence is medium, and if no GCMs agree, it is uncertain. Panels focus on areas around Chattisgarh and Odisha (area enclosed by the red box in the map of India) which are two major rainfed rice growing States and have large numbers of small land-holders. White areas are where there is no rainfed rice, or little rainfed rice grown (based on 15% threshold criterion; Fig 3.1).

3.5. Discussion and Conclusions

Rainfed food production systems are highly dependent on climate and our study maps the locations where the production of rainfed rice is at risk from future climate change. Our results predict that between 15%- 40% of locations where rainfed rice is currently grown may be less suitable or even unsuitable for that method of agriculture by 2050. Rice production is a function of yield, cropping area and cropping frequency, and it has been shown that changes in cropping area (and frequency) contribute more to changes in agricultural output than changes in yield (Cohn *et al.*, 2016). Hence, our predictions, that up to 40% of existing rainfed rice areas in India may be at risk in future, highlight the considerable vulnerability of rainfed rice production to climate change.

3.5.1. Declining climate suitability in important rainfed rice areas

Both CEM and BRT models project that 15% - 40% of current rainfed rice locations may be at risk from climate change by 2050, based on the consensus across multiple GCMs. These declines in suitability were most pronounced in eastern India, in the States of Odisha, Assam and Chattisgarh. These States predominantly use rainfed cultivation methods and contribute more than a quarter of India's annual rice production. The farming communities in these States are dominated by small-landholders (usually owning less than 2 ha) (Joshi, 2015), with little opportunity to produce surplus grain for consumption or for generating income. In addition, small-holders often have limited access to financial markets or crop insurance (Thapa & Gaiha, 2011), and so these projected climate-driven declines in rainfed rice cultivation would be expected to be detrimental to local livelihoods. My model outputs agree with other studies projecting declines in rainfed rice yields in future, based on outputs of process-based crop models (Soora *et al.*, 2013; Rao *et al.*, 2016) and statistical crop models (Auffhammer *et al.*, 2012). Rainfed areas already have a large yield gap compared with irrigated areas (Mueller *et al.*, 2012) and further reductions in the extent of climatically-suitable areas could widen these yield gaps with negative consequences for regional food security (Aggarwal *et al.*, 2008). Both

CEMs and BRTs identified similar areas at risk in the states of Chattisgarh and Odisha, although they differ in the projected severity of risk in these locations (i.e. they differ in the number of cells projected to become less suitable or unsuitable in future). The major difference between the projections for the two approaches across the GCM ensemble is that CEMs project more cells becoming less suitable but with high confidence, whereas BRTs project more cells to be unsuitable but with only medium confidence. This difference in model outputs could be due to differences in the climate variables deemed as the most influential by the two approaches (see below).

3.5.2. Rainfall is generally more important than temperature-derived variables for mapping rainfed rice areas

The CEM and BRT models were very good at mapping rainfed rice at a regional (~18 km cell) scale using only monsoon climate variables, confirming the dependency of rainfed rice cultivation on climate. Of the four climate variables included in our models, *PER* was the most important for mapping the occurrence of rainfed rice using CEMs, but all four variables were important for projecting extent of rainfed rice cultivation using BRTs, although there was some indication that rainfall variables were slightly more important. Previous studies have shown that monsoon rainfall affects important decisions such as planting dates (Zhao *et al.*, 2016) and choice of rice cultivar (Xiong *et al.*, 2014), and that rainfall is also important for other rainfed crops such as wheat (Mavromatis, 2016), sunflowers (Valverde *et al.*, 2015), and sorghum (Alemaw & Simalenga, 2015). It is most likely that planting decisions by farmers are based on monsoon conditions in the initial growing periods (*PER* and T_{max}) as opposed to variables during the final growing periods (T_{min} and *Rain*). This may explain why *PER* was the most important predictor in CEMs, and why there was more spatial consensus in outputs from CEMs than from BRTs. *PER* is a ratio of rainfall and potential evapotranspiration, both of which are expected to increase in the future, although projections for rainfall are less certain (Jayasankar *et al.*, 2015; Sharmila *et al.*, 2015) than those for temperature (Chaturvedi *et al.*, 2012). However, increased temperatures will increase potential evapotranspiration and hence reduce water available to plants, showing that both rainfall and temperature changes are important. Nonetheless, since GCMs have less agreement on future rainfall patterns compared with temperature, any model that relies predominantly on rainfall, rather than *PER* which combines rainfall and temperature, might be expected to show more spatial heterogeneity across different GCMs. This explanation could be why there was less consensus for BRTs (i.e. fewer high confidence cells) compared with CEMs.

3.5.3. Use of statistical models to map areas at risk

Statistical models are usually important tools for undertaking regional studies similar to ours if sufficient fine-scale data are unavailable. My statistical models used averaged decadal measures of rice cultivation and climate rather than yearly or finer temporal scale information as used in process-based crop models (Chun *et al.*, 2016; Rao *et al.*, 2016). By aggregating data, my statistical models provide information on changes in the suitability of rice cultivation at relatively large spatial scales, and so provide risk maps rather than predictions of short-term changes in yield at specific locations. I recommend running finer scale processed-based models (e.g. DSSAT; Corbeels *et al.*2016) to examine if the conclusions I have obtained using low data-intensive statistical models are in agreement with projections from more mechanistic models that include physiological, genetic, soil and management information for rice. Studies that combine the two modelling approaches may provide more robust projections about changes to rice yields and areas suitable for cultivation (Watson *et al.*, 2015).

3.5.4. Can locations with improved suitability compensate for declining suitability elsewhere?

Although our CEM and BRT models projected large areas to decline in climate suitability, some areas are projected to have improved climate suitability for rainfed rice cultivation in future. In addition, some areas which currently do not cultivate rainfed rice may potentially become climatically suitable in future. However, it is unlikely that any increases in new locations will offset the declines in existing rainfed rice growing areas, because local communities in these new areas may not practise agriculture, or rice may not constitute a major part of local diets and there may be a preference for other cash crops in these areas (Semwal *et al.*, 2004; Behera *et al.*, 2015). In addition, many of these potential new areas are already cultivating irrigated rice (Nirmalendu *et al.*, 2016) or supporting other land-uses such as forests and urban areas (Pandey & Seto, 2015). Some locations where rice is currently grown are projected to increase in climate suitability in future, but these areas may already have reached the maximum attainable yield (Conway & Toenniessen, 1999) or already grow irrigated rice, and improved climate suitability may offer small additional returns in these locations, unless supported by new rice cultivars or irrigation infrastructure. Hence, I conclude that any benefits from increased climate suitability are unlikely to compensate for large–scale declines in the occurrence and extent of rainfed rice cultivation that my models project in future, and that local communities, especially in north-eastern states of India, are particularly vulnerable to climate changes.

3.5.5. Adaptation options for lowering the risk in climatically unsuitable locations

My models map regions at risk from future climate change, and regional food security and local livelihoods in these high risk areas will depend largely on the capacity of small holders to adapt to these climate changes, for example by the take-up of new drought-tolerant cultivars, or improved management practise. The development of irrigation systems would reduce the dependence on rainfall and would enable the planting of high-yielding rice varieties (Fischer et al., 2005). The results from my work highlight locations (e.g. eastern Odisha and central Chattisgarh) most at risk and where such new initiatives should be targeted.

3.6. Acknowledgements

This work was funded by the Biotechnology and Biological Sciences Research Council, the Department for International Development and (through a grant to

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Chapter 4 Selecting for drought-tolerance may increase the sensitivity of rainfed rice to heat-stress

Rice cultivars in a breeding trial for drought-tolerance at National Rice Research Institute, India

4.1. Abstract

Global climate change is affecting rainfall patterns, and growing more drought-tolerant crops may help farmers maintain yields under increasingly unpredictable rainfall. However, it is unclear whether cultivars developed to be drought-tolerant are also resistant to other climate stresses, or if there are trade-offs for yields. I examined whether rainfed rice cultivars that are tolerant of water-stress (measured as net water deficit, in mm) are also resistant to heat-stress (measured as the sum of growing degree days above 35°C). I analysed yield data from rainfed rice trials (All India Coordinated Rice Improvement Project (AICRIP) data), comparing 112 locally-grown rice cultivars with 5 widely-grown national cultivars. My results show that local cultivars had higher yields (~14% higher yields; 2252 kg/ha for local cultivars versus 1972 kg/ha for national cultivars), and declined less under water-stress (42% decline versus 59% decline in national cultivars), but that local cultivars declined more under heat-stress (81% decline versus 58% in national cultivars). Thus, local cultivars are better adapted to drought conditions, but are less heat-stress tolerant than national cultivars. This greater sensitivity of local cultivars to heat-stress reduced their yield advantage over national cultivars from ~556 kg/ha higher yield under mild heat-stress to ~193 kg/ha lower yield under extreme heat-stress. Thus, farmer decisions to grow local cultivars, which are best suited to local drought conditions, result in higher yields currently. However, future climate projections for India indicate greater incidences of extreme heat-stress, and our findings suggest that local cultivars will lose their yield advantages under these conditions. Rice crop breeders must target plant traits that confer heat-stress tolerance in addition to drought-tolerance in their breeding programmes in order to ensure crops are resilient to future climate changes.

4.1. Introduction

The global human population is expected to reach 9 billion by mid-century (United Nations, Department of Economic and Social Affairs, 2015) and this increase in population size will require food production to increase by about 60% (Alexandratos & Bruinsma, 2012). This demand will exert pressure on current agriculture systems and may lead to expansion of croplands into previously uncultivated areas, as well as intensification of agriculture (Foley *et al.*, 2011; Davis *et al.*, 2016). In addition, this increased food demand has to be met under a changing climate, which is expected to become more variable and extreme in the future (Fischer *et al.*, 2013; Donat *et al.*, 2016). Average global temperature is predicted to increase by 2.6°C to 4.8°C by the end of this century, relative to 1850-1900 levels, under the high emission scenario of RCP 8.5 (IPCC, 2013). Rainfall patterns are likely to become more erratic leading locally to a greater intensity and frequency of droughts (Prudhomme *et al.*, 2014; Diffenbaugh *et al.*, 2015). In spite of any potential production benefits from increased atmospheric CO_2 concentrations (van der Kooi *et al.*, 2016), any positive impacts are unlikely to compensate for the projected declines in productivity of major crops due to climate change (Lobell *et al.*, 2011; Challinor *et al.*, 2014), which could lead to higher food prices and reduced food security (Nelson *et al.*, 2014; Rosenzweig *et al.*, 2014).

Drought is one of the major abiotic stresses currently affecting more than a quarter of the global agricultural area (Geng *et al.*, 2015). In particular, drought threatens crop yields and farmers' livelihood in rainfed agricultural areas (i.e. areas that are predominantly dependent on natural rainfall to meet the crop water requirements). Given that rainfed areas contribute considerably to regional food security (Valverde *et al.*, 2015; Anderson *et al.*, 2016; Siderius *et al.*, 2016), it is important that drought-tolerant cultivars are developed to help farmers mitigate some of the economic losses associated with drought-induced crop losses, to ensure that food security is not compromised (Sánchez, 2010; Foley *et al.*, 2011; Godfray *et al.*, 2012). Thus, crops have been developed, focusing on plant characteristics such as root architecture, stomatal conductance, flowering time, drought recovery ability, membrane stability and osmolyte accumulation, that help plants survive drought conditions and maintain yields (Pantuwan *et al.*, 2002; Venuprasad *et al.*, 2007; Bernier *et al.*, 2008; Kumar *et al.*, 2008).

However, drought is not the only stress that crops experience, and climate conditions that cause water-stress can also cause heat-stress for rainfed crops, because dry periods with little cloud cover are associated with high temperatures (Lobell & Asseng, 2017; Schauberger *et al.*, 2017). Damage from heat-stress can affect important crop growth stages such as flowering and grain ripening and could reduce yields because of pollen sterility, increased plant respiration costs and shortening of the grain filling period (Peng *et al.*, 2004; Welch *et al.*, 2010). Generally, plant responses to drought and heat-stress are different and, to some extent, antagonistic (Rizhsky *et al.*, 2004). For example, under drought conditions, plants reduce stomatal conductance through stomatal closure to conserve water, whereas heat-stress requires plants to open stomata for transpiration cooling (Ciais *et al.*, 2005; Miyashita *et al.*, 2005). These antagonistic responses imply that tolerance towards drought comes at the cost of reduced tolerance towards heat-stress, suggesting potential trade-offs whereby plants benefit from improvements in one physiological process while the efficiency of another process is compromised (Weih, 2003; Koziol *et al.*, 2012). Therefore, it is important to understand whether breeding exclusively for drought-tolerance may affect rice plant tolerance to heat-stress, leading to crop yield trade-offs.

Rice (*Oriza sativa*) is one of the most important cereals grown under rainfed conditions, and about 3 billion people depend on this crop for more than 20% of their daily calorie intake (Seck *et al.*, 2012). In India, rainfed rice is cultivated by more than 60 million small-landholding farmers (Joshi, 2015), and drought stress is a major factor limiting rainfed rice productivity (Li *et al.*, 2015a). Hence, considerable breeding effort has focussed on developing greater drought tolerance in rice (Lafitte *et al.*, 2006; Kumar *et al.*, 2014), with more than 80 drought-tolerant rice cultivars developed between 1996-2012 (DRR, 2013). The uptake of these local cultivars varies across India, driven by whether local conditions are suitable for a specific cultivar at a given site, as well as by socio-economic factors (such as seed availability). By contrast to these local cultivars, there are also widely-grown national cultivars, including 'elite' cultivars that are frequently used as parental stock in breeding programmes, which retain good yield performance across many locations and environments but are not adapted to any specific local conditions. Farmers in rainfed areas use their knowledge of local water availability to select the most appropriate cultivars for maximising yield (Upadhya *et al.*, 2016). Therefore, local cultivars are expected to produce higher yields and be more drought-tolerant than widely-grown national cultivars grown at the same site, assuming that water-stress is the main climate factor affecting yield at a location. However, it is unclear whether rice cultivars that have greater drought tolerance are also able to maintain high yields under heat-stress.

In this paper, I examine the impacts of water-stress and heat-stress on rainfed rice cultivars by analysing long-term field trial data from rainfed upland experiments conducted under the All India Coordinated Rice Improvement Project (AICRIP) (ICAR-IIRR, 2015). The AICIRP data are from 39 sites over 15 years, and test the yield performance of drought-tolerant rice cultivars following standardised field protocols, thereby allowing examination of the impacts of heat-stress and water-stress on yield without data being confounded by factors such as changing management practises or planting procedures. I analyse the AICRIP data to test the following hypotheses: (1) locally grown cultivars (n = 112 cultivars) have higher yields and are more drought-tolerant than widely-grown national cultivars (n = 5) grown at the same sites; and (2) there are trade-offs between tolerance of water-stress and heat-stress such that more drought-tolerant cultivars are also more sensitive to heat-stress. Hence, I test the prediction that local cultivars will be more sensitive to heat-stress than widely-grown national cultivars, assuming there are trade-offs between water-stress and heat-stress.

4.2. Materials and Methods

4.2.1. Sources of yield data for local and widely-grown cultivars

I obtained yield data for two groups of drought-tolerant cultivars: locally-grown cultivars (n = 112 cultivars) and more widely-grown national cultivars (n = 5 cultivars). Yield data during the summer monsoon season were obtained from 39 rainfed upland sites in India for the period 1996-2010 (Fig. 4.1). While the local cultivars are unique to each site and year (i.e. different local cultivars were grown from year to year and site to site), the national cultivars are relatively less variable across space and time. The spatially varying nature of local cultivars is because they are developed for local drought conditions and hence differ from site to site. Similarly, at a given site, local cultivars change over time because new local cultivars adapted to local environmental conditions replace previous local cultivars based on farmers' feedback. National cultivars, on the other hand, are often used as parents in the AICRIP breeding programme and have wider climatic ranges but are not as well-adapted to any specific local drought conditions. The yield data were recorded as part of the annual progress report of AICRIP published by the Directorate of Rice Research and were provided by the National Rice Research Institute (NRRI) at Cuttack, India (ICAR-IIRR, 2015). At each site, local and national cultivars are grown together, and the following data are recorded during the summer monsoon period (June-September): date of sowing (same for all the cultivars at a site), number of days after sowing to when 50% of plants have flowered, panicles per m^2, plant height (in cm), and yield (kg/ha). The data set comprised 39 rainfed upland sites studied over 15 years (1996 - 2010), resulting in 586 yield values (site by year by cultivar combinations; see Table A3.1 for the names of the local and national cultivars). The trials are conducted across multiple sites, representing all major Indian rice growing areas, using a standardised management protocol (Table A3.2).

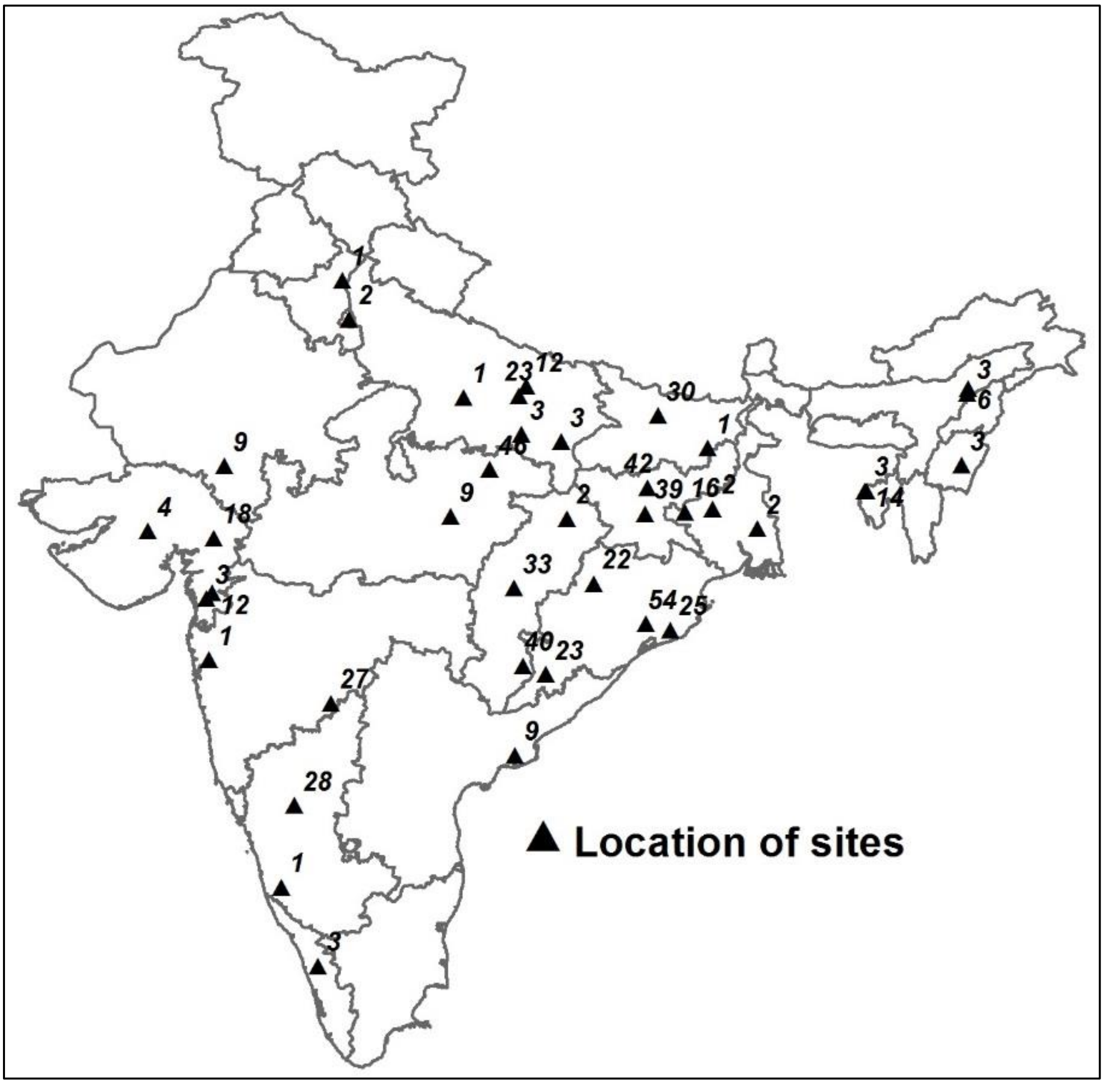

Figure 4.1. Location of the AICRIP upland rainfed rice trial sites (n = 39) for the period 1996-2010. For each site and year, a local and national cultivar were grown simultaneously under rainfed conditions. The numbers indicate the total number of trials held at each site during the 15 years (total number of annual trials = 586). Names of cultivars under each group are shown in Table A3.1.

4.2.2. Climate data

I used Global Risk Assessment toward Stable Production of Food (GRASP) daily meteorological data at 0.5° latitude/longitude resolution (Iizumi *et al.*, 2014) to generate eight climate variables important for rice reproduction and ripening. The reproductive stage covered the period from date of sowing to the date of 50% flowering (as recorded in the AICRIP data), and the ripening stage spanned the date of 50% flowering to the date of harvesting, which was assumed to be 30 days after flowering (GRiSP, 2013). For the reproductive stage, I examined five climate variables: (1) net water deficit in mm (NWD), measured as the cumulative sum of the difference between daily potential evapotranspiration and daily rainfall; (2) day-time heat-stress in deg. C (DHS), measured as the cumulative sum of growing degree days above 35° C; (3) average maximum temperature (T_{max}), which is important for rice plant growth rate and spikelet sterility; (4) number of wet days (WET) and (5) dry days (DRY), measured as the cumulative sum of number of days above and below one standard deviation of the long term site mean, respectively, which capture intra-seasonal distribution of rainfall and availability of water. For the ripening stage, I examined three climate variables: (6) night-time heat-stress in deg. C (NHS), measured as the cumulative sum of growing degree days above 25° C; (7) average minimum temperature (T_{min}), which is important because higher minimum temperatures lead to higher respiration rates which deplete carbon stores, leading to empty grains; and (8) number of wet days (WGR) during grain ripening, which causes physical damage to the standing crop. I chose NWA and DHS as my primary measures of water-stress and heat-stress because they capture the impacts of drought and heat-stress on rice growth and development. Other climate variables were included to account for other variables important for rice growth and development. Table 4.1 has a full description and computation of these variables, and their importance to individual plant growth stages. The duration of vegetative and ripening phases differed among the cultivars because of different dates of flowering (Fig. A3.1), and so the eight climate variables were calculate individually for local and national cultivars using their respective growth and development patterns.

Table 4.1. List of eight climate variables used to model yields of local and national cultivars. These climate variables were selected based on their importance to rice physiology and capture different aspects of water -availability and temperature-availability.

Variable	Description	Importance
Average maximum temperature of the reproductive stage, Tmax (°C)	average of the daily maximum temperature from the date of sowing till date of 50% flowering	Temperature accelerates growth-rate and phenological development. Temperature exceeding 35°C causes heat-damage in rice. Major effects include chloroplast damage, pollen unviability, reduction in number of flower, impaired pollen tube, limited pollen release, spikelet sterility (Prasad *et al.*, 2006; Welch *et al.*, 2010; Jagadish *et al.*, 2015)
Day heat-stress of the reproductive stage, DHS (deg. C)	Sum of degrees Celsius accumulated over 35° C from the date of sowing till days to 50% flowering $DHS.g = \sum_{date\ of\ sowing}^{date\ of\ 50\%\ flowering} \max(0, Tmax - 35\,°)$ Where, Tmax = average daily maximum temperature	

Variable	Description	Importance
Number of wet days in the reproductive stage, WET	Total number of days from date of sowing till date to 50% flowering for which the standard precipitation anomaly (*SPA*) was greater than 1. *SPA* for a day *n* is calculated as: SPA_n = ($rainfall_n$ - mean of $rainfall_n$)/standard deviation	Number of wet days and dry days represent the distribution of rainfall within the growing season. Uneven rainfall distribution has been shown to overturn the benefits of increased total precipitation (Fishman, 2016)
Number of dry days in the reproductive stage, DRY	Sum of all days from date of sowing till days to 50% flowering where the standard precipitation anomaly (*SPA*) was less than -1. *SPA* for a day *n* is calculated as: SPA_n = ($rainfall_n$ - mean of $rainfall_n$)/standard deviation	

<table>
<tr><th>Variable</th><th>Description</th><th>Importance</th></tr>
<tr><td>Net water deficit during the reproductive stage, NWD (mm)</td><td>$$NWD = \sum_{date\ of\ sowing}^{date\ of\ 50\%\ flowering} PEP - Rainfall$$
where,
PEP = daily potential evapotranspiration calculated using the Hamon’s equation (in mm),
rainfall = daily rainfall derived from the GRASP data (in mm)</td><td>Drought negatively affects plant growth and development, causes cell membrane injury, enzymatic inactivity and other physiological and morphological changes that leads reduced yield in rice. Drought stress, in particular, during the flowering stage causes early onset of floral development and sterility (Venuprasad et al., 2007; Su et al., 2013; Zandalinas et al., 2017).</td></tr>
<tr><td>Average minimum temperature of the ripening stage, Tmin (°C)</td><td>average of the daily minimum temperature from the date of 50% flowering till the date of harvest.</td><td rowspan="2">High minimum temperature increases night-time respiration that reduces non-structural carbohydrates in plant tissues, leading to yield and grain quality losses. It also accelerates rate of grain filling that leads to empty grains or decreased grain weight (Mohammed & Tarpley, 2010; Nagarajan et al., 2010; Shi et al., 2013)</td></tr>
<tr><td>Night-time heat-stress of the ripening stage, NHS (deg. C)</td><td>Sum of degrees Celsius accumulated over 25° C from the date of 50% flowering sowing till date of</td></tr>
</table>

Variable	Description	Importance
	harvesting $$NHS = \sum_{date\ of\ 50\%\ flowering}^{date\ of\ harvesting} \max(0, Tmax - 25\,°)$$ where, Tmin = average daily minimum temperature	
Number of wet days in the ripening stage, WGR	Sum of all days from date of 50% flowering to date of harvesting where the standard precipitation anomaly (*SPA*) was greater than 1. *SPA* for a day *n* is calculated as: SPA_n = (rainfall$_n$- mean of rainfall$_n$/standard deviation	Extreme rainy days during the ripening phases when the crops are maturing causes physical damage to plants (Auffhammer *et al.*, 2012)

4.2.3. Comparing yields performance of local vs national cultivars

In order to test whether local cultivars have higher yields than national cultivars (and whether they differed in other phenotypic measures), I examined whether there was a significant difference in mean yields of local versus national cultivars, after accounting for the effect of site and year in a mixed modelling approach. I allowed the mean yield per cultivar, as well as differences in the mean yields of the two cultivar groups (local versus widely-grown), to vary across sites and years, following a 'random-intercept and random-slope' modelling approach. I also used the same method to examine how local and national cultivars differed in other phenotypic measures important for yield, including plant height, days to flowering, and spikelet abundance per m^2.

4.2.4. Examining sensitivity of cultivars to heat-stress and water-stress

I examined differences between local and national cultivars in their sensitivity to water-stress and heat-stress in two ways. First, I modelled local and national cultivar yields (i.e. two models, separately analysing data for local and national cultivars) in relation to the eight climate variables listed in Table 4.1:

$$log(Y_{i,t}) = \beta_{i,0} + \beta_{t,0} + \beta_1 X + \beta_2 X^2 + \varepsilon_{it} \qquad (1)$$

where, $Y_{i,t}$ is the crop yield of each cultivar grown at site *i* in year *t* (ln-transformed), and β_1 and β_2 are vectors of regression coefficients for individual climate variables and their squared terms respectively (included to capture any non-linearity in yield responses; Schlenker & Roberts, 2009; Burney & Ramanathan, 2014). I included 'site' and 'year' as random effects in models to control for spatially and temporally varying factors that could affect yield, such as such as soil type, topography, or change in cultivar grown at sites. All eight climate variables were standardised by subtracting their respective mean and dividing by the standard deviation. I estimated sensitivity to heat-stress by predicting yield while holding all climate variables except DHS constant at their mean value and expressing the sensitivity in terms of changes in absolute yield per unit change in DHS. The same approach was used to examine sensitivity to water-stress, NWD.

Secondly, I analysed the differences in yield between local and national cultivars in relation to the eight climate variables (i.e. a single model analysing data on yield differences). My response variable for this analysis was the relative yield performance ($YD_{i,t}$) computed as the absolute difference in yield between local and national cultivars for each site and year combination (local cultivar yield – national cultivar yield). A positive value of $YD_{i,t}$ implied local cultivar yield was greater than national cultivar yield, and vice versa.

$$YD_{i,t} = \beta_{i,0} + \beta_{t,0} + \beta_1 X + \beta_2 X^2 + \varepsilon_{it} \qquad (2)$$

Where, $YD_{i,t}$ is the yield difference (in kg/ha) between local and national cultivars for site *i* and year *t*, β_1 and β_2 are vectors of regression coefficients for individual climate variables and their squared terms respectively. As in the first analysis, I included 'site' and 'year' as random effects, and all eight climate variables were standardised by subtracting their respective mean and dividing by their standard deviation. I estimated relative yield performance $YD_{i,t}$ under water-stress, NWD by predicting the yield difference while holding all climate variables except NWD constant at their mean value. The same was done to estimate relative yield performance under heat-stress, DHS. However, because cultivar development times resulted in the time-span of climate variables differing slightly among the two cultivar groups grown at the same site and year, I included climate data in models in Eq. (2) for whichever cultivar was harvested later (i.e. I used climate data derived for national cultivars if they were harvested after local cultivars, and vice versa).

4.3. Results

4.3.1. Yield and phenotypic differences between local and national cultivars

Local cultivars were generally taller (9% taller than national cultivars), had more panicles per m^2 (2.3% more than national cultivars), and flowered about a day later than national cultivars (Table 4.2). These phenotype differences were associated with the mean yield of local cultivars (2252 kg/ha), on average, 14% higher than the mean yield of national cultivars (1972 kg/ha). This suggest that local cultivars performed better than national cultivars probably due to more panicles resulting in more grain and hence higher yields in local cultivars, supporting my prediction that local cultivars perform better than national cultivars growing at the same sites.

Table 4.2. Post-hoc comparisons of local and national cultivars in relation to: mean yield (square-root transformed), days to 50% flowering, plant height (square-root transformed) and panicles per m^2. The estimates shown are transformed values (except days to 50% flowering and panicles per m^2). N.S. refers to comparisons of local and national cultivar values that are not significantly different.

	National cultivar – Local cultivar	Std. Error	z value	P-value
Yield (square-root transformed)	-3.04	0.72	-4.23	**<0.05**
Days to 50% flowering	-1.06	0.97	-1.09	N.S.
Plant height (square-root transformed)	-0.4	0.11	-3.44	**<0.05**
Panicles/m2	-5.66	4.54	-1.24	N.S.

4.3.2. Sensitivity of drought-tolerant cultivars to heat-stress and water-stress

I compared the sensitivity of the local and national cultivars to water-stress and heat-stress by predicting yield under net water deficit (NWD; where more positive/less negative values represent more drought conditions) and day-time heat-stress (DHS), and holding all other climate variables constant. My results showed that yields of both cultivar groups increased initially with increasing NWD and DHS, but then declined after crossing threshold values (Fig. 4.2). Overall, local cultivars had a higher water-stress threshold but a lower heat-stress threshold compared to national cultivars. Maximum yield was achieved for local cultivars at a water-stress threshold value (NWD = -422 mm) which was about 20% more water-stressed than the national cultivar threshold (NWD = -536 mm). Conversely, under heat-stress, national cultivars achieved maximum yield at a heat-stress threshold (DHS = 22 deg. C) which was about 22% greater than the threshold for local cultivars (DHS = deg. C). Thus, local cultivars can withstand more water-stressed but lower heat-stressed conditions, and the further the DHS or NWD value is beyond the threshold value, the faster the yield decreases for both the cultivars (Fig. 4.2). The maximum values for heat-stress (DHS) and water-stress (NWD) experienced across the 39 sites during the 15-year study were 57 deg. C for DHS (representing yield declines of 81% for local cultivars, compared to 58% declines in national cultivars), and +521 mm for NWD (representing 42% declines in yield for local cultivars and 59% declines in national cultivars). Thus, local cultivars suffered more damage from heat-stress (~81% yield declines) than from water-stress (~42% yield declines) supporting my hypothesis that more drought-tolerant local cultivars are more sensitive to heat-stress.

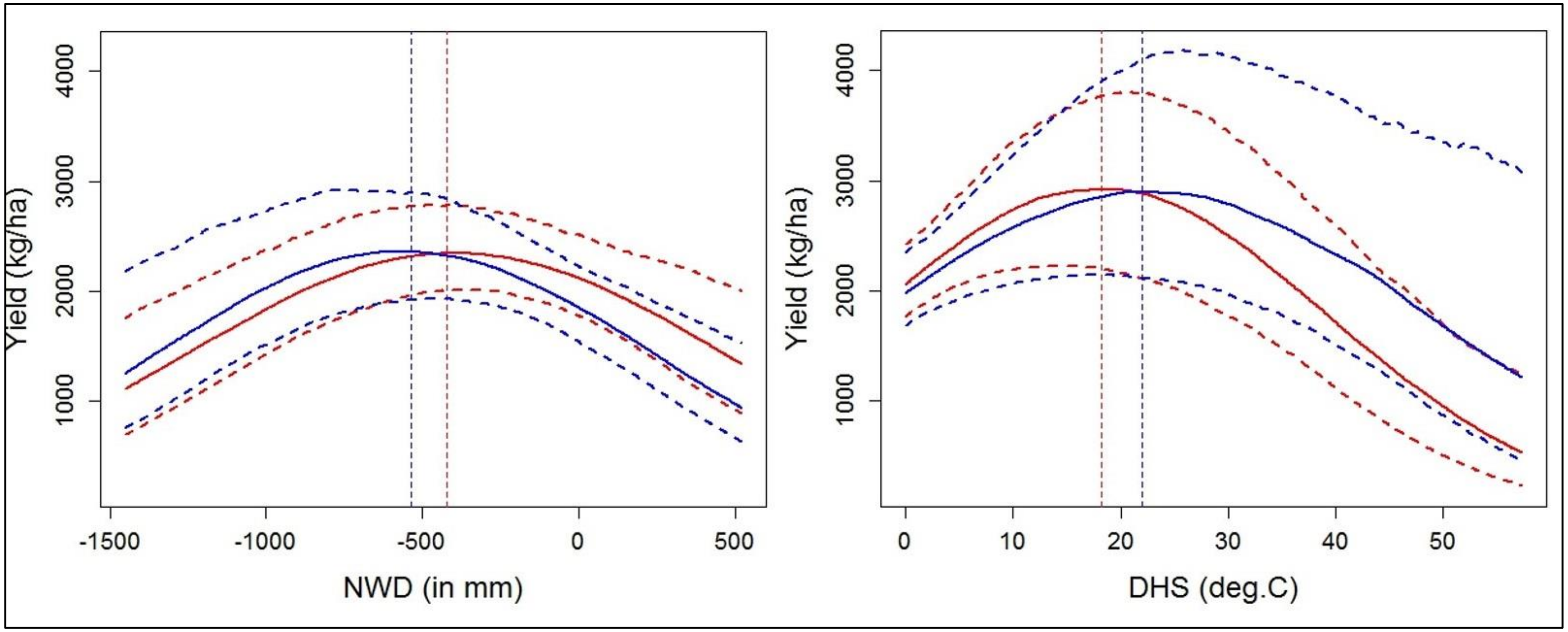

Figure 4.2. Modelled absolute yields of local (red line) and national (blue line) cultivars for (a) net water deficit (NWD, in mm) and (b) day-time heat-stress (*DHS,* in deg. C). The vertical lines show the threshold value of NWD and DHS when the maximum yield was reached. Yield predictions are made using estimates from Eq. 1 (see Methods) for both DHS and NWD by holding other climate variables constant at their mean values. The dotted lines shows the 95% confidence intervals.

Analyses of yield differences (Eqn. 2) showed that the yield advantage of local cultivars over national cultivars increased with increasing water-stress (NWD; Fig 4.3a). Local cultivars outperformed national cultivars when NWD was greater (i.e. more droughted conditions) than -820 mm. Under relatively mild drought conditions (NWD between -823 mm to -489 mm), mean yield advantages of local cultivars were ~90 kg/ha over national cultivars. However, this advantage was almost eight times higher in more severe droughts (NWD +187 mm to +521 mm) when the yield benefits of local cultivars reached almost 700 kg/ha. However, the opposite pattern was found in relation to heat-stress, whereby national cultivars had higher yield advantages over local cultivars under very high day-time heat-stress conditions (DHS > 49 deg. C; Fig 4.3b). For example, between DHS values of 40 deg. C to 49 deg. C (accumulated day-degrees summed over 35°C), the yield advantage of local cultivars was only 151 kg/ha, and above DHS = 49 deg. C, national cultivars had higher yields. However, the DHS values above which national cultivars performed better than local cultivars are relatively rare in the current climate, and only 16% of the 586 yield trial data between 1996-2010 experienced DHS values greater than 49 deg. C. Therefore, under current climate conditions, local cultivars give better yields under both water-stress and heat-stress conditions. However, under future climate scenarios, heat-stress conditions under which yield advantages of local cultivars start to diminish relative to national cultivars (i.e. DHS > 20 deg. C) are expected to become much more common (Fig 4.4; RCP 8.5 scenario), undermining the advantages of local cultivars over national cultivars.

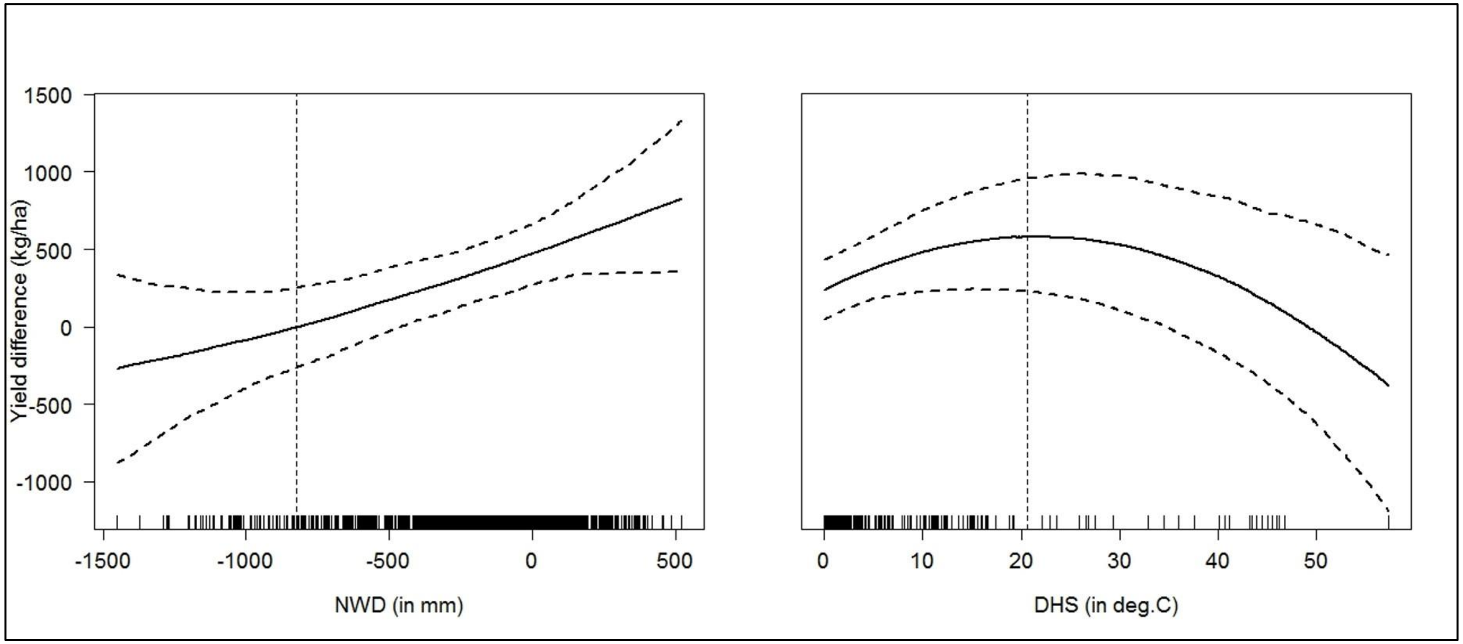

Figure 4.3. Modelled yield advantages of local versus national cultivars (from Eqn. 2; see Methods) for (a) water-stress, NWD (in mm) and (b) day-time heat-stress, DHS (in deg. C). The vertical line in (a) shows the value of NWD above which local cultivars outperform national cultivars. Similarly, the vertical line in (b) shows the value of DHS above which the yield advantage of local cultivars relative to national cultivar starts to reduce. The rug plot on the x-axis shows the distribution of NWD and DHS values under current climate conditions (1996-2010).

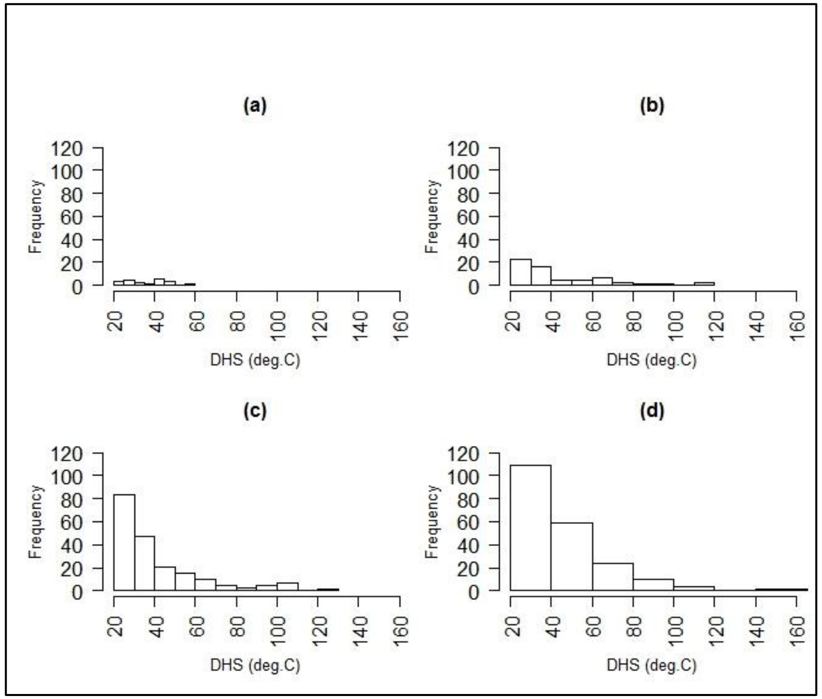

Figure 4.4. Distribution of day-time heat-stress conditions (DHS) >20° C under (a) current climate and (b) – (d) 2050 climate using RCP 8.5 scenario. Temperature projections from multiple GCMs were used to calculate day-time heat-stress (DHS) for 2050; (b) BCC-CSM1-1, (c) HadGEM2-ES (d) MIROC-ESM-CHEM.

4.4. Discussion

In this study, I examined the sensitivity of drought-tolerant rice cultivars to water-stress and heat-stress and the subsequent impacts on relative yield performance. My results suggest two important conclusions. First, I find there are trade-offs between water-stress and heat-stress tolerance, such that yields of more drought-tolerant rainfed rice cultivars are more sensitive to heat-stress. Secondly, in spite of greater yield advantages under current climate conditions, local cultivars might lose their yield advantage over national cultivars due to more frequent extreme heat-stress events in future.

4.4.1. Differences between local and national cultivars in tolerance to heat-stress and water-stress

My results showed that as water-stress increased, the yield performance of local cultivars increased over widely-grown cultivars (yield advantage was ~700 kg/ha under the most water-stressed conditions experienced during the study). Both local and national cultivars had reduced yields under increasing water-stress, but national cultivars suffered relatively greater yield losses because they were more sensitive to water-stress (Fig. 4.2). A similar but opposite effect was observed for heat-stress, whereby the relative yield advantages of local cultivars over national cultivars declined with increasing heat-stress, and above a threshold value, national cultivars outperformed local cultivars. However, given the range of heat-stress and water-stress experienced at sites under current climate conditions, local cultivars consistently offer higher yield advantages over national grown cultivars under the current climate. Only 16% of yield trials analysed in this study experienced extreme heat-stress beyond which national cultivars outperformed local cultivars. However, it is likely that heat-waves will become more intense and frequent in future, that could make heat-stress much more common in the near future (IPCC, 2013; Horton *et al.*, 2016). Given the greater sensitivity of local cultivars to heat-stress, my results suggest that the yield advantages of local cultivars over national cultivars may reduce in the near future.

My results can be interpreted from a farmer's perspective. The terminology 'local' and 'national' cultivar is based on the popularity of different cultivar among farmers. Local cultivars are popular with farmers at particular sites to which they are locally adapted, but are not popular at other sites. The impacts of drought tend to dominate farmers' decisions in choosing the best cultivars to grow, probably because the signs of water-stress impacts (e.g. cracked soil, leaf rolling and drying, stunted plant height) are relatively easy to see (Kumar *et al.*, 2008). This could explain why local cultivars, which represent farmer knowledge of local drought conditions, have better water-stress tolerance and hence higher yields, and have been chosen by farmers to perform best under local environmental conditions. In addition, severity of water-stress conditions are influenced by local soil type and topography (Van Wesemael *et al.*, 2003; Dai, 2013) and farmers across the rainfed regions adjust their cultivar preferences primarily based on local water availability rather than temperature.

4.4.2. Antagonistic stress-response pathways for heat-stress and water-stress in rice

My results reveal that heat-stress is a strong driver of yield among drought-tolerant rice cultivars. Given that more heat extremes are projected in the future, I conclude that tolerance to heat-stress should be a key trait for crop breeders to target. However, simultaneous tolerance towards heat-stress and water-stress could be problematic if there are antagonistic physiological stress-response pathways (Rizhsky *et al.*, 2004) as found in other studies. For example, the effects of heat-stress, at a cellular level, cause membrane fluidity, denatured proteins and the formation of reactive oxygen species in rice (Chao *et al.*, 2009; Chou *et al.*, 2012; Bokszczanin *et al.*, 2013; Driedonks *et al.*, 2016). As a response to heat-stress, plants produce more heat shock proteins, which prevent deleterious effects in other proteins (Mittal *et al.*, 2012; Grover *et al.*, 2013), and enhance mitochondrial respiration to avoid build-up of reactive oxygen species that could damage proteins, lipids and DNA (Wahid *et al.*, 2007). These responses make plant growth and development possible under heat-stress. Under drought conditions, plants accumulate osmoprotectants to maintain the osmotic potential in cells, but the synthesis of osmoprotectants takes place in mitochondria and produces toxic compounds, causing reduced mitochondrial respiration which in turn interferes with repair processes needed under heat-stress (Rizhsky *et al.*, 2004). Hence, there are antagonistic effects if drought conditions co-occur alongside heat-stress. In addition, heat-stress enhances stomatal conductance in plants in order to cool their leaves by transpiration (Rizhsky *et al.*, 2002; Mittler & Blumwald, 2010). However, if drought-stress occurs at the same time, the need to conserve water means plants reduce their stomatal opening (Hetherington & Woodward, 2003; Tombesi *et al.*, 2015), leading to increased leaf/tissue damage from high temperatures in the absence of transpiration cooling, together with reduced carbon uptake and hence reduced yield (Chaerle *et al.*, 2005; Hirasawa *et al.*, 2010; Roche, 2015). In addition, even if the soil water returns to optimal levels after a period of drought, there are time lags in plant recovery processes, such as photosynthesis and transpiration rates (Liang *et al.*, 2002). Other examples of plant physiological trade-offs exist in literature, for example, faster growth rates of invasive species are associated with reduced shade tolerance (Martin *et al.*, 2010), higher reproductive rates result in reduced tolerance to abiotic stresses (Koziol *et al.*, 2012), and there are trade-offs between biomass allocation to shade-tolerance (greater above-ground biomass) versus drought-tolerance (more roots and fewer leaves to reduce evapotranspiration; Ninements & Valladares, 2006). These examples support my findings that plant responses to heat-stress and water-stress could potentially be antagonistic (Barnabás *et al.*, 2008). These results present a unique challenge for crop breeders in scenarios where heat-stress and water-stress occur simultaneously, in developing cultivars that are tolerant to multiple abiotic stresses.

4.4.3. Achieving tolerance to multiple abiotic stresses in crops

Co-occurrence of heat-stress and water-stress has greater impacts on plant productivity and yield compared with just a single abiotic stress acting independently (Mittler, 2006). Due to antagonistic stress-response pathways in plants to conditions of heat- and water-stress, one of the biggest challenges to breeders is to examine traits that might take account of some of the antagonistic aspects of the stresses. At a plant level, examination of transcriptomes and metabolomes under the combined effects of heat- and water-stress might lead to better understanding of the factors affecting plant tolerance to multiple stresses (Rizhsky *et al.*, 2002; Mittler, 2006). At a plot level, better irrigation will buffer against high temperatures by ensuring sufficient water availability during the growing season, leading to cooling via transpiration (Julia & Dingkuhn, 2013). I conclude that the development of irrigation infrastructure should be a key priority for policy-makers, to support food security and livelihoods of farmers.

4.4.4. Can the current drought-tolerant cultivars help farmers adapt to future climate change?

Local cultivars are adapted to local drought conditions and have yield advantages over national cultivars, supporting farmers' decisions to grow local rather than national cultivars. However, future climate projections show that many rainfed rice growing areas are likely to decline in climate suitability (Singh *et al.*, 2017a), and be exposed to greater frequency of heat-stress conditions (Gourdji *et al.*, 2013). Given that local cultivars have greater yield declines under heat-stress, national cultivars may become advantageous in future. However, farmers may be reluctant to choose national cultivars, making it important to develop new drought-tolerant rice cultivars that are also tolerant of heat-stress. I provide evidence of the sensitivity of rice cultivars to abiotic stresses, but statistical models such as those I used in this study, may be less sensitive to rainfall compared to temperature (Lobell & Asseng, 2017), and statistical models may underestimate the importance of drought (Watson & Challinor, 2013). In addition, my measures of water-stress and heat-stress are derived from relatively coarse-scale GRASP climate data (~55 km spatial resolution). Hence, more studies are needed to examine whether the findings I report on the relative importance of water- versus heat-stress on crop yields are found more widely in other crops.

I conclude that the vulnerability of popular drought-tolerant rice cultivars to heat-stress, and the impacts of reduced yield on the livelihoods of farmers dependent on rainfed crops makes it important to develop new cultivars with improved heat-stress tolerance. My findings projecting a trajectory of declining yield advantage of popular local rice cultivars under future climate change scenarios implies that local cultivars may not retain their yield advantages over national cultivars in future. Hence, there is a need to develop crop breeding programmes aimed at developing tolerance to multiple abiotic stresses in crops for rainfed areas.

4.5. Acknowledgements

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Chapter 5 General Discussion

A farmer overlooking her rainfed rice fields in Madhya Pradesh, Central India.

5.1. Summary of thesis findings

The main aim of my thesis is to understand the relationship between climate and rainfed rice productivity. I focused on rainfed rice growing areas in India, which are dependent on the summer monsoon for meeting the water requirements of rainfed crops, and I examined the risks to rainfed rice cultivation from climate change. Specifically, I examined changes in historical patterns of summer monsoon rainfall (Chapter 2), and the main climatic drivers of rainfed rice yield (Chapters 2 and 4). I also examined future risks to rainfed rice production by modelling how the extent of rice cultivation might change in the future as a consequence of climate change (Chapter 3). In this General Discussion chapter, I will present a summary of my thesis findings in relation to the specific hypotheses that I tested in each of the individual chapters, and the conclusions arising from these studies. I will discuss the implications of my findings, where there are uncertainties and potential sources of errors, and I will suggest new future research on the impacts of climate change for food security, based on the findings from my thesis.

Chapter 1: General Introduction

The main objective of the General Introduction Chapter was to highlight the key gaps in existing literature that my subsequent Chapters address. This Chapter provided an overview of existing literature on climate and its relationship with food security and specifically pointed to the following knowledge gaps.

1. Existing literature examining crop – climate relationship has focused mainly on a cumulative measure of rainfall even though there are evidences that within season distribution of rainfall is crucial for plant crop growth and development.
2. Both yield and cropping area are important driver of total agriculture output and are sensitive to climate change. However, majority of studies have focused on examining the impact of climate change on yield while less attention has been given to how area under crop would respond to climate change.

3. Often studies estimating crop-climate relationship examines historical data from pooled data at an administrative level, which hides the sensitivities of individual cultivars grown across different environment to changes in climate.

Chapter 2 to Chapter 4 addresses these knowledge gaps as explained below**.**

Chapter 2: Short-term daily reductions in monsoon rainfall reduce yield of rainfed rice.

Main objectives of this chapter:

1. Examine long-term historical changes over the past five decades in quantity (total rainfall), distribution (number of wet and dry days) and timing (onset and withdrawal dates) of the Indian summer monsoon.
2. Examine the relative importance of quantity, distribution and timing of monsoon on rainfed rice yield.

In this chapter, I analysed historical data on summer monsoon rainfall (1951 – 2007) using daily gridded (~55 km x 55 km grid resolution) APHRODITE rainfall data for rainfed areas in India using non-parametric and generalised linear models. I also examined the relative importance of five monsoon variables (total monsoon rainfall, number of wet and dry days, and onset and withdrawal dates of monsoon) on rainfed rice yield at a district level, using an information theoretic (IT) model selection approach using Akaike's information criterion (AIC). I found that more locations showed a trend towards drying (i.e. either total rainfall was reduced, number of dry days increased or number of wet days decreased) than a trend towards getting wetter. In total, 26% of grid squares showed a trend towards drying as opposed to 15% of grids that showed a trend towards wetting. Drying trends were primarily due to decreases in the number of wet days, rather than increases in the number of dry days. Overall, the distribution of monsoon rainfall (i.e. number of wet and dry days) was a more important driver of rice yield than quantity or timing of rainfall. The number of dry days had the highest (negative) impact on rainfed rice, with each additional dry day reducing yield by ~16 kg/ha. This work highlights the risks to rainfed rice cultivation from short-term within-season rainfall patterns, and demonstrates the importance of timely water availability for plants. Recommendations from this study are for the development of better irrigation infrastructure and more drought-tolerant rice cultivars. This work is also of potential importance to weather-based insurance sector revealing that rainfall distribution is a more important index than cumulative rainfall.

Chapter 3: Mapping regional risks from climate change for rainfed rice cultivation in India.

Main objectives of this Chapter:

1. Examine if the current extent of rainfed rice cultivation can be modelled using climate variables derived from rainfall and temperature.
2. Examine changes in climate suitability of rainfed rice growing areas in India, to highlight areas at risk from future climate change.

In this chapter, I examined if the extent of rainfed rice cultivation (18 km x 18 km grid-level data downscaled from collated district-level data) can be modelled using climate variables derived from rainfall and temperature. I used 'species distribution models' to model the extent (in ha; continuous variable) and occurrence (presence or absence) of rainfed rice using four monsoon climate variables: moisture availability (precipitation-evapotranspiration ratio), average maximum temperature, average minimum temperature during the rice plant growing period and total rainfall during harvesting. I found that rainfed rice growing areas can be modelled using these four climate variables, and that variables representing water-availability (precipitation-evapotranspiration ratio) were more important than temperature variables. Using future climate projections from multiple GCMs and RCPs scenarios, I predicted that by 2050, approximately 14% - 40% of current rainfed rice growing areas might become climatically unsuitable for rainfed rice cultivation. These results help in identifying locations that might be at risk from future climate change, and where livelihoods of low-income farmers and regional food security may be threatened in the next few decades by climate change.

Chapter 4: Selecting for drought-tolerance may increase the sensitivity of rainfed rice to heat-stress.

Main objectives of this chapter:

1. Examine the yield performance of a wide range of different upland rice cultivars, comparing local cultivars with those grown more widely (national cultivars).
2. Examine if there are trade-offs between tolerance of water-stress and heat-stress, and whether more drought-tolerant cultivars are also more sensitive to heat-stress.

Farmers are knowledgeable about local climatic conditions and grow rice cultivars that are best suited to local environments. In this chapter, I used a multi-location (39 sites) and multi-year (15 years) upland breeding trial data set (AICRIP) to examine if cultivars chosen by local farmers ('local cultivars') had significantly higher yields and better water and heat stress tolerance than elite cultivars ('national cultivars'). I found that local cultivars had ~14% higher yields than national cultivars and were more drought tolerant. However, local cultivars, in spite of being more drought-tolerant were also more sensitive to heat-stress, suggesting a potential trade-off whereby developing increased tolerance to one abiotic stress could lead to reduced tolerance of another. Future climate projections suggest more incidences of extreme heat and so current local cultivars may lose their yield advantage over national cultivars. The conclusions of this work are to inform rice breeders about the relative importance of heat-stress and drought, and the importance of developing cultivars that are tolerant to multiple abiotic stresses. However, there are likely to be physiological limitations to achieving tolerances to multiple stresses in plants.

In the rest of this Chapter, I discuss the implications of my findings and some important conclusions arising from my study.

5.2. Key factors affecting rainfed rice productivity

Total agriculture output (measured by total production) is a function of yield and area under crop and so it is important that studies of climate impacts should consider these two aspects of crop production (Cohn *et al.*, 2016; Leng & Huang, 2017). My findings in Chapter 3 highlight the risks to area under rainfed rice while Chapter 2 and 4 shows the risk to rice yield from climate change. In addition, analyses in this study included data at different spatial and temporal resolutions. Lack of consensus across different studies in their conclusions about drivers of crop yields could be due to spatial scale and results from this thesis suggests that analysing crop yield in isolation without considering spatial scale of measurement could lead to ambiguity in conclusions about the impacts of climate on productivity. To illustrate, a district in western India with annual rainfed rice production of 200 kg from 100 ha of land will have the same yield (2 kg/ha) as another district in eastern India with annual production of 500 kg from 250 ha. Yet in spite of the second district having 150% more production and area under rainfed rice, these two districts have the same yield and therefore, could lead to biased model parameters and misinterpretation of agricultural performance of the two districts in relation to climate. Therefore, this thesis not only highlights the risks of rainfed rice yield to climate change, but it also quantifies the extent of area under rice cultivation that might become climatically unsuitable in future and it does it by analysing yield and areas data at different spatial resolutions.

This thesis analysed rainfed rice area and yield in relation to climate variables derived from rainfall and temperature during the summer monsoon. Overall, the findings from the thesis conclude that rainfall patterns have changed over time in India, with more locations showing a drying trend (26% of locations) than a wetting trend (15% of locations). However, there was considerable heterogeneity with similar changes in rainfall localised within different regions, and many regions showing contrasting responses. Conclusions about long-term changes in rainfall patterns are often validated by comparisons with other studies carried out at similar resolution (Ghosh *et al.*, 2009) or by questioning how farmers and the general public perceive changes in rainfall (Howe *et al.*, 2014; Niles & Mueller, 2016). For example, in surveys conducted across rainfed regions of western India, 95% of the farming household interviewed reported that drought has become frequent in the recent years (Udmale *et al.*, 2014) while a similar study in eastern India showed that ~50% of farmers considered that rainfall patterns had become more erratic (Sahu & Mishra, 2013). These two contrasting studies support my conclusions, that monsoon rainfall has become more erratic over time, but that there is spatial variation in changes in rainfall patterns. Given the semi-aquatic nature of rice plants, it is important that there is sufficient water availability for rice growth. However, a trend towards increasingly erratic rainfall implies more extreme events and that there are long 'breaks' in rainfall as well as too much rainfall, both of which could detrimentally affect rice yield. Long periods of dry spells during the monsoon induce drought responses in rice, which could cause a decline in photosynthesis and other morphological and physiological changes that lead to yield declines. Similarly, too much water in a short period could cause flooding of rice fields, leading to submergence of plants, reduced interception of light and hence declines in photosynthesis. Therefore, it is important that farmers have more control of water supply in fields, for example by better irrigation infrastructure. Growing more resilient rice cultivars that can withstand periods of extreme rainfall patterns and water availability will also be advantageous.

However, sufficient and timely rainfall does not guarantee sufficient water-availability to plants if there is a high atmospheric evaporative demand. High temperatures are associated with increased evaporation from soil and increased transpiration from leaves and therefore the net water available to plants after accounting for these two effects will be less than the total rainfall. Hence, derived climate variables such as those used in Chapter 3 (potential evapotranspiration ratio) and Chapter 4 (net water-availability) synthesize the combined effects of temperature and rainfall, and capture the role of temperature in reducing the amount of water available to rice plants. In addition to increasing the detrimental effects of drought on rice, high temperatures can also have direct negative effects on plant reproductive organs and grain characteristics (Jagadish *et al.*, 2015) and thereby reduce yields. As shown in Chapter 4, negative effects of high temperatures on yield were greater than the negative effects of drought, and so it is important that rice cultivars with improved heat-stress tolerance are developed. However, part of the reason why rice cultivars analysed in Chapter 4 were more sensitive to heat stress than water stress was probably because they were bred exclusively for drought tolerance. In contrast to my analyses of yield, I found that rainfall played a more important role in determining the extent of rainfed rice cultivation, as shown in Chapter 3. It is often the case that farmers decide on whether or not to grow rainfed rice before the start of the growing season, based on the initial water conditions before the monsoon, and their perceived risk of rainfall changes during the initial weeks of sowing as a way of minimising their losses (Leng & Huang, 2017). This may contribute to my findings that variables measuring water availability were more important than temperature in determining the extent of rice cultivation, whereas temperature played a greater role in analyses of rice yield (e.g. Chapter 4).

This thesis, however, did not examine other factors such as ozone (Ainsworth, 2008, 2016), CO_2 concentrations (Long *et al.*, 2004; Ainsworth & Long, 2005), solar radiation (Peng *et al.*, 2004), soil properties (Wiesmeier *et al.*, 2016; Ockenden *et al.*, 2017) or pests and diseases that play an important role in affecting yield. Such factors may also interact with water and temperature (e.g. pests may be more abundant at higher temperatures), and these additional factors deserve further study.

5.3. Robustness of results and uncertainties

There are wide range of sources that could affect the robustness of the results in this thesis and I discuss some of these potential sources of errors in general, and for uncertainties specific in individual chapters.

5.3.1. Uncertainties in data on yield

In this thesis, I analysed district-level yield and cultivation area as response variables in models. These data on yield and area of extent of rice were collated from regions that cultivate rainfed rice under the assumption that these regions are completely dependent on rainfall for meeting crop water requirements i.e. these areas are 100% rainfed. However, in the strictest sense, no regions are truly 100% rainfed since almost everywhere rainfed and irrigated system coexists. Even within a village, for example, wealthy farmers have access to irrigation sources such as private wells, canals or pumping generators whereas the poorer farmers rely solely on rainfall for maintaining their agriculture fields. Therefore, the data analysed in this thesis are from regions that are 'predominantly rainfed' i.e. rice is mostly cultivated under rainfed conditions. Thus some of the unexplained variation in my statistical models may have been due to variation in rainfed versus irrigated agriculture within these predominantly rainfed regions. Therefore, conclusions from Chapter 2 and 3 are likely to be more confounded by the presence of irrigated rice compared to Chapter 4, which was exclusively based on 100% rainfed conditions.

The data I analysed on rice yield and area data were collected and compiled by governmental statistical agencies (for example, Directorate of Economics and Statistics) and research institutions (National Rice Research Institute, India) at a district-level scale. There are different rice environments (i.e. rainfed versus irrigated) within a district, and within each ecosystem, multiple rice cultivars are grown. However, these aggregated district-level data obscure any finer scale heterogeneity in the data. For example, the district-level yield data analysed in Chapter 2 were not segregated between rainfed versus irrigated systems and so cultivars, which were irrigated could have contributed to the reported district-level yield data, and hence mask some of the impacts of rainfall that I found, due to the presence of irrigated rice. Therefore, detailed information on management practises, such as those used in Chapter 4 are required in order to make conclusions that are more robust at an administrative-level.

5.3.2. Uncertainties in temperature and rainfall data

Obtaining reliable climate data for both present-day as well as for future projections for 2050, are important in climate-impact studies, such as in this thesis, because weather data are used in analyses of yield (Chapter 2 and 4) and area under cultivation (Chapter 3). In this thesis, I used three spatially-interpolated gridded climate dataset: (1) APHRODITE (Yatagai *et al.*, 2012) at 0.5° grid square resolution (~ 55 km x 55 km grid size) in Chapter 2; (2) WorldClim (Hijmans *et al.*, 2005; Fick & Hijmans, 2017) at 0.16° grid square resolution (~ 18 km x 18 km grid size) in Chapter 3 and (3) GRASP (Iizumi *et al.*, 2014) at 0.5° grid square resolution (~ 55 km x 55 km grid) in Chapter 4. These three datasets all differed in their temporal resolution; WorldClim provided monthly averaged (1970 – 2000) temperature and precipitation data, whereas APHRODITE and GRASP provided the same data but at a daily time scale. The advantage of using daily data is that it allowed me to generate climate variables that captured fine-scale within-season variation in rainfall and temperature (for example, number of wet days, dry days and accumulation of heat-stress). On the other hand, monthly-averaged data from WorldClim are more suitable for future projections of yield and area changes because there are too many uncertainties in GCMs to produce reliable data at fine temporal scale, especially for rainfall projections. In addition to the differences in temporal resolution and the relative advantages and disadvantages of the various data sets, gridded datasets have certain errors that may introduce some uncertainties in the results. Firstly, gridded climate data are interpolated from weather stations and so their accuracy depends on the distribution and number of met stations in India. For India, weather stations are generally at low density in eastern montane regions and parts of central-east India (Guhathakurta & Rajeevan, 2008), and so these gridded climate data may be less reliable in locations where interpolation was carried out using fewer met stations. Secondly, new weather stations have been established during the period over which the data sets have been established, which could affect long-term patterns of rainfall at these sites, and so affect the ability of statistical models to assess associations between climate and rice productivity. More specifically in Chapter 2, the grid-level (55 km X 55 km) results of changes in summer monsoon patterns could be affected if a grid overlapped a region with a wide range of elevation (for example, eastern India which covers parts of Himalayas). Therefore, a cautionary approach should be adopted while interpreting the results of monsoon changes from Himalayan regions in eastern India. In Chapter 3, I used future climate projections from WorldClim across multiple GCMs and RCPs scenarios to account for model uncertainties and assumptions on greenhouse gas emissions respectively (Wilcke & Barring, 2016). The WorldClim data was constructed by statistically downscaling the outputs of GCMs; however, statistical downscaling has been criticised by for its degrading of the GCM outputs and reducing the variances and overall giving a false sense of accuracy (Baron *et al.*, 2005; Ramirez-Villegas & Challinor, 2012). Therefore, dynamical downscaling of GCMs output using regional climate models (RCMs) are increasingly being used in climate impact studies since they translate coarser GCM output to finer spatial scales much accurately (Macadam *et al.*, 2016). In addition, risks category of grids in Chapter 3 does not take into account any adaptation on behalf of farmers and policymakers that could likely reduce the risk. For example, farmers could alter date of sowing, or grow new cultivars as mitigation to altered climate suitability. However, the extent of future climate projections in these analyses suggest that any adaptation by farmers may not be sufficient to account for long-term climate changes, and this analysis does provide information on where such adaptation actions may be needed in the near future. In Chapter 4, I used GRASP climate data (~55 km x 55 km grid resolution) to model variation in yields of local and national cultivars that had been grown at plot-level (15 m x 15 m plots) and so there was a mismatch in the spatial resolution of yield and climate data sets. Future analyses of these AICRIP data using site-specific meteorological station data would be an improvement over using gridded climate data, however, given that management practises are standardised in AICRIP data, it is unlikely that inter-annual variation in yield were driven by local conditions rather than climatic variables.

5.4. Increasing the climate resilience of rainfed systems

This thesis examined the climatic risks to rainfed areas, and in particular to rainfed rice in India. There has been a rise of almost ~77% in the number of smallholder farmers in India in the last three decades, the majority of whom live in the rainfed regions of India that I examined in this thesis (Joshi, 2015). Given the large population of farmers, the role of rainfed rice for regional food security and local livelihoods, and the risks to rainfed rice cultivation from climate change, it is important to discuss some key adaptation options that could potentially make rainfed rice cultivation (and other crops) more climate resilient in these areas.

5.4.1. Resilience through breeding

Genotype modification that involves breeding more resilient cultivars through the modification of traits that determine plant tolerance to multiple abiotic stresses is one of the key adaptation strategies for crops under increasingly variable climate (Singh *et al.*, 2017b). Genotype modification involves breeding cultivars with desirable traits that confer tolerances to multiple stresses and hence provide stable yields (Ramirez-Villegas & Challinor, 2016). Such traits could include improved photosynthetic rates, reduced leaf area, more carbohydrate-rich seeds, and reduced night-time transpiration (Coupel-Ledru *et al.*, 2016; Ramirez-Villegas & Challinor, 2016; Srinivasan *et al.*, 2017). Historically, breeding was carried out by selectively choosing those traits that conferred high yields, but this has resulted in loss of genetic diversity in seed stocks available to farmers (McCouch, 2013). Therefore, new genetic approaches for developing novel rice cultivars are being undertaken, to increase the amount of genetic variation and hence likelihood of developing desirable traits. For example, recent research is being carried out on transferring drought-conferring genes from wild relatives of rice plants to modern cultivars (McCouch, 2004; Phillips *et al.*, 2017). In spite of this new breakthrough in breeding research, one study estimates that it could take up to 30 years for the entire process of breeding, development and adoption of new cultivars to be completed (Challinor *et al.*, 2016), and therefore faster cultivar development is required so that new improved cultivars can replace obsolete cultivars with declining yields. A study recommended growing cultivars that were bred in the last 10 years, and so more likely to be resilient to recent changes in climate (Atlin *et al.*, 2017). Recently, there has been increasing use of crop simulation models to design 'model crops' or 'ideotypes' for specific environments, including rainfed environments, which may fast-track the breeding process (Rotter *et al.*, 2015). 'Ideotypes' are virtual crops with the desired morphological and physiological traits that are suited to a specific environment. Using crop models, scientists can predict the yield improvements if the ideotype is developed as a cultivar (Rotter *et al.*, 2015) and this approach can help make decisions *a priori* on whether or not to undertake breeding to develop the cultivar. An important insight relevant to this discussion was generated by my results in Chapter 4 in which I found that local cultivars (popular among local farmers) were more high- yielding and better adapted to drought than widely-grown cultivars. Thus, farmers are apparently selecting the best local varieties for producing high yields in their local region. This result suggests that breeding programmes should incorporate farmers' knowledge of local climate and their preference of traits because it could lead to development of new cultivars that are reflective of their knowledge and social contexts (Samberg, 2016). Usually breeding programmes address this issue by adopting participatory approaches such as field schools to engage farmers in the process of cultivar development (Upadhya *et al.*, 2016), and results from Chapter 4 will be important evidence in these participatory approaches, providing information to farmers about the effectiveness of their sowing decisions and selection of cultivars.

5.4.2 Resilience through improved management and new infrastructure

Management practices can be improved to further enhance yield in rainfed regions. These management practices include planting methods, such as system of rice intensification (SRI) (Stoop *et al.*, 2002; Satyanarayana *et al.*, 2007), optimising planting dates, conservation agriculture practises such as no-till agriculture (Powlson *et al.*, 2014), integrated nutrient management (Pathak *et al.*, 2003; Mondal *et al.*, 2016; Parkes *et al.*, 2017), and development of irrigation infrastructure. Irrigation, in particular plays an important role because it acts as a buffer against the direct effects of heat-stress, as well as maintaining a steady water supply throughout the year, enabling cultivation of more than one crop per year (Jain *et al.*, 2013; Tao *et al.*, 2015). There is also a separate issue about the over-reliance on certain crops for meeting global calorie requirements. Currently, around 20 plant species supply 90% of the world's calories, suggesting a highly uniform diet globally (Massawe *et al.*, 2016). This over-reliance on a limited number of crops may not be sustainable in the long term because these major crops are mostly grown under intensive agriculture and thus put great pressure on existing land resources. Diet diversification, for example by eating more 'orphan' crops such as tubers, roots and pulses that can grow more easily in marginal environments, may reduce the pressure of intensive agriculture on existing land, and hence ensure better food security under a changing climate. Therefore, resilient cultivars, improved management, irrigation infrastructure as well as food diversification are the major pillars of achieving complete food security.

Many of above-mentioned factors could not be achieved because of lack of financial incentives. Market factors, such as lack of crop insurance, is a major hurdle for farmers to enhance investment in farm inputs, such as using more fertilizers or purchasing higher yielding seeds, as well as coping with yield losses in extreme climatic events such as drought or heat-stress (Carter *et al.*, 2017). Uninsured weather risks discourage farmers from investing in their fields due to a perceived risk of yield loss under extreme climatic events, and this lack of investment has kept realised yields much lower than the maximum attainable yield in rainfed areas (Rao *et al.*, 2016). Adequate crop insurance would help remove such hurdles and encourage farmers to invest in their fields by providing a financial safety net in the event of a major climate disaster. Recently, Index-based insurance has become a promising adaptation tool in mitigating climate risks and is implemented by several national governments, including India(Miranda & Farrin, 2012; Carter *et al.*, 2017). This form of Index-based insurance uses an index, such as cumulative rainfall, and payments are made to farmers if the index (i.e. rainfall) crosses a predetermined threshold. Such insurance schemes have advantages over more conventional insurance schemes because there is no need to objectively assess the damages, and so this method has a shorter implementation time. However, given my conclusions on the role of within-season short-term variation in patterns of rainfall on rainfed rice yield, I would recommend using a rainfall index that captures both the short-term variation as well as cumulative rainfall to determine the threshold level for paying insurance. Regardless of the specifics, such new insurance methods may help farmers to invest in their fields and so develop more resilience to future climate change.

5.5. Statistical versus process-based approaches

This thesis used statistical approaches to examine the risks to rainfed rice from climate change. Recently, process-based crop simulation models have been used in understanding interactions among plant genotype, environment and management (Jones & Thornton, 2003; Keating *et al.*, 2003; Challinor *et al.*, 2004). Crop models simulate the responses of cropping systems to changing climate, management and cultivar choice based on parameterising key processes important to plant productivity, and these models have the potential to provide useful insights into climate change impacts and adaptation in the agricultural sector (Ewert *et al.*, 2015; Ruane *et al.*, 2016). Process-based crop models allow users to simulate daily plant responses to environment and management changes given certain genetic traits and incorporating plant processes. The development of these models has led to their wider application in examining impacts of climate on yield, genotype by environment interactions, phenological development, and designing crop 'ideotypes' (Hammer *et al.*, 2006; Chapman, 2008; Boote *et al.*, 2013; Kumudini *et al.*, 2014; Webber *et al.*, 2014; Capa-Morocho *et al.*, 2016; Salmerón & Purcell, 2016; Singh *et al.*, 2016). In addition, recent initiatives such as the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig *et al.*, 2013) have shown that ensembles of crop models can predict yield with greater accuracy than single models, and also provide a way of quantifying uncertainties associated with different modelling methods (Asseng *et al.*, 2013; Li *et al.*, 2015b; Martre *et al.*, 2015). However, process-based crop models are very data intensive, and they require spatially and temporally detailed, location-specific data on plant genotype, environmental information, weather, soil and management data, and so are sensitive to the quality of the input data. Such detailed information to parameterise models is rarely available over large regions (for example, district-level as used in this study) (van Bussel *et al.*, 2015) and so hinders the applicability of crop models to explore climate change at spatial scales larger than field-scale. However, climate data are usually available at a spatial scale that is coarser than the plot-scale at which crop models usually operate. Therefore, an ideal crop model should be able to simulate key growth stages at a spatial scale at which climate data are available, as well as avoiding the need for very detailed information on management practices, environmental information and plant genetic traits (Challinor *et al.*, 2004). Hence, there are many new opportunities to develop new modelling approach to tackle this issue.

Statistical models, such as those used in this thesis, have been used to examine relationships between crop yield and climate at a relatively coarse scale using data collected by official government agencies (Lobell *et al.*, 2011; Auffhammer *et al.*, 2012; Burney & Ramanathan, 2014). In contrast to crop models, statistical models can capture relationships between crop yield and climate over large regions (Lobell & Burke, 2010). However, the key climatic variables that are included and the functional form describing the relationships with crop productivity are decided *a priori* in statistical models and so there is some degree of subjectivity in formulating statistical models and a subsequent lack of mechanistic understanding of plant growth and development (Moore *et al.*, 2017). In addition, aggregated crop and climate data at coarser resolution in statistical models can mask underlying heterogeneity in climate and yield and may lead to biased regression parameters (Lobell & Asseng, 2017).

Given the pros and cons of statistical versus process-based models, it has been suggested that both of these approaches should be used to complement the functionalities of the two approaches. For example, crop models can be used to guide the selection of key climate variables and interactions during the formulation of statistical models. Similarly, statistical models can be used as a guide to improving process-based models by highlighting new processes to include, such as ozone damage to yields in crop models (Lobell & Asseng, 2017). In addition, a statistical model can be fitted to modelled yield produced from crop model, which can then be subsequently interpolated for any values of temperature or rainfall. This will allow a user to calculate threshold values of rainfall or temperature above or below which there is a loss or gain in yield without the need of re-running the original crop model for other values of temperature and rainfall (Makowski *et al.*, 2015). Hence, studies that include both statistical and process-based models are likely to provide the most in-depth understanding of climate-change impacts.

5.6. Future research and final conclusion

Based on the discussions in the previous sections, this research could be extended to use process-based crop models in order to study the responses of individual rice cultivars to drought and heat-stress. Specifically, crop models could aid in interpreting the genotype by environment by management interactions (Yan *et al.*, 2007; Rakshit *et al.*, 2016; Van Eeuwijk *et al.*, 2016), which are not investigated in this thesis. Crop models can also help in designing rice 'ideotypes' that could guide the morphological or physiological changes required in the current popular rice cultivars so that yields can be maintained or enhanced under future climate change. Crop models could also be coupled with disease models and global economic models such as the Global Trade Analysis Project (Moore *et al.*, 2017), to estimate the welfare consequences of yield changes. In conclusion, rainfed areas can contribute to meeting the increasing demand for additional food grains by 2050. However, dependence on monsoon rainfall for meeting the water requirements for crop cultivation makes rainfed regions inherently vulnerable to changes in climate. Developing irrigation infrastructure and new rice cultivars that are resilient to multiple abiotic stresses should be a key priority for climate proofing rainfed systems in India.

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Figure A3.1. Difference in days to 50% flowering between local and national cultivars

Appendix 1 – Supporting information for Chapter 2

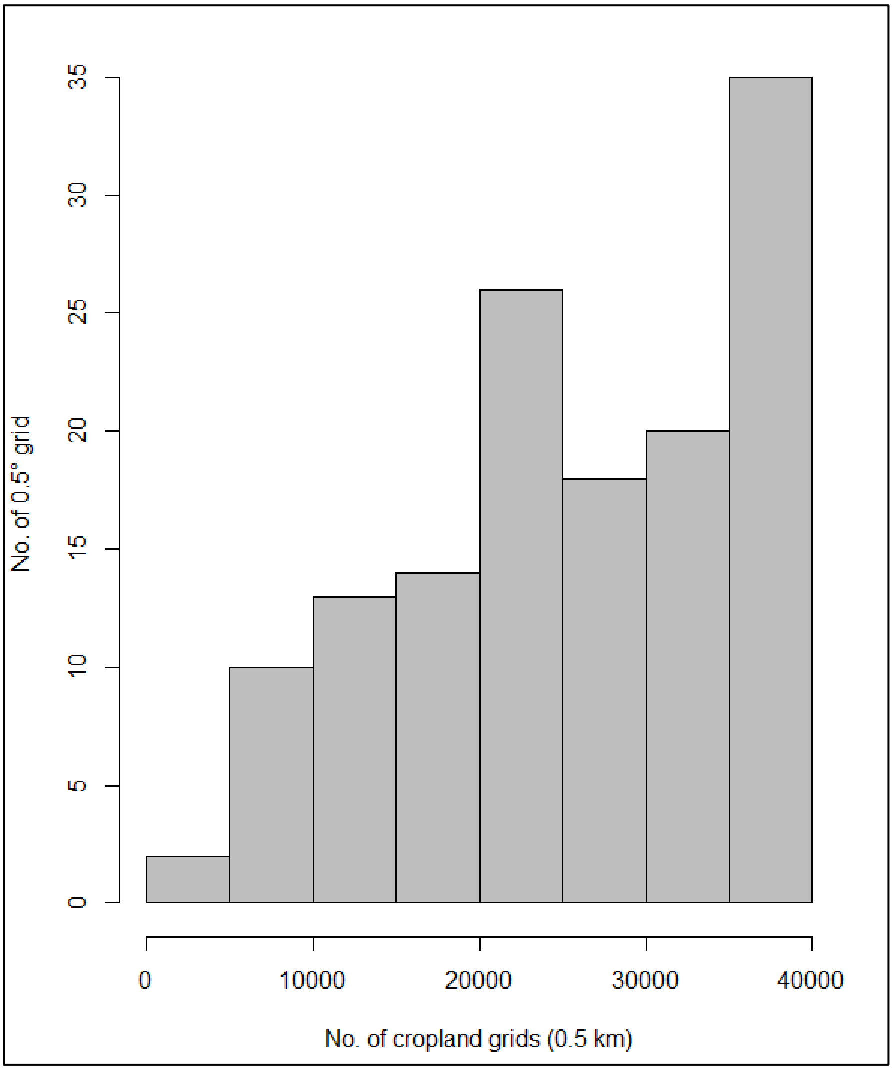


Figure A1.1. Histogram of number of cropland pixels (x-axis) and number of ~55 km grid square from where the rainfall data was collected. Cropland data were obtained from Moderate Resolution Imaging Spectroradiometer (MODIS) landcover map (2001-10) at 0.5 km spatial resolution for India (Broxton *et al.*, 2014). The plot shows the number of cropland pixels for each 0.5 (~55 km) grid square and confirm that all the grid squares, which I analysed, had cropland pixels in it.

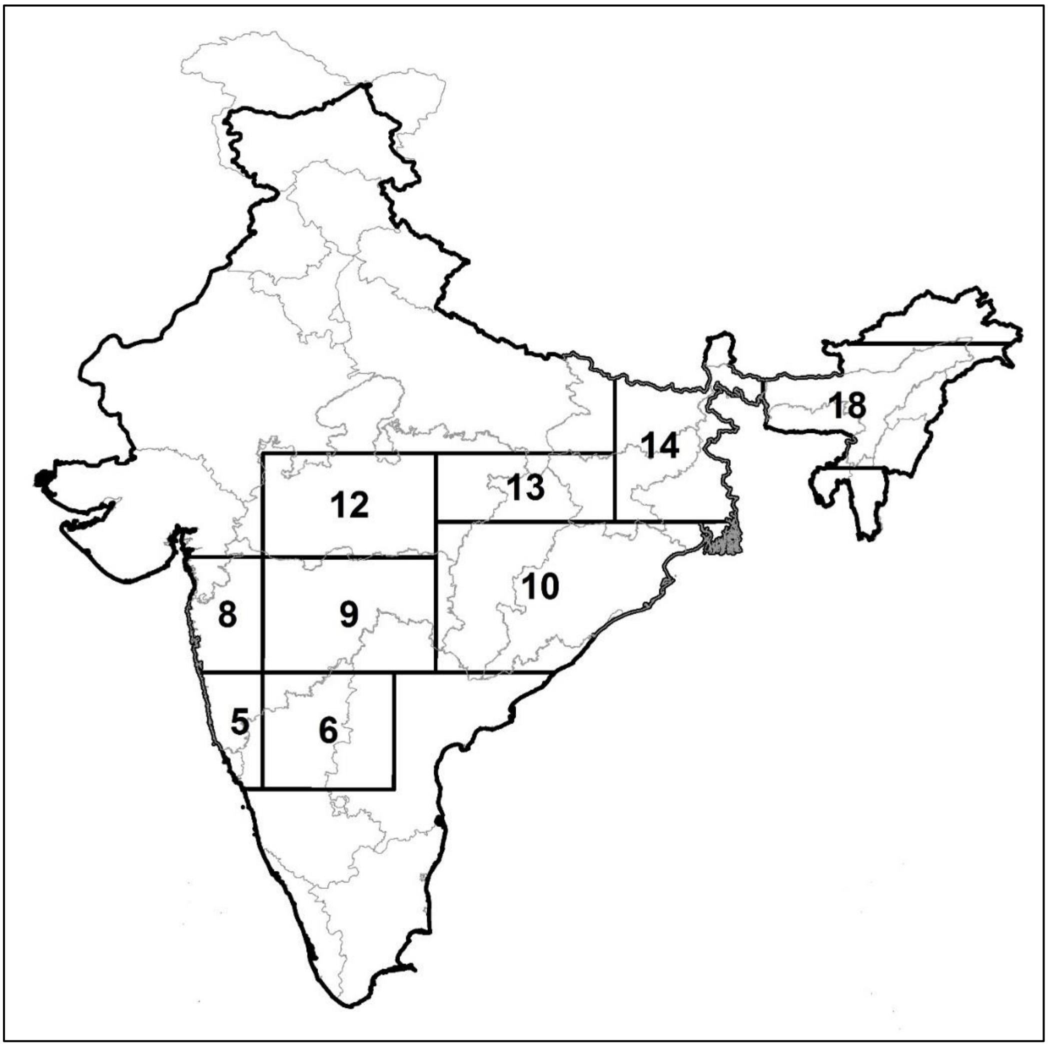


Figure A1.2. Location of the 9 subregions for which the onset and withdrawal dates were analysed in the main text for the period 1975-2007. The numbers refer to the sub-regions as used by (Singh and Ranade, 2010).

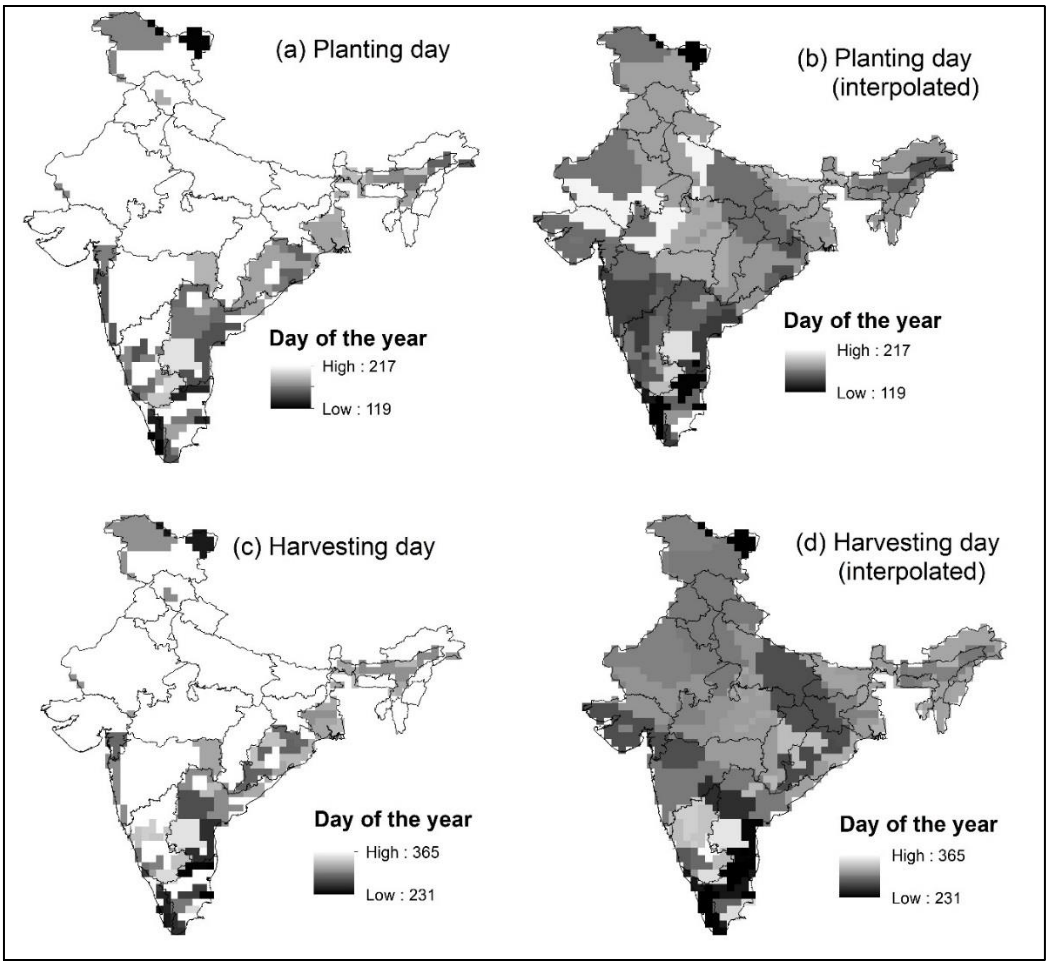
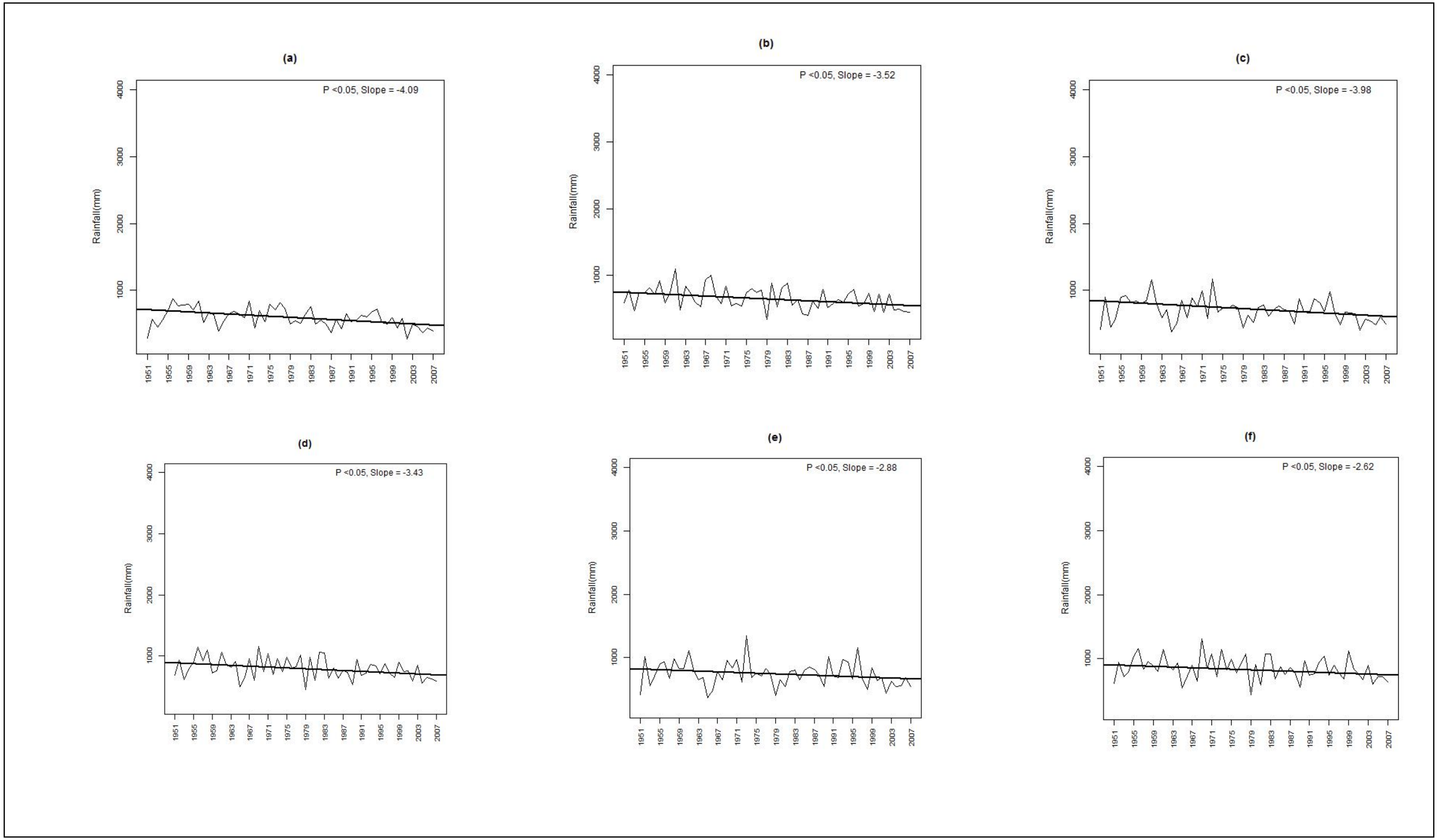
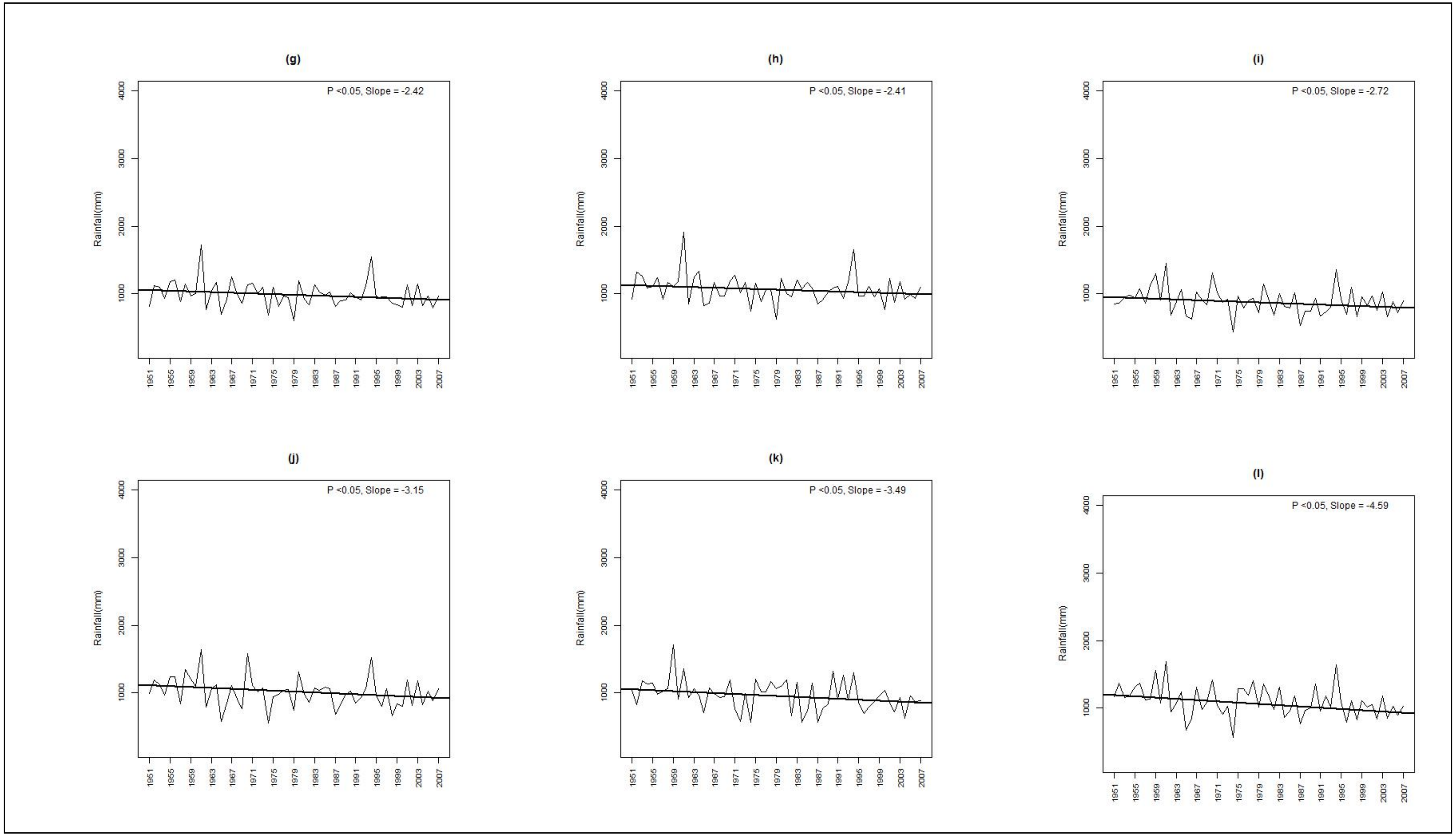


Figure A1.3. Gridded maps (0.5° lat/long resolution) of rice planting (a) and (b) and harvesting dates (c) and (d). (a) and (c) show the unfilled maps with data only for grid cells in regions where Sacks et al. (2010) actually have crop calendar observations. (b) and (d) show the filled maps contain spatially extrapolated crop calendar data.


(a)
P <0.05, Slope = -4.09
(b)
P <0.05, Slope = -3.52
(c)
P <0.05, Slope = -3.98
(d)
P <0.05, Slope = -3.43
(e)
P <0.05, Slope = -2.88
(f)
P <0.05, Slope = -2.62
Rainfall(mm)
1951
2007


(g)
P <0.05, Slope = -2.42
(h)
P <0.05, Slope = -2.41
(i)
P <0.05, Slope = -2.72
(j)
P <0.05, Slope = -3.15
(k)
P <0.05, Slope = -3.49
(l)
P <0.05, Slope = -4.59
Rainfall(mm)
1000
2000
3000
4000
1951
1955
1959
1963
1967
1971
1975
1979
1983
1987
1991
1995
1999
2003
2007

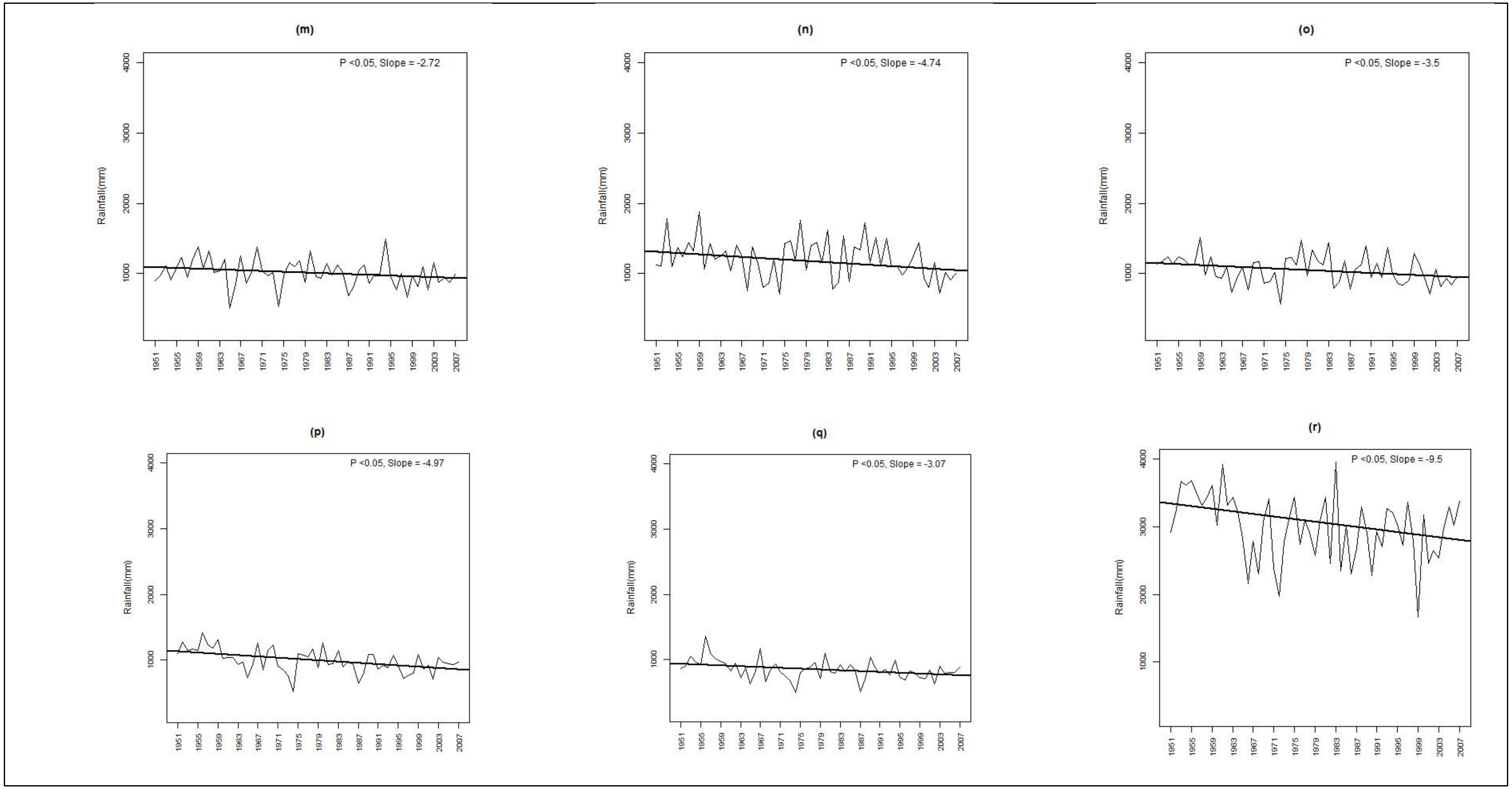
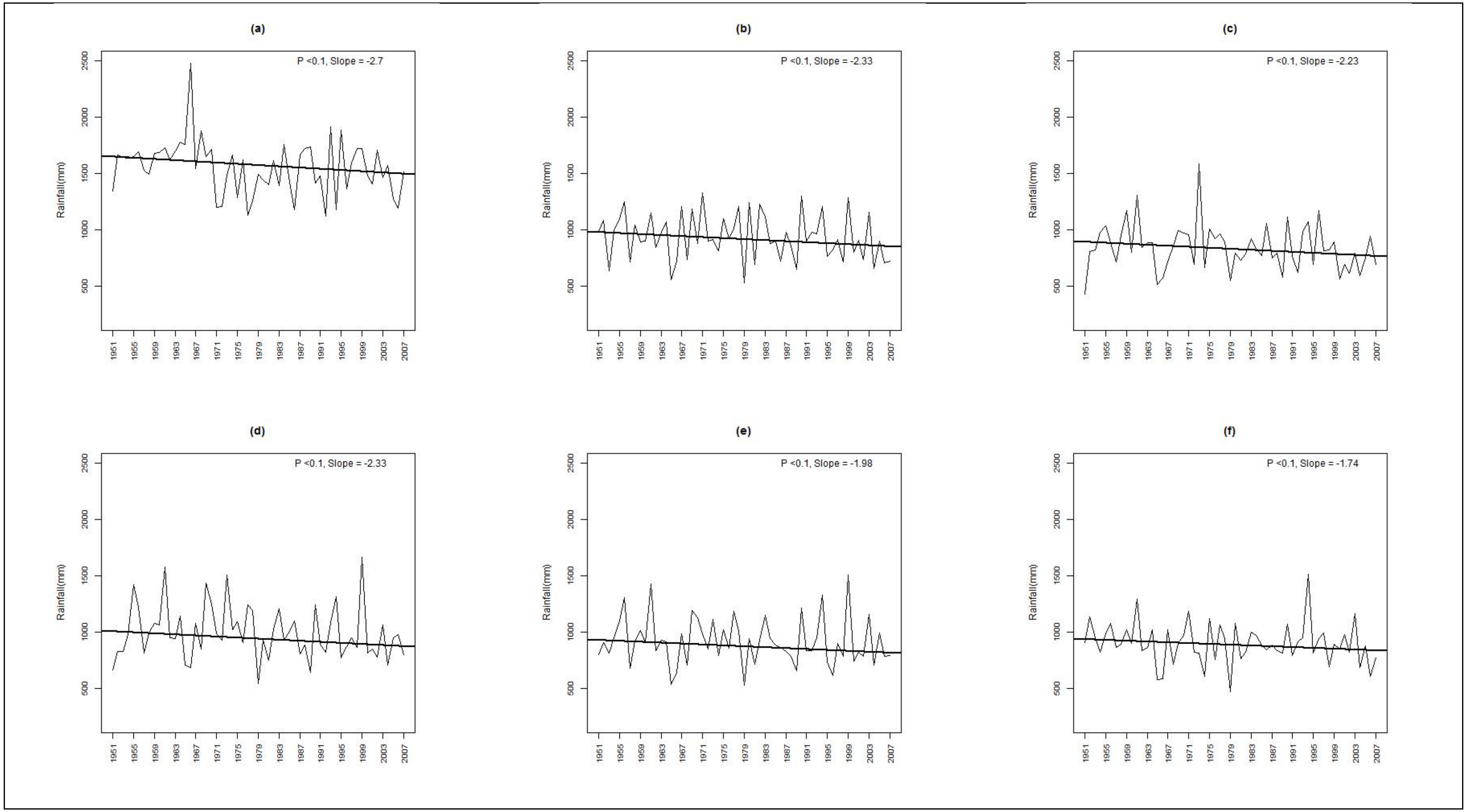


Figure A1.4. Linear trend in total rainfall (1st June – 30th September) (in mm/year) for 0.5° grid square shown in Fig. 2.1a in the main text. Time series plot of grids showing declining rainfall ($P<0.05$) for the period 1951-2007 in Fig 2.1a are shown here.


(a)
P <0.1, Slope = -2.7
(b)
P <0.1, Slope = -2.33
(c)
P <0.1, Slope = -2.23
(d)
P <0.1, Slope = -2.33
(e)
P <0.1, Slope = -1.98
(f)
P <0.1, Slope = -1.74
Rainfall(mm)

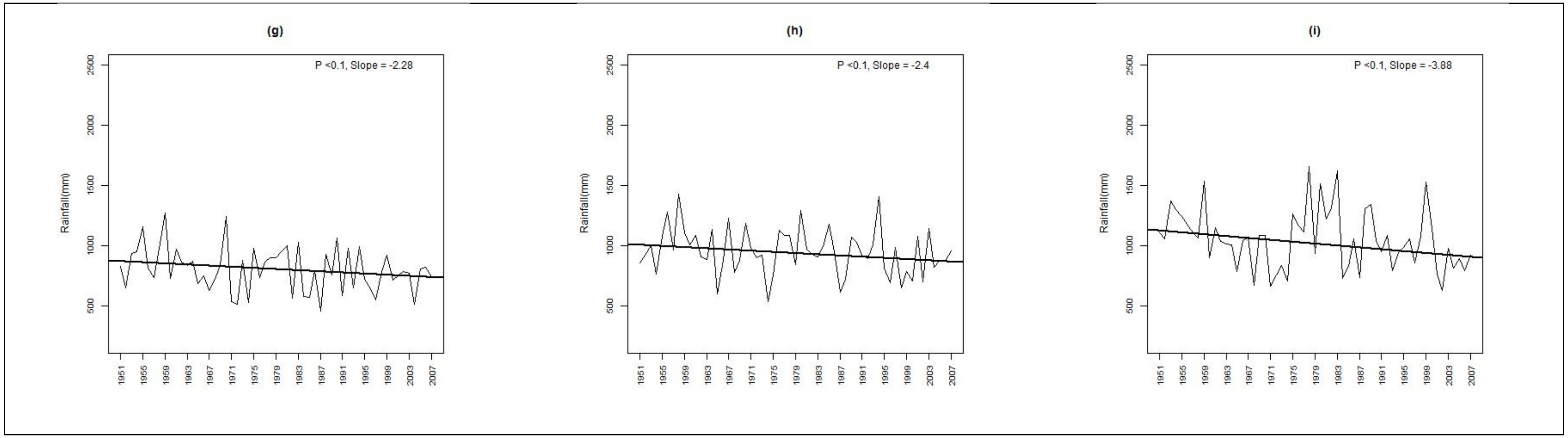


Figure A1.5. Linear trend in total rainfall (1st June – 30th September) (in mm/year) for 0.5° grid square shown in Fig. 2.1a in the main text. Time series plot of grids showing declining in rainfall (P<0.1) for the period 1951-2007 in Fig 2.1a are shown here.

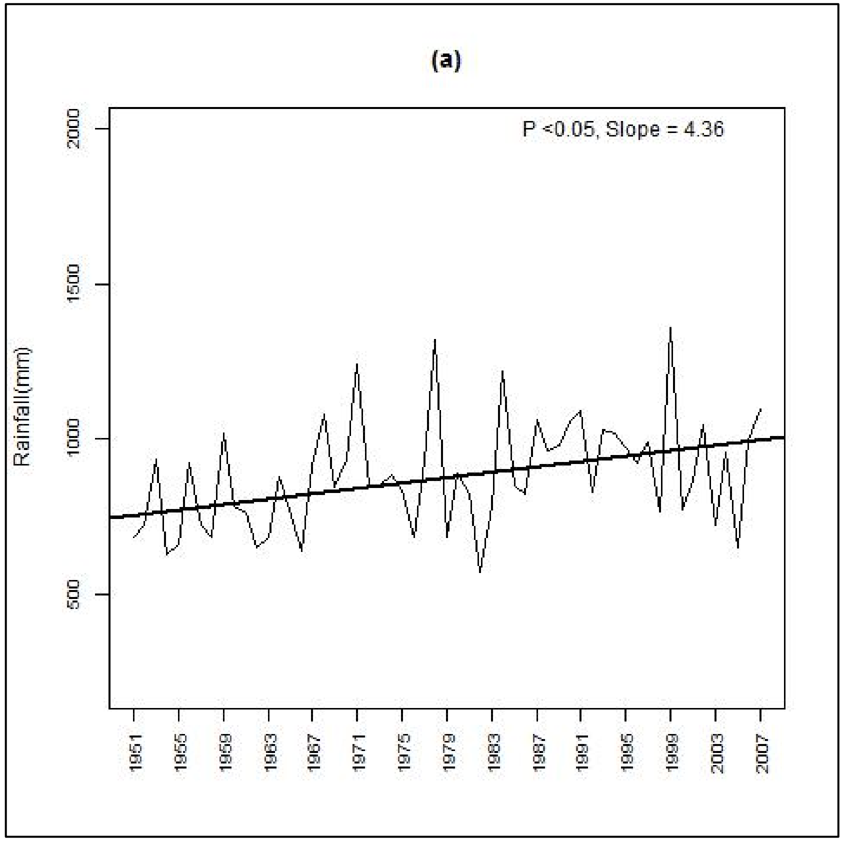


Figure A1.6. Linear trend in total rainfall (1st June – 30th September) (in mm/year) for 0.5° grid square shown in Fig. 2.1a in the main text. Time series plot of grid showing increase in rainfall (P<0.05) for the period 1951-2007 in Fig 2.1a is shown here.

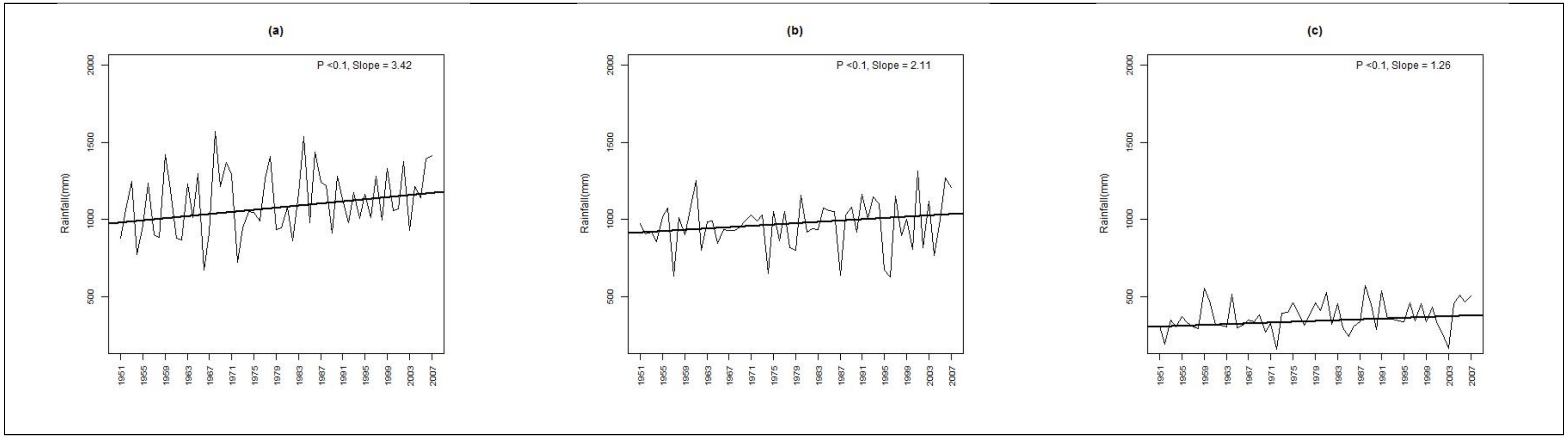


Figure A1.7. Linear trend in total rainfall (1st June – 30th September) (in mm/year) for 0.5° grid square shown in Fig. 2.1a in the main text. Time series plot of grids showing increase in rainfall (P<0.1) for the period 1951-2007 in Fig. 2.1a are shown here.

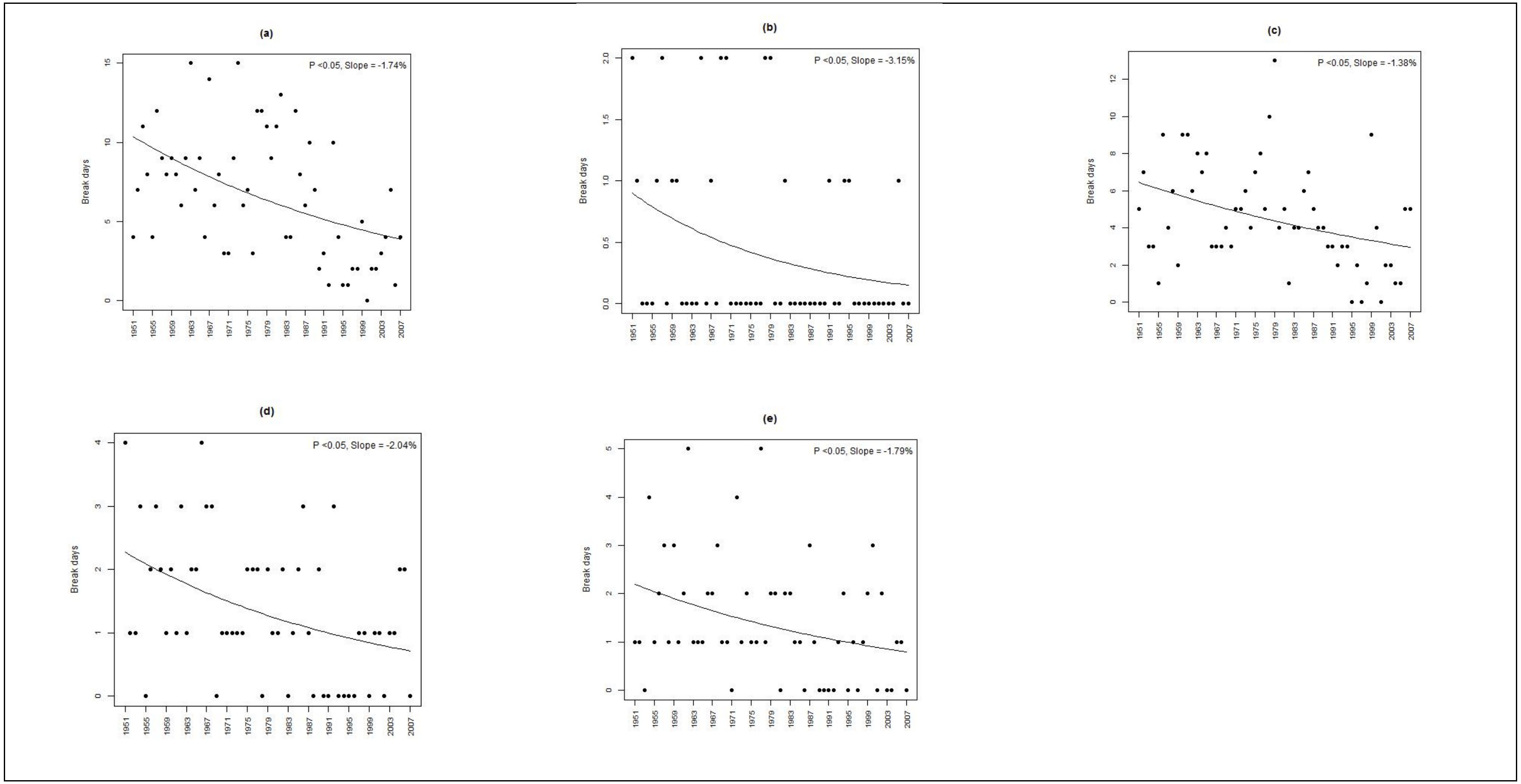


Figure A1.8. Trend in total dry days (1st June – 30th September) (in %/year) for 0.5° grid square shown in Fig. 2.1b in the main text. Time series plot of grids showing declining in dry days ($P<0.05$) for the period 1951-2007 in Fig. 2.1b are shown here.

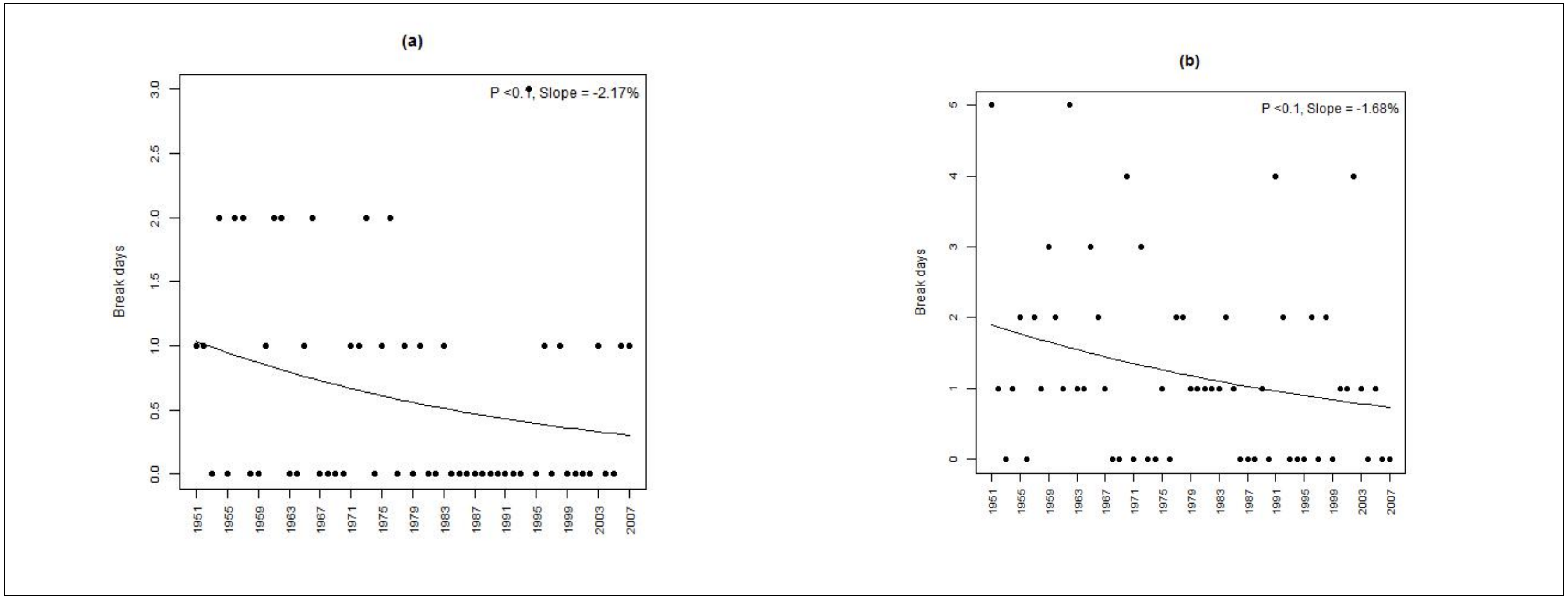


Figure A1.9. Trend in total dry days (1st June – 30th September) (in %/year) for 0.5° grid square shown in Fig. 2.1b in the main text. Time series plot of grids showing declining in dry days (P<0.1) for the period 1951-2007 in Fig. 2.1b are shown here.

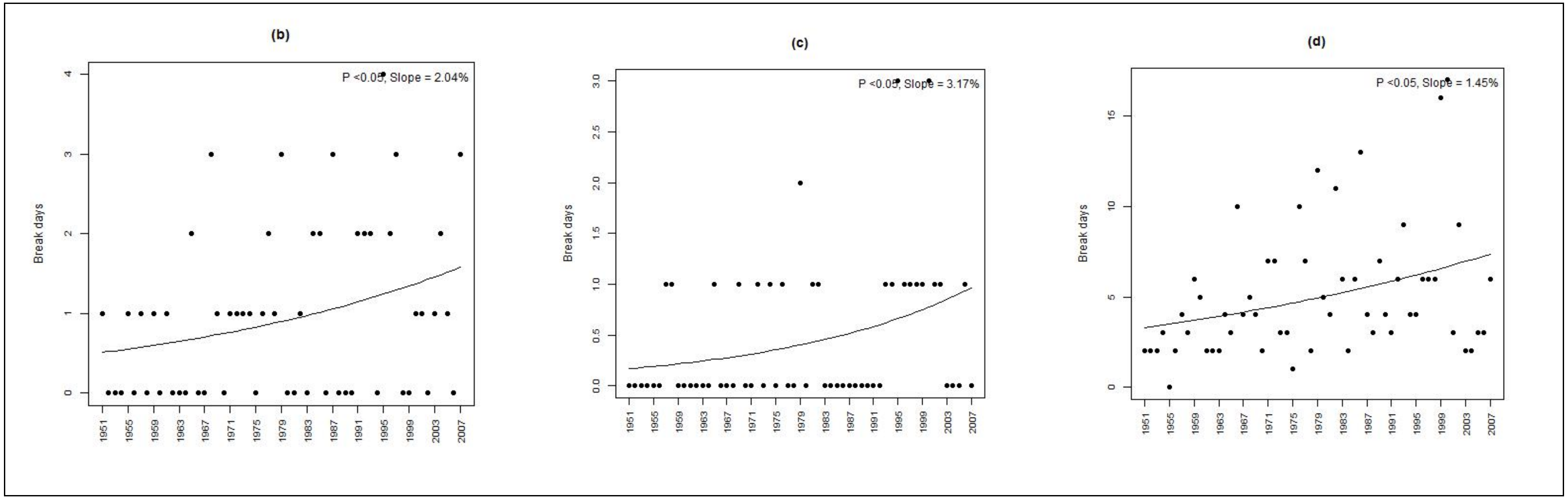


Figure A1.10. Trend in total dry days (1st June – 30th September) (in %/year) for 0.5° grid square shown in Fig 2.1b in the main text. Time series plot of grids showing increasing dry days (P<0.05) for the period 1951-2007 in Fig 2.1b are shown here.

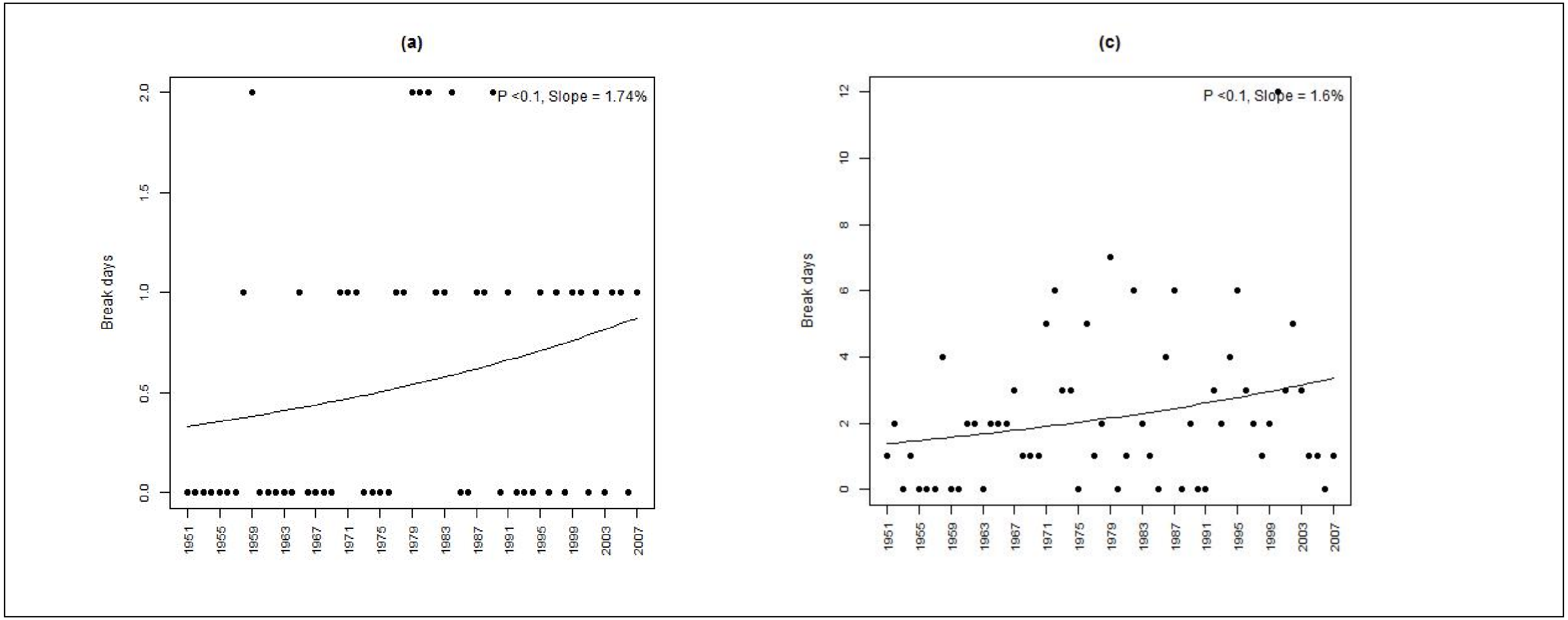
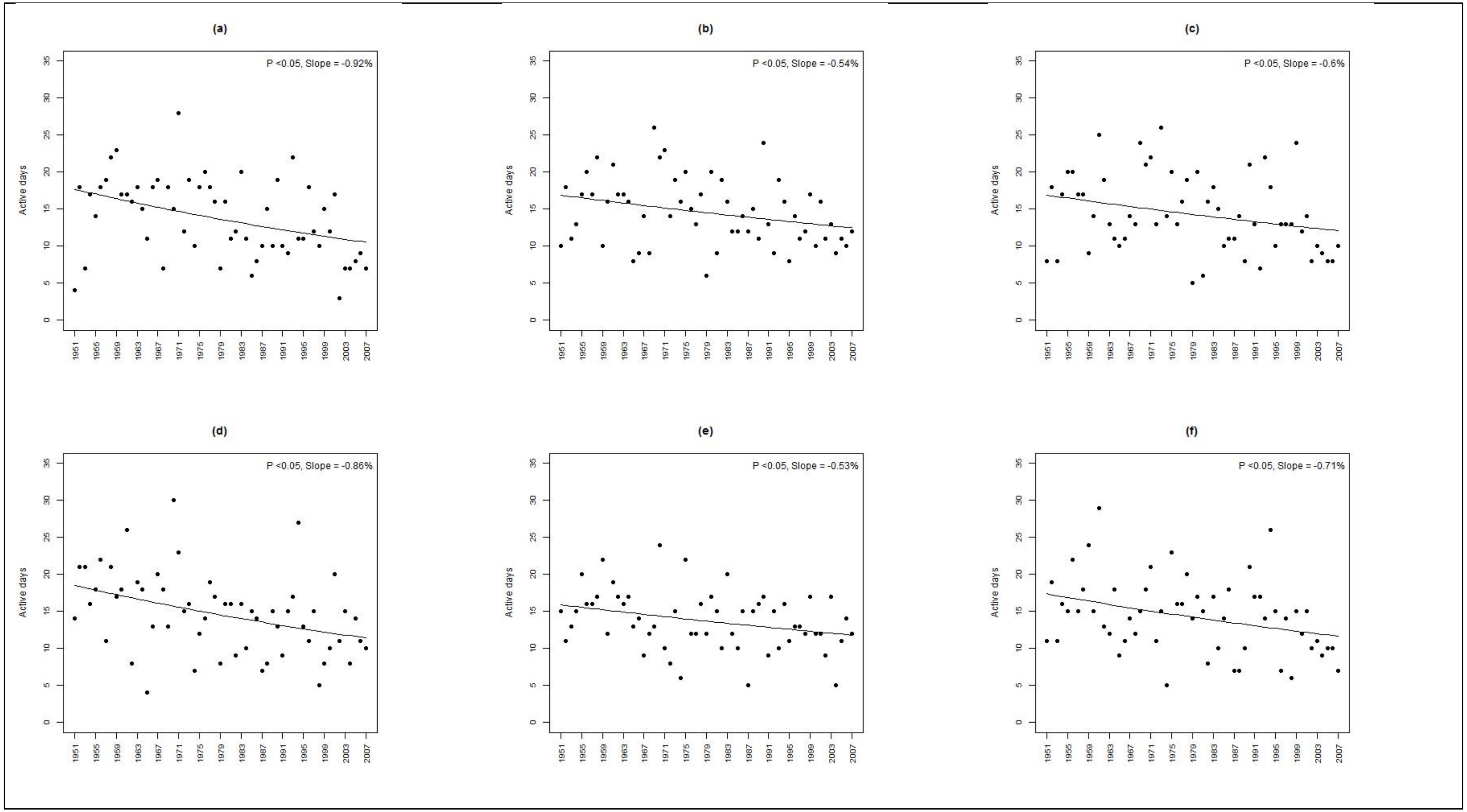


Figure A1.11. Trend in total dry days (1st June – 30th September) (in %/year) for 0.5° grid square shown in Fig 2.1b in the main text. Time series plot of grids showing increasing dry days (P<0.1) for the period 1951-2007 in Fig 2.1b are shown here.


(a)
P <0.05, Slope = -0.92%
(b)
P <0.05, Slope = -0.54%
(c)
P <0.05, Slope = -0.6%
(d)
P <0.05, Slope = -0.86%
(e)
P <0.05, Slope = -0.53%
(f)
P <0.05, Slope = -0.71%
Active days
0
5
10
15
20
25
30
35
1951
1955
1959
1963
1967
1971
1975
1979
1983
1987
1991
1995
1999
2003
2007

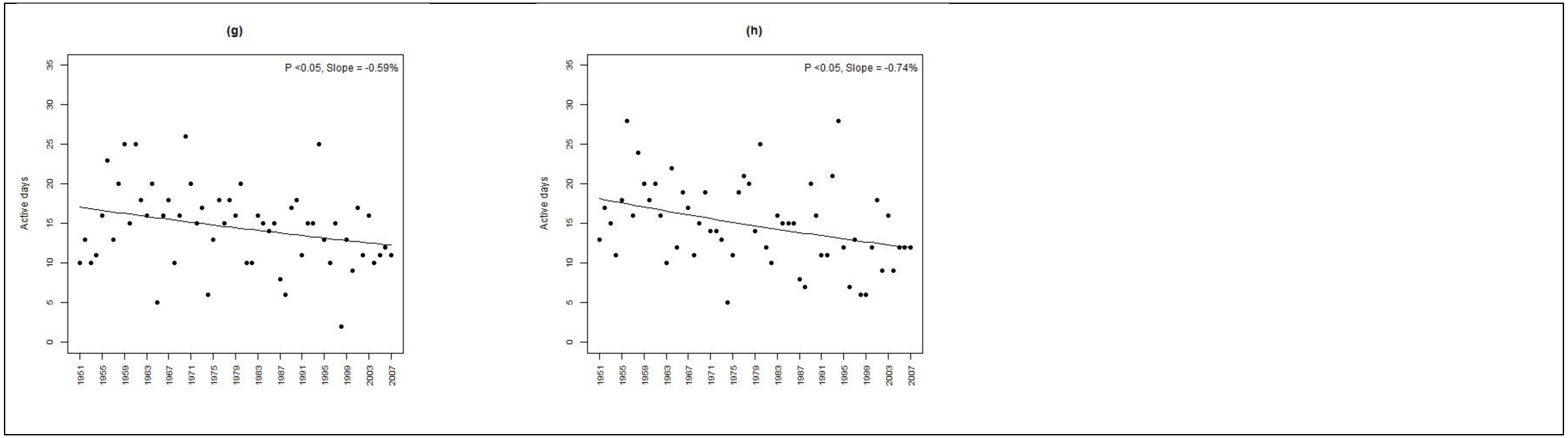


Figure A1.12. Trend in total wet days (1st June – 30th September) (in %/year) for 0.5° grid square shown in Fig 3.1c in the main text. Time series plot of grids showing decreasing wet days (P<0.05) for the period 1951-2007 in Fig 3.1c are shown here.

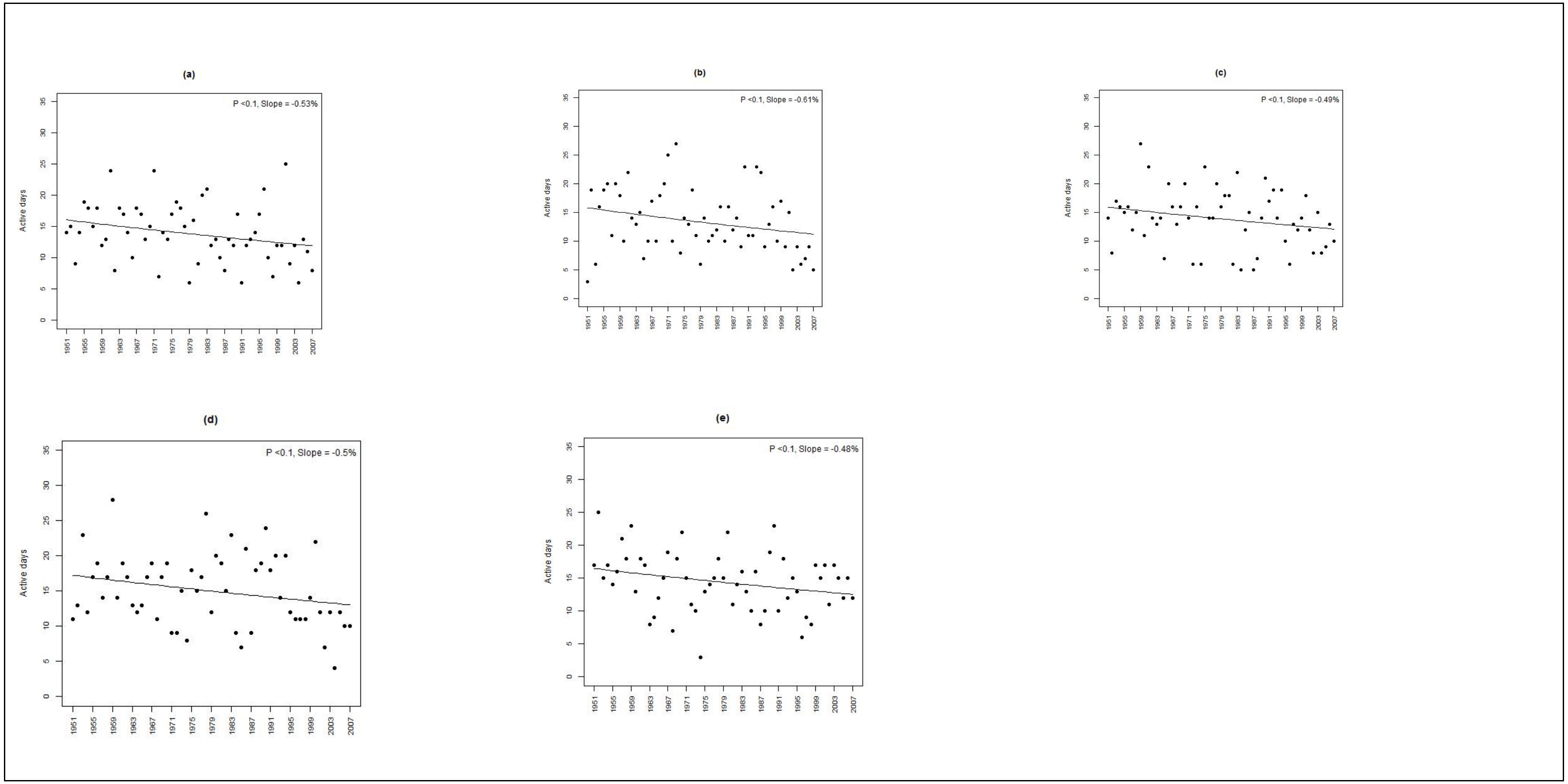
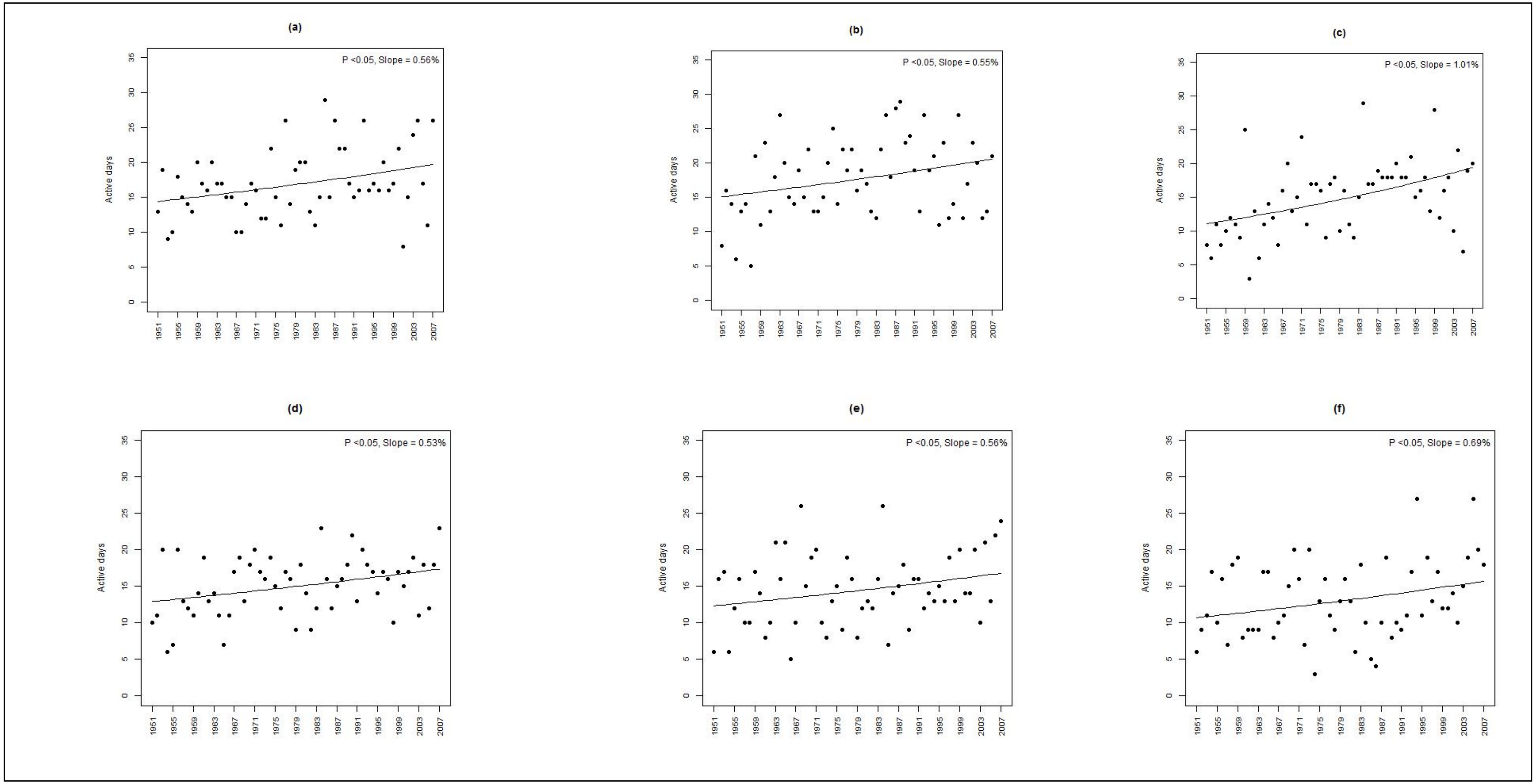


Figure A1.13. Trend in total wet days (1st June – 30th September) (in %/year) for 0.5° grid square shown in Fig 3.1c in the main text. Time series plot of grids showing decreasing wet days (P<0.1) for the period 1951-2007 in Fig 3.1c are shown here.


(a)
P <0.05, Slope = 0.56%
(b)
P <0.05, Slope = 0.55%
(c)
P <0.05, Slope = 1.01%
(d)
P <0.05, Slope = 0.53%
(e)
P <0.05, Slope = 0.56%
(f)
P <0.05, Slope = 0.69%
Active days

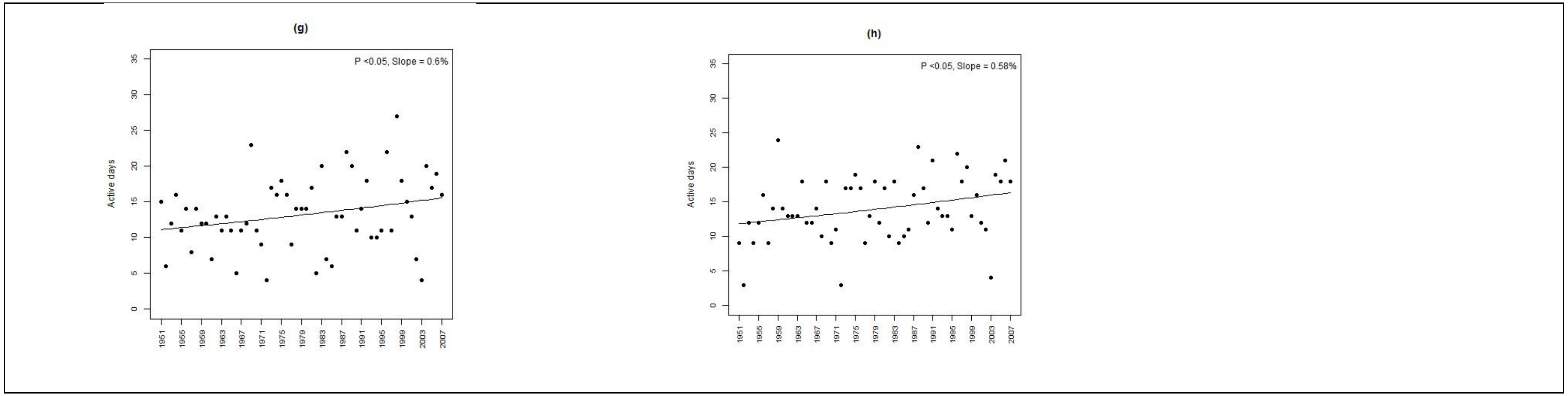


Figure A1.14. Trend in total wet days (1st June – 30th September) (in %/year) for 0.5° grid square shown in Fig. 3.1c in the main text. Time series plot of grids showing increasing wet days ($P<0.05$) for the period 1951-2007 in Fig. 3.1c are shown here.

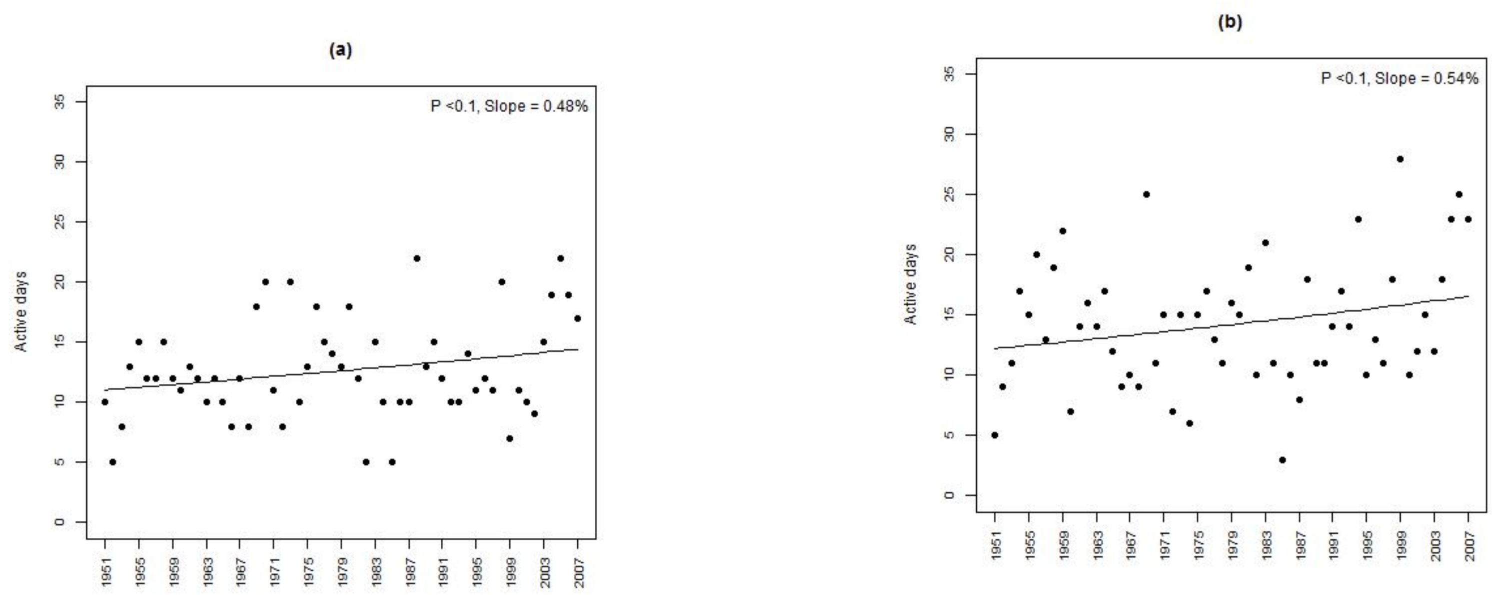


Figure A1.15. Trend in total wet days (1st June – 30th September) (in %/year) for 0.5° grid square shown in Fig. 3.1c in the main text. Time series plot of grids showing increasing wet days ($P<0.1$) for the period 1951-2007 in Fig. 3.1c are shown here.

Table A1.1. Summary of the collinearity (Pearson's r) between summer monsoon variables included in analyses of rice yield. The variables are total monsoon rainfall, wet days, dry days, monsoon onset and withdrawal from pooled data from 180 rainfed districts in Fig 2.1.

	Onset	Withdrawal	Rainfall	Dry Day
Onset	1			
Withdrawal	-0.38	1		
Rainfall	-0.34	0.11	1	
Dry Day	-0.38	0.27	0.11	1
Wet Day	-0.22	0.18	0.29	-0.17

Appendix 1.1.

Calculation of yield lost due to dry days.

In the main text, I quote the effects of dry days on rice yield, based on the outputs of my analyses. Here I explain how I made these calculations.

Calculation of effect size of dry days on yield

In the main text, I present effect sizes for the best models using standardised variables (Fig. 2.3a). I repeated this analysis, but using unstandardised variables. As previously, I first fitted a global model with rice yield as the dependent variable and all five monsoon variables (total monsoon rainfall, dry days, wet days, onset and withdrawal) as independent variables and 'district' and 'year' as random effect. I then generated sub-models using all possible combinations of monsoon variables. Models with ΔAICc <2 were selected in the best set of candidate models, followed by model averaging to calculate the mean effect size of monsoon variables across all the best models. Since input variables were not standardised in this analysis, the effect sizes correspond to the actual slope values of the relationships between rice yield and dry days which was equal to 16 i.e. for every additional dry day, there was ~16 kg/ha loss of yield.

Calculation of average yield lost because of dry days

In the main text, I reported a range of 1.4% to 15% average yield loss per year due to dry days. Here, I explain how I calculated these values.
For each district, I calculated the average fitted raw yield for the period 1998-2010 by fitting a linear trend of observed raw yield against time (1998-2010) and took the average of fitted yield for the period 1998-2010

$$yld_{avg.fit,i} = (yld_{fit.1998} + yld_{fit.1999} + \ldots\ldots yld_{fit.2007})/10$$

where,
$i = i^{th}$ district for 1 to 180 districts

$yld_{fit.1998}$ = fitted yield value for 1998 for the i^{th} district from the linear regression
$yld_{avg.fit,i}$ = average fitted yield value for the i^{th} district

For each district, I calculated the average number of dry days per year:

$$DD_{avg,i} = (DD_{1998,i} + DD_{1999,i} + ...DD_{2007,i})/10$$

The average number of dry days for each district was multiplied by the effect size from my best models for dry days (16 kg/ha) which gave average yield loss per year due to dry days per year for each district.

$$yldloss_{avg,i} = effect\ size * DD_{avg,i}$$

For each district, $yldloss_{avg,i}$ was subtracted from $yld_{avg.fit,i}$ and expressed as percentage of the average fitted yield.

$$yldloss.na_{avg,i} = yld_{avg.fit,i} - yldloss_{avg,i}$$
$$yldloss.per_{avg,i} = (1 - yldloss.na_{avg,i} / yld_{avg.fit,i})*100$$

This was repeated for each district and the range of yield loss ($yldloss.per_{avg,i}$) (in percentage) was expressed in the main text as:
"I estimate that average loss in yield per year due to dry days ranged from 1.4% to 15% of the average rainfed rice yields per year"

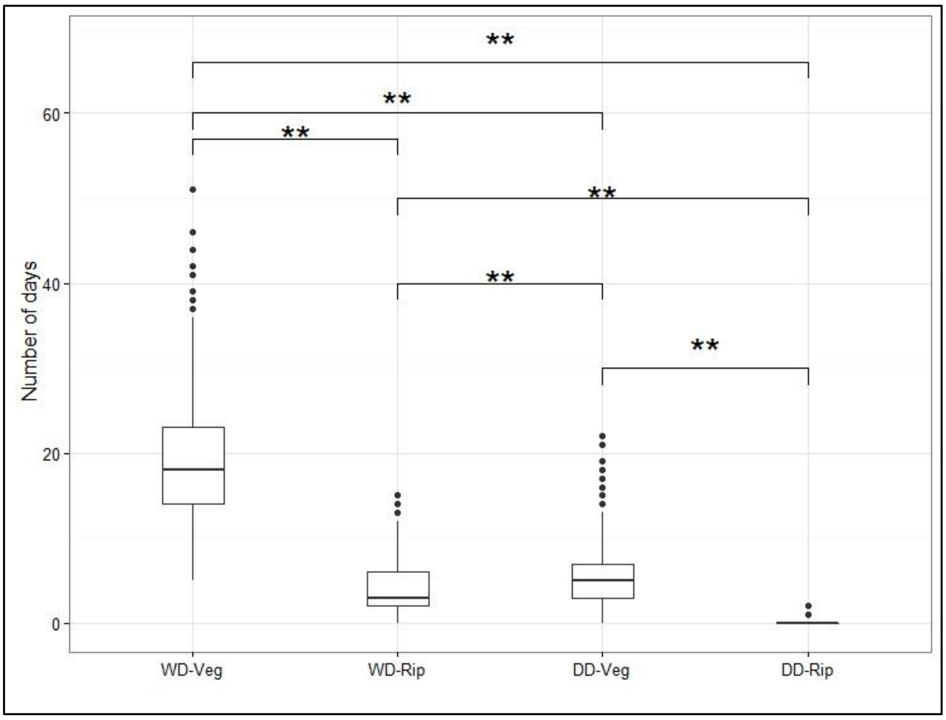


Figure A1.16. The occurrence of wet days and dry days for the period 1998-2007 for each growth stage of rice at district-level. Mean number of wet days during the vegetative- reproductive stage and ripening stage was ~19 and ~4 respectively. Mean number of dry days during the vegetative- reproductive stage and ripening stage was ~5 and ~0 respectively. Occurrences of wet and dry days in the two stages were significantly different at the 5% level following post-hoc comparisons. WD-Veg: number of wet days during the vegetative and reproductive stage; WD-Rip: number of wet days during the ripening stage, DD-Veg: number of dry days during the vegetative and reproductive stage and DD-Rip: number of dry days during the ripening stage.

Appendix 2 – Supporting information for Chapter 3

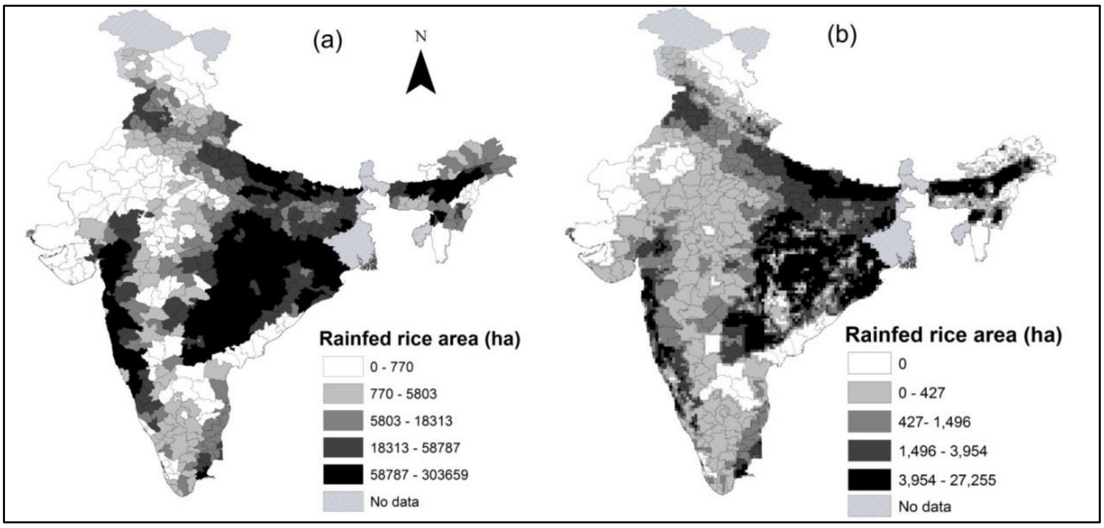


Figure A2.1. (a) Distribution of rainfed rice area at district level resolution (ha) averaged over 1998-2013. Net irrigated rice area was subtracted from total rice area to obtain the rainfed rice area for each district, averaged over 1998-2013. The original data were downloaded from Ministry of Agriculture, Government of India (http://eands.dacnet.nic.in/) (b) Cell -level rainfed rice area (ha) averaged over 1998-2013. The coarse-scale district-level data were downscaled and converted into a gridded dataset (10 arc-minute resolution; ~18 km cell spatial resolution at the equator) by incorporating cropland distribution obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) landcover map (Broxton *et al.*, 2014). For methodological details, refer to the Appendix A2.1.

Appendix 2.1

Downscaling of district-level rainfed rice area data to a gridded dataset (10 arc-minute resolution; ~18 km cell spatial resolution at the equator)

In order to incorporate fine-scale data on the distribution of present-day rice cultivation into our models, the coarse-scale district-level data (n= 519 districts, Fig A2.1a) were downscaled and converted into a gridded dataset (10 arc-minute resolution; ~18 km cell spatial resolution at the equator; Fig. A2.1b). This produced data on the distribution of rainfed rice cultivation at the same resolution as the climate datasets I used (see main text). To do this downscaling, I first obtained a Moderate Resolution Imaging Spectroradiometer (MODIS) landcover map for India (2001-10) at 0.5 km spatial resolution (Broxton *et al.*, 2014) and extracted data for two landcover categories: cropland and cropland mixed with natural vegetation (henceforth referred to as 'cropland'). I calculated the total number of 0.5 x 0.5 km cropland cells within each district. I then allocated each district's rainfed rice area equally among all the cropland cells within that district to produce an estimate of the area of rainfed rice at 0.5 km resolution. I then calculated the distribution of rainfed rice at 18 km cell resolution by summing the area of rainfed rice at 0.5 km resolution, for all 0.5 km cells falling within each 18 km cell.

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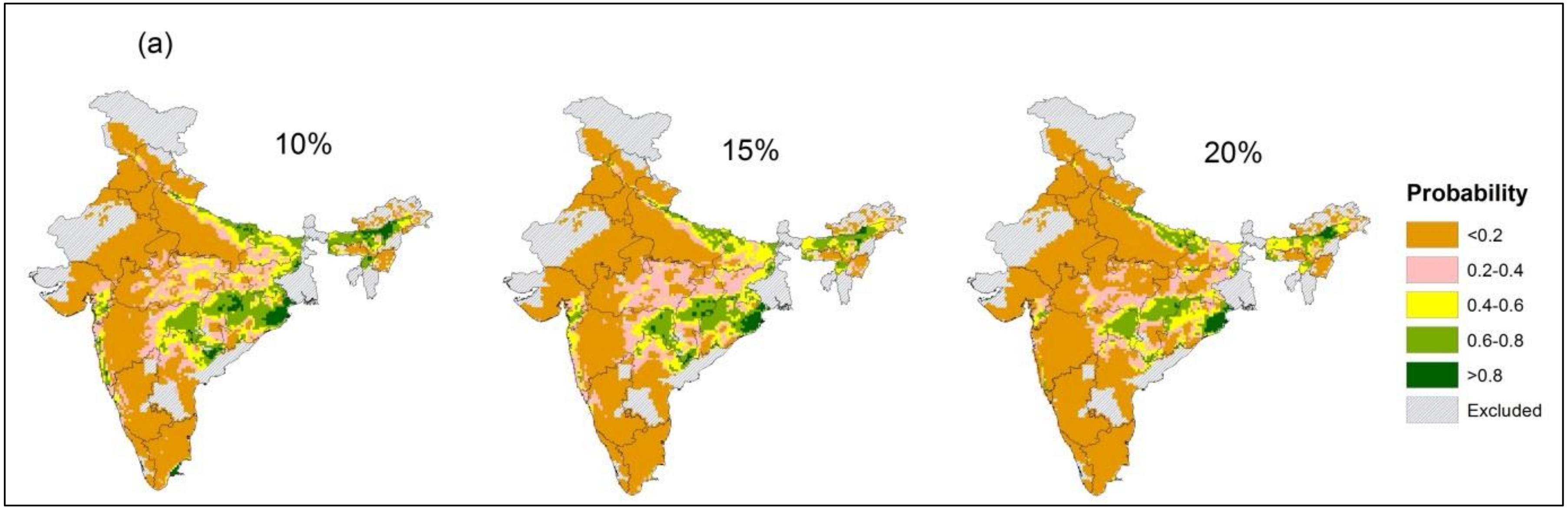
(a)
10%
15%
20%
Probability
<0.2
0.2-0.4
0.4-0.6
0.6-0.8
>0.8
Excluded

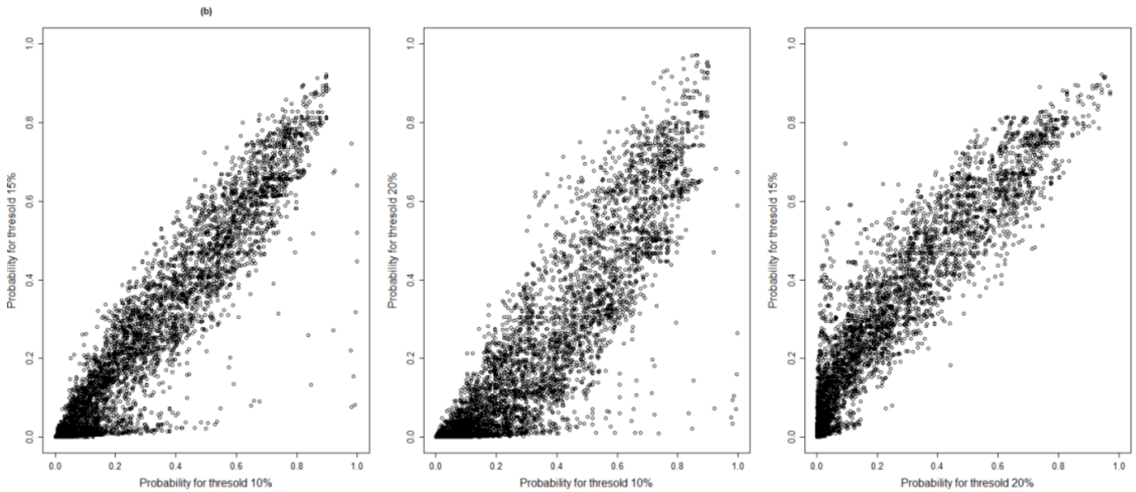

Figure A2.2. In the main text, my analyses of rice extent are based on a threshold criterion of 15% for rice presence/absence (percentage of cell area covered by rainfed rice) i.e. all cells where rainfed rice covered ≥15% cell area were selected as presences. These panels show how changes in that threshold affect my results (for 7974 study cells). (a) CEM outputs (current probability of occurrence, shown only for MAXENT) for different threshold criteria: (panel a) ≥10% (presence=1747, absence = 6227); (panel b) ≥15% (presence = 1171, absence = 6803); (panel c) ≥20% (presence =705, absence = 7269). Inspite of different threshold selection, almost the same cells are assigned to the different probability classes shown in the legend. (b) scatter plot for probability values of different threshold level: (panel a) 15% (y-axis) and 10% (x-axis), Pearson's r= 0.95; (panel b) 20% (y-axis) and 10% (x-axis), Pearson's r= 0.91; (panel c) 15% (y-axis) and 20% (x-axis), Pearson's r= 0.94). Strong correlations were observed between CEM outputs for different threshold criteria implying that the threshold for selecting presence and absence has little impact on CEM outputs.

Appendix 2.2

Calculation of potential evapotranspiration using Hamon's equation.

To calculate *PER*, I first derived the potential evapotranspiration (in mm) using Hamon's equation (Hamon, 1961):

$$PE = 715.5 * (\mathrm{H}/24) * \mathrm{svp} * (\mathrm{Tm})/(\mathrm{Tm} + 273.2) \qquad \text{Eq. 1}$$

where, PE = Potential evapotranspiration (mm) for the 15th day of each month

H = day length, days

svp= saturation vapour pressure [kPa]; svp = $6.108e^{(17.27\mathrm{Tm}/\mathrm{Tm}+237.3)}$

Tm = average monthly temperature [°C]

Day length was calculated for the middle Julian day of each month (day 15) following Forsythe *et al.* (1995) and monthly PE was estimated by multiplying PE for day 15 (estimated by Eq. 1) by 30.4 (assuming 30.4 days in each month of the summer monsoon). The total rainfall (mm; June – September) was divided by total PE (mm, June – September) to compute *PER* (June-September). The same calculation was carried out to compute *PER* for the 2050 RCP 2.6 and 8.5 scenarios.

For analyses using Boosted Regression Trees, to minimise predictive error and overfitting, I optimised three parameters: learning rate (*lr*), bag fraction (*bag*) and interaction depth (*tc*) (De'ath, 2007) following Elith et al. (2008). The best combination of parameters that minimised the predictive error (as determined by 10-fold cross validation) was a *tc* of 2, a *lr* of 0.1 and a *bag* of 0.75, with *family = Gaussian*.

Table A2.1. Summary of collinearity (Pearson's correlation coefficient) between the four climate predictor variables PER, Rain, T_{max} and T_{min} for the 7974 cells plotted in Fig. 3.1a. Values are quoted to two decimal points.

Variable	PER	Rain	T_{max}	T_{min}
PER	1			
Rain	0.23	1		
T_{max}	-0.47	-0.21	1	
T_{min}	0.04	0.47	0.44	1

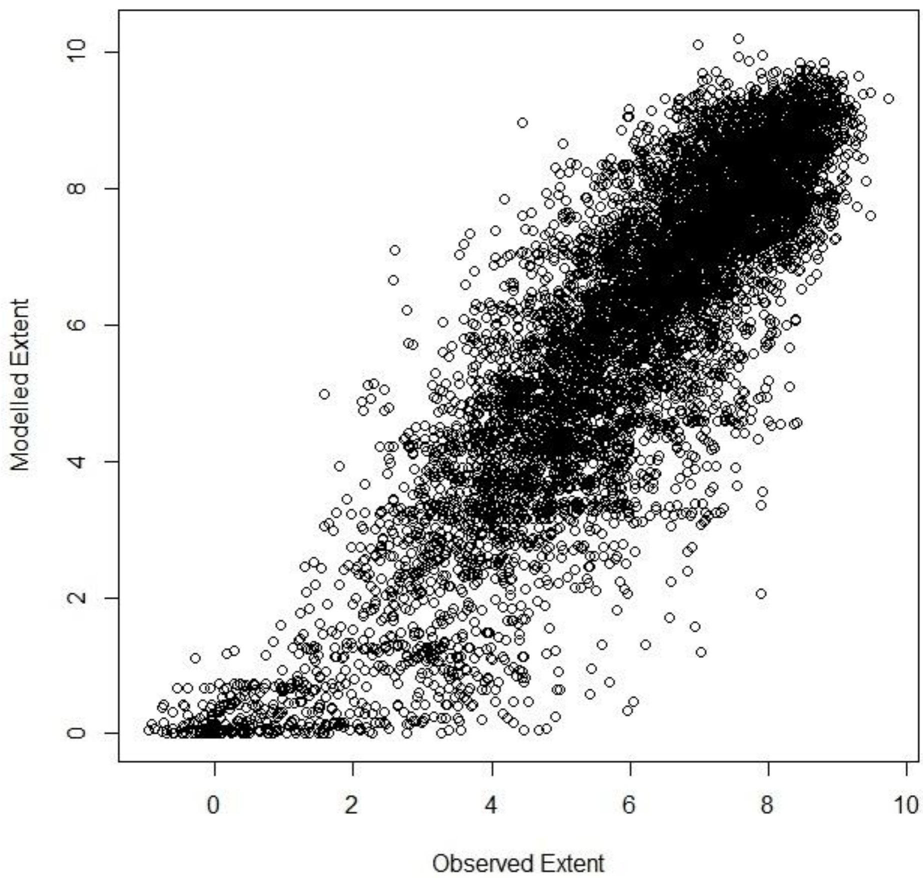

Figure A2.3. Scatter plot of modelled and observed extent (data on both axes transformed (ln extent + 1) of rainfed rice cultivation in ha per 18 km cell; Pearson's r = 0.87. Modelled extent is the output from BRTs. Plot shows high predictive power of BRTs.

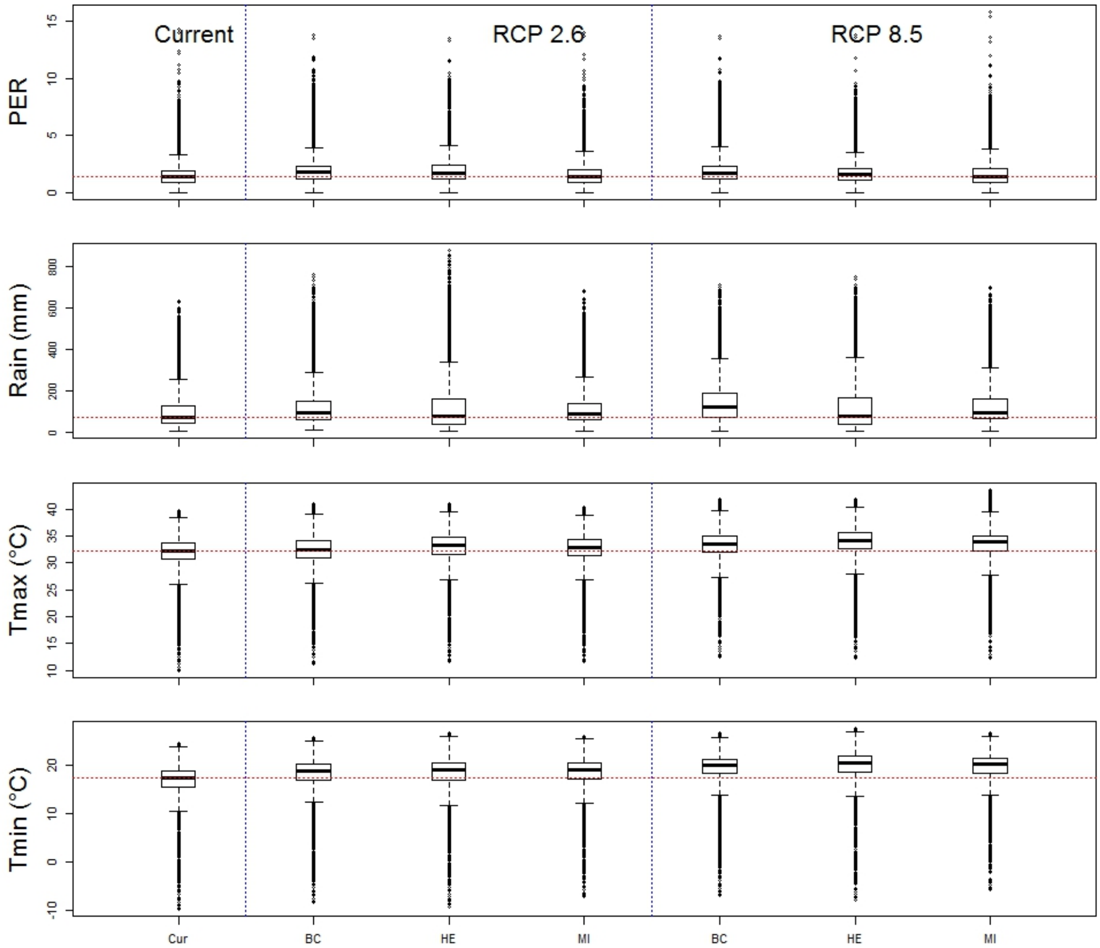

Figure A2.4. Current and future (2050) values for the current rainfed rice growing areas (n=1171 cells) for the four climate variables used in our models: PER, Rain (mm), T_{max} (°C) and T_{min} (°C) under two IPCC RCPs (2.6. and 8.5) and three GCMs. *Cur* = Current climate, *BC*= BCC-290 CSM1-1, *HE*= HadGEM2-ES and *MI*= MIROC-ESM-CHEM. The horizontal red line refers to the median value under current (1950-2000) climate. Individual box-plots show range, median and IQR values for different GCM x RCP combinations.

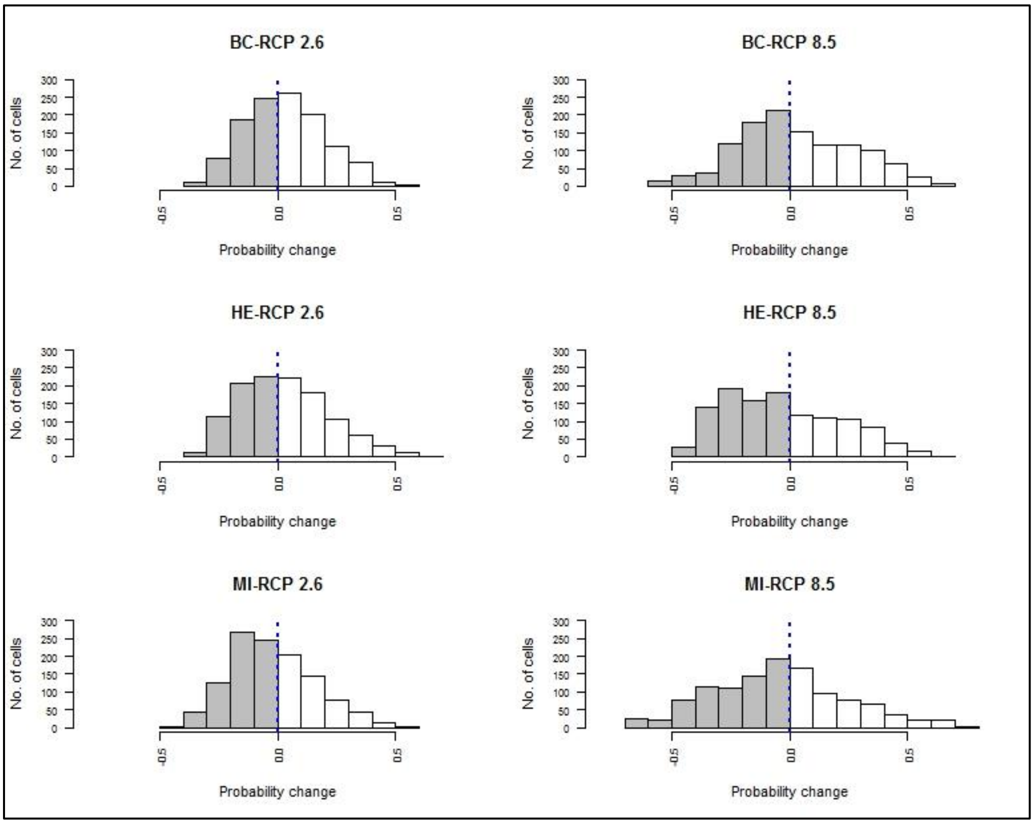

Figure A2.5. Changes in the probability of rainfed rice occurrence in 2050. Data plot changes in the climatic suitability of cells in future for CEM outputs, across two RCPs (2.6 and 8.5) and three GCMs (*BC*= BCC-CSM1-1, *HE*= HadGEM2-ES and *MI*= MIROC-ESM-CHEM). Change in probability = future probability – current probability, n=1171 cells (refer to Fig 3.1a for location of these cells). Plots show that a significant number of cells have declining probability in the future (grey shading) compared with the number of cells increasing in suitability (white shading). The vertical blue dotted line plots no change in suitability.

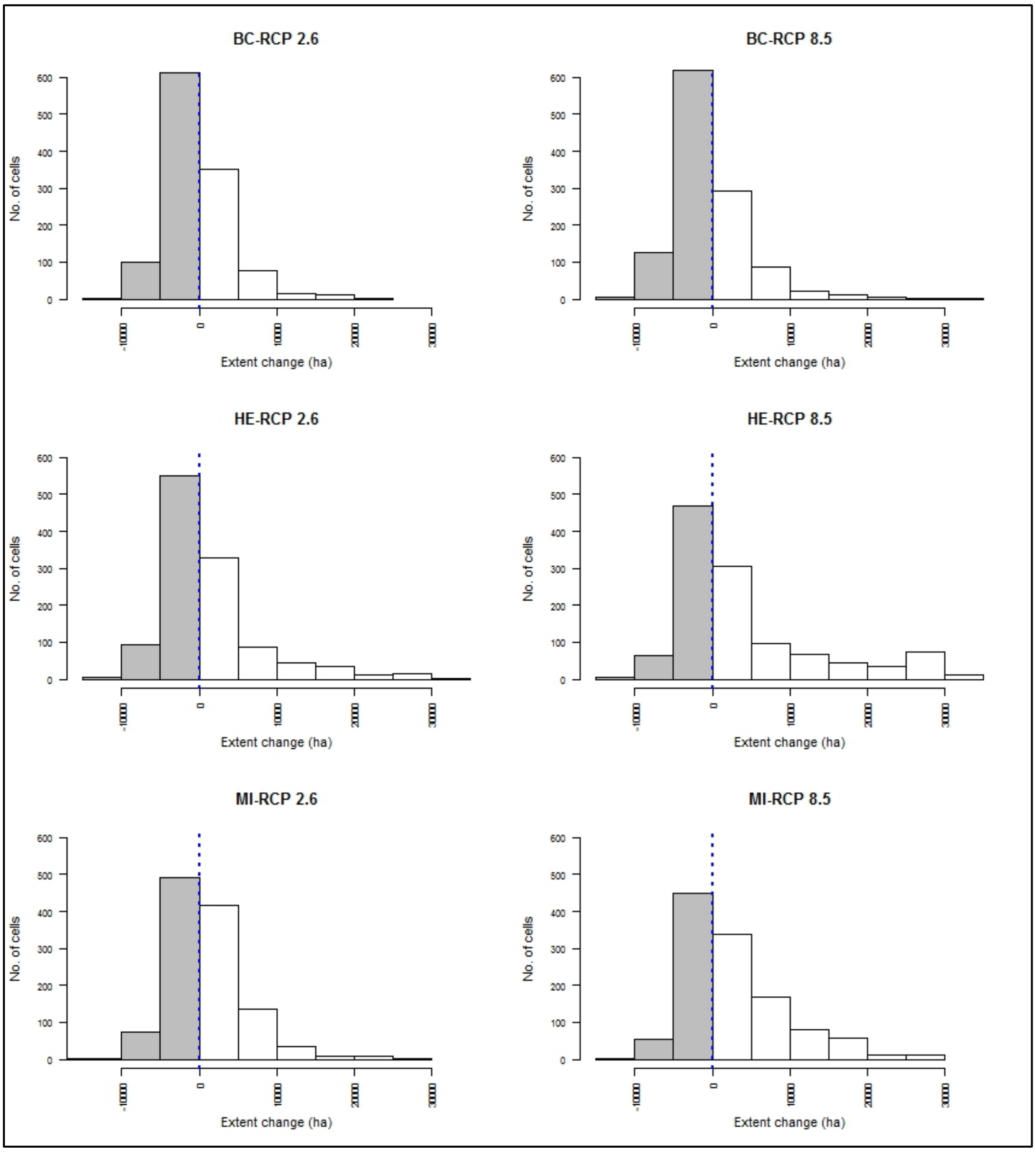

Figure A2.6. Changes in the modelled extent of rainfed rice occurrence in 2050. Data plot changes in the climatic suitability of cells in future from BRT outputs, for two RCPs (2.6 and 8.5) and three GCMs (*BC*= BCC-CSM1-1, *HE*= HadGEM2-ES and *MI*= MIROC-ESM-CHEM). Change in extent = future modelled extent – current modelled extent, n=1171 cells (refer to Fig 3.1a for location of these cells). Plots show that a significant number of cells have declining extent of rainfed rice in the future (grey shading) compared with increasing extent (white shading). The vertical blue dotted line plots no change in suitability.

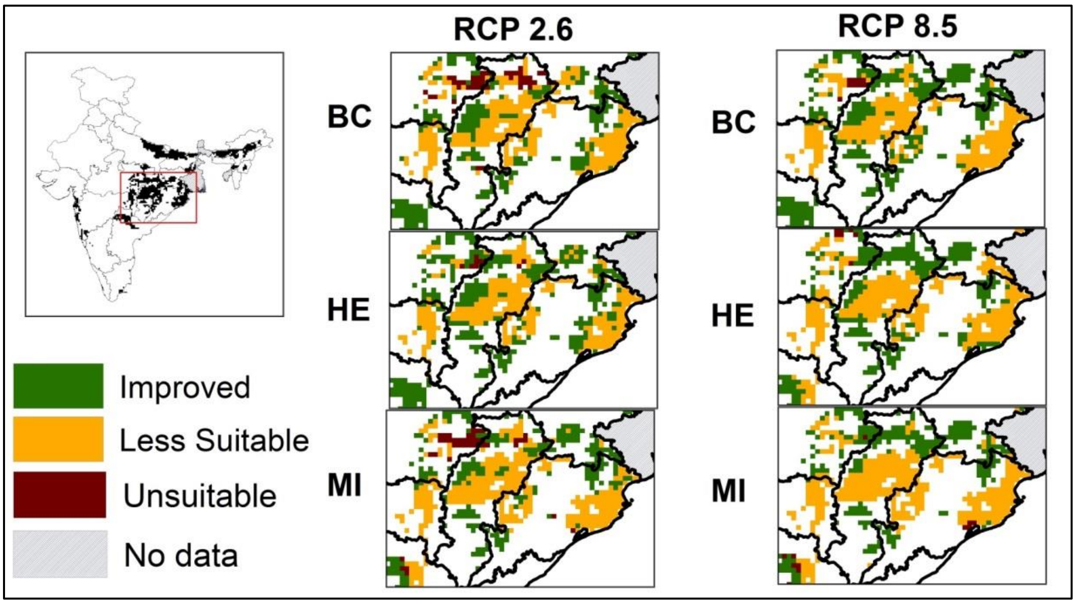

Figure A2.7: CEM outputs showing predictions according to different suitability categories (unsuitable, less suitable and improved) under two RCP scenarios (2.6 and 8.5) and three GCMs (*BC*= BCC-290 CSM1-1, HE= HadGEM2-ES and *MI*= MIROC-ESM-CHEM). Refer to main text for the definition of the three suitability categories. The panels show fine spatial resolution rainfed rice areas in Chattisgarh and Odisha, which are two major rainfed rice cultivating States with large number of small land-holders. The maps show good spatial agreement in cells at risk, and severity of risk across three GCMs and two RCPs.

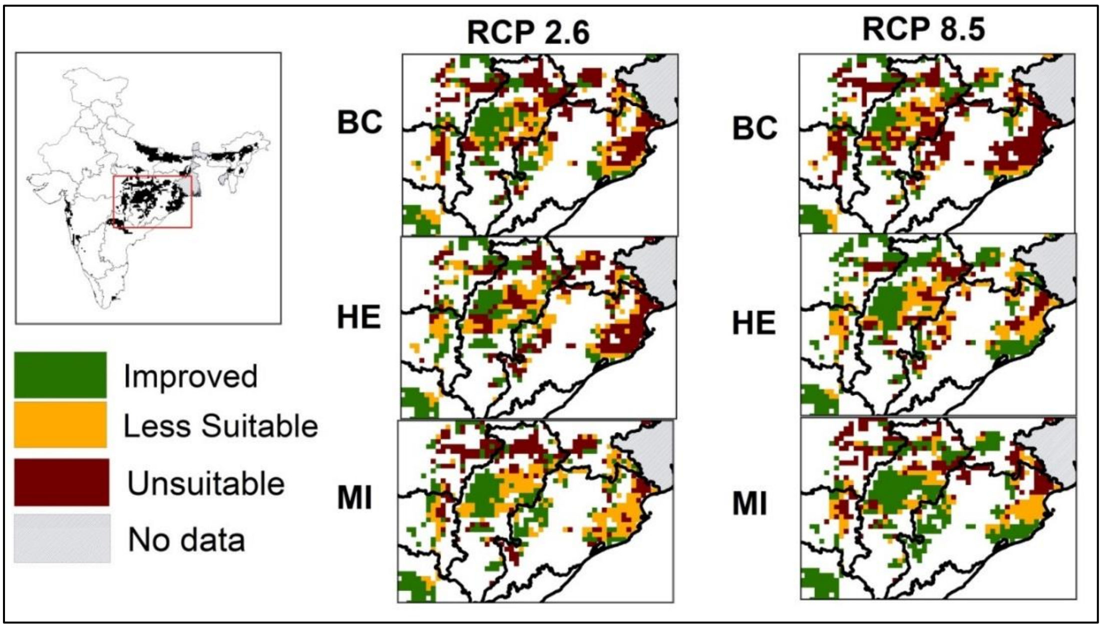

Figure A2.8. BRTs outputs showing predictions according to different outputs showing predictions according to different suitability categories (unsuitable, less suitable and improved) under two RCP scenario (2.6 and 8.5) and three GCMs (*BC*= BCC-290 CSM1-1, *HE*= HadGEM2-ES and *MI*= MIROC-ESM-CHEM). Refer to main text for the definition of the three suitability categories. The panels show fine spatial resolution rainfed rice areas in Chattisgarh and Odisha, which are two major rainfed rice cultivating States with large number of small land-holders. The maps show good spatial agreement in cells at risk but relatively less spatial agreement in severity of risk across three GCMs and two RCPs).

Appendix 3 – Supporting information for Chapter 4

Table A3.1: Names of the drought-tolerant local cultivars (n=112) and national cultivars (n = 5) analysed in the main text. These cultivars were grown across 39 rainfed upland sites (shown in Fig. 4.1 in the main text) during the 1996-2010 period under the AICRIP programme.

Local cultivars				National Cultivars
1. AAUDR-1	29. GP-5	57. Kopilee	85. Prsvat	1. Annada 2. Heera 3. Aditya 4. Tulasi 5. Anjali
2. Aditya	30. GR-5	58. Lalat	86. PTB – 50	
3. Amrut	31. GR-8	59. Lalitgiri	87. Rajendra Bhagwati	
4. Anjali	32. GR-9	60. Luchai	88. Rashmi	
5. Annada	33. Heera	61. Luit	89. Rasi	
6. AR-II	34. HKR-120	62. Mahisuganda	90. RAU 4045-2A	
7. Ashoka-200	35. HVD-110	63. Malviya Dhan-3022	91. Richarya	
8. Ashwani	36. IET-12131	64. MGD-101	92. RR 347-5	
9. Badami	37. IR-36	65. MTU-1001	93. Rudra	
10. BhataKunda	38. IR-75	66. MTU-9993	94. S.Chilo	
11. Bhupen	39. IRTP-10	67. Nagina-22	95. Sadabahar	
12. Birsa Dhan- 105	40. JaldiDhan-8	68. Narendar	96. Saket-4	
13. Birsa Gora-102	41. Jawahar Rice 3-45	69. Narendar-118	97. Samleshwari	
14. BirsaDhan-101	42. JDP13-1	70. Narendar-359	98. Saroj	
15. BirsaDhan-108	43. JDP-377	71. Narendar-97	99. Sathaka	
16. BirsaVikasDhan-110	44. Joli	72. Nauri	100. Sati	
17. BirsaVikasDhan-111	45. JR-353	73. Naveen	101. Shankar	
18. BirsaViksaDhan-109				

Local cultivars				National Cultivars
19. Browngora 20. Chaita-4 21. Chharia 22. Cottondora Sannalu 23. CS5 24. Dangar 25. Danteshwari 26. Dhala Heera 27. Dihula 28. Govind	46. JR-75 47. Kakro 48. Kalinga-III 49. Kalvand 50. Kalyani-2 51. Kanchana 52. KD-5-3-14 53. Khanda 54. Khandagiri 55. Khanika 56. Koni	74. Naveen 75. Nilgiri 76. Palghar-1 77. Parijat 78. Pathara 79. Patheria 80. Phalguna 81. PNR-381 82. Poornima 83. Prabhat 84. Prasanna	102. Sidhanta 103. Swarna 104. Terna 105. TRC-87-251 106. Turanta Dhan 107. Udayagiri 108. Vanaprava 109. Vandana 110. VL3288 111. VRA55 112. WR 3-2-6-1	

Table A3.2. Management protocol for the AICRIP trial data for 39 upland sites shown in Fig 1. The same management protocols were applied at every site and in every year for the period 1996-2010.

Management Practise	Value
Plot size	15 square meters
Plant spacing	20 cm between rows and 15 cm between hills
Fertilizer application	50% of nitrogen application at 10-15 days after planting, 25% at active tillering, 25% at panicle initiation
Irrigation	Absent
Layout	Randomised Block Design
Replication	3
Plant protection	need based

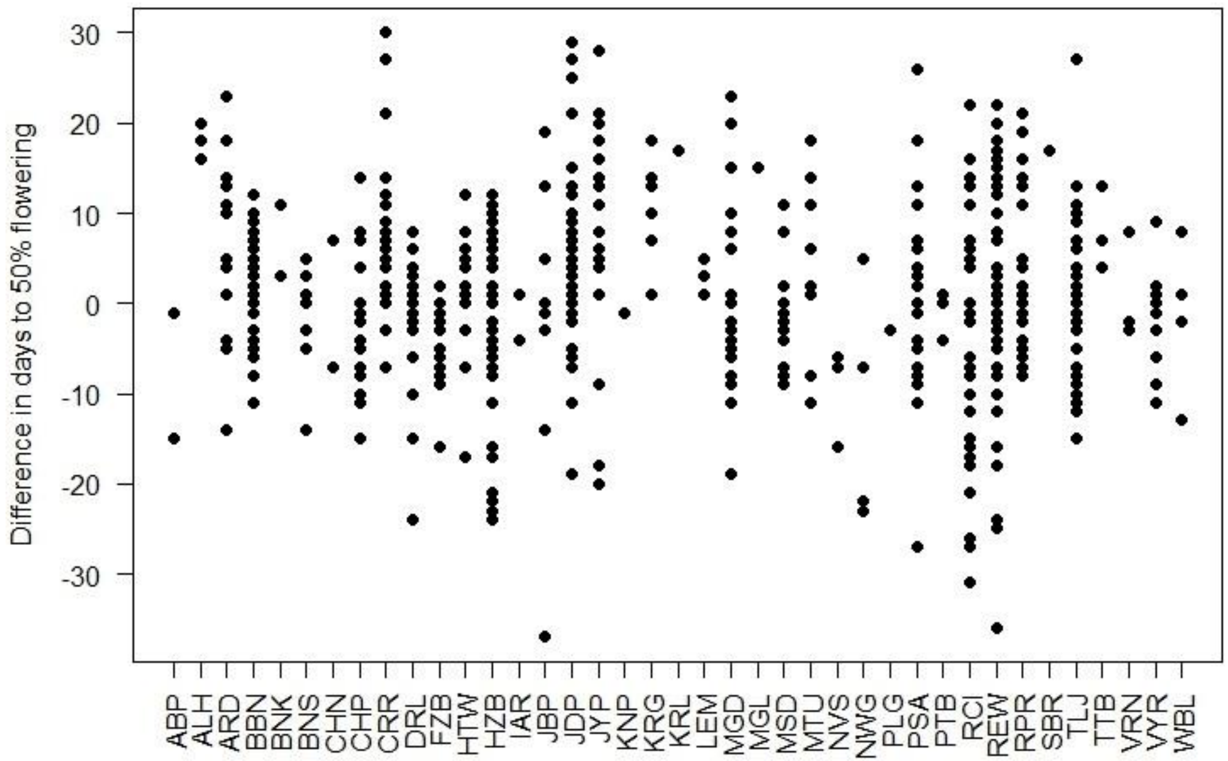

Figure A3.1. Difference in number of days to 50% flowering between local and national cultivars, for the yield data analysed in the main text. Positive values indicate that local cultivars flowered later than national cultivars. The sowing dates for a given site in a given year were the same for both local and national cultivars. The x-axis shows the name of all the sites, while the y-axis shows the difference in days to 50% flowering between local and national cultivars for all years at a given site.

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