"Understanding Temperature and Moisture Interactions in the Economics of Climate Change Impacts and Adaptation on Agriculture"

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Understanding Temperature and Moisture Interactions in the Economics of Climate Change Impacts and Adaptation on Agriculture*

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Abstract

Growing econometric and statistical evidence points to high temperature as the main driver of large negative effects of climate change on US agriculture. This literature also suggests a limited role for precipitation in overall impacts. This paper shows this finding stems from the widespread use of calendar precipitation variables, which poorly represent water availability for rainfed crops. I rely on a state-of-the art dataset with very high spatial (14km) and temporal (1h) resolution to develop a statistical model and unpack the effects of temperature and drought stress and analyze their interactions. Using a 31-year panel of corn yields covering 70% of US production, I account for nonlinear effects of soil moisture with varying effects throughout the growing season, in addition to nonlinear temperature effects. I show that yield is highly sensitive to soil moisture toward the middle of the season around flowering time. Results show

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that omission of soil moisture leads to overestimation of the detrimental effects of temperature by 30%. Because climate change affects intra-seasonal soil moisture and temperature patterns differently, this omission also leads to very different impacts on US corn yields, with a much greater role for water resources in overall impacts. Under the medium warming scenario (RCP6), models omitting soil moisture overestimate yield impacts by almost 100%. The approach shows a more complete understanding that climate change impacts on agriculture are likely to be driven by both heat and drought stresses, and that their relative role can vary depending on the climate change scenario and farmer ability to adapt.

JEL Classification Codes: Q54, Q15, Q51, R15

Keywords: climate change, agriculture, impacts, adaptation, drought, temperature stress, nonlinear effects, omitted variable bias, spatial error panel model.

1 Introduction

Agriculture is arguably one of the most vulnerable sectors to climate change. Much economic work has focused on developing econometric approaches to evaluate overall impacts of climate change on the sector implicitly (Mendelsohn, Nordhaus and Shaw, 1994; Schlenker, Hanemann and Fisher, 2005; Deschênes and Greenstone, 2007). Controversy even on the sign of these impacts persists and remains unresolved because of the inherent vulnerability of these highly-reduced-form approaches to various forms of omitted variable bias (see Deschênes and Greenstone, 2007; Fisher et al., 2012). Although these approaches differ by the structure of the underlying data (cross-sectional or panel), they share an important common characteristic in how they capture water availability and heat effects through the use of precipitation and temperature variables.

Most innovation in econometric climate change impact studies regarding climate variables concerns the measurement of heat exposure. In their seminal hedonic paper, Mendelsohn, Nordhaus and Shaw (1994) regressed US land price data on linear and quadratic terms of average monthly precipitation and temperature for the months of January, April, July and October. However, Schlenker et al. (2006) triggered a small revolution by suggesting that monthly averaging eliminates valuable information regarding daily exposure to very high temperatures. They proposed accounting separately for the cumulative exposure to moderate (8-32ºC) and high (34ºC) temperatures over the entire growing season. This approach has been found to improve the fit of the hedonic model, and can be found in leading studies such as Schlenker et al. (2005) and Deschênes and Greenstone (2007).

Further work on this area has been carried out by Schlenker and Roberts (2009, henceforth SR), who have developed the most advanced approach to date for capturing the nonlinear effects of temperature on crop yields. They make use of highly detailed weather data and flexible semi-parametric techniques that allow each temperature bin to have separate effects on yield.

Although econometric and crop yield studies have attempted to account for heat in increasingly flexible ways, little attention has been given to how these studies treat water availability. Most studies simply rely on monthly or pluri-monthly precipitation variables. A possible explanation is the growing consensus across econometric and statistical crop yield studies that precipitation plays a limited role in climate change impacts. My word shows that improving the representation of water availability has been undervalued.

For instance, based on worldwide observational data, Lobell and Burke (2008) explore the relative role of temperature, precipitation, and choice of climate model on climate change impact uncertainty. They find for most crops and regions that uncertainties related to temperature, in particular yield sensitivity to temperature, represents a greater contribution to climate change impact uncertainty related to precipitation. They conclude that understanding crop responses to temperature is one of the most important needs for climate change impact assessments and adaptation efforts for agriculture.

The growing consensus from econometric models (e.g. Schlenker et al., 2005) and statistical yield models is that climate change impacts will be largely driven by exposure to heat. For instance, SR find that substituting a single full day of the growing season at 29°C with a full day at 40°C translates into a predicted decline of 7% for corn yields holding all else constant. According to this study, corn, soybean and cotton yields would decrease by 30–46% before the end of the century under the slowest warming scenario, and by 63–82% under the most rapid warming scenario, if current growing regions and seasons remain fixed. A surprising result is that a hypothetical drop of 50% in precipitation reduces corn yield by just over 10%.

The evidence that changes in precipitation may have only a marginal role in overall climate change impacts presages a dire future for US agriculture. Indeed, it implies that water management practices that provide greater control of soil moisture, such as irrigation, would not offer a significant counterbalancing effect to yield losses from heat stress.

However, this evidence is difficult to reconcile with agronomic experimental evidence. For sentence, yield reductions in excess of 90% for corn can occur when water-deficits span key stages of the season (NeSmith and Ritchie, 1992). A possibility is that heat and drought stresses are statistically confounded in the modeling efforts to date. This is plausible for three major reasons. First, heat waves and drought have a well-known interconnection. Second, drought significantly affect crop yields. Third, variables used to capture water availability for rainfed crops, such as precipitation aggregated over several months, are a poor representation of water supply. in the form of soil moisture, which is the form in which it matters for crop production.

Relying on season-long precipitation as a measure of water availability to crops has potentially crucial shortcomings. A pivotal concern is the implicit assumption that rainfall is a perfectly substitutable input over time within a season. This implies that it does not matter when it rains as long as it rains within the season. The agronomic literature suggests otherwise and, specifically, that crop sensitivity varies considerably throughout the season. For instance, Fageria et al. (2006, p.89, 93, 157, 180) argue that water deficiency and extreme temperatures during the mid-season flowering period of cereal and leguminous crops has greater implications for yield than any other period.

Another potential issue is that water availability for crop growth should arguably be more closely related to the *stock* of water in the soil (soil moisture) at any given point in time than to the *inflow* of water to the ground over a long period (such as measured by pluri-monthly precipitation for rainfed crops). For instance, the soil is quickly saturated during intense rainfall and additional rain runs off and is no longer available to crops. Thus, the same amount of rainfall spread over time yields greater availability of water to crops because it allows rain to seep in the soil. Indeed, the fraction of rain that infiltrates the soil and becomes available for crop growth depends on how wet the soil is initially. Also, rain water evaporates more rapidly during hot, dry and windy conditions. Thus, a given rainfall event in the summer is not as effective in keeping the soil wet as in the cooler spring or fall. Precipitation also seeps to deeper soil layers out of root reach in more porous soil (e.g. sandy soil). As a consequence, factors such as recent rainfall, temperature, humidity, soil type, slope or crop stage affect the extent to which precipitation can be effectively available for crop growth. In summary, precipitation is only a part of the equation of water availability to crops whereas soil moisture itself is arguably a more appropriate metric.

Unpacking the relative contributions of heat and drought stress in climate change impact scenarios is a major priority for econometric analysis because it should improve understanding of potential impact and adaptation mechanisms. Ortiz-Bobea and Just (2012) emphasize that clarifying the structure of adaptation mechanisms facilitates the assessment of potential welfare impacts. Informed assessment of adaptation possibilities depends fundamentally on capturing the mechanisms that facilitate farmers' abilities to adapt to new climatic inputs and constraints. As a consequence, the timing of environmental conditions within the season may matter if farmers can choose to limit their exposure to adverse intra-seasonal conditions by shifting planting times, changing the crop mix, or making other counteracting production decisions.

In essence, the choice of climate variables is intimately related to the structure of the farmer's optimization problem. For instance, choosing fixed calendar periods for climate variables assumes a fixed growing season. Ortiz-Bobea and Just show that such a restriction overestimates corn yields damages by 30 to 70% under a 5ºF warming scenario in the Upper Midwest. They rely on the fact that a warmer climate results in a longer non-freezing period that provides greater flexibility in the choice of planting date. Because yield sensitivity to high temperatures is stronger around the middle of the season (when corn is flowering), earlier planting by two to three weeks shifts the sensitive period away from the most detrimental summer heat. Thus, under-representation of adaptation possibilities leads to overestimation of impacts.

In this paper, I expand the horizons of literature by unpacking the effects of heat stress and drought stress, and identifying their interactions. I build on previous frontier work by SR on nonlinear effects of temperature and explore the nonlinear effects of soil moisture on yields at different points during the growing season. The emphasis on timing has the ultimate purpose of improving representations of farmer adaptation possibilities given changes in relevant environmental conditions forecasted by accepted climate change models. This should facilitate econometric adaptation analysis based on revealed preference data that accounts for intra-seasonal changes of environmental conditions associated with climate change.

To develop my model of the role of soil moisture as well as other climate variables, I rely on a state-of-the-art soil moisture and weather dataset from the North American Land Data Assimilation System (NLDAS), which offers very high resolution in both space (14km) and time (1h). I replicate the SR panel model for corn yield and contrast it with a model that accounts for the timing and level of soil moisture using various flexible semi-parametric specifications. To demonstrate these issues clearly, I focus only on corn production in the Upper Midwest, which is the most productive area for high-valued field crops in the US.

Results suggest sizable nonlinear effects of soil moisture on crop yields that are particularly large toward the middle of the season around the flowering period. Results show that failure to account for soil moisture not only significantly reduces model fit, but leads to overestimation of the detrimental effects of heat stress by about 30%. This stems from the fact that soil moisture has so far been confounded with high temperatures leading to omitted variable bias. Because soil moisture and temperature change patterns differ within the season, this omission also leads to an overestimation of overall impacts by almost 100% by the end of the century under the medium warming scenario (RCP6). These results imply that water resources will play a major role in the overall impacts, in stark contrast to models based on calendar precipitation variables.

This paper is organized as follows. Section 2 describes data sources and how regressors and climate change scenarios were constructed. Section 3 presents estimates of the leading reference model using this refined dataset and contrasts these results with a model augmented with the soil moisture possibilities facilitated by this dataset. Section 4 projects climate change impacts for these models under various climate change scenarios and compares results in terms of overall impacts with focus on the relative roles played by heat and drought stress. Section 5 presents discussion about the implications of this model for climate change impact assessment and outlines an agenda for the future research it motivates. I conclude in section 6.

2 Data sources and variables

2.1 Soil moisture and weather Data

This paper seeks to improve understanding of drought stress for the purposes of climate change impact assessment by improving the representation of water availability to crops. Rather than using precipitation variables, I rely directly on measures of water content in the soil. While disaggregated weather data can be obtained with relative ease, this is not the case for soil moisture. Detailed soil moisture measurements are typically confined to experimental fields in some states. The feasible alternative for broad-based geographic models is to rely on the latest model-generated soil moisture estimates which serve as proxies.

The North American Land Data Assimilation System (NLDAS, Mitchell et al., 2004) is a joint project by the National Oceanic and Atmospheric Administration's National Centers for Environmental Prediction (NOAA/NCEP), the National Aeronautics and Space Administration (NASA), Princeton University, and the University of Washington. It offers state-of-the-art gridded weather and soil moisture datasets. The NLDAS uses weather station, satellite, radar and reanalysis data together with four different land surface models to generate estimates of soil moisture across North America.[1] These estimates account for parameters such as soil type, land cover, and slope with a 1km resolution. Specifically, the second stage of the NLDAS project, or NLDAS-2, provides model output data in the form of water mass for several soil layers as well as the model input weather data at an impressive level of detail. The large dataset contains hourly observations in near real time with a spatial resolution of 14km over North America since January 1979.[2]

The NLDAS project team is particularly attentive to the accuracy of its forcing weather data (precipitation and temperature, etc.) as well as of its model output (soil water content, etc.). Cosgrove et al. (2003) describe the techniques used to generate the hourly NLDAS weather data. They perform a cross-validation for the 1/1/1998 to 11/30/1999 period against observed data from U.S. Department of Energy's Atmospheric Radiation Measurement program Clouds and Radiation Testband (ARM CART) sites. For instance, the cross-validation regression for hourly temperature exhibits an R^2 of 0.980 with a small bias of -0.479ºC. This is accomplished with an ARM CART site in the Southern Great Plains that covers hundreds of thousands of square kilometers and contains the world's largest collection of advanced remote sensing instruments, which is considered one of the best outdoor laboratories in the world. Its purpose is to serve as a gold standard to cross-validate the output of global climate models. Needless to say, the measurements from this facility are superior to that of any

[1] The soil model names are Noah, Mosaic, Sacramento Soil Moisture Accounting (SAC-SMA), and Variable Infiltration Capacity (VIC).

[2] The size of the NLDAS-2 weather and soil moisture hourly dataset for 1979-2011 for the North American domain in gridded format exceeds 2,000GB for only one of the four soil models.

standard weather station. Although this validation spans less than a year of observations, this is an impressive level of precision for cross-validation of hourly NLDAS weather data.

At the time of this writing, the cross-validation for NLDAS-2 model output (soil water storage) was under submission and unavailable.[3] However, Schaake et al. (2004) carried out a cross-validation for the first phase of the NLDAS project, NLDAS-1, which might provide a hint on how these soil models compare for NLDAS-2. They show that simulated water storage values from both the SAC and Noah soil models agree well with the measured values in several sites across Illinois, one of the major producing states in the sample of this paper. Their study also shows that the ranges of variability of SAC-SMA, Noah, and VIC water storage are close to the observed range. Expectations are that simulated water storage has been improved further in the NLDAS-2 data that I use in this paper.

The NLDAS dataset provides several advantages. First, it arguably offers the most reliable proxy of soil moisture across North America. Second, it offers spatial and temporal resolutions that allow a high level of detail in constructing county-level variables with the temporal detail necessary to match environmental conditions in critical parts of the growing season. Third, its hourly resolution eliminates the need to make assumptions about the temperature-time curve within a day (often assumed to follow a sine curve) which could provide more accurate measures of the distribution of temperature exposure.

The dataset could also present some shortcomings. First, it offers four different soil models. Although they yield qualitatively similar soil moisture contents, which one provides the best estimates is still unclear. However, the cross-validation for the NLDAS-1 project could provide a hint into which models perform better. Second, the NLDAS does not account for actual soil depth. The models apply over a fixed 2 meter soil column divided into 4 layers (0-10cm, 10-40cm, 60-100cm, 100-200cm). Locations with shallow soils have a lower water holding capacity and become saturated or dry out more quickly, which would interfere with correct estimation. However, my study region has some of the deepest soils in the US and this

[3] David Mocko (NASA), personal communication, November 21, 2012

should not be a concern. Third, the NLDAS soil moisture estimates only account for water supplied through precipitation. As a result, they do not offer an accurate representation of soil moisture in irrigated areas. At best, they estimate the soil moisture deficit that is made up by irrigation in these locations.

For the above reasons, not withstanding the shortcomings, I rely on the NLDAS-2 dataset to extract hourly weather (precipitation and temperature) and water soil content for the upper soil layer based on the Noah soil model.[4] To my knowledge, this is the first study to use the NLDAS dataset in this literature.

To construct county-level observations, I account for the amount of cropland within each NLDAS soil moisture and weather data grid. I proceed by overlaying USDA's 2011 Crop Data Layer (with 30m resolution) over the NLDAS data grid (with 14km resolution) to compute the total amount of cropland falling within each data grid. I then overlay the NLDAS grid over US county boundaries and compute the share of each grid falling within each county. I finally generate the hourly county-level observations by weighting each NLDAS data grid within a county by the amount of cropland it contains. Figure 1 offers a representation of crop cover, the NLDAS data grid, and county boundaries for the state of Maryland.

For illustrative purposes, figure 2 presents hourly soil moisture, precipitation, and temperature for in a midwest county. Panel A illustrates how soil moisture (shown in blue in the upper part of the graph) suddenly increases after a precipitation event (shown in green in the lower part of the graph) and then gradually decreases as the soil dries out. Panel B illustrates how soil moisture varies rather slowly over time (aside from the spikes at precipitation events) when compared to daily fluctuations in temperature (shown in red).

Panel A in figure 3 shows the temperature variation within each bin for the March-August time window within the sample. For each temperature bin, the central line, box edges, and

[4]The moisture in this superficial layer (0-10cm) is highly correlated with moisture in deeper layers although the correlation weakens with depth and varies throughout the year. Because simulating climate change impacts consists in multiplying estimated parameters by the projected change in the associated variables, assessing the effect of deeper soil moisture changes would require climate change data on these layers. Unfortunately, data is only available for the superficial layer and, therefore, I cannot directly assess the contribution of deeper soil moisture changes.

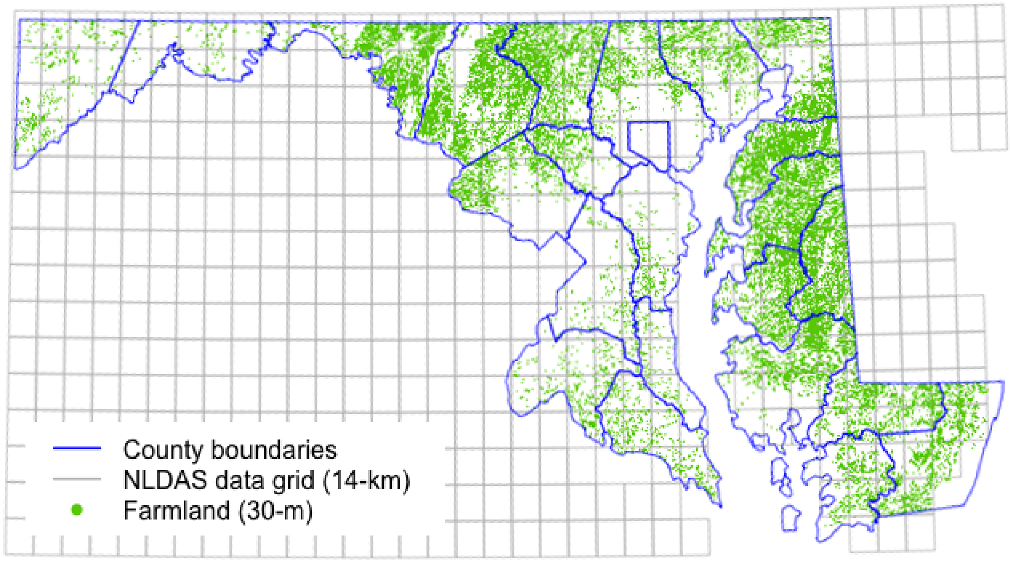
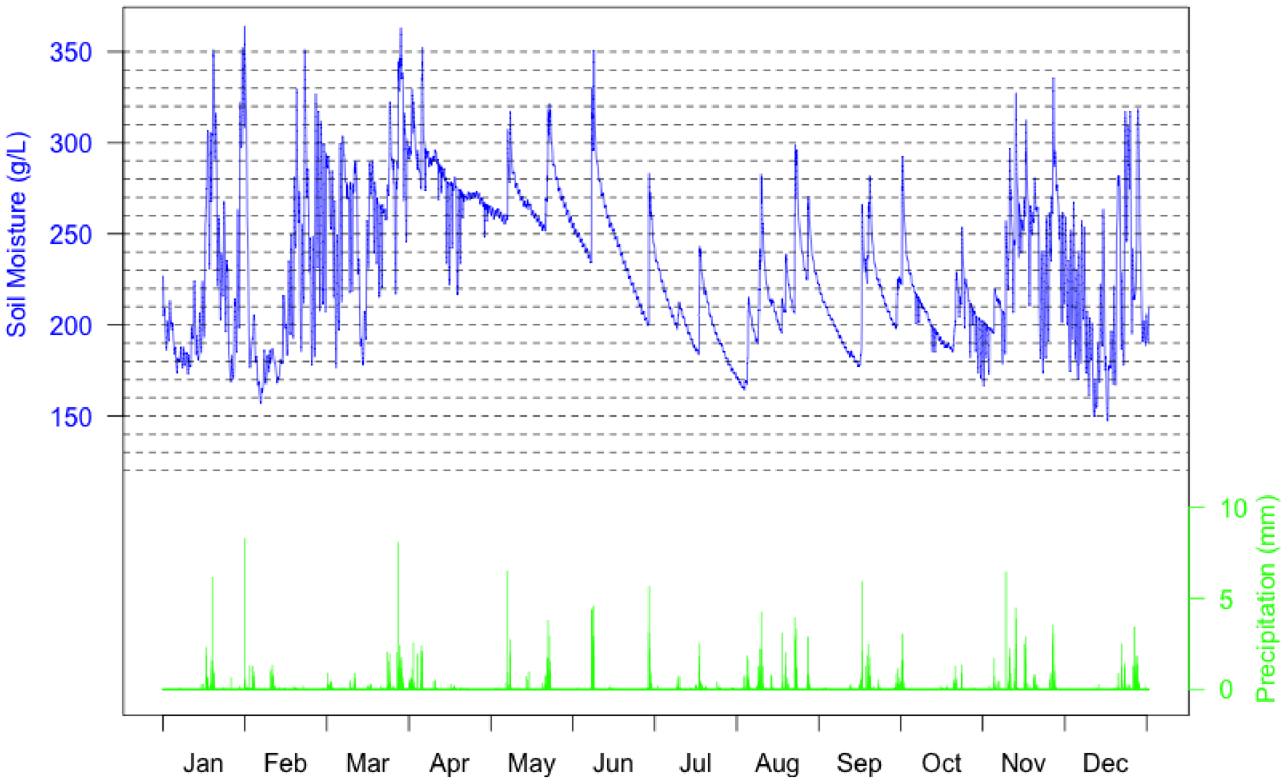


Figure 1: The construction of county-level observations.

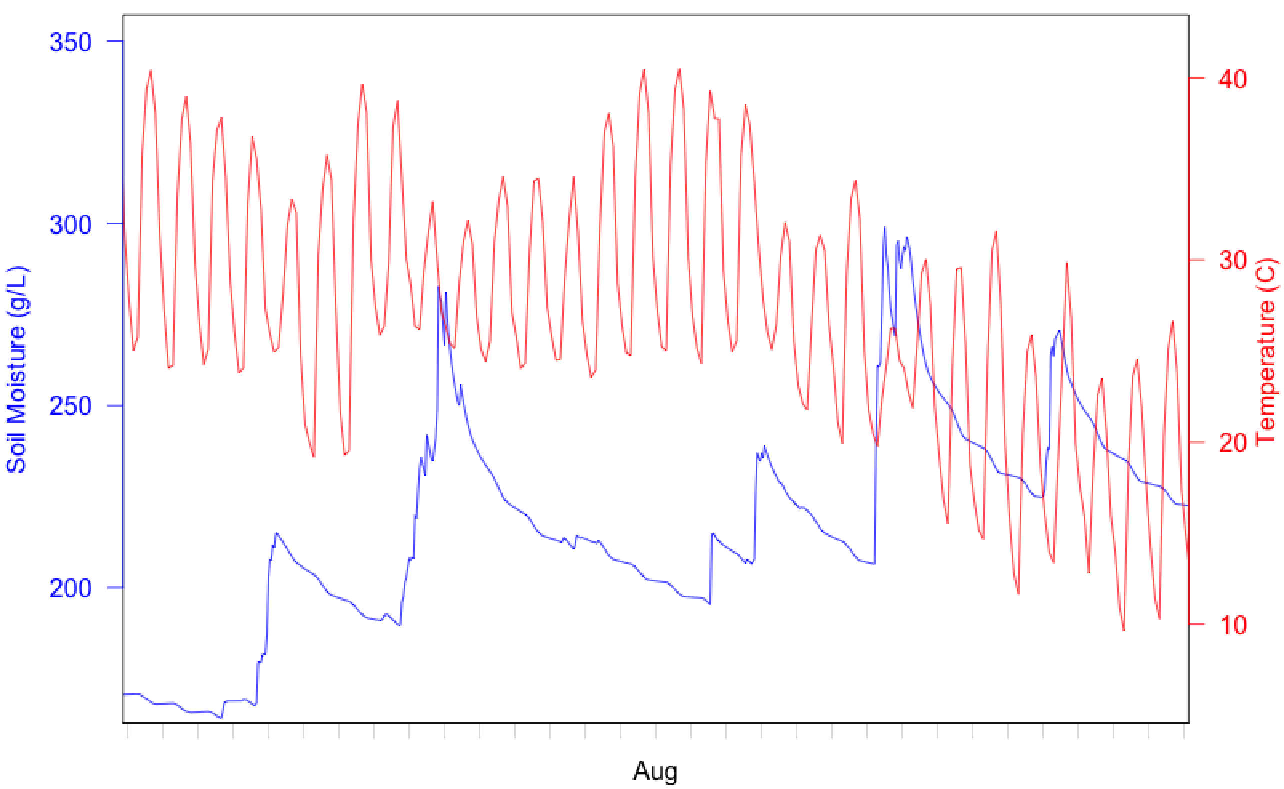
whiskers, represent the median, quartiles, and extremums, respectively. The most frequent temperatures fall between 20 and 25ºC. Temperature exposure under -5ºC was collapsed to the same bin and explains the tall bar and whiskers on the left. This is mainly driven by northern counties in the sample for which exposure to sub-freezing temperatures in march is not uncommon.

In a similar fashion, panel B of 3 illustrates the soil moisture variation within each bin for March-August. The most frequent soil moisture level is 280 grams of water per liter of soil (g/L). Soil moisture at or above 400g/L is collapsed to a single bin which explains the taller bar on the right. It is worth emphasizing that exposure to high levels of moisture, say above 350g/L, are often short-lived and typically correspond to exposure driven by moisture "spikes" after rainfall events (as illustrated in figure 2).

In order to assess the non-linear effects of soil moisture, I construct variables corresponding to the time spent within each 10g/L soil moisture interval in the 120-350 g/L range. These moisture bins are represented by the dashed lines in figure 2A. Because moisture outside this interval occurs, on average, less than 8 days in the March-August period, I aggregate exposure to these extreme levels to its closest moisture bin. In a similar fashion to SR, I also



A. Precipitation and resulting soil moisture



B. Temperature and soil moisture in August

Figure 2: Environmental variables for 1988 in Adams county, Illinois

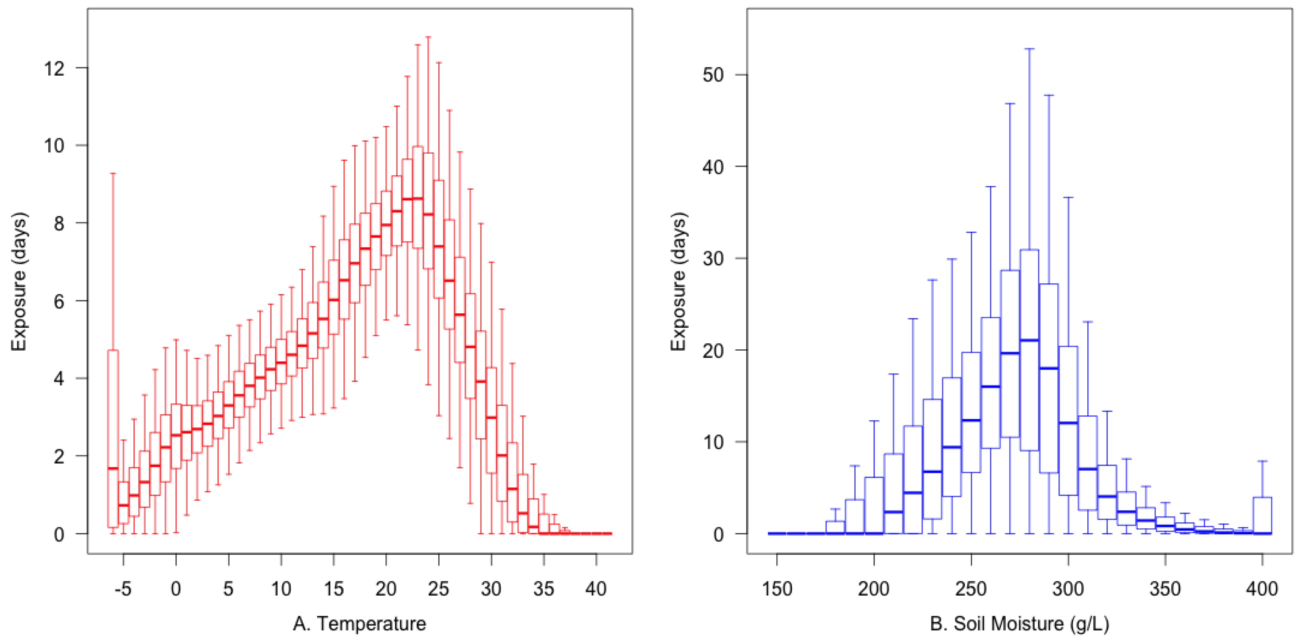


Figure 3: Temperature and soil moisture exposure distributions

construct variables for the exposure to temperature bins used to account for heat stress. In particular, I collapse temperature exposure above 40ºC to the same bin.

The dataset developed in this paper compares to the dataset generated by SR, which is the most sophisticated weather dataset previously used for this type of analysis. They developed a daily weather dataset by interpolating daily but spatially sparse data from weather stations, with monthly but spatially detailed (4km) data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) dataset developed by Oregon State University. According to their cross-validation, the spatio-temporal interpolation yields fairly accurate values for daily temperature but not for daily precipitation. Although this dataset has a longer time coverage (1950-2005), its obvious limitation for the purpose of this paper is the lack of soil moisture information.

As a way to verify the existence of a meaningful difference between the SR dataset and the data I derived from the NLDAS, labelled as "OB", I illustrate temperature exposure and precipitation densities from both datasets in figure 4. The figure shows data for the overlapping period across datasets (1979-2005) and for 800 counties in the rainfed sample of this study.

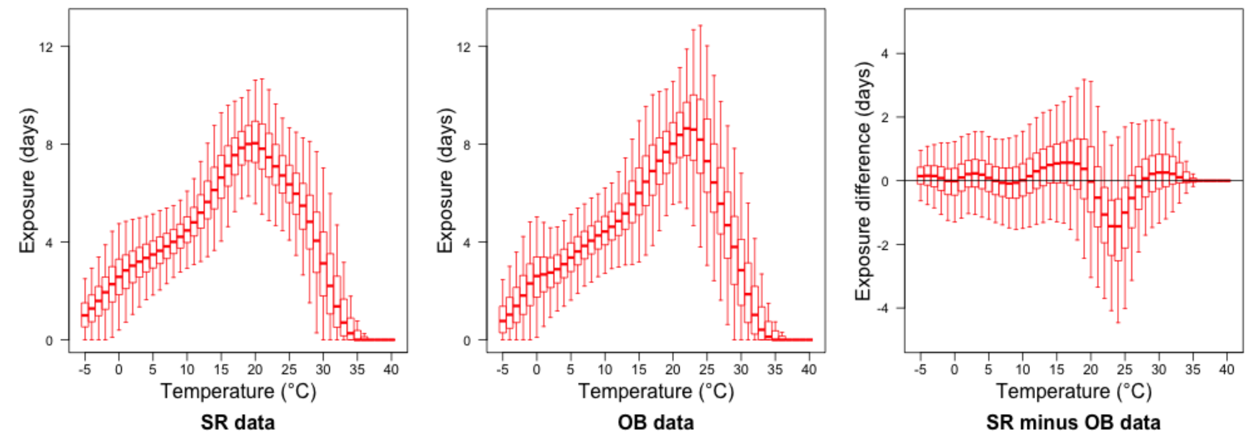
Panel A shows that the relative frequency of temperatures are somewhat different. The most common temperature range in the SR dataset is around 17-20ºC while it is 20-23ºC in the OB dataset. Also, in the OB dataset, the decrease in exposure around the most frequent temperatures is steeper toward higher temperatures (>23ºC) than toward lower ones (<20ºC). This is not exactly the case for the SR data. The graph on the right in panel A, illustrates the difference in exposure between both datasets and shows that the frequency of temperatures in the 20-27ºC range is lower in the SR data, but higher for lower and higher ranges. Particular attention should be given to the higher frequency of 28-35ºC temperatures in the SR dataset because observations in this range are used to estimate the effects of extreme temperature on yield. These differences are possibly due, in whole or in part, to the assumption of a daily sine curve in the temperature variation, or the spatio-temporal interpolation used to generate the temperature exposure data used by SR.

Finally, panel B shows that precipitation distributions are similar and differences for the large majority of cases do not exceed 50mm, or 2 inches, over the March-August period.

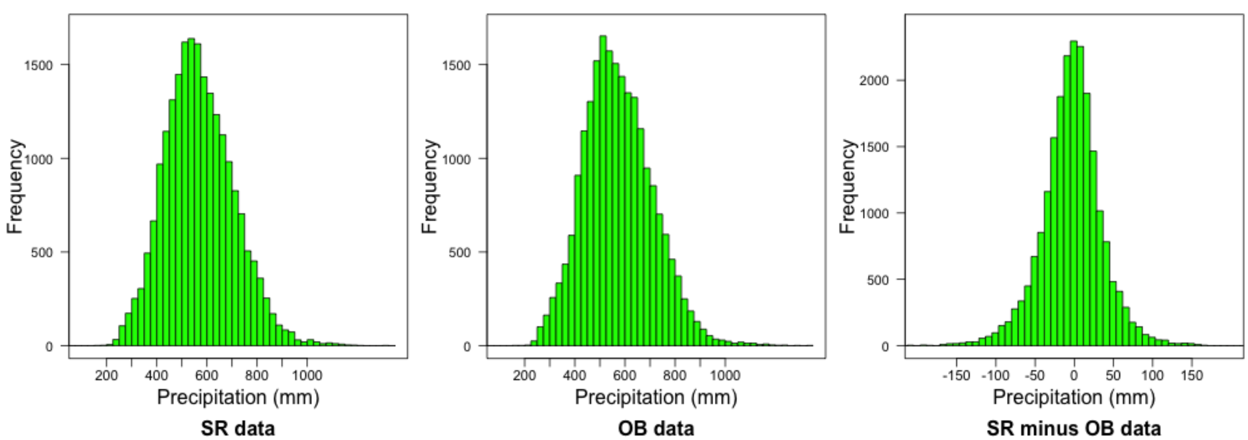
2.2 Accounting for timing of soil moisture conditions

My major contribution is to account for the nonlinear effects of soil moisture and timing in the growing season, which permits putting the role of temperature variation in context. This should facilitate more accurate econometric analysis of adaptation possibilities to climate change that accounts for changes in intra-seasonal environmental conditions.

Accounting for the timing effect requires information on crop stages. I thus rely on the Crop Progress and Conditions weekly survey by USDA/NASS which provides state-level data on farmer activities and crop phenological stages from early April to late November. Reporting across states and years is not balanced. Although state reports date back to 1979, reporting for corn that includes both the onset (planting/emergence) and the end of the season (maturation/harvesting) begin in 1981 for the major producing states.



A. Temperature exposure for March-August



B. Precipitation distribution for March-August

Figure 4: Comparison of SR and OB datasets (sample counties, 1979-2005).

Specifically, this survey reports the percentage of a state's corn acreage undergoing certain farming practices and reaching specific crop stages.[5] As a consequence, it does not offer clear "boundary" dates between stages because of the timing variations within states.[6] For the purpose of defining such boundaries of the growing season for each county, I obtain stage median acreage dates. These correspond to the dates at which 50% of the acreage in a given state has reached each stage in a given year.[7]

Crop stages reported by the USDA are not equally spaced in the growing season. They arguably correspond to visible markers that can be easily verified to simplify data collection. Some past studies (e.g.Kaufmann and Snell, 1997) have relied on weather variables matched to precise crop stages. However, results are sometimes difficult to interpret, especially for non-agronomists. In order to convey a more accessible crop advancement metric, I divide the growing season into eight segments centered around flowering (i.e. silking), which is considered the midpoint of the season. Four equally-spaced periods occur in the vegetative phase (between planting and silking) and four equally-spaced periods occur in the reproductive or grain-filling phase (between silking and maturation). For simplification, the crop advancement division is converted into percentages with intervals of 12.5%. Thus, the 0-12.5% and 87.5-100% stages correspond, respectively, to the first and last segments just after planting and just before maturation, and 37.5-50% and 50-62.5% correspond, respectively, to the segments just before and just after flowering.

Natural scientists have found that crop development or phenology is proportional to

[5] The report includes progress of farming activities (planting and harvesting) and of corn phenological stages (emerged, silking, doughing, dented and mature). The USDA defines these crop stages as follows. Emerged: as soon as the plants are visible. Silking: the emergence of silk-like strands from the end of corn ears, which occurs approximately 10 days after the tassel first begins to emerge from the sheath or 2-4 days after the tassel has emerged. Doughing: normally half of the kernels are showing dent with some thick or dough-like substance in all kernels. Dented: occurs when all kernels are fully dented, and the ear is firm and solid, and there is no milk present in most kernels. Mature: plant is considered safe from frost and corn is about ready to harvest with shucks opening, and there is no green foliage present.

[6] Visual inspection of district-level crop progress reports, which are available for only a few states, surprisingly reveals variation similar to overall state progress for most years.

[7] For a few states and years, crop progress reporting began too late (the state had already surpassed the 50% acreage level) or stopped too early (the state had not yet reached the 50% acreage level). For these cases, which represent less than 5% of the cases, I obtained the median acreage date by extrapolation. More details are provided in the appendix.

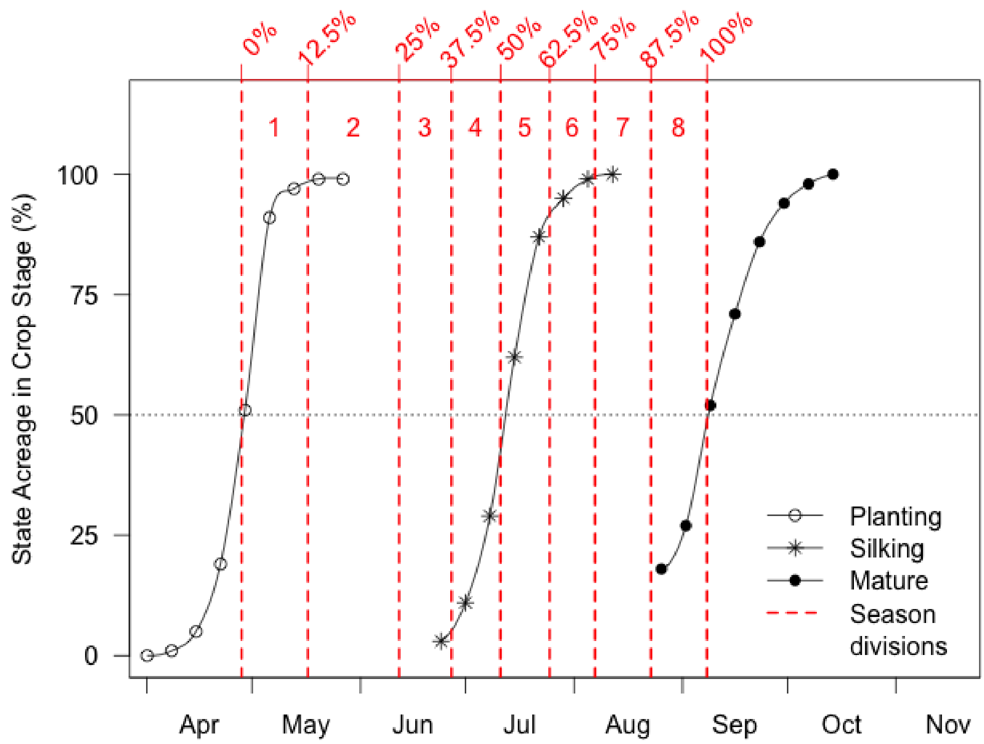


Figure 5: Season divisions for Illinois corn in 2001.

accumulated Growing Degree-Days (GDD, see e.g. Hodges, 1991; Smith and Hamel, 1999; Fageria et al., 2006; Hudson and Keatley, 2009). This variable is defined by the area under the temperature-time curve that falls between two temperature thresholds (10 and 30ºC for corn) and two time periods. Warmer conditions generally lead to faster GDD accumulation and more rapid crop development. This concept can be used to split the growing season into equally-spaced segments.

Following this approach, I compute a cumulative GDD variable starting at planting for each state and year and use it to represent the eight segments of the season. Figure 5 illustrates how these season segments are located in the 2001 calendar for Illinois. Although the segments have a different number of days, segments 1-4 and 5-8 are equally spaced in terms of GDD. Thus, wider segments signal slower development due to cooler conditions.

Exposure to moisture bins is aggregated within each one of these segments. As a result, the moisture variables account for exposure to different moisture levels during each one of

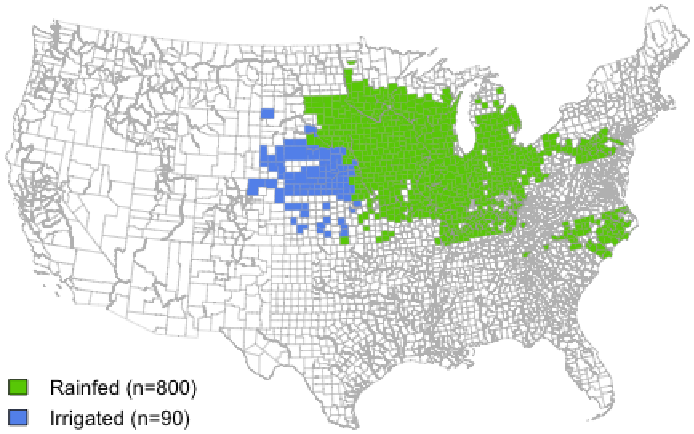


Figure 6: Rainfed and irrigated counties in the sample

the eight segments of the growing season. This allows assessment of how drought sensitivity varies with crop advancement.

2.3 Agricultural data and sample counties

Agricultural data were obtained from publicly available USDA/NASS sources and include county-level corn yield and acreage. Yield is the dependent variable in estimation models and acreage is used to weight county-level climate change impacts to obtain aggregate estimates for the sample.

Because rainfed and irrigated corn yields are expected to respond differently to exogenous environmental conditions, their respective parameters must be estimated separately. For this purpose, I split the sample into rainfed and irrigated counties where a county is considered rainfed if at least 75% of its acreage, on average, is non-irrigated. Figure 6 illustrates how the sample is divided. The dataset corresponds to a balanced panel of 800 rainfed and 90 irrigated counties for 1981-2011. Although this paper focuses on rainfed counties located in 14 different states, results for irrigated counties are reported in the appendix for illustrative and falsification purposes.

2.4 Climate Change Data and Scenarios

Climate change data were obtained from the second version of the Hadley Centre Global Environment Model (HadGEM2). The HadGEM2 is one of the latest and most advanced climate models. It has a higher spatial resolution and improved representation of the atmosphere compared to the earlier HadCM3 model which is commonly used in the literature (Collins et al., 2008). The HadGEM2 model is also being used in the preparation for the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5), scheduled for publication in late 2013.

In the upcoming AR5 report, the nature of climate change scenarios has been modified. They no longer represent "emission scenarios" but are "representative concentration pathways" (RCPs). Instead of describing economic scenarios and their resulting emissions (e.g., the familiar A1B, A1, B1 scenarios), they now represent sets of a wide range of projections for the main drivers of climate change, which are greenhouse gases, air pollutants and land use change. These scenarios are classified in terms of their "radiative forcing", which roughly represents the strength of different human and natural agents in causing climate change (See IPCC 2007, p.131 for a detailed definition). The convention is to associate the radiation level by 2100 to the scenario name. For instance, the most severe RCP8.5 scenario represents a rising radiative forcing pathway leading to 8.5 watts/m^2 in 2100.[8] The higher the radiative forcing, and the greater is the resulting warming.

Because the crop stage time windows do not correspond to calendar periods, I cannot rely on widely used monthly data. Instead, I obtain daily data corresponding to the RCP2.6, RCP6, and RCP8.5 scenarios for average temperature, precipitation, and soil moisture for the superficial soil layer (0-10cm) for periods 1985-2005, 2039-2059, and 2079-2099. The first period serves as a reference period for current climate. The others represent the mid-century and end-of-century climates.

The variable changes for each grid are obtained by subtracting the mid-century and

[8] A watt is the standard unit of power, which is a transfer of energy per unit of time.

end-of-century means from the current climate reference period. These changes are then matched to the corresponding counties. However, regression models are based on nonlinear transformation of these variables and, thus, the original level of the variable for the reference period 1985-2005 matters. Accordingly, I add the change in the untransformed variables to the NLDAS variables before performing nonlinear transformations. As explained in Fisher et al. (2012), this approach maintains the spatial smoothness of projected climate changes.

Figure 7 presents projected changes in temperature, precipitation, and soil moisture for the three scenarios for the mid-century and end-of-century periods. Panel A shows that the frequency of temperatures below 20-25°C will almost uniformly decrease while the frequency increases would be clustered around 30-35°C. This is a manifestation of the nonlinear changes in exposure to high temperature from an increase in temperature.

Panel B shows that precipitation changes are mixed, although most counties will see their March-August precipitation decrease in most scenarios. With a mean precipitation around 550mm (see figure 4B), mean precipitation reductions hover around 0-7% except for the most severe scenario, which has mean precipitation reductions in the 10-25% range.

Panel C illustrates how soil moisture is expected to vary for each of the eight seasonal segments (using current average segment windows). The lower (upper) part of each graph represents early (late) segments of the season. The general pattern is that more humid soils will be more frequent at the beginning of the season while decreases in their frequency occur towards the latter stages. This is represented by blue (red) areas located toward the bottom right (left) corner, and red (blue) areas located toward the upper right (left) corner. Only the more severe RCP8.5 scenario does not follow this pattern with almost universal decreases in the frequency of humid soils. This is represented by blue (red) areas toward the left (right) side of the graph.

A interesting pattern arises in panel C that is highly meaningful for econometric adaptation analysis. A moisture "inversion" occurs during the season. The early season becomes more humid, while the end of the season becomes drier. This suggests that farmers may be able to adapt to this intra-seasonal change by altering planting dates to limit their exposure to detrimental parts of the season. This pattern is not perceptible in the March-August precipitation changes that solely suggest modest season-long decreases.

3 Models for heat and drought stress

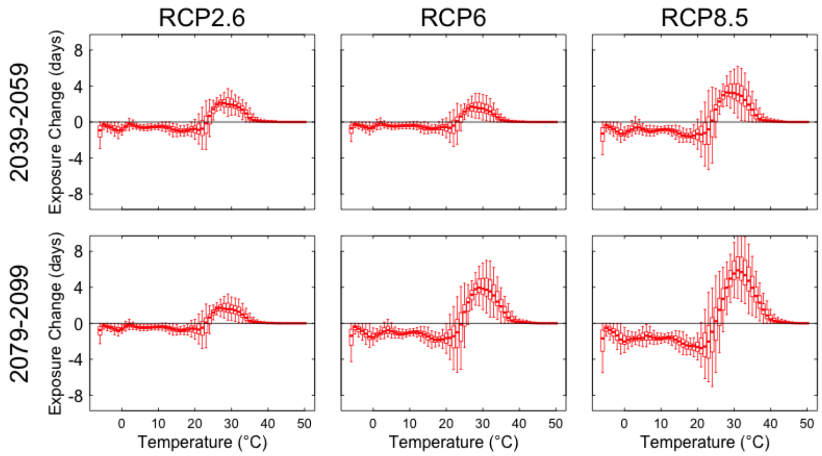
3.1 Replication of a reference model for heat stress

Statistical models that have regressed crop yields on weather variables have traditionally relied on monthly or pluri-monthly average temperature and precipitation data. Early examples can be traced back to the early part of the last century (Wallace, 1920; Hodges, 1931). Since then, the convention has long been to include linear and quadratic variables based on temporally aggregated data to capture the nonlinear effects of both temperature and precipitation on yield. Marginal effects of these variables are typically expected to exhibit an "inverted U" shape, suggesting diminishing marginal effects of each weather variable with a unique optimum.

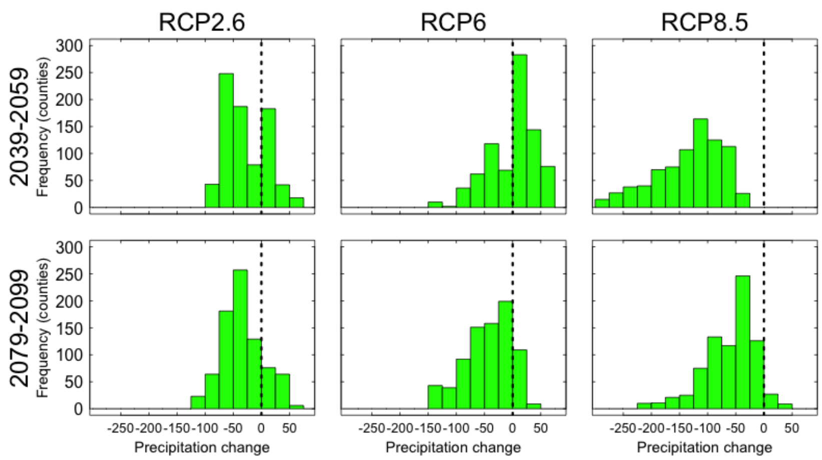
Schlenker et al. (2006) made an important contribution by recognizing that daily average temperature fails to convey the consequences of exposure to extreme temperature and, thus, may not be adequate for capturing nonlinear effects of temperature on farm prices. Hypothetically, two days with equal average temperature may represent very different exposures to very high temperatures. This suggests that the shape of the daily time curve matters.

To address this needed refinement, SR developed an innovative approach that estimates the effect of exposure to different levels of temperature on yield separately. They compute the amount of time spent during the season (March-August for corn) in each of many temperature bins. The exposure to each degree bin is then adapted to various specifications.

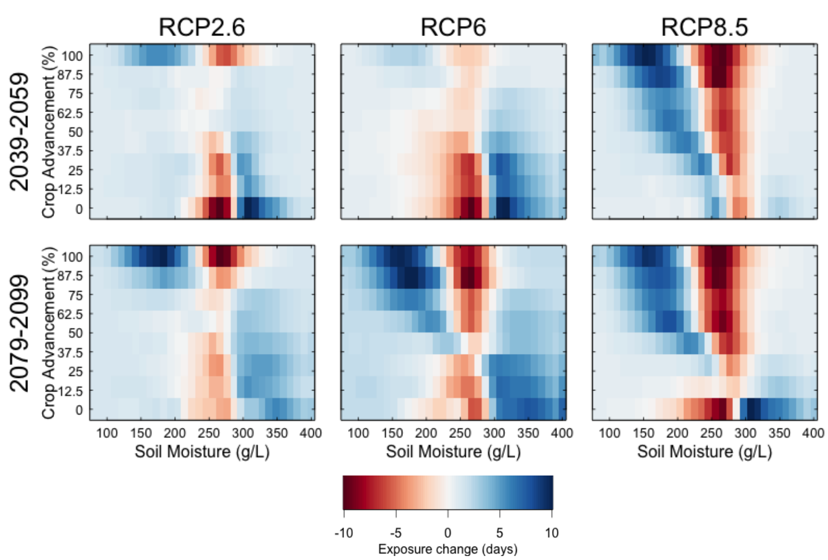
Here, I replicate their model for corn for purposes of comparison. As stated in the data section, I restrict the sample period to 1981-2011. This is shorter and later than the 1950-2005 period used by SR. However, their results are reported to be similar for temporal subsets of the sample. The balanced panel dataset in this paper represents over 70% of US corn production annually.



A. Temperature exposure change for March-August



B. Precipitation change for March-August



C. Soil moisture change for each season stage

Figure 7: Changes in environmental variables with climate change scenarios

Their general model assumes that temperature effects on yield are cumulative and substitutable over time. The nonlinear effect of temperature on yield are captured by the function $g(h)$ representing "yield growth" that depends on temperature h. Logged corn yield y_{it} in county i and year t are represented as:

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

where $\phi_{it}(h)$ is the time distribution of temperature (i.e., the temperature-time path) for March-August, p_{it} is precipitation, z_{it} is a state-specific quadratic time trend and the c_i are county fixed-effects. The maximum likelihood estimation procedure accounts for spatial correlation of the errors. Over thirty 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 yielded the highest value of the likelihood function at the optimum parameter values and thus was selected.[9]

Equation (1) cannot be estimated directly because of the integral. Therefore, I follow SR and consider different specifications to approximate the integral as a sum: a step function allowing different effects at each 1ºC interval (SR1), another step function allowing different effects at 3ºC intervals (SR2), an eighth-degree polynomial (SR3), and a cubic B-spline with eight degrees of freedom (SR4).[10] The specification for SR1 is:

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

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

[9]The weighting matrices included eight neighboring structures and four weighting schemes. The neighboring structures are: 5 through 10 nearest neighbors, neighbors within 200km, and neighbors using the Delaunay triangulation. The weighting schemes are: binary, inverse distance, inverse squared distance, and inverse square root of distance.

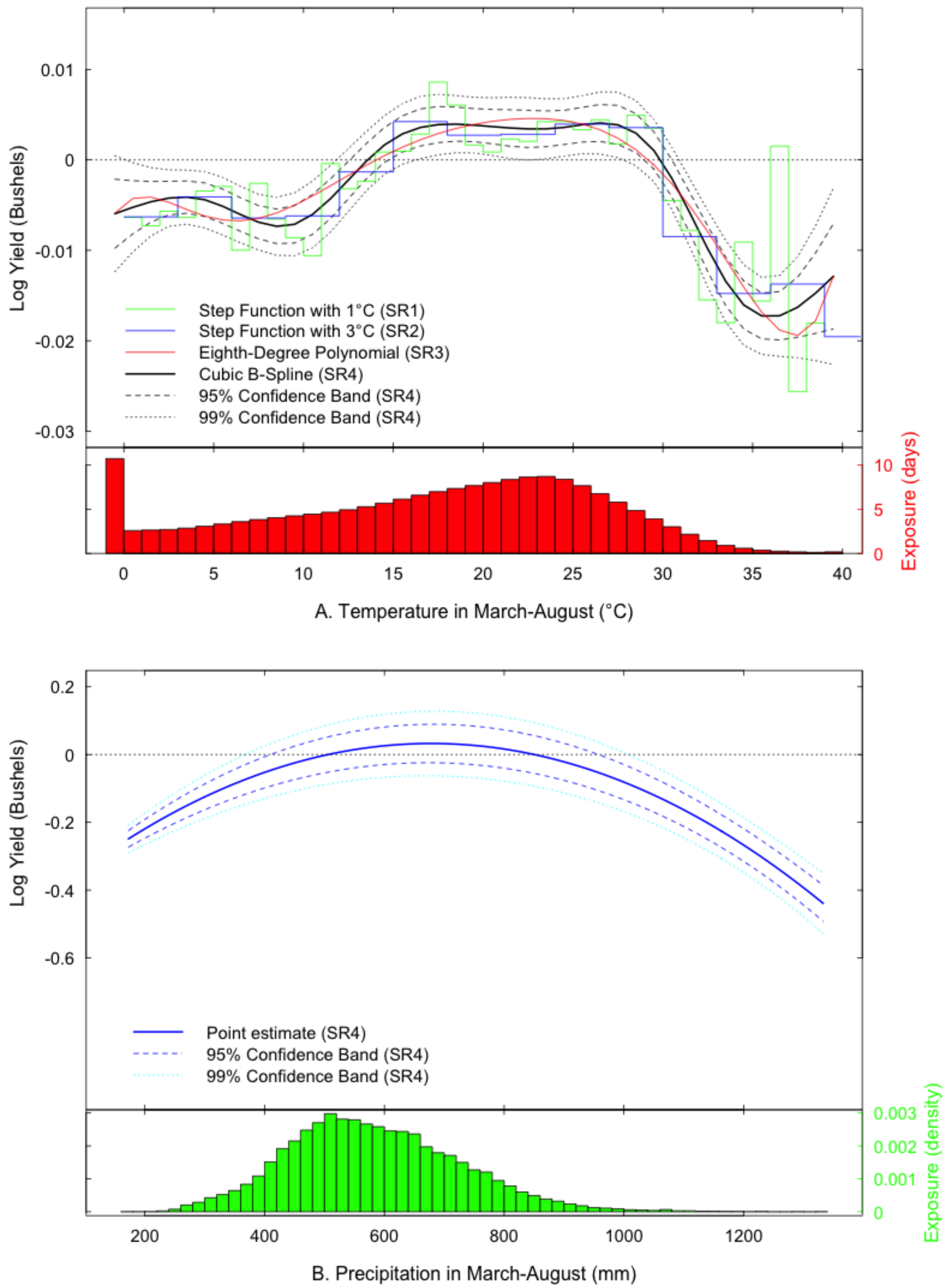
[10]Only SR2 and SR3 are part of the original SR study. In addition, SR developed a piecewise linear model which yields similar results to the other specifications. The SR1 was included to assess the effects of narrow temperature bins and SR4 to allow for a more flexible less susceptible to extreme polynomial curvature near the end points specification.

in the appendix.

Results are summarized in figure 8. The effects of exposure to various levels of temperature vary considerably. Exposure to temperature in the 12-30ºC range are beneficial while exposure is increasingly detrimental above 30ºC. These results are qualitatively similar to what SR report. However, replication suggests that extreme temperature is considerably less damaging. While SR report that exchanging a single day at 29ºC with a day at 40ºC reduces yield by approximately 7%, none of the specifications in this replication suggest a yield reduction exceeding 3%.

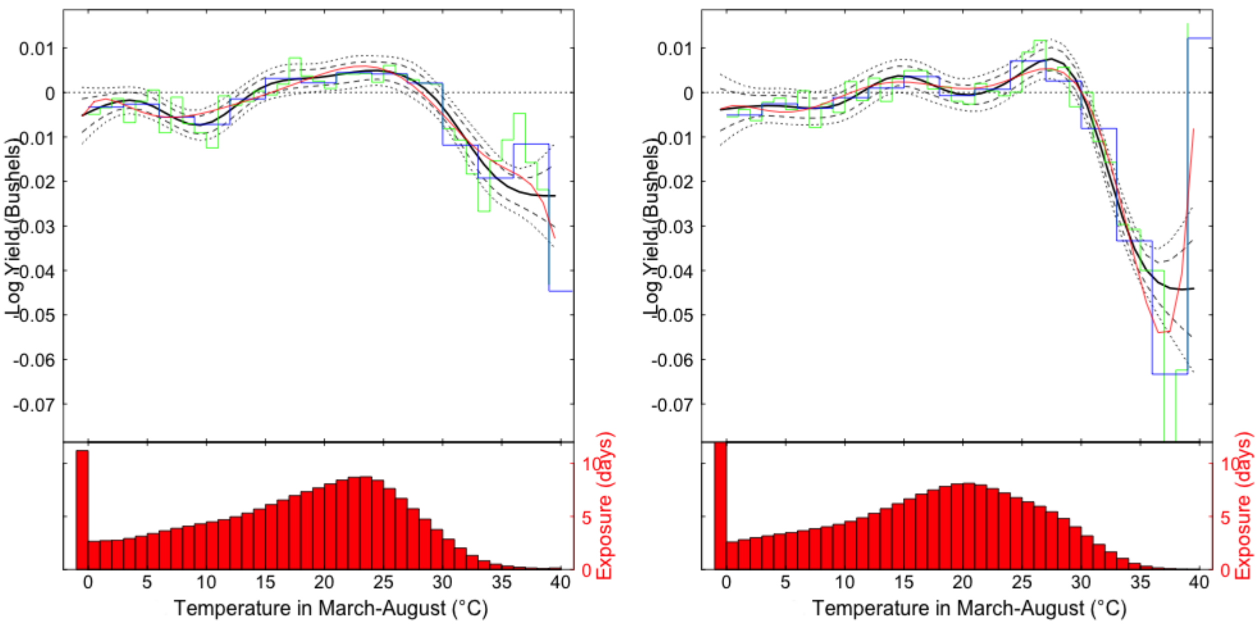
To verify this discrepancy, I compare all specifications (SR1-SR4) applied to the OB and SR datasets for the overlapping 1979-2005 period. Results are shown in figure 9. Surprisingly, estimates of the same model used in the original SR study in panel B, show twice the sensitivity to high temperature when based on the SR data as when based on the OB data as shown in panel A. This is particularly striking given the seemingly small differences between the temperature distributions shown in figure 4. Figure 4 reveals the datasets exhibit relatively small differences for most temperature bins. However, these differences can exceed be relatively large for the very high temperatures. The average exposure in the March-August period to temperature above 35ºC is 14.4 hours and 22.3 hours in the SR and OB datasets, respectively. These 7.9 hours represent a 55% difference. The lower exposure to very high temperature recorded in the SR dataset is consistent with extreme temperature appearing more damaging.

In an attempt to discriminate between the OB and SR datasets, I performed a J-test between models based on these datasets. However, the test is inconclusive with t-statistics for the fitted values of the alternative model in excess of 10. Although the test is not conclusive, the implicit damaging effects of extreme temperatures are highly sensitive to nature of the weather data, particularly to small absolute differences in recorded exposure



Response curves are centered around zero and weighted by temperature bin exposure or precipitation density. As a result areas above zero correspond to the most beneficial half of occurrences. Confidence bands for the temperature curve correspond to SR4.

Figure 8: The SR model



A. OB data B. SR data

Figure 9: Comparison of the spline specification using OB and SR data (1979-2005)

to very high temperature.[11]

On the other hand, this replication suggests an optimal level of precipitation of 678 mm for March-August, higher than the sample mean of 584 mm. Reaching the optimal precipitation level through a 15% increase, implies an insignificant yield gain of just 1%. Similarly, a dramatic 50% drop in precipitation only represents a 15% yield reduction. Given that most climate change scenarios predict mean decreases ranging from 0 to 10% (see figure 7), these precipitation changes are expected to generate small to modest changes in yield according to this model. This is consistent with the small role attributed to precipitation in SR and other studies such as Schlenker et al. (2005), Schlenker et al. (2006) and Deschênes and Greenstone (2007). These results are at odds with agronomic evidence that emphasizes the pivotal role of water in crop production (NeSmith and Ritchie, 1992; Blum, 1996; Barnabás et al., 2008).[12]

[11] In analysis not shown in the paper, I swapped the exposure to extreme temperature (>35°C) across SR and OB datasets and re-ran the models with the hybrid datasets. This resulted in an exchange of the shape of the temperature response curve at these extreme temperature levels. This confirms that the difference in the slope of the temperature response function for very high temperature mainly stems from the difference in recorded exposure to temperature exceeding 35°C between both datasets.

[12] In the appendix I also present results for irrigated counties. Although results are not as clear, temperatures above 30°C appear as detrimental as for rainfed counties. This is in contrast to the findings in SR

3.2 A model accounting for soil moisture

The models of Section 3.1 that mirrors prior methodology attempt to capture water availability to crops with a season-long precipitation variable. My hypothesis is that this is an inappropriate measure of water availability for crops because it does not represent soil moisture conditions and their timing of these conditions in the growing season.

To address this potential shortcoming, I develop a model that assumes that crop yield also responds to soil moisture in possibly nonlinear and varying magnitudes throughout the season. Effectively, my model pools the SR model and the new soil moisture variables I introduce. The new model, which I label "OB", assumes that the effects of soil moisture m on yield are cumulative but non- substitutable over time in the season. The nonlinear effects of soil moisture on yield are captured by the function $f(m,s)$ representing the dependence of yield growth on soil moisture m at each stage of the season s. Logged corn yield y_{it} in county i and year t are represented as:

$$y_{it} = \underbrace{\int_{\underline{h}}^{\overline{h}} g(h)\phi_{it}(h)d(h) + p_{it}\delta_1 + p_{it}^2\delta_2 + +z_{it}\tau + c_i}_{\text{SR model}} + \underbrace{\int_{\underline{s}}^{\overline{s}}\int_{\underline{m}}^{\overline{m}} f(m,s)\psi_{it}(m,s)d(m)d(s)}_{\text{Moisture effects}} + \epsilon_{it} \tag{2}$$

where $\psi_{it}(m,s)$ is the distribution of soil moisture (i.e., the soil moisture-time path illustrated in figure 2) at each stage of the season s.

As in the SR model, equation (2) cannot be estimated directly. The objective is to approximate the double integral on $f(m,s)$ as a double sum. The first sum is over different moisture levels. I consider the same four approximation specifications I used to estimate the SR model: a step function allowing different effects for each 10g/L soil moisture interval (OB1), a step function allowing different effects at 30g/L intervals (OB2), an eighth-degree polynomial (OB3) and a cubic B-spline with eight degrees of freedom (OB4).

that show in their appendix that temperatures above 30ºC are more than twice as damaging for eastern and mostly rainfed counties. The main discrepancy between my results and theirs concerns rainfed counties.

The second sum is over different season stages. For this purpose the season is split into eight segments as described in the data section so that $\underline{s}$ and $\bar{s}$ correspond, respectively, to planting and maturation.[13]

Note each SR specification is nested in the corresponding OB specification such that SR1 is nested in OB1, SR2 in OB2, etc. The specification for OB1, for example, is:

$$\begin{aligned} y_{it} &= \sum_{h=0}^{40} g(h+0.5)[\Phi_{it}(h+1) - \Phi_{it}(h)] + p_{it}\delta_1 + p_{it}^2\delta_2 + z_{it}\tau + c_i \\ &\quad + \sum_{s=1}^{8}\sum_{m=120}^{350} f(m+5,s)[\Psi_{it}(m+10,s) - \Psi_{it}(m,s)] + \epsilon_{it} \end{aligned}$$

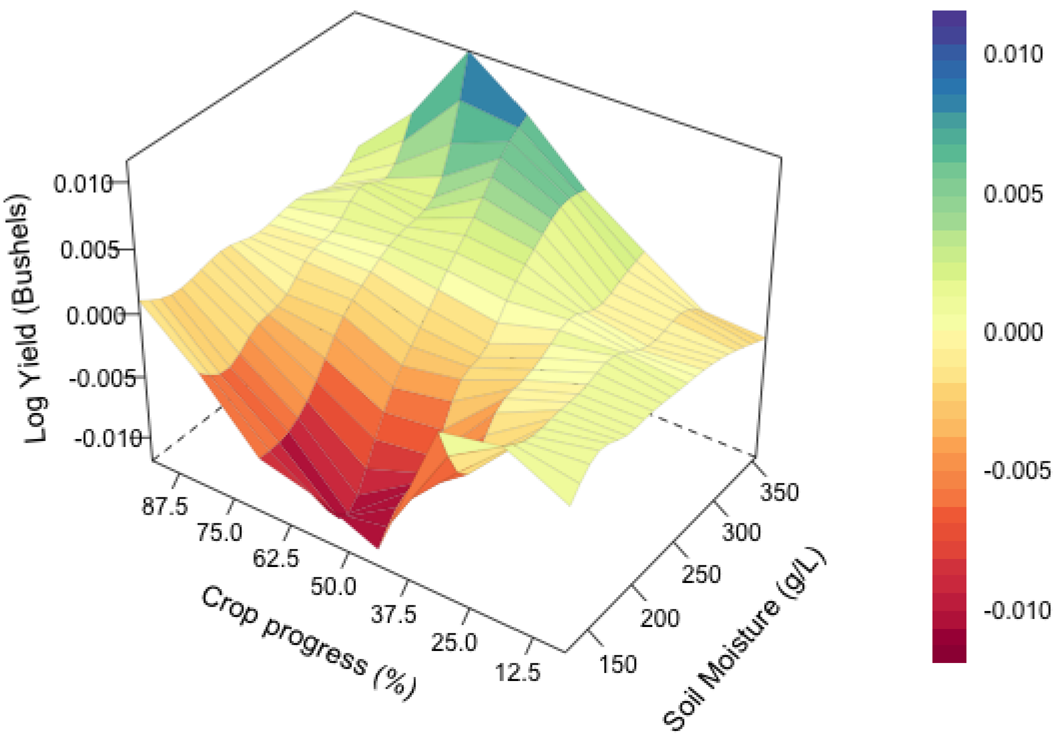
where $\Psi_{it}(m,s)$ is the cumulative distribution of moisture for the s-th season segment in county i and year t. Specifications for OB2, OB3, and OB4 and more detailed results for each specification are provided in the appendix.

Results are summarized in figures 10 and 11. The 3-dimensional graph in panel A of figure 10 corresponds to the soil moisture effects on yield based on the cubic B-spline specification (OB4). It shows that yield effects vary considerably over the season.[14] Early in the season (at low crop progress) the yield response function is fairly flat, suggesting that deficient levels of moisture at this stage do not affect yield very much. In fact, high levels of moisture (>300g/L) at this stage are slightly detrimental, which is consistent with well-known damages from water-logging to young plants.

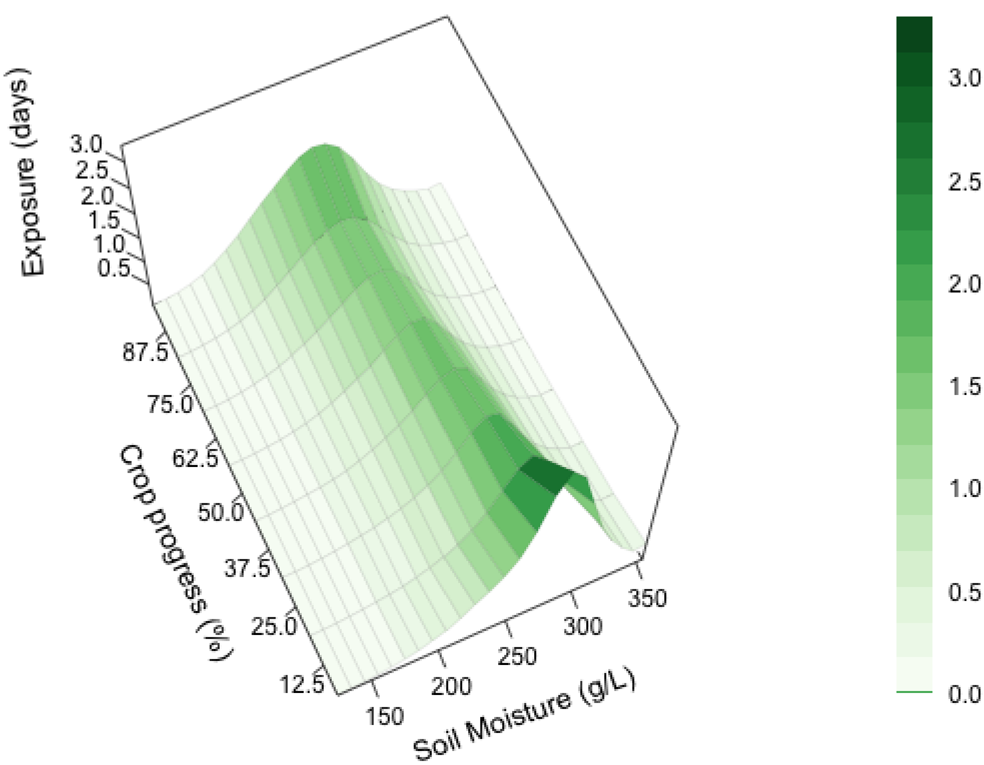
As the season advances, soil moisture levels around 265g/L imply crop yields on the trend, but lower or higher levels of moisture lead, respectively, to low and high yields. Yield damages are the most severe, as expected, right around the middle of the season when corn flowering occurs. Replacing a single day at 265 g/L with a day at 125g/L represents

[13] Soil moisture conditions after maturation do not have an impact on yield although they might affect other quality characteristics such as kernel humidity.

[14] The tessellation is obtained by joining the stage-specific soil moisture yield responses (presented individually with confidence bands in the appendix) at regular intervals of soil moisture. A look at the individual stage-specific yield responses and their confidence bands (in the appendix) shows that this pattern is statistically significant.



A. Soil moisture effects at different season stages



B. Distribution of soil moisture at different season stages

Figure 10: Soil moisture effects for the OB model

approximately a 1% yield decrease.

Although this result is 3 times lower than for the hypothetical exchange of a full day at 29ºC with a day at 40ºC (see the previous section), comparisons should be considered with care. Figure 2 illustrates that soil moisture deviations are much more persistent than temperature deviations, suggesting that the potential exposure to detrimental levels of moisture are likely to last days or even weeks. On the other hand, the daily fluctuations of temperature require several days to build up to an extreme day or two of exposure to high temperatures (>30ºC).

Higher than normal levels of moisture, on the other hand, seem beneficial to yield. This is particularly the case in the second half of the season. Replacing a full day at 265 g/L with a day at 355g/L causes a yield increase in the range of $0.4 - 1\%$. This is consistent with the high water demand during flowering and grain-filling stages in corn.

At the end of the season the yield response flattens. Variations in soil moisture still make a difference but not as much as in the middle of the season. Because the statistical model and the climate change impact scenarios only consider the superficial 10cm soil layer, these results may overlook the fact that adult plants extract water from deeper soil layers late in the season.

A somewhat puzzling result is that very high soil moisture is virtually always found to be beneficial except for very early stages in the season. Extreme events such as flooding are undoubtedly detrimental, but these are not captured by the soil moisture variables. This is likely due to the division of the growing season into relatively short segments that do not account for cumulative exposure to very high levels of moisture spanning several segments. Perhaps these extreme events are captured by a season-long precipitation variable, which exhibits a significant role only for very high levels of precipitation as shown in the bottom of figure 11.

Interestingly, the precipitation response curve in figure 11 is similar to that of irrigated counties (see the appendix), which suggests that, after accounting for moisture, season-long

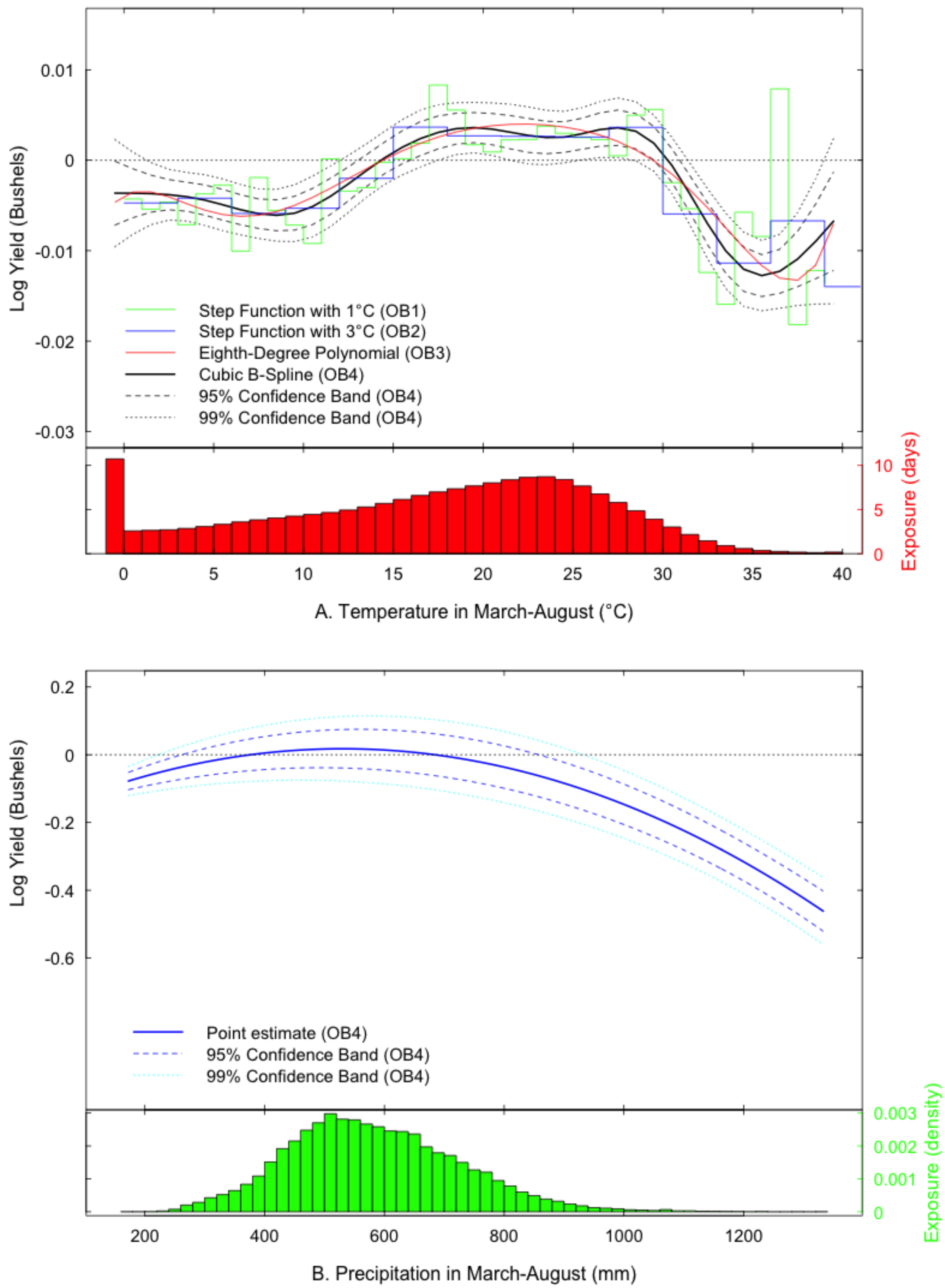


Figure 11: Temperature and precipitation effects for the OB model

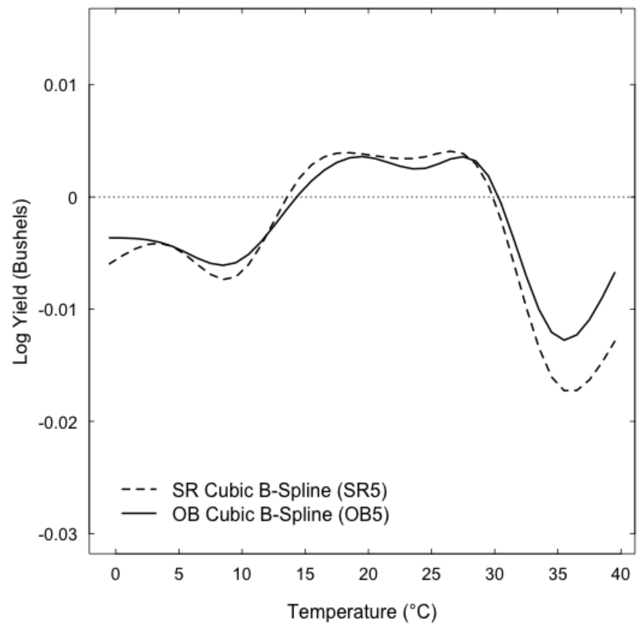


Figure 12: Comparing temperature effects between the SR and OB models.

precipitation captures only extreme events such as flooding in both rainfed and irrigated areas. This provides additional evidence that season-long precipitation is a rather poor measure of water supply for rainfed crops because it fails to account for the timing of soil moisture levels throughout the season.

A crucial finding is that the temperature response in the OB model, on the top of figure 11, is flatter for high temperatures than in the SR model. I superimpose the temperature response in both models in figure 12. In particular, high temperatures appear to be about 30% less detrimental to yield when soil moisture is considered. This difference is consistent with omitted variable bias and can occur if low soil moisture is both correlated with high temperature and is a good predictor of yield.

The correlation between dry soil and maximum daily temperature does not come as a surprise because this phenomena is well understood and documented in the climate science literature.[15] In a recent paper, Mueller and Seneviratne (2012) show evidence on a global

[15]The reason is that water in the soil plays a crucial role in the partition of energy transfers between "latent heat" and "sensible heat." When the soil is wet, solar energy is spent evaporating this water without generating a temperature change (latent heat). However, when the soil is dry, no water is available to

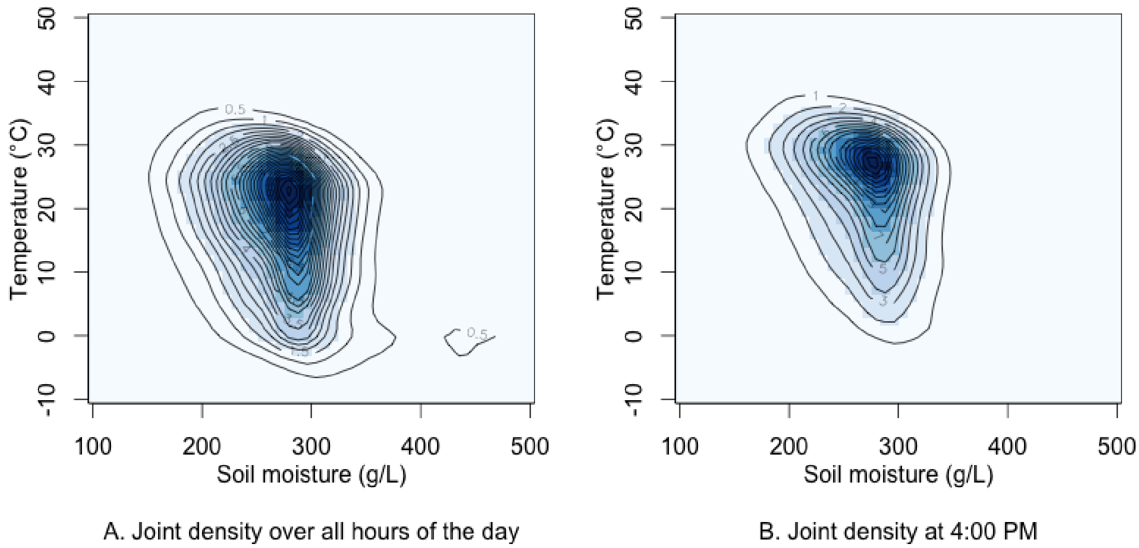


Figure 13: Empirical joint density of hourly soil moisture and temperature for rainfed counties during the March-August period (1979-2011).

scale that dry soil is correlated with high temperatures, particularly during the hot months of the year. This phenomenon is also acknowledged by climate scientists and weather forecasters in their models. Global Climate Models (GCMs), such as the HadGEM2 used in this paper, include soil moisture modules precisely to account for the role of soil water in atmospheric energy balances. As an illustration, the original motivation for developing soil moisture estimates by the NLDAS was to improve weather forecasts: *"specifically, this system is intended to reduce the errors in the stores of soil moisture and energy which are often present in numerical weather prediction models, and which degrade the accuracy of forecasts"* (NLDAS website).

Figure 13 shows the empirical joint-density of soil moisture and temperature using the hourly NLDAS data for the March-August window. The shape of the density and iso-density curves clearly show that high temperatures are more likely when soil moisture is low. This pattern is even more salient during hot periods of the day (e.g., 4:00PM), suggesting that the high temperatures of the day are particularly correlated with low levels of soil moisture.

evaporate so solar energy is directly spent heating up the surroundings (sensible heat).

The fact that high temperatures are correlated with dry soil and that dry soil is a good explanatory variable for yield gives clear evidence that soil moisture is an omitted variable in models using season-long precipitation variables such as the SR model, Schlenker et al. (2005) and Deschênes and Greenstone (2007). Because dry soil negatively affects yield, the direction of the bias is downward, toward greater damages from extreme temperature. Thus, the results in this section imply to an overestimation of extreme temperature effects of about 30% in models that use only a season-long measure of precipitation.

3.3 Robustness analysis

Aside from the qualitative implications of accounting for soil moisture in the OB model, the inclusion of soil moisture also yields improved statistical fit. However, the OB model introduces a relatively large number of parameters.[16] A genuine concern is that the improvement is only artificial. To test this possibility, I rely on the fact that the SR model is nested within the OB model to run likelihood ratio tests of whether the improved fit is statistically significant given the number of additional parameters. The tests strongly reject the hypotheses ($p < 0.000001$) that the improved fit is random.

Figure 14 shows out-of-sample reductions of root mean squared error (RMSE) with respect to a model that regresses log yield only on a county time-trend. Years were sampled 1000 times at random for sample splits representing 20, 50 and 80% of the observations in the sample. Estimated parameters at each round were used to forecast out-of-sample observations. The reductions in average RMSE are reported. The RMSE reductions range from 40 to 75%.

The OB model outperforms the SR model in out-of-sample predictions for all sample splits. If the model is over-fitting observations, the out-of-sample superiority would be expected to deteriorate as larger splits of the data are used for out-of-sample prediction. However, this is not the case.

[16]Specifications OB1, OB2, OB3, and OB4 introduce an additional 192, 71, 64 and 64 parameters ,respectively, with respect to the corresponding SR specifications.

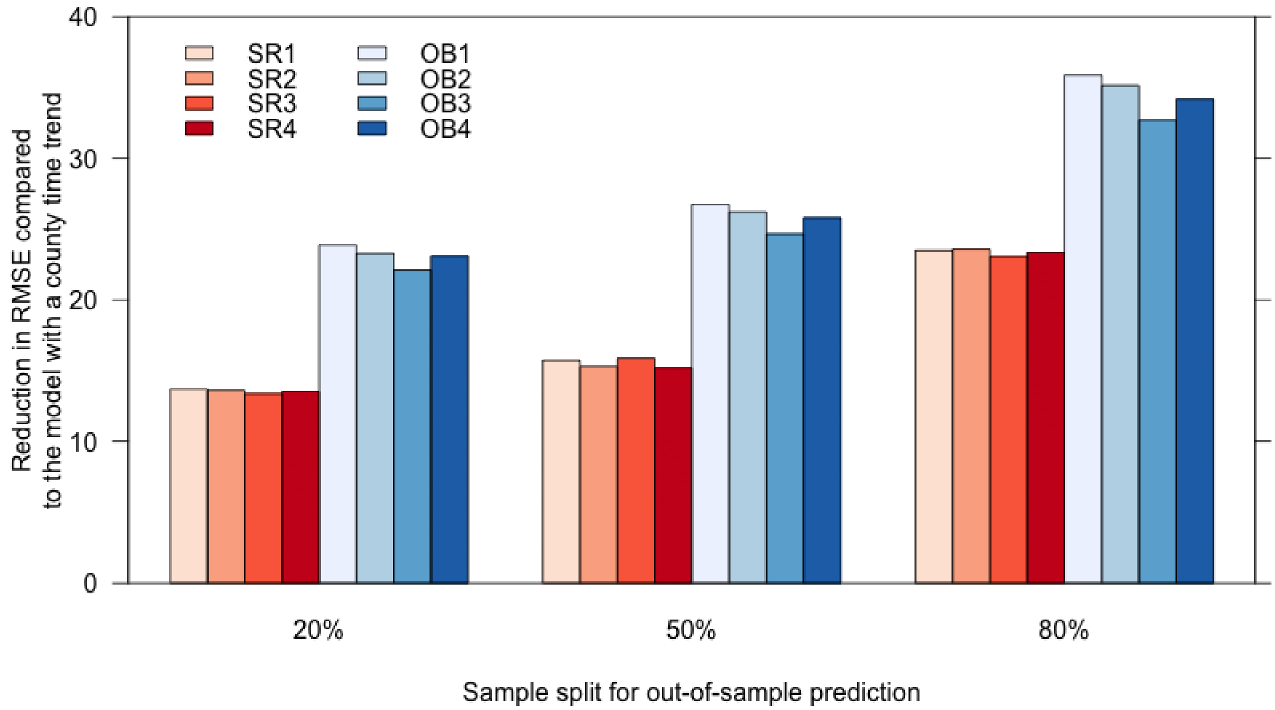


Figure 14: Model fit and out-of-sample predictions.

4 Climate Change Impacts

Statistical models are commonly used to assess the potential impacts of climate change on agriculture. The conventional approach is to multiply the estimated parameters by the projected mean changes in regressors under alternative climate scenarios. Effectively, this approach relies on the estimated yield sensitivity to environmental conditions during the sample period, and predicts yield changes conditional on the projected changes in those conditions.

The changes in temperature, precipitation, and soil moisture conditions are presented in figure 7. The general pattern for temperature is an increase in the frequency of high temperatures, particularly around 30 to 35°C. The general pattern for precipitation is toward a slight to moderate decrease under all scenarios. Soil moisture changes, on the other hand, present a rich picture of seasonal dependence because predicted changes vary at different stages of the season. The general pattern points to an increase in soil moisture earlier in the season and a drying-out towards the end of the current growing season such as could not be

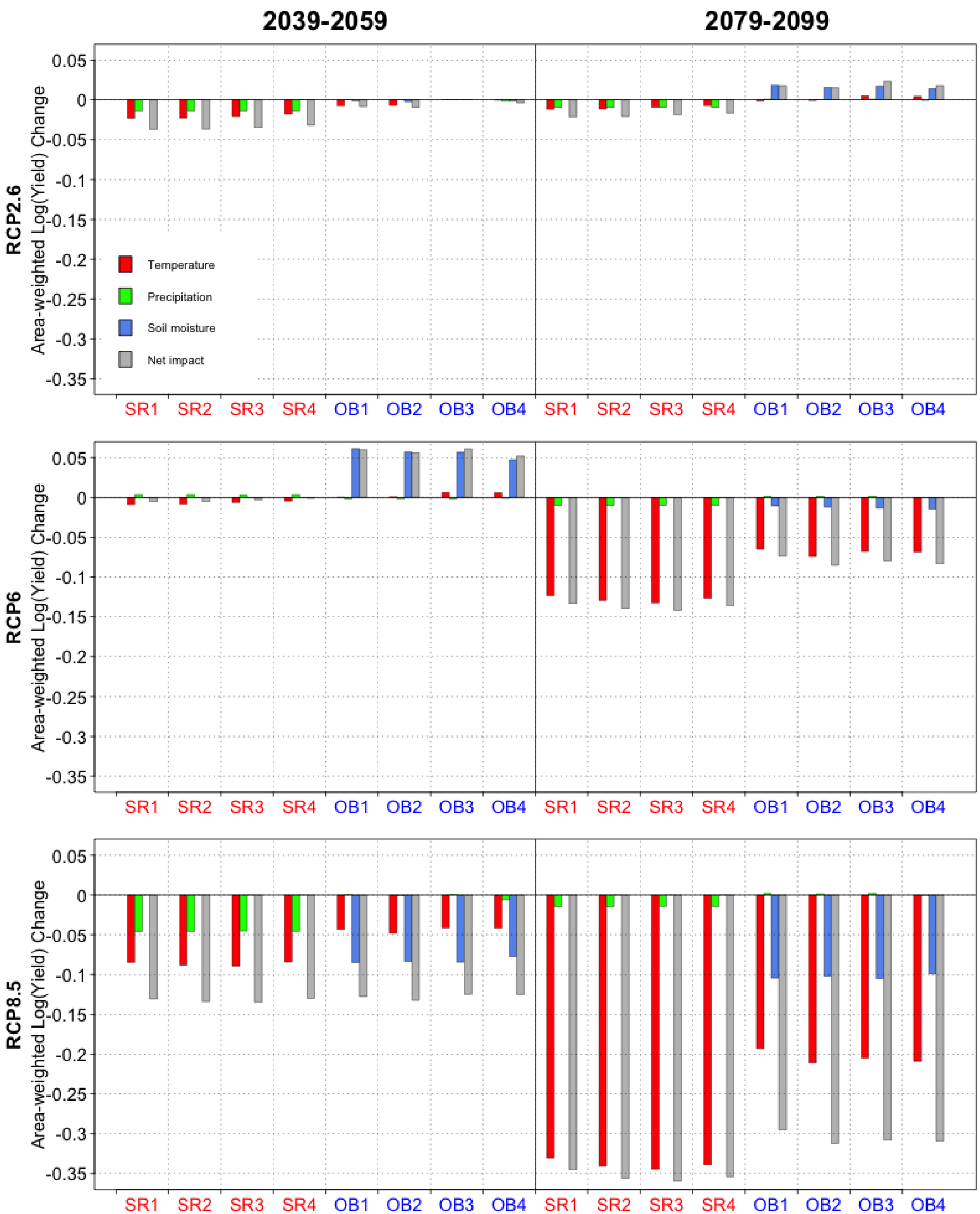


Figure 15: Climate change impacts and individual variable contributions

captured by a season-long variable.

The contribution of each variable (temperature, precipitation and soil moisture) as well as their joint net effect on yield are presented in figure 15 for all models and climate change scenarios for the 2039-2059 and 2079-2099 periods.

Impacts for the low warming scenario RCP2.6 are close to zero (in the top row). The SR model predicts mid-century yield reductions of about 3% while the OB model predicts even smaller yield effects of about 1%. For the end of the century, the SR model predicts even smaller yield reductions than in mid-century, while the OB model predicts slight yield increases of about 2%. Under the RCP2.6 scenario, the temperature stabilizes around the middle of the century, which explains why detrimental temperature effects do not increase over the century. However, soil moisture patterns change as shown in figure 7C. In particular, soil moisture increases over much of the season with the exception of sharp moisture reductions in the last two season stages when lower soil moisture is less damaging. While the SR model predicts small damages from lower precipitation, the OB model predicts small gains from increases in soil moisture during key stages, particularly at the end of the century. This underscores the importance of accounting for the timing of climate changes within the growing season.

Impacts for the most severe scenario RCP8.5 (in the bottom row) are negative for both models although they are somewhat smaller for the OB model at the end of the century (right column in figure 15). However, the impact channels, as shown by the relative role of variables in each model, differ considerably. In the SR model, temperatures overwhelmingly drive negative impacts as indicated by the long red bars. The reduction in season-long precipitation plays a slightly negative and relatively small role.

The OB model suggests a very different relative role of variables in the most severe scenario. At mid-century, negative effects from soil moisture exceed negative effects from temperature. These negative impacts of soil moisture stem from detrimental decreases of soil moisture during the middle and the end of the growing season. At the end of the century, temperature damages exceed soil moisture damages, but their relative role is much lower than in the SR model. Damages from temperature are over 30% lower when soil moisture is considered. This stems from the lower damages from high temperatures in the OB model as illustrated in the model section by figure 12.

The medium warming scenario RCP6 presents the most interesting and contrasting impacts for both mid-century and end-of-century periods. For the mid-century period, the SR model implies virtually no impacts while the OB model suggests positive effects of about 5%, driven by increases in soil moisture during the first half of the growing season (see the central column of figure 15C). Toward the end of the century, the SR model predicts impacts of about -13% while the OB model predicts damaging effects of little more than half as much at about -8%. Again, temperature effects in the OB model play a relatively smaller role (about half) and end-of-season soil drying explains the remaining part of the damage.

In summary, these findings suggest that accounting for soil moisture changes both overall impacts for some scenarios, but especially the relative role of variables driving these impacts. While precipitation is found to have a very small role in the SR model, soil moisture is a major factor in explaining impacts in the OB model. Furthermore, accounting for soil moisture reduces the share of the impacts attributable to heat stress by half in scenarios with the largest damages.

Finally, it is crucial to emphasize that these results assume a fixed growing season. A warmer climate, for instance, lengthens the growing season and provides added planting flexibility. In this context, the added intra-seasonal soil moisture representations of this model provide unique insights. A shift toward earlier planting dates, which is the direction found to be possible and beneficial in Ortiz-Bobea and Just (2012), would undoubtedly move the growing season in the direction where critical soil moisture levels are increased under the more severe climate change scenario. In other words, these findings show that much of the negative impacts found in these simulations are due to detrimental conditions that can be avoided, even more than could be accounted for by models ignoring intra-seasonal moisture changes.

5 Discussion

Statistical yield models are and will be a critical component of econometric climate change impact assessment models for agriculture as an alternative to biophysical process-based impact models. The fundamental strength of the structural econometric approach will be the ability to include farmer adaptation behavior grounded in the revealed preference paradigm. Observed yield fluctuations reflect optimal decisions based on within-season adaptations to cope with a changing and exogenous weather.

Climate change impacts will depend critically on the ability of farmers to adapt to changing environmental situations. For reliable estimates of adaptation possibilities and assessment of plausibility, the role of major variables must be unpacked in overall estimates. The current widespread approach of relying on season-long precipitation variables for capturing water availability underestimates the role of drought stress in climate change impact studies. This underestimation leads to an almost doubling of overall implicit damages for the middle warming scenario RCP6 at the end of the century. Because low soil moisture negatively affects crop yield but is correlated with high temperatures, the exclusion of soil moisture variables leads to omitted variable bias that suggests an even higher detrimental effect of temperature.

Models that suggest that water supply plays a limited role in climate change impacts in contrast to the central detrimental role of high temperature have suggested a dire future for US agriculture. These models suggest that access to water management practices, such as changing planting dates, or changing irrigation or no-till farming practices that help control the timing or keep moisture in the soil, would play only a marginal role if the overwhelming impacts are driven by heat stress alone.

On the contrary, however, accounting for soil moisture and its timing throughout the season shows that water availability is and could be a major factor in explaining potential impacts. For the mid-century projections, soil moisture appear to be the most determining factor in explaining yield impacts. This offers a more complete picture of agricultural impacts, and makes clear the fact that both, heat and drought stress will play major roles.

Turning to policy implications, agricultural adaptation policy should be concerned not only about resilience to heat but also to drought. Better modeling of channels is crucial to attribute effects to interrelated environmental variables. Relying on simple variables such as total precipitation can omit factors that are correlated with other variables in the model and thus generate bias in predicted patterns of climate change impact channels.

Because soil moisture data is difficult to obtain, some might be tempted to justify the use of models that omit soil moisture conditions, suggesting instead that temperature effects serve as a valid proxy for both heat and drought related stress. However, the results of this paper show that this justification is flawed. The validity of a proxy depends not only on its good correlation with the variables of interest during the estimation sample period, but also on whether this correlation is *maintained* during the projection period, which in this case is many decades into the future.

That temperature and soil moisture conditions will maintain the same correlation in the future is a cavalier assumption. For instance, an important implication is that the patterns emerging from the HadGEM2 point to a wetter early season but dryer late season. This is not the same pattern found for temperature. Thus, the correlation justifying extreme temperature as an appropriate proxy is not warranted for climate change analysis.

Moreover, given that the non-freezing period will be longer with warmer temperatures, farmers will very likely have greater flexibility in choosing planting dates. Given that the most sensitive period to drought is toward the middle of the season, earlier planting would possibly lead to substantial yield damage reductions through summer and fall drought avoidance. Ortiz-Bobea and Just (2012) show this mechanism is important in avoiding heat stress during the sensitive flowering period in corn. Their results suggest that earlier planting, ranging from 2 to 3 weeks depending on the state, reduces corn yield impacts of a uniform 5ºF warming scenario by 30 to 70% in the Upper Midwest. Interestingly, this is the same direction of change in planting dates that would tend to increase soil moisture in the critical time of crop development under all climate change scenarios analyzed in this paper. In summary, shifting the growing season earlier in the calendar will plausibly lead to substantial gains both from heat and drought stress avoidance.

6 Conclusion

This paper develops a statistical crop yield model that accounts for both nonlinear temperature effects and nonlinear soil moisture effects throughout the crop season. Because soil moisture is not recorded over large areas, the model makes use of the state-of-the-art NLDAS dataset with hourly and 14km resolution observations of environmental conditions. I contrast this model with a leading model in the literature by Schlenker and Roberts (2009) that accounts for water availability through a season-long precipitation variable.

Findings suggests that water availability plays a much greater role than previously suggested by the competing model. Yields are found to be very sensitive to soil moisture conditions particularly toward the middle of the season, precisely when high water demand and sensitivity to drought are expected.

Because of well-known correlations between soil moisture and high temperatures, omitting soil moisture conditions from statistical models overestimates damages by almost 100% by the end of the century for the medium warming scenario (RCP6). This is also reflected in the projected climate change impacts. Temperature effects play a substantially smaller role, ranging from a third to a half less in overall impacts, than in models omitting soil moisture. On the other hand, patterns in climate change projections from the HadGEM2 model suggest that temperature alone should not be considered as an appropriate proxy to capture dry soil conditions because the correlation between these two variables is not warranted in the climate change forecasts (although it might serve as a good proxy in the sample period).

The inclusion of soil moisture conditions also substantially and significantly improves model fit. Results indicate that the improved fit is not the result of over-fitting as out-of-sample predictions do not deteriorate as smaller shares of the sample are used for prediction.

This paper suggests that precipitation, and more precisely soil moisture, is a crucial aspect of climate change impact assessment for agriculture. It also warns that the omission of soil moisture conditions can lead to overestimation of heat related stress. This counters the prevailing view in the statistical literature that future impacts and adaptation possibilities would primarily hinge upon crop resilience to heat stress. These results point to a more complete understanding that both heat and drought stress will have fairly large roles in driving impacts, and these roles might change depending on the scenario under consideration.

The empirical model validated by this paper can have a number of useful applications both within and beyond climate change impact assessment. Most importantly, a model with the richness of soil moisture conditions is needed to add assessment of farmer adaptation possibilities using revealed preference data and models. However, in the short run, extreme weather can jeopardize harvests and lead to drastic increases in food prices with serious economic and social implications. This model coupled with the rising availability of remote sensing data for weather and phenological information could be an important part of an early-season warning system for regional or global food crises.

Another related application could be in improving early-season crop yield forecasts. For example, the USDA produces early season forecasts of crop production based on extensive survey data obtained by expensive agronomic sampling techniques requiring localized quantification of crop yield components (plant density, number of kernels per ear, kernel weight, etc). By using highly detailed remote sensing data, the approach of this paper could yield competing estimates at a fraction of the cost. These early-season forecasts could eventually compete with heavily parametrized process-based crop models used by traders in agricultural commodity futures markets.

A final word of caution applies to this form of climate change impact assessment. Because greenhouse gas concentrations do not vary significantly during 1981-2011, the approach cannot possibly account for the effects of CO_2 fertilization. In addition, the approach generally accounts for changes in mean climate and ignores the potentially crucial impacts of change in climate variability. However, this approach offers a first approximation of potential damages if the overall sensitivity of yields, growing regions, and seasons remain unchanged. Complementary studies can account for other additional sources of adaptation and yield more nuanced climate change impact scenarios.

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Appendix

A1. Determining growing season boundaries

As indicated on footnote 7, crop progress reporting began too late (the state had already surpassed the 50% acreage level) or stopped too early (the state had not yet reached the 50% acreage level) for a few states and years. For these cases, I obtain the median acreage date by extrapolation.

For this purpose I estimate, through non-linear least squares, a 2-parameter logistic model for all observations for a given stage and state. The model has a common slope or discrimination parameter a and year-specific threshold or difficulty parameters b_{year}. The model regresses stage progress $PROG$ on day of the year DOY for a given state and stage. The model is:

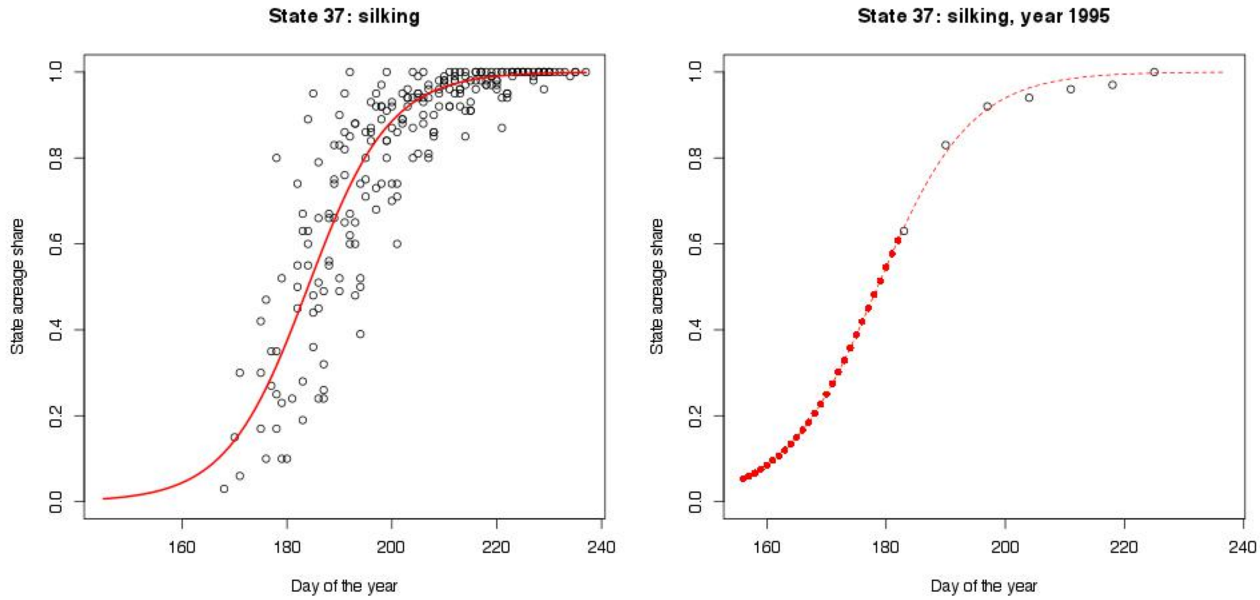
$$PROG_{DOY,year} = \left(1 + \exp\left(-a\left(DOY - b_{year}\right)\right)\right)^{-1} + \epsilon_{DOY,year}$$

Figure 16, on the left, shows the fit of the model for North Carolina (red line) corresponding to the silking stage for the average year, i.e. for $b = \bar{b}$. The common parameter a assumes that silking progress has a similar "shape" from year to year. The year-specific threshold parameter b_{year} allows the curve to be shifted horizontally. Allowing for b to vary over years is important because it is precisely for unusually early-planting and late-harvesting years that progress data lacks median progress dates. The fit of the model for the incomplete year of 1995 (shown on the right) is shown in a red dotted line and the extrapolated progress observations are shown as red dots. The crop stage boundary is obtained when the extrapolated curve reaches 50% of the state's acreage.

The paper requires stage boundary dates for 14 states, 3 crop stages (planted, silking, mature) and 31 years (1981-2011), or a total of 1302 stage boundaries. The interpolation procedure was necessary for only 55 cases or less than 5% of the cases. This concerned the states of North Carolina (42 cases), Pennsylvania (3), Missouri (2), Illinois (1), Indiana (1), Kansas (1), Kentucky (1), Michigan (1), Ohio (1), South Dakota (1) and Wisconsin (1).

A2. More on the SR model

The specification for the model with a step function allowing different effects at each 3ºC interval (SR2) is:



The graph on the left shows the 2-parameter logistic fitted model for the average year in red. On the right, the dotted red line represents the model for year 1995 and the red dots are the extrapolated progress levels. The boundary date for year 1995 is obtained from the extrapolated progress reaches 50% of the state's acreage that year.

Figure 16: Stage boundaries for years with incomplete progress data

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

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:

$$y_{it} = \sum_{h=-1}^{39} \sum_{j=1}^{8} \gamma_j T_j(h+0.5)[\Phi_{it}(h+1) - \Phi_{it}(h)] + p_{it}\delta + z_{it}\tau + c_i + \epsilon_{it}$$

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

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 defined by eight control points.

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

Figure 17 and 18 presents the results for all specification for rainfed and irrigated counties.

Figure 17 shows, for rainfed counties on the left, a close agreement across specifications for the damaging effects of temperatures above 30ºC. The polynomial (SR3) and spline specifications (SR4) show a peculiar upward bent which is not significant due to the low number of observations over that extreme range. For irrigated counties on the right, results are not as clear. Temperatures around 15 and 30 appear beneficial but temperatures around 10 and 22 and above 30 are detrimental. This repeated inversion on the sign of temperature effects is odd and has no clear physical underpinning. A possibility is that this pattern reflects mixing effects of day-time and night-time temperature exposure. However, the damaging nature of temperatures over 30ºC is of similar magnitude to rainfed counties.

Regarding precipitation in figure 18, the response curve for rainfed counties is very similar across specifications, with very low (<400mm) and very high (>800mm) precipitation levels reducing yield. However, this response curve is almost flat for irrigated counties on the right column, as expected. Indeed, Farmers in irrigated areas control the water supply for very dry years. However, very high levels of precipitation seem to reduce yield, and this could be consistent with damages from flooding events.

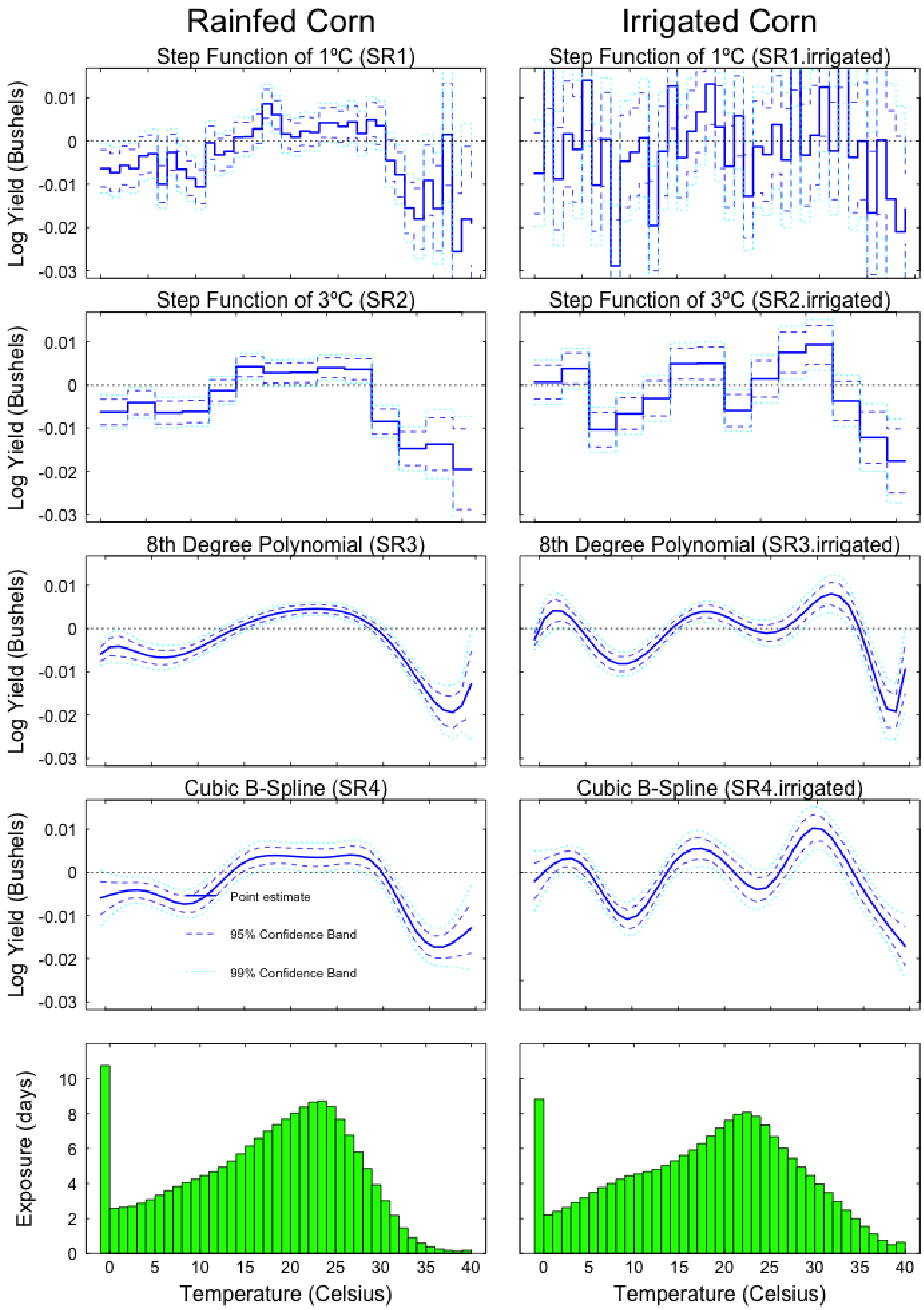


Figure 17: Temperature effects for the SR model

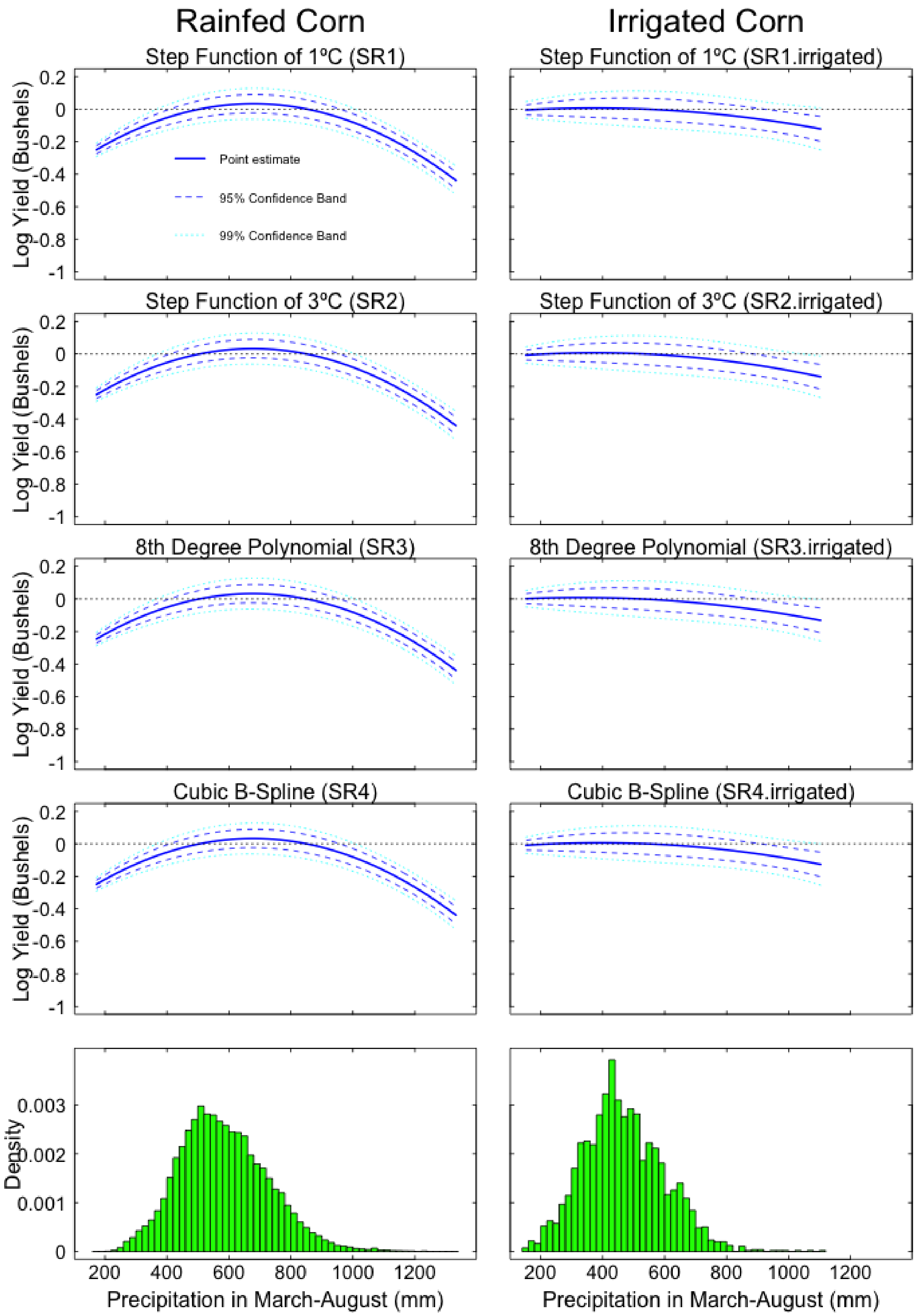


Figure 18: Precipitation effects for the SR model

A3. More on the OB model

The specification for the model with a step function allowing different effects at each 30 g/L interval (OB2) is:

$$
\begin{aligned}
y_{it} \;=\; & \sum_{h=0,3,6,9...}^{39} \gamma_h \underbrace{[\Phi_{it}(h+3) - \Phi_{it}(h)]}_{x_{it,h}} + p_{it}\delta_1 + p_{it}^2\delta_2 + z_{it}\tau + c_i \\
& + \sum_{s=1}^{8} \sum_{m=100,130...}^{340} f(m+15,s) \underbrace{[\Psi_{it}(m+30,s) - \Psi_{it}(m,s)]}_{z_{it,m}} + \epsilon_{it}
\end{aligned}
$$

Model OB3 assumes that the "yield growth" function $g(h)$ is an eighth-degree polynomial of the form $f(m,s) = \sum_{j=1}^{8} \lambda_{js} M_j(m,s)$ where where $M_j()$ is the jth order Chebyshev polynomial. Replacing $f(m,s)$ with this expression yields:

$$
\begin{aligned}
y_{it} \;=\; & \sum_{h=-1}^{39} \sum_{j=1}^{8} \gamma_j T_j(h+0.5)[\Phi_{it}(h+1) - \Phi_{it}(h)] + p_{it}\delta_1 + p_{it}^2\delta_2 + z_{it}\tau + c_i \\
& + \sum_{s=1}^{8} \sum_{m=120}^{350} \sum_{j=1}^{8} \lambda_{js} M_j(m+5,s)[\Psi_{it}(m+10,s) - \Psi_{it}(m,s)] + \epsilon_{it} \\
=\; & \sum_{j=1}^{8} \gamma_j \underbrace{\sum_{h=-1}^{39} T_j(h+0.5)[\Phi_{it}(h+1) - \Phi_{it}(h)]}_{x_{it,j}} + p_{it}\delta_1 + p_{it}^2\delta_2 + z_{it}\tau + c_i \\
& \sum_{s=1}^{8} \sum_{j=1}^{8} \lambda_{js} \underbrace{\sum_{m=120}^{350} M_j(m+5,s)[\Psi_{it}(m+10,s) - \Psi_{it}(m,s)]}_{z_{it,m}} + \epsilon_{it}
\end{aligned}
$$

The model effectively regresses yield on eight temperature variables $x_{it,j}$ and eight moisture variables for eight different stages $z_{it,m}$. Each variable represents the jth-order Chebyshev polynomial evaluated at each temperature and moisture bin.

In a similar fashion, model OB4 assumes that $f(m,s) = \sum_{j=1}^{8} \lambda_{js} Z_j^3(m,s)$ where $Z_j^3()$ is the piece-wise cubic polynomial evaluated for each jth interval defined by eight control points:

$$
\begin{aligned}
y_{it} &= \sum_{j=1}^{8} \gamma_j \underbrace{\sum_{h=-1}^{39} S_j(h+0.5)[\Phi_{it}(h+1) - \Phi_{it}(h)]}_{x_{it,j}} + p_{it}\delta + z_{it}\tau + c_i \\
&\quad + \sum_{s=1}^{8}\sum_{j=1}^{8} \lambda_{js} \underbrace{\sum_{m=120}^{350} Z_j(m+5,s)[\Psi_{it}(m+10,s) - \Psi_{it}(m,s)]}_{z_{it,m}} + \epsilon_{it}
\end{aligned}
$$

Figures 19 through 23 present the results for all specifications for rainfed and irrigated counties.

Figure 19 shows the temperature response functions for the OB model. The left column on rainfed counties shows that agreement over all for damages above 30ºC. The confidence bands become much wider for extreme temperature and the polynomial (OB3) and spline specifications (OB4) show the same peculiar upward bent than in SR3 and SR4. However, this quirk is not significant. The right column for irrigated counties exhibit a rather different response function, although it also suggests negative effects of high temperature.

Figure 20 shows the precipitation response functions for the OB model. Aside from the width of confidence bands, all response functions are extremely similar across specifications and for both rainfed and irrigated counties. They are also very similar to the precipitation response function for the SR model over irrigated areas (on the right column of figure 18). This is evidence that once soil moisture is accounted for in rainfed areas, precipitation only captures yield variation for very high precipitation levels (e.g. flooding).

Figure 21 shows the soil moisture response functions for the polynomial (OB3) and spline (OB4) specifications. The exhibit fairly similar results for rainfed counties, with the strongest yield responses toward the middle of the season. These response functions are statistically significant as shown in the left columns of figures 22 and 23, which show confidence bands.

The soil moisture response functions for irrigated counties were included in figure 21 as a falsification exercise. Because soil moisture data do not account for irrigation, we should expect the variable to explain yield variation much. Indeed, the surfaces are rather flat, with the exception of very high moisture values which happen to be insignificant, as shown on the left columns of figures 22 and 23. This clearly shows that very low levels of predicted moisture do not explain yield in irrigated counties, as expected.

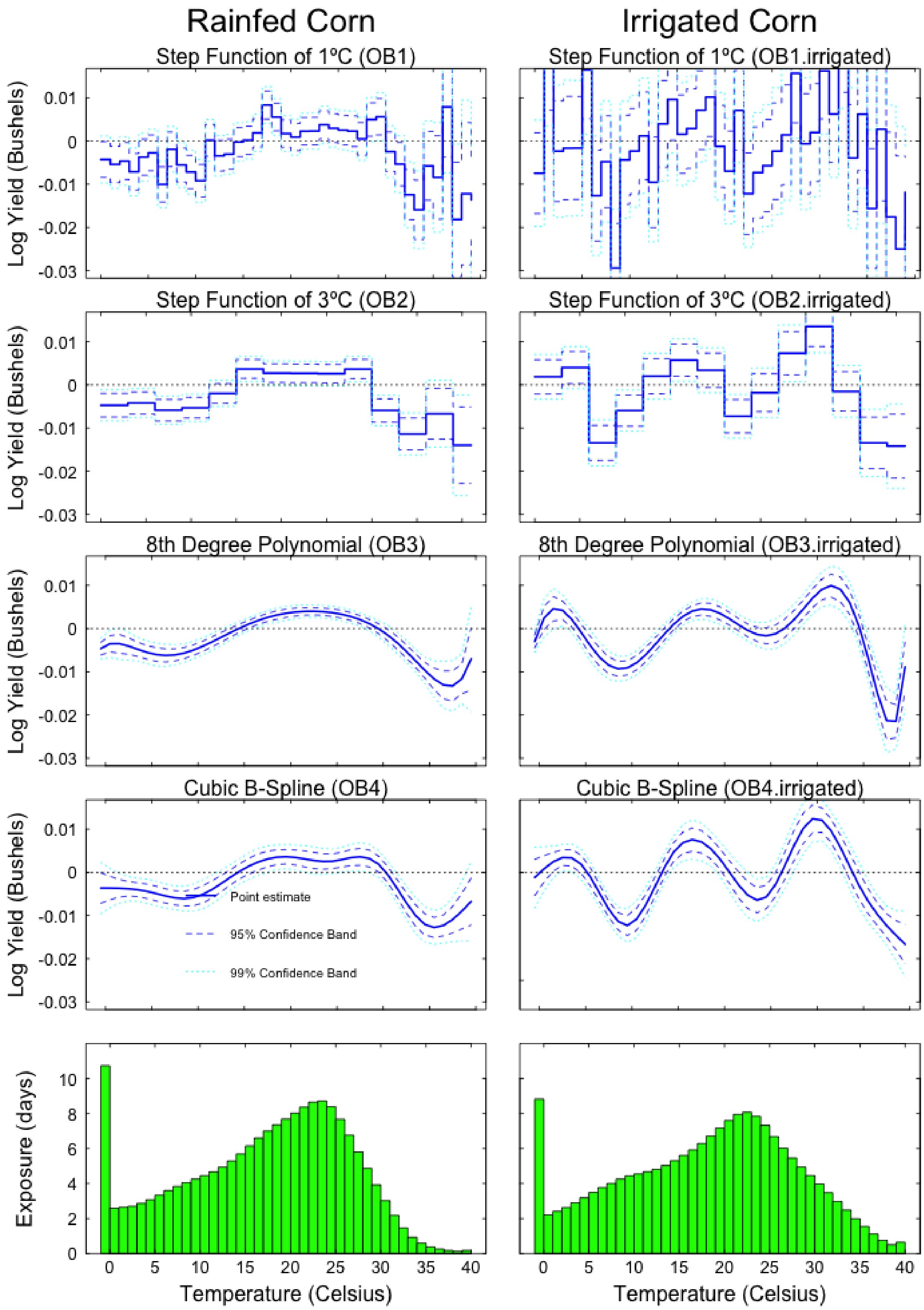


Figure 19: Temperature effects for the OB model

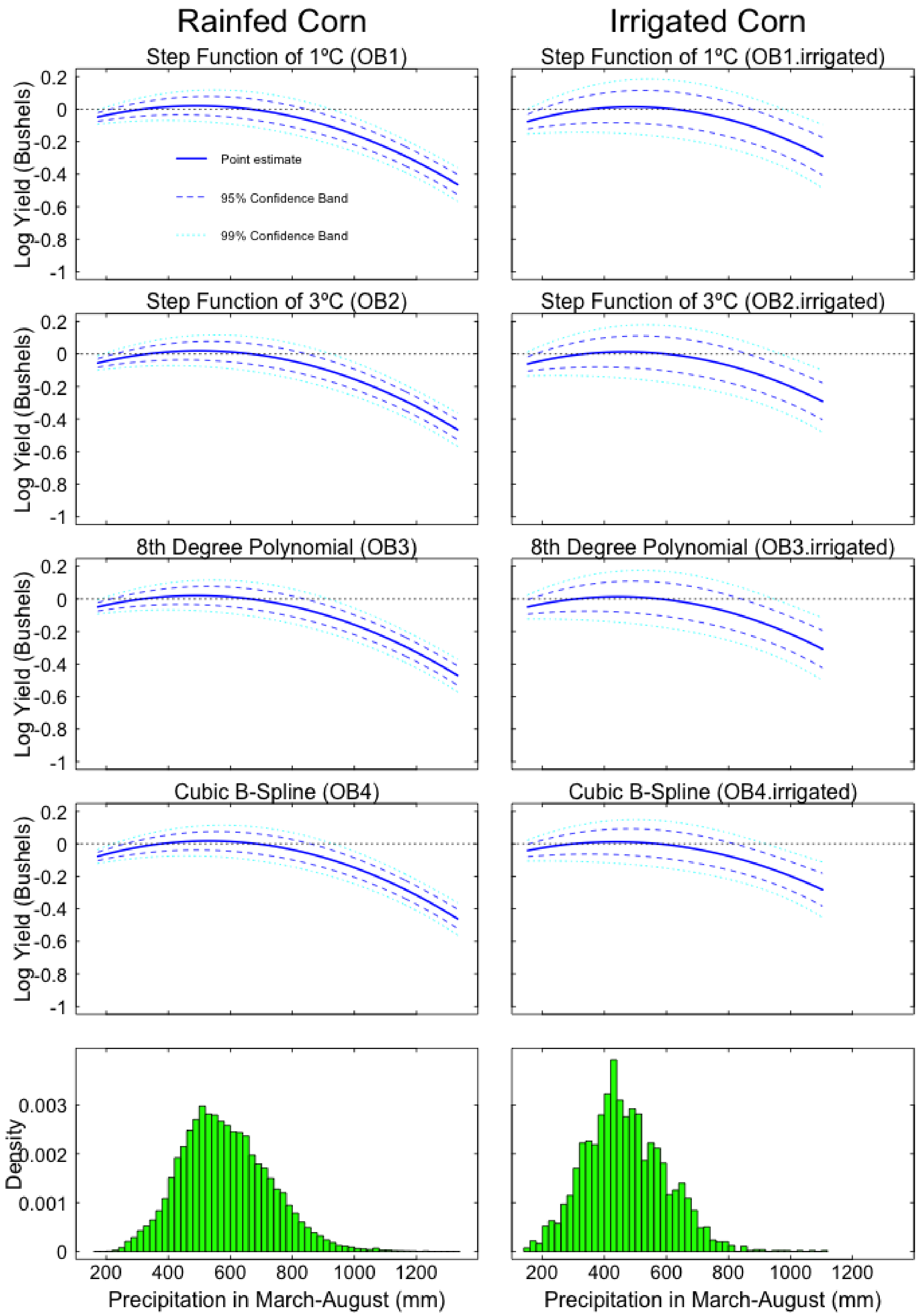


Figure 20: Precipitation effects for the OB model

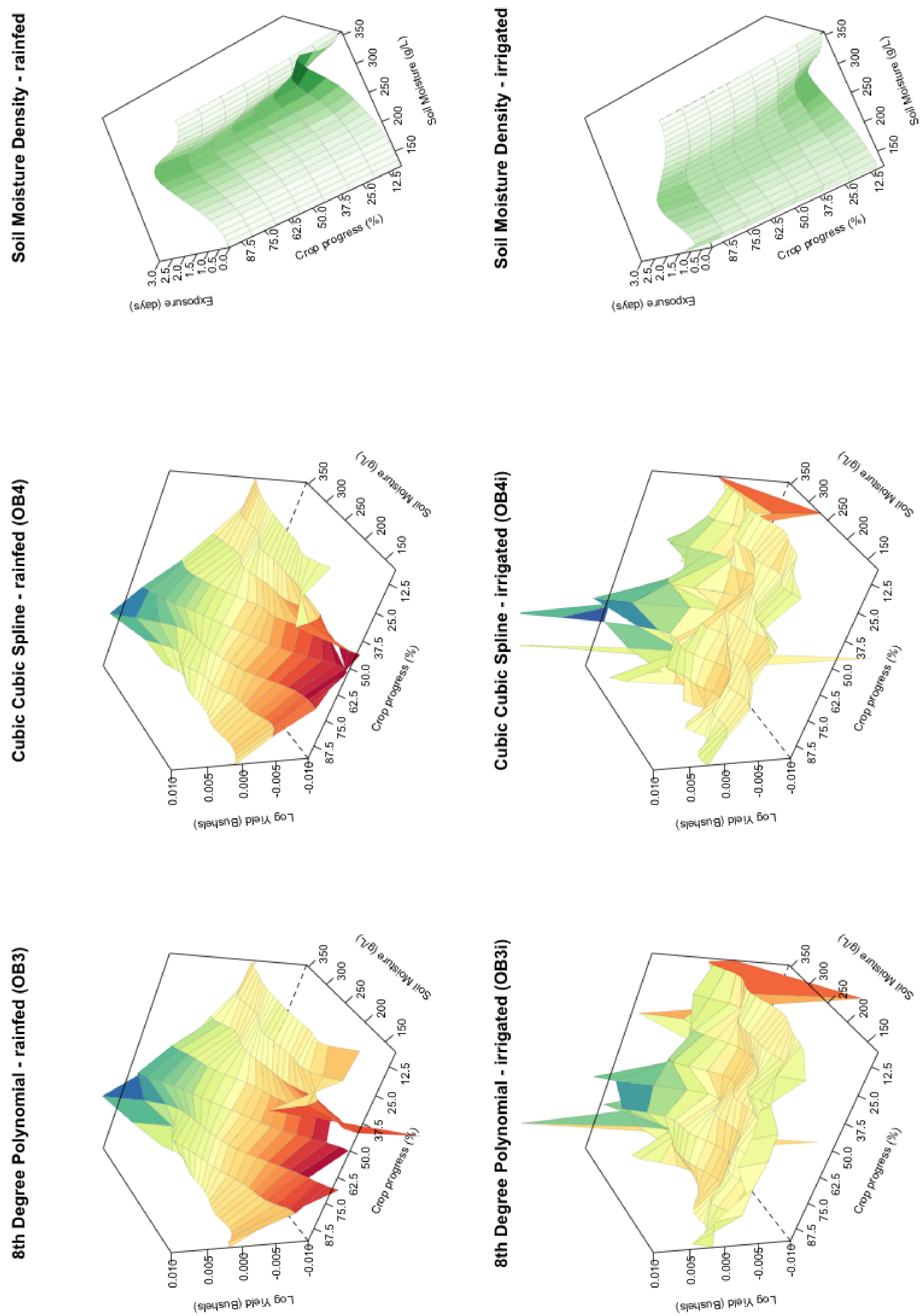


Figure 21: Soil moisture effects for the OB model

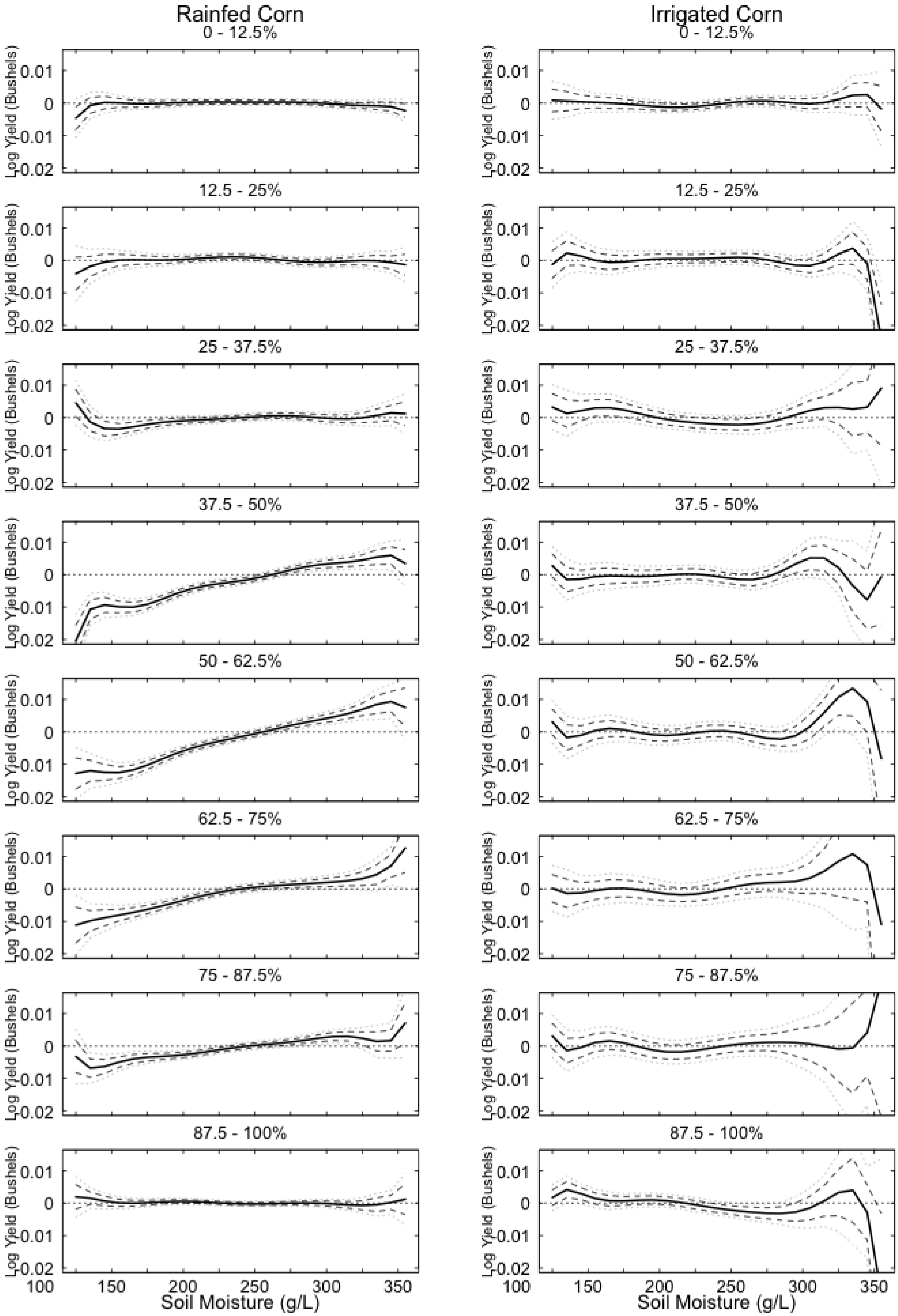


Figure 22: Soil moisture effect for the 8th Degree Polynomial specification (OB3)

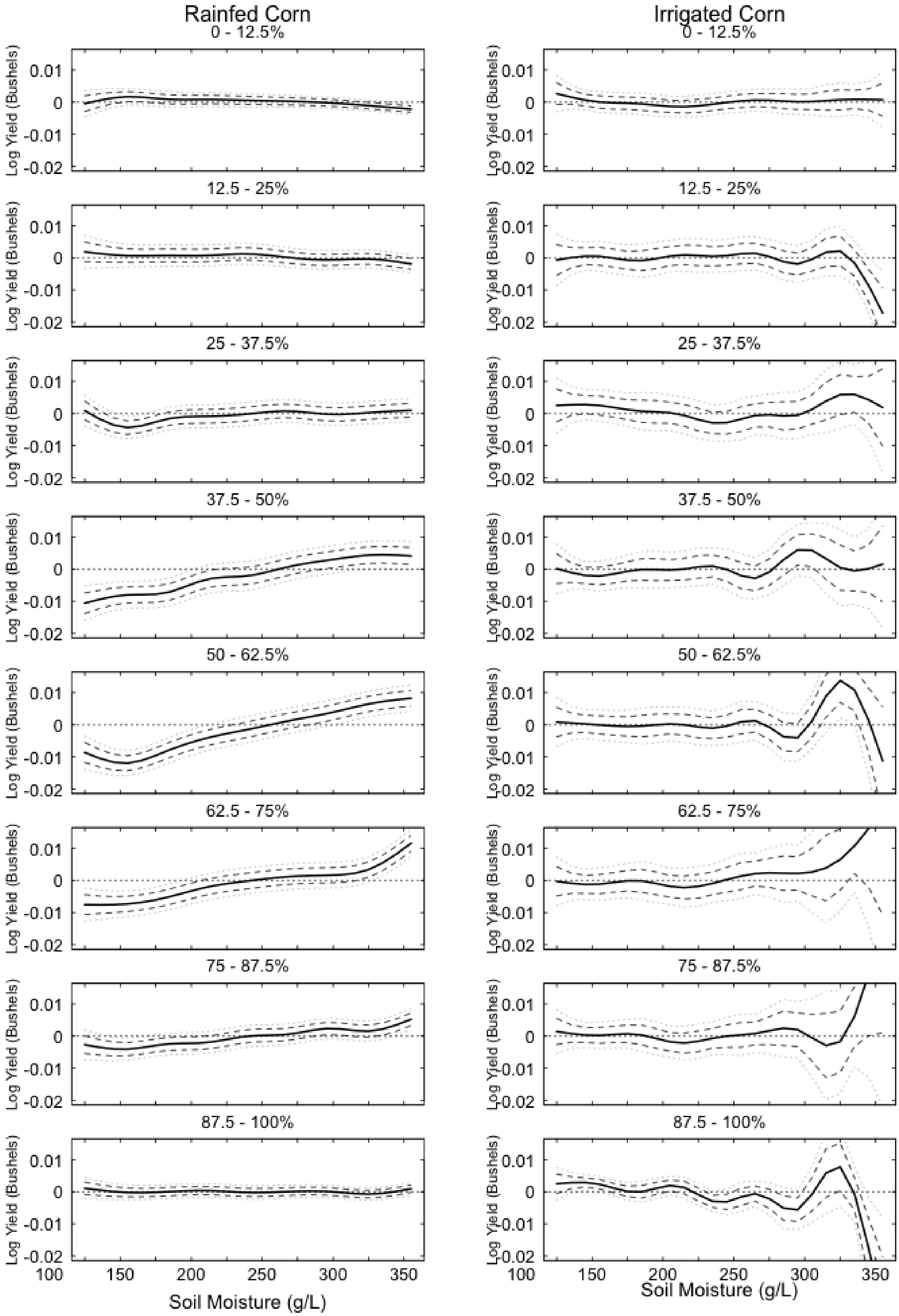


Figure 23: Soil moisture effect for the Cubic B-Spline specification (OB4)