Response of climate-smart agriculture to weather shocks

Shalika Vyas, Alliance of Bioversity International & CIAT, Email: Shalika.vyas@wur.nl
Contributong authors: Tobias Dalhaus, Miranda P.M. Meuwissen (Wageningen University), Pramod Aggarwal (Borlaug Institute for South Asia, BISA-CIMMYT), Martin Kropff (Consultative Group on International Agricultural Research, CGIAR), Julian Ramirez-Villegas (Alliance of Bioversity International and CIAT)

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Introduction

Weather shocks can destroy crops globally and cause widespread damage across all sectors of agriculture-cropping systems, fisheries and aquaculture, and livestock (Cottrell et al., 2019; Park et al., 2019; Vogel et al., 2019) (IPCC, 2021). The impact of such shocks on yields (Schlenker & Roberts, 2009), cropped area (Lesk et al., 2016), cropping patterns (Cui, 2020) and crop quality (Dalhaus et al., 2020) depends on the vulnerability and coping mechanism of the farms. To offset and counter-balance these effects of weather shocks, farmers continuously adapt their farming practices such as the planting date (Korres et al., 2017) and cultivar choice (Fisher et al., 2015), among many others. Where these practices increase productivity, contribute to climate adaptation, and/or reduce greenhouse gas emissions they are considered to be climate-smart agriculture (CSA) (Lipper et al., 2014). CSA has the potential to achieve food security goals under changing climate, by adapting farming systems to extreme weather, and also contribute towards mitigation goals (De Pinto et al., 2020). While these farming practices (classified as CSA) have been promoted for over a decade as the cornerstone of agricultural climate change adaptation and mitigation, little understanding exists on how different CSA farming practices affect the crop production response to weather shocks. This understanding is crucial as there is a greater likelihood of frequent and severe weather shocks across the world due to climate change (Jehanzaib et al., 2020; Sun et al., 2019; Tabari, 2020).

We address this research gap by analysing how different farming practices under climate-smart agriculture perform under different types of weather shocks. We define weather shocks as deviations from the average exposure at a production location as proxied by temperature and rainfall. We use a unique dataset from the climate-smart villages project in India (covering in total 53,616 yield by year observations), which aims to scale CSA activities in vulnerable smallholder farming systems with diverse cropping patterns include wheat, maize and soybean production (Aggarwal et al., 2018). The study contributes to the growing discourse on climate-smart agriculture, by quantifying the production (and income) response to extreme weather under different CSA management practices. We also identify thresholds of weather indices that significantly affect crop production, which are useful to design risk management policies like agricultural insurance for farmers to cover weather impacts beyond managable weather thresholds.

Several studies have presented evidence on the impacts of weather shocks on food systems (Gisbert-Queral et al., 2021; Moore and Lobell, 2014; Ortiz-Bobea et al., 2021; Schlenker and Roberts, 2009; Turvey et al., 2021) through the use of different methods (Auffhammer et al., 2013; Blanc and Schlenker, 2017; Kolstad and Moore, 2020). However, such evidence is limited for low and middle income countries (Ortiz-Bobea et al., 2019; Powell and Reinhard, 2016) and different farm management practices (Tack et al., 2017; T. J. Troy et al., 2015) due to data scarcity. Data scarcity is one of the most important challenges in scaling adaptation and risk management policies throughout the world, especially for smallholder agriculture. Advances in remote sensing have filled this information gap to an extent, however, most of the publicly available data focus on weather and other biophysical characteristics (like vegetation greenness, soil moisture and water stress, among others) (Jung et al., 2021; Karthikeyan et al., 2020) whereas information on long-term (panel) farm management is still missing. How farmers manage their fields, is a key determinant to farm production and climate vulnerability. The management effects on crop production can exceed the effects of weather and management information is thus key for designing risk management policies like agricultural insurance. Due to a lack of information about the farm management practices, the design of risk management instruments can be strongly impaired(Aggarwal et al., 2019; Norton et al., 2016; Vyas et al., 2021). In addition, evidence on how CSA farm management practices and weather events interact is even more limited (Keil et al., 2021).

We use farm-level data of 29,524 farms in India collected from 2015 to 2020. The dataset includes information on crop production (i.e. yields of major crops in the study area including rice, wheat, maize, gram, greengram and soybean) under different CSA practices. Using the spatial coordinates of the sample farms, we complement the farm information with heat and drought indicators at the farms' locations. More specifically, we use the number of extreme heat days above critical thresholds and the rainfall sum during the growing season. The study focuses on heat and drought indicators as these farms are located in hot, arid agro-climatic zones of India (in Rajasthan and Madhya Pradesh states), characterized by low precipitation, high aridity and frequent occurrence of heat stress and droughts. In addition, extreme heat and drought events are the most important risks affecting farm production according to the farmers in the study area (as determined during baseline farm survey-please refer supplementary information for more details). We use regression analysis to causally link a change in weather conditions with variation in crop yields. By sub-sampling by CSA measures, we can compare production responses to weather extremes along different management practices. By doing so we provide the first systematic assessment of how CSA practices affect the vulnerability of smallholders to weather shocks.

The rest of the paper is divided in four sections—we first provide a background on how the crops in our study region respond to heat and drought shocks. Using available literature, we discuss the crop physiological consequences of extreme weather events, and derive hypotheses on the role of adaptation in offsetting these responses. In the data and methods section, we describe the farm survey conducted to collect management information, discuss the choice of weather indices used (and the data sources), and explain the panel regression model. This is followed by the results section where we describe in detail how different farm management practices affect the response of farms to heat shocks, and finally the implications of the results in the context of climate change adaptation and broader risk management are summarized in the discussion and conclusion section.

Background

Impact of extreme weather events on crop production

Extreme weather events are known to impact food systems, causing food production shocks, decline in crop quality and farming efficiency, among others. In particular, drought and heat stress are known to trigger a range of morphological and physiological processes across growth stages in crops—ranging from poor germination and decline in germination potential, loss of biomass accumulation and cell growth, reduction in grain formation (sterility), reduction in grain filling and a resulting decline in grain yields (Daryanto et al., 2016; Dubey et al., 2020; Fahad et al., 2017). Droughts and extreme heat have shown to reduce national cereal production by 10% (Lesk et al., 2016), at the cost of 190 billion dollars globally, unevenly distributed among major food producing countries (Mehrabi and Ramankutty, 2017). In particular, the cropping systems of the study area also show significant vulnerability to drought and heat stress in India. For instance, rice crop shows upto 85% decline in productivity and 35% reduction in spikelet fertility when exposed to drought and extreme temperature, especially during the reproductive stage (Kumar et al., 2020; Nath et al., 2017). Similarly for wheat, literature shows 56% reduction in grain yield in India, when exposed to heat (accumulated degree days) and drought stress during crop reporoductive stage, apart from changes in grain quality (Qaseem et al., 2019; Song et al., 2020). For soybean, the reduction in seed yield was up to 64% under different temperature exposure levels (Jumrani and Bhatia, 2017). Gram crop also shows significant yield reduction by 40-50% and grain quality decline from drought and heat stress during flowering and grain filling stages (Devasirvatham and Tan, 2018; Rani et al., 2020).

The plant responses to drought and heat stress risks are highly dependent on the type and severity of event, the physiological stage of the crop, and changing interactions between weather events and agricultural systems (Glotter and Elliott, 2017). These responses are often non-linear, with higher losses observed with increasing growing season temperature (Burke et al., 2015; Friedrich et al., 2016;

Gammans et al., 2017a; Lobell et al., 2011), having implications for climate change. With expected increase in frequency and intensity of droughts and heat events from climate change , the plant responses can further be exacerbated (Xu et al., 2019).

Farm management practices including adaptation to changing climate can influence how crops respond to such events. Farm management practices such as stress tolerant cultivars (Martey et al., 2020; Wossen et al., 2017), change in planting dates and irrigation (Tack et al., 2017; T J Troy et al., 2015) and fertilizer management can help in limiting the damage from drought and heat stress, by escaping risk exposure, shifting the response thresholds or/and decoupling crops from climate sensitivity. Climate-smart agriculture combines these farm adaptation (and mitigation) strategies to increase farm resilience and enhance food security. Reported evidence of CSA suggests improvement in yields, farm income and enhanced drought resilience for CSA practicing farms in low and middle income countries (Acevedo et al., 2020; Dinesh et al., 2015; Lopez-Ridaura et al., 2018; Martey et al., 2020; Pal et al., 2021; Wossen et al., 2017), and changes in productivity, soil quality, resource-use efficiency and mitigation potential in rice-wheat systems in South Asia (Jat et al., 2021, 2020; Kakraliya et al., 2018; Roy et al., 2022; Singh et al., 2020). Combining multiple adaptation and mitigation activites together in the farm, can lead to synergies and trade-offs between different portfolios of activities, and can be useful to understand farm adoption of different CSA practices (Jagustović et al., 2021).

Hypothesis

The farm data used in this analysis has detailed information on farm management practices adopted in the study region. The data are available individually for each farm and farmers are also classified as super-champion, champion, and CSA farmers (based on portfolio of CSA activities adopted in their farms-please refer supplementary information for more details). Previous literature has documented the risk-reducing effects of specific CSA practices. We therefore test the response of production being managed under different types of CSA portfolios to weather shocks. In particular, we test the hypothesis that as the number of CSA activities increase, the farm response to weather risk decreases (due to compound risk-reducing effects of adaptation activities under CSA). Therefore, farm production response (production, yield and income loss) to weather shocks of the super champion farmers is hypothesized to be less (in magnitude) than champion farmers, followed by CSA farmers (with least number of CSA activities). We also hypothesize that the production response of individual farm management activities like (presence or absence of) irrigation, fertilizer, improved seed/cultivar, seed treatment, tillage interventions, precision nutrient management, intercropping and farm risk management activities (climate information services and crop insurance) to weather shocks is less in magnitude (than the absence of these practices) and compare the results with available literature.

Data and Methods

Farm data

The CGIAR research program on Climate Change, Agriculture and Food Security (CCAFS) has implemented the "climate-smart village project" with different national and international partners to promote climate-smart agriculture. Climate-smart agriculture aims to integrate climate change into policy design, planning and implementation of sustainable agriculture practices from local to regional scales. It focuses on three key aspects of food production—adaptation, mitigation and food security, in addition to building food systems resilience to climate extremes. Climate-smart village (CSV) is a community approach to leverage local institutions, public and private partnerships to scale climate-smart agriculture across different geographies (Aggarwal et al., 2013). The climate-smart village activities are based on five key dimensions of interventions—weather, water, seed, carbon and institutions (Aggarwal et al., 2018). These interventions are implemented through different mechanisms (involving individual farmers and farmer groups) and local institutions, depending on location and context-specific characteristics. The CSV approach is thus flexible and is implemented in different regions accordingly.

For this study, the panel data collected from the Climate-smart village project in India will form the basis of analysis. A survey was conducted to collect data on farm management across different portfolios of CSA across two different states in India (Madhya Pradesh and Rajasthan) from 2015-2020. Three levels of CSA packages were implemented by farmers and the farmers were categorized into super champion, champion and CSA farmers based on their portfolios and activities in the field. The super champion farmers are the influential promoters of CSA activities in the project area and have highest number of CSA activities in their farms, followed by champion and CSA farmers (Chanana et al., 2020) The survey includes farm-specific information on management conditions like farm inputs used (crop variety, fertilizer and irrigation amount, labour), farm size, outputs (yield and income) and type of adaptation/mitigation strategies implemented (including precision nutrient management, agro-advisories, insurance, intercropping, conservation tillage, among others-please refer supplementary information for more details). The farm data (unbalanced panel data) is available for 29,524 households in 695 villages from the year 2015 to 2020, with a total of 51,707 yield observations. The data covers maize, rice, wheat, gram, green gram and soybean crops. The survey data has detailed information on farm management inputs and adaptation practices including calendar dates of key agricultural operations, type, amount and frequency of inputs used, and types of CSA practices followed (the details are given in supplementary information). Since the objective of the project is to scale-out CSA interventions across target villages, the data was collected only for farms with project interventions and not for control farms (with no CSA interventions). This study thus focuses on the effect of different types of CSA intervetions and compares farm responses under different levels of CSA portfolios (and does not compare CSA with control non-CSA farms).

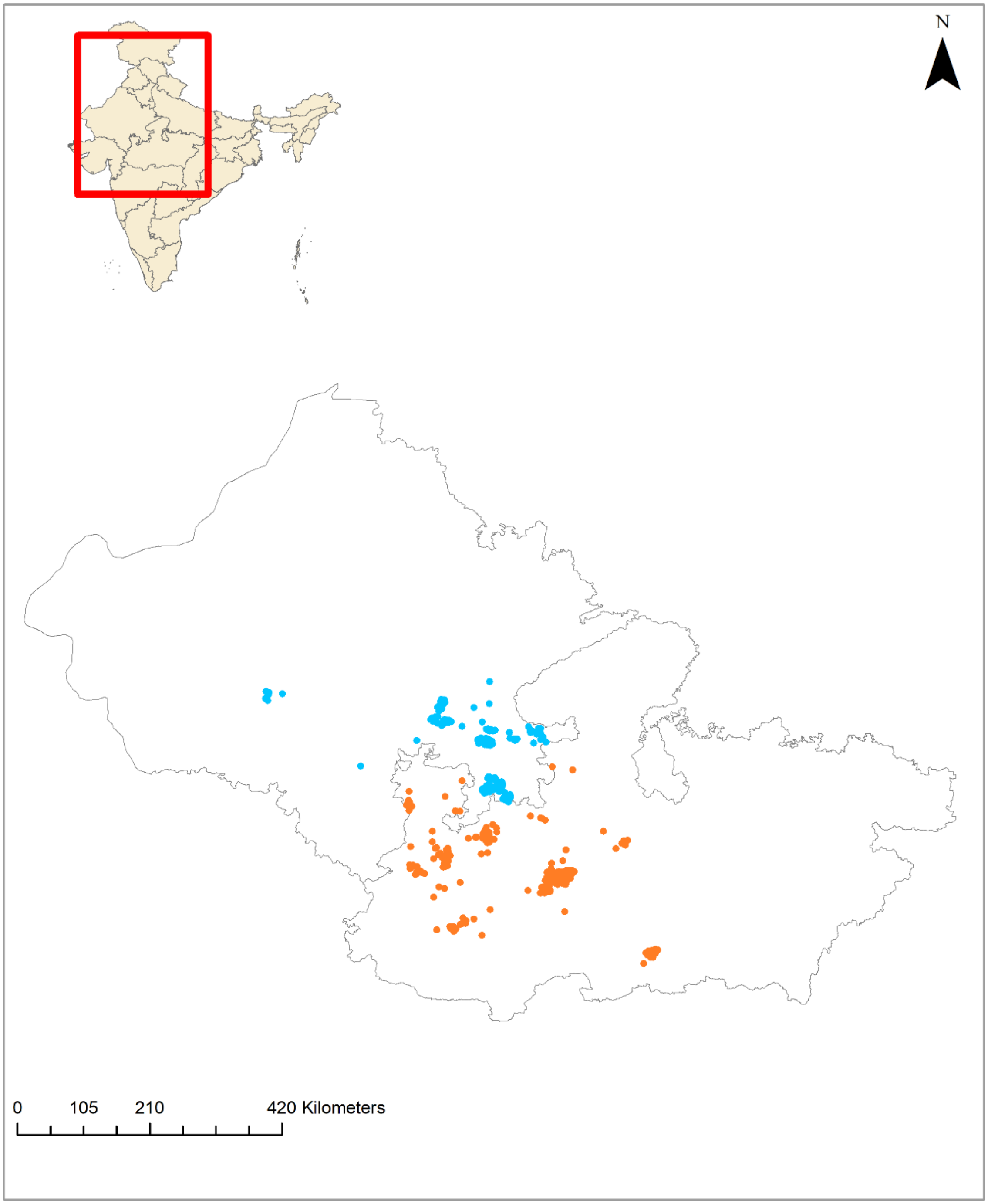

Fig 1: Spatial distribution of the villages selected for this study. Colors differentiate two project states- blue (Rajasthan) and orange (Madhya Pradesh).

Table 1: Summary statistics of farm management data (categorical variables)

Summary statistics of key categorical variables			
Variable code	Variable name	Categories	N
Q8	Type of farmer	Super champion = 2334; Champion= 46,832; CSA= 5,777; Others= 50	54,993
Q18	Seed treatment	Yes= 45,199; No= 7,970	53,536
Q22	Zero Tillage	Yes= 5071; No= 49,285	54,356
Q26	Use of broad-based furrow (BBF)	Yes= 10,272; No= 43,760	54,032
Q29	Crop Insurance	Yes= 41,348; No= 13,534	54,992
Q31	Irrigation	Yes= 20,695; No= 28,214	49,412
Q56	Intercropping with legumes, vegetable	Yes= 519; No= 52,330	52,849
Q53	Use of Precision nutrient management	Yes= 33,837; No= 19,103	52,940
Q68	Climate information, agro-advisory and market information	Yes= 50,468, No= 2470	52,940
Q89	Season	Summer= 30,186; Winter= 24,817	55,003
Q12	Crop	Gram= 620; Maize= 4,346; Rice= 248; Soybean= 24,028; Wheat= 23,854; Green gram= 176	53,616
Q90	Year	2015= 482; 2016= 483, 2017= 1,085; 2018= 19,259 , 2019= 24,153 , 2020= 9,541	55,003

Table 2: Summary statistics of farm management data (numeric variables)

Summary statistics of key numeric variables						
Variable code	Variable name	N	Mean	Min	Max	St dev
Q71	Total Cost of Cultivation (Rs/Acre)	51,026	7111.38	1030	27350	2695.99
Q80	Net Return (Rs)	51,461	14,805.22	-17849	1,64,752	12,360.4
Q76	Market price of grain (Rs/Qt)	52,373	2605.05	1000	7350	848.87
Q30	Cost of Crop Insurance (Rs/Acre)	35,798	229.42	0	8750	185.97
Q9	Total Cultivated Area (in Acre)	41,169	2.533	0.081	480	4.988

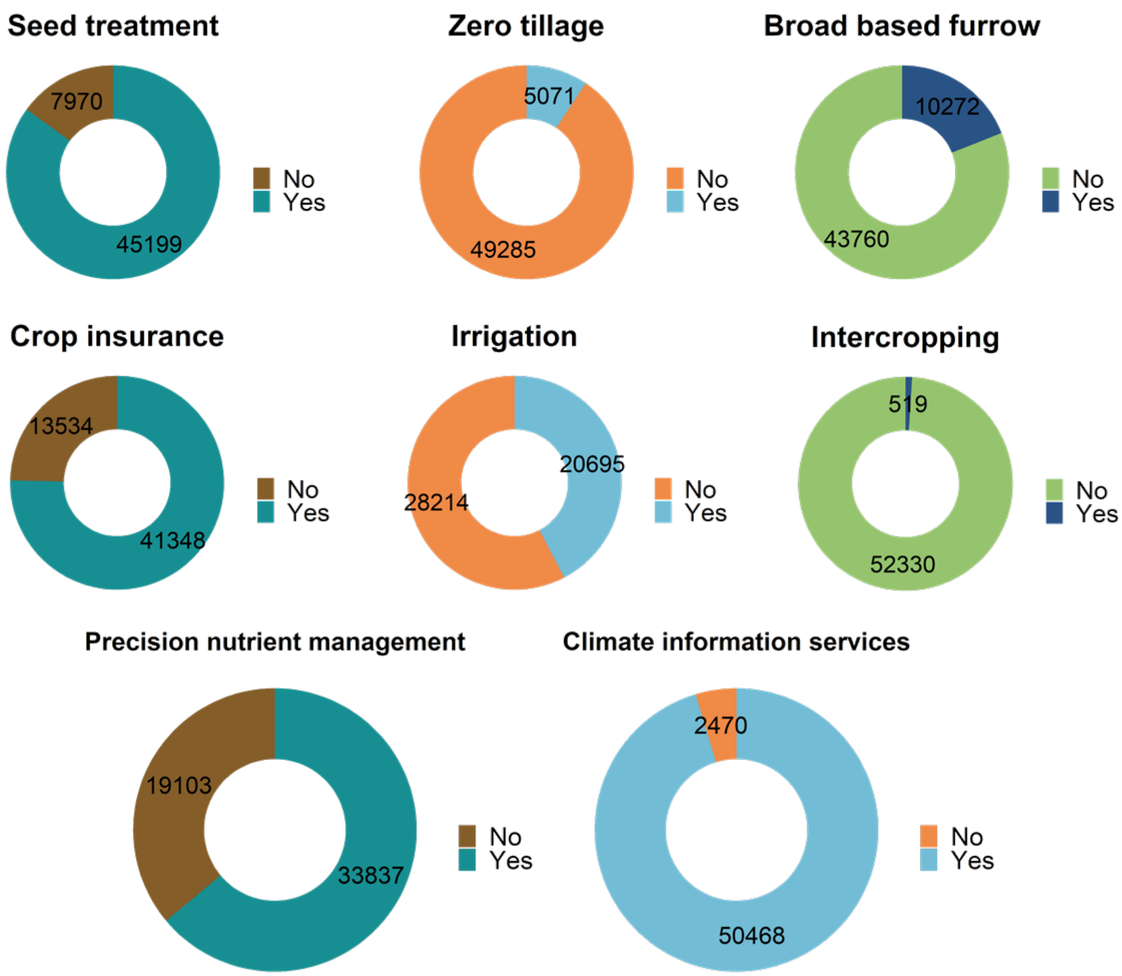

Fig 2: Overview of select CSA practices implemented in the study area

Weather data

The study areas (states of Madhya Pradesh and Rajasthan) have semi-arid and dry crop-growing conditions with high temperatures, dry spells and droughts, especially in the summer season. The seasonal rainfall volume ranges from 300 to 1500 mm in summer and 15 to 200 mm in winters[1], and the maximum temperature varies from 25 to 45 degrees in summers (with records of even upto 50 degrees in a few places). The region is also characterized by intense and frequent droughts (Guhathakurta et al., 2017). During the baseline survey for the project, the farmers reported the following as the most

[1] https://ccafs.cgiar.org/resources/publications/ccafs-agriculture-monitor-cam

important weather-related risks for their farms—high temperature, less rainfall and drought, heatwaves, frequent hailstorm, frost, strong wind/storms causing crop lodging, changes in rainfall volume, cold wave and intense spells of rainfall.

Based on observed weather risk exposure and farmers' perception of weather risks in the case study region, we focus on heat stress and drought (including dry spells) as main hazards in the study area. Daily temperature data will be used for assessing heat stress in the region. For drought, we focus on different sub-seasonal drought indicators—standardized precipitation index, soil moisture index and number of dry days. These indices are selected as drought and heat stress are major climatic risks for our region of interest and they can capture complex crop physiological-water stress interactions and soil moisture dynamics comprehensively (instead of using a single drought indicator). In addition, they can be useful for designing risk financing policies (Bucheli et al., 2021). The weather data sources are described in table 3.

Table 3: Weather data sources

Risk/Data source	Source	Year	Timescale	Resolution
Heat stress				
Daily max and min temperature	ERA5 (ECMWF Reanalysis 5th Generation Description) https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5	1979-present	Daily	.25 X .25 degree
Drought				
SPI	a) Calculated from CHIRPS rainfall data	1901-present	Monthly	.05 X .05 degree

The weather data were aggregated at different time steps to compute sub-seasonal and sesaonal indices. Daily temperature data was used to compute temperature bins for heat stress. Daily (soil moisture), number of dry days and monthly SPI are used in the analysis.

Methodology

We use fixed effects panel regression to estimate the impact of a random and exogenous weather shock on crop yield. We subset our dataset by different CSA portfolios and test for differences in the weather response along different CSA strategy bundles to show their effectiveness in offsetting the impact of extreme weather. We therefore estimate the following model:

$$y_{jit} = \beta_j EHD_{it} + \gamma_{1j} PREC_{it} + \gamma_{1j} PREC_{it}^2 + a_{ik} + a_{tk} + \varepsilon_{ijt}$$

where y_{ijt} is the log yield at farm i in year t. We subset the overall dataset by crop $j \in \{Soy, Wheat, Maize\}$ and estimate three different models. EHD_{it} is the number of extreme heat days at farm i in year t defined by the daily maximum temperature exceeding a threshold temperature of 30 °C. The extreme heat days are calculated based on the growing season for the crop—June to September for summer crops and October to March for winter crops. We systematically shift this threshold between 30°C and 45°C. Consequently, β_j is the marginal impact of one extreme heat day on yields of crop j. Since the number of extreme heat days likely correlated with the precipitation sum during the growing season, we control for $\gamma_{1j} PREC_{it} + \gamma_{1j} PREC_{it}^2$, which captures the potentially inverse u-shaped impact of precipitation on yields. a_{ik} is a farm fixed effects that controls for all time invariant characteristics of the farm and the farm's location. Besides, a_{tk} is a year fixed effect that controls for all factors that are similar for all farms within one year, such as technological development, market, or policy changes. Our specificaition thus allows us to estimate the effect of weather shocks on production shocks. That is, how does a deviation from normal heat exposure at a farm's location cause a deviation from its normal production quantity. We can assume that these weather shocks occur random and exogenously, which is why we are able to interpret the effect of weather on production as a causal effect. ε_{ijt} is the error term that is likely correlated in space and time. We therefore, cluster the error by farm and year to allow for spatial and temporal autocorrelation. Since the fixed effects model requires atleast three years of panel data, only farms who have three or more years of data are included in the model. Distribution of different variables used in the regression model are provided as a supplementary file.

Various studies have used a similar reduced form model to to estimate (non-linear) response of different cropping systems to weather (Gammans et al., 2017b; Lobell et al., 2013; Schlenker and Roberts, 2009a) (Gammans et al., 2017b; Lobell et al., 2013; Schlenker and Roberts, 2009a). However, while these studies were able to establish causality between the weather shock (in our case extreme heat days) and the outcome variable, little data has been available on management decisions that potentially affect the mechanisms between weather and production. Reduced form models with observational farm- or county-level data estimate an adapted response to weather. That is, the production response that remains after farmers potentially applied agronomic management practices such as irrigation (see Tack et al. 2015). Thereby, the boundaries beyond which weather becomes harmful that arise from these estimates can differ from experimental crop physiology literature. We here have explicit information on CSA practices that were applied to reduce the effect of weather shocks. The extent to which these are able to achieve this is however unknown. We therefore estimate our above model across subsets of different CSA practice bundles and compare the estimated responses.

Results

We here present preliminary result on the impact of heat shocks (number of days with a daily maximum temperature above 45°C) on soybean yields. A total of 4,733 farm-yield observations were used in this model. As mentioned in the previous section, the region of study experiences very high heat stress and drought. We therefore choose the threshold of daily maximum tempetaure above 45 degree Celsius as extreme heat day. Our results show a significant negative impact of extreme heat days on soybean yields (table 4). A unit increase in extreme heat days compared to the average at the farm location, causes a 0.38 decline in log of soybean yields compare to the average production at the farm.

Table 4: Regression results

Dependent Variable:	log(Soybean yield Kg/Ha)
Extreme heat days (no. of days above 45 C)	-0.3840** (0.0755)
Summer rain	-0.00003936
Summer rain square	3.88e-6** (9.07e-7)
Fixed-Effects by farm and year, S.E. Clustered by farm and year	
Observations= 4,733, R-squared= .58, Within R-square= .18	

Discussion

Our results show a significant yield decline for soybean crop for a temperature threshold of 45 degrees. The results are in agreement with published literature which describe the optimum growing temperature at 32 degrees after which the crops show steady decline (Cook et al., 2021; Parent and Tardieu, 2012; Thomey et al., 2019). Here we show the impact of extreme heat on soybean yield for only one threshold of 45 degrees, we plan to systematically shift this threshold between 30 to 45 degrees to assess the sequential impact of extreme heat on soybean yield (and returns). Further, we will subset these results by different farming practices to better understand the impact of CSA practices on crop exposure to extreme heat. We will also replicate this analysis for other drought and heat indicators like SPI, and crops (like maize and wheat).

This analysis has important implications for farm risk management and agricultural insurance policies. Risk management often combines two or more strategies to safeguard crop production from shocks. Adaptation should ideally cover moderate to severe climate stress, insurance should kick in for the right tail (extreme climate risk). In CSA, a combination of adaptation, climate information services and financial risk management (through insurance) are used to protect farms from shocks, while increasing their efficiency and production levels. There are many synergies and trade-offs between different management activities implemented under CSA (Prestele and Verburg, 2020). In such a scenario, risk management needs to be aligned with these management conditions, to design an effective policy. Limited literature is available on the risk management dimensions of CSA, with respect to climate stress and extreme weather events (Awondo et al., 2020). Therefore, it is important to establish the risk-reducing properties of CSA and identify the risk thresholds. We capitalize on a detailed farm survey on CSA farms to identify the effects of management portfolios on yield/income response to climate risks. This helps in identifying thresholds beyond which CSA might not work, which is essential to design risk management policies like an agroicultural insurance products for CSA. According to these thresholds, index insurance products can be designed with customized deductibles and premiums. For instance, farmers with intensive CSA portfolios may have a higher deductible or lower premiums. The results from this study can be used to develop a more comprehensive and efficient insurance scheme for CSA farms (by reducing design and basis risk) (Vyas et al., 2020).

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