ESSAYS IN ENVIRONMENTAL AND DEVELOPMENT ECONOMICS

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ESSAYS ON ENVIRONMENTAL AND DEVELOPMENT ECONOMICS

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This dissertation lies at the intersection of environmental economics and development economics. It includes three essays that empirically examine the effects of climate change and extreme weather events on agriculture in both developed and developing countries.

The first essay explores how the choice of weather data sets could affect estimates of climate change impacts. A large body of empirical literature finds that high temperatures are detrimental to a wide range of economic outcomes. These effects are often identified from the within-location temporal variation in exposure to the extreme right tail of the temperature distribution. Here, we document large discrepancies in exposure to extreme temperatures across six high-resolution gridded weather data sets in the US, where weather data is considered to be of high quality. We explore and illustrate the consequences of these data discrepancies in the estimation of potential climate change impacts on agriculture. We find that most climate change impacts based on different climate data sets are not statistically different from each other. Yet, the choice of the underlying weather data set can account for up to 48 percent of estimated warming damages on US crop yields. These findings highlight an important, but generally unrecognized, source of uncertainty in estimates of climate change impacts and the need for more systematic intercomparisons of widely used geospatial data sets in environmental social sciences.

In the second essay, we estimate the impact of self-reported occurrences of droughts and floods on crop and livestock net income in Sub-Saharan Africa during the period 2009–2016. Based on a pooled data set for five countries, we find robust negative and heterogeneous impacts of droughts and floods across different levels of irrigation, poverty, and agricultural diversification, including reductions of net crop income by 34 percent and 61 percent due to droughts and floods, respectively. The study also confirms the importance of poverty alleviation and agricultural diversification to cope with the adverse effects of droughts and floods.

The third essay studies the effects of droughts and floods on agricultural livelihoods in Zambia. The adverse effects of weather extremes produce widespread damage and cause severe alterations in the normal functioning of household agricultural production in Zambia. The intensity and frequency of extreme weather events, such as droughts and floods, are expected to increase due to climate change. Coupled with high poverty levels and limited institutional capacity, the country is highly vulnerable to the impact of extreme events. We quantify the effects of economic diversification on the agricultural productivity of poor farm households with a skew-normal regression approach while accounting for drought and flood shocks. Our analysis finds that economic diversification is a strategy to increase agricultural productivity and mitigate the adverse impact of droughts and floods on agricultural households. The results also support the country's policies to encourage hybrid maize production and to provide crop seeds and fertilizers to poor farmers. This paper provides a framework to plan and inform interventions to enhance household economic resilience to weather shocks through agricultural diversification in Zambia and other countries.

BIOGRAPHICAL SKETCH

Shun Chonabayashi was born in Tokyo, Japan. He received a BA degree from Soka University in Tokyo in 2007 and an MA degree in International and Development Economics from Yale University in New Haven, CT in 2008. After spending two years working as a consultant for the World Bank and a postgraduate fellow at Yale University, he began his doctorate study at Cornell University, NY, in 2010. He was selected for the World Bank Young Professionals Program in 2015, and since then has been working on climate change and environmental issues as an economist at the World Bank.

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CHAPTER 1

1. Introduction

1.1. Climate Change and Agriculture

Climate change has been one of the most important global issues for humankind. Climate change affects numerous problems that the world is currently facing, including a rise in sea level, food security, extreme events, etc. From among these issues, this dissertation studies the impact of climate change on agriculture, particularly in African countries.

Climate change, along with impacts of climate risks such as droughts and floods, has been widely recognized and acknowledged worldwide. According to the Fifth Assessment Report of the United Nations Intergovernmental Panel on Climate Change (Stocker et al., 2014), climate change is predicted to increase temperatures as well as alter precipitation and water supply patterns over the course of the twenty-first century.

Agriculture is one of the sectors that is most affected by climate change. Global warming is likely to increase the productivity of crops relative to livestock in places with a cool climate and reduce crop productivity in relatively warm locations. In order to cope with these heterogeneous effects of climate change on agriculture throughout the world, adaptation strategies are likely to be necessary (Rose and McCarl, 2008; Mendelsohn, 2012). Lobell, Baldos, and Hertel (2013) report that, on the basis of mitigation cost alone, investing in agricultural adaptation appears to be a reasonable mitigation strategy. A good understanding of the economic impact of climate change on agriculture is crucial to design cost-effective climate adaptation strategies.

As most of the continent's population is dependent on agricultural activities, Africa is especially vulnerable to the adverse impacts of climate change and extreme weather events, which additionally makes the eradication of poverty difficult. Previous literature reveals that climate change and weather shocks cause losses in agricultural household income and assets in the relatively warmer areas of the world (Mendelsohn, Dinar, and Williams, 2006; Lobell, Schlenker, and Costa-Roberts, 2011). Poor people are more likely to be dependent on agricultural income, which is directly influenced by changes in agricultural productivity and generally negatively associated with a warmer and drier climate. Baarsch et al. (2020) reported that a growth loss of 10 percent to15 GDP per capita was caused by climate variability in most African countries during the period 1986–2015 and projected that future climate risks will likely lead to lower GDP growth in every African region. Similarly, Kala et.al (2012) estimated that Africa would be hit hard with annual welfare losses ranging between USD 14 billion and USD 70 billion in the period 2070–2100, depending on the climate scenarios and cropland measures employed. In addition, several studies conclude that rainfall and drought shocks negatively affect farmers' agricultural income at the national level (Arslan et al., 2016; Asfaw et al., 2016; Skoufias, Bandyopadhyay, and Olivieri, 2017; Sesmero, Ricker-Gilbert, and Cook, 2018; Chuang, 2019; Chonabayashi, Jithitikulchai, and Qu, 2020).

Zambia, among other sub-Saharan African countries, is extremely vulnerable to climate risks due to its relatively high poverty level and high proportion of agriculture engagement. Thurlow et al. (2012) conclude that a severe drought reduces agricultural GDP by 22.7 percent and moves, on average, 7.5 percent of the population into poverty. Chonabayashi et al. (2020) discovered that droughts lead to a reduction of 29% in agricultural value added per worker for poor farmers who produce either

crops or produce livestock products and a reduction of 18% for those who produce a mix of crops and livestock.

Although the linkage between climate change and agriculture in both developing and developed countries has been actively studied by researchers, there remain several areas in which further research would be beneficial. First, most of the previous literature assumes that climate and weather data sets do not have measurement errors. Yet, recent studies reveal that this is frequently not the case and this has important implications for researchers and policymakers (Parkes et al., 2019; Sohnesen, 2020). Without accounting for such measurement errors in climate change impact studies, there are risks in creating policies based on the biased estimates of the economic losses from climate change and extreme weather events.

Second, the effects of extreme weather events, such as droughts and floods, on agricultural livelihoods in Africa should be further studied, particularly in a multi-country setting. While numerous country studies are available, droughts and floods are cross-border issues by nature and can affect areas across multiple countries. A regional study to assess the impacts of weather shocks would help to obtain a better and more comprehensive understanding of such shocks. Furthermore, the first research gap in the measurement errors of weather data sets is also related to this second gap, as measurement errors can be larger in the extreme tails of temperature and precipitation distributions. Understanding how extreme events affect agriculture would complement and strengthen existing estimates for long-term impacts of climate change.

Third, there is no established methodology to accurately measure droughts and floods that can be used to study the impact of these extreme events on agricultural households' livelihoods. Although the recent proliferation of satellite data provides spatially disaggregated weather data, the accuracy and spatial disaggregation of such data still need improvement, as extreme events such as droughts and floods are local

events. While we have household surveys that include information on weather shocks, self-reported measures may be biased, as households tend to recall severe events that have negative impacts on their livelihoods.

Fourth, there have been only a few studies that use geo-referenced household survey data to study climate change impacts on agriculture due to limited data availability. Yet, it is crucial to conduct such analysis at the spatially disaggregated level (e.g. household-level) and account for spatial dependency in the econometric strategies, considering that climate change and extreme weather events have similar effects on households that are in close proximity when such events occur.

These are a few examples of knowledge gaps in previous literature that seek to study the impacts of climate change on agriculture. While this list is obviously not comprehensive, it suggests a few important areas of research that could be addressed to advance our knowledge in the field, which would also help policymakers plan national strategies and policies to cope with climate change.

1.2. Overview and Contributions of the Dissertation

The objective of this dissertation is to contribute to the research gaps discussed above. The first essay (Chapter 2) entitled "Climate Change Impacts are more Uncertain than they Appear" mainly contributes to the research gap on measurement errors of climate data sets. A large body of empirical literature finds that high temperatures are detrimental to a wide range of economic outcomes. These effects are often identified from the within-location temporal variation in the exposure to the extreme right tail of the temperature distribution. In this chapter, we document large discrepancies in exposure to extreme temperature across six high-resolution gridded weather data sets in the US, where weather data quality is considered high. We explore and illustrate the

consequences of these data discrepancies in the estimation of potential climate change impacts on agriculture. We find that the choice of the underlying weather data set can account for up to 48 percent of global warming damages on US crop yields. These findings highlight an important, but generally unrecognized, source of uncertainty in estimates of climate change impacts and the need for more systematic intercomparisons of widely used geospatial data sets in environmental social sciences.

The second essay (Chapter 3) entitled "Estimating the Impact of Droughts and Floods on African Farmers" contributes to the research gap in understanding the short-term effects of extreme events on agriculture by providing empirical evidence from Africa. We estimate the impact of self-reported occurrences of droughts and floods on crop and livestock net income in sub-Saharan Africa during the period 2009–2016. Based on a repeated cross-sectional data set for five countries, we find robust negative and heterogeneous impacts of droughts and floods across different levels of poverty and agricultural diversification, including reductions in net crop income by 40.2 percent and 98.8 percent due to droughts and floods, respectively. The study also confirms the importance of poverty alleviation and agricultural diversification to cope with the adverse effects of droughts and floods.

The third essay (Chapter 4) entitled "Does Agricultural Diversification Build Economic Resilience to Droughts and Floods? Evidence from Poor Households in Zambia" also contributes to the second research gap identified above in terms of understanding the effects of extreme weather events on agriculture by providing additional empirical evidence in Zambia and exploring the effects of different policy interventions. The adverse effects of weather extremes include widespread damage and severe alterations in the normal functioning of household agricultural production in Zambia. Further, extreme weather events such as droughts and floods are expected to increase in intensity and frequency due to climate change. Coupled with high

poverty levels and limited institutional capacity, the country is highly vulnerable to the impact of extreme events. We quantify the effects of economic diversification on the agricultural productivity of poor farm households with a skew-normal regression approach while accounting for drought and flood shocks. Our analysis finds that economic diversification is a strategy to increase agricultural productivity and mitigate the adverse impact of droughts and floods on agricultural households. The results also support the country's policies to encourage hybrid maize production and to provide crop seeds and fertilizers to poor farmers. This paper provides a framework to plan and inform interventions to enhance household economic resilience to weather shocks through agricultural diversification in Zambia and other countries.

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CHAPTER 2

2. Climate Change Impacts Are More Uncertain Than They Appear

2.1. Introduction

There is an increasing number of studies that examine climate change impacts on the economy in terms of a wide range of aspects, including GDP, agriculture, health, crime, conflict, migration, etc[Hsiang et al., Burke et al., b]. This study proceeds in two steps: first, an empirical investigation connects climate or weather to economic outcomes, and second, a counterfactual simulation is presented based on econometric estimates. Typically, two types of uncertainty are acknowledged. One type of uncertainty comes from the statistical and econometric models used in extant literature.An expanding body of statistical and econometric literature documents the linkage between agricultural outcomes, weather, and climate [Mendelsohn et al., Schlenker et al., b]. Since climate change impacts depend on the estimated regression coefficients, it is important to account for dependence on extremely high temperature. The other type of uncertainty originates from the climate projections related to the general circulation models (GCMs) and representative concentration pathway (RCP) scenarios [Bishop and Beier, Angelil et al., Burke et al., a].

We tend to take temperature at face value. However, the characterization of the linkages between climate and the economy hinges profoundly on the accuracy of temperature data. It is well known in climate science that there are systematic biases in numerous data sets, but these are not accounted for by users downstream. In particular, the important issue is that a misrepresentation of extreme temperature can potentially lead to incorrect inferences. A lot of attention is paid to the effect of extreme temperature in previous literature, but it is unclear how well these extremes are measured. We generally assume that historical climate, particularly temperature extreme, is correctly measured, but a few studies use other proxies to study the short-term impact of extreme

high-temperature events, such as drought on crop yields and net income [Kuwayama et al., Chonabayashi et al.].

A few questions still remain unanswered in this thread of literature on the climate change impact on agriculture in the US. First, do we see differences in nonlinear effects of temperature on crop yields based on alternative historical climate data sets? Second, if there are differences, do they translate in to differences in climate change impact projections? If so, do they vary by crop? What drives the differences? Third, what can researchers do when faced with such differences?

To attempt to answer these questions, we expand the study by Schlenker and Roberts (hereafter referred to as SR) by incorporating additional climate data sets and econometric specifications. We first find heterogeneity in exposure to high temperature above the specified thresholds across different climate data sets used, including station-based and reanalysis data. Furthermore, we find that the climate change impact projection could reduce by half compared to the previous literature in which alternative climate data sets are used. These results indicate the importance of incorporating measurement errors and uncertainty of historical climate data sets in studies that seek to understand climate change impacts on agriculture as well as other subjects.

The remainder of the paper is structured in the following manner. In section II, we discuss the model used in the literature and this study. In section III, we discuss alternative weather data sets considered for this study. In section IV, we present the summary statistics and results based on alternative weather data sets, and in section V, we present the conclusion.

2.2. Model

Statistical models that regress crop yields on weather variables have traditionally relied on monthly or pluri-monthly average temperature and precipitation data. Initial

examples can be traced back to the early part of the last century (Wallace, Hodges). Ever since, the convention has been to include linear and quadratic variables based on temporally aggregated data to capture the nonlinear effects of both temperature and precipitation on crop yield. The marginal effects of these variables are typically expected to exhibit an "inverted U" shape, thereby suggesting diminishing marginal effects of each weather variable with a unique optimum.

SR made an important contribution by recognizing that daily average temperature fails to convey the consequences of exposure to extreme temperature and, thus, may not be adequate for capturing the nonlinear effects of temperature on corn yields. Hypothetically, two days with equal average temperature may represent very different exposures to rather high temperatures. This suggests that the shape of the diurnal temperature curve is of significance.

To address this required refinement, SR developed an innovative approach that estimates the effects of exposure to different levels of temperature on crop yield separately. They compute the amount of time spent during the growing season (March to August for corn and soybean and April to October for cotton) in temperature intervals of 1°C. The exposure to each degree interval is then adapted to various specifications. This is an extension of previous hedonic work on land prices in Schlenker et al. [a], but with greater flexibility in the specification of the temperature response function.

Here, we replicate their yield model for corn, cotton, and soybean—which are also studied in SR—as well as sorghum, spring wheat, and winter wheat. We restrict the sample period to 1980–2005, which is an overlapping period of various climate data sets used and is shorter than the period 1950–2005 used by SR.[1]

Their general model assumes that temperature effects on yield are cumulative and substitutable over time. The nonlinear effects of temperature on yield are captured by the function $g(h)$ representing "yield growth," which depends on temperature

[1] SR report that their results are similar for temporal subsets of the sample.

h. Logged yield y_{it} in county i and year t is represented in the following manner:

$$y_{it} = \int_{\underline{h}}^{\overline{h}} g(h)\phi_{it}(h)d(h) + p_{it}\delta_1 + p_{it}^2\delta_2 + z_{it}\tau + c_i + \varepsilon_{it} \quad (1)$$

where $\phi_{it}(h)$ is the time distribution of temperature (i.e., the temperature-time path) for a growing season, p_{it} is precipitation, z_{it} is a state-specific quadratic time trend, and c_i are county fixed-effects. The growing season for each crop is defined in the followng manner: April to August for corn, May to November for cotton, May to August for Sorghum, July to September for soybean, January to July for spring wheat, and March to May for winter wheat. We allow spatial correlation of the errors following Conley. Over 30 different spatial weight matrices were evaluated by comparing models that only differ by the weight matrix. The weight matrix based on the inverse distance of the seven nearest neighboring counties was selected because it yielded the highest value of the likelihood function at the optimum parameter values.[2]

Equation 1 cannot be estimated directly because of the integral. Therefore, we follow SR and also consider a couple of different specifications to approximate the integral as a sum: a step function allowing different effects at each interval of 1°C (SR1), another step function allowing different effects at intervals of 3°C (SR2), an eighth-degree polynomial (SR3), and a cubic B-spline with eight degrees of freedom (SR4).[3] The specification for SR1 is given below:

$$y_{it} = \sum_{h=0}^{40} g(h+0.5)[\Phi_{it}(h+1) - \Phi_{it}(h)] + p_{it}\delta_1 + p_{it}^2\delta_2 + z_{it}\tau + c_i + \varepsilon_{it} \quad (2)$$

[2]The weighting matrices included eight neighboring structures and four weighting schemes. The following are the neighboring structures: five to ten nearest neighbors, neighbors within a range of 200 km, and neighbors using the Delaunay triangulation. The weighting schemes are binary, inverse distance, inverse squared distance, and inverse square root of distance.

[3]Only SR2 and SR3 are part of the original SR study. In addition, SR developed a piecewise linear model, which yields results that are similar to the other specifications. SR1 was included to assess the effects of narrow temperature intervals of 1°C. SR4 was also included, as it is more flexible and less susceptible to overfitting.

where $\Phi_{it}(h)$ is the cumulative distribution of temperature in county i and year t. Specifications for SR2, SR3, and SR4 and more detailed results for each specification are provided in the appendix 2.

For the SR1 specification, the effects of the data differences explored in section are evident. A thicker right tail for temperature distributions in the NLDAS and NARR data sets results in higher values of $\Phi_{it}(h+1)-\Phi_{it}(h)$ for very high temperatures (e.g., $h \geqslant 35$°C). All else being equal, this should result in lower estimated effects of $g(h+0.5)$. In other words, the detrimental effects of temperature would appear lower at such high values. A similar reasoning applies to the other specifications, although these assume a certain degree of dependence on the effects of neighboring temperature intervals.

2.3. Data

2.3.1. Data Sources

Agricultural data were obtained from the US Department of Agriculture's National Agricultural Statistics Service (USDA-NASS). Because production data for cotton, corn, sorghum, soybean, spring wheat, and winter wheat are available only at the county-level, the hourly gridded weather data must be spatially aggregated for each county. We do so by weighting each weather data grid within a county by the amount of cropland in each grid. The cropland area is derived from the USDA-NASS's 2011 Crop Data Layer, which has a 30-meter resolution. This allows weighting weather data grids according to the amount of farmland they include in constructing county-level observations. Hourly observations are subsequently used to construct exposure to each interval of 1°C for the period March to August for each year and county. The sample period of the data we use for this study is 1980–2005 because of the limited temporal coverage of climate data.

Following SR, we limit the analysis to counties east of the 100° meridian for

corn, soybean, and winter wheat, as cropland in the West often relies on heavily subsidized irrigation systems. We include all counties in the contiguous US for cotton, sorghum, and spring wheat because there are fewer observations and larger shares of these crops are grown in the West. The underlying assumption here is that rainfed and irrigated crop yields are expected to respond differently to exogenous environmental conditions and, thus, their respective parameters must be estimated separately. The resulting data set corresponds to a panel of US rainfed counties for 1980–2005. This sample period is restricted to the overlapping period of the weather data sets used for this study. Figure A1 illustrates the location of the sample counties for each crop.

This study seeks to explore the role of the measurement error of extreme temperature exposure in the estimation of nonlinear temperature effects on crop yields. To do so, we replicate the statistical crop yield models developed in SR using nine different weather data sets.[4] Alternative weather data sets are derived from Daily Surface Weather and Climatological Summaries (Daymet), Global Land Data Assimilation System (GLDAS), North American Land Data Assimilation System (NLDAS), North American Regional Reanalysis (NARR), and Parameter-elevation Regressions on Independent Slopes Model (PRISM). The key features of these data sets, including spatial and temporal resolution and coverage, are summarized in Table 11. All data sets are publicly available for download. The weather data sets are selected based on the following criteria related to spatial and temporal resolution. First, a data set covers at least the contiguous US. Second, a data set measures temperature at the daily level if not at the hourly level. Third, a grid size is, at most, the size of a county. Figure A2 demonstrates the spatial resolution of the selected data sets for a sample county.

It is worth discussing the differences between station-based and reanalysis

[4] The original SR data set was kindly provided by the authors.

weather data sets used in this study. Station-based data are constructed by interpolating or smoothing data from irregularly spaced stations to a regular grid. Reanalysis data are based on the data assimilation that seeks to minimize a loss function subject to a large set of difference equations, which are derived from fundamental physical principles (e.g., the conservation of energy).

To the best of our knowledge, no existing study addresses whether observation or reanalysis data are appropriate to use for the measurement of hourly extreme high temperature, although a few studies address a similar question on daily maximum temperature [Ceccherini et al., Sheridan et al., Walton and Hall, Lader et al.]. Since our objective is to analyze the effects of exposure to hourly temperature intervals on annual crop yields at the county level, the best data set for our study would be one that best represents the hourly temperature in eastern US for the growing season. While station-based data sets often used as the "reference" data set in climatological research, some of them are biased near the coast and in complex terrain due to inaccurate lapse rates and have large unphysical trends due to unhomogenized or missing station data.[5] On the other hand, reanalysis-based data sets may not be suitable for capturing climatologies because of their systematic biases. Which data are sutiable for studying the effects of exposure to extreme high temperature on socioeconomic and biophysical outcomes remains an open and empirical question. At least, the previous literature appears to agree that the use of multiple weather data sets is recommended to understand the uncertainty associated with the reported estimates due to the choice of weather data set [Parkes et al., Massetti et al.].

In our study, NLDAS, NARR, and GLDAS are reanalysis data sets. NLDAS is derived from NARR. Details regarding the NLDAS and NARR are provided in Mitchell et al. and Mesinger et al., respectively. NLDAS was developed to account for the role of soil water in surface energy fluxes, which are important for weather forecasting. NARR

[5] Certain data sets fix this issue by using homogenization algorithms.

was developed to provide a time and spatially consistent weather data set over North America. NLDAS uses a spatially downscaled and temporally disaggregated version of the NARR data set as input and features hourly observations for each 8.6×8.6 mile grid over the contiguous US since January 1, 1979.[6] Cosgrove et al. reveal that the NLDAS data set closely matches the highly precise weather observations of the Department of Energy's Atmospheric Radiation Measurement (ARM) program in the Great Plains.

2.3.2. The Transformation of Temperature Data

SR provide the details of how the weather data set is constructed in the appendix of their paper. In summary, the authors generate daily weather data by interpolating daily and spatially sparse weather station data using monthly and spatially detailed model-generated weather data from PRISM, which is developed at the Oregon State University. The interpolation yields daily precipitation as well as minimum, maximum, and average temperature for each 2.5×2.5 mile grid over the contiguous US for the period 1950–2005. County-level weather data are obtained by aggregating grids covered with agricultural land, as measured by a LandSat satellite image. As discussed in the previous section , the semi-parametric crop yield model relies on variables representing the exposure to individual temperature intervals during the growing season.

To replicate their results, we construct daily county-level weather data by deriving the distribution of temperature exposure for each degree interval. For daily data sets, we fit a double sine curve going through temperature minimum and temperature maximum of subsequent days under the assumption of a sine-shaped temperature curve.[7] For

[6] The source NARR data set features 32-km and 3-hour resolution.

[7] In the appendix of SR, the authors insist that the distribution of temperature for each degree must be performed for each individual grid prior to aggregating at the county level. This procedure is more computationally demanding than the one we describe and yields virtually identical results. The likely reason for this is that there is almost perfect correlation of temperature for bins that are part of the agricultural land of a given county.

each grid cell, we compute the amount of time spent in each interval of 1°C from -15°C to 50°C. For data sets with hourly or trihourly observations—such as GLDAS, NLDAS, and NARR—we perform a linear interpolation between observations and double sine interpolation.

Figure A3 illustrates the comparison of exposure to high temperatures above 30°C among the selected climate data sets used in this study. Since agricultural data is at the county level, gridded climate data sets are aggregated up to the county level. For this aggregation, we take weighted averages using cropland grid counts from the USDA Crop Data Layer for ther period 2008–2014 as weights. Maps of aggregation weights are presented in Figure A4.

2.4. Results

2.4.1. Comparison of Climate Data sets

Figure 1 presents a comparison of temperature distributions across climate data sets for the period 1980–2005. We find that the distribution of extremely high temperature differs across the data sets. Specifically, two groups appear to emerge; the exposure to temperatures above 34°C for March to August based on PRISM, SR, Daymet, and GLDAS is clearly lower than that of NARR and NLDAS. This difference could be partially explained by the fact that data sets in the latter group are all reanalysis or reanalysis-derived data sets, while most of the data sets in the former group are not. GLDAS has a different distribution from that of NLDAS and NARR in the former group as it is a global data set.

There might be systematic differences in extreme temperatures between daily and hourly data sets. For example, the GLDAS daily data set has approximately 1.5 more days above the threshold of 34°C than the GLDAS hourly data set does. This discrepancy was introduced by the difference between the method used to downscale

GLDAS to hourly data and the double sine interpolation method used in our study. In fact, previous literature reveals that the direct measurement of hourly temperature may be necessary if the accurate timing of temperature input to models is critical [Reicosky et al.]. A common practice used to interpolate hourly temperature from daily data is to compute a modified sine curve from minimum and maximum daily temperature, following the method of Running et al. and Parton and Logan, which is different from the sine curve used in the literature and this study [8].

To estimate climate change impacts, we also compute changes in temperature exposure from the current climate to a few climate change scenarios, including uniform increases of 1°C, 3°C, and 5°C. Since we simply compute the temperature changes based on uniform temperature increases, the same two groups of climate data sets mentioned above appear again. Figure 2 depicts greater exposure of NLDAS and NARR to high temperatures above approximately 28°C than that in other data sets. Simultaneously, NLDAS and NARR have less exposure to temperature between approximately 22°C and 28°C as compared to other data sets.

2.4.2. Temperature Response Functions

Figure figure 3 shows the nonlinear effects of temperature on corn yield based on the different climate data sets.[9] Temperature effects exhibit similar thresholds—approximately

[8] For example, Waichler and Wigmosta model daylight air temperature using three quadrants of a sine wave with the minimum value at sunrise, maximum value at solar noon, and mean value at sunset. Sunrise and sunset times were computed with a solar geometry model [Bowling and Lettenmaier, Gates], thereby assuming that the level ground is free from topographic shading. Nighttime air temperature was modeled as a linear interpolation between the sunset temperature of the previous day and the sunrise temperature of the following day. The modified sine curve approach can be viewed as the minimum viable method for generating temperature. Shifting the resulting sine curve to two hours earlier yielded the best match for the observations.

[9] The precipitation response function is omitted, but it remains very flat. We also rely on the precipitation data from the SR data set only so that we isolate the effect of the precipitation difference. Nevertheless, the results based on season-long precipitation variables from the NLDAS data set are virtually identical.

29°C for corn, but detrimental effects of high temperature with SR, PRISM, Daymet, and GLDAS are approximately twice as large as those with NLDAS and NARR. We observe similar differences between the data sets for cotton, sorghum, and soybean as well. These patterns can be attributed to the lower recorded exposure to high temperatures in SR, PRISM, Daymet, and GLDAS than those recorded in NLDAS and NARR.

As expected, the result based on the SR data set is very similar to that reported in SR. Yet, we also observe a sharp decrease in the negative effects at the highest temperature intervals for corn and cotton with SR, PRISM, and Daymet, while we do not observe such a decrease with NLDAS and NARR. It is counterintuitive to observe such a sharp decrease, as we expect that the higher the extreme temperature, the more detrimental its effect becomes.

In section we show that the difference between data sets is not a systematic bias in temperature. Such bias would simply shift the temperature response function horizontally in Figure 3, which it does not. Rather, the evidence clearly implies that the high detrimental effects of temperature obtained by SR stem from the "thinness" of the right tail of the temperature distribution in their data set.

We can also verify that the difference in the right tail of the temperature distribution does not originate from the assumption of a sine-shaped temperature curve because similar results are obtained for daily and hourly data of NLDAS and NARR in Figure 3.

2.4.3. Climate Change Impacts

Figure 4 presents the climate change impacts on crop yields based on the regression estimates and uniform temperature increase scenarios. Overall, most of the differences in climate change impacts across different climate data sets are not statistically different. However, the expected effects based on the different climate data sets vary. Because the

extreme temperature responses with SR, PRISM, Daymet, and GLDAS are much more detrimental, the total negative impacts of climate change with these data sets for corn, cotton, soybean, and winter wheat are higher than those with NLDAS and NARR, even though NLDAS and NARR have higher exposure to high temperature than other data sets. For example, with a uniform temperature increase of 1°C, the negative impact with NLDAS and NARR data sets is approximately half of that with SR, PRISM, Daymet, and GLDAS.

We also examine the contribution of each temperature interval to the overall climate change impacts. Figure 5 presents the climate change impacts disaggregated by temperature interval under a uniform temperature increase of 5°C. We observe a similar pattern here: differences in the total impacts—that is, the distribution of the impacts across temperature intervals—appears to be fairly similar for each crop in general.

Further, we examine the spatial distribution of the climate change impacts on crop yields. For corn, sorghum, soybean, and winter wheat, we tend to find more negative impacts in southern counties that already have warm climate, while northern counties benefit from temperature increases (Figures A5, A7, A8 and A10). For cotton, counties in the East are more negatively impacted than those in the West. This can be due to the availability of irrigation in the West, but further analysis is required to untangle the precise mechanism (Figure A6). For spring wheat that is cropped in the northern part of the country, a temperature increase of 1°C is beneficial, while temperature increases of 3°C and 5°C increases can be harmful (Figure A9).

We also find heterogeneous impacts across different climate data sets. NLDAS and NARR show more detrimental effects for corn, sorghum, and soybean in southern counties than SR, PRISM, and Daymet do. For cotton, NLDAS and NARR have more negative effects than other data sets across the country, while the spatial pattern is similar. For spring and winter wheat, the spatial distribution of impacts is relatively similar across weather data sets. This spatial heterogeneity appears to contribute to differences

in the overall climate change impact across the data sets discussed above.

2.5. Discussion and Conclusion

SR have made an important methodological contribution by indicating, with large-scale weather and production observational data, that temperature has highly nonlinear effects on crop yields. They find that major US crops would be dramatically affected under climate change with yield losses in the range of 30–82 percent, depending on the crop and climate scenario. However, this study shows that their quantitative result is highly sensitive to the choice of weather data set. More specifically, the replication of their model based on alternative weather data sets shows less detrimental responses of crop yields to extreme high temperature as well as smaller mean effects of climate change on crop yields.

A closer examination of the differences in temperature distributions between the SR and other climate data sets reveals that the critical difference is that reanalysis data sets, such as NLDAS and NARR, have a slightly "thicker" right tail. The difference is small in absolute terms, but it is large relative to the total exposure to high temperature above the specified temperature thresholds. Such differences are shown to be the source of the discrepancy in the regression results as well as in the mean effects of climate change.

The implications of these results for climate change impact assessments on agriculture are important. A long debate on the climate change impacts on agriculture in the US has been partially due to the differences in the climate data sets used [Mendelsohn et al., Schlenker et al., a, Deschenes and Greenstone, Fisher et al., Massetti et al., Ortiz-Bobea et al.] SR and related studies suggest that extreme temperature is the greatest threat to agriculture under climate change. The evidence they present highlights the highly negative effects of extreme high temperature on crop yields, which

is also reflected in hedonic models of agricultural land prices. In parallel, they find that precipitation changes play a small role, even for rainfed areas. Thus, the accepted wisdom is that climate change impacts are primarily driven by the shift of the temperature distribution to the right. This would increase the frequency of exposure to detrimental temperature levels and generate large losses to the sector.

However, the simple replication performed in this study, based on alternative data sets from highly respected sources employing advanced interpolation techniques, indicates that the estimated mean effecst of climate change on crop yields could be approximately half of those reported by SR. More importantly, the results of this study raise questions regarding the robustness of models similar to SR to alternative weather data sets, as results appear highly dependent on small differences in extreme temperature recordings.

The implications of this study provide suggestions for future research. The economics community would greatly benefit from a better understanding of the suitability of various weather data sets to the study of the effects of extreme temperature on crop yields, particularly at the temporally and spatially disaggregated levels. For example, accounting for uncertainty and the measurement error associated with spatial climate variables could potentially lead to unbiased estimates of temperature response functions and inferences of climate change impacts [Stoklosa et al.]. There are clearly large differences in climatology among weather data sets, including station-based and reanalysis data, but it is difficult to definitively ascertain which data set is most realistic, particularly when the location is at a distance from the station locations [Walton and Hall]. Thus, data uncertainty could be explicitly incorporated in the econometric model if and where such measures are available. Lastly, it would also be useful to obtain a better understanding of which method must be used to interpolate hourly temperature from daily maximum and minimum temperature data.

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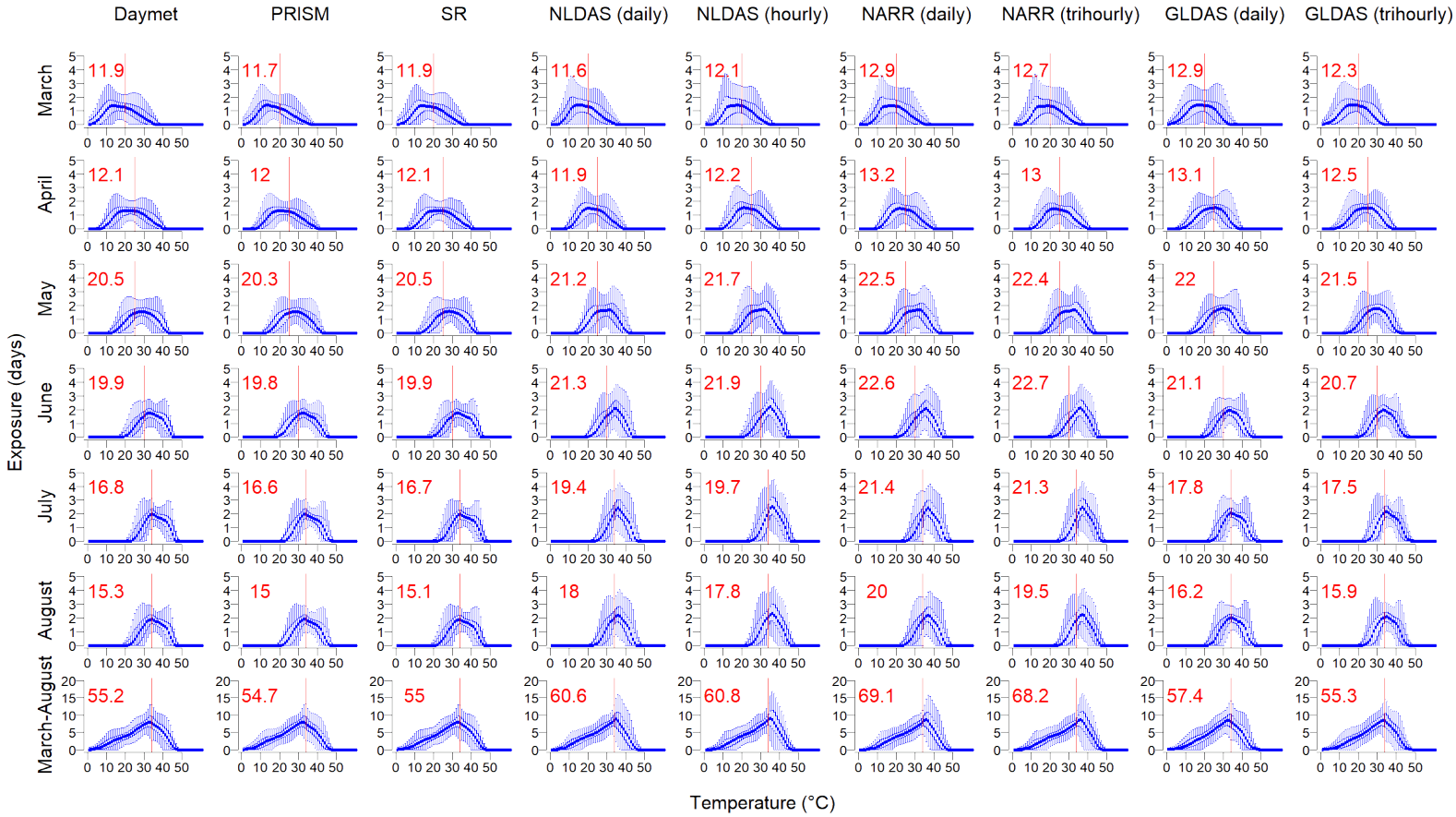
Table 1: Climate datasets used for this study

Name	Abbreviation	Spatial		Temporal		Type	Reference
		Resolution	Coverage	Resolution	Coverage		
Daily Surface Weather and Climatological Summaries	Daymet	1 km	North America, Hawaii, Puerto Rico	Daily	1980-present	Station-based	Thornton et al.
Global Land Data Assimilation System	GLDAS	0.25° (~28 km)	Global	3-hour, daily	1979-present	Reanalysis	Rodell et al.
North American Land Data Assimilation System	NLDAS	0.125° (~14 km)	North America	1-hour, daily	1979-present	Reanalysis	Mitchell et al.
North American Regional Reanalysis	NARR	32 km	North America	3-hour, daily	1979-present	Reanalysis	Mesinger et al.
Parameter-elevation Regressions on Independent Slopes Model	PRISM	4 km	Contiguous US	Daily	1950-present	Station-based	Group
Schlenker and Roberts (2009)	SR	4 km	Contiguous US	Daily	1950-2005	Station-based	Schlenker and Roberts

Table 2: Climate change impacts on yields by crop type and climate dataset

Climate data	Crop	1°C increase			3°C increase			5°C increase		
		Lower	Mean	Upper	Lower	Mean	Upper	Lower	Mean	Upper
Daymet	Corn	-7.79	-5.85	-3.88	-29.05	-24.43	-19.50	-51.50	-45.89	-39.64
GLDAS (daily)	Corn	-6.33	-4.50	-2.63	-25.29	-20.56	-15.53	-47.72	-41.48	-34.51
GLDAS (trihourly)	Corn	-6.70	-4.88	-3.01	-26.81	-22.17	-17.24	-50.17	-44.20	-37.52
NARR (daily)	Corn	-5.80	-3.57	-1.29	-22.38	-16.84	-10.90	-40.90	-33.76	-25.75
NARR (trihourly)	Corn	-6.00	-3.70	-1.34	-23.10	-17.38	-11.24	-42.02	-34.70	-26.45
NLDAS (daily)	Corn	-5.81	-3.59	-1.32	-22.64	-17.11	-11.18	-41.57	-34.36	-26.26
NLDAS (hourly)	Corn	-6.18	-3.81	-1.39	-23.95	-18.07	-11.73	-43.56	-36.03	-27.48
PRISM	Corn	-7.24	-5.25	-3.21	-26.99	-22.06	-16.80	-47.65	-41.26	-34.09
SR	Corn	-7.54	-5.59	-3.60	-28.32	-23.60	-18.58	-50.38	-44.56	-38.07
Daymet	Cotton	-12.39	-9.34	-6.18	-38.11	-31.11	-23.31	-56.77	-48.35	-38.29
GLDAS (daily)	Cotton	-10.82	-7.57	-4.21	-35.87	-28.64	-20.59	-56.17	-47.85	-37.95
GLDAS (trihourly)	Cotton	-10.94	-7.66	-4.26	-35.75	-28.43	-20.27	-56.29	-47.86	-37.80
NARR (daily)	Cotton	-8.52	-5.21	-1.79	-29.80	-22.54	-14.53	-49.60	-41.52	-32.14
NARR (trihourly)	Cotton	-8.93	-5.73	-2.42	-30.92	-24.00	-16.39	-50.81	-43.03	-34.02
NLDAS (daily)	Cotton	-8.92	-5.83	-2.63	-31.19	-24.29	-16.69	-51.88	-44.02	-34.88
NLDAS (hourly)	Cotton	-9.50	-6.41	-3.22	-32.70	-25.98	-18.58	-53.43	-45.82	-36.97
PRISM	Cotton	-12.65	-9.67	-6.58	-37.92	-31.00	-23.31	-55.31	-46.94	-36.99
SR	Cotton	-13.04	-10.04	-6.94	-39.36	-32.53	-24.93	-58.09	-49.93	-40.18
Daymet	Sorghum	-8.18	-5.69	-3.13	-26.31	-20.05	-13.27	-44.41	-36.03	-26.37
GLDAS (daily)	Sorghum	-8.82	-5.95	-2.99	-26.96	-19.76	-11.86	-43.97	-34.56	-23.57
GLDAS (trihourly)	Sorghum	-9.01	-6.29	-3.49	-27.98	-21.28	-13.96	-46.12	-37.47	-27.43
NARR (daily)	Sorghum	-9.07	-5.99	-2.80	-30.66	-21.32	-10.71	-52.43	-37.69	-18.36
NARR (trihourly)	Sorghum	-9.88	-6.86	-3.74	-31.80	-22.85	-12.72	-52.63	-38.61	-20.43
NLDAS (daily)	Sorghum	-8.48	-5.81	-3.05	-28.68	-21.37	-13.30	-49.83	-38.85	-25.46
NLDAS (hourly)	Sorghum	-9.41	-6.63	-3.77	-31.05	-23.29	-14.67	-53.28	-41.20	-26.00
PRISM	Sorghum	-6.66	-4.22	-1.73	-20.73	-14.79	-8.41	-35.44	-27.55	-18.70
SR	Sorghum	-8.18	-5.60	-2.94	-26.33	-19.84	-12.77	-44.39	-35.72	-25.70
Daymet	Soybeans	-5.46	-3.77	-2.05	-20.86	-16.68	-12.29	-37.93	-32.65	-26.92
GLDAS (daily)	Soybeans	-4.75	-3.27	-1.77	-19.46	-15.70	-11.77	-37.49	-32.54	-27.20
GLDAS (trihourly)	Soybeans	-5.09	-3.58	-2.04	-20.56	-16.78	-12.81	-39.22	-34.31	-29.00
NARR (daily)	Soybeans	-4.22	-2.61	-0.98	-15.78	-11.75	-7.51	-28.83	-23.40	-17.56
NARR (trihourly)	Soybeans	-4.32	-2.65	-0.95	-16.07	-11.83	-7.36	-29.42	-23.57	-17.22
NLDAS (daily)	Soybeans	-4.28	-2.71	-1.11	-16.44	-12.52	-8.43	-30.51	-25.36	-19.83
NLDAS (hourly)	Soybeans	-4.50	-2.85	-1.17	-17.04	-12.92	-8.59	-31.38	-25.96	-20.10
PRISM	Soybeans	-5.58	-3.90	-2.18	-21.51	-17.29	-12.85	-39.57	-33.95	-27.81
SR	Soybeans	-5.03	-3.38	-1.71	-19.67	-15.51	-11.13	-36.33	-30.98	-25.17
Daymet	Spring wheat	-1.99	1.01	4.10	-13.23	-5.70	2.47	-30.84	-21.48	-10.84
GLDAS (daily)	Spring wheat	-2.49	0.32	3.22	-11.64	-3.87	4.58	-25.45	-14.65	-2.29
GLDAS (trihourly)	Spring wheat	-2.66	0.68	4.14	-11.62	-2.60	7.34	-24.27	-12.42	1.29
NARR (daily)	Spring wheat	-3.52	-1.95	-0.35	-14.85	-10.62	-6.17	-28.64	-22.01	-14.76
NARR (trihourly)	Spring wheat	-3.17	-1.61	-0.02	-13.67	-9.40	-4.92	-26.68	-20.12	-12.98
NLDAS (daily)	Spring wheat	-2.45	-0.86	0.76	-12.76	-8.61	-4.27	-27.68	-21.60	-15.01
NLDAS (hourly)	Spring wheat	-1.98	-0.39	1.23	-11.30	-7.14	-2.79	-25.83	-19.80	-13.29
PRISM	Spring wheat	-0.99	2.43	5.96	-9.53	-1.02	8.29	-25.23	-14.86	-3.06
SR	Spring wheat	-1.50	1.32	4.21	-11.51	-4.39	3.30	-28.64	-19.54	-9.27
Daymet	Winter wheat	-4.69	-2.89	-1.06	-16.31	-11.06	-5.49	-30.55	-21.94	-12.26
GLDAS (daily)	Winter wheat	-5.98	-4.10	-2.18	-18.27	-12.83	-7.02	-30.27	-21.44	-11.50
GLDAS (trihourly)	Winter wheat	-5.77	-3.88	-1.95	-17.68	-12.15	-6.25	-29.44	-20.39	-10.19
NARR (daily)	Winter wheat	-3.97	-2.47	-0.96	-13.44	-8.83	-3.96	-24.80	-17.08	-8.56
NARR (trihourly)	Winter wheat	-4.02	-2.55	-1.06	-13.46	-8.99	-4.29	-24.76	-17.31	-9.12
NLDAS (daily)	Winter wheat	-3.68	-2.26	-0.82	-12.74	-8.34	-3.72	-24.01	-16.62	-8.52
NLDAS (hourly)	Winter wheat	-4.04	-2.60	-1.13	-13.46	-9.11	-4.53	-24.76	-17.51	-9.56
PRISM	Winter wheat	-4.44	-2.78	-1.09	-15.75	-10.75	-5.45	-29.78	-21.38	-11.98
SR	Winter wheat	-4.82	-3.06	-1.26	-16.70	-11.51	-5.99	-31.04	-22.58	-13.07

Figure 1: Temperature distribution in the eastern U.S. by month and climate dataset



Note: Thresholds: 20°C for March, 25°C for April and May, 30°C for June, 34°C for July, August and March-August. Numbers in red show the total numbers of days exposed above the thresholds. For each temperature interval, the range between minimum and maximum time across counties and years is shown by whiskers, the 25%-75% percentile range is outlined by a box, and the median is added as a solid bold line. The sample counties are east of the 100° meridian.

Figure 2: Temperature exposure changes under a 3°C uniform increase

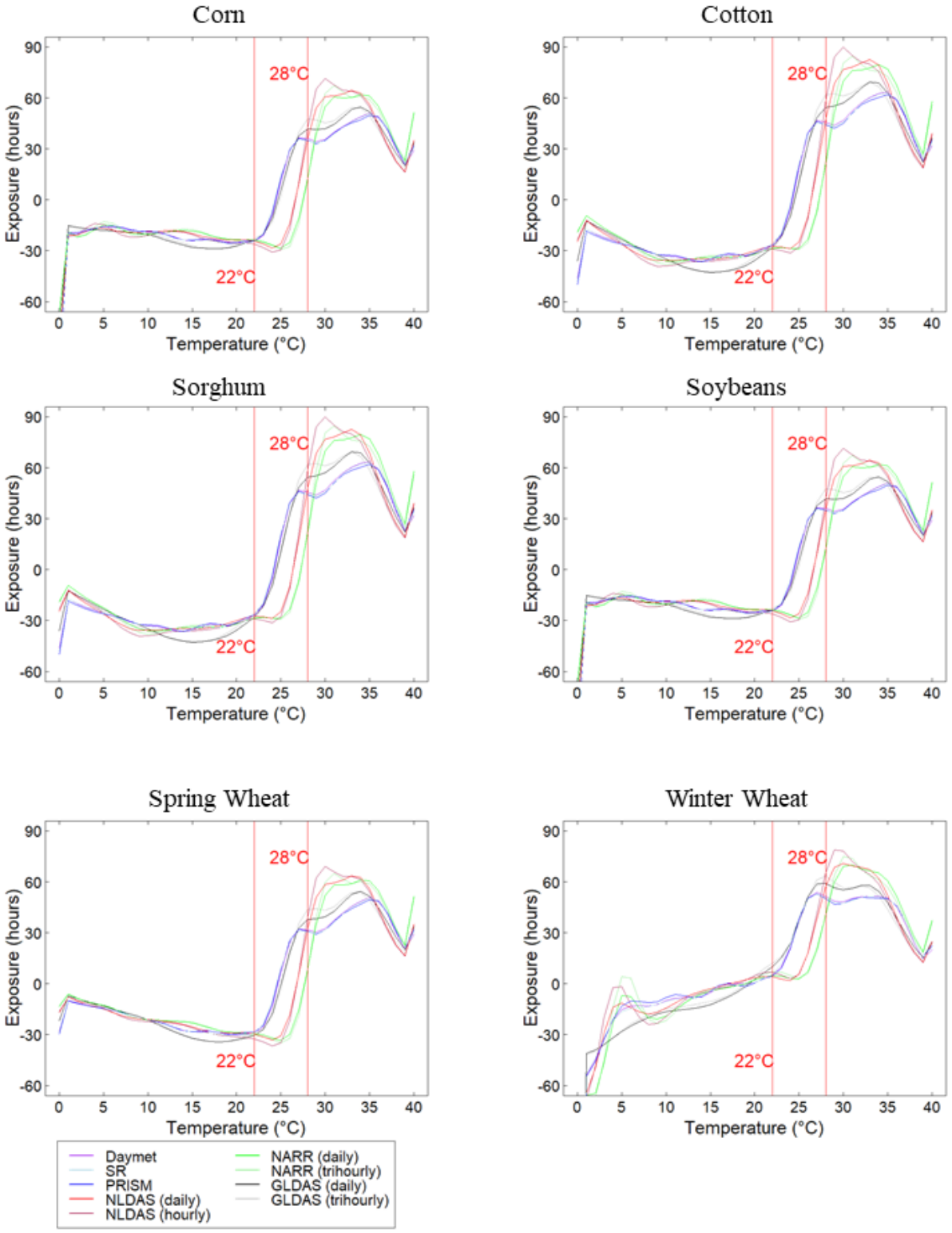
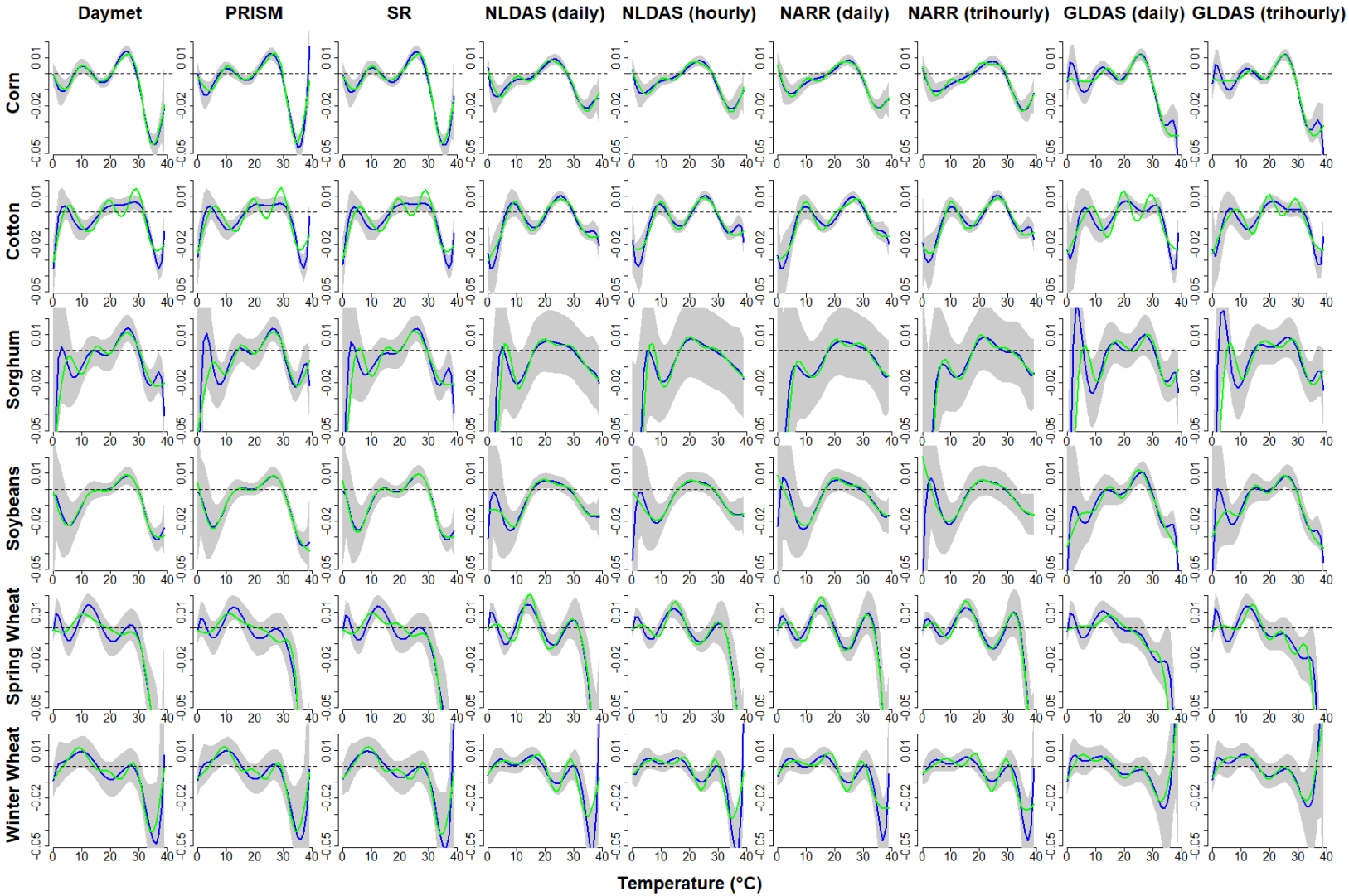
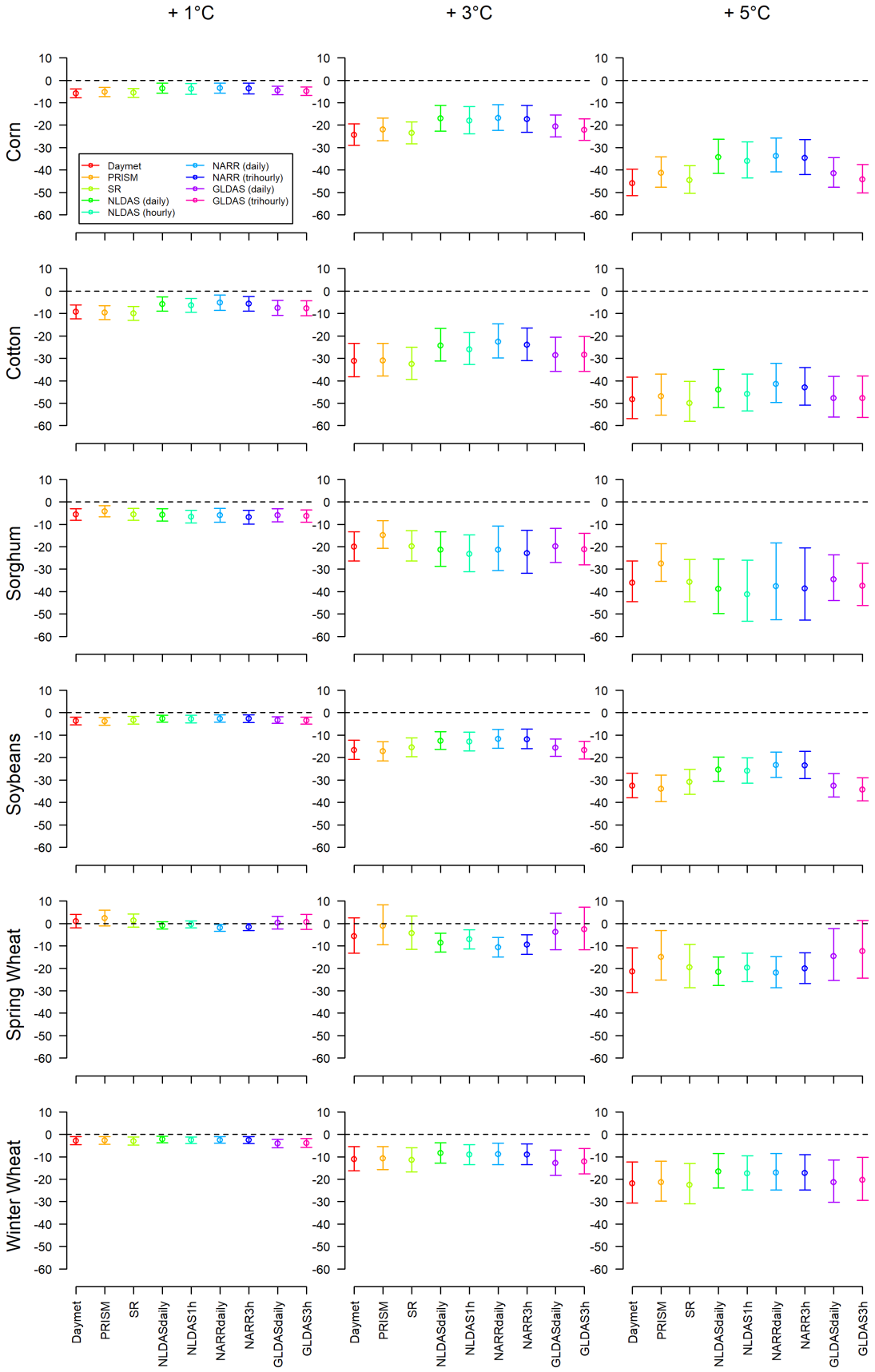


Figure 3: Nonlinear temperature effects on yields by crop and climate dataset



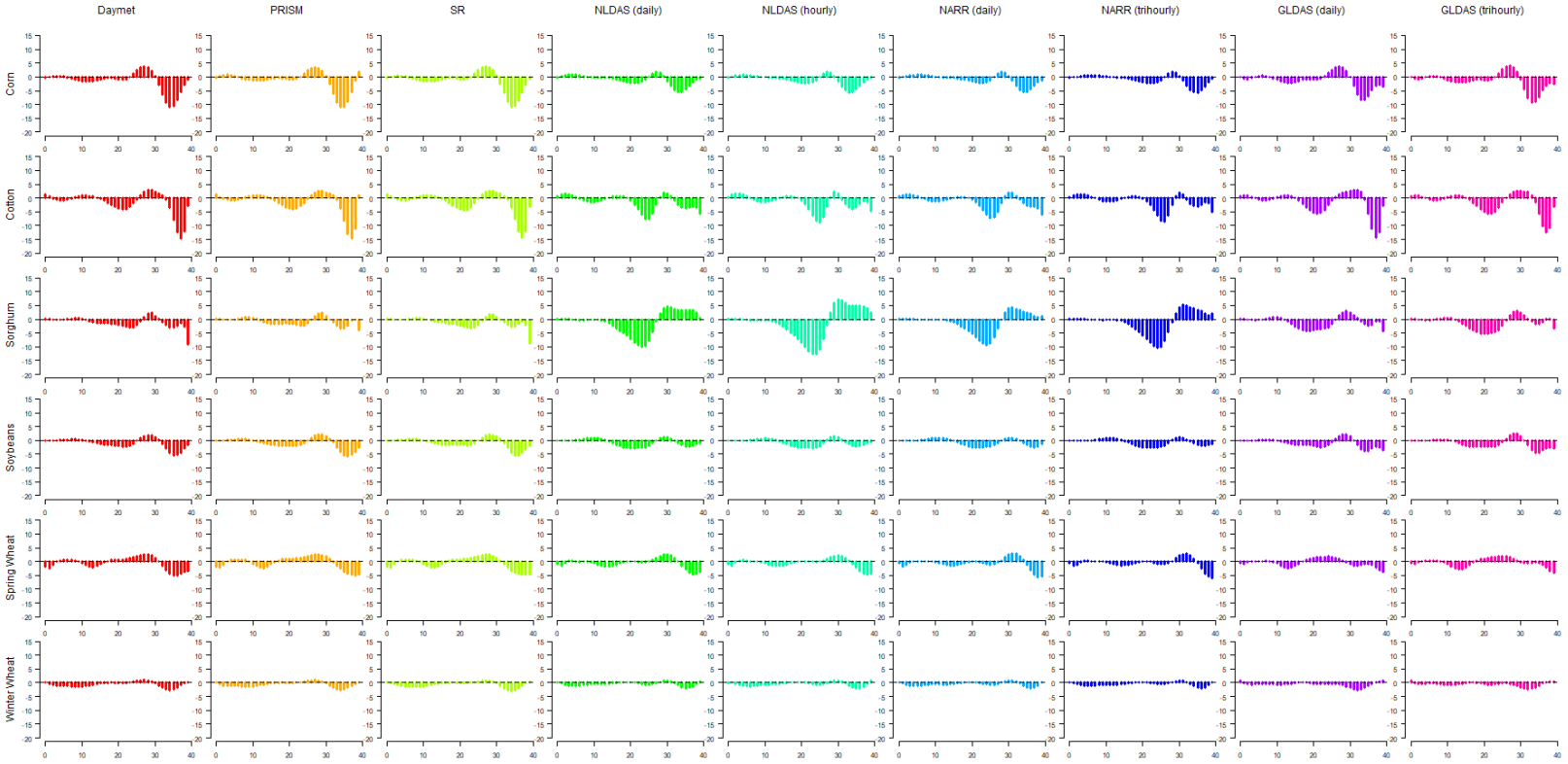
Note: Blue and green lines are based on an eighth-degree polynomial (SR3) and a cubic B-spline with eight degrees of freedom (SR4), respectively. The 95% confidence band, after adjusting for spatial correlation, is added as gray area for the eighth-degree polynomial regression.

Figure 4: Climate change impacts on yields by crop type and cliamte dataset



Note: Estimates are based on an eighth-degree polynomial (SR3). The circles indicate the point estimates. Whiskers show the 95% confidence interval after adjusting for spatial correlation.

Figure 5: Climate change impacts on crop yields by temperature interval under a uniform temperature increase of 5°C



Note: Estimates are based on an eighth-degree polynomial (SR3).

Appendix

Regression Models

The specification for the model with a step function, thereby enabling different effects at each interval of 3°C (SR2) is given below:

$$y_{it} = \sum_{h=0,3,6,9...}^{39} \gamma_h \underbrace{[\Phi_{it}(h+3) - \Phi_{it}(h)]}_{x_{it,h}} + p_{it}\delta_1 + p_{it}^2\delta_2 + z_{it}\tau + c_i + \varepsilon_{it} \tag{3}$$

The model effectively regresses yield on the time spent within each interval in a given county and year $x_{it,h}$.

Model SR3 assumes that the "yield growth" function $g(h)$ is an eighth-degree polynomial of the form $g(h) = \sum_{j=1}^{8} \gamma_j T_j(h)$, where $T_j()$ is the jth order Chebyshev polynomial. Replacing $g(h)$ with this expression yields

$$\begin{aligned} y_{it} &= \sum_{h=-1}^{39} \sum_{j=1}^{8} \gamma_j T_j(h+0.5)[\Phi_{it}(h+1) - \Phi_{it}(h)] + p_{it}\delta + z_{it}\tau + c_i + \varepsilon_{it} \\ &= \sum_{j=1}^{8} \gamma_j \underbrace{\sum_{h=-1}^{39} T_j(h+0.5)[\Phi_{it}(h+1) - \Phi_{it}(h)]}_{x_{it,j}} + p_{it}\delta + z_{it}\tau + c_i + \varepsilon_{it}. \end{aligned} \tag{4}$$

The model effectively regresses yield on eight temperature variables $x_{it,j}$ which represent the jth-order Chebyshev polynomial evaluated at each temperature bin.

In a similar fashion, model SR4 assumes that $g(h) = \sum_{j=1}^{8} \gamma_j S_j^3(h)$ where $S_j^3()$ is the piece-wise cubic polynomial evaluated for each jth interval, which is defined by eight control points.

$$y_{it} = \sum_{j=1}^{8} \gamma_j \underbrace{\sum_{h=-1}^{39} S_j(h+0.5)[\Phi_{it}(h+1) - \Phi_{it}(h)]}_{x_{it,j}} + p_{it}\delta + z_{it}\tau + c_i + \varepsilon_{it} \tag{5}$$

Figure A1: Harvested area by crop

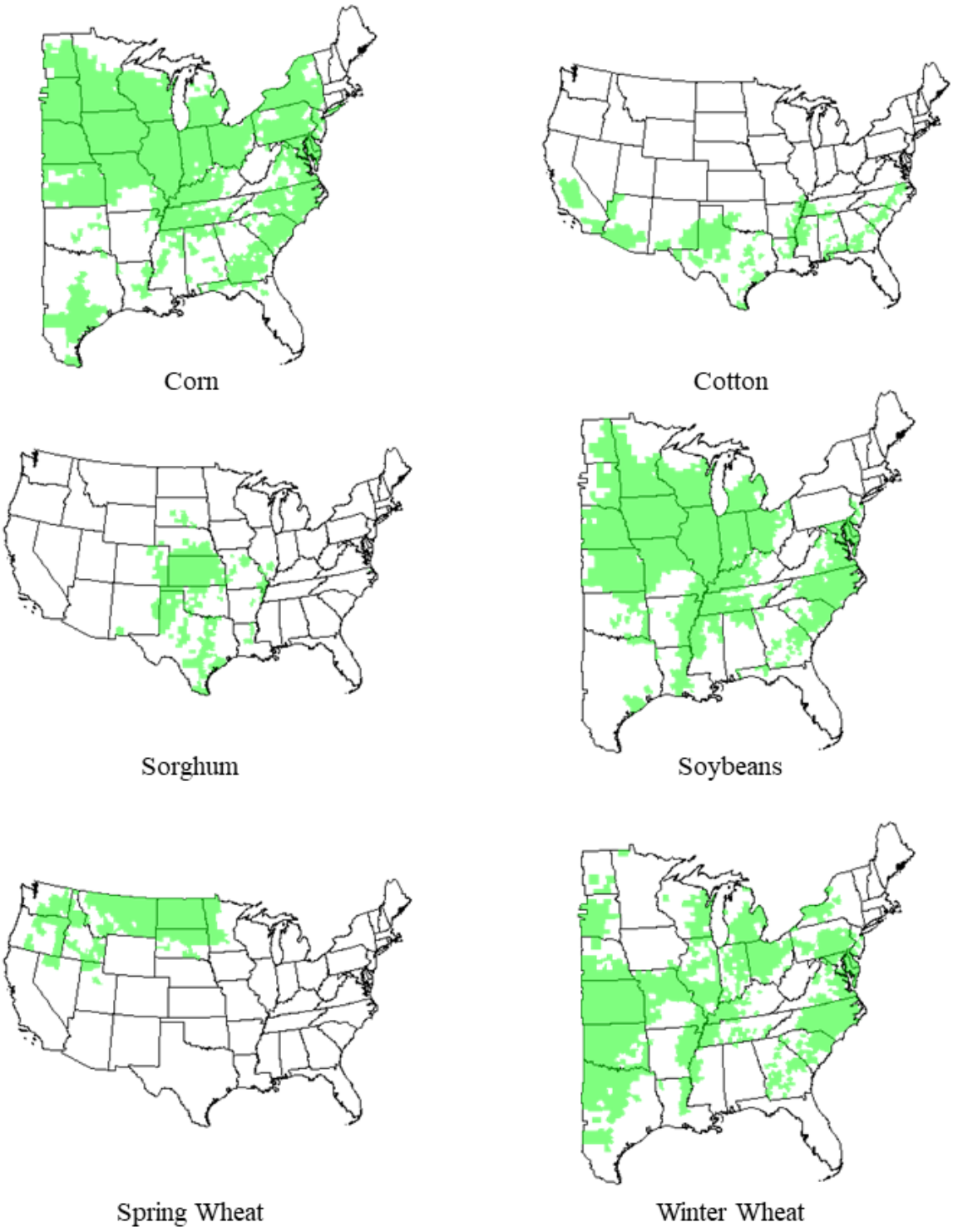
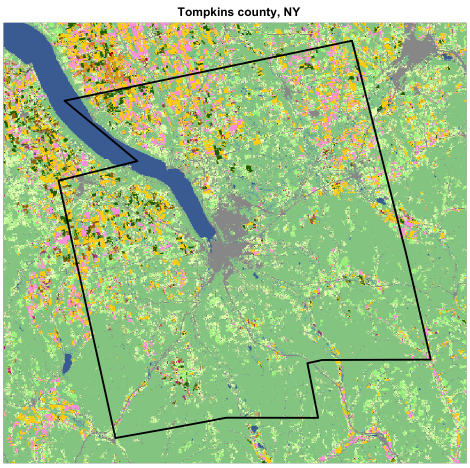
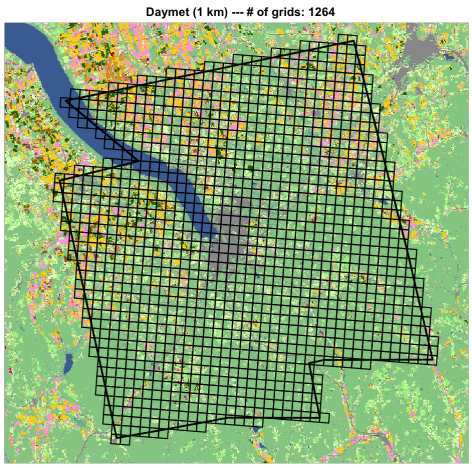


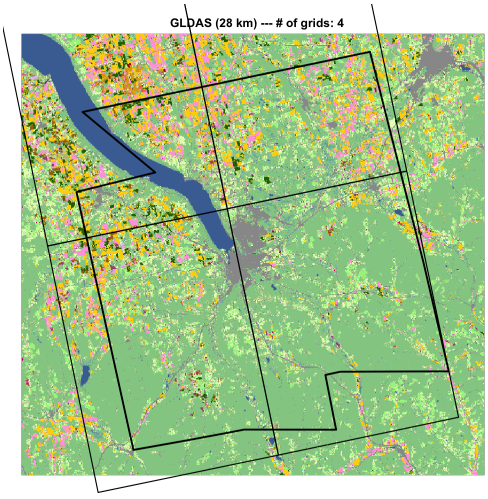
Figure A2: Spatial resolution of the selected climate datasets



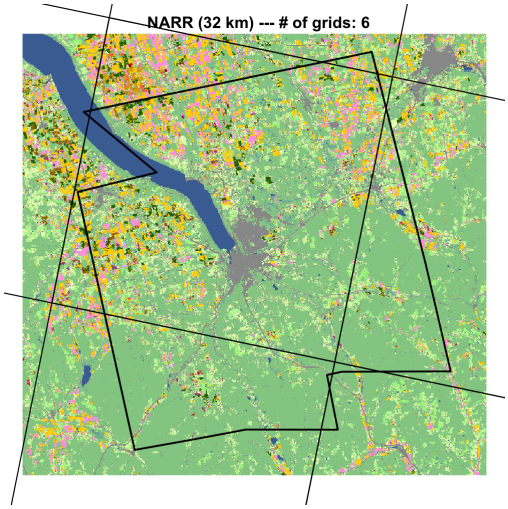
Base map



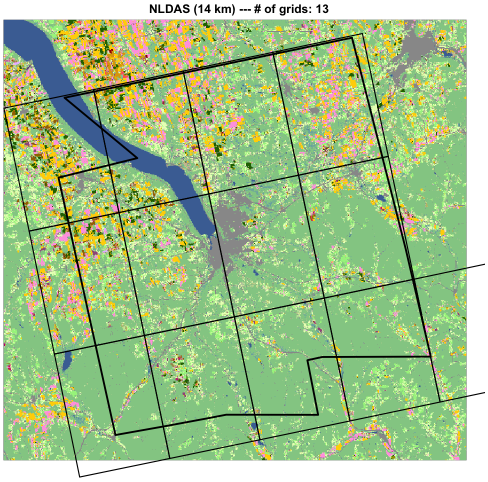
Daymet



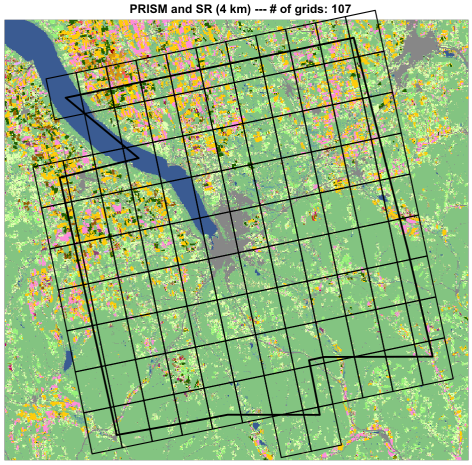
GLDAS



NARR

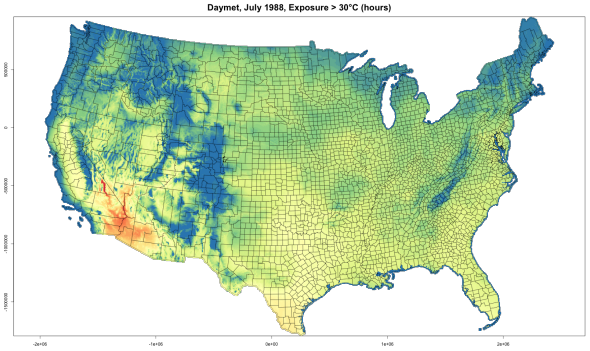


NLDAS

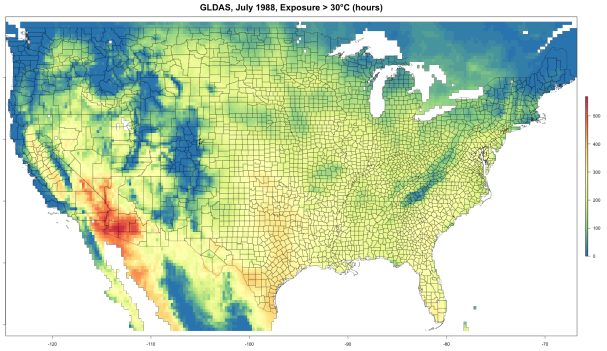


PRISM

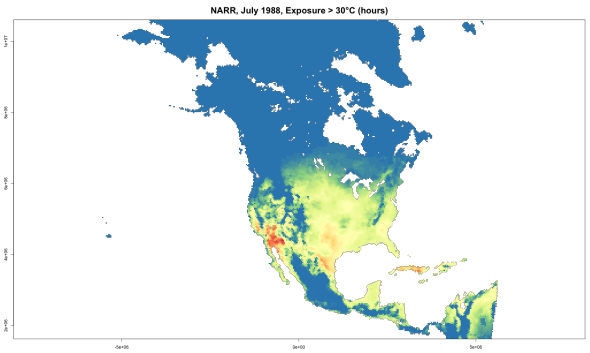
Figure A3: Comparison of high temperature exposure between climate datasets used in this study



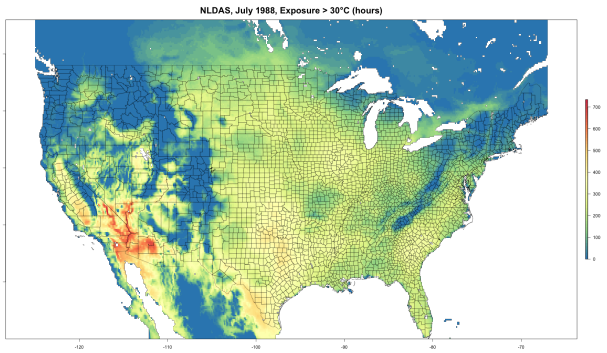
Daymet



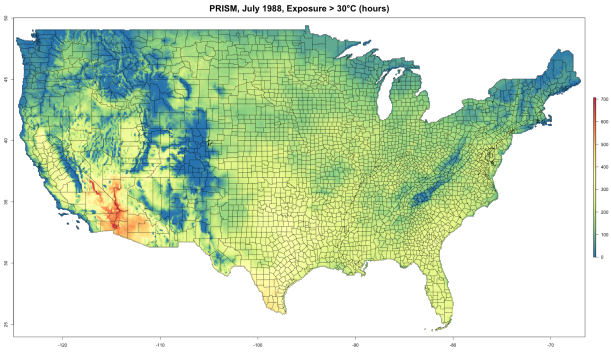
GLDAS



NARR

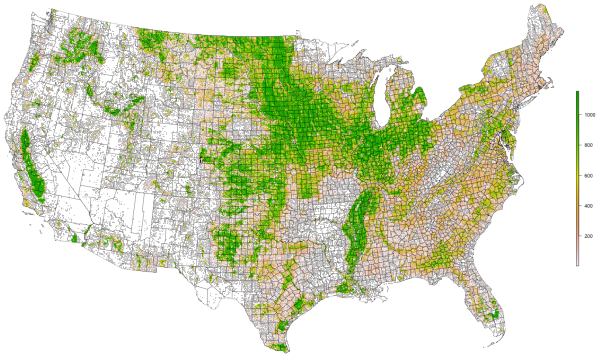


NLDAS



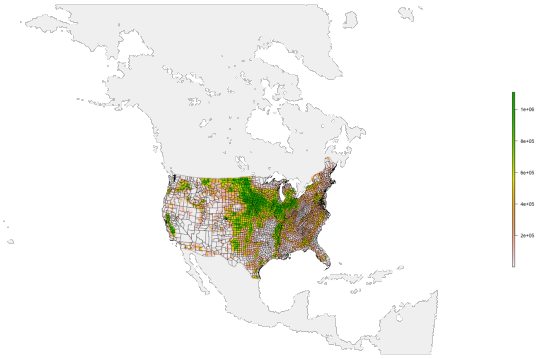
PRISM

Figure A4: Aggregation weights produced from the USDA Crop Data Layer for 2008-2014

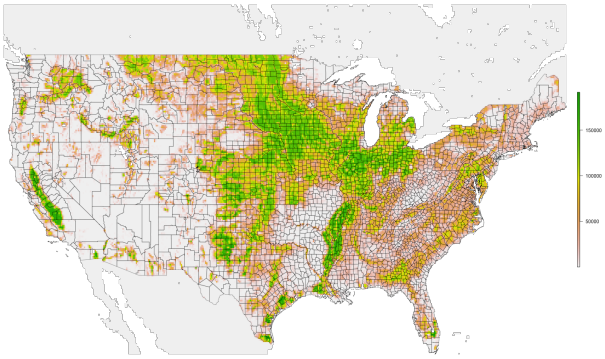


Daymet

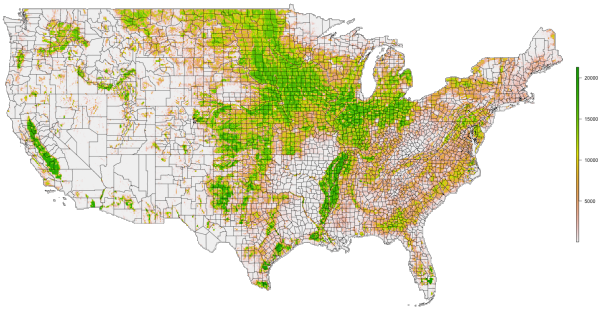
GLDAS



NARR



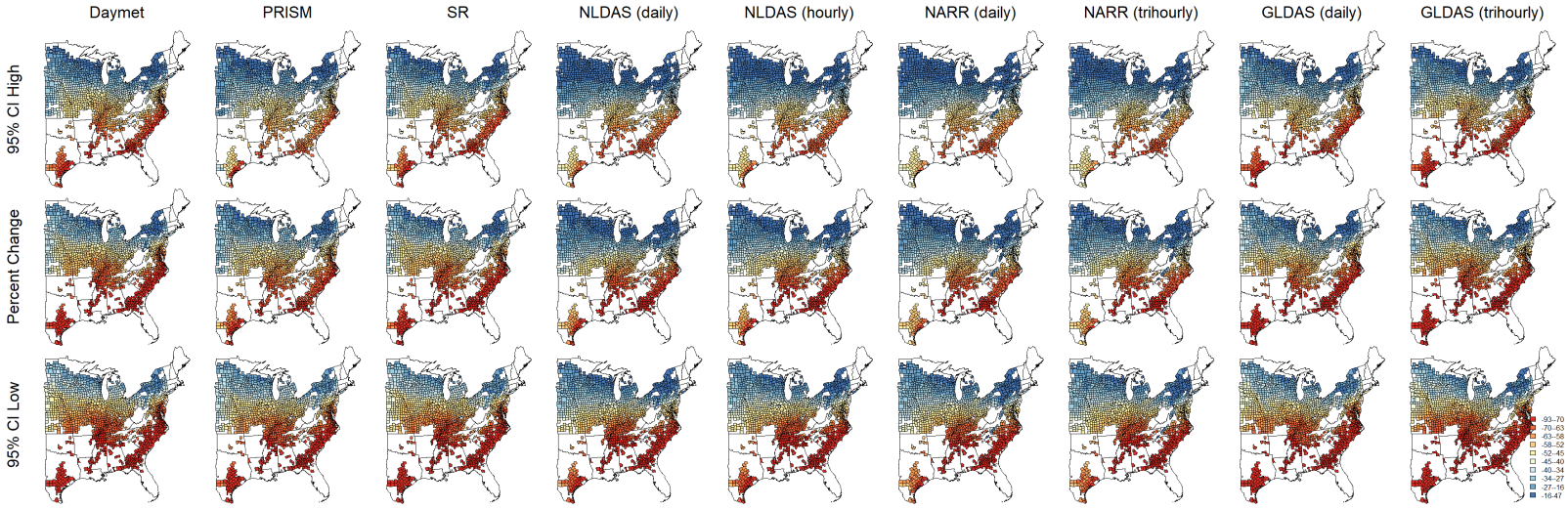
NLDAS



PRISM

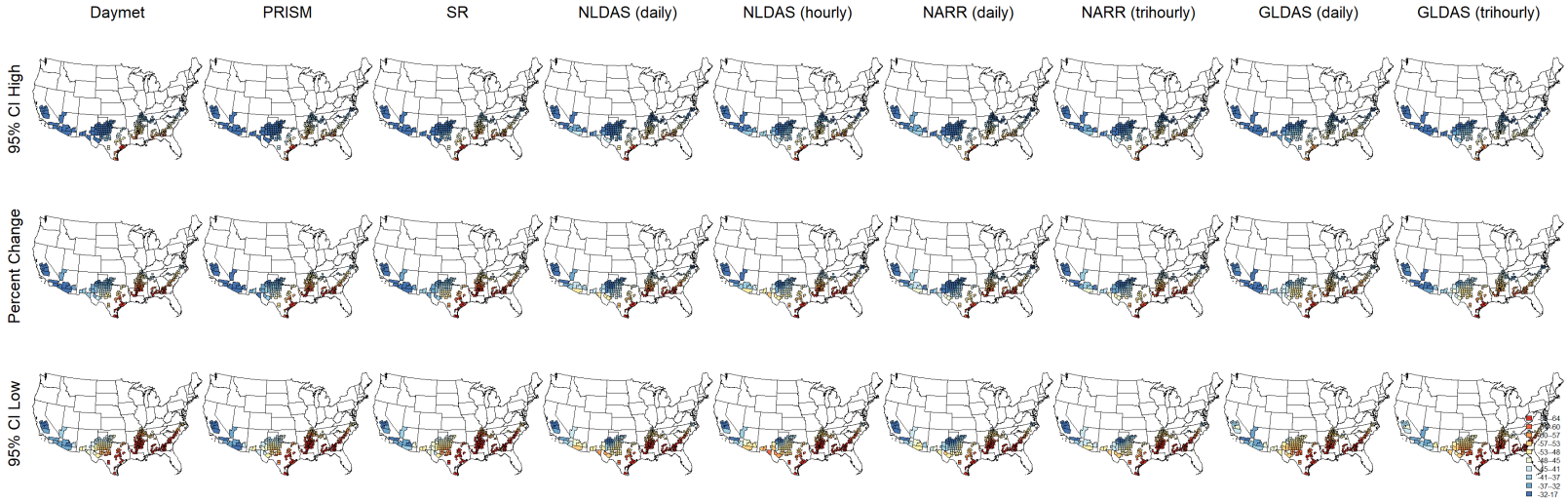
Note: A legend of each maps indicates a total number of cropland cells in each county. Grid sizes of climate datasets are shown in Table 1.

Figure A5: Climate change impacts on corn yields



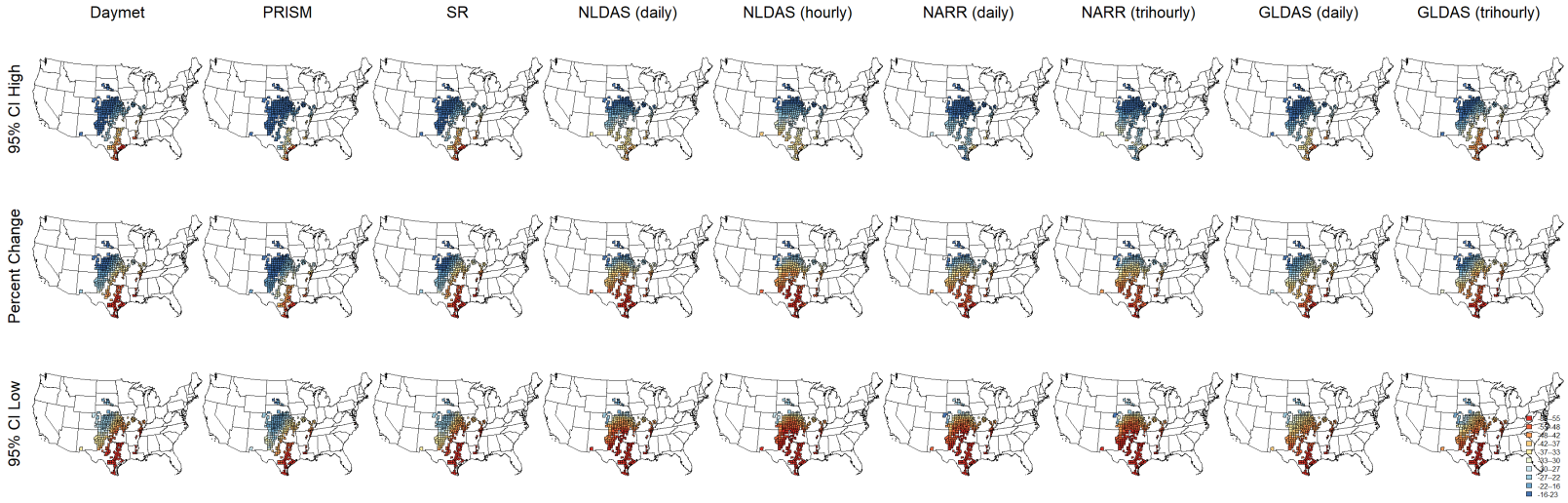
Note: Estimates are based on an eighth-degree polynomial (SR3). Maps in the middle row show the predicted climate change impacts in percentage. Maps in the top and bottom rows show the upper and lower bounds of the 95% confidence interval.

Figure A6: Climate change impacts on cotton yields



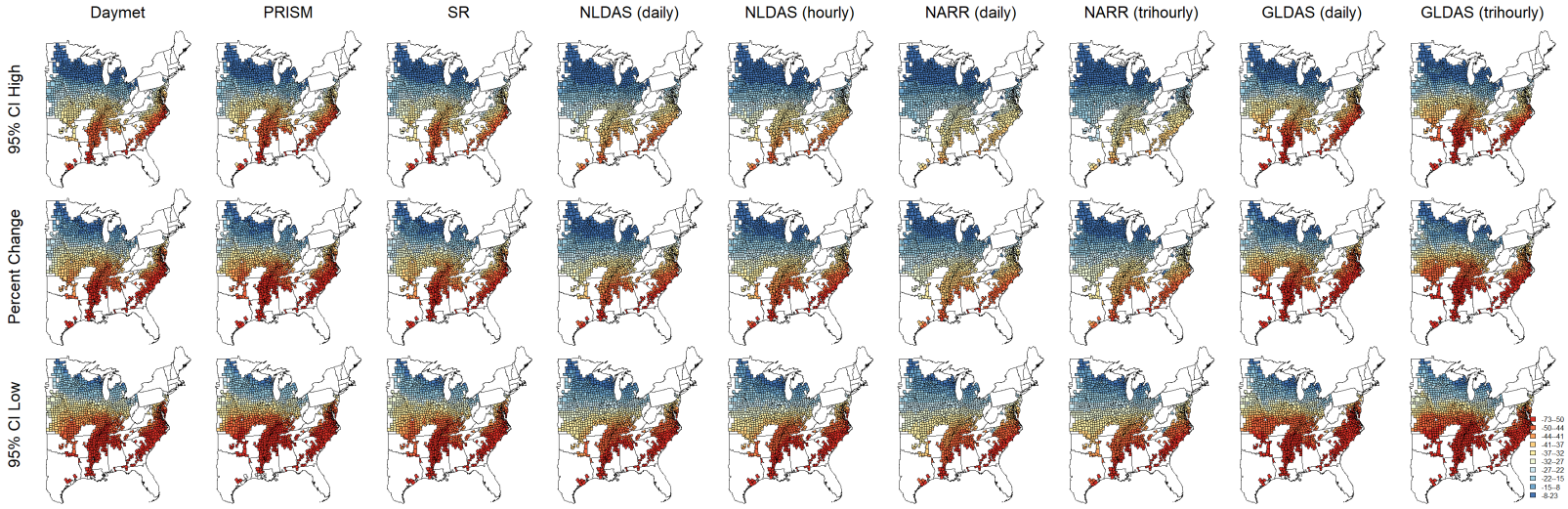
Note: Estimates are based on an eighth-degree polynomial (SR3). Maps in the middle row show the predicted climate change impacts in percentage. Maps in the top and bottom rows show the upper and lower bounds of the 95% confidence interval.

Figure A7: Climate change impacts on sorghum yields



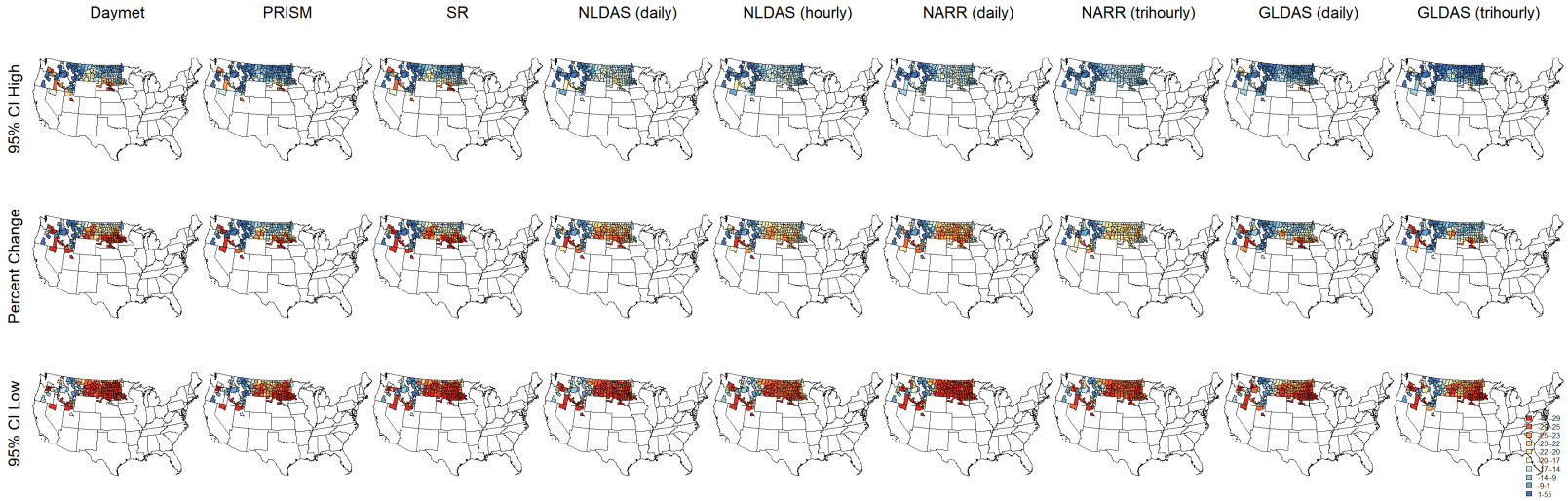
Note: Estimates are based on an eighth-degree polynomial (SR3). Maps in the middle row show the predicted climate change impacts in percentage. Maps in the top and bottom rows show the upper and lower bounds of the 95% confidence interval.

Figure A8: Climate change impacts on soybeans yields



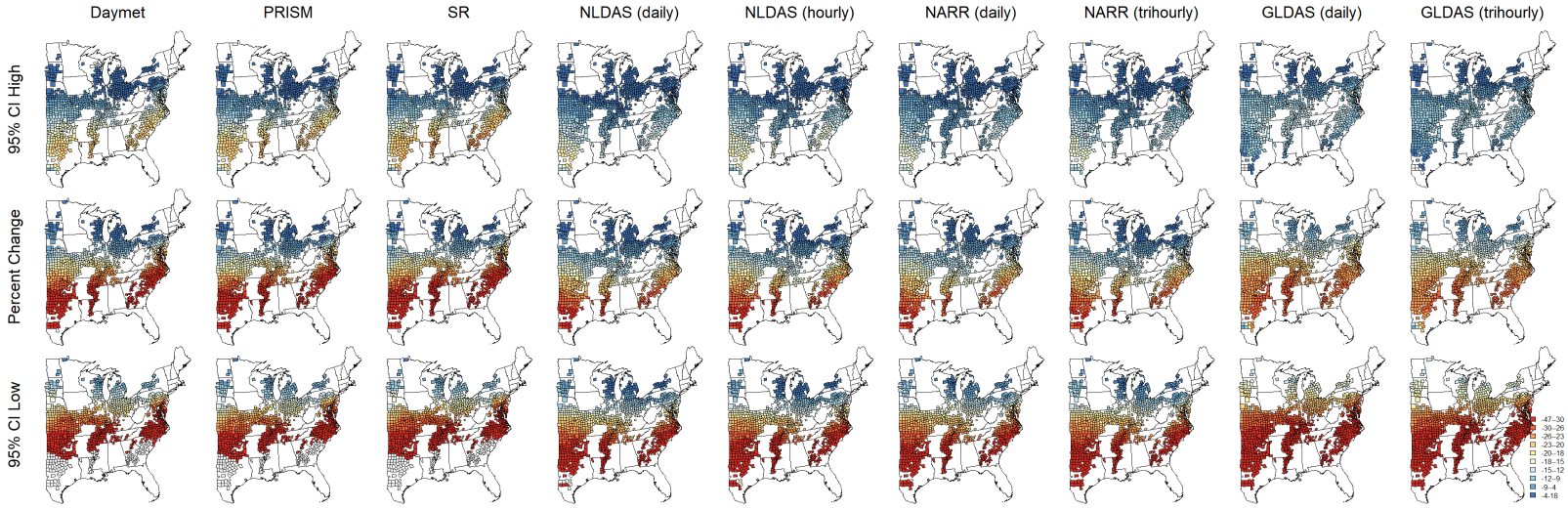
Note: Estimates are based on an eighth-degree polynomial (SR3). Maps in the middle row show the predicted climate change impacts in percentage. Maps in the top and bottom rows show the upper and lower bounds of the 95% confidence interval.

Figure A9: Climate change impacts on spring wheat yields



Note: Estimates are based on an eighth-degree polynomial (SR3). Maps in the middle row show the predicted climate change impacts in percentage. Maps in the top and bottom rows show the upper and lower bounds of the 95% confidence interval.

Figure A10: Climate change impacts on winter wheat yields



Note: Estimates are based on an eighth-degree polynomial (SR3). Maps in the middle row show the predicted climate change impacts in percentage. Maps in the top and bottom rows show the upper and lower bounds of the 95% confidence interval.

CHAPTER 3

3. Estimating the Impact of Droughts and Floods on African Farmers

3.1 Introduction

Climate change, along with impacts of climate risks, such as droughts and floods, have been widely recognized and acknowledged worldwide. The average global temperature has increased by almost 1°C since 1901 and is projected to continue increasing anywhere in the range of 2°C–5°C by the end of the twenty-first century, depending on the effectiveness of the methods to reduce greenhouse or heat-trapping gases (The United States Global Change Research Program [USGCRP], 2018). Temperatures in Africa are projected to rise faster than the increase in the global average temperature. Along with the projection of decreasing long-term precipitation in Africa (Nhemachena & Hassan, 2007; Gannon et al., 2014), extreme weather shocks are expected to occur with greater severity and frequency in the region in the future (IPCC, 2014; Ault, 2020).

The adverse effects of more frequent and intense extreme weather events are economic losses and slower economic growth. Kuwayama et al. (2019) find that statistically significant negative effects of drought on crop yields are equivalent to reductions in the range of 0.1%–1.2% for corn and soybean yields for each additional week of drought in dryland counties of the US and 0.1%–0.5% in irrigated counties. In the other parts of the world, several studies conclude that rainfall and drought shocks negatively affect farmers' agricultural income (Arslan et al., 2016; Asfaw et al., 2017; Skoufias et al., 2017; Sesmero et al., 2018; Chuang, 2019; Chonabayashi et al., 2020).

Further, poor people have low-quality assets that fail to resist shocks, such as houses located in vulnerable areas during a flood shock (Mano & Nhemachena, 2007; Skoufias, 2012; Hallegatte et al., 2016; Nikoloski et al., 2018; Sesmero et al., 2018). There are numerous reasons for this. They may select *ex-ante* risk mitigation strategies that invest effort and resources in low-risk and low-return activities to avoid potential income loss, but they might not invest in more profitable alternatives (Hallegatte et al., 2016). This effect can be lifelong and can even be transmitted to future generations that trap the household in poverty (Damania et al., 2017). For example, a downside risk in consumption due to rainfall shocks is decreased fertilizer application rates, as households face liquidity constraints (Dercon & Christiaensen, 2011). In Nigeria, the variation of rainfall has significant negative effects on fertilizer purchases (Adjognon et al., 2017).

Africa is extremely vulnerable to droughts and floods because the majority of the continent's population is engaged in agricultural activities, which are directly affected by the climate, thereby making it difficult to eradicate poverty. D'Alessandro et al. (2015) estimate that the losses of livestock due to droughts that occurred from 2005–2015 amount to $1.08 billion and crop losses during the period 1980–2012 to account for 2 percent of the contribution of agriculture to GDP in Kenya. Pauw et al. (2010) indicate that the loss in agricultural GDP varies from 1 percent to 21.5 percent due to different return periods of droughts in Malawi. Thurlow et al. (2012) conclude that a severe drought reduces the contribution of agriculture to GDP by 22.7 percent and, on average, moves 7.5 percent of the population into poverty in Zambia.

While there has been active research on the effects of droughts and floods on agricultural outcomes, the magnitude and, occasionally, sign of the estimated impact varies, as described above, and is further summarized in the literature review presented in Table 1. This is likely due to several reasons. First, the available data on both agriculture and extreme weather events remains scarce in Africa. Second, there is a variation in the measurements of droughts and floods and agricultural outcome variables used in previous literature. Third, the various econometric and modeling strategies used also affect the reported results. While there is a general consensus that droughts and floods negatively affect agricultural outcomes, more research is required to more precisely understand the magnitude of these impacts.

In particular, an important gap in previous literature is that there are only a few studies that analyze the economic impacts of droughts and floods on agricultural households' livelihoods at a regional scale in Africa, while numerous studies have been conducted at the country scale. This could be due to the lack of household survey data with comparable information on agricultural livelihoods and weather shocks across countries. Yet, extreme weather events are cross-border issues by nature and can affect areas across multiple countries when they occur. A multi-country study enables a more comprehensive assessment of the impacts of weather shocks in the region.

To fill this research gap, we quantitatively estimate the impacts of droughts and floods on agricultural productivity in five Sub-Saharan African countries—Ethiopia, Malawi, Niger, Nigeria, and Uganda. To the best of our knowledge, this is

the first study to analyze the relationship between agricultural income and extreme weather events, such as droughts and floods, on a multi-country scale in Africa.

3.2 Data

We use the nationally representative household-level data from the Living Standards Measurement Study-Integrity Surveys on Agriculture (LSMS-ISA). LSMS-ISA is a household survey project established with a grant from the Bill and Melinda Gates Foundation and implemented by the World Bank and the national statistics office of its partner countries in sub-Saharan Africa. In each partner country, LSMS-ISA provides multiple rounds of multi-topic and nationally representative surveys with a strong focus on agriculture. To partially satisfy user interest in geo-referenced location, while preserving the confidentiality of sample households and communities, modified coordinates at the enumeration-area level are provided as part of the household geographical and climate variables. Modified coordinates are generated by applying a random offset within a specified range to the average value of the enumeration area.

While LSMS-ISA covers eight countries, we only consider five countries for our study—Ethiopia, Malawi, Niger, Nigeria, and Uganda—for a few reasons. First, Mali and Tanzania are excluded since the data for these countries only include weather shock variables for the past three and five years, respectively, but not the single past year.[1] Second, we exclude Burkina Faso because data on important elements for this study such as climate, geography, and livestock production are missing.

[1] In the Tanzania 2008 survey, the weather shock variable does not distinguish between droughts and floods, which is another reason why it is excluded from our study.

The resulting data is a pooled multi-country household survey with 82,281 observations for the period 2009–2016. Collectively, the total population of countries included in this study is approximately 367 million, which is approximately 36 percent of the total population in sub-Saharan Africa in 2016. Due to the data availability, most of the sample data used for this paper comes from two countries—Nigeria and Ethiopia. A list and geographical locations of the surveys used for this study as well as summary statistics of key variables are provided in Map 1 and Table 2 and Table 3. The following is a description of the methods used to generate the key variables for our study. First, following the methodology used to construct the FAO Rural Income Generating Activities (RIGA) Database,[2] we generate crop, livestock, and net agricultural income, respectively. Net agricultural income is the sum of crop and livestock net income. According to the Organization for Economic Co-operation and Development (OECD), agricultural output comprises output sold, changes in stocks, output for own final consumption, output produced for further processing by agricultural producers, and intra-unit consumption of livestock feed products. To ensure consistency and comparability among the surveys from different countries, all income variables are temporally converted to 2011 USD using consumer price index (CPI) and purchasing power parity (PPP) exchange rates.

We construct weather shock dummy variables, such as the incidence of droughts and floods, for households that experience the respective shock during the

[2] Information on the RIGA database can be found at http://www.fao.org/economic/riga/en. The RIGA database comprises a series of constructed variables regarding rural and urban income-generating activities created from original data sources, such as the World Bank's Living Standards Measurement Study and RAND.

last 12 months from the data in the shocks and coping strategy section of the surveys. For Nigeria, we use the incidence during the previous and current calendar years as a proxy of the previous 12 months, considering that the surveys were implemented in the first three months of each year.

3.3 Methodology

Building on recent research on the association between extreme weather events and net agricultural income (Chonabayashi et al., 2020; Kuwayama et al., 2019) as well as previous studies on the impacts of climate change on net agricultural income in Africa (Kurukulasuriya & Mendelsohn, 2007; Seo & Mendelsohn, 2008; Seo et al., 2009; Kurukulasuriya et al., 2011; Kala et al., 2012;), we estimate the impact of droughts and floods on agricultural productivity in sub-Saharan Africa for the period 2009–2016. Our identification strategy relies on exploiting variation in net farm income and drought occurrence across sample households. We use a pooled data set that is constructed by pooling the household survey data from LSMS-ISA for Ethiopia, Malawi, Niger, Nigeria, and Uganda.

We assume that farmers manage their farm to maximize their net farm income from various farming activities, taking the existing climate as given. We consider the following equation to analyze the impacts of droughts and floods on net crop income:

$$\textit{Equation 1: } ihs\left(Y_{i(t),t,p}\right) = \beta_0 + \beta_D D_{i(t),t,p} + \beta_F F_{i(t),t,p} + \delta' \boldsymbol{X}_{i(t),t,p} + \epsilon_t + \vartheta_c + \varepsilon_{i(t),t,p},$$

where $ihs(Y_{i(t),t,p})$ is the inverse hyperbolic sine transformed version of net crop income per hectare for household *i(t)* in cross-sectional time or year *t*; $D_{i(t),t,p}$ and $F_{i(t),t,p}$ are dummy variables that indicate an incidence of a drought and flood, respectively; $\boldsymbol{X}_{i(t),t,p}$ are covariates that include both time-varying and invariant observable variables, such as socioeconomic, geographic, climatic, household, and farmland characteristics; ϵ_t and ϑ_c are year and country dummy variables to control for the possible year effect and time-invariant unobservable country differences, respectively; and $\varepsilon_{i(t),t,p}$ is an error term. Our data set consists of eight independent cross-sections or years. As households in different cross-sections are not the same ones, we index the variables by a double subscript *i(t)*.[3]

We use the inverse hyperbolic sine (IHS) transformation of the outcome variable instead of a linear term or the natural logarithm transformation as it retains zero and negative values. This is a common transformation in the applied microeconomics literature (Pence, 2006; Jeon and Pohl, 2019; Card et al., 2020). We interpret the regression coefficients as we do for a log-linear specification because the semi-elasticity in an arcsinh-linear specification is approximately equal to the corresponding regression coefficient (Bellemare & Wichman, 2020).

In addition to the main specification described above, we also conduct additional analyses. First, we estimate the above equation using alternative dependent variables, such as livestock net income and total net agricultural income, which is a sum of net crop income and livestock net income. Second, following the previous

[3] A few households included in the cross-sectional data from the national household surveys used for this study are panel data.

literature on climate change and drought impacts on US agriculture (Schlenker et al., 2005; Kuwayama et al., 2019), we explore potentially heterogeneous effects on irrigated and rainfed areas. To accomplish this, we conduct the regression analysis based on the subsamples of irrigated and rainfed areas separately. Since the irrigation rate in our sample data is only 3.5 percent, we also include an irrigation dummy variable in the main specification. In addition, we conduct subsample regression by poverty incidence and types of agricultural diversification strategies.

Throughout the paper, we present standard errors corrected for spatial correlation using a radius of 50 km around each household's agricultural plot (Conley, 1999).[4] The sample weight is applied to account for survey stratification. We conduct a number of robustness checks using alternative sets of control variables and fixed effects, different cutoff distances to correct spatial correlation of the standard errors, and cluster-robust standard errors that enable the calculation of intragroup correlation at the survey strata level.

Further, it is important to mention that the self-reported droughts and floods measures used for this study have a couple of potential caveats. First, the definition of droughts and floods is subjective, as the survey questionnaire only asks whether a household or any household member has been affected by droughts or floods during the previous 12 months, respectively, without specifically defining them. Moreover, the questionnaires do not ask for information on the duration or magnitude of drought or flooding in most of the surveys. Second, survey respondents are more likely to

[4] We implement the standard error correction for spatial correlation (Conley, 1999) in Stata using the acreg.ado file (Colella et al., 2019).

remember those shocks that had a welfare effect (Weerdt, 2008). This implies that self-reported measures could likely be endogenous to agricultural income and potentially provide an upward bias in the estimated impacts.

A potential alternative method could be to construct measures for droughts and floods from other weather data sources, but we do not consider this as part of this study for the following reasons. First, since the actual household coordinates of the LSMS-ISA data are not available, it is not feasible to spatially merge external data with household data accurately at the household level. Second, accurately measuring extreme events remains challenging, particularly droughts, as they are caused by a combination of different factors, including hydro-meteorological and socio-economic factors, along with the stochastic nature of water demand (Wilhite, 2000; Udmale et al., 2014). For example, recent empirical evidence reveals large discrepancies in exposure to extreme temperature across high-resolution gridded weather data sets that are widely used in the literature. Accordingly, the reported choice of the underlying weather data set can significantly affect the estimates of climate change impacts on crop yields, which are often identified from within-location temporal variation in the exposure to the extreme right tail of the temperature distribution (Parkes et al., 2019; Chonabayashi & Ortiz-Bobea, 2021). Furthermore, another recent study suggests that drought indicators derived from satellite data showed no or limited signs of an agricultural drought—based on vegetation indices and predicted crop losses—during Ethiopia's historical 2015 drought, which is reported to be the worst in five decades according to various drought indicators (Sohnesen, 2020). For these reasons, I chose to

use self-reported droughts and floods measures in this study with the understanding that there is no established alternative in literature thus far.

To mitigate potential distortion resulting from the potential endogeneity issue discussed above, we take the following countermeasures. First, to overcome the issue of a non-standardized definition used in the survey, droughts and floods dummy variables in this study simply indicate whether a household experienced a drought or a flood, although a few surveys include information on the frequency and magnitude of the impact (e.g. positive and negative effects, subjective severity levels, etc.). By not only considering households that report negative impacts from drought but also those that report positive or no impacts, we can mitigate a potential upward bias caused in the estimated impact from the regression analysis. Second, we only use household surveys that have the shortest recall period (12 months in the question on shocks) because the shorter the recall period, the less severe the recall bias is expected to be (Weerdt, 2008). In addition, it is reasonable to use weather shocks during the last 12 months as opposed to a longer period to analyze short-term impacts on current net agricultural income.

3.4 Results

Regression results and the marginal effects of droughts and floods on net crop income are reported in columns (1)–(7) of Table 4 and Table 5.[5] Occurrences of both droughts

[5] The robustness check using alternative regression specifications and different methods for spatial correlation correction of standard errors is reported in the Appendix and produces qualitatively the same results.

and floods are found to have significant negative effects on net crop income, respectively. The net crop income of farmers decreases by 34 percent and 61 percent if they have experienced droughts and floods in the last 12 months, respectively. I also find non-significant negative effects of both droughts and floods on the net crop income of irrigation farmers. Further investigation is likely required in this direction, as the sample size of irrigated farmers is small (only 3.5 percent).[6]

From the results using the main specification in column (1) of Table 4, it is evident that the log of the cultivated farmland area reduces net crop income. This finding is consistent with previous research that reports that small farms are productive in the African context and that staple cereal yields decline as the scale of production increases (Kurukulasuriya & Mendelsohn, 2007; Larson et al., 2014).

Further, the female household head is significantly and negatively associated with crop, livestock, and total net agricultural income, while the ages of the household members are significantly and positively associated with livestock and total net agricultural income. The presence of electrical service on the farm turns is negatively associated with crop, livestock, and total net agricultural income in rural areas, while it increases net crop income in urban areas. While this result appears counterintuitive, a recent study also reports a similar finding that while access to urban electricity has positive and significant impacts on agricultural productivity, the effect of rural electrification is insignificant (Omoju et al., 2020). Further, rural households have

[6] Additionally, F-test was conducted to compare coefficients for drought and flooding variables in the following columns of Table 4 are statistically significantly different: a) crop only vs mixed production and b) poor vs non-poor. Table A3 shows that those coefficients are not statistically different from each other.

higher livestock and total net agricultural income than urban households, which likely reflects the fact that urban households depend more on non-agricultural income.

3.5 Discussion and Conclusion

This paper finds robust negative impacts of droughts and floods on net crop income in Africa. The analysis quantitively confirms recent findings that the effectiveness of electricity in increasing agricultural productivity depends on other household and geographical factors, such as farmland area size and distance to roads, particularly in the African context.

The results of this study lead to the following policy recommendations. First, irrigation and agricultural diversification could be promoted as mitigation strategies to cope with the adverse effects of extreme weather events, such as droughts and floods, on crop production. Second, poverty reduction builds household resilience to extreme events. Third, the promotion of rural electrification may not be sufficient, in and of itself, to enhance agricultural productivity in Sub-Saharan Africa. Policymakers must carefully design this intervention to support the entire agricultural value chain. Finally, in order to be effective, farm input support programs to promote fertilizer use must consider factors such as transportation costs and farm size.

The analytical framework developed in this paper makes a useful contribution to the existing literature on the linkages between agriculture, climate, and extreme weather. More specifically, the Ricardian approach normally consists of a cross-sectional regression of farmland values on climate and other control variables, but it is also used to study climate change impacts on agricultural productivity using net

revenue values in countries in which data on land value are not readily available (Kurukulasuriya & Mendelsohn, 2007; Seo & Mendelsohn, 2008; Seo et al., 2009; Kurukulasuriya et al., 2011; Kala et al., 2012). Generally, land values are easier to analyze because they reflect the long term productivity of the land, while net revenues capture the annual productivity and can be influenced by numerous factors that are peculiar to a given year like the weather (Mendelsohn, 2008). Therefore, the effects of extreme weather events, such as droughts and floods, on agriculture can be incorporated in the climate change impact studies by using available data on household revenue and weather shocks.

There are numerous areas of possible future research inspired by the results of this study. Building on previous literature and this paper, future research could assess the historical impacts of drought in Africa by exploring drought and climate measures based on satellite climate data. In addition, extreme weather effects on net farm income or land values can also be incorporated in studies on climate change impacts on agriculture, like the Ricardian analysis where the association between climate change and extreme weather events also must be taken into account. Despite these potential areas for improvement, this study provides robust estimates of the historical impact of droughts and floods on agriculture in Africa. These findings could be useful for both policymakers and agricultural households in the creation of planning strategies to cope with increasing extreme weather events due to climate change.

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Map 1: Locations of agricultural plots in LSMS-ISA data

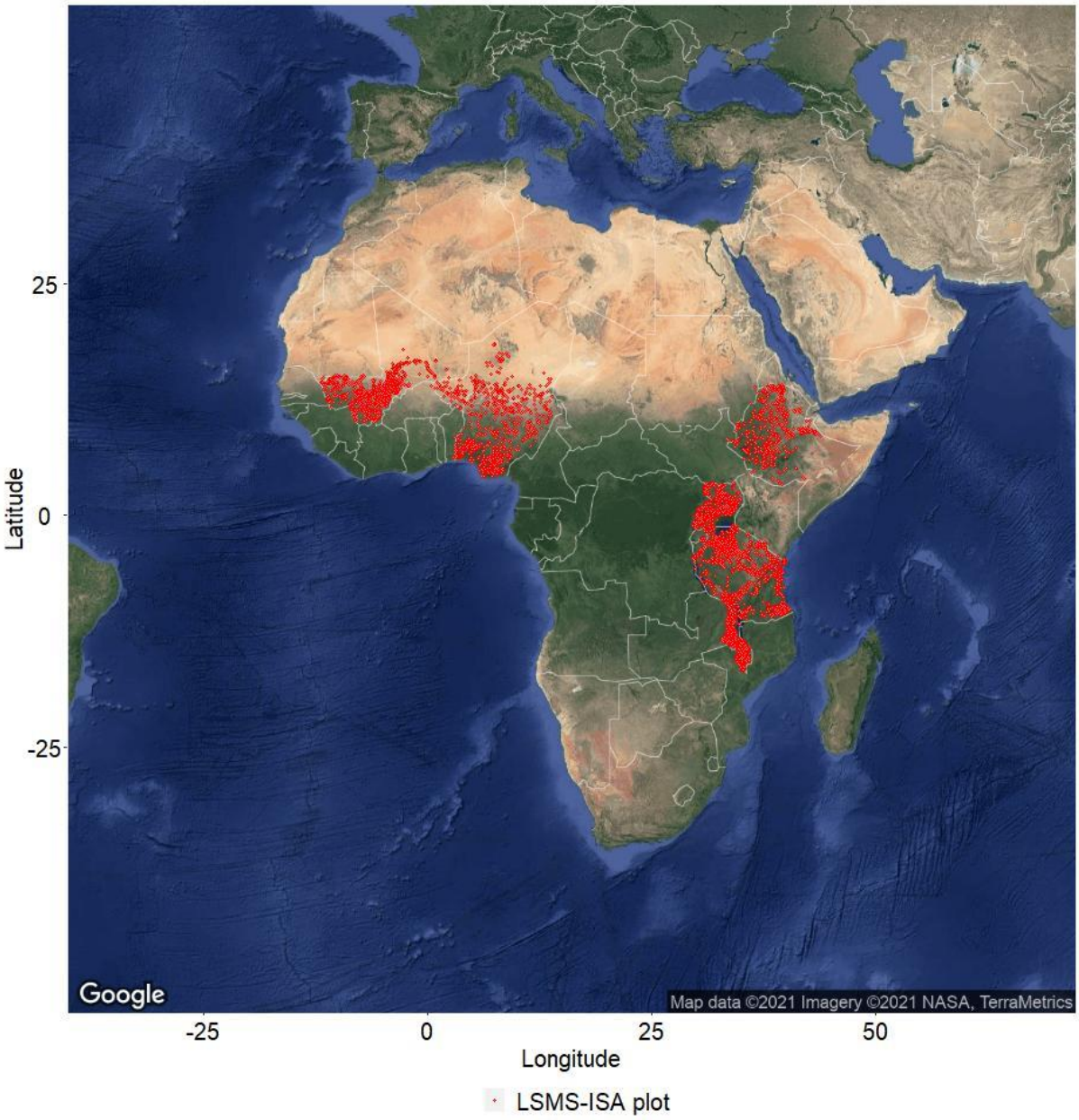
25
0
-25
Latitude
Google
Map data ©2021 Imagery ©2021 NASA, TerraMetrics
-25
0
25
50
Longitude
LSMS-ISA plot

Table 1: Literature review on the economic impact of weather shocks and climate change on agricultural productivity

Study	Country/Region	Spatial Coverage	Model	Weather Shock Measure	Dependent Variable	Impact Estimate
Amare et al., 2018	Nigeria	National	IV-FE	Deviation of rainfall	Consumption	-37.0%
Asfaw et al., 2017	Zambia	Subnational	GLS-RE	Deviation of rainfall	Consumption	-2.9%
Blanc, 2012	SSA	Multi-country	Fixed Effect	Standardized precipitation index (SPI)	Crop Yield	-7.1%
Chonabayashi et al., 2020	Zambia	National	SNR	Self-reported drought	Agricultural income	-24.3%
Chonabayashi et al., 2020	Zambia	National	SNR	Self-reported flooding	Agricultural income	-23.4%
Chuang, 2019	India	Subnational	SUR	Deviation of rainfall	Agricultural Income	-1.5%
Chuang, 2019	India	Subnational	SUR	Deviation of rainfall	Income	-0.8%
Cissé & Barrett, 2018	Kenya	National	GLM	Area average predicted losses ≥ 15% per the IBLI index	TLU	-18.0%
Gao & Mills, 2018	Ethiopia	National	Fixed Effect	Deviation of rainfall	Consumption	-18.2%
Gao & Mills, 2018	Ethiopia	National	Fixed Effect	Extreme heat degree days	Consumption	-2.4%
Horridge et al., 2005	Australia	National	CGE	Rainfall deficit	Income	-20.0%
Kubik & Maurel, 2016	Tanzania	National	OLS	Standardized precipitation evapotranspiration index (SPEI)	Crop Revenue	-31.0%
Kuwayama et al., 2019	United States	National	Panel Fixed Effect	Weeks of drought based on USDM classifications	Yield	-1.2%
Macours, 2012	Nicaragua	Subnational	2SLS	Self-reported drought	Consumption	-9.0%
Macours, 2012	Nicaragua	Subnational	2SLS	Self-reported drought	Income	-11.0%
Porter, 2012	Ethiopia	National	DIFF	Bottom quintile of rainfall distribution	Consumption	-19.6%
Porter, 2012	Ethiopia	National	Fixed Effect	Bottom quintile of rainfall distribution	Crop Income	-16.6%
Roberts et al., 2012	USA	Subnational	Nonlinear	Extreme heat degree days	Crop Production	-6.2%
Salvucci & Santos, 2020	Mozambique	National	DID	Flooded areas	Consumption	-11.0%

Notes: DID—Difference-in-Difference; DIFF—Arellano & Bond's (1991) estimator; FE2SLS—fixed effects two-stage least squares; GLM: Generalized linear model; GLS-RE—generalized least squares random-effects; SNR—Skew-normal regression; SUR—seemingly unrelated regressions; 2SLS—two-stage least squares

Table 2: Countries and years of the household survey data used in this study

	2009	2010	2011	2012	2013	2014	2015	2016	Total
Ethiopia					x		x		2
Malawi		x			x			x	3
Niger			x						1
Nigeria		x		x			x		3
Uganda	x	x	x						3
Total	1	3	2	1	2	0	2	1	13

Data source: LSMS-ISA

Table 3: Summary statistics of variables used in regressions

	mean	sd	min	max
Net agricultural income (2011 PPP USD)	923.065	1443.919	-8810.421	43947.324
Net crop income (2011 PPP USD)	400.026	972.321	-5936.709	18811.576
Livestock net income (2011 PPP USD)	228.655	707.512	-5853.908	43947.324
Droughts in the last 12 months	0.102	0.303	0.000	1.000
Floods in the last 12 months	0.034	0.180	0.000	1.000
IHS of cultivated land	0.461	0.607	0.000	5.785
Number of agricultural workers	3.366	5.356	0.000	131.615
Number of agricultural workers squared	40.020	200.738	0.000	17322.506
Use of inorganic fertilizer	0.094	0.292	0.000	1.000
Inorganic fertilizer × Distance to road over 3 km	0.061	0.239	0.000	1.000
Use of organic fertilizer	0.065	0.247	0.000	1.000
Organic fertilizer × Cultivated land over 1 ha	0.023	0.150	0.000	1.000
Irrigation	0.033	0.180	0.000	1.000
Age of household head	47.775	16.749	0.000	113.000
Female household head	0.216	0.411	0.000	1.000
Electricity	0.420	0.494	0.000	1.000
Urban	0.324	0.468	0.000	1.000
Electricity × Urban	0.264	0.441	0.000	1.000
Absolute value of latitude	8.248	3.711	0.000	18.747
Ethiopia	0.246	0.430	0.000	1.000
Malawi	0.069	0.254	0.000	1.000
Niger	0.017	0.129	0.000	1.000
Nigeria	0.563	0.496	0.000	1.000
Uganda	0.105	0.307	0.000	1.000
Year 2009	0.034	0.181	0.000	1.000
Year 2010	0.232	0.422	0.000	1.000
Year 2011	0.051	0.221	0.000	1.000
Year 2012	0.194	0.395	0.000	1.000
Year 2013	0.139	0.346	0.000	1.000
Year 2014	0.000	0.000	0.000	0.000
Year 2015	0.325	0.469	0.000	1.000
Year 2016	0.025	0.156	0.000	1.000
Year of survey conducted	2012.597	2.096	2009.000	2016.000
Latitude	6.240	6.547	-17.095	18.747
Longitude	19.169	14.711	0.405	43.871
Observations	65004			

Data source: LSMS-ISA

Table 4: Regression results for net agricultural income in Sub-Saharan Africa

	Net crop income per ha							Livestock net income	Net agricultural income
	All farms	Irrigated	Rainfed	Crop only	Mix	Poor	Non-poor		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Droughts in the last 12 months	-0.416**	-0.361	-0.420**	-0.388	-0.416**	-0.417*	-0.388*	0.041	-0.216*
	(0.034)	(0.147)	(0.037)	(0.137)	(0.034)	(0.053)	(0.064)	(0.786)	(0.062)
Floods in the last 12 months	-0.940**	-1.109**	-0.935**	-1.137**	-0.940**	-0.989***	-0.949**	0.307	-0.578**
	(0.010)	(0.018)	(0.014)	(0.036)	(0.010)	(0.008)	(0.035)	(0.151)	(0.029)
IHS of cultivated land	-0.382***	-0.491**	-0.386***	-0.556**	-0.382***	-0.516***	-0.316**	0.659***	0.776***
	(0.003)	(0.011)	(0.003)	(0.011)	(0.003)	(0.000)	(0.017)	(0.000)	(0.000)
Distance to road over 3 km	0.456**	0.488*	0.428**	0.408	0.456**	0.306	0.546***	0.123	0.331***
	(0.011)	(0.051)	(0.015)	(0.107)	(0.011)	(0.114)	(0.006)	(0.447)	(0.010)
Age of household head	0.006	0.007	0.005	0.005	0.006	0.006	0.005	0.007*	0.006**
	(0.117)	(0.169)	(0.204)	(0.383)	(0.117)	(0.173)	(0.222)	(0.060)	(0.011)
Female household head	-0.491**	-0.903***	-0.486**	-0.907***	-0.491**	-0.567***	-0.625**	-0.327**	-0.474***
	(0.014)	(0.001)	(0.019)	(0.002)	(0.014)	(0.005)	(0.012)	(0.013)	(0.000)
Electricity	-0.982***	-1.045***	-0.953***	-0.991**	-0.982***	-0.846***	-1.039***	-0.486**	-0.700***
	(0.000)	(0.005)	(0.000)	(0.011)	(0.000)	(0.010)	(0.000)	(0.016)	(0.000)
Urban	-0.571	-0.703	-0.585	-0.739	-0.571	-0.892*	-0.376	-0.624**	-1.222***
	(0.135)	(0.186)	(0.129)	(0.175)	(0.135)	(0.071)	(0.321)	(0.010)	(0.000)

Electricity × Urban	1.095**	1.436**	1.050*	1.313*	1.095**	1.129*	1.172**	-0.335	0.081
	(0.041)	(0.038)	(0.052)	(0.069)	(0.041)	(0.088)	(0.029)	(0.321)	(0.832)
Absolute value of latitude	0.074	0.050	0.083	0.086	0.074	0.145**	-0.010	-0.228***	-0.141***
	(0.191)	(0.499)	(0.146)	(0.263)	(0.191)	(0.016)	(0.869)	(0.000)	(0.000)
Ethiopia	7.021***	7.477***	7.109***	7.797***	7.021***	7.361***	6.825***	5.018***	1.888***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Malawi	5.366***	5.741***	5.359***	5.823***	5.366***	4.891***	5.835***	6.885***	2.390***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Niger	0.000	0.000	0.000	0.000	0.000	0.000	0.000	4.148***	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(0.000)	(.)
Nigeria	3.754***	4.709***	3.847***	5.404***	3.754***	4.162***	3.810***	4.182***	1.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Uganda	5.246***	5.694***	5.389***	6.511***	5.246***	6.107***	4.570***	3.175***	0.307
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.518)
Year 2010	1.793***	1.214***	1.455	1.221***	1.793***	1.527***	1.777***	-0.354	1.208***
	(0.000)	(0.000)	(0.105)	(0.000)	(0.000)	(0.000)	(0.000)	(0.107)	(0.000)
Year 2012	1.134***	0.143	0.814	0.151	1.134***	0.795*	0.977**	0.234	0.858***
	(0.006)	(0.829)	(0.471)	(0.831)	(0.006)	(0.059)	(0.046)	(0.347)	(0.000)
Year 2013	-1.331***	-1.273*	-1.687	-1.009	-1.331***	-1.550***	-1.121***	1.009***	1.106***
	(0.000)	(0.064)	(0.101)	(0.134)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Year 2014	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Year 2015	-3.068***	-3.607***	-3.419***	-3.700***	-3.068***	-3.292***	-3.139***	1.591***	0.804***
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Irrigation	0.033			0.662*	0.033	0.131	0.134	-0.162	0.271
	(0.903)			(0.085)	(0.903)	(0.736)	(0.593)	(0.455)	(0.232)
Observations	44635	18875	42495	16735	44635	29979	31391	30986	48072
R-squared	0.129	0.131	0.130	0.134	0.129	0.132	0.130	0.072	0.068

Notes: The dependent variables are the inverse hyperbolic sine transformed version of net crop income per hectare, livestock net income, and net agricultural income, respectively. Standard errors are given in parentheses and account for spatial correlation of disturbances. Asterisks indicate the following p-values: *** = $p < 0.01$, ** = $p < 0.05$, and * = $p < 0.1$.

Table 5: Marginal effects of droughts and floods on net agricultural income in Sub-Saharan Africa

	Net crop income per ha							Livestock net income	Net agricultural income
	All farms	**Irrigated**	**Rainfed**	**Crop only**	**Mix**	**Poor**	**Non-poor**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Incidence of droughts	-0.341 **	-0.311	-0.344 **	-0.328	-0.341 **	-0.342 *	-0.323 *	-0.235	-0.196 *
	(0.034)	(0.147)	(0.037)	(0.137)	(0.034)	(0.053)	(0.064)	(0.786)	(0.062)
Incidence of floods	-0.609 **	-0.67 **	-0.607 **	-0.68 **	-0.609 **	-0.628 ***	-0.613 **	0.344	-0.439 **
	(0.01)	(0.018)	(0.014)	(0.036)	(0.01)	(0.008)	(0.035)	(0.151)	(0.029)

Notes: Standard errors are given in parentheses and account for spatial correlation of disturbances Marginal effects for temperature and precipitation are evaluated at the mean climate of the sample used for regressions. Asterisks indicate the following p-values: *** = $p < 0.01$, ** = $p < 0.05$, and * = $p < 0.1$.

Appendix

Table A1: Robustness check for the marginal effects of drought on net agricultural income in sub-Saharan Africa

Crop net income per ha							Livestock net income	Agricultural net income	Control variables			Fixed effects		Distance for spatial correlation
All farms	**Irrigated**	**Rainfed**	**Crop only**	**Mix**	**Poor**	**Non-poor**			**Ag**	**HH**	**Geo**	**Year**	**Country**	
-0.696 ** (0.025)	-0.737 * (0.075)	-0.688 ** (0.039)	-0.711 (0.143)	-0.696 ** (0.025)	-0.735 ** (0.041)	-0.661 * (0.057)	0.525 (0.184)	-0.28 (0.579)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**50 km**
-0.265 * (0.081)	-0.242 (0.279)	-0.272 * (0.065)	-0.221 (0.2)	-0.265 * (0.081)	-0.256 (0.136)	-0.246 * (0.091)	-0.242 (0.626)	-0.265 *** (0.01)	**No**	**Yes**	**Yes**	**Yes**	**Yes**	**50 km**
-0.249 * (0.1)	-0.233 (0.484)	-0.255 * (0.085)	-0.231 (0.568)	-0.249 * (0.1)	-0.246 (0.136)	-0.212 (0.203)	-0.3 (0.874)	-0.173 (0.143)	**Yes**	**No**	**Yes**	**Yes**	**Yes**	**50 km**
-0.22 (0.213)	-0.247 (0.193)	-0.219 (0.238)	-0.216 (0.196)	-0.22 (0.213)	-0.225 (0.309)	-0.225 (0.136)	-0.262 (0.688)	-0.256 ** (0.012)	**Yes**	**Yes**	**No**	**Yes**	**Yes**	**50 km**
-0.443 *** (<0.001)	-0.334 ** (0.048)	-0.445 *** (<0.001)	-0.283 * (0.067)	-0.443 *** (<0.001)	-0.438 *** (<0.001)	-0.385 *** (0.002)	-0.335 (0.874)	-0.321 *** (<0.001)	**Yes**	**Yes**	**Yes**	**No**	**Yes**	**50 km**
-0.252 (0.106)	-0.243 (0.225)	-0.252 (0.109)	-0.204 (0.249)	-0.252 (0.106)	-0.264 (0.127)	-0.213 (0.163)	-0.295 (0.776)	-0.259 ** (0.01)	**Yes**	**Yes**	**Yes**	**Yes**	**No**	**50 km**
-0.216 (0.229)	-0.274 (0.15)	-0.214 (0.262)	-0.246 (0.11)	-0.216 (0.229)	-0.255 (0.134)	-0.197 (0.376)	-0.22 (0.202)	-0.365 *** (<0.001)	**Yes**	**Yes**	**Yes**	**No**	**No**	**50 km**
-0.696 ** (0.025)	-0.737 * (0.075)	-0.688 ** (0.039)	-0.711 (0.143)	-0.696 ** (0.025)	-0.735 ** (0.041)	-0.661 * (0.057)	0.525 (0.184)	-0.28 (0.579)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**10 km**
-0.279 **	-0.243	-0.282 **	-0.199	-0.279 **	-0.268 *	-0.249 *	-0.298	-0.257 **	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**25 km**

(0.049)	(0.189)	(0.045)	(0.176)	(0.049)	(0.085)	(0.065)	(0.785)	(0.012)						
-0.279 **	-0.248	-0.282 **	-0.212	-0.279 **	-0.268 *	-0.251 *	-0.293	-0.257 **	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**75 km**
(0.041)	(0.225)	(0.037)	(0.25)	(0.041)	(0.088)	(0.092)	(0.774)	(0.026)						
-0.278 ***	-0.23 *	-0.281 ***	-0.203	-0.278 ***	-0.265 ***	-0.249 *	-0.264	-0.257 ***	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Cluster**
(0.006)	(0.06)	(0.01)	(0.201)	(0.006)	(0.004)	(0.073)	(0.721)	(0.003)						

Notes: Climate variables include temperature and precipitation. Agricultural controls include cultivated land, number of agricultural workers, and inorganic and organic fertilizer use. Household controls include household head age and gender and electricity access. Geographical variables include latitude and urban dummy. Cluster-robust standard errors enable intragroup correlation at the survey strata level. Standard errors are given in parentheses and account for spatial correlation of disturbances. The marginal effects for temperature and precipitation are evaluated at the mean climate of the sample used for regressions. Asterisks indicate the following p-values: *** = $p < 0.01$, ** = $p < 0.05$, and * = $p < 0.1$.

Table A2: Robustness check for the marginal effects of floods on net agricultural income in sub-Saharan Africa

Crop net income per ha							Livestock net income	Agricultural net income	Control variables			Fixed effects		Distance for spatial correlation
All farms	Irrigated	Rainfed	Crop only	Mix	Poor	Non-poor			Ag	HH	Geo	Year	Country	
-0.643 ** (0.05)	-0.78 ** (0.031)	-0.635 * (0.062)	-0.771 * (0.057)	-0.643 ** (0.05)	-0.678 ** (0.045)	-0.671 * (0.073)	0.426 (0.19)	-0.524 ** (0.047)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**50 km**
-0.607 *** (0.001)	-0.407 ** (0.042)	-0.643 *** (<0.001)	-0.524 *** (<0.001)	-0.607 *** (0.001)	-0.621 *** (0.002)	-0.563 *** (0.005)	0.223 (0.354)	-0.226 (0.209)	**No**	**Yes**	**Yes**	**Yes**	**Yes**	**50 km**
-0.59 *** (0.001)	-0.371 * (0.07)	-0.623 *** (0.001)	-0.453 *** (0.001)	-0.59 *** (0.001)	-0.595 *** (0.003)	-0.538 *** (0.007)	0.299 (0.297)	-0.218 (0.328)	**Yes**	**No**	**Yes**	**Yes**	**Yes**	**50 km**
-0.595 *** (0.002)	-0.427 ** (0.042)	-0.624 *** (0.001)	-0.499 *** (<0.001)	-0.595 *** (0.002)	-0.6 *** (0.004)	-0.556 *** (0.005)	0.245 (0.347)	-0.227 (0.24)	**Yes**	**Yes**	**No**	**Yes**	**Yes**	**50 km**
-0.564 *** (0.002)	-0.392 ** (0.032)	-0.607 *** (0.001)	-0.492 *** (<0.001)	-0.564 *** (0.002)	-0.573 *** (0.004)	-0.533 *** (0.005)	0.314 (0.281)	-0.231 (0.562)	**Yes**	**Yes**	**Yes**	**No**	**Yes**	**50 km**
-0.603 *** (0.001)	-0.421 ** (0.048)	-0.631 *** (0.001)	-0.484 *** (<0.001)	-0.603 *** (0.001)	-0.622 *** (0.002)	-0.521 ** (0.012)	0.259 (0.327)	-0.23 (0.213)	**Yes**	**Yes**	**Yes**	**Yes**	**No**	**50 km**
-0.428 ** (0.032)	-0.37 * (0.082)	-0.469 ** (0.022)	-0.47 *** (<0.001)	-0.428 ** (0.032)	-0.494 ** (0.018)	-0.381 * (0.092)	-0.154 (0.732)	-0.212 (0.314)	**Yes**	**Yes**	**Yes**	**No**	**No**	**50 km**
-0.643 ** (0.05)	-0.78 ** (0.031)	-0.635 * (0.062)	-0.771 * (0.057)	-0.643 ** (0.05)	-0.678 ** (0.045)	-0.671 * (0.073)	0.426 (0.19)	-0.524 ** (0.047)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**10 km**

-0.61 *** (<0.001)	-0.425 ** (0.043)	-0.638 *** (<0.001)	-0.493 ** (0.014)	-0.61 *** (<0.001)	-0.613 *** (0.001)	-0.564 *** (0.002)	0.28 (0.303)	-0.218 (0.189)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**25 km**
-0.61 *** (0.005)	-0.426 * (0.07)	-0.638 *** (0.004)	-0.493 ** (0.014)	-0.61 *** (0.005)	-0.613 ** (0.01)	-0.564 ** (0.01)	0.278 (0.31)	-0.229 (0.252)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**75 km**
-0.61 *** (0.002)	-0.425 ** (0.036)	-0.638 *** (<0.001)	-0.493 ** (0.017)	-0.61 *** (0.002)	-0.613 *** (<0.001)	-0.564 ** (0.021)	0.325 (0.153)	-0.213 (0.144)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Cluster**

Notes: Climate variables include temperature and precipitation. Agricultural controls include cultivated land, number of agricultural workers, and inorganic and organic fertilizer use. Household controls include household head age and gender and electricity access. Geographical variables include latitude and urban dummy. Cluster-robust standard errors enable intragroup correlation at the survey strata level. Standard errors are given in parentheses and account for spatial correlation of disturbances. The marginal effects for temperature and precipitation are evaluated at the mean climate of the sample used for regressions Asterisks indicate the following p-values: *** = $p < 0.01$, ** = $p < 0.05$, and * = $p < 0.1$.

Table A3: F-test for equality of coefficients from different regression models

Variable	Subsample regression models compared	Chi-squared	Probability
Drought	Irrigated	0.117	0.732
Flood	Rainfed	0.190	0.663
Drought	Crop only	0.017	0.897
Flood	Mixed production	0.158	0.691
Drought	Poor	0.027	0.868
Flood	Non-poor	0.015	0.901

Table A4: Subsample regression results for net agricultural income in East Africa (Ethiopia, Malawi, and Uganda)

	Net crop income per ha							Livestock net income	Net agricultural income
	All farms	Irrigated	Rainfed	Crop only	Mix	Poor	Non-poor		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Drought in the last 12 months	-0.326*	-0.260	-0.330**	-0.207	-0.326*	-0.308*	-0.284*	-0.046	-0.297**
	(0.055)	(0.224)	(0.048)	(0.227)	(0.055)	(0.096)	(0.081)	(0.777)	(0.011)
Flood in the last 12 months	-0.942***	-0.552**	-1.017***	-0.679***	-0.942***	-0.949***	-0.830***	0.293	-0.229
	(0.001)	(0.039)	(0.001)	(0.000)	(0.001)	(0.002)	(0.005)	(0.318)	(0.237)
IHS of cultivated land	-0.528***	-0.897***	-0.533***	-1.064***	-0.528***	-0.654***	-0.571***	0.635***	1.052***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Distance to road over 3 km	0.312*	0.223	0.325*	0.282	0.312*	0.293	0.306	-0.104	0.244*
	(0.093)	(0.271)	(0.084)	(0.123)	(0.093)	(0.117)	(0.106)	(0.614)	(0.067)
Age of household head	0.005	0.007	0.004	0.003	0.005	0.002	0.007*	0.010**	0.004*
	(0.164)	(0.105)	(0.293)	(0.555)	(0.164)	(0.507)	(0.060)	(0.024)	(0.087)
Female household head	-0.185	-0.346*	-0.155	-0.252	-0.185	-0.217	-0.193	-0.482***	-0.384***
	(0.187)	(0.055)	(0.281)	(0.203)	(0.187)	(0.111)	(0.286)	(0.002)	(0.000)
Electricity	-1.259***	-2.502***	-1.105***	-2.367***	-1.259***	-1.525***	-1.287***	-0.542	-0.525***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.008)	(0.001)	(0.143)	(0.008)
Urban	-0.550***	-0.856***	-0.544***	-0.802***	-0.550***	-0.772***	-0.482**	-0.404	-1.395***
	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)	(0.001)	(0.043)	(0.147)	(0.000)

Electricity × Urban	0.038	1.243	-0.011	1.217	0.038	0.470	0.121	-0.587	-1.161**
	(0.942)	(0.184)	(0.982)	(0.220)	(0.942)	(0.578)	(0.823)	(0.269)	(0.011)
Absolute value of latitude	0.200***	-0.010	0.214***	-0.028	0.200***	0.237***	0.059	-0.081*	0.002
	(0.008)	(0.916)	(0.004)	(0.723)	(0.008)	(0.003)	(0.395)	(0.085)	(0.937)
Ethiopia	3.529***	0.088	3.366***	-0.025	3.529***	1.373***	-0.070	5.264***	0.032
	(0.000)	(0.884)	(0.000)	(0.967)	(0.000)	(0.007)	(0.874)	(0.000)	(0.883)
Malawi	2.672**	0.000	2.463**	0.000	2.672**	0.000	0.000	5.830***	0.000
	(0.022)	(.)	(0.033)	(.)	(0.022)	(.)	(.)	(0.000)	(.)
Niger	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Nigeria	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Uganda	5.736***	0.304	5.743***	0.178	5.736***	3.682***	1.213	3.349***	-0.110
	(0.000)	(0.808)	(0.000)	(0.867)	(0.000)	(0.001)	(0.203)	(0.000)	(0.808)
Year 2010	1.070***	6.816***	1.082***	7.111***	1.070***	1.167***	1.040***	-0.616***	0.226*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.099)
Year 2012	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Year 2013	0.713***	6.451***	0.774***	6.788***	0.713***	0.759**	0.745***	-0.435	0.463**
	(0.006)	(0.000)	(0.002)	(0.000)	(0.006)	(0.013)	(0.007)	(0.191)	(0.022)

Year 2014	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Year 2015	-0.450	5.785***	-0.369	6.790***	-0.450	-0.464	-0.176	0.015	0.286
	(0.264)	(0.000)	(0.365)	(0.000)	(0.264)	(0.321)	(0.684)	(0.970)	(0.292)
Irrigation	0.054			0.482	0.054	0.145	0.104	-0.059	0.004
	(0.880)			(0.176)	(0.880)	(0.778)	(0.713)	(0.784)	(0.988)
Observations	34190	15060	32391	13261	34190	23624	23827	22814	36401
R-squared	0.061	0.061	0.061	0.058	0.061	0.067	0.053	0.036	0.117

Notes: The dependent variables are the inverse hyperbolic sine transformed version of net crop income per hectare, livestock net income, and net agricultural income, respectively. Standard errors are given in parentheses and account for spatial correlation of disturbances. Asterisks indicate the following p-values: *** = $p < 0.01$, ** = $p < 0.05$, and * = $p < 0.1$.

Table A5: Subsample regression results for net agricultural income in West Africa (Niger and Nigeria)

	Net crop income per ha							Livestock net income	Net agricultural income
	All farms	Irrigated	Rainfed	Crop only	Mix	Poor	Non-poor		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Droughts in the last 12 months	-1.190**	-1.332*	-1.164**	-1.232	-1.190**	-1.328**	-1.080*	0.439	-0.160
	(0.025)	(0.075)	(0.039)	(0.143)	(0.025)	(0.041)	(0.057)	(0.184)	(0.579)
Floods in the last 12 months	-1.029**	-1.514**	-1.006*	-1.474*	-1.029**	-1.133**	-1.109*	0.373	-0.740**
	(0.050)	(0.031)	(0.062)	(0.057)	(0.050)	(0.045)	(0.073)	(0.190)	(0.047)
IHS of cultivated land	-0.276	-0.278	-0.281	-0.311	-0.276	-0.381*	-0.187	0.593***	0.468***
	(0.126)	(0.265)	(0.122)	(0.243)	(0.126)	(0.078)	(0.337)	(0.000)	(0.000)
Distance to road over 3 km	0.546*	0.526	0.479*	0.364	0.546*	0.262	0.639**	0.474**	0.488**
	(0.055)	(0.154)	(0.082)	(0.305)	(0.055)	(0.426)	(0.029)	(0.039)	(0.016)
Age of household head	0.004	0.008	0.003	0.006	0.004	0.007	0.002	-0.000	0.003
	(0.498)	(0.322)	(0.573)	(0.426)	(0.498)	(0.319)	(0.709)	(0.934)	(0.483)
Female household head	-1.170***	-1.438***	-1.175***	-1.441***	-1.170***	-1.347***	-1.192***	-0.281	-0.788***
	(0.005)	(0.003)	(0.006)	(0.003)	(0.005)	(0.001)	(0.010)	(0.219)	(0.002)
Electricity	-0.929***	-0.688	-0.945***	-0.710*	-0.929***	-0.708*	-0.933***	-0.610**	-0.827***
	(0.005)	(0.100)	(0.005)	(0.090)	(0.005)	(0.066)	(0.008)	(0.012)	(0.000)
Urban	-0.642	-0.593	-0.688	-0.702	-0.642	-1.072	-0.342	-0.843**	-1.114***
	(0.326)	(0.481)	(0.291)	(0.407)	(0.326)	(0.207)	(0.571)	(0.039)	(0.009)

Electricity × Urban	1.451*	1.452	1.404*	1.344	1.451*	1.480	1.383*	0.000	0.603
	(0.059)	(0.123)	(0.069)	(0.165)	(0.059)	(0.114)	(0.061)	(0.999)	(0.218)
Absolute value of latitude	-0.014	0.043	-0.008	0.086	-0.014	0.078	-0.064	-0.359***	-0.226***
	(0.855)	(0.641)	(0.912)	(0.351)	(0.855)	(0.354)	(0.413)	(0.000)	(0.000)
Ethiopia	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Malawi	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Niger	3.088***	0.000	0.000	0.748	3.088***	2.081*	3.300***	6.391***	8.030***
	(0.007)	(.)	(.)	(0.567)	(0.007)	(0.089)	(0.003)	(0.000)	(0.000)
Nigeria	6.351***	4.447***	3.347***	0.000	6.351***	5.811***	1.346	5.163***	7.836***
	(0.000)	(0.000)	(0.000)	(.)	(0.000)	(0.000)	(0.133)	(0.000)	(0.000)
Uganda	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Year 2010	0.000	0.000	0.000	5.867***	0.000	0.000	5.394***	0.000	0.000
	(.)	(.)	(.)	(0.000)	(.)	(.)	(0.000)	(.)	(.)
Year 2012	-0.904*	-1.373**	-0.878*	4.526***	-0.904*	-1.030**	4.352***	0.745***	-0.317
	(0.063)	(0.018)	(0.078)	(0.000)	(0.063)	(0.025)	(0.000)	(0.003)	(0.116)
Year 2013	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)

Year 2014	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Year 2015	-5.313***	-5.373***	-5.309***	0.473	-5.313***	-5.293***	0.000	2.192***	-0.380*
	(0.000)	(0.000)	(0.000)	(0.656)	(0.000)	(0.000)	(.)	(0.000)	(0.095)
Irrigation	-0.276			0.580	-0.276	-0.146	-0.052	-0.396	0.600*
	(0.502)			(0.453)	(0.502)	(0.794)	(0.912)	(0.420)	(0.079)
Observations	10445	3815	10104	3474	10445	6355	7564	8172	11671
R-squared	0.133	0.127	0.133	0.127	0.133	0.132	0.131	0.072	0.036

Notes: The dependent variables are the inverse hyperbolic sine transformed version of net crop income per hectare, livestock net income, and net agricultural income, respectively. Standard errors are given in parentheses and account for spatial correlation of disturbances. Asterisks indicate the following p-values: *** = $p < 0.01$, ** = $p < 0.05$, and * = $p < 0.1$.

CHAPTER 4

4. Does agricultural diversification build economic resilience to drought and flood? Evidence from poor households in Zambia

4.1. Introduction

The impact of climate change, along with the expectation of more severe and frequent extreme weather shocks, has made poverty reduction in Africa difficult because a large share of the continent's population is engaged in agricultural activities. The previous literature shows that climate change and weather shocks cause losses in agricultural household income and assets in the relatively warm areas of the world (Mendelsohn *et al*. 2006, Lobell *et al*. 2011). Poor people are more likely to be dependent on agricultural income, which is directly influenced by changes in agricultural productivity and generally negatively associated with a hotter and drier climate. For instance, Africa is expected to suffer heavy annual welfare losses by 2070 to 2100, ranging between USD 14 billion and USD 70 billion, depending on the climate scenario and cropland measure considered (Kala *et al*. 2012). Low crop yields can drive up food prices and cause poor households to suffer more from higher food expenditure. Poor people lose more because the quality of their assets fails to resist the regressive impacts of climate change (Mano and Nhemachena 2006; Skoufias 2012; Hallegatte *et al*. 2016). Despite these negative effects of climate change and weather shocks, poor agricultural households may select low-risk and low-return strategies to avoid potential income losses, thereby perpetuating poverty (Hallegatte *et al*. 2016). For example, downside risk in consumption due to rainfall shocks lowers fertiliser application rates, since fertiliser is considered a costly input in Ethiopia (Dercon and Christiaensen 2011).

In Zambia, climate change has become a major threat to sustainable development. Extreme events such as droughts, floods and heavy rainfall have already been occurring and having a negative effect on agricultural production. They also are expected to increase in intensity and frequency. For example, the drought in Zambia from 2004 to 2005 affected 1.2 million people and caused an estimated maize production loss of 740 000 metric tons (United Nations Development Programme [UNDP] 2010; Makano 2011; Gannon *et al*. 2014). Southern Africa has experienced increasing long-term temperatures and decreasing long-term precipitation. Many studies have found that these trends can be projected to continue for the next few decades (Nhemachena and Hassan 2007; Hassan and Nhemachena 2008; Gannon *et al*. 2014; IPCC 2014). Droughts and floods are more likely to occur with greater severity and more frequency in the future (IPCC 2014; World Bank 2014).

Vulnerability to the adverse effects of climate change and weather shocks is not evenly distributed across the country in Zambia (UNDP 2010). Several studies acknowledge that the central and southern regions of Zambia, which have less average annual rainfall, are especially prone to such effects. Thurlow *et al*. (2011) estimate that around 85% of the agricultural GDP losses occurred in the southern and central areas of Zambia from 2006 to 2016, while the northern areas remained relatively unaffected by climate variability. Furthermore, it is also estimated that, using historical data, severe drought is responsible for a 3% to 8% increase in poverty across agro-ecological zones in Zambia for the period from 1976 to 2007 (Thurlow *et al*. 2011).

Farmers do perceive the increasing temperature and decreasing precipitation, and they are using various adaptation strategies in response to the changing climate. According to Nhemachena and Hassan (2007), the top three adaptations in Zambia are i) use of different crop varieties, ii) diversification of crops, and iii) switching from farm to non-farm activities. Drought-resistant crop varieties are introduced in many studies

as an effective adaptation to climate change (Nhemachena and Hassan 2007; Pauw *et al*. 2010; Nikoloski *et al*. 2015; Damania *et al*. 2017). To reduce vulnerability and increase access to services for the rural poor, rural non-farm activities need to be an important aspect of their livelihood strategies (World Bank 2017). Crop diversification can serve as important insurance to avoid complete crop failure due to rainfall and temperature shocks. Mixed production of crops and livestock is also a common adaptation strategy to build resilience to climate shocks.

Irrigation is believed to be positively associated with crop intensification and an effective adaptation strategy to increase household resilience to extreme events and climate change (Nhemachena *et al*. 2010; Bryan *et al*. 2013; Nikoloski *et al*. 2015; Binswanger-Mkhize and Savastano 2017). However, small-scale agricultural production in Zambia is mostly rain-fed. Only 5% of the cultivated land is irrigated, which makes Zambian farmers highly vulnerable to both short-term disasters and long-term changes in precipitation patterns (Funder *et al*. 2013). One reason for the low irrigation rate is that a pump-based irrigation system generally requires electricity, which the nation has limited capacity to provide.

Multiple studies have confirmed that access to extension services, fertiliser subsidies, credit markets and other social protection programmes is positively associated with higher agricultural diversification, productivity and income (McCarthy 2011; Bryan *et al*. 2013; D'Alessandro *et al*. 2015; Arslan *et al*. 2016; Asfaw *et al*. 2016; Nagler and Naudé 2017; Lipper *et al*. 2018). Better promotion of and more investment in these areas should be considered as an effective way to increase income and build resilience.

Building on the previous literature, we quantitatively investigated a hypothesis that agricultural diversification could enhance household resilience to the negative impacts of extreme events on agricultural productivity and welfare in Zambia. Using the

nationally representative household surveys of 2010 and 2015, this study evaluates the effects of farm diversification on agricultural value added per worker when droughts or floods occur. To the best of our knowledge, this is the first study of its kind to analyse the association between agricultural productivity, diversification and extreme events in Zambia.

4.2. Data

We used the nationally representative household-level data from the Living Conditions Monitoring Surveys (LCMS) of 2010 and 2015, conducted by the Central Statistical Office (CSO) of Zambia. The LCMS 2010 and 2015 provide detailed information on the agricultural production, living conditions, economic activity and employment status of household members, among several others, that is representative for both the entire country and provincial areas. Descriptive statistics of key variables are available in the Appendix (Table A1).

In this study, agricultural households are defined as households that have at least one of their members engaged in any of the following agricultural activities: growing of crops, livestock and poultry ownership, fish farming, or a combination of some of the above. This is the formal definition used by the CSO. Agricultural diversification is measured using available proxies such as the number of agricultural activities and household farm types. There are four agricultural activities, namely the production of crops, livestock and poultry, and fish farming. Household farm types are categorised into crops only, livestock only, and both crops and livestock. The incidence of drought and flood is derived from the survey questions on shocks to household welfare. The survey asks whether a household experienced drought and flood in the last 12 months.

We used agricultural value added per worker as a measure of agricultural productivity. The value added in agriculture measures the value of outputs from the agricultural sector (ISIC divisions 1 to 5), less the value of intermediate inputs. The agricultural sector comprises forestry, hunting and fishing, as well as the cultivation of crops and livestock production. To avoid underestimating the total number of farmworkers, as in McCullough (2017), this study estimates the number of hired workers based on total costs of hired laborers in all agricultural activities and the average wage in the agricultural sector. The total number farmworkers in a household thus consist of family members who are self-employed or unpaid family workers and hired agricultural workers. This study calculates the number of family members who participate in farm production by using the adult equivalent scale to take into account the lower productivity per child. We use the same scales as the CSO (De la Fuente *et al*. 2015), which uses per adult equivalent expenditure for poverty analysis rather than per capita expenditure.

All monetary values in this study are temporally and spatially adjusted to the 2015 values using the consumer price index and the Laspeyres spatial price indices, 1F.[7] Also, because the Zambian currency was rebased in 2013 (1 000 old Kwacha = 1 new Kwacha), monetary values reflect this adjustment as well.

We consider only poor households to eliminate the effects of resources and investment capacity that non-poor households might have. The poverty measurement is based on the incidence of per capita consumption lower than the official poverty line constructed by the World Bank and the CSO (De la Fuente *et al*. 2015).

[7] The Laspeyres price index is "the price index defined as a fixed weight, or fixed basket, index that uses the basket of goods and services of the base period. The base period serves as both the weight reference period and the price reference period" (ILO *et al*. 2004). For further details, please refer to the methodology documentation (World Bank 2015).

4.3. Methodology

We tested a hypothesis that diversification of agricultural production increases poor farmers' economic resilience to drought and flood based on a repeated cross-sectional dataset that was constructed by pooling data from the LCMS 2010 and 2015. Agricultural value added per worker is used as a measure of agricultural productivity. Agricultural value added is obtained by subtracting the value of agricultural intermediate input from the value of agricultural output. An agricultural worker is defined as an individual engaged in the agricultural sector.

For the identification of the diversification effects on economic resilience, we regressed agricultural value added per worker on drought dummy, flood dummy and other control variables, with year and province fixed effects for the sub-samples with and without agricultural diversification respectively. In this study, we considered a household as being diversified if it had either at least two agricultural activities or was categorised as both crops and livestock. We assumed that households managed their farm to maximise their net revenue from various farming activities, taking the existing climate as given.

This study considers the following equation to analyse the impacts of drought and flood on the productivity of farm households:

$$Y_{i(t),t,p} = \beta_0 + \beta_D D_{i(t),t,p} + \beta_F F_{i(t),t,p} + \delta' \boldsymbol{X}_{i(t),t,p} + \epsilon_t + \vartheta_p + \varepsilon_{i(t),t,p}, \quad (1)$$

where $Y_{i(t),t,p}$ is the log of the value added per worker from agricultural production activities for a household, *i(t)*, in cross-sectional time *t*, $D_{i(t),t,p}$ and $F_{i(t),t,p}$ are dummy variables that indicate the incidences of droughts and floods respectively, $\boldsymbol{X}_{i(t),t,p}$ are covariates that include both time-varying and time-invariant observable characteristics,

such as socioeconomic and geographical characteristics, ϵ_t and ϑ_p are year and province dummy variables to control for the possible year effect and time-invariant unobservable provincial differences respectively, and $\varepsilon_{i(t),t,p}$ is an error term. Our dataset consists of two independent cross-sections at different points in time. As individuals in different periods are not the same people, we index the variables by a double subscript. In this setting, we estimated the equation for farm households with and without economic diversification respectively. Then we tested a hypothesis of equality of impacts of drought and flood on households with and without economic diversification.

The preliminary OLS regression results showed that the distribution of the error term is skewed, which would not allow us to perform statistical hypothesis testing and generate reliable confidence intervals and prediction intervals. To overcome this, we estimated drought and flood effects on observed farm productivity with a skew-normal regression approach that permits the estimation of the effects on mean, variance and skewness (Henze 1986; Azzalini and Dalla Valle 1996; Azzalini and Capitanio 1999; Gupta and Chen 2001).

The skew-normal distribution, denoted by $SN(\xi, \omega^2, \alpha)$, has the following density:

$$f_{SN}(y;\ \xi, \omega^2, \alpha) = 2\ \omega^{-1}\varphi(z)\Phi(\alpha z) \qquad (2)$$

for $y \in (-\infty, \infty)$, where $z = \omega^{-1}(y - \xi)$, $\xi \in (-\infty, \infty)$ is a location parameter, $\omega > 0$ is a scale parameter, and $\varphi(.)$ and $\Phi(.)$ are the probability density function and cumulative distribution function of the standard normal distribution. This distribution is skewed to the right when $\alpha > 0$, is skewed to the left when $\alpha < 0$, and reduces to a normal distribution when $\alpha = 0$.

From centred parameterisation for the univariate skew-normal distribution (Azzalini 1985), one can obtain $\gamma = (4-\pi)\text{sign}(\alpha)\ (\mu_z/\sigma_z^2)^3/2$, which denotes the skewness index, where $\mu_z = \sqrt{2/\pi}\delta$, $\sigma_z^2 = 1 - 2\delta^2/\pi$, and $\delta = \alpha/\sqrt{1+\alpha^2}$. This centre-parameterised skewness index γ, acquired by centering $Y \sim SN(\xi, \omega^2, \alpha)$, can be used to infer the actual magnitude of the departure from normality.

Consequently, this study fits the skew-normal regression model using the following equation:

$$Y_{i(t),t,p} = \beta_0 + \beta_D D_{i(t),t,p} + \beta_F F_{i(t),t,p} + \gamma' \boldsymbol{X}_{i(t),t,p} + \delta_t + \epsilon_p + v_{i(t),t,p}, \quad (3)$$

where $v_{i(t),t,p}$ is the skew-normal error term $v_{i(t),t,p} \sim SN(0, \omega^2, \alpha)$. This model setting is consistent with the empirical evidence that skewness parameters are statistically significant, as shown in Table 1.

The approach used in this study is robust to heteroskedasticity and spatially correlated errors, since the statistical inference for estimated coefficients is based on their cluster-robust standard errors, which allow intragroup correlation at the survey strata level. The sample weight is applied to account for survey stratification.

This study endeavours to evaluate the country's economic impacts of drought and flood with different agricultural diversification scenarios for agricultural households whose per-adult equivalent consumption is below the national poverty line. This study also considers the scenarios in which poor farmers produce hybrid maize[8] or receive crop seeds and fertiliser from the Farmer Input Support Program (FISP). Using the regression results and data on the characteristics of poor agricultural households, we

[8] Hybrid maize is non-traditional maize. It is a high-yielding, early-maturing or disease-resistant type of maize, like Pioneer, MM604, MM10, etc. Hybrid maize that has been replanted is no longer hybrid maize and should therefore be recorded as local maize. Local maize is traditional maize, usually planted from own produce.

estimated the economic losses from extreme events, gains from climate-resilient practices such as producing hybrid maize, and benefits from seed and fertiliser received from the government through the FISP at the household level. Finally, we aggregated the household-level estimates to the country level.

To obtain the counterfactual predictions, we first estimated Equation (3) using the following five data subsets with different diversification types:

1. All poor agricultural households.
2. Poor agricultural households with only one agricultural activity of crop, livestock, poultry or fish farming.
3. Poor agricultural households with any combination of at least two activities of crop, livestock, poultry and fish farming.
4. Poor agricultural households with either crop or livestock production.
5. Poor agricultural households with both crop and livestock production.

Next, we take the following steps to obtain the baseline predictions for the 2015 total agricultural value added under each of the five diversification scenarios above. First, we compute the fitted agricultural value added per worker evaluated for the year 2015 for all poor households. Second, we multiply the mean fitted value by the product of the average number of agricultural workers in a poor agricultural household for 2015 by the total number of poor agricultural households.

We also computed the counterfactual predictions to explore the potential impacts of the adoption of hybrid maize and agricultural assistance from the FISP on agricultural value added under each diversification scenario. To accomplish this, we took the same steps as in the baseline calculation and first estimated the total agricultural value added of all poor households with the counterfactual data of all households producing hybrid maize and receiving FISP assistance respectively. We then subtracted

the baselines from the counterfactual predictions to obtain the effects of the potential policy interventions.

Lastly, we explore how policy interventions could mitigate the adverse impact of droughts and floods. For this, we first multiplied the baseline predictions by the regression coefficients for drought and flood for each diversification scenario respectively to estimate the impact of the extreme event. We then subtracted the intervention effects from the impact of the extreme event under all combinations of policy options. We also computed the percentage effects of extreme events and policy interventions on agricultural productivity to make them comparable across the diversification scenarios.

4.4. Results

Drought is the most common weather shock at the national level. Based on the LCMS, about 39% of poor agricultural households reported experiencing drought shocks in 2015, while only 7% experienced drought in 2010. Flood experience was reported by 9% and 2% of the poor agricultural households in 2010 and 2015 respectively.

The descriptive statistics show that the diversification of agricultural activities is somewhat limited in Zambia. About 37% of the poor agricultural households in Zambia relied solely on one kind of agricultural production in 2015. On the other hand, there were increasing trends for hybrid maize production and FISP assistance. The fraction of poor farm households producing hybrid maize increased from 27% in 2010 to 46% in 2015. Similarly, the fractions receiving FISP increased from 11% in 2010 to 26% in 2015.

Agricultural value added per worker of farm households with at least two agricultural activities or both crop and livestock production is higher than of those with

only one agricultural activity or either crop or livestock production. The two-sample Kolmogorov-Smirnov tests for equality of distribution functions and the graphical illustrations in the Appendix (Figure A1) reveal that a higher degree of agricultural diversification is associated with higher productivity. Moreover, from the regression analysis, we find that agricultural diversification significantly improves poor farmers' productivity, especially if their farm type is both crop and livestock production, as shown in Table 1.

The regression results show that the impact of drought and flood on agricultural productivity are heterogeneous across types of extreme events and different levels of diversification. Drought has significant negative impacts on agricultural value added per worker of poor farm households, but agricultural diversification can mitigate the impacts of drought. For instance, drought occurrence could lead to a reduction of about 29% in agricultural value added per worker for poor farmers who produce either crops or livestock, while the adverse impact decreases to only an 18% reduction for those who produce both crops and livestock. We also find that agricultural diversification could potentially alleviate the negative economic shock of flood on poor farm households, but the relationship is not as robust as drought.

The regression coefficients for the quintile dummies of farmland size indicate an increasing return to scale. In other words, farmers earn more productivity at an increasing rate as they increase their farmland size. We observe significant positive effects of the adoption of hybrid maize on agricultural productivity. This could be because hybrid maize has a higher yield per hectare than traditional maize and thus, coupled with remunerative selling prices, could generate more income. Being a hybrid maize producer could lead to an increase of around 50% in agricultural value added per worker. We also find that the FISP subsidy has positive impacts on agricultural productivity. The age of the household head has a decreasing return to scale, but the

gender of the household head does not have a statistically significant association with agricultural value added. Poor farmers in rural areas have significantly lower productivity than those in urban areas, perhaps because of less access to output and input markets and irrigation systems.

The effects of agricultural diversification, policy interventions and extreme weather events on the 2015 total agricultural value added are summarised in Tables 2 and 3. The baseline prediction for the 2015 total agricultural value added of all poor households with the actual diversification practice in Zambia is 1 973 million Zambian kwacha (ZMK) (equivalent to USD 229 million in 2015). Other baselines in the first row of Table 2 are for poor households with only one agricultural activity, at least two activities, either crop or livestock production, and both crop and livestock production respectively. If all poor farm households shift their agricultural diversification to produce both crops and livestock, the 2015 total agricultural value added would increase significantly, to 2 623 million ZMK (equivalent to USD 304 million). Additionally, if all poor agricultural households from the baseline in the actual agricultural diversification scenario produce hybrid maize with all other things held constant, the 2015 total agricultural value added would increase to 3 021 million ZMK, which is equivalent to a 53% increase from the baseline. Furthermore, if all poor agricultural households from the baseline in the actual agricultural diversification scenario produce hybrid maize and receive assistance benefits from the FISP, with all other things held constant, the total agricultural value added of all poor households would increase to 3 460 million ZMK, which is equivalent to a 75% increase from the baseline.

The economic impacts of droughts and floods are substantial according to the estimated coefficients from econometric regressions for different diversification scenarios. Comparing the estimated percentage reductions in total agricultural value added in Table 3, we find that agricultural diversification could considerably mitigate

the negative economic shocks. For example, drought and flood could wipe out the agricultural value added by 30% and 39% respectively, in the scenario of all poor agricultural households producing either crops or livestock. On the other hand, the negative impacts of drought and flood reduce to 19% and 8% decreases respectively if all poor agricultural households produce both crops and livestock.

Furthermore, the counterfactual predictions indicate that producing hybrid maize can compensate economic losses from drought and flood. For example, with the actual agricultural diversification, drought reduced the nation's total agricultural value added of all poor households by 480 million ZMK in 2015 (equivalent to USD 56 million) in Table 2, or by 24% in Table 3. However, if all poor agricultural households produce hybrid maize, the negative impacts are compensated for and the total agricultural value added would increase to 569 million ZMK in 2015 (equivalent to USD 66 million), which is equivalent to a 19% increase. While the total agricultural value added decreases due to drought, the reduction is mitigated by hybrid maize production, as well as by seed and fertiliser assistance from the FISP.

4.5. Discussion and conclusion

Our main findings from the regression analyses are three-fold. First, a higher degree of agricultural diversification of poor farm households leads to higher productivity and economic benefits for the country. Second, agricultural diversification is a strategy for poor farm households to escape from poverty and mitigate the adverse impact of droughts and floods. Third, policy interventions such as hybrid maize promotion and seed and fertiliser assistance also help Zambian farmers cope with the adverse impacts of droughts and floods.

We can draw a few policy implications from these findings. First, increasing agricultural diversification could promote more resilient agricultural development for the country, with positive effects on poor agricultural households. Second, researchers and policymakers need to respond to the country's need to improve farmers' productivity via climate-smart agricultural diversification and extension services in an effective and timely manner, and encourage farmers to apply modern inputs in a more effective and productive way that raises their returns and strengthens their resilience. Third, better access to rural credit markets, especially with respect to modern agricultural input use, would help poor farmers build more resilience to weather shocks and climate change.

There are huge uncertainties about how climate change will influence agricultural and food production, both directly and indirectly, and the related vulnerabilities of farm households in Zambia and other countries. Building resilience now is central to being prepared for future changes and uncertainties. It is thus crucial to increase the adaptive capacity of farmers to be prepared for changes and to recover from shocks. At the same time, there is a need to sustainably increase farm productivity and income to help the poor escape poverty. Therefore, it also becomes vitally important for the resilience policies and strategies to increase agricultural productivity in order to secure enough food for the growing population.

This study is subject to some limitations. A limited set of years is used to study the effects of droughts and floods because the LCMS for previous years does not include data on the incidences of droughts and floods. Better estimates might arise using repeated cross-sectional data for a longer period, or panel household data. Due to limited data availability, our analysis cannot incorporate the distance to main roads or input and output markets to control for heterogeneity in market accessibility. Future research could improve the analysis with better data and alternative models and estimators. For

instance, the effects of the actual weather variables, such as temperature, precipitation and counts of extremely hot and wet days, on the mean regressions could be explored. Despite the limitations, this study adds value to the literature by presenting findings on the linkage between agricultural diversification and the economic resilience of poor households, and extreme weather events in Zambia.

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Table 1: Regression results on agricultural productivity of poor households

Dependent variable: Log of agricultural value added per worker	**Agricultural activities**			**Farm type**		
	All poor households	**Only one activity**	**2-4 activities**	**All poor households**	**Either crops or livestock**	**Both crops and livestock**
2-4 activities (relative to "Only one activity")	0.165*** (< 0.001)					
Both crops and livestock (relative to "Either crops or livestock")				0.641*** (< 0.001)		
Drought occurrence	-0.243*** (< 0.001)	-0.269*** (0.001)	-0.212*** (< 0.001)	-0.256*** (< 0.001)	-0.295*** (0.002)	-0.194*** (0.005)
Flood occurrence	-0.234*** (0.008)	-0.329*** (< 0.001)	-0.176** (0.035)	-0.222** (0.027)	-0.385 (0.122)	-0.081 (0.234)
Farmland: Quintile 2 (relative to quintile 1)	0.175 (0.158)	0.193** (0.041)	0.179 (0.208)	0.153 (0.248)	0.208 (0.212)	0.003 (0.98)
Farmland: Quintile 3 (relative to quintile 1)	0.425*** (0.001)	0.512*** (< 0.001)	0.400*** (0.007)	0.340*** (0.008)	0.460*** (0.001)	0.104 (0.428)
Farmland: Quintile 4 (relative to quintile 1)	0.846*** (< 0.001)	0.791*** (< 0.001)	0.900*** (< 0.001)	0.726*** (< 0.001)	0.835*** (< 0.001)	0.522*** (< 0.001)
Farmland: Quintile 5 (relative to quintile 1)	1.562*** (< 0.001)	1.300*** (< 0.001)	1.655*** (< 0.001)	1.408*** (< 0.001)	1.434*** (< 0.001)	1.236*** (< 0.001)
Hybrid maize producer	0.532*** (< 0.001)	0.498*** (< 0.001)	0.548*** (< 0.001)	0.499*** (< 0.001)	0.525*** (< 0.001)	0.468*** (< 0.001)
Farmer Input Support Program (FISP)	0.223*** (< 0.001)	0.323*** (0.001)	0.190*** (< 0.001)	0.181*** (< 0.001)	0.431*** (< 0.001)	0.047 (0.318)
Household head: Age	0.031*** (0.004)	0.040** (0.018)	0.024*** (0.001)	0.026** (0.019)	0.026* (0.054)	0.024** (0.023)
Household head: Age^2	-0.000*** (< 0.001)	-0.001*** (0.002)	-0.000*** (< 0.001)	-0.000*** (0.001)	-0.000*** (0.004)	-0.000*** (0.004)
Household head: Male	0.079 (0.113)	0.041 (0.639)	0.077*** (0.007)	0.071 (0.139)	0.052 (0.419)	0.094** (0.04)
Year 2015 (relative to year 2010)	0.345*** (< 0.001)	0.492*** (< 0.001)	0.245*** (< 0.001)	0.441*** (< 0.001)	0.568*** (< 0.001)	0.291*** (< 0.001)
Rural area (relative to urban area)	-0.577*** (< 0.001)	-0.702*** (< 0.001)	-0.450*** (< 0.001)	-0.646*** (< 0.001)	-0.690*** (< 0.001)	-0.566*** (< 0.001)

Dependent variable: Log of agricultural value added per worker	Agricultural activities			Farm type		
	All poor households	Only one activity	2-4 activities	All poor households	Either crops or livestock	Both crops and livestock
Province: Copperbelt (relative to Central)	0.117**	0.126	0.096	0.136**	0.295**	0.021
	(0.019)	(0.456)	(0.438)	(0.039)	(0.023)	(0.883)
Province: Eastern (relative to Central)	-0.418***	-0.466***	-0.398***	-0.407***	-0.269***	-0.460***
	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)
Province: Luapula (relative to Central)	-0.584***	-0.720***	-0.720***	-0.594***	-0.664***	-0.506***
	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)
Province: Lusaka (relative to Central)	-0.049	-0.049	-0.049	0.082	0.050	0.201*
	(0.348)	(0.402)	(0.402)	(0.146)	(0.799)	(0.091)
Province: Northern (relative to Central)	-0.427***	-0.427**	-0.427**	-0.411***	-0.370***	-0.434***
	(< 0.001)	(0.046)	(0.046)	(< 0.001)	(0.001)	(< 0.001)
Province: North Western (relative to Central)	0.023	-0.039	-0.039	0.079*	0.166*	-0.023
	(0.586)	(0.797)	(0.797)	(0.084)	(0.076)	(0.765)
Province: Southern (relative to Central)	-0.429***	-0.483**	-0.483**	-0.409***	-0.459***	-0.377***
	(< 0.001)	(0.011)	(0.011)	(< 0.001)	(0.005)	(< 0.001)
Province: Western (relative to Central)	-0.332***	-0.705***	-0.705***	-0.283***	-0.315***	-0.168***
	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(0.003)	(0.002)
Constant	5.176***	5.169***	5.169***	5.160***	5.058***	6.005***
	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)
Gamma (Skewness coefficient)	-0.179***	-0.200***	-0.200***	-0.150***	-0.196***	-0.061
	(0.002)	(0.009)	(0.009)	(0.004)	(< 0.001)	(0.335)
Ln(sigma)	0.435***	0.473***	0.473***	0.416***	0.533***	0.282***
	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)
Wald χ^2 (*d.f.* = 22 for pool data models, and 21 otherwise)	2 149.414	572.212	572.212	2 478.836	841.350	1 004.607
	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)
Number of observations	7 678	2 537	2 537	7 678	3 437	4 241

Notes: Authors' estimates using household-level data from the LCMS 2010 and 2015. This table reports the impacts of drought and flood on the agricultural productivity of poor agricultural households with and without diversification. The four agricultural activities are the production of crops, livestock, poultry and fish farming. Coefficients are the estimates of the skew-normal regression of agricultural value added per worker. Cluster robust *p*-values are in parentheses (* p < 0.10, ** p < 0.05, *** p < 0.01).

Table 2: Predicted effects of diversification, policy interventions and extreme weather events on the 2015 total agricultural value added of poor households in Zambia (2015 million ZMK)

	Actual agricultural diversification	Agricultural activities		Farm type	
		Only one activity	2-4 activities	Either crops or livestock	Both crops and livestock
2015 total agricultural value added of all poor households					
Baseline	1 973	1 860	1 988	1 514	2 623
Baseline + FISP	2 412	2 460	2 367	2 167	2 747
Baseline + hybrid maize	3 021	2 787	3 078	2 309	3 852
Baseline + FISP + hybrid maize	3 460	3 387	3 456	2 962	3 976
Benefits from policy interventions					
FISP	439	600	378	653	124
Hybrid maize	1 049	927	1 090	795	1 229
FISP + hybrid maize	1 488	1 527	1 468	1 448	1 353
Impact of extreme events: Baseline					
Drought	-480	-501	-421	-447	-508
Flood	-462	-612	-349	-583	-212
Impact of extreme events: Baseline + FISP					
Drought	-41	99	-43	206	-383
Flood	-22	-12	29	70	-87
Impact of extreme events: Baseline + hybrid maize					
Drought	569	426	668	349	721
Flood	587	315	740	212	1 017
Impact of extreme events: Baseline + FISP + hybrid maize					
Drought	1 008	1 026	1 047	1 002	845
Flood	1 026	915	1 118	865	1 142

Table 3: Predicted effects of diversification, policy interventions and extreme weather events on the 2015 total agricultural value added of poor households in Zambia (percentage)

	Actual agricultural diversification	Agricultural activities		Farm type	
		Only one activity	2-4 activities	Either crops or livestock	Both crops and livestock
Benefits from policy interventions					
FISP	22%	32%	19%	43%	5%
Hybrid maize	53%	50%	55%	53%	47%
FISP + hybrid maize	75%	82%	74%	96%	52%
Impact of extreme events: Baseline					
Drought	-24%	-27%	-21%	-30%	-19%
Flood	-23%	-33%	-18%	-39%	-8%
Impact of extreme events: Baseline + FISP					
Drought	-2%	4%	-2%	10%	-14%
Flood	-1%	0%	1%	3%	-3%
Impact of extreme events: Baseline + hybrid maize					
Drought	19%	15%	22%	15%	19%
Flood	19%	11%	24%	9%	26%
Impact of extreme events: Baseline + FISP + hybrid maize					
Drought	33%	37%	34%	43%	22%
Flood	34%	33%	36%	37%	30%

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Appendix

Table A1: Mean and standard deviation of key variables

Variables	All households	Households with agricultural activities		Households with farm type	
		Only one activity	2 to 4 activities	Either crops or livestock	Both crops and livestock
Agricultural value added per worker (2015 Zambian kwacha)	2 716 (39 712)	2 045 (30 438)	3 029 (43 359)	2 851 (45 956)	2 606 (33 772)
At least two activities (relative to "only one activity")	0.68 (0.47)	0.00 (n.a.)	1.00 (0.00)	0.50 (0.50)	0.83 (0.38)
Both crops and livestock (relative to "either crops or livestock")	0.55 (0.50)	0.30 (0.46)	0.67 (0.47)	0.00 (n.a.)	1.00 (0.00)
Drought occurrence	0.22 (0.41)	0.20 (0.40)	0.23 (0.42)	0.23 (0.42)	0.22 (0.41)
Flood occurrence	0.06 (0.23)	0.06 (0.24)	0.05 (0.22)	0.06 (0.24)	0.05 (0.23)
Hybrid maize producer	0.36 (0.48)	0.29 (0.46)	0.40 (0.49)	0.30 (0.46)	0.42 (0.49)
Farmer Input Support Program (FISP)	0.18 (0.39)	0.16 (0.36)	0.19 (0.40)	0.14 (0.35)	0.22 (0.41)
Household head: age	43.9 (14.6)	42.9 (15.4)	44.4 (14.2)	43.9 (15.3)	44.0 (14.0)
Household head: male	0.80 (0.40)	0.76 (0.43)	0.81 (0.39)	0.77 (0.42)	0.82 (0.39)
Year 2015 (relative to year 2010)	0.47 (0.50)	0.55 (0.50)	0.44 (0.50)	0.56 (0.50)	0.40 (0.49)
Rural area (relative to urban area)	0.96 (0.19)	0.93 (0.25)	0.98 (0.14)	0.95 (0.22)	0.98 (0.15)
Number of observations	7 678	2 537	5 141	3 437	4 241

Notes: Final household sample from the LCMS 2010 and 2015 for all analyses in this paper. Standard deviations are in parentheses. n.a. = not applicable

Figure A1: Kernel density estimation of log of agricultural value added per worker (2015 ZMW)

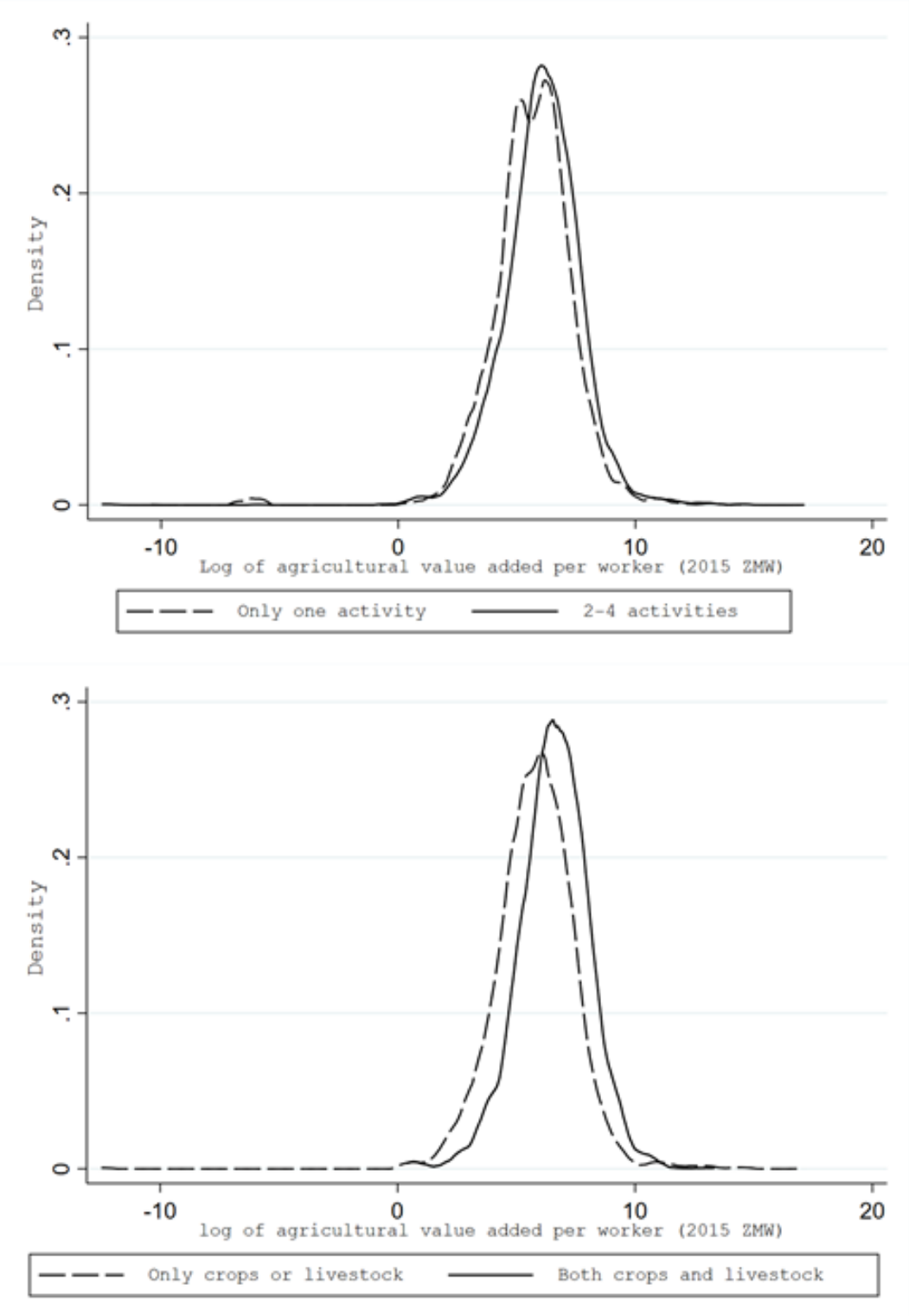

Table A2: Standard errors of predicted effects of diversification, policy interventions and extreme weather events on the 2015 total agricultural value added of poor households in Zambia (2015 million ZMK)

	Actual agricultural diversification	Agricultural activities		Farm type	
		Only one activity	2-4 activities	Either crops or livestock	Both crops and livestock
2015 total agricultural value added of all poor households					
Baseline	625	763	592	761	1,206
Baseline + FISP	766	1,019	703	1,008	1,222
Baseline + hybrid maize	973	1,170	927	1,160	1,545
Baseline + FISP + hybrid maize	1,113	1,426	1,038	1,407	1,562
Benefits from policy interventions					
FISP	141	256	111	247	17
Hybrid maize	347	407	334	399	339
FISP + hybrid maize	488	663	445	646	356
Impact of extreme events: Baseline					
Drought	152	212	123	189	215
Flood	143	242	100	340	377
Impact of extreme events: Baseline + FISP					
Drought	11	44	12	58	199
Flood	2	14	11	93	394
Impact of extreme events: Baseline + hybrid maize					
Drought	196	195	212	211	124
Flood	205	165	235	60	716
Impact of extreme events: Baseline + FISP + hybrid maize					
Drought	336	451	323	458	141
Flood	345	421	345	307	733

Table A3: F-test for equality of coefficients from different regression models

Variable	Subsample regression models compared	Chi-squared	Probability
Drought	Only one activity vs 2-4 activities	0.276	0.599
Flood	Only one activity vs 2-4 activities	12.157	0.000
Drought	Either crops or livestock vs Both crops and livestock	0.035	0.851
Flood	Either crops or livestock vs Both crops and livestock	3.021	0.082

Table A4: Regression results on agricultural productivity of poor households (with hybrid maize and drought interaction)

	Agricultural activities			Farm type		
Dependent variable: Log of agricultural value added per worker	**All poor households**	**Only one activity**	**2-4 activities**	**All poor households**	**Only crop or livestock**	**Both crop and livestock**
2-4 activities (relative to "Only one activity")	0.170***					
	(<0.001)					
Both crop and livestock (relative to "Only crop or livestock")				0.454***		
				(<0.001)		
Drought Occurrence	-0.243***	-0.283***	-0.207***	-0.283***	-0.315***	-0.283***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.009)
Flood Occurrence	-0.228**	-0.318***	-0.168**	-0.298*	-0.442*	0.316
	(0.012)	(<0.001)	(0.043)	(0.074)	(0.062)	(0.29)
Farm land: Quintile 2 (relative to quintile 1)	0.283***	0.298***	0.292**	0.409***	0.368***	0.476***
	(0.009)	(<0.001)	(0.048)	(<0.001)	(0.001)	(<0.001)
Farm land: Quintile 3 (relative to quintile 1)	0.540***	0.624***	0.521***	0.648***	0.701***	0.441***
	(<0.001)	(<0.001)	(0.001)	(<0.001)	(<0.001)	(0.006)
Farm land: Quintile 4 (relative to quintile 1)	0.963***	0.899***	1.025***	0.994***	0.964***	0.990***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Farm land: Quintile 5 (relative to quintile 1)	1.680***	1.399***	1.783***	1.654***	1.501***	1.753***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Hybrid Maize Producer	0.555***	0.531***	0.565***	0.398***	0.476***	0.218**
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.032)
Hybrid Maize Producer * Drought	0.000	0.016	-0.001	0.125**	0.182**	0.169
	(0.988)	(0.911)	(0.967)	(0.013)	(0.035)	(0.134)
Farmer Input Support Program (FISP)	0.225***	0.335***	0.187***	0.148	0.322***	0.014
	(<0.001)	(0.001)	(<0.001)	(0.216)	(0.005)	(0.899)
Household Head: Age	0.031***	0.041***	0.023***	0.029**	0.031**	0.018

	(0.001)	(0.006)	(0.001)	(0.041)	(0.031)	(0.236)
Household Head: Age^2	-0.000***	-0.001***	-0.000***	-0.000**	-0.000***	-0.000
	(<0.001)	(<0.001)	(<0.001)	(0.013)	(0.007)	(0.146)
Household Head: Male	0.065	0.037	0.055*	0.123**	0.176***	0.002
	(0.125)	(0.588)	(0.06)	(0.019)	(0.002)	(0.975)
Year 2015 (relative to year 2010)	0.330***	0.455***	0.244***	1.293***	1.262***	0.356***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Rural area (relative to urban area)	-0.570***	-0.699***	-0.447***	-0.893***	-0.943***	-0.572***
	(<0.001)	(0.001)	(<0.001)	(<0.001)	(0.001)	(<0.001)
Province: Copperbelt (relative to Central)	0.117**	0.072	0.131	0.246***	0.441***	0.077
	(0.019)	(0.734)	(0.264)	(<0.001)	(<0.001)	(0.289)
Province: Eastern (relative to Central)	-0.422***	-0.485***	-0.399***	-0.429***	-0.160***	-0.699***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.009)	(<0.001)
Province: Luapula (relative to Central)	-0.528***	-0.661***	-0.467***	-0.440***	-0.352***	-0.426***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.005)	(<0.001)
Province: Lusaka (relative to Central)	-0.074	-0.346	0.041	0.412***	0.420***	0.610***
	(0.194)	(0.333)	(0.74)	(<0.001)	(0.001)	(<0.001)
Province: Northern (relative to Central)	-0.391***	-0.396*	-0.402***	-0.304***	-0.177*	-0.398***
	(<0.001)	(0.098)	(<0.001)	(<0.001)	(0.086)	(<0.001)
Province: North Western (relative to Central)	0.059	-0.003	0.074	0.061	0.213	-0.103
	(0.207)	(0.984)	(0.243)	(0.444)	(0.158)	(0.54)
Province: Southern (relative to Central)	-0.413***	-0.511***	-0.400***	-0.106	0.040	-0.254***
	(<0.001)	(0.009)	(<0.001)	(0.16)	(0.447)	(<0.001)
Province: Western (relative to Central)	-0.306***	-0.706***	-0.023	-0.148**	-0.040	-0.087
	(<0.001)	(<0.001)	(0.701)	(0.015)	(0.364)	(0.347)
Constant	5.056***	5.055***	5.224***	4.152***	3.952***	5.829***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Gamma (Skewness coefficient)	(0.003)	(0.007)	(0.003)	(0.001)	(0.001)	(0.028)

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Ln(sigma)	0.429***	0.468***	0.403***	0.481***	0.562***	0.299***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Loglikelihood	2149.414	572.212	1571.106	2478.836	841.350	1004.607
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Number of observations	7,503	2,424	5,079	3,347	2,023	1,324

CHAPTER 5

5. Conclusions

5.1. Overview

Achieving a better understanding of measurement errors in weather data sets and the effects of extreme weather events on agriculture is necessary to further improve the estimates of climate change impacts given in the previous literature. Careful consideration and integration of uncertainty in climate data sets and the adverse effects of extreme events is a key area for further advancement of studies on climate change impacts, particularly in the agricultural sector that is expected to be severely affected by climate change. The field of climate change economics will significantly benefit from interdisciplinary research to better understand the appropriate use of satellite climate data that has recently become available.

Each of the three foregoing essays on the economics of climate change and extreme events suggests conclusions and policy recommendations that might lead to more effective adaptation to climate change in the US and African countries as well as other countries worldwide. A few of the broader lessons learned and future research directions are discussed below.

5.2. Lessons learned

Two main lessons can be learned from Chapters 2–4. First, as mainly discussed in Chapter 2, measurement errors do exist in climate data sets and these have significant implications for the results of climate change impact studies. Simple replication based on alternative data sets from highly respected sources that employ advanced interpolation techniques indicates that the detrimental response of crop yields to extremely high temperature and the estimated climate change impacts on crop yields could be approximately half of those reported in previous literature. More importantly, the results here raise questions regarding the robustness of econometric models used to quantify climate change impacts in alternative weather data sets, as the results appear highly dependent on small differences in extreme temperature recordings.

Second, extreme weather events such as droughts and floods adversely affect the livelihoods of agricultural households in Africa. Chapter 3 finds robust negative impacts of droughts and floods on net crop income in five African countries—Ethiopia, Malawi, Niger, Nigeria, and Uganda. These extreme event effects are heterogeneous across different levels of poverty and agricultural diversification. Poor farmers and those who only grow crops experience decreased net crop income due to droughts and floods more than non-poor and mix-production farmers, respectively. Furthermore, the analysis quantitively confirms recent findings that the effectiveness of electricity in increasing agricultural productivity depends on other household and geographical factors, such as farmland area size and distance to roads, particularly in the African context.

Chapter 4 also provides additional empirical evidence on the adverse effects of droughts and floods on agricultural households' livelihoods by considering Zambia as a country of study. The study finds that the impacts of droughts and floods on agricultural productivity are heterogeneous across types of extreme events and different levels of diversification. Drought has significant negative impacts on agricultural value added per worker of poor farm households, but agricultural diversification can mitigate the impacts of drought. For example, a drought could lead to a reduction of approximately 29% in agricultural value added per worker for poor farmers who produce either crops or livestock, while the adverse impact decreases to only a reduction of 18% for those who produce both crops and livestock.

5.3. Future research

Chapter 2 identifies possible future research in the area of measurement errors that characterize climate data sets, particularly those pertaining to US agriculture, although these could be also applicable to the rest of the world as well as non-agricultural sectors. First, the economics community would greatly benefit from a better understanding of the suitability of various weather data sets in the analysis of the effects of extreme temperature on crop yields, particularly at temporally and spatially disaggregated levels. Second, it would also be useful to have a better understanding of the method that must be used to interpolate hourly temperature from daily maximum and minimum temperature data. Third, data uncertainty could be explicitly incorporated in econometric modelling if such measures are available. For

example, a conceptual model could be created that yields a series of predictions for climate change impacts from simulation based on mathematically derived equations that incorporate uncertainty in temperature distribution.

As an extension of Chapter 3, given the limitations of the self-reported drought data for Africa, one could model the reporting of droughts and floods. When are farmers more likely to report a drought or a flood? Modelling these processes by combining household survey data and satellite climate data would require further research and provide a more solid methodological footing. For example, one could regress the dummy variables of drought and flooding on precipitation and temperature and interact these variables with key characteristics of the household, region, or country, which would enable a deeper exploration of the drivers of the reporting. Furthermore, one could also explore dynamic modeling to study the mechanism of the self-reporting of droughts and floods over time using panel data.

As discussed in Chapter 4, further research is needed to improve the analysis of drought impacts on agriculture in Zambia. The availability of alternative data, models, and estimators—particularly geo-referenced household data with information on extreme events—would be useful. For example, the effects of actual weather variables—such as temperature, precipitation, and counts of extremely hot and wet days—on agricultural production and livelihoods could be explored through a regression analysis. With such data, one could also incorporate the distance to main roads or input and output markets to control for heterogeneity in market accessibility. Furthermore, geo-referenced data would enable researchers to explore and account for the spatial heterogeneity of the effects of droughts and floods on their spatial autocorrelation in econometric modeling.