IRRIGATION, ADAPTATION, AND WATER SCARCITY

by

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This dissertation is dedicated to

my wife, the light of my life.

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ABSTRACT

Economics is about the management of scare resources. In agricultural production, water stress and excess heat are the main constraints. The three essays of this dissertation try to improve our understandings of how climate and water resources interact with agricultural markets, and how global changes in agricultural markets may affect water resources. I construct empirical and simulation models to explain the interplay between agriculture and water. These models integrate economic theories with environmental sciences to analyze the hydroclimatic and economic information at different geospatial scales in a changing climate.

In the first essay, I illustrate how irrigation, as a potential adaptation channel, can reduce the volatility of crop yields and year-on-year variations caused by the projected heat stress. This work includes estimation of yield response to climate variation for irrigated and rainfed crops; and global projections of change in the mean and the variation of crop yields. I use my estimated response function to project future yield variations using NASA NEX-GDDP climate data. I show that the impact of heat stress on rainfed corn is around twice as big as irrigated practices.

In the second essay, I establish a framework for estimating the value of soil moisture for rainfed production. This framework is an extension of Schlenker and Roberts (2009) model enabled by the detailed soil moisture information available from the Water Balance Model (WBM). An important contribution is the introduction of a cumulative yield production function considering the daily interaction of heat and soil moisture. I use this framework to investigate the impacts of soil moisture on corn yields in the United States. However, this framework can be used for the valuation of other ecosystem services at daily basis.

In the third essay, I have constructed a model that explains how the global market economy interacts with local land and water resources. This helps us to broaden the scope of global to local analysis of systems sustainability. I have employed SIMPLE-G-W (a Simplified International Model of agricultural Prices, Land use, and the Environment- Gridded Water version) to explain the reallocation across regions. The model is based on a cost minimization behavior for irrigation technology choice for around 75,000 grid cells in the United States constrained by water rights, water availability, and quasi-irreversibility of groundwater supply. This model is used to examine the vulnerability of US land and water resources from global changes.

1. IRRIGATION ADAPTATION AND PRODUCTION VOLATILITY

This essay measures the impacts of irrigation, as a potential adaptation channel, on the volatility of global and regional crop yields and year-on-year variations. This work includes the estimation of yield response to climate variation for irrigated and non-irrigated crops; and global projections of change in the mean and the variation of crop yields. Following Schlenker and Roberts (2009), I estimate corn yields as a function of daily plant growth based on seasonal precipitation and heat. Then I use the estimated response function to project future yield variations using future climate data. I find that the impact of heat stress on non-irrigated corn is around twice as big as irrigated practices. By mid-century, US non-irrigated corn yields will be significantly more volatile compared to irrigated practices assuming no change in the spatial distribution of crop area. To keep the annual yield variation at the current levels, the US needs to increase the share of irrigated area from 15% in 2010 to around 70% by 2050.

1.1 Introduction

How economic agents adjust to climate change has been a central question in many economic studies and is important for policy at local, regional or global levels (Syud A. Ahmed, Diffenbaugh, & Hertel, 2009; Annan & Schlenker, 2015; Bellemare, 2015; D'Agostino & Schlenker, 2016; Hsiang & Kopp, 2018; Liu et al., 2017; McCarl & Hertel, 2018; Ortiz-Bobea, 2019; Sesmero, Ricker-Gilbert, & Cook, 2017). Economic agents require information for making adjustment decisions. This information includes the likely change in expenditure, costs, and returns of current choices compared to alternative options. Also, they may consider the flow of or variation in the variable of interest. This information is partially provided by hydroclimatic, biophysical, geospatial, earth and atmospheric sciences. However, they need to be transformed into economic variables, like benefits or costs, to be useful in economics. There has been significant progress to create communication from climate science to economics in this regard. However, as the climate data are not meant to be produced only for economists, there have been empirical challenges that limit our ability to test our theoretical achievements.

Agriculture is potentially vulnerable to climate change. Future severe hot conditions will sharply increase the volatility of US corn yields as a response to global warming projected to occur by mid-century (Diffenbaugh, Hertel, Scherer, & Verma, 2012; Lobell et al., 2013; Schlenker & Roberts, 2009; Urban, Roberts, Schlenker, & Lobell, 2015). In agricultural production, water stress and excess heat are the main constraints as they affect the agricultural revenue. They can affect the farmer's decisions about entering the market, the scale of production, the technology of production, management of uncertainty, investment, et cetera. Climate and land models can tell us about the historical simulations and future projections of change in water and heat for agriculture. There have been econometric exercises to capture the impacts of climate change on agricultural yield. They employ cross-sectional variation or temporal variation to compare the impacts of excess heat on mean crop yields.

While looking at the impacts of change in heat stress on them mean annual yield informs us about the likely impact of the future changes, it may not be the best indicator of yield response to climate. Looking at aggregate yield response can be misleading. Heat stress can be overestimated in climate impact studies if not separating irrigated practices from rainfed practices (Siebert et al. 2017). Also, the yields are reported usually after the annual decisions of farmers observing the change in the weather. In particular, the farmers may choose supplementary irrigation to offset a possible yield loss. If agents can adjust within a reporting period, then the estimates from reported yield responses to weather might underestimate the observed damage.

In this paper, I show that the coefficients on the excess heat in the estimation of irrigated corn yield is significantly different from non-irrigated corn. This result is robust to temporal and spatial sample selection. I believe the findings are particularly important as irrigation is considered a major adaptation channel for climate change (Troy, Kipgen, & Pal, 2015). To show the consequences of this finding, I discuss the implications for future adaptation through investment for irrigation. A key unknown is how big are the benefits of irrigation in buffering the yield variation. I project future year-on-year variation of irrigated and non-irrigated corn and show how irrigation can affect the climate impact on the mean and volatility of agricultural production. The main question is how much irrigation is required to keep the yield volatility at the historical levels?

The findings of this study are critical for global food security as well as the regional resilience of agroecosystems. Here I show that US corn yields exhibit higher volatility due to climate change. However, irrigation can buffer the effects of climate change in terms of mean yield damage and year-on-year variations. This paper is also an important contribution to the climate impact literature as it sheds light on the significance of irrigation in reducing the negative impacts of global warming. This research will be also helpful for economic studies trying to measure the benefits and costs of irrigation and water projects.

The next section provides an overview of related literature. Then section 2.3 introduces the empirical model. It also introduces different data sets used in the estimation. Section 2.4 provides estimation results and robustness checks. Section 2.5 contains a discussion on the implications of the findings for climate impact research. And section 2.6 concludes.

1.2 Literature review

The impacts of climate change are mainly driven by the intensification of extreme conditions. Current empirical studies measure the impacts of heat on mean crop yields (Lobell & Burke, 2010; Lobell et al., 2013; Roberts, Schlenker, & Eyer, 2013; Schlenker & Roberts, 2006, 2009; Urban et al., 2015). Some studies also highlight the need for irrigation to compensate for soil moisture deficits (McDonald & Girvetz, 2013; Meng et al., 2016). There are some studies that separate rainfed from irrigated practices (Schauberger et al., 2017; Tack, Barkley, & Hendricks, 2017; Troy et al., 2015). We follow the current literature and estimate the yield response to climate based on Schlenker and Roberts (2009) and extend it to separate irrigated form non-irrigated practices for corn and soybeans. This is one of the first attempts to quantify the benefits of irrigation in buffering the volatility of crop yields at the global level.

For projecting the variations in yields, Diffenbaugh et al. (2012) employ the response functions from Schlenker and Roberts (2009) and climate heat projections. They found that, without any adaptation, the variation in year-on-year yield changes will increase from around 20% to around 50% due to climate change. They also considered adaptation through market integration, a shift in the production location, and though the development of heat-resistance seed varieties. I extend this study to include the impacts of irrigation as an important adaptation channel. While they concentrated on the US, I extend the analysis to global corn production. I will also consider 21 different climate models to include various projections of the future climate.

1.3 Methods

I seek to quantify the impacts of irrigation on the mean and the volatility of agricultural yields by mid-century. The hypothesis is that “irrigation can significantly reduce the yield variations by mid-century". Specifically, I empirically estimate the marginal impacts of growing degree days between 10C to 29C (DD10-29) and stress degree days above 29C (DD29) on irrigated and non-irrigated crop yields for corn and soybeans for counties of the united states for 1981-2015. Then I project the impacts of climate change on the mean and variation of crop yields based on estimated yield response functions.

Here I introduce the empirical model and data and describe how I build the indicators of beneficial heat and harmful heat for crops based on climate data. Then I describe the future climate data and future projections of yield change and variations.

1.3.1 Empirical model

I construct an empirical model based on the assumption that plants generate biomass each day using the available resources like heat, water, and soil nutrients. I follow Schlenker and Roberts (2009) and use beneficial heat index, harmful heat index, and cumulative rainfall as an index of water availability. The assumption is that the effects of heat are cumulative over the growing season. In other words, the end-of-season yield (y) is the integral of daily heat impacts over the growing season. This relationship can be demonstrated via the following equation:

$$y_{it} = \int_{\underline{h}}^{\overline{h}} g(h)\varphi_{it}(h)dh + z_{it}\boldsymbol{\delta} + c_i + \epsilon_{it}$$

where $\varphi_{it}(h)$ is the time distribution of heat (h) over the growing season in county i and year t, while the heat ranges between the lower bound $\underline{h}$ and the upper bound $\overline{h}$; precipitation and other control factors are denoted as z_{it}, and c_i is a time-invariant county fixed effect. I assume a piece-wise linear form for $g(h)$. Considering the exposure to each temperature interval, the integral can be approximated with the following:

$$y_{it} = \sum_j \gamma_j[\emptyset_{it}(h+1) - \emptyset_{it}(h)] + z_{it}\boldsymbol{\delta} + c_i + \epsilon_{it}$$

where j indexes the pre-determined temperature intervals and $\emptyset_{it}$ is the heat cumulative distribution function for county i at year t. Following D'Agostino and Schlenker (2015), the daily distribution of temperatures is approximated assuming a cosine function between the daily minimum and maximum temperature. Let $\overline{t} = \text{acos}\left(\frac{2b - T_{max} - T_{min}}{T_{max} - T_{min}}\right)$, then degree days at each day is defined using

$$DD(b) = \begin{cases} \dfrac{(T_{max} + T_{min})}{2} - b & if\ b \leq T_{min} \\ \dfrac{\bar{t}}{\pi}\left[\dfrac{(T_{max} + T_{min})}{2} - b\right] + \dfrac{(T_{max} - T_{min})}{2\pi} sin(\bar{t}) & if\ T_{min} < b \leq T_{max} \\ 0 & if\ T_{max} < b \end{cases}$$

where b is the base for calculating degree days and can take the base values as well as critical values. The major assumption is that plant growth is approximately linear between two bounds. For example, regarding corn growth, degree days between 10C to 29C can be considered linearly beneficial and degree days above 29C are considered linearly harmful. Degree Days between two bounds are simply degree days above the smaller bound minus degree days above the larger bound. The model is estimated using a panel fixed-effect approach clustering US counties by state.

1.3.2 Future yield projections

We calculate corn yield ratios following Diffenbaugh et al. (2012) for global corn-growing areas. I use my estimated yield response function. By taking the difference between the two consecutive years. This response function can be employed to project the year-on-year yield change as the yield ratio:

$$YR_{i,t} = \frac{y_{i,t}}{y_{i,t-1}} = exp\left(\alpha\left[\emptyset_{i,t}^{-} - \emptyset_{i,t-1}^{-}\right] + \beta\left[\emptyset_{i,t}^{+} - \emptyset_{i,t-1}^{+}\right] + \delta_1\left[P_{i,t} - P_{i,t-1}\right] + \delta_2\left[P_{i,t}^2 - P_{i,t-1}^2\right]\right)$$

$$YR'_{i,t} = \frac{y'_{i,t}}{y'_{i,t-1}} = exp\left(\alpha'\left[\emptyset_{i,t}^{-} - \emptyset_{i,t-1}^{-}\right] + \beta'\left[\emptyset_{i,t}^{+} - \emptyset_{i,t-1}^{+}\right] + \delta'_1\left[P_{i,t} - P_{i,t-1}\right] + \delta'_2\left[P_{i,t}^2 - P_{i,t-1}^2\right]\right)$$

where $y_{i,t}$ is the log of non-irrigated corn yield, $y'_{i,t}$ is the log of non-irrigated corn yields, $\emptyset_{i,t}^{-}$ is the growing-season GDDs between the base of 10 °C and 29 °C, $\emptyset_{i,t}^{+}$ is the growing-season GDDs above 29 °C. I aggregate gridded variables to the regional level (*r*) using regional production share.

$$YR_{r,t} = \sum_i \omega_i YR_{i,t}$$

$$YR'_{r,t} = \sum_i \omega_i YR'_{i,t}$$

1.3.3 Data

For the empirical estimation, I employ county level yield data of corn and soybeans for the continental US. Table 2-1 reports the yields for irrigated and non-irrigated corn and soybeans for the years 1981-2015 as reported by the U.S. Department of Agriculture's National Agricultural Statistical Service (USDA-NASS). Yield is defined as production at the county level divided by harvested area. Schlenker and Roberts (2009) discuss that planted acres may not be harvested in a low-yielding year. Thus, considering the harvested area can cause a bias. However, they show that the results with the planted area are very similar to the results using harvested acres. I focus on yield per harvested acre in this study.

Table 1-1. Descriptive statistics for all US counties 1981-2015

Crop	Obs	Mean	Std.Dev	Min	Max
Corn Yield (Bushels / Acre)	71,721	110.0	37.8	4.5	246.0
Irrigated*	8,950	141.7	33.0	15.0	245.0
Non-irigated*	8,491	73.6	33.1	4.5	209.0
Soybeans Yield (Bushels / Acre)	58,050	33.7	10.5	0.7	73.1
Irrigated *	5,534	43.3	9.6	15.0	70.3
Non-irigated*	5,839	27.6	9.8	5.2	59.8

*Note: * only for counties with irrigated practice. Based on USDA-NASS.*

Precipitation is defined in millimeters as accumulative rainfall during the growing season (Apr-Sep) calculated based on PRISM (Parameter-elevation Regressions on Independent Slopes Model) daily information and aggregated to each county according to cropland area weights. We calculate county-level seasonal degree days based on daily fine-scale weather information. Degree days are initially calculated for each day at each grid cell during the growing season. Then they are aggregated for the whole growing season from the first day of April through the last day of September. Finally, they are aggregated to the county level using cropland area weights. The weather information on daily precipitation, maximum temperature, and minimum temperature are obtained from PRISM at 2.5 x 2.5 arc min grid cells over the continental US for 1981-2015. Table 1-2 summarizes the aggregated variables calculated based on PRISM and used in the regression.

We need reliable future projections of daily temperature (maximum and minimum). While there are various climate products projecting future daily temperatures, the choice of climate model requires extreme caution and should be compatible with the special needs of each study. I employ NEX-GDDP (NASA Earth Exchange Global Daily Downscaled Projections) climate dataset. This is a downscaled and bias-corrected database for the globe from 21 models from the Coupled Model Intercomparison Project Phase 5 (CMIP5). For the future scenario, I use pathway 8.5 of Representative Concentration Pathways (RCPs). It is a high-resolution dataset at 25-km horizontal resolution and the bias correction has improved the simulation of temperature extremes. I look at the 2036-2065 period and take the average change in meteorological conditions from 1976-2005.

Table 1-2. Descriptive statistics for all US counties 1981-2015

Variable	Mean	Std. Dev	Min	Max
Degree Days				
dday10_29C Apr-Sep	1864.0	438.4	692.7	3082.5
dday10_30C Apr-Sep	1884.1	451.7	692.8	3171.2
dday29C Apr-Sep	62.3	60.8	0.0	723.0
dday30C Apr-Sep	42.2	47.0	0.0	623.7
Temperature (C)				
Mean Apr-Sep	19.8	3.1	7.9	30.2
Mean Apr-May	14.7	3.9	1.5	27.6
Mean Jun-Jul	23.3	2.8	9.5	34.3
Mean Aug-Sep	21.6	3.1	9.0	33.6
Precipitation (mm /day)				
Mean Apr-Sep	3.1	1.0	0.0	8.5
Mean Apr-May	3.1	1.5	0.0	14.1
Mean Jun-Jul	3.3	1.5	0.0	13.6
Mean Aug-Sep	2.8	1.4	0.0	14.9
Number of Observations	73014			

Notes: *Table reports descriptive statistics for major variables in this study. The mean and standard errors are calculated over US counties for the 1981-2015 period. All weather data are calculated for each 2.5 x 2.5 arcmin grids, averaged over the time interval, and then averaged to counties using cropland area weights.*

This study will project the variations for all NEX-GGDP models. However, I choose CCSM4 in illustrating global maps for two reasons. First, Sriver et al. (2018) have evaluated NEX_GDDP models and conclude CCSM4 performs relatively well in projecting GDD above 29C. In addition, while the performance of raw CMIP5 models in replicating observed precipitation varies among models, the CCSM4 model stands among the best (Yuan & Quiring, 2017). I illustrate the DD29 from the CCSM4 model from NEX-GDDP climate data sets for the RCP 8.5 scenario at 15 x 15 arc minutes across the globe. This model is validated for projecting GDD above 29C against historical observations.

Employing NEX-GDDP, I calculate degree days from 10C to 29C as well as degree days above 29C for 1976-2005 and 2036-2065. Note that the growing season varies for each part of the world. Thus, I consider grid-specific growing seasons according to the SAGE growing calendar (Sacks, Deryng, Foley, & Ramankutty, 2010). Then I calculate degree days for each day at each grid cell and then sum it over the growing season. Figure 2-2 shows historic and future degree days above 29C calculated based on NEX-GDDP CCSM4 for RCP8.5. According to this projection, degree days above 29C are expected to increase significantly in the US by the mid-century. As shown in this figure, the pattern of mean DD29 is expected to change. The Southern part of the US is expected to experience a considerable increase in harmful heat (Note that the increase in standard deviation is more widespread and covers most of the Corn Belt; This raises concerns about the volatility of agricultural outputs, farmers' income, and prices).

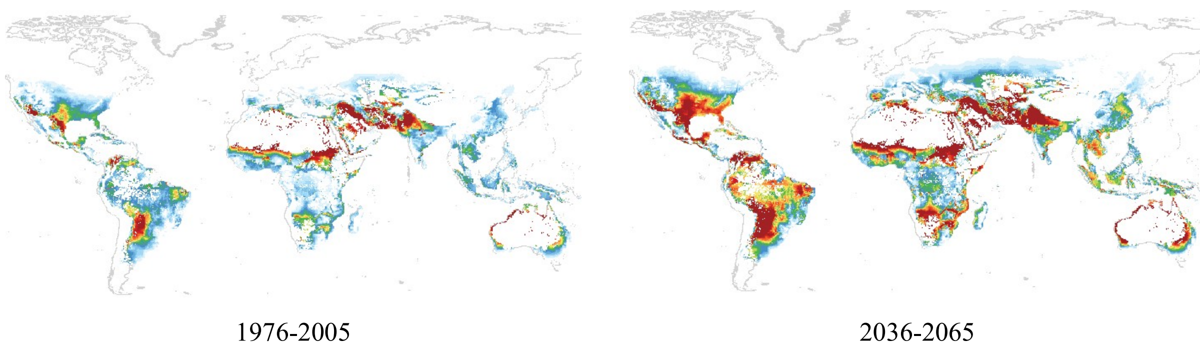


Figure 1-1. Degree days above 29C for 1976-2005 and 2036-2065 with RCP8.5.

1.4 Results

The results from our main specifications for corn yields are given in Table 2-3 and shown graphically in Figure 2-3. The figure illustrates the estimated response function for irrigated and non-irrigated corn for splines and piecewise linear models. In column 1 of the table, I run the model on average county corn yields. Columns 2-3 are similar estimates but on irrigated and non-irrigated corn. The results suggest that the impact of heat on yield is positive before the critical temperature threshold (29C) and is negative for higher temperatures. However, the damage is more severe for non-irrigated corn. Table 2-3 shows the result of the piecewise linear model. The marginal impact of a degree-day within 10-29C is significantly positive while that from an additional degree day above 29C is strongly negative for both non-irrigated and irrigated corn.

Table 1-3. Estimating yields of irrigated and non-irrigated corn in the US

	(1) logCornYield	(2) logCornYield Irrigated	(3) logCornYield Non-Irrigated
Degree Days 10-29°C Apr-Sep	0.00028***	0.00040***	0.00027***
	(0.00007)	(0.00007)	(0.00007)
Degree Days above 29°C Apr-Sep	-0.00517***	-0.00225***	-0.00528***
	(0.00063)	(0.00017)	(0.00066)
Precipitation Apr-Sep	0.00086***	0.00059***	0.00129***
	(0.00022)	(0.00010)	(0.00030)
Precipitation Apr-Sep Square	-0.00000***	-0.00000***	-0.00000***
	(0.00000)	(0.00000)	(0.00000)
cons	3.00027***	3.21564***	2.86993***
	(0.14026)	(0.13594)	(0.15920)
Obs.	136103	14585	136103
R-squared	0.76786	0.80668	0.72669

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table lists regression coefficients and shows standard errors in brackets. Temperature is in degree Celsius, precipitation in mm. Precipitation and temperature are taken from PRISM at 2.5 arcmin. They are aggregated from grid cells to counties based on crop area weight. Yield data is acquired from the USDA.

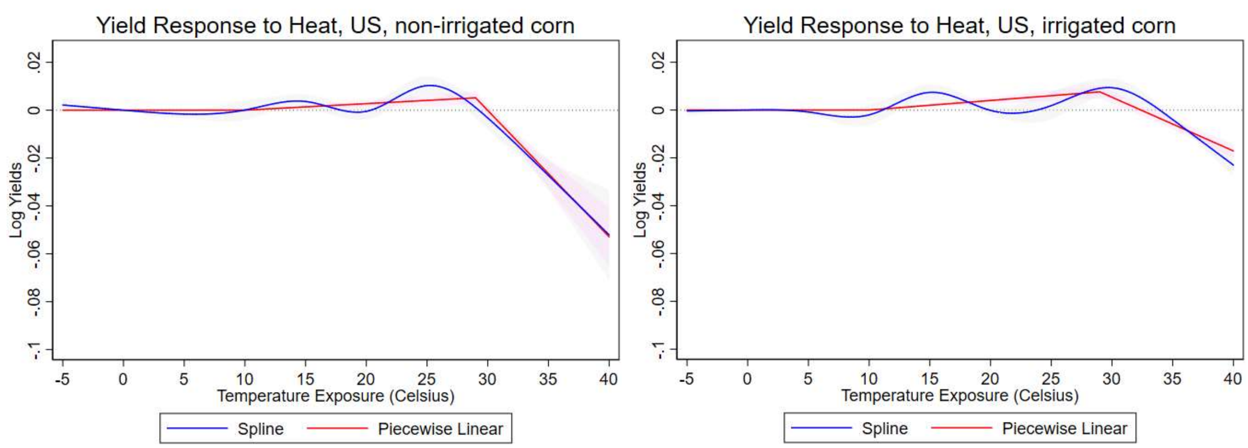


Figure 1-2. Estimated impacts of heat on corn yields for non-irrigated and irrigated. Graphs display changes in log yield if the crop is exposed for one day to a particular 1° C temperature interval where I sum the fraction of a day during which temperatures fall within each interval. The 95% confidence band is added as shaded area for the regressions.

The marginal impact of GDD29 on irrigated corn is almost 57% smaller than the impact on non-irrigated corn (-0.00225 versus -0.00528). It implies that exposure of corn to temperatures above 29C may result in sharp declines in yields for non-irrigated corn but smaller damage for irrigated corn. The coefficient on the excess heat in the estimation of irrigated corn yield is significantly different from non-irrigated corn.

I did several checks to make the finding is robust. I estimated the piecewise linear model for different geographical samples. Table 4 shows the results for the Eastern US (defined as the areas located east of -100 meridian). The findings are robust and the marginal impact of GDD29 on irrigated corn is still much lower than rainfed corn. More robustness checks are available at the appendix A for temporal and spatial samples. However, in all the samples we reject that the estimates on the excess heat (above 29C) are the same for irrigated and non-irrigated.

Table 1-4. Estimating yields of irrigated and non-irrigated corn in the Eastern US

	(1) logCornYield	(2) logCornYield Irrigated	(3) logCornYield Non-Irrigated
Degree Days 10-29°C Apr-Sep	0.00027***	0.00039**	0.00027***
	(0.00007)	(0.00011)	(0.00008)
Degree Days above 29°C Apr-Sep	-0.00545***	-0.00264***	-0.00557***
	(0.00066)	(0.00023)	(0.00068)
Precipitation Apr-Sep	0.00107***	0.00055*	0.00139***
	(0.00022)	(0.00024)	(0.00029)
Precipitation Apr-Sep Square	-0.00000***	-0.00000**	-0.00000***
	(0.00000)	(0.00000)	(0.00000)
cons	2.97372***	3.24761***	2.88451***
	(0.14720)	(0.19817)	(0.15481)
Obs.	120928	8053	120928
R-squared	0.77884	0.83190	0.76309

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

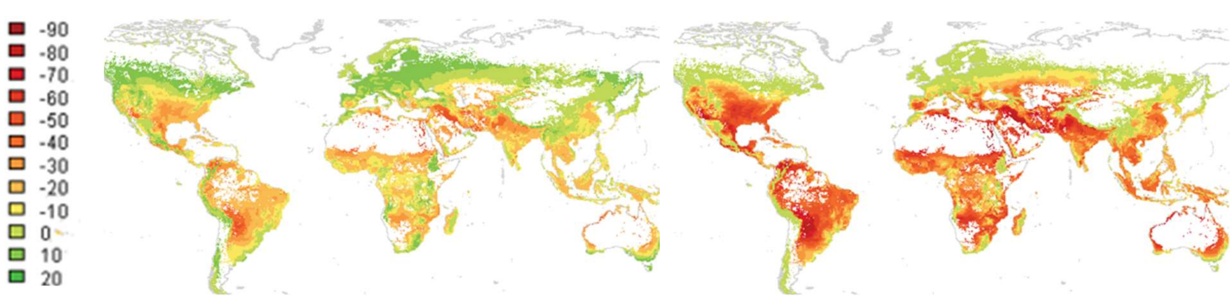
Notes: *Sample of counties east of the 100th meridian. The table lists regression coefficients and shows standard errors in brackets. Temperature is in degree Celsius, precipitation in mm. Precipitation and temperature are taken from PRISM at 2.5 arcmin. They are aggregated from grid cells to counties based on crop area weight. Yield data is acquired from the USDA.*

1.5 Discussion and Implications

We find that irrigation significantly changes the yield response to excess heat. This has significant implications for a wide range of climate-related issues. I expect that irrigation will become more attractive to farmers in the future. The expansion in irrigation can reduce the projected market volatility and price fluctuations (Diffenbaugh et al., 2012) and agricultural risks (Rosenzweig et al., 2014) by reducing the damage from extreme heat. It may also lead to lower vulnerability (Dilling, Daly, Travis, Wilhelmi, & Klein, 2015) and higher food security (Syud A. Ahmed et al., 2009) for the human system. On the other hand, a smaller volume of international trade can be expected to be required as the change in comparative advantage is smaller (Costinot, Donaldson, & Smith, 2016). This may also reduce the negative impact on crop insurance (Annan & Schlenker, 2015). It can also moderate future heat wave frequency, duration, and intensity (Lu & Kueppers, 2015). Here I discuss some of these implications in more detail.

1.5.1 Implications for the impact of climate change on mean yields

Climate impacts are calculated using the change in degree days and underlying estimated coefficients. Although the coefficients are estimated for the Continental US, I may apply them to other regions of the world for projecting yield changes as they embody biophysical relationships that are expected to apply regardless of where the crop is grown. This may underestimate the global damage as the US has more drought resistance varieties. However, as the impact of precipitation is estimated to be negligible (Burke & Emerick, 2016), it will not affect the main conclusion.



% change in yields of irrigated corn

% change in yields of non-irrigated corn

Figure 1-3. Future climate impact on irrigated and non-irrigated corn yields.
For NEX-GDDP CCSM4 at 15 x15 arc min grid cells, for 2036-2065 compared to 1976-2005.

I focus on the potential change in irrigated and non-irrigated corn yields under climate change at the global level for all the cropland. Figure 2-3 shows the impacts of climate change on corn yields at the global level for irrigated and non-irrigated practice for NEX-GDDP CCSM4 model outputs. The calculations show that irrigation can reduce the damage of climate change on average corn yields in the US by 10-30%.

1.5.2 Implications for year-on-year variation of yields

The climate change increases the year-on-year variation of yield. Here, I calculate the changes for all the grid cells for all climate models for all the years. Then I aggregate them to market regions. Figure 2-4 shows the distribution of year-on-year yield ratios for the continental US for future and historical climate for corn assuming no change in irrigated and rainfed area. All the models suggest an increase in standard deviation.

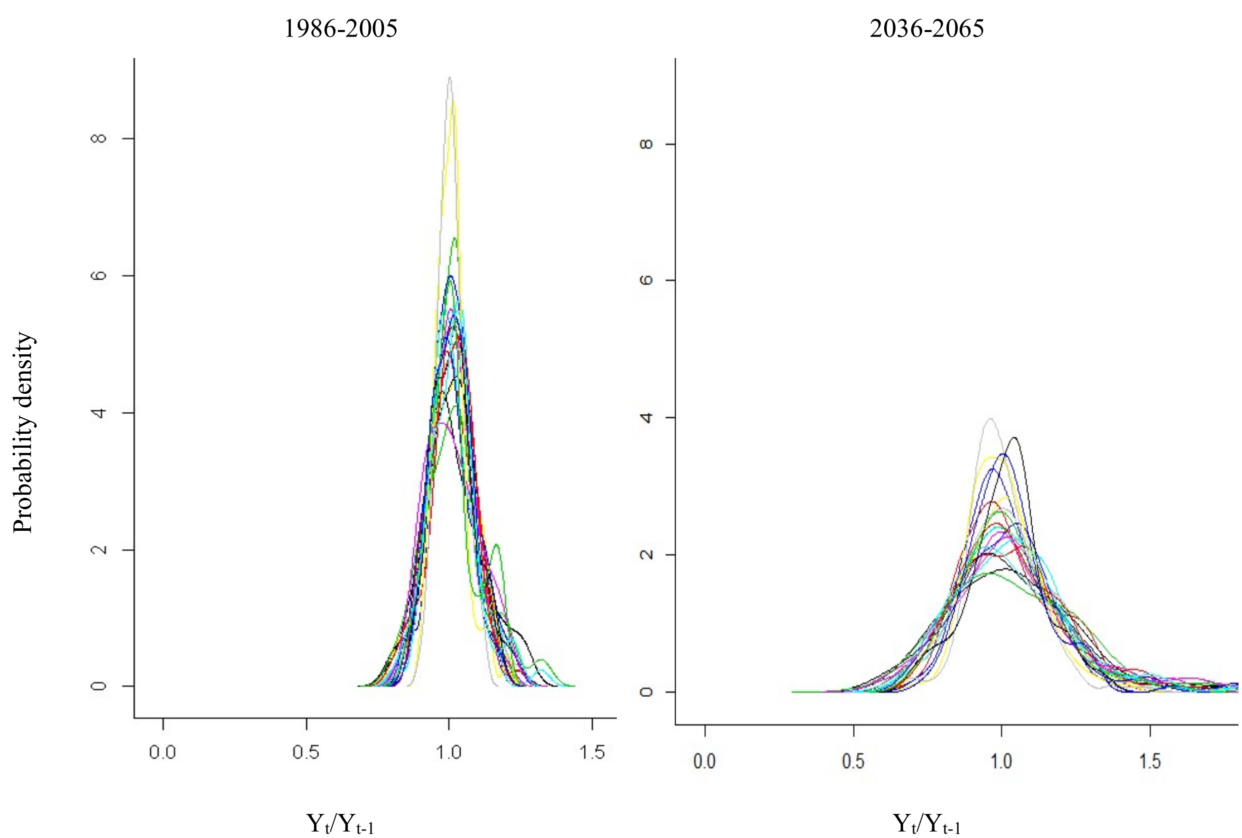


Figure 1-4. Simulated distributions of year-on-year non-irrigated yield ratios.
By climate model for the US, for 1986-2005 (left) and 2036-2065 (right).

Then, I calculate the impact of adaptations on the year-on-year yield ratio. Figure 2-5 illustrates the standard deviation of the year-on-year yield ratio for the US assuming two adaptation strategies. The adaptation through heat tolerance is shown on the horizontal axis. This suggests that to keep the variations at historical levels, heat tolerance must increase to 34C. On the other hand, to keep the variation at the historical level, the share of irrigation areas must increase from 15% to around 70%. A combination of 50% share of irrigation area and heat tolerance to 31C can keep the variations at the historical level.

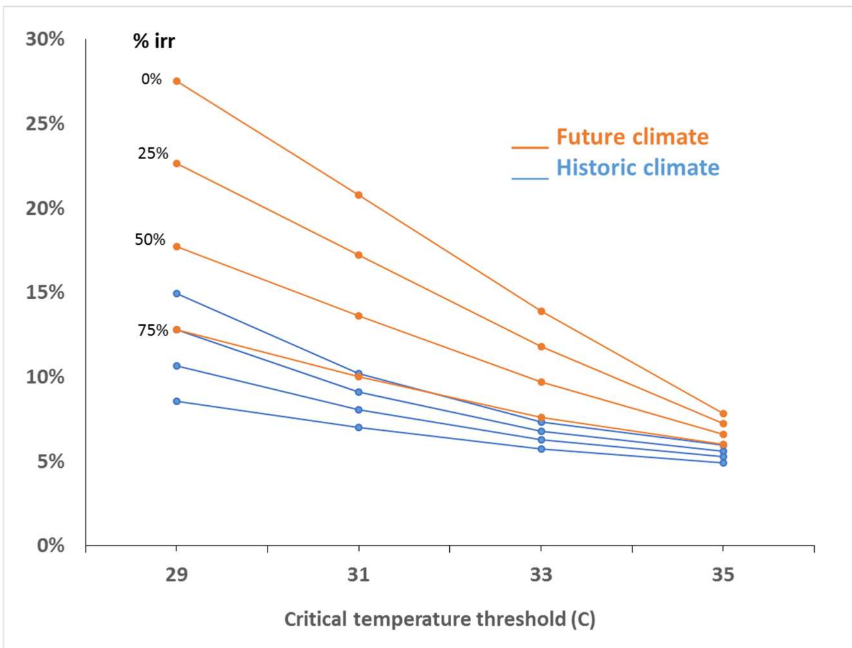


Figure 1-5. Volatility of US corn yields to heat resistance and irrigation.
Based on NEX-GDDP CCSM4 model for the US, for 1986-2005 and 2036-2065.

1.5.3 Implications for market integration

Another adaptation strategy can be market integration. However, further research is required to find the right methodology for using climate data for this strategy. The advantages of adaptation through market integration are uncertain and climate models do not agree on spatial correlation of year-on-year shocks. Figure 2-6 demonstrates this correlation as calculated for GFDL-ESM2M and CCSM4 models. The idea is to integrate with a region with a negative correlation of year-on-year shocks. As the climate models largely disagree on this, it is necessary to develop or find a climate model which has better performance in replicating the spatial correlations. We are not able to combine the advantages of irrigation with market integration.

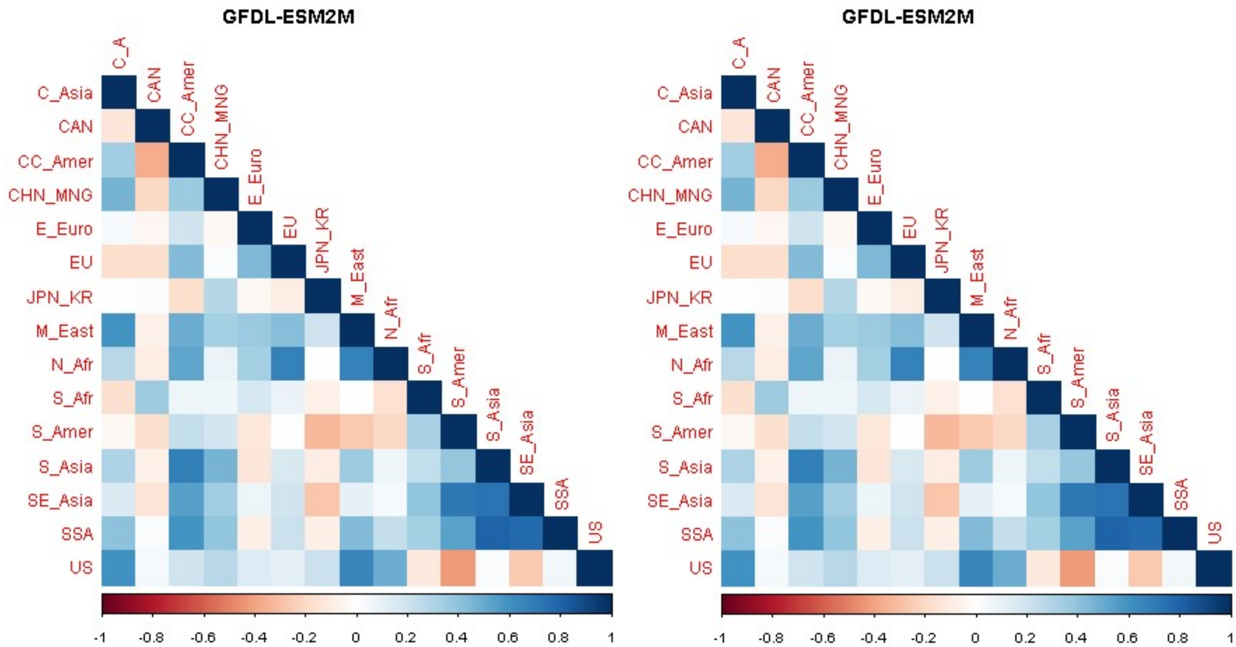


Figure 1-6. Correlation of year on year yield shocks by NEX-GDDP climate models

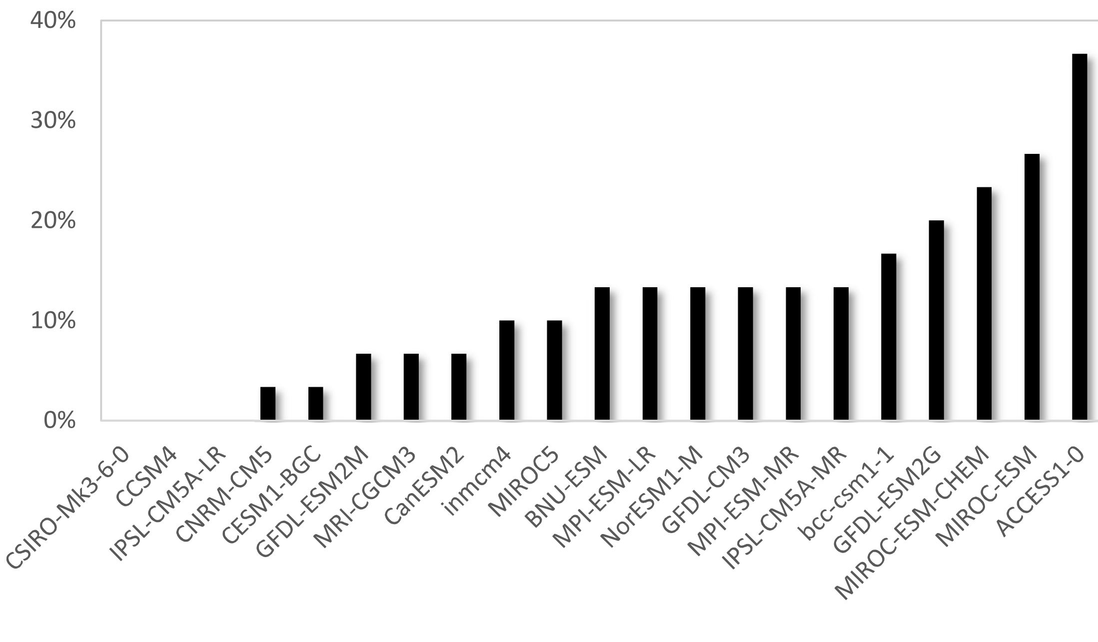


Figure 1-7. Change in the likelihood of consecutive negative climate impact (US crop yield < 95% of 30 year mean) by NEX-GDDP climate models.

1.5.4 Implications for water stress

While irrigation provides yield benefits, expansion of irrigated areas may add to water stress issues as a critical global challenge. So, it is critical to consider the tradeoffs regarding irrigation expansion policies. Specifically, my calculations suggest a considerable increase in successive hot years as shown in Figure 2-7. This implies an irrigation water withdrawal at an increasingly fast rate compared to groundwater recharge. An increase in frequency, duration, and intensity of hot years may lead to the fast depletion of water resources around the planet.

1.5.5 Limitations from soil moisture

The main difference between irrigated and non-irrigated practice is soil moisture availability. While we expect that soil moisture always stays at desired levels for irrigated agriculture, climate change may affect the soil moisture availability of non-irrigated production. Thus, the impacts of soil moisture on yields and the implications of climate change need to be studied. In places predicted to be drier in the future, water stress will intensify the impacts of heat stress. And for places predicted to be moist in the future, the impact of heat stress will be smaller. It is important to consider the likelihood of compound stress (hot and dry years versus hot and wet years).

1.6 Conclusion

Econometric estimation of agricultural response to climate can provide insightful information for adaptation. In the coming decades, global warming will dramatically increase heat stress on global agriculture. In addition to yield loss due to extreme heat, there have been projections of increased volatility in agricultural yields. However, choosing an adaptation strategy requires information on its potential benefits in reducing the average damage or buffering the volatility.

Here, I show that the coefficient on heat stress is significantly different for irrigated and non-irrigated corn. In other words, we statistically showed that irrigation can reduce the damage from heat stress. Employing estimated coefficients, I examine the volatility in corn yields as a major global field crop. Although the volatility of yields will increase in many areas, I find that irrigation can reduce the standard variation of year-on-year yield changes.

This study underscores the importance of irrigation as an effective strategy of adaptation to climate change. This adaptation can moderate production declines and commodity price hikes in the presence of climate extremes, thereby benefiting food security. However, the expansion of irrigation in many areas may lead to further increases in unsustainable groundwater withdrawals. Such tradeoffs are inevitable as environmental stresses in agriculture increase in the future. However, I do not recommend irrigation expansion policies without carefully looking at the environmental and economic costs of such policies.

2. THE VALUE OF SOIL MOISTURE FOR AGRICULTURE

Green water, the stored soil moisture in a crop's root zone, is a critical input for agriculture and is embodied in the economic value of farm products and cropland. Fluctuations in soil moisture account for more than 70% of crop indemnities in the US (drought or flooding) during the 2001-2015 period (USDA-RMA). In this paper, I estimate the value of soil moisture in US corn production using daily hydroclimatic information. I extend the work of Schlenker and Roberts (2009) by estimating corn yields as a function of the daily interaction of soil moisture and heat. I employ a unique, fine-scale daily database of soil moisture content for the continental US for the 1981-2015 period based on the Water Balance Model. Quantifying the impacts of heat and soil moisture combinations on yield, I estimate the conditional marginal value product of soil moisture.

2.1 Introduction

Research Gap: The importance of green water, stored soil moisture in the root zone of agricultural crops, is well known for farmers and agronomists but less explored in broad-scale national statistical and agricultural economics studies. Recent work by Ortiz-Bobea et al. (2019) has highlighted the importance of soil moisture for crop yields in the US. impacts of soil moisture on crop yields (Ortiz-Bobea et al. 2019). I contribute to this literature by measuring the conditional marginal value of soil moisture considering current soil moisture levels, temperature, and market conditions. This exercise also shows the potential application of fine scale hydroclimatic information for research in the economics of climate change, global environmental changes, and coupled human and environmental systems.

Significance: I believe this exercise is important for global food security, regional resilience of agroecosystems, and for future climate impact studies. It can help farmers to quantify the daily importance of soil moisture for future climate adaptation which can indirectly ensure food security. At the policy level, this study improves our understandings of the implications of compound climate extremes which crucially matter for many economic outcomes at local and global levels. This provides a better measurement of climate-related variables which is highly valuable for economic studies (McCarl and Hertel 2018; Hsiang and Kopp 2018). In the scientific community, scientists are generally concerned with the impact of climate change on soil moisture and its implications (Jung et al. 2010; Taylor et al. 2013; Rodell et al. 2018). Although current studies were exceptionally successful in capturing the impacts of heat on crop yields (Schlenker and Roberts 2006; 2009; Lobell and Burke 2010; Lobell et al. 2013; Roberts, Schlenker, and Eyer 2013; Urban et al. 2015), there has been limited success using soil moisture (Bradford et al. 2017; Peichl et al. 2018). Despite existing theoretical frameworks and controlled experiments, only a limited number of studies have been able to pinpoint a statistically significant relationship between soil moisture and crop yields at the national level. There is also no robust predictive framework regarding the implications of daily interaction of soil moisture and heat in the determination of national crop yield (Bradford et al. 2017; Ortiz-Bobea et al. 2019). This article is a significant contribution to the climate impact literature as it approximates the monetary value of damages from compound hydroclimatic extremes for agriculture.

Contribution: I establish a framework for the estimation of the conditional marginal value of green water based on daily hydroclimatic information. This framework is an extension of Schlenker and Roberts (2009) model enabled by the detailed soil moisture information available from the Water Balance Model (Grogan 2016). An important contribution is the introduction of a daily cumulative yield production function considering the interaction of heat and soil moisture. I apply this approach to investigate the marginal impact of each combination of heat-moisture interval on crop yields. This study also demonstrates the advantages of using soil moisture metrics over current proxy variables in capturing climate-driven variations. The hypothesis is that “soil moisture index and its daily interaction with heat perform better in predicting corn yields compared to the commonly used proxy variables such as precipitation”. Specifically, I investigate: 1) the marginal impacts of seasonal-mean soil moisture content on crop yields; 2) the marginal impact of daily soil moisture extremes on crop yields, and 3) the conditional marginal impact of soil moisture on crop yields.

The next section provides an overview of the empirical challenges. Then I introduce four models to explain the importance of soil moisture for crop yields. I also describe different data sets used in the estimation. Section 2.5 provides estimation results and robustness checks. Section 2.6 contains a discussion on the implications of the findings for climate impact research. And section 2.7 concludes.

2.2 Literature review and emprical challenges

There are four major challenges with which any study seeking to estimate the marginal contribution of water in crop production must come to grips: 1) spatial aggregation, 2) temporal aggregation, 3) daily interactions of soil moisture and heat, and 4) data availability.

2.2.1 Spatial aggregation

The value of water in production depends on local hydroclimatic conditions. An important aspect of yield estimation is the spatial scope of the study. Although estimates based on geographically limited observations can be informative for those locations, a fine-scale analysis of yield response to climate is necessary for market-level predictions (Kucharik 2003; Kudamatsu 2018; Martin 2018). There is considerable heterogeneity in the geographical distribution of water resources and the location of producers. There is also significant spatial heterogeneity in soil properties, which modulate temperature and precipitation signals through their capacity to hold water as soil moisture. Due to these differences, spatially heterogeneous changes in precipitation and temperature will lead to an uneven distribution of crop responses. Considering relatively connected markets, the overall national impacts depend on fine-scale geographical responses.

2.2.2 Temporal aggregation

Another empirical challenge in estimating the yield is that yields data are reported annually and at the county level (only a limited number of countries have sub regional data on yields), while weather data have a higher temporal resolution. While many empirical studies employ annual or monthly weather indicators like average temperature, recent studies tend to utilize daily climate information by introducing growing degree days and harmful degree days through the growing season (Mueller et al. 2012; D'Agostino and Schlenker 2016). One of the most influential studies in this field is Schlenker and Roberts (2009) which uses the growing degree days approach along with an index of cumulative rainfall to proxy for water availability. However, cumulative precipitation, monthly mean, or seasonal average metrics do not capture extreme events during the season (e.g. early-season floods or late-season droughts). This will be even more important in the future, as the climate scientists are predicting more extreme drought and precipitation events. I believe it is important to introduce different metrics of daily water availability to measure the value of water at the time which is most needed.

2.2.3 Water availability index

While soil moisture plays a crucial role in climate impacts on agricultural yields, there have been only a few successful studies in measuring this relationship. Many researchers have acknowledged the need for soil moisture data to predict the response of crop yields to variations in water availability. Some studies also highlight the need for irrigation to compensate for soil moisture deficits (McDonald and Girvetz 2013; Meng et al. 2016; Williams et al. 2016; Li et al. 2017). One major barrier has been limited availability of daily fine-scale soil moisture data and inconsistency of soil moisture data with heat information. As a result, it has become a standard practice for current studies either to focus on a limited geographical area (Rizzo et al. 2018; Wang et al. 2017) or to employ a proxy variable like precipitation, evapotranspiration, or vapor pressure deficit estimates (Roberts, Schlenker, and Eyer 2013; Comas et al. 2019). In this study, I will show that a validated and detailed hydrological model like WBM can provide valuable information on soil moisture.

2.2.4 Interaction of soil moisture and heat

To accurately measure the marginal productivity of soil moisture margin, we need to draw on biogeochemistry, hydrology, and plant physiology perspectives on crop yields and soil moisture. We view soil moisture as an integrative variable that contains information on precipitation, temperature, and soil types, as well as the behavior of the crops themselves. Crop yields at the end of the growing season depend on daily growth during the season (Hatfield and Prueger 2015). Plants require water for germination, transpiration, transporting nutrients, and for buffering against temperature fluctuations (Teixeira et al. 2014; Maharjan et al. 2016). Therefore, timely irrigation can play an important role in boosting yields (Siebert et al. 2017; Tack, Barkley, and Hendricks 2017; Troy, Kipgen, and Pal 2015; Carter et al. 2016). While the amount of daily water requirement depends on the biophysical properties of soil and crop, it also changes with temperature, solar radiation, humidity and wind speed. In this framework, climate change can affect soil moisture supply and demand by affecting the abundance and frequency of precipitation or increasing the water required to compensate evapotranspiration and evaporation. If the temperature is high and there is not enough soil moisture for a long period – i.e., there is a drought -, this may cause severe damage to agricultural crops (Denmead and Shaw 1960). I believe considering the daily interaction of soil moisture and heat can capture these impacts.

2.3 Methods

There are various methods to measure the value of water for agriculture. In this study, I rely on the marginal product and marginal value product of soil moisture content. I estimate the marginal impact of soil moisture on yields assuming year on year variation in temperature and precipitation. By considering yield as an index of production, I implicitly assume no change in the land input. I also assume a trend for yield which can represent the total factor productivity. Also, I do not model the changes in other inputs. While this must be tested in future studies, a look at the trend of fertilizer use in the US reveals small changes in fertilizer application per land.

In the following paragraphs, I introduce the empirical models used for yield estimation across the US. For each model, I will describe the variables and data sources related to them. After describing all the models, data sources are introduced in more detail. The models are estimated using a panel fixed-effect approach clustering US counties by state.

We propose four models to estimate the impacts of *water* on yields of corn in the US. I construct the models based on the assumption that plants generate biomass each day using the available resources like heat, water, and soil nutrients. The first model replicates Schlenker and Roberts (2009) to make a base for comparison; this model uses cumulative rainfall as an index of water availability. In the second model, I introduce a new index of simulated soil moisture content over the growing period that is a more precise measure of water availability. In the third model, indicators of extreme soil moisture conditions are introduced; these metrics are constructed based on our daily soil moisture data set. Finally, the fourth model considers the daily interaction of heat and soil moisture to estimate the impact of each combination of soil moisture and heat on plant growth.

2.3.1 Model (1) mean precipitation

Model (1) is the same as the piecewise linear model in Schlenker and Roberts (2009) and assumes that the effects of heat are cumulative over the growing season. In other words, the end-of-season yield is the integral of daily heat impacts over the growing season. This relationship can be demonstrated via the following equation:

$$y_{it} = \int_{\underline{h}}^{\overline{h}} g(h)\varphi_{it}(h)dh + z_{it}\boldsymbol{\delta} + c_i + \epsilon_{it}$$

where $\varphi_{it}(h)$ is the time distribution of heat (h) over the growing season in county i and year t, while the heat ranges between the lower bound $\underline{h}$ and the upper bound $\overline{h}$; precipitation and other control factors are denoted as z_{it}, and c_i is a time-invariant county fixed effect. I assume a piece-wise linear form for $g(h)$. Considering the exposure to each temperature interval, the integral can be approximated with the following:

$$y_{it} = \sum_j \gamma_j[\emptyset_{it}(h+1) - \emptyset_{it}(h)] + z_{it}\boldsymbol{\delta} + c_i + \epsilon_{it}$$

where j indexes the pre-determined temperature intervals and $\emptyset_{it}$ is the heat cumulative distribution function for county i at year t. Precipitation is defined in millimeters as accumulative rainfall during the growing season (Apr-Sep) calculated based on PRISM daily information and aggregated to each county according to cropland area weights. The data on yield are obtained from USDA-NASS at the county level for 1981-2015. Following D'Agostino and Schlenker (2015), the daily distribution of temperatures is approximated assuming a cosine function between the daily minimum and maximum temperature. Let $\bar{t} = \operatorname{acos}\left(\frac{2b - T_{max} - T_{min}}{T_{max} - T_{min}}\right)$, then degree days at each day is defined using

$$DD(b) = \begin{cases} \dfrac{(T_{max} + T_{min})}{2} - b & if\ b \le T_{min} \\ \dfrac{\bar{t}}{\pi}\left[\dfrac{(T_{max} + T_{min})}{2} - b\right] + \dfrac{(T_{max} - T_{min})}{2\pi} sin(\bar{t}) & if\ T_{min} < b \le T_{max} \\ 0 & if\ T_{max} < b \end{cases}$$

where b is the base for calculating degree days and can take the base values as well as critical values. I consider a piecewise-linear function to aggregate the degree days. The major assumption is that plant growth is approximately linear between two bounds. For example, regarding corn growth, degree days between 10C to 29C can be considered linearly beneficial and degree days above 29C are considered linearly harmful. Degree days between two bounds is simply degree days above the smaller bound minus degree days above the larger bound. Degree days are initially calculated for each day at each 2.5 x 2.5 arc min grid cell during the growing season. Then they are aggregated for the whole growing season from the first day of April through the last day of September. Finally, they are aggregated to the county level using cropland area weights.

2.3.2 Model (2) seasonal mean soil moisture

In model (2), I introduce the soil moisture index. While cumulative precipitation is significant in previous studies, it may not be a good representation of available water for plants due to runoff. It is only relevant if stored in the soil for plant use during the season. I construct a database of soil moisture utilizing WBM simulated outputs based on PRISM data. I include the soil moisture index in z'_{it} in the following model to see how significant it will be:

$$y_{it} = \sum_j \gamma_j [\emptyset_{it}(h+1) - \emptyset_{it}(h)] + z'_{it}\boldsymbol{\delta} + c_i + \epsilon_{it}$$

where soil moisture is calculated as the mean of soil moisture content (in mm in 1000 mm topsoil) during the growing season (Apr-Sep) for each 2.5 x 2.5 arc min grid cell, and then averaged at county level using cropland area weights for the 1981-2015 period.

Full documentation for WBM can be found in Wisser et al. (2010) with updates in Grogan (2016). Here, WBM's soil moisture module is described. In WBM, crop-specific soil moisture balance within each grid cell is calculated with an accounting system that tracks a grid cell's water inputs and outputs, and is limited by the soil moisture pool's water holding capacity.

$$\frac{\delta W_s}{\delta t} = \begin{cases} g(Ws)(I - PET)\ if\ I < PET \\ I - PET\ if\ PET\ \leq I\ and\ (I - PET) < (W_{cap} - W_s) \\ W_{cap} - W_s\ if\ PET\ \leq I\ and\ \left(W_{cap} - W_s\right) \leq (I - PET) \end{cases}$$

where W_s is soil moisture, t is time, I is the sum of all water inputs to the soil moisture pool, PET is potential evapotranspiration, and W_{cap} is available water capacity. Water inputs to the soil come in the form of precipitation as rain and as snowmelt. Water intercepted by the canopy reduces how much precipitation reaches the soil. Here, I use the Hamon method for estimating PET (Hamon, 1963; Federer et al. 1996), and $g(W_s)$ is 1 for all crops. Crop-specific potential evapotranspiration values, PETc, are calculated following the FAO-recommended crop-modeling methodology outlined in Allen et al (1998):

$$PET_c = k_c \cdot PET$$

where k_c [-] is a crop-specific, time-varying scalar. Crop scalar values are from Siebert and Döll (2010), and crop maps that identify the area of each rainfed crop type within a grid cell are from the Crop Data Layer (CDL, USDA NASS, 2017). When soil moisture is insufficient for crops to extract water equal to PET_c, actual crop evapotranspiration is limited to available soil water volumes. Available water capacity, W_{cap}, is a function of vegetation-specific rooting depth, a crop-specific depletion factor, soil field capacity, and soil wilting point:

$$W_{cap} = D_c R_c (F - W_p)$$

where D_c is the depletion factor for crop c, R_c is the rooting depth of crop c, F is the soil field capacity, and W_p is the soil wilting point. Here I use the Harmonized World Soil Database (Fischer et al. 2008) as model input for all soil properties. Corn rooting depth is set to 1 meter and the corn depletion factor is 0.55; soybean rooting depth is 0.6 meters and the depletion factor is 0.5, following Siebert and Döll (2010). Once the soil moisture content reaches field capacity, no further water is added to the soil moisture pool; excess inputs move to the groundwater pool via percolation and the river system via runoff.

2.3.3 Model (3) extreme conditions of soil moisture

We are also interested in measuring the significance of various soil moisture indicators in predicting yield considering (i) seasonal mean of below normal soil moisture, (ii) seasonal mean of above normal soil moisture, and (iii) the number of soil moisture extreme incidences in the growing season. Normal soil moisture for each location is defined as the average of WBM output on daily root zone soil moisture content during Apr-Sep from 1981 to 2015.

In models (1) and (2), I considered cumulative precipitation and mean soil moisture. However, the mean can be misleading as the plants respond more to the day to day variability. Furthermore, mean soil moisture index may not represent hydrological extremes (Schaffer, Nordbotten, and Rodriguez-Iturbe 2015; D'Odorico and Porporato 2004; Werner and Cannon 2016; Lobell and Burke 2010). The soil moisture level fluctuates during the growing season and is not always at the mean level. While the average conditions are important, exposure to extreme soil moisture stress can cause permanent unrecoverable damage to the plant (Denmead and Shaw

1960). Note that too much water can cause flooding, waterlogging, or may wash out soil nutrients and fertilizers (Schmidt et al. 2011; Urban et al. 2015; Kaur, Nelson, and Motavalli 2018). Therefore, it is necessary to introduce indicators of extreme soil moisture stress. Figure 3-1 visualizes four soil moisture conditions that are unfavorable for crop yield. Both too much water [a] and intense moisture stress [b] can cause severe damage to crop yields. Similarly, a long period of mild moisture stress [c] or a short period of severe moisture stress [d] can also cause significant yield loss.

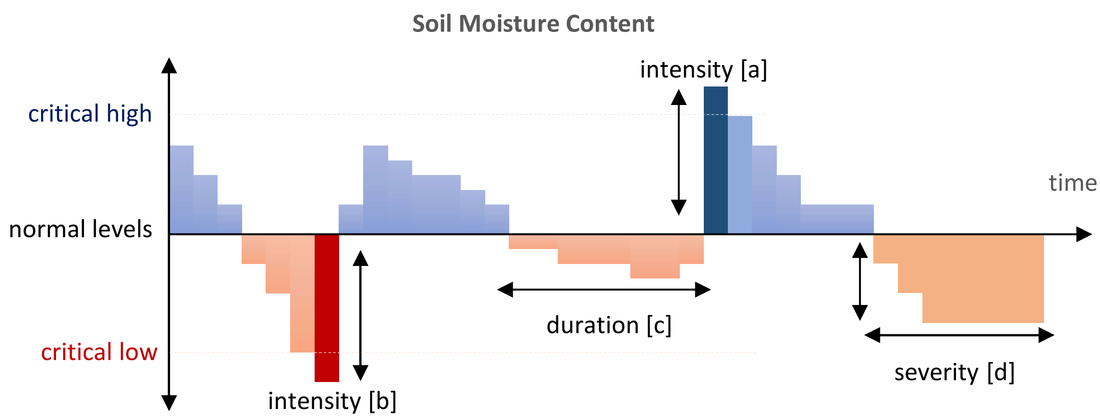


Figure 2-1. Conceptual model shows the dynamics of soil moisture.
It shows the soil moisture extremes which can be harmful to crops: excess wetness [a], moisture stress intensity[b], duration of moisture stress [c], and severity of soil moisture stress [d]. The figure is replicated based on (Mishra and Singh 2010)

We include various soil moisture extreme indicators in w_{it} in the following model:

$$y_{it} = \sum_j \gamma_j[\emptyset_{it}(h+1) - \emptyset_{it}(h)] + z'_{it}\boldsymbol{\delta} + w_{it}\boldsymbol{\theta} + c_i + \epsilon_{it}$$

where w_{it} includes: number of days with low soil moisture; number of days with high soil moisture; mean of soil moisture for days with low moisture; mean of soil moisture for days with high moisture. High soil moisture is defined as soil moisture above the critical upper threshold; while low soil moisture is defined as soil moisture below the critical lower threshold. For the base model, soil moisture level is considered critical if it is 25 mm below/above normal condition. The critical level for soil moisture is selected after carefully examining the impacts of various intervals of soil moisture deviation from normal. The threshold is obtained by testing the impacts of 5-mm intervals of soil moisture deviation from normal.

2.3.4 Model (4) daily interaction of soil moisture and heat

Finally, in Model 4 I focus on the interaction of available soil moisture and heat as major indicators of plant growth. The growth effects of heat and soil moisture are not separated in the real world. The beneficial heat is less beneficial without enough soil moisture. On the other hand, soil moisture is not beneficial without enough heat. In addition, harmful heat can be less harmful when there is enough soil moisture (Hauser, Thiery, and Seneviratne 2018).

So, I consider the daily interaction of heat and soil moisture in the model as:

$$y_{it} = \int_{\underline{m}}^{\overline{m}} \int_{\underline{h}}^{\overline{h}} g'(h,m)\varphi(h)dhdm + z"_{it}\boldsymbol{\delta} + c_i + \epsilon_{it}$$

where the crop growth is different for each combination of soil moisture level, *m,* and heat, *h*. This integral can be approximated using

$$y_{it} = \sum_{m}\sum_{j} \gamma'_{jm}[\emptyset_{it}(h+1) - \emptyset_{it}(h)]_m + z"_{it}\boldsymbol{\delta} + c_i + \epsilon_{it}$$

where m takes the desired soil moisture interval and j takes the assumed temperature intervals. Here, $\emptyset_{it}$ is the heat cumulative distribution function for county i at year t at each soil moisture interval m. I will consider different approaches to this interaction as described in the results.

2.4 Data

This study estimates the impacts of soil moisture and heat on corn yields. We calculate county-level seasonal degree days based on daily weather information. The weather information on daily precipitation, maximum temperature, and minimum temperature are obtained from PRISM at 2.5 x 2.5 arc min grid cells over the continental US for 1981-2015. Table 1-2 summarizes the aggregated variables calculated based on PRISM and used in the regression.

Daily soil moisture content and soil moisture fraction are obtained from Water Balance Model (Wisser et al. 2010; Grogan 2016) daily simulations based on PRISM data at 6 x 6 arc min grid cells for the 1981-2015 period over the continental US. One limitation for historical analysis is the inconsistency of WBM and PRISM grid cells as they have different extent, different resolution, and non-matching centroids. I interpolate WBM to PRISM using several methods, including nearest neighbor and bilinear methods. The main regression results are reported for bilinear interpolation. However, the regression results with nearest neighbor interpolation method are very similar. The interpolation provides soil moisture information at 2.5 x 2.5 arc-minute grid cells. I first calculate soil moisture normal defined as historical average soil moisture over the growing season for each grid cell. Then I sum up degree days for each temperature interval for each soil moisture deviation interval. These fine-scale metrics are checked with a satellite scans of cropland area to exclude grid cells with no cropland. Finally, I aggregate all the grids in each county using cropland area weight.

Table 2-1. Descriptive statistics for all counties 1981-2015 (Apr-Sep)

Variable	Mean	Std.Dev	Min	Max
Corn Yield (Bushels / Acre)	109.8	37.8	4.5	246.0
Degree Days				
dday10_29C	1864.0	438.4	692.7	3082.5
dday29C	62.3	60.8	0.0	723.0
Mean Soil Moisture (mm)	46.7	38.9	0.1	261.3
Precipitation (mm /day)	3.1	1.0	0.0	8.5
Soil Moisture Fraction	0.71	0.18	0.01	1.00
Soil Moisture Deviation* (seasonal normal)				
Mean daily deviation	-0.04	17.13	-130.81	113.05
Mean negative daily deviation	-9.24	12.60	-130.81	0.00
Mean positive daily deviation	10.31	11.97	0.00	113.05
Number of Observations	73014			

Notes: Table reports descriptive statistics for major variables in this study. The mean and standard error are calculated over US counties for the 1981-2015 period. All weather data are calculated for each 2.5 x 2.5 arcmin grids, averaged over the time interval, and then averaged to counties using cropland area weights. (*) Soil moisture seasonal normal is defined as the average of 1981-2015 daily soil moisture level from the first day of April to the last day of September. (**) Soil moisture monthly normal is defined as the average of 1981-2015 daily soil moisture level from the first day of each month to the last day of the month.

Figure 2.2 illustrates the normal soil moisture, temporal average of daily soil moisture data over April-September over 1981-2015, for the Continental US. This map shows the rich heterogeneity of the data across regions. However, there are similarities in the average soil moisture too. For the Corn Belt, the soil moisture level is relatively high compared to other regions. To standardize this metric, I will consider soil moisture deviation from normal. I will also define the soil moisture thresholds relative to normal.

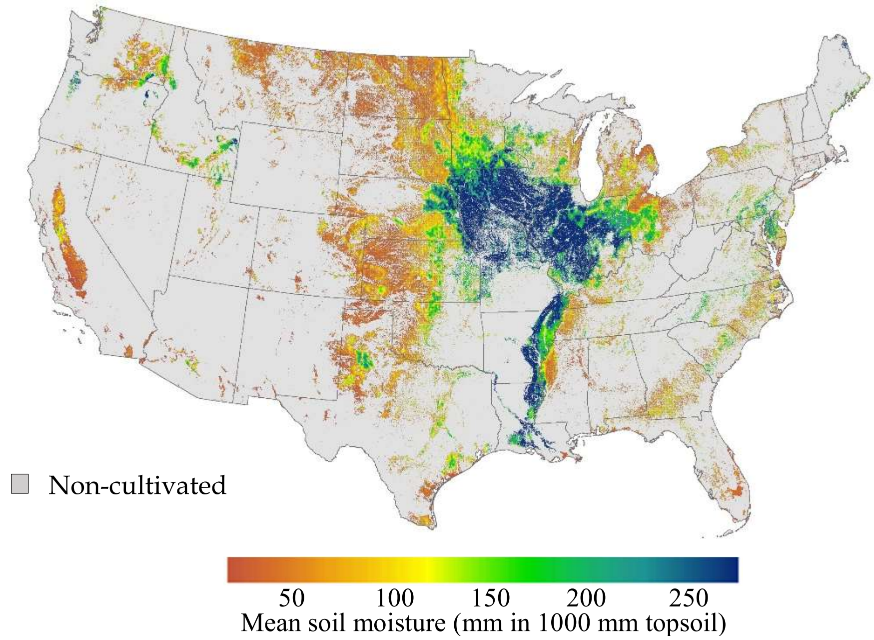


Figure 2-2. Growing season mean soil moisture content (in mm in 1000 mm topsoil)
As calculated based on daily root-zone soil moisture level from Apr-Sep for 1981-2015 at 2.5 x 2.5 arc min grids excluding non-cultivated area. Soil moisture level is obtained from Water Balance Model (WBM) and non-cultivated area information is from USDA National Cultivated Layer. This map illustrates the heterogeneity of simulated soil moisture over the Continental US and even within states.

Note that variation in seasonal mean soil moisture may not follow the variation in seasonal mean precipitation. Figure 2.3 illustrates the year on year variation of them aggregated over the corn areas in the US. In general, variation in soil moisture average is higher than in precipitations.

Figure 2.4 shows the bivariate density of daily temperature and soil moisture deviation from normal for all the grid cells in the Corn Belt for 1981-2015 by month of the year, capturing the daily variation of the heat and soil moisture combinations. Even for the Corn Belt, the data shows significant month to month variation with the second half of the season facing hotter and dryer days. Also, July has the highest variation in soil moisture deviation.

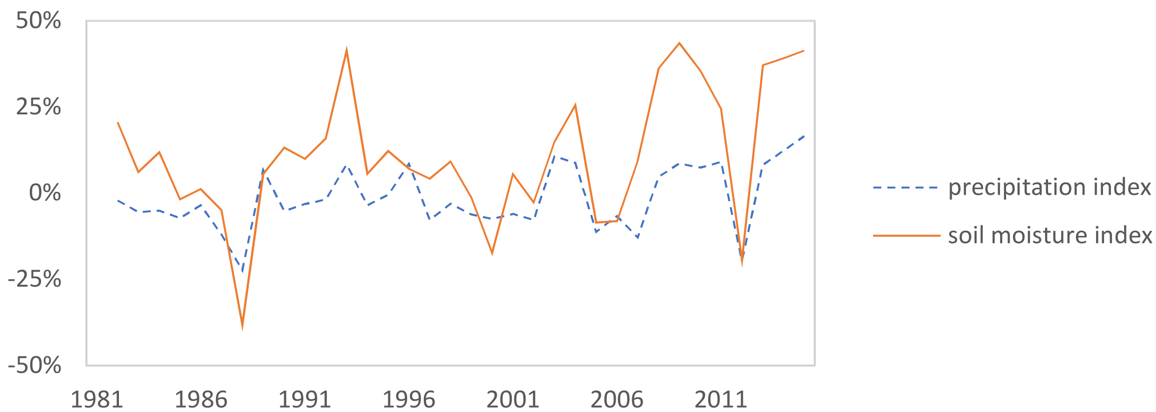


Figure 2-3. Variations of average precipitation versus average soil moisture
Over corn areas in the US for Apr-Sep.

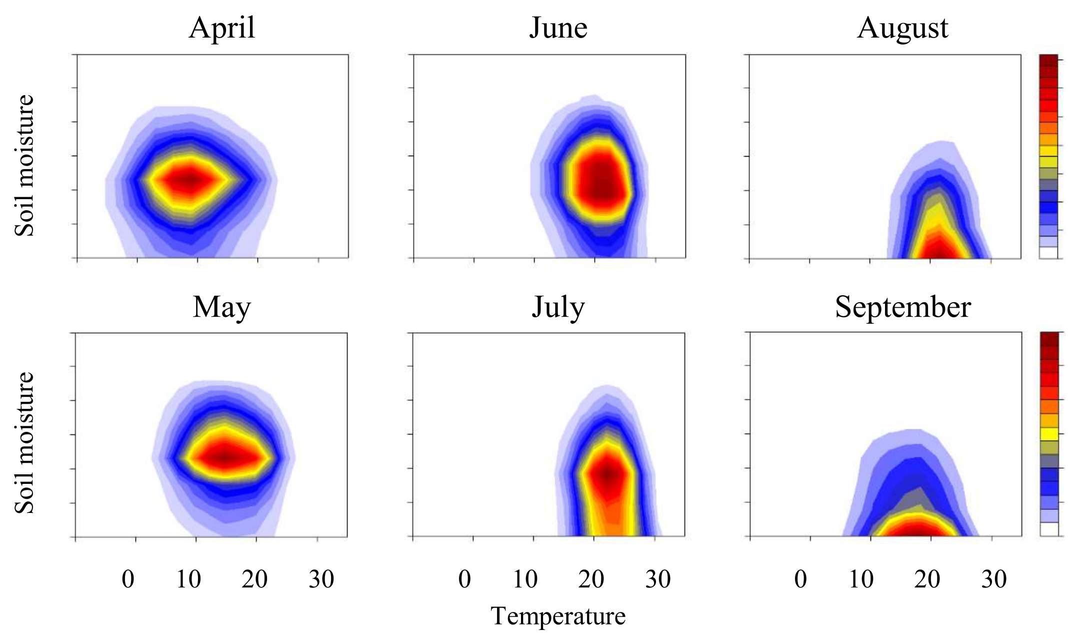


Figure 2-4. Bivariate density of heat and soil moisture by month for 1981-2015
For all the grid cells in the US Corn Belt.

2.5 Results

This section presents the empirical estimation of models 1-4 for predicting the impacts of soil moisture and heat on yields of corn. Regression coefficients, standard errors, and R-squared values for models 1-3 are reported in Table 1-3 for corn. The first model (1) shows a strong relationship between corn yields and heat and precipitation. The marginal impact of a degree-day within 10-29C is significantly positive while that from an additional degree day above 29C is strongly negative. The second model, with mean soil moisture index, slightly improves the fit, but sharply decreases the significance of precipitation (2a), while the marginal relationship with soil moisture is significant. The second model, excluding precipitation (2b), shows that the marginal relationship with soil moisture is increasing up to ~92 mm and decreasing for higher values. The third model, with metrics of soil moisture extremes (3), further improves the fit with a negative marginal relationship associated with the number of days with low/high soil moisture. Note that the third model decreases the marginal relationship with degree days above 29. However, this effect is not statistically different from that produced by the first model.

Table 2-3 provides further estimations. To see whether it makes a difference to use extreme soil moisture metrics, I estimate the model (3) while considering the cumulative positive soil moisture deviations and cumulative negative soil moisture deviations. Looking at figure 1 for illustration, I calculate the area of all the blue bars to calculate the amount of soil moisture above normal levels. Then, I calculate the area of all the red bars to find the negative soil moisture deviation. This is a cumulative measure showing the volume of soil moisture required to stay at normal level.

We find that soil moisture deviation metrics are significant. Column 1 shows the estimated coefficients when considering soil moisture deviation from normal instead of average seasonal soil moisture. It shows that, the marginal impact of negative soil moisture deviation is significant and positive. This indicates the positive contribution of additional soil moisture when the soil moisture levels are below normal. On the other hand, the marginal impact of a positive soil moisture deviation is negative. In other words, this suggests that plants will benefit from reduction in soil moisture when the soil moisture levels are above normal. (This is an indicator of the value of drainage for agriculture). Column 2 displays the results when adding the squared term for soil moisture deviations. This helps to capture a potential curvature for soil moisture deviation metrics. The coefficient on the square terms is significant only for negative deviations. Column 3 shows the estimated coefficients with interaction of soil moisture deviation and heat. I find that only the interaction of DD10-29 and negative soil moisture deviation is significant. Which suggests the marginal contribution of soil moisture in yields increases with increase in beneficial heat.

Table 2-2. Estimating corn yield in the US with mean soil moisture and moisture stress

	(1) Log CornYield	(2a) Log CornYield	(2b) Log CornYield	(3a) Log CornYield
Degree Days 10-29°C Apr-Sep	0.00034***	0.00036***	0.00034***	0.00033***
	(0.00009)	(0.00008)	(0.00008)	(0.00007)
Degree Days above 29°C Apr-Sep	-0.00531***	-0.00521***	-0.00512***	-0.00478***
	(0.00067)	(0.00068)	(0.00069)	(0.00064)
Precipitation Apr-Sep	0.00066**	0.00027		
	(0.00025)	(0.00026)		
Precipitation Apr-Sep Square	-0.00000**	-0.00000		
	(0.00000)	(0.00000)		
Seasonal Mean Soil Moisture Content		0.00442***	0.00368***	0.00303***
		(0.00092)	(0.00067)	(0.00108)
Seasonal Mean Soil Moisture Content Square		-0.00002***	-0.00002***	-0.00002***
		(0.00000)	(0.00000)	(0.00000)
Days of High Soil Moisture Apr-Sep [b]				-0.00251***
				(0.00035)
Days of Low Soil Moisture Apr-Sep [a]				-0.00332***
				(0.00048)
_cons	3.71496***	3.65171***	3.76221***	4.00694***
	(0.17190)	(0.16065)	(0.10832)	(0.12526)
Obs.	69753	69753	69753	69753
R-squared	0.46885	0.47536	0.47185	0.49866

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table lists regression coefficients and shows standard errors in brackets. Temperature is in degree Celsius, precipitation in mm, soil moisture in mm in 1000 mm topsoil. The soil moisture is obtained from WBM at 6 arcmin output while precipitation and temperature are taken from PRISM at 2.5 arcmin. They are aggregated from grid cells to counties based on crop area weight. Yield data is acquired from USDA. (a). Defined as days with soil moisture level at least 25 mm below normal (historical mean) (b). Defined as days with soil moisture level at least 25 mm above normal (historical mean)

Table 2-3. Estimating corn yield in the US with soil moisture deviation metrics

	(3b) Log CornYield	(3c) Log CornYield	(3d) Log CornYield
Degree Days 10-29°C Apr-Sep	0.000306***	0.000315***	0.000375***
	(0.000069)	(0.000067)	(0.000084)
Degree Days above 29°C Apr-Sep	-0.005086***	-0.004841***	-0.004153***
	(0.000608)	(0.000607)	(0.000659)
Negative Soil Moisture Deviation	0.000044***	0.000094***	0.000040***
	(0.000007)	(0.000022)	(0.000013)
Positive Soil Moisture Deviation	-0.000040***	-0.000048***	-0.000029**
	(0.000003)	(0.000012)	(0.000014)
Negative Soil Moisture Deviation Sqr		0.000000***	0.000001***
		(0.000000)	(0.000000)
Positive Soil Moisture Deviation Sqr		-0.000000	-0.000000
		(0.000000)	(0.000000)
DD29 x Negative Soil Moisture Deviation			0.000011
			(0.000018)
DD29 x Positive Soil Moisture Deviation			-0.000013
			(0.000021)
DD10-29 x Negative Soil Moisture Deviation			0.000005**
			(0.000002)
DD10-29 x Positive Soil Moisture Deviation			-0.000002
			(0.000002)
_cons	4.158267***	4.198319***	4.045938***
	(0.108836)	(0.117717)	(0.131086)
Obs.	70243	70243	70243
R-squared	0.491583	0.498344	0.505434

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table lists regression coefficients and shows standard errors in brackets. Temperature is in degree Celsius, precipitation in mm, soil moisture in mm in 1000 mm topsoil. The soil moisture is obtained from WBM at 6 arcmin output while precipitation and temperature are taken from PRISM at 2.5 arcmin. They are aggregated from grid cells to counties based on crop area weight. Yield data is acquired from USDA.

2.5.1 Soil moisture deviation from normal

Does it make a difference to consider seasonal mean soil moisture or the deviation from normal index? Figure 2-5 illustrates the difference by comparing the impacts of soil moisture on log corn yield using the estimated coefficients. The black curve shows the relationship between soil moisture and log corn yield assuming model 2. This indicates a more general relationship which applies to all the locations. The dotted lines show the relationship assuming model 3 considering deviation from normal. This figure shows that both approaches will give a similar result near the normal conditions. However, the marginal impacts are different when the deviation from normal is large.

2.5.2 Conditional impacts of soil moisture and heat

Model 4 introduces heat-soil moisture interactions to test whether a) soil moisture availability can change the marginal impact of heat, b) heat can change the marginal impact of soil moisture, and c) water availability can change the critical temperature threshold. First, I consider the interaction of the seasonal heat index and seasonal soil moisture index. Then I assume the plant growth depends on daily interaction of heat and soil moisture and is additive over the growing season. For the daily interaction, I use T for temperature, DD for degree days, and SMD for soil moisture deviation.

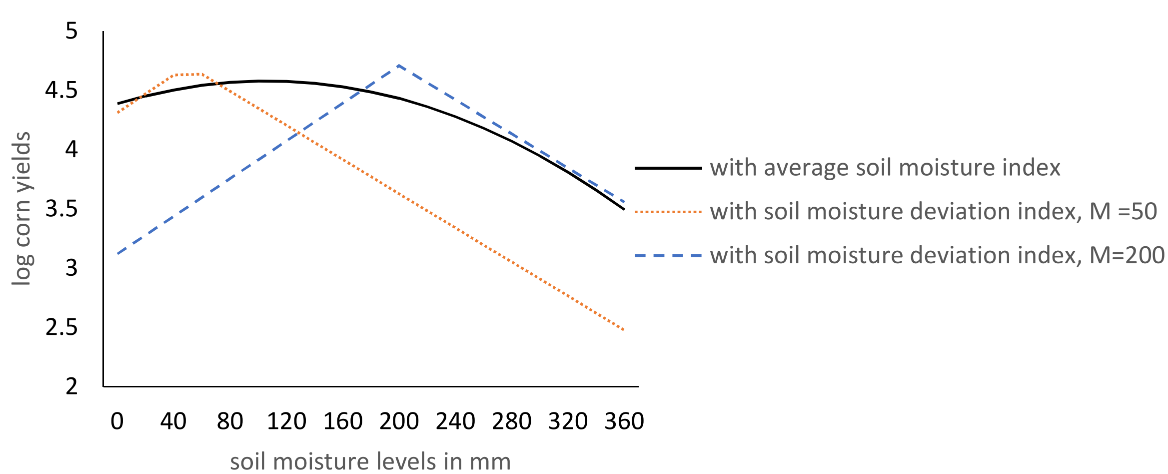


Figure 2-5. Impact of soil moisture on log corn yields.

We consider DD by SMD bins and SMD by T bins. For example, SMD25b-00b_T5-20C shows the sum of soil moisture deviations for days when the deviation is between -50mm and -25mm and average temperature is between 5C to 20C. On the other hand, DD10-29_SMD00a-25a shows the sum of degree days from 10 to 29 for days when the soil moisture deviation if from 0 mm to +25mm. The marginal impact of soil moisture can be measured in two different approaches. In Method (1), I directly take the coefficients on soil moisture bins as shown in Figure 9. In method (2), I take the difference from the coefficients on heat. For example, the difference in coefficient on DD10-29_SMD25b-00b and DD10-29_SMD00a-25a is only change in soil moisture. The first approach gives us the constant marginal impact within a bin while the second approach gives us the marginal impact across the bins. Figure 2-6 and Figure 2-7 show the marginal impact of heat using method 1 and method 2 respectively. For figure 6, I consider DD29 and DD10-29 in interaction of unequal SMD bins. This shows that the marginal contribution of heat on corn yields depends on soil moisture conditions.

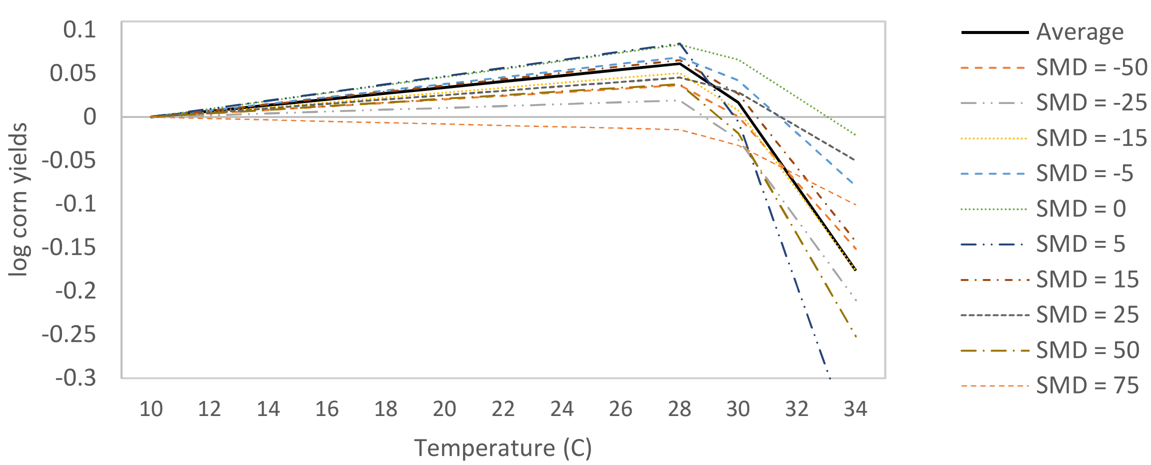


Figure 2-6. Conditional marginal impacts of heat. Method 1, within degree days bins.

In figure 2-7, the marginal impact of heat is determined using method 2. These are the coefficients on three SMD indicators by 5C temperature bins. In general, the results are similar to method 1. However, here the contribution of heat on corn yield is negative when the soil moisture is less than 25mm below normal levels.

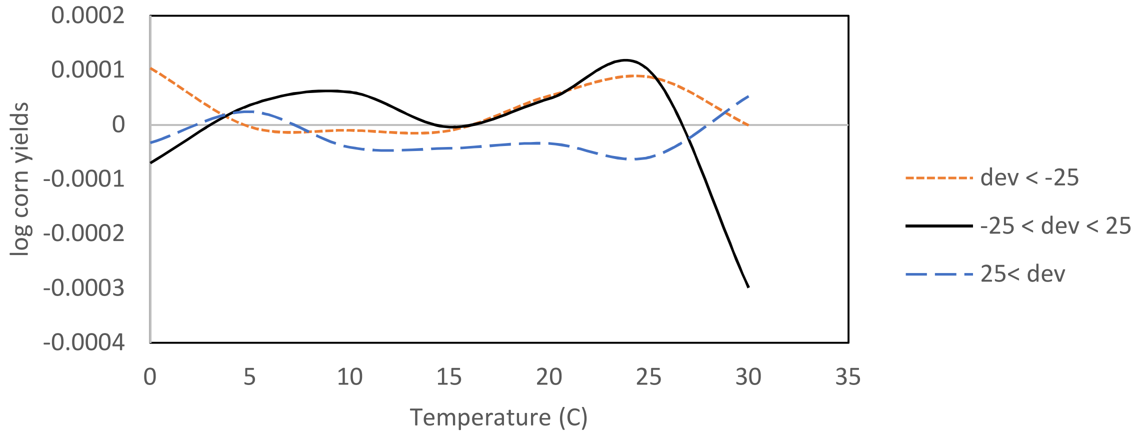


Figure 2-7. Conditional marginal impacts of heat. Method 2, across temperature bins.

The conditional marginal impacts of soil moisture are calculated using sum of SMD and average temperature bins. These coefficients are shown in Figure 2-8. The marginal impact below -25mm are generally positive, while the marginal impacts above 25mm are generally negative. The marginal impacts for T05-20 has the expected curvature, increasing for negative SMDs and declining for negative SMDs. However, the coefficients around normal soil moisture are not significant and do not follow the expected sign for T20-25 and T25. I suspect this is coming from the possible impact of heat on soil moisture thresholds and the possible impact of soil moisture on temperature thresholds. Note that T20-25 are days with average temperature between 20C and 25C, which may include several days with harmful temperatures.

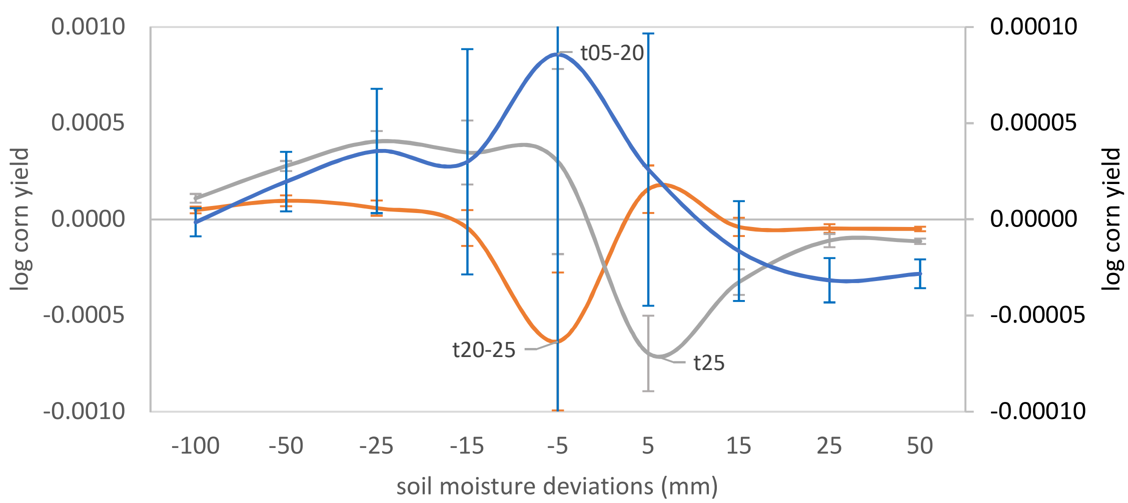


Figure 2-8. Conditional marginal impacts of soil moisture, within soil moisture bins.

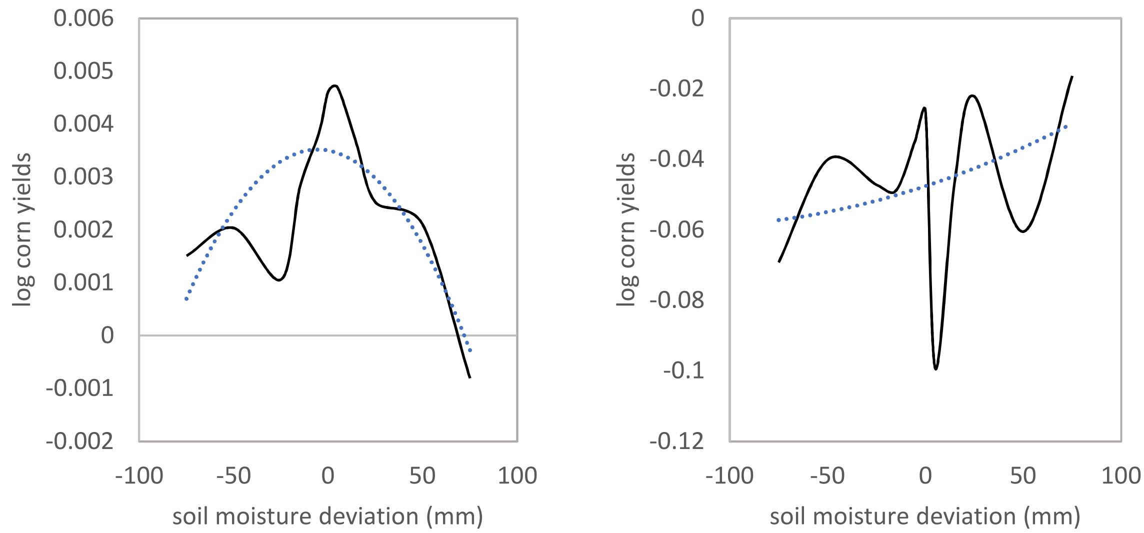


Figure 2-9. Conditional marginal impacts of soil moisture, across degree days bins.

Figure 2-9 shows the contribution of soil moisture on yields using method 2. In general, the coefficients for DD10-29 are significant and follow the expected sign. However, the coefficients for DD29 around normal soil moisture are not significant which may be a result of changes in critical temperature or soil moisture thresholds.

2.5.3 Implications: interaction of soil moisture deviations and temperature

The findings suggest that the marginal impact of soil moisture on crop yields depend on soil moisture deviations from normal as well as daily temperature. Considering the estimated coefficients for model 4, I construct the daily marginal product of soil moisture conditional on a given normal soil moisture and temperature. Figure 10 shows one example of this marginal productivity assuming normal moisture is 200mm and temperature is 25C. In the left panel, the marginal contribution is displayed. In the right panel, marginal value product is illustrated assuming price of corn is \$3.5 per Bu in a normal year and is \$7.0 per Bu in a dry year. Note that even at normal soil moisture levels, the value of water is positive. In other words, farmers would potentially benefit from enhancing soil moisture. However, irrigation is costly, so this is not undertaken when this marginal benefit is below the marginal cost of irrigation.

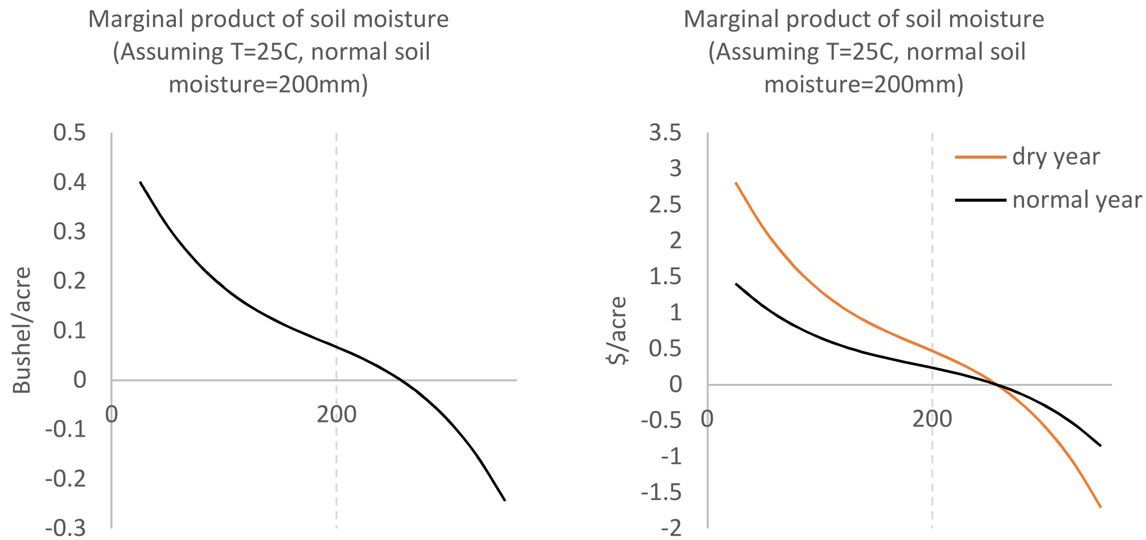


Figure 2-10. The marginal product and marginal value product of soil moisture

2.5.4 Soil moisture and the critical temperature thresholds

Here, I conduct an exercise to test the impact of soil moisture on the critical temperature threshold. However, finding the critical soil moisture and temperature thresholds is complex and challenging. One major challenge could be the temporal change in heat and drought resistance of varieties which can affect the thresholds in interaction.

Table 2-4 summarizes the results from model 4 considering 27C, 28C, 29C, and 30C as critical thresholds for heat, and 25 mm below/above normal as the critical threshold of soil moisture (soil moisture intervals are defined as mm deviation from normal conditions). I construct degree days at each soil moisture interval, calculated at the grid cell level and aggregated to counties. Model 4-T27 shows a strong positive marginal relationship with degree days within the 10C-27C interval and a strong negative relationship with degree days above 27C. However, the magnitude of this beneficial effect is larger when the soil moisture deviation from normal is less than 25mm. Model 4-T28 shows a positive relationship with degree days in 10-28C and a strong negative relationship with degree days above 28C. Note that this model decreases the significance of soil moisture and *beneficial* degree days on very dry days. Models 4-T29 and 4-T30 with critical thresholds of 29C and 30C respectively show a similar pattern with less significance of soil moisture and *beneficial* degree days on very dry days.

Table 2-4. Estimating corn yield in US with different temperature threshold

	(4-T27) Log CornYield	(4-T28) Log CornYield	(4-T29) Log CornYield	(4-T30) Log CornYield
	T = 27C	T = 28C	T = 29C	T = 30C
Soil Moisture Average Apr-Sep	0.00212**	0.00151	0.00088	0.00025
	(0.00100)	(0.00099)	(0.00098)	(0.00099)
Soil Moisture Average Apr-Sep Squared	-0.00001***	-0.00001***	-0.00001***	-0.00001***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Degree Days from 10C to T	0.00036***	0.00022*	0.00008	-0.00006
Soil Moisture Lower than 25 mm Below Normal	(0.00013)	(0.00012)	(0.00011)	(0.00011)
Degree Days from 10C to T	0.00062***	0.00051***	0.00040***	0.00029***
Soil Moisture within ±25 mm around Normal	(0.00007)	(0.00007)	(0.00007)	(0.00006)
Degree Days from 10C to T	0.00036***	0.00029***	0.00022***	0.00014**
Soil Moisture Higher than 25 mm Above Normal	(0.00006)	(0.00005)	(0.00005)	(0.00005)
Degree Days above T	-0.00396***	-0.00435***	-0.00481***	-0.00533***
Soil Moisture Lower than 25 mm Below Normal	(0.00073)	(0.00089)	(0.00111)	(0.00141)
Degree Days above T	-0.00339***	-0.00387***	-0.00445***	-0.00513***
Soil Moisture within ±25 mm Around Normal	(0.00028)	(0.00034)	(0.00043)	(0.00056)
Degree Days above T	-0.00257***	-0.00330***	-0.00439***	-0.00606***
Soil Moisture Higher than 25 mm Above Normal	(0.00069)	(0.00087)	(0.00114)	(0.00157)
_cons	3.58204***	3.72275***	3.87520***	4.03241***
	(0.13045)	(0.12630)	(0.12273)	(0.12003)
Obs.	69753	69753	69753	69753
R-squared	0.51164	0.50909	0.50448	0.49761

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table lists regression coefficients and shows standard errors in brackets. Temperature is in degree Celsius, soil moisture in mm in 1000 mm topsoil. The soil moisture is obtained from WBM at 6 arcmin output while degree days calculated based on temperatures from PRISM at 2.5 arcmin. They are aggregated from grid cells to counties based on crop area weight. Yield data is acquired from USDA.

Note that the coefficient of degree days above 27C at a normal level of soil moisture has the lowest standard error among all *harmful* degree day indicators. I have considered 5mm and 25mm intervals of soil moisture deviation from normal. This figure illustrates the marginal impact of degree days 10-29C with more intervals and assuming a smooth curve. This figure clearly shows that beneficial heat is more helpful when soil moisture is around its normal level. In other words, the benefits of degree days from 10C to 29C is higher when the soil moisture is around its normal level.

2.6 Discussion

The appendix of this article provides several sensitivity tests and robustness checks. To test the sensitivity of the model to the choice of variables, I consider alternative soil moisture indicators including the mean of soil moisture fraction, the mean of evapotranspiration for rainfed as well as within season standard deviation of them. The appendix also provides the estimation results with and without considering cumulative rainfall. I report the results for an alternative interpolation of WBM data to PRISM resolution (nearest neighbor versus bilinear). To test for time separability, I estimate the models for two-month intervals (Apr-May, Jun-Jul, Aug-Sep) as well as for the whole season.

What are the broader implications of this work? In the coming decades, global warming will dramatically increase the heat stress on global agriculture. It is also expected to give rise to changes in both the mean and the variability of soil moisture. I calculated the change in mean and standard deviation of monthly soil moisture based on CAM5 model simulations at 0.25 degree. The calculations show that mean soil moisture will decline by 10% to 30% in the Corn Belt. Reductions in soil moisture will increase the sensitivity of yields to extreme heat.

One challenge in projecting future climate impacts on agriculture is projecting the changes in compound extremes. Figure 4 illustrates the dynamics of change in daily distribution of heat and simulated soil moisture over the Corn Belt for 1981-2015 period. Through the growing season, the density moves towards lower soil moisture and warmer conditions. For future projections, we need reliable future projections of daily temperature (maximum and minimum). We also need consistent projections of daily soil moisture. While there are various climate products projecting future daily temperature, the choice of climate model requires extreme caution and should be compatible with special needs of each study. Although there are some projections of future levels of soil moisture, there is a great deal of inconsistency among the models regarding this variable. Further research is required to improve the ability of climate models in projecting bivariate distribution of heat-moisture (Sarhadi et al. 2018).

In places predicted to be drier or hotter in the future, adaptation through soil moisture management will be more attractive to farmers. This may motivate an increase in irrigation and supplemental irrigation. Also, farm management practices such as no-till farming, cover cropping, and soil conservation can increase soil moisture without (or in addition to) irrigation. Farmers may also consider water use efficiency, both by crops and by irrigation systems, as one way to address the need for increased irrigation. However, expansion of irrigation can increase the stress on global water resources.

One challenge is how to define low and high soil moisture levels, as soil moisture metrics (volumetric or fraction) may vary over the space. The appropriate method likely depends on soil type, crop cover, and other biophysical variables. Generally, soil moisture thresholds are defined in terms of the soil plant available water or soil wilting point, not a constant depth of water, as the critical threshold for water availability is different for different soils. In this paper, I decided to use deviation from normal levels as this can remove the location-specific variables from soil moisture. While various soil moisture deviation intervals are examined, I found that any deviation of more than 25 mm from soil moisture has a significant negative impact on the yield. However, determining appropriate bounds of soil moisture deviation is open to debate.

2.7 Conclusion

This study employs a new fine-scale dataset on daily soil moisture content across continental United State to estimate the impacts of green water on yields of corn for the 1981-2015 period. I employed the mean of soil moisture content as well as soil moisture extreme indicators. The major contribution of this study is introducing a daily cumulative yield production function considering the interaction of heat and soil moisture. Here I summarize the major implications of this work.

First, seasonal mean soil moisture performs well in statistically predicting corn yield. While the majority of current empirical studies employ precipitation as a proxy of water availability for crops, our estimation shows that the precipitation coefficient is not significant when I consider soil moisture in the model. This makes sense, as soil moisture content is a more precise indicator of water availability to crops. This study suggests that soil moisture content should be used in estimating crop yields instead of cumulative rainfall.

Second, the indicators of soil moisture extremes can explain a portion of the damages to corn yield which has hitherto been erroneously attributed to extreme heat. The studies using degree days above a critical threshold capture part of the damages from low soil moisture as there is a correlation between hot degree days and low soil moisture days. This is mainly due to feedbacks and dynamics of temperature and soil moisture as abundant soil moisture can reduce the temperature and extreme heat can reduce the soil moisture (Seneviratne et al. 2010; D'Odorico and Porporato 2004). These studies are unable to capture the different impacts of dry heat versus wet heat (Feng and Zhang 2015; Schoof, Ford, and Pryor 2017).

Third, there is remains a very strong and significant relationship between yields and extreme heat index even after soil moisture interactions. However, the magnitude of benefits and damage depends critically on soil moisture. This study suggests the use of a variable threshold for estimating yields that must be linked to the soil moisture content. However, further empirical and experimental research is required to find the correct threshold for each soil moisture level.

Fourth, the marginal impact of heat index on crop yields depends on the soil moisture level. This study suggests that the value of so-called beneficial heat is higher when soil moisture is within ±25 mm of normal levels; the damage from harmful heat is lower when soil moisture is within ±25 mm of normal levels; and wet heat is also harmful to corn (degree days above 29C when soil moisture is higher than 25 mm above normal levels). However, the appropriate bounds for soil moisture deviation from normal and the definition of normal soil moisture are still open to debate and provide fertile ground for future research.

Fifth, I also find that excess soil moisture has a negative impact on yield. This is in line with the current agronomic literature (Torbert et al. 1993; Urban et al. 2015). It also makes sense as a high soil moisture content can result in nutrient loss through excess water flows. In addition, at high humidity, the plants may have difficulty remaining cool at high temperatures. There is also a risk of waterlogging soils. With a few notable exceptions (e.g., rice), most crops do not grow well in inundated conditions as the plant roots need oxygen, so the direct impact of excess water stress is because of the anoxic conditions.

Finally, this study suggests the need for a careful revision of the concepts of *beneficial* degree days and *harmful* degree days. Current studied only focus on temperature thresholds to define these concepts. However, the results suggest that *beneficial* degree days, defined based on temperature, may not be beneficial without soil moisture. I recommend considering soil moisture as another important component of the definition.

A strength of our findings is that they can be used widely by the research community, as many hydrology and land surface models can simulate soil moisture. Also, this method can be tailored for use with different climate model outputs as well as different soil maps. It can also accommodate analysis of hypothetical situations (e.g., drought) which may vary by study location and research question at hand. Modeled soil moisture is difficult (some would say impossible) to validate because of the scarcity of soil moisture observations. Therefore, this study shows that WBM is capable of simulating soil moisture in a manner consistent with historical corn yield values; this makes WBM an ideal candidate for simulating future soil moisture under climate change conditions. Other models simulating soil moisture should be assessed for historical consistency with crop yields as well before they are used for studies of future climate change scenarios.

This study further serves to bridge the gap between statistical studies of climate impacts on crops and their biophysical counterparts and underscores that findings of statistical models based on county level data are in line with experimental agronomic studies. The results emphasize on the importance of soil moisture management as an effective means of adaptation to climate change. This adaptation can moderate production declines and commodity price hikes in the presence of climate extremes, thereby benefiting food security. However, expansion of irrigation in many areas may lead to further increases in unsustainable groundwater withdrawals. Such tradeoffs are inevitable as environmental stresses in agriculture increase in the future.

3. GLOBAL DRIVERS OF LOCAL WATER STRESSES

The economic study of water as a scarce resource motivated the search for water demand and supply. While we have been successful in determining the demand for water, finding the water supply schedule has been a challenge. Here, I introduce SIMPLE-G-W, a Simplified International Model of agricultural Prices, Land use, and the Environment- gridded water version, for evaluating water policies considering significant feedback from the human system. This is a global multi-scale partial equilibrium model with local demand and supply for water. Employing this model, I investigate the contribution of global changes in population, technology, and income in US water and land use by mid-century. Then I show why some of the suggested local environmental solutions may fail to provide national or global solutions. Primary projections indicate that half of US water and land sustainability stresses by 2050 are caused by increased demand from other countries. In addition, a comprehensive analysis suggests that local restrictions on water withdrawal can move agricultural production to other parts of the world and may create new environmental issues. This model can help us to design more effective and efficient sustainability policies.

3.1 Introduction

Economics is about the management of scarce resources. The second fundamental theorem of welfare economics states that a Pareto efficient equilibrium can be obtained using the market economy. However, the distribution of initial endowments is important. A classic example is the Paradox of Value or water-diamond paradox discussing why water is often priced at zero despite it is essential to human life. In the market economy, demand and supply of water determine the allocation of it. It may result in a low or high price of water.

A fundamental challenge in economic studies of water resources is determining water supply and demand. While the supply of water is local, the demand for water can be linked to global changes. There have been some successful studies in the estimation of demand for water. However, the supply schedule for water has been less addressed. Depending on the scale of studies, it has been a common practice to consider a perfectly inelastic or perfectly elastic water supply. While these assumptions may be helpful for specific studies, further investigation is required for a more general water supply function.

Another challenge in estimating the demand for water is the spatial allocation of human activities. In studying the economic impacts of future changes on water resources, it is a common practice to assume no change in the location of human activities and allocation of land and water resources – often simply by assuming that crop area weights remain at the reference year level. While this assumption can be appropriate for some studies, in general, it is not. For example, it is expected that climate change reduces the corn yield for southern parts of the Corn Belt and increases the yields for the northern parts. This implies a natural response from farmers to move to places with better growing conditions (Diffenbaugh et al., 2012). Moreover, the reallocation of land and water resources is a result of increasingly interconnected agricultural markets which hence may alter the effectiveness of local water policies.

In this paper, I construct an economic model to explain the interplay between water supply and demand considering possible reallocation of agricultural crop production. For estimating water use, I consider global demand for food, regional trade, and local agricultural production as drivers of water demand. For the supply of water, I consider biophysical characteristics of each location, sustainable levels, and maximum available water. This model integrates economic theories with environmental sciences to analyze the hydrological and economic information at different geospatial scales in a changing world. In the demand side, growth in income and population lead to changes in food consumption baskets and changes in agricultural trade patterns. On the supply side, heterogeneity in local constraints leads to different rates of change in land and water use.

I believe this study is important as water scarcity and water pollution are together among the biggest environmental problems in the US, as well as worldwide. The pressure on US farmers to produce more output has led to the unsustainable use of land and water resources in many locations (McGuire, 2017; Reitz, Sanford, Senay, & Cazenas, 2017; Rodell et al., 2018; Russo & Lall, 2017; Valley, 2009). In 2017 the Gulf of Mexico summer "dead zone" reached a record size of 8,776 square miles, while the 2019 forecast is also close to that record (NOAA, 2019). In addition, reductions in groundwater storage could threaten the nation's ability to meet future water needs (Cook, Ault, & Smerdon, 2015). As we look forward to the mid-century, growth in the global population and income will continue to boost the demand for agricultural products and therefore, indirectly, for land and water resources. This affects water quality and water withdrawals globally.

This study can inform the farmers and policy makers about the likely impacts of future global and local changes on water stress at each location.

To show the applications of the model, I conduct two exercises. Employing the proposed model in this study, I investigate the contribution of global changes in population, technology, and income on US water and land use by mid-century. This will spot the vulnerable locations to land and water stress. Then I measure the impacts of US groundwater sustainability policies on crop production around the world. This will highlight the possible global-to-local-to-global linkages. The goal is to is highlight the importance of global reallocation of production, and hence land and water use, in the face of local sustainability stresses. Such relocation of human activities plays a significant role in the adaptation to climate change and environmental shocks. However, this relocation of production is often ignored in the evaluation of local water policies.

Our findings suggest that due to trade costs – including transportation as well as trade barriers -- crop output growth in each part of the world is influenced first and foremost by the interplay between domestic supply and demand. However, developments in international markets also play an important role – particularly in those regions that are heavily reliant on crop exports or imports. We also evaluate the impacts of a counterfactual groundwater sustainability policy in the US. Any restriction in water resource abstraction in 2050 will necessarily result in a reallocation of the pattern of crop production and water use worldwide. I find that crop productions shift eastward in the US, much of the displace production shifts overseas.

The next section is the literature review. Section 4.3 provides an overview of the model. It also introduces different information used in the construction of the database. Section 4.4 provides the projection results and the impacts of sustainability policy. Section 4.5 contains a discussion on the implications of climate change. And section 4.6 concludes.

3.2 Literature review

This study is based on the SIMPLE, a Simplified International Model of agricultural Prices, Land use, and the Environment (Baldos & Hertel, 2014; Liu et al., 2017; Liu, Hertel, Taheripour, Zhu, & Ringler, 2014). The SIMPLE model which has been validated for the study of the long run sustainability and food security (Baldos & Hertel, 2014; Hertel, 2018). Within this framework global food and agricultural markets link developments around the world; the changes in population affect the regional demand for food and water; the dietary changes due to income growth affect the food basket; the technological changes lead to higher productivity and lower water use per unit of output.

I extend this model to include costs of irrigation, surface water, and groundwater for the continental United States. I also introduced three levels of relocation. First, crop production can shift within regions (for this purpose, I will refer to USDA Farm Resource Regions); these regions tend to produce similar products (e.g., the ‘Fruitful Rim’ and the ‘Heartland’). Second, production may shift across Farm Resource Regions within the United States; this may involve changes in production technology as well as shifts in crop types. Third, I consider the consequences of international trade. Changes in US imports and exports imply shifts of production to other parts of the world. The database and the model are described in the methods section in more detail.

3.3 Methods

SIMPLE-on-a-Grid or SIMPLE-G is a partial equilibrium agricultural trade model focused on land and water use in crop production. This model is multi-scale. In other words, it involves sixteen demand regions and tens of thousands of supply grids. It includes gridded cropland use, crop production, nitrate leaching, and water use for the US, while employing regional production units for other parts of the world. US crop production is modelled at the level of georeferenced grid-cell units at 5 arc min resolution (10 km square at the equator). This allows SIMPLE-G to explicitly incorporate local economic and environmental constraints in its projections, account for sub-national heterogeneity of global drivers such as climate change and water scarcity, and assess local land and water use.

Within the market regions in SIMPLE, crop demands are aggregated into four uses (direct consumption, feedstuffs for livestock, the raw material for processed foods, and feedstock for biofuels). Within each region, demand is driven by prices, population, per capita income, and biofuel mandates (all exogenous in the model). Consumers may purchase either from domestic or global markets depending on relative prices. This follows the method of Armington (Armington, 1969) which assumes imperfect substitution between domestic and foreign products.

Figure 1 summarizes the main demand and supply components of the SIMPLE-G model. In each region, crop production follows a nested constant elasticity of substitution (CES) function of nitrate, water, land, and other inputs for irrigated and non-irrigated crop production. Allocation of land to rainfed and irrigated production is determined endogenously for each grid cell assuming a constant elasticity of transformation (CET) function and constrained by water rights. Domestic output can be sold domestically or globally.

For the US, regional crop supply is obtained by aggregating across the Farm Resource Regions. Each resource region includes thousands of grid cells (5 arc-min). Crop production in each grid cell allows for substitution between nitration fertilizer, water, land, and other inputs (the latter is an aggregate of capital, labor, chemicals, energy, etc). The allocation of land to rainfed and irrigated production is determined endogenously for each grid cell assuming a constant elasticity of transformation function (Syud Amer Ahmed, Hertel, & Lubowski, 2008). Water is an explicit input used by the irrigated sector only. Water use is endogenously determined through the interaction of supply constraints and irrigation demand for crop production. Withdrawal of surface water is constrained by maximum surface water available at each grid cell after subtracting non-agricultural water use. Withdrawal of groundwater is constrained by maximum available ground water and a rapidly increasing cost of extraction. Water availability at each grid cell is exogenous.

The model solves for equilibrium levels and prices of land, water, and crops. Equilibrium water withdrawal is endogenously determined at each grid cell assuming market clearing. Crop price in homogeneous across Farm Resource Regions. However, land and water resources have grid-specific markets and prices. Parameters of the CES and CET functions are either estimated or obtained from the literature (Baldos & Hertel, 2014; Jame, Bowling, Hertel, Jing, & Haqiqi, 2017).

The next section describes the water module of the SIMPLE-G model. First, I introduce water demand for irrigated crop production by deriving a simplified input demand system assuming a nested constant elasticity of substitution. Then I describe the water supply for each grid cell based on the hydrological characteristics of each grid cell. I also separate the water supply by surface water and groundwater.

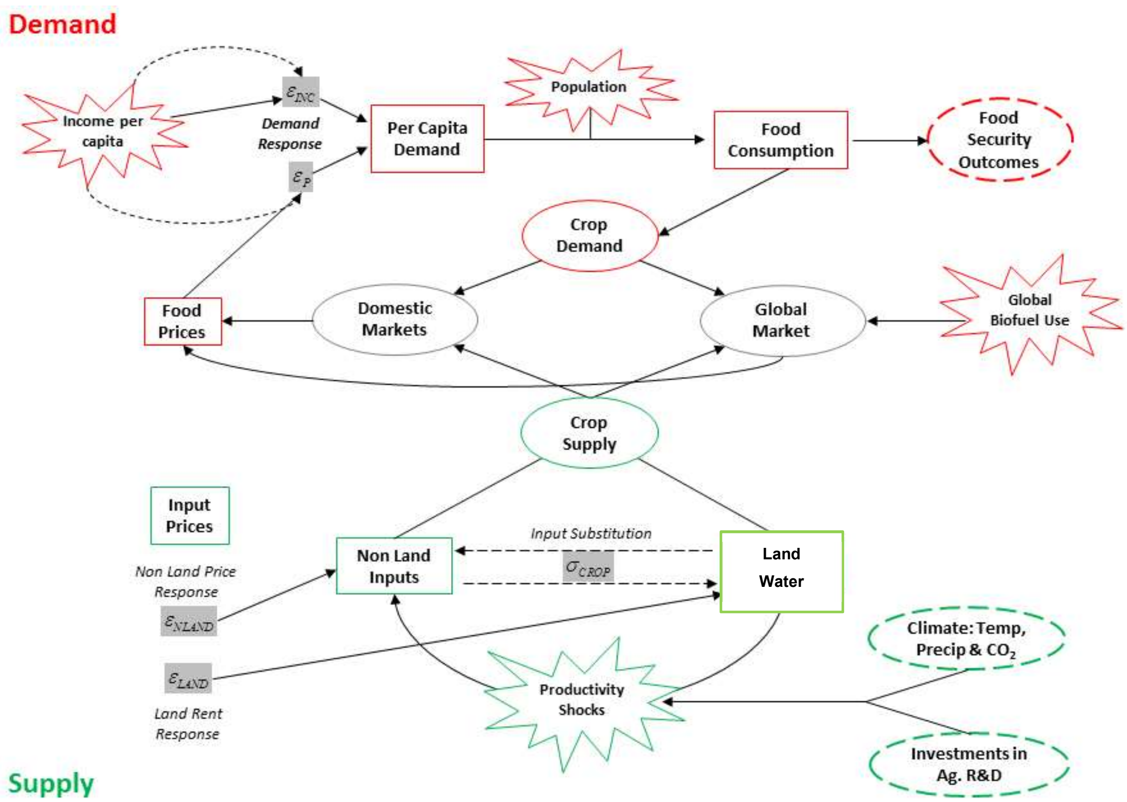


Figure 3-1. Structure of SIMPLE-G model

3.3.1 Irrigation water demand

Each grid cell produces one commodity (Y) which is the corn equivalent of all the crops produced in the grid cell. Production inputs are nitrogen fertilizer (N), land (L), water (W), and aggregate other inputs (M). Aggregate other inputs include chemicals, seeds, energy, capital, labor, etc. Here I introduce the irrigated production technology. However, the non-irrigated technology will be similar except it does not include water.

Given the output prices, equilibrium levels of N_i, L_i, W_i, and M_i can be obtained by solving the dual problem for production optimization as:

$$minimize\ PN_i.N_i + PL_i.L_i + PW_i.W_i + PM_i.M_i$$
$$st\ Y_i = f_i(N, L, W, M)$$

where PN_i, PL_i, PW_i, and PM_i are input prices at each grid cell i. Assuming weak separability, I consider a nested constant elasticity of substitution (CES) structure as shown in Figure 4-2. At the bottom level, surface water (WS) and groundwater (WG) are aggregated to make total water composite (W) assuming imperfect substitution among them. Then, there is a substitution between land (L) and total water (W). This nest governs the flexibility of water applied per acre of land. Then, I assume a substitution between the land-water aggregate and other inputs (M). Finally, nitrogen is aggregated with aggregated WLM at the top level.

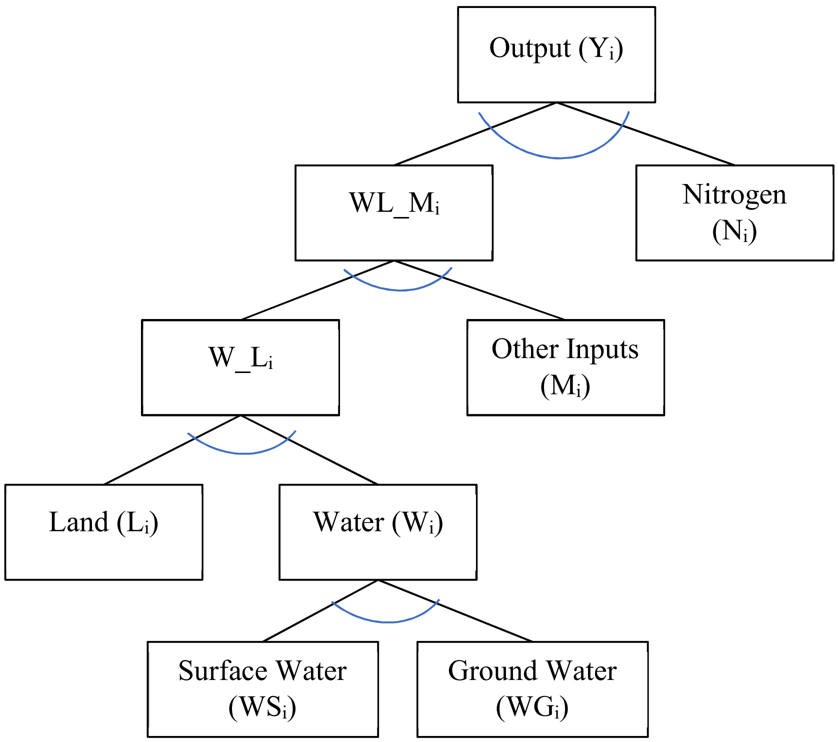


Figure 3-2. Structure of crop production at each grid cell

For ease of calculations, I split the optimization problem into four smaller problems (for four nests of production). In other words, I try to find the optimum mix of inputs at each nest, given the upper level prices. This will help keep track of changes and decompose the changes to individual nests. The problems are to minimize the cost of each composite assuming constant elasticity of substitution:

$$minimize\ PN_i.N_i + PWLM_i.WLM_i \qquad s.t.Y_i = f_i(N, WLM)$$

$$minimize\ PWL_i.WL_i + PM_i.M_i \qquad s.t.WLM_i = g_i(M, WL)$$

$$minimize\ PL_i.L_i + PW_i.W_i \qquad s.t.WL_i = h_i(L, W)$$

$$minimize\ PWS_i.WS_i + PWG_i.WG_i \qquad s.t.W_i = k_i(WS, WG)$$

Let $\sigma_{i,z}, \beta_{i,x}$ show the elasticity of substitution at layer z for grid cell i, and CES parameter of input x for grid cell i, respectively. The solution to the optimization problem will be a set of input demand equations. Input demands are determined by relative prices, elastithe city of substitution, and the CES parameter. I define a price index for each level as a function of the layer elements' prices as shown in Table 4-1.

Table 3-1. Input demands obtained by solving a cost minimization problem for each bundle.

Demand for input or composite input	Price index
$WLM_i = \beta_{i,wlm} Y_i \left(\frac{PY_i}{PWLM_i}\right)^{\sigma_{i,y}}$ $N_i = \beta_{i,n} Y_i \left(\frac{PY_i}{PN_i}\right)^{\sigma_{i,y}}$	$PY_i = \left(\beta_{i,wlm} PWLM_i^{1-\sigma_{i,y}} + \beta_{i,n} PN_i^{1-\sigma_{i,y}}\right)^{\frac{1}{1-\sigma_{i,y}}}$
$WL_i = \beta_{i,wl} WLM_i \left(\frac{PWLM_i}{PWL_i}\right)^{\sigma_{i,wlm}}$ $M_i = \beta_{i,m} WLM_i \left(\frac{PWLM_i}{PM_i}\right)^{\sigma_{i,wlm}}$	$PWLM_i = \left(\beta_{i,wl} PWL_i^{1-\sigma_{i,wlm}} + \beta_{i,m} PM_i^{1-\sigma_{i,wlm}}\right)^{\frac{1}{1-\sigma_{i,wlm}}}$
$W_i = \beta_{i,w} WL_i \left(\frac{PWL_i}{PW_i}\right)^{\sigma_{i,w}}$ $L_i = \beta_{i,l} WL_i \left(\frac{PWL_i}{PL_i}\right)^{\sigma_{i,w}}$	$PWL_i = \left(\beta_{i,w} PW_i^{1-\sigma_{i,wl}} + \beta_{i,l} PL_i^{1-\sigma_{i,wl}}\right)^{\frac{1}{1-\sigma_{i,wl}}}$
$WS_i = \beta_{i,ws} W_i \left(\frac{PW_i}{PWS_i}\right)^{\sigma_{i,w}}$ $WG_i = \beta_{i,wg} W_i \left(\frac{PW_i}{PWG_i}\right)^{\sigma_{i,w}}$	$PW_i = \left(\beta_{i,ws} PWS_i^{1-\sigma_{i,w}} + \beta_{i,wg} PWG_i^{1-\sigma_{i,w}}\right)^{\frac{1}{1-\sigma_{i,w}}}$

We can also approximate this system with its linearized form. Table 4-2 shows this approximation, where $\theta_{i,x}$ shows the cost share of input x in its underlying layer and the "prime" over the variables indicate percentage change in that variable. Note that these are simplifies equations to show the major components of the demand system. In these tables, I have dropped all the tax /subsidy variables as well as productivity variables. In this demand system, major components are relative prices, substitution elasticities, and cost share parameters.

Table 3-2. Linear approximation of the input demand functions

Demand for input or composite input	Price index
$WLM'_i = Y'_i + \sigma_{i,y} * (PY'_i - PWLM'_i)$	$PY'_i = (\theta_{i,wlm} PWLM'_i + \theta_{i,n} PN'_i)$
$N'_i = Y'_i + \sigma_{i,y} * (PY'_i - PN'_i)$	
$WL'_i = WLM'_i + \sigma_{i,wlm} * (PWLM'_i - PWL'_i)$	$PWLM'_i = (\theta_{i,wl} PWL'_i + \theta_{i,m} PM'_i)$
$M'_i = WLM'_i + \sigma_{i,wlm} * (PWLM'_i - PM'_i)$	
$W'_i = WL'_i + \sigma_{i,wl} * (PWL'_i - PW'_i)$	$PWL'_i = (\theta_{i,w} PW'_i + \theta_{i,l} PL'_i)$
$L'_i = WL'_i + \sigma_{i,wl} * (PWL'_i - PL'_i)$	
$WS'_i = W'_i + \sigma_{i,w} * (PW'_i - PWS'_i)$	$PW'_i = (\theta_{i,ws} PWS'_i + \theta_{i,wg} PWG'_i)$
$WG'_i = W'_i + \sigma_{i,w} * (PW'_i - PWG'_i)$	

3.3.2 Irrigation water supply

Water supply at each grid cell is limited by hydrological constraints. I assume a Fréchet type function for water supply as:

$$QW = \alpha e^{-\left(\frac{PW-\varepsilon}{\kappa}\right)^{-\sigma}}$$

where, $\sigma, \alpha, \varepsilon, \kappa$ are shape parameter, asymptote, location of minimum, and scale parameter respectively; QW is the volume of water supplied and PW is the price of water. Figure 4-2 illustrates one example of this function. This function is slowly increasing at the beginning and then rapidly increasing when it is approaching the asymptote.

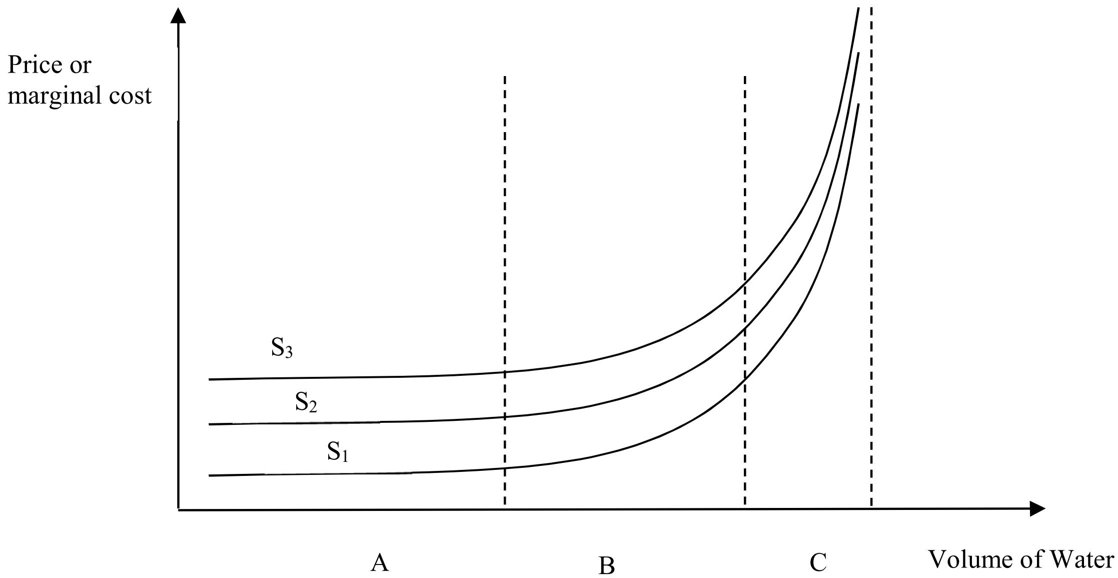


Figure 3-3. The quasi-irreversible water supply function.
At each period, the marginal cost of water supply is almost fixed up to point A (annual groundwater recharge). The marginal cost starts increasing at a moderate speed up to point B. From B to C the marginal cost increases rapidly (due to change in the water table and PSI). In the next period we may face a new cost schedule S_1, S_2, or S_3 (depending on the water table and ground water recharge).

We can linearize this function for groundwater (GW) according to the following relationship:

$$\Rightarrow \frac{dGW_g}{GW_g} = -\sigma_g \ln\left(\frac{GW_g}{GWM_g}\right)\frac{dPW_g}{PW_g}$$

Here, the supply elasticity of water is changing and depends on the ratio of water extracted to the maximum available groundwater (GWM). I calibrate this function for surface water and groundwater at each grid cell. I consider annual withdrawal, maximum available water by source, and estimated cost of water withdrawal by source.

3.3.3 Data

The base regional data for 2010 is taken from Baldos and Hertel (2014) which includes regional data on supply and demand for crops. I add gridded information for US crop production at 5 arc min grid cells for cultivated areas for irrigated and non-irrigated practices. This includes the value and quantity of crop output, land input, nitrogen fertilizer input, water, and aggregated other inputs. Aggregated output at each grid cell is the corn-equivalent crop output which is calculated as the value of crop sold divided by the price of corn. I take the value of crop sold per acre from USDA-NASS by county, and use GCWM simulated yields to generate gridded yield for all the grid cells in each county. GCWM is aggregated over all crops using USDA/FAO actual prices to calculate corn-equivalent crop output for each grid cell.

We split the base data to irrigated and rainfed crop production employing various satellite data sets, and county level information from USDA and USGS, as well as the simulated yield of irrigated and non-irrigated crops. Cropland area is obtained from USDA Cropland Data Layer (CDL) and aggregated to 5 arc min. Irrigated cropland is from the Moderate Resolution Imaging Spectroradiometer (MODIS) Irrigated Agriculture Dataset for the United States (MIrAD-US) provided by USGS (Brown & Pervez, 2014) and aggregated to 5 arc min. For yield estimation, I assume that grid cell aggregated yield per hectare is equal to the county that the grid cell is located in. The information on county's aggregate yield is obtained from USDA Value of Crop Sold and Total Market Value of Agricultural Products Sold which I converted them to corn equivalent yields. I split the gridded total yield to irrigated and non-irrigated using the following formula:

$$YL = Y'_i L'_i + Y''_i L''_i$$

$$Y''_i = \alpha_i Y'_i$$

$$\alpha_i = \sum_{c=crops} \omega_{i,c} \alpha_{i,c}$$

where, Y, Y', Y'' show aggregated, irrigated, and non-irrigated yield; L, L', L'' show total, irrigated, and non-irrigated land as obtained from MIrAD-US and CDL; and α is the coefficient of non-irrigated yield gap as estimated based on Siebert and Döll (2010) for 29 crop categories and aggregated according to production value weights. Total cropland from CDL is matched with USDA county level cropland to ensure consistency of yield and area at the county level.

We considered spatial heterogeneity of nitrogen fertilizer (N) application rates from Historical Nitrogen Fertilizer Use (Cao, Lu, & Yu, 2018) and EarthStat (Mueller et al., 2012). Total nitrogen fertilizer from these datasets is matched with USDA state level fertilizer use. Then I split it to irrigated and non-irrigated application rate using the following formula.

$$NL = N'_i L'_i + N''_i L''_i$$

$$N''_i = \beta_i N'_i$$

where, N, N', N'' show aggregated, irrigated, and non-irrigated N rate; L, L', L'' show total, irrigated, and non-irrigated land as obtained from MIrAD-US and NLCD; and β is the coefficient of non-irrigated fertilizer rate to irrigated fertilizer rate as estimated based on Agro-IBIS simulated fertilizer application rate for irrigated and non-irrigated (Kucharik & Brye, 2003).

Irrigation water withdrawal rates are estimated using USGS county level water use data (Maupin et al., 2014) and Water Balance Model (WBM) simulated water use by 6 arc min grid cells (Grogan, 2016). I calculate total water withdrawal per irrigated acre from WBM and split it to ground water and surface water using USGS county level water use by source.

The information about groundwater recharge is taken from the Annual Estimate of Recharge (Reitz et al., 2017). Figure 2 depicts the ratio of groundwater withdrawal to local recharge in 2010. The red color shows the locations with a very rapid depletion of groundwater. A ratio equal to ten means the amount of groundwater withdrawal in one year is equal to ten years of groundwater inflow. The High Plains Aquifer, the Central Valley of California, the Snake River Basin and western Washington show dramatic levels of unsustainability.

The maximum surface water available at each grid cell is calculated after subtracting non-agricultural water use from locally-generated runoff (Wolock, 2003). Maximum available ground water available is determined with groundwater stock (Befus, Jasechko, Luijendijk, Gleeson, & Cardenas, 2017; Gleeson, Befus, Jasechko, Luijendijk, & Cardenas, 2016).

Land rents are obtained from USDA-NASS cropland Cash Rents by County for irrigated and non-irrigated cropland (USDA-NASS, 2019). I estimate grid cell rents using homogeneous within a county. Nitrogen fertilizer prices are also obtained from USDA at the state level assuming homogeneous prices for grid cells within each state. I estimated the value of irrigation and water resources using USDA Farm and Ranch Irrigation Surveys (FRIS) by state and USDA Production Expenses by county (USDA-ERS, 2019).

For projecting forward, I consider changes in population, income and total factor as in Baldos and Hertel (2014) based on Shared Socioeconomic Pathways two (SSP2). Regarding productivity, I assume that the historical productivity growth rates persist to the mid-century (Fuglie, 2012). I evaluated the impacts of another scenario of US productivity growth in the appendix. South Asia and China are projected to have the greatest income growth by around 640% and 607% respectively. Regarding population growth, Sub Saharan Africa is expected to experience a dramatic population growth by 139.4%. However, East Europe and Japan and Korea will experience a decline in populations.

Table 1. Projected changes in population, income, and productivity from 2010 to 2050. Productivity is measured by growth in Total Factor Productivity (TFP).

Region	Population	Income	TFP
East Europe	-12.7	239.5	63.2
North Africa	44.0	224.7	59.1
Sub Saharan Africa	**139.4**	401.0	5.4
South America	31.1	176.3	57
Australia	33.8	70.7	16.6
Europe	0.0	66.3	23.7
South Asia	40.8	**640.6**	33.5
Central America	41.2	154.6	33.6
South Africa	16.0	239.5	43.9
South East Asia	32.1	363.6	58
Canada	25.8	56.4	41.6
United States	25.0	58.6	41.6
China	-6.3	**606.7**	53.2
Middle East	65.2	102.6	21.2
Japan Korea	-14.5	97.6	45.6
Central Asia	52.3	394.2	**63.2**

Sources: Changes in population and income is obtained from Baldos and Hertel (2014) aggregated to 16 regions from country level information based on SSP2 (O'Neill et al., 2014). The changes for productivity are calculated based on Fugli (2012).

3.4 Results

I have calibrated the gridded water supply schedule for the continental United states for 2010. For groundwater, the elasticity of supply is endogenously determined according to the ratio of groundwater withdrawal to groundwater recharge. Figure 4-3 illustrates the pattern of this ratio. The red areas in the map have a high ratio of withdrawal to recharge. In these grid cells, the expansion of irrigation requires higher price motivation compared to grid cells with a lower ratio. In other words, given a similar increase in crop prices, a larger expansion is expected in areas with a lower ratio.

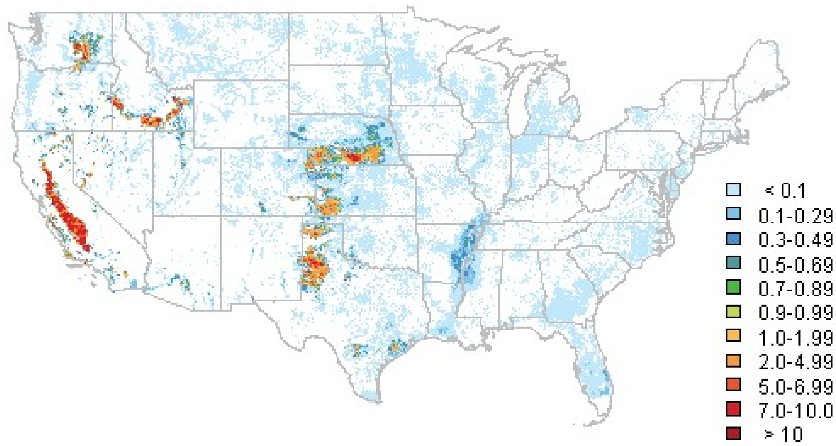


Figure 3-4. Ratio of groundwater extraction over local groundwater recharge
By 5 arc min grid cells for 2010.

3.4.1 Baseline 2010-2050

In the coming decades, changes in population, income, and technology will change the pattern of agricultural crop consumption, production and international trade. We expect that productivity growth leads to higher yields and therefore moderates the demand for land and water resources. On the other hand, we expect the changes in population and income growth will partially offset this.

Figure 4-5 summarizes the projected change in crop production and the contribution of each driver. In the US, production is expected to rise by nearly 60% or roughly one billion metric tons over this four-decade period. The drivers of US crop output growth are fairly evenly divided between increases in population – both domestic and foreign (red bar), rising per capita incomes around the world (green bar) and improved productivity in global crop production (blue bar). I also include projected growth of US biofuels as a driver of change which mainly influences US crop output. In Europe and China, regions with little projected population growth, income is the main driver of crop demand. Income growth is also a key driver of output growth in South Asia, whereas population growth is the most important food demand driver in Africa. Latin America and China are two regions where there have been significant investments in productivity-enhancing research and development in recent decades so improved crop productivity accounts for a larger share of their projected output growth.

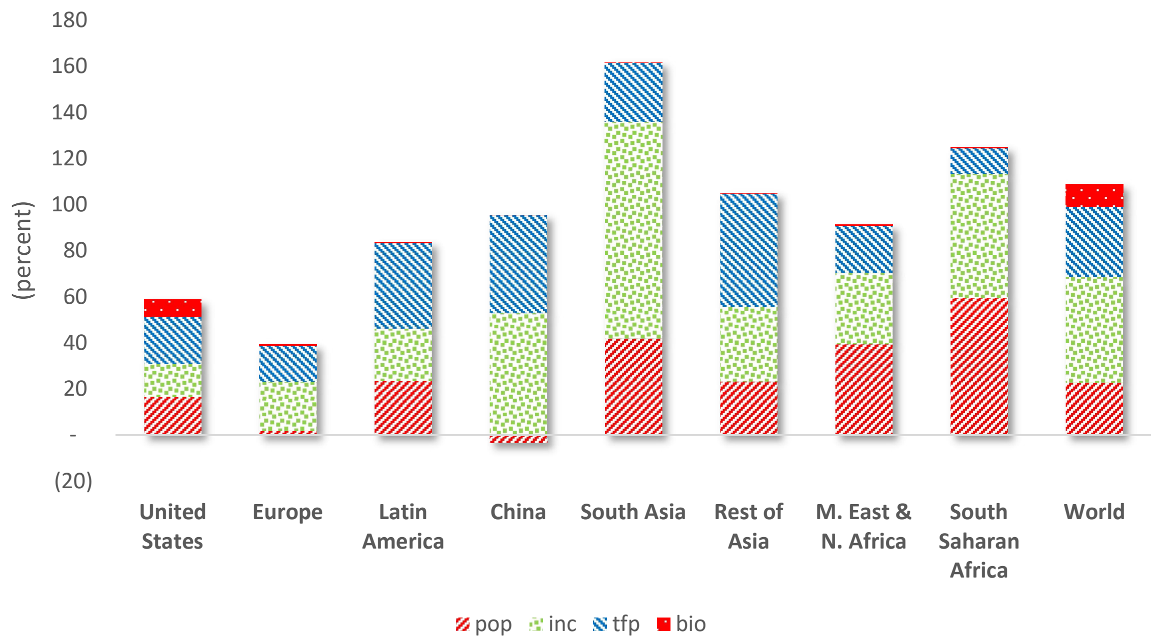


Figure 3-5. Percent change in crop production from 2010 to 2050.
Due to the combined effect of changes in per capita income (inc), population (pop) and technology (tfp), around the world, as well as growth in US biofuels (bio) demand. Growth in domestic and foreign populations and incomes boosts demand, raises prices and output. Growth in productivity lowers costs, thereby depressing prices and boosting demand.

Although productivity growth leads to higher yields and therefore moderates the demand for land, the impact of population and income growth on land use is dominant in all regions except Europe. Sub-Saharan Africa (+155 Mha) and South Asia (+66Mha) are projected to have the largest increases in cropland due to strong demand growth in those two regions. the analysis indicates that a quarter of the projected US cropland expansion is due to demand growth in South Asia and China (Figure 4-6). Overall, growth in income and population outside the US is far more important in driving US crop production than growth within the US. This is due to higher income growth rates in the developing and emerging economies and higher rates of population growth in Africa and other low-income regions.

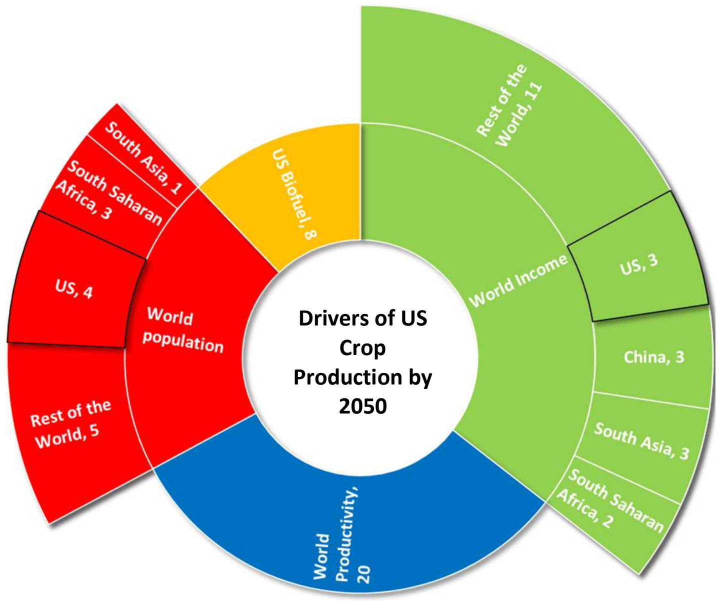


Figure 3-6. Drivers of US Crop Production by 2050

Figure 4-7 shows the pattern of cropland expansion across the US as a percent change from 2010. This is a better indicator of sustainability stress than absolute changes. It reveals that, absent any policy interventions, the greatest land use change stresses will arise in the marginal areas on the edges of the Corn Belt. These are precisely the areas where the largest land use stresses arose during the 2008-2012 period (Lark, Salmon, & Gibbs, 2015). These changes can be explained statistically by both biophysical and economic variables(Villoria & Liu, 2018).

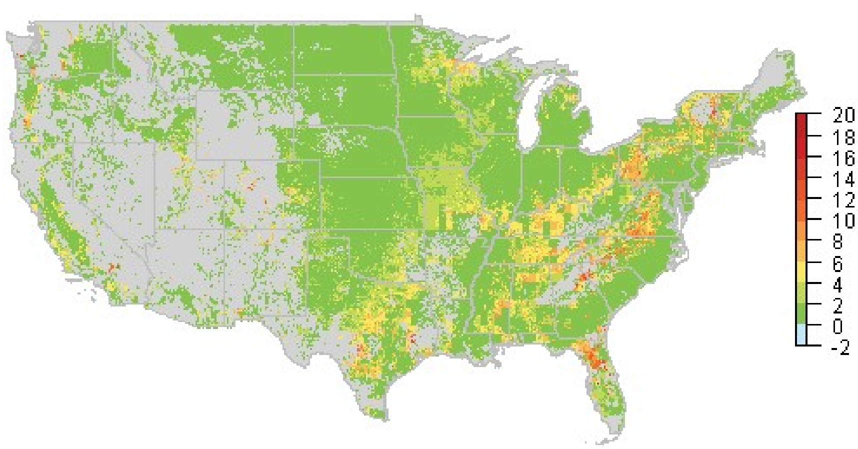


Figure 3-7. Projected percentage change in US cropland from 2010 to 2050 by 5 min grid cell

Figure 4-8 illustrates the pattern of change in water use across the US as a percentage change growth from 2010. Overall, the pattern is similar to cropland expansion. However, the growth in water use is smaller than cropland expansion due to water constraints. However, I find that the biggest irrigation expansion will occur in the Eastern US. This is in line with current observations as USDA reports steady growth in Eastern US irrigation from 2002 to 2017 (USDA, 2019).

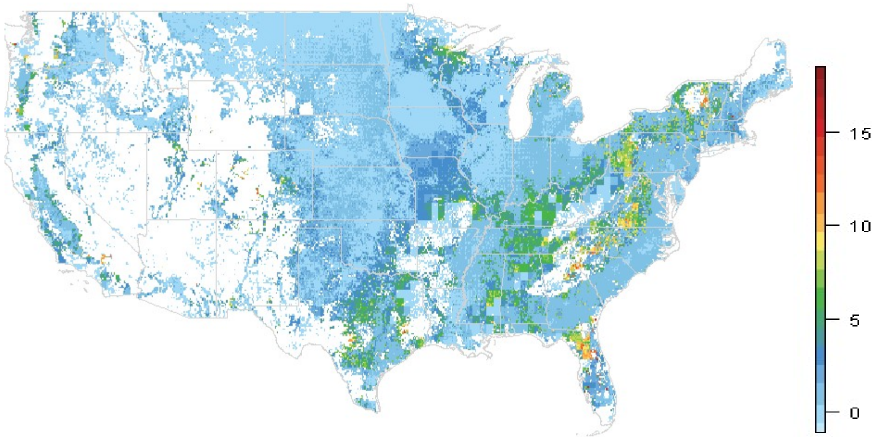


Figure 3-8. Percentage change in US water use from 2010 to 2050

We also find that despite constraints on water resources, groundwater withdrawals will increase and will intensify the stress mainly for currently stressed locations. Specifically, more stress is expected for California Central Valley, Snake River, and Ogallala Aquifer. However, as costs rise due to the need for deeper wells, and efficiency improves, the rate at which groundwater withdrawals for irrigation in these regions are increasing is slowing. For most of the country, growth in water use will not lead to water stress.

Figure 4-9 summarizes the change in yields and output for all the grid cells in the US. In general, the average percentage change in yield of rainfed land is higher than the average percentage change in yield of irrigated land. This represents additional constraints from water resources on production expansion.

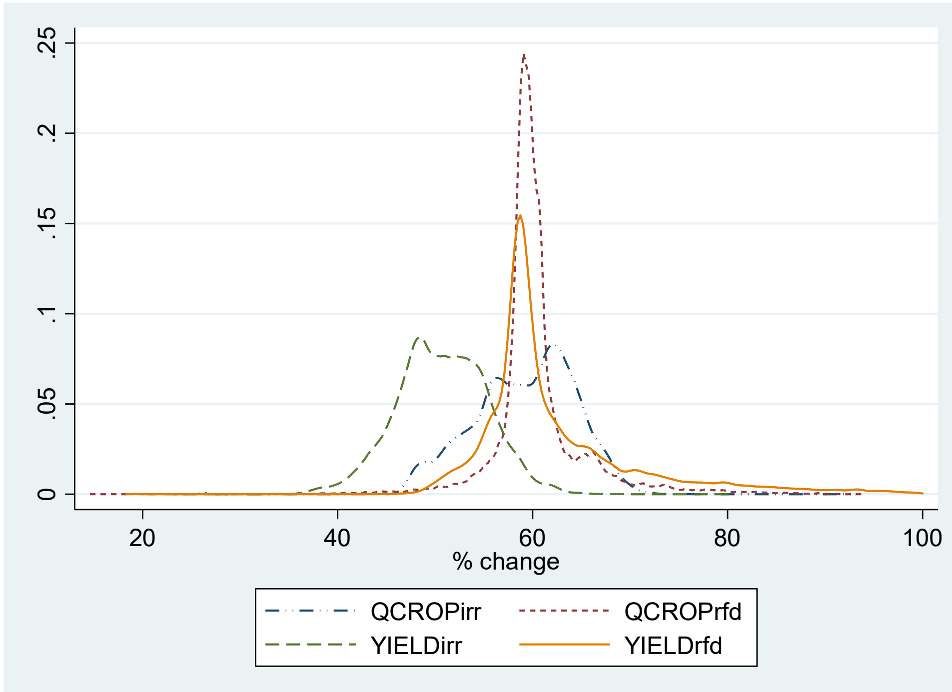


Figure 3-9. Kernel density of percentage change in production and yield for US grid cells

3.4.2 Groundwater sustainability policy

Here I assume a capping policy for groundwater withdrawal to a sustainable level (not more than annual recharge). Any attempt to move to a more sustainable rate of groundwater withdrawals in 2050 will necessarily result in a reallocation of the pattern of crop production worldwide. Each outcome will depend on the method used to limit abstractions, including pricing withdrawals in vulnerable regions, accelerated investments in irrigation efficiency, and institutional reforms designed to reallocate water to its highest value uses. I am not in a position to explore all of these reforms here, but I illustrate the potential reallocation of production via a simple 'thought experiment': What if groundwater withdrawals in each US grid cell were limited to a sustainable level? I implement this by reducing future withdrawals to the rate of recharge. Figure 4-10 shows the resulting change in groundwater withdrawals by grid cells. The shaded blue areas would require more than 50% reduction in groundwater withdrawal.

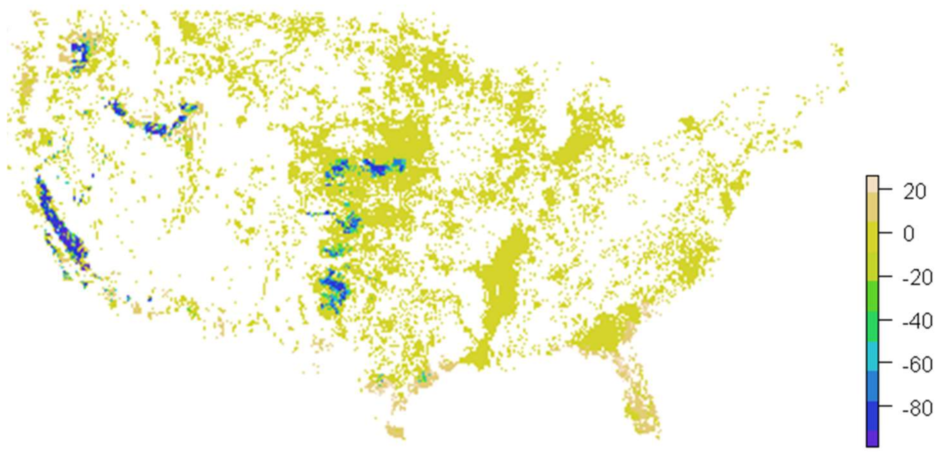


Figure 3-10. Change in groundwater withdrawal due to restriction

US crop markets will reallocate cropland based on prices and economic returns to farming. Figure 4-11 shows the resulting shift in production and land use in the United Sates. In those locations where rainfed production is possible, I predict that the irrigated land would be converted to dryland cropping. Furthermore, the ensuing rise in crop prices will also encourage increased crop production in other regions of the US – particularly in the more water-abundant Eastern US. The results also indicate a shift of production to within the Fruitful Rim, for example shifting fruit and vegetable production from California to Florida.

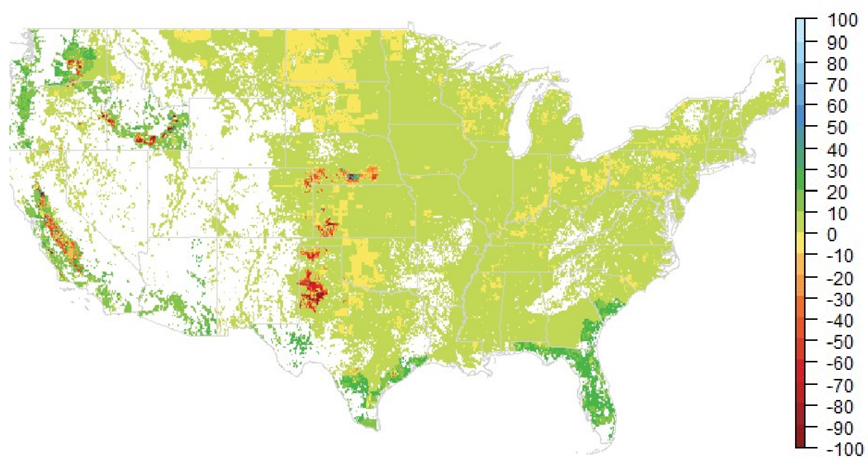


Figure 3-11. Impacts of water restriction policy on US production (% change).

Global crop markets will also re-allocate cropland based on prices and economic returns to farming. Some crop production will shift overseas. Figure 4-12 demonstrates the change in the global cropland area due to groundwater sustainability restrictions in 2050. As production shifts to other parts of the world, cropland use will expand. However, the target locations in the US are among the most productive regions and produce very high value crops. As other parts of the world are less productive, the re-allocation will result in larger global land, fertilizer and water use.

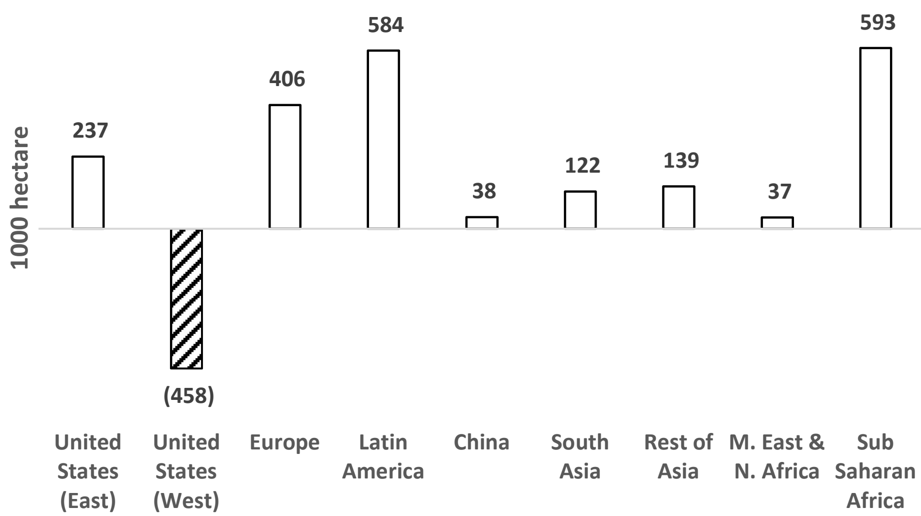


Figure 3-12. Impacts of water restriction policy on global land use.
The impacts of imposing a US groundwater sustainability constraint in 2050 on cropland use around the world. Global crop markets will re-allocate cropland based on prices and economic returns to farming.

3.5 Discussion

In closing, it is important to note some of the most significant limitations of the study. I did not consider climate change which may have several impacts. First of all, I have not considered the future changes in water supply; this can affect crop composition within any given grid cell or changes in irrigation extent. Another limitation has to do with the impacts of changes in water requirements by crops due to heat stress. Such changes could moderate or intensify the reallocation of crop production. I will discuss these in the following paragraphs.

3.5.1 Climate change impacts on water supply

Climate change will affect precipitation and soil moisture which are critical for agriculture. It is predicted that the future will be drier in currently dry places and wetter in currently wet regions

(Feng & Zhang, 2015). This will reduce the groundwater recharge rate in the Western and Southern parts of the United States. It is also predicted that these regions will experience more successive dry years which affects the water table and will result in more severe stress on groundwater resources.

3.5.2 Climate change and irrigation intensity

Water intensity can be defined as water requirement by crop multiple by field application efficiency. Global warming will increase water requirement per acre of irrigated area and per volume of output. While I predict that farmers will continue to increase the irrigation water efficiency (field application efficiency), a hot and dry future may offset the efforts to reduce water intensity by increasing water requirement by crop. However, projecting future water intensity of irrigated agriculture requires further investigation.

3.5.3 Climate change and irrigation expansion

Climate change will affect crop yields. However, the damage to irrigated production is smaller than non-irrigated. This will increase the irrigation yield gap and thus motivates more irrigation. I expect that climate impacts on the irrigation yield gap will intensify stress on US groundwater resources. Note that the rate of water withdrawal growth will decline for the Western US and will increase for Eastern US, especially around the Mississippi river basin.

3.5.4 Economic foundations of spatial reallocation

The most significant limitation of the study is improving the estimates of the spatial re-allocation parameters. This parameter governs the re-allocation or cropland within a Farm Resource Region. In this study, I considered a σ=5 for relocation possibility between grid cells within a Farm Resource Region, assuming they have similar farm characteristics, commodities produced, soil, water, and climate conditions. Another level of re-allocation is across the Farm Resource Regions, for which I considered a σ=2 relocation possibility. While I found that the global results are not sensitive to this parameter, gridded results are largely affected by this parameter as shown in Figure 4-13. This opens an interesting topic for future research to further investigate the possibility of spatial re-allocation.

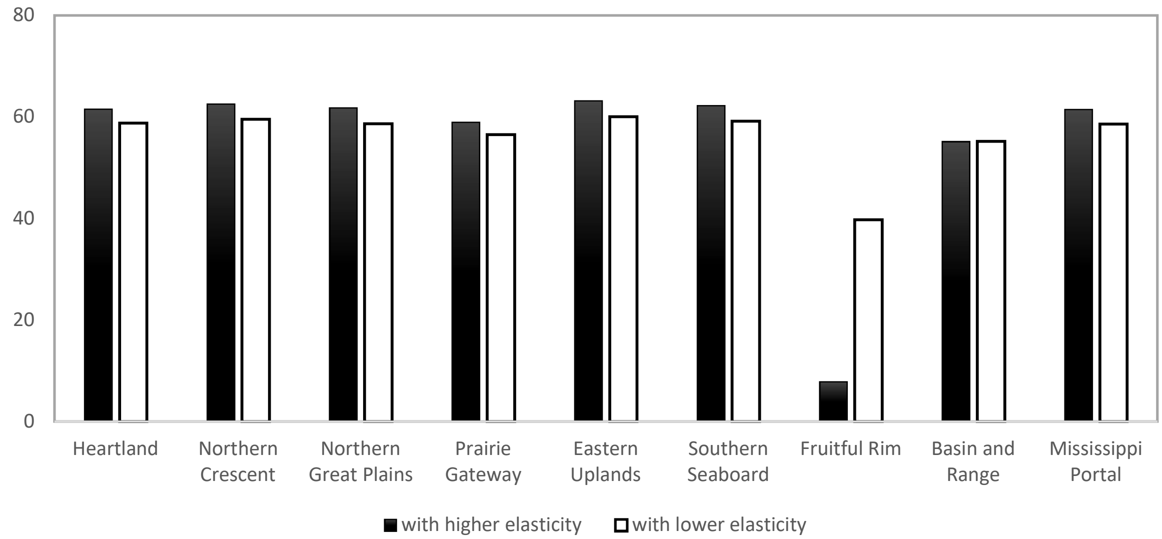


Figure 3-13. Projected production growth (% change) by Farm Resource Regions. By 2050 with groundwater restriction (SIMPLE-G).

3.6 Conclusion

I propose a global partial equilibrium model for evaluating local and regional water policies to consider significant feedback from the human system. Projecting to 2050, increasing stresses on water and land resources are expected to emerge as a consequence of anticipated growth in crop output in the US. The underlying drivers of these stresses are global in nature, with demand growth in South Asia and China alone accounting for roughly one-quarter of US cropland expansion. I expect the land use stresses to be greatest in marginal areas where the current cropland base is modest. However, overall cropland expansion is modest in the baseline, and, while surface withdrawals increase, the emerging challenge would appear to be posed by unsustainable groundwater withdrawals. Pumping for irrigation and other uses now exceed annual recharge rates by more than 10 times in the Central Valley of California, the High Plains Aquifer, and the Snake River Basin. Despite improvements in efficiency and higher pumping costs, this figure is expected to further deteriorate in the absence of regulation. Furthermore, any attempt to restrict water for irrigation will result in the reallocation of cropping activity overseas, as well as to other regions of the country. And the longer sustainability regulations are delayed, the more difficult will be this adjustment. Dealing with this sustainability challenge will no doubt require multiple interventions as well as institutional reforms.

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APPENDIX A

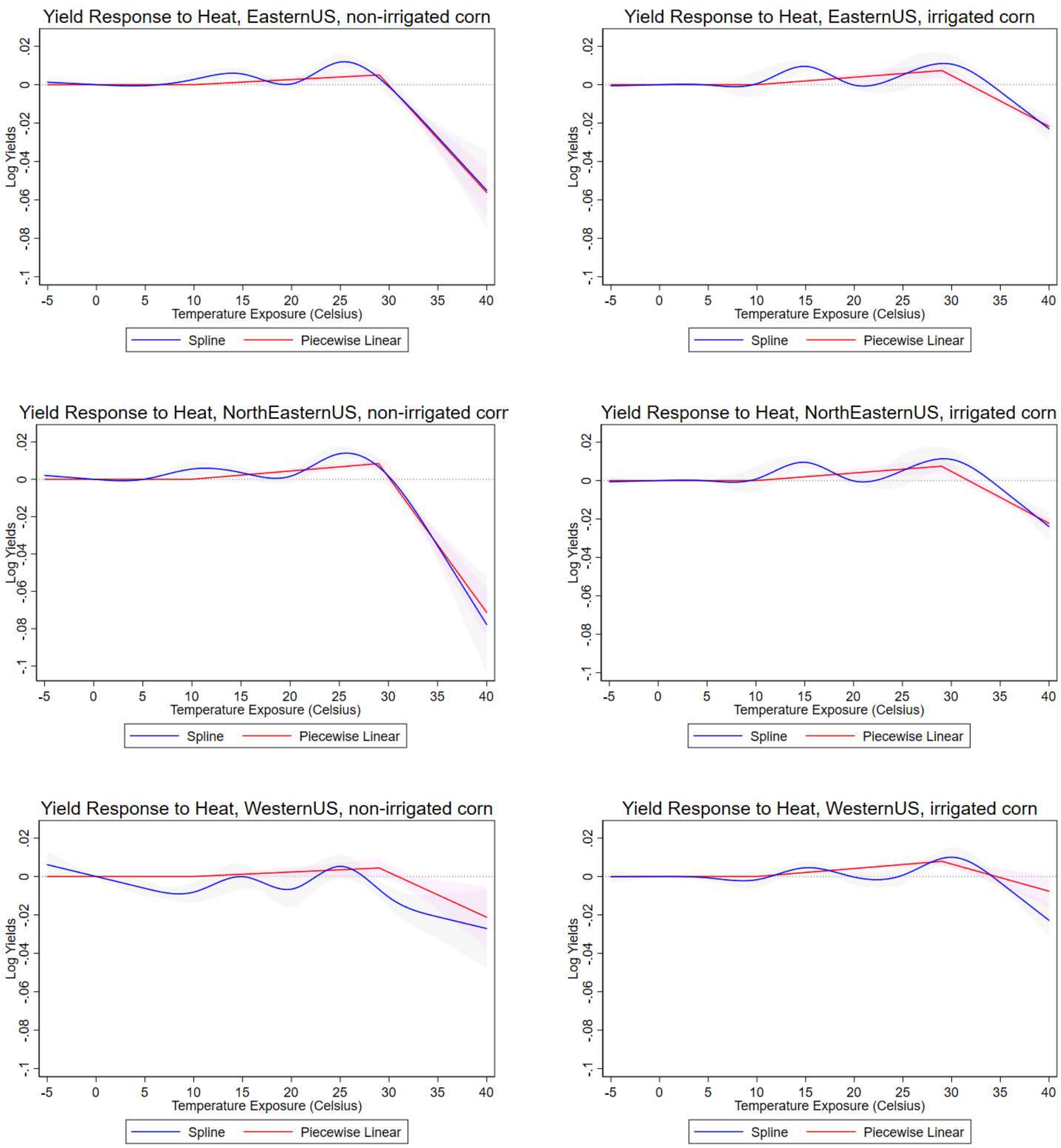
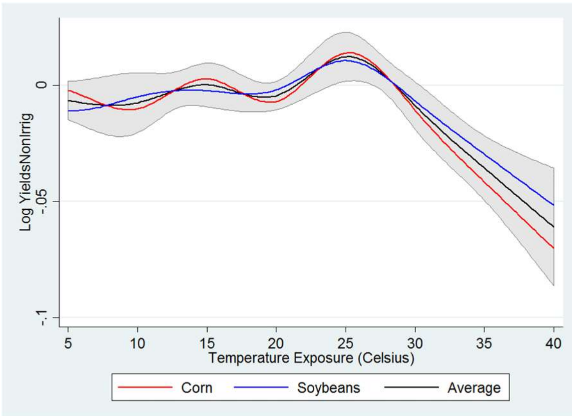


Figure A-1. The results for Western, Eastern and North Eastern US, divided by -100 longitude and 36 latitude. Nonlinear relation between temperature and yields for non-irrigated (left) and irrigated (right) corn. Graphs display changes in log yield if the crop is exposed for one day to a particular 1° C temperature interval where I sum the fraction of a day during which temperatures fall within each interval. The 95% confidence band is added as gray area for the polynomial regression.

Figure A-2. The results for two time period samples 1986-2000 and 2001-2015. Nonlinear relation between temperature and yields for noni-irrigated (left) and irrigated (right) corn. Graphs display changes in log yield if the crop is exposed for one day to a particular 1° C temperature interval where I sum the fraction of a day during which temperatures fall within each interval. The 95% confidence band is added as gray area for the polynomial regression.



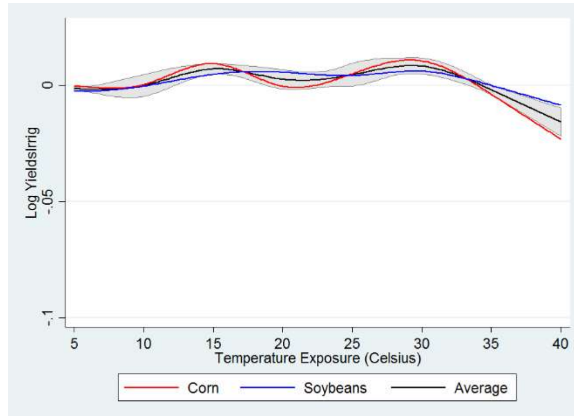


Figure A-3. The results for both corn and soybeans. I assume that the critical temperature threshold for soybeans is 30C and for corn is 29C. Nonlinear relation between temperature and yields for noni-irrigated (left) and irrigated (right) corn and soybeans over the United States. Graphs display changes in log yield if the crop is exposed for one day to a particular 1° C temperature interval where I sum the fraction of a day during which temperatures fall within each interval. The 95% confidence band is added as gray area for the polynomial regression.

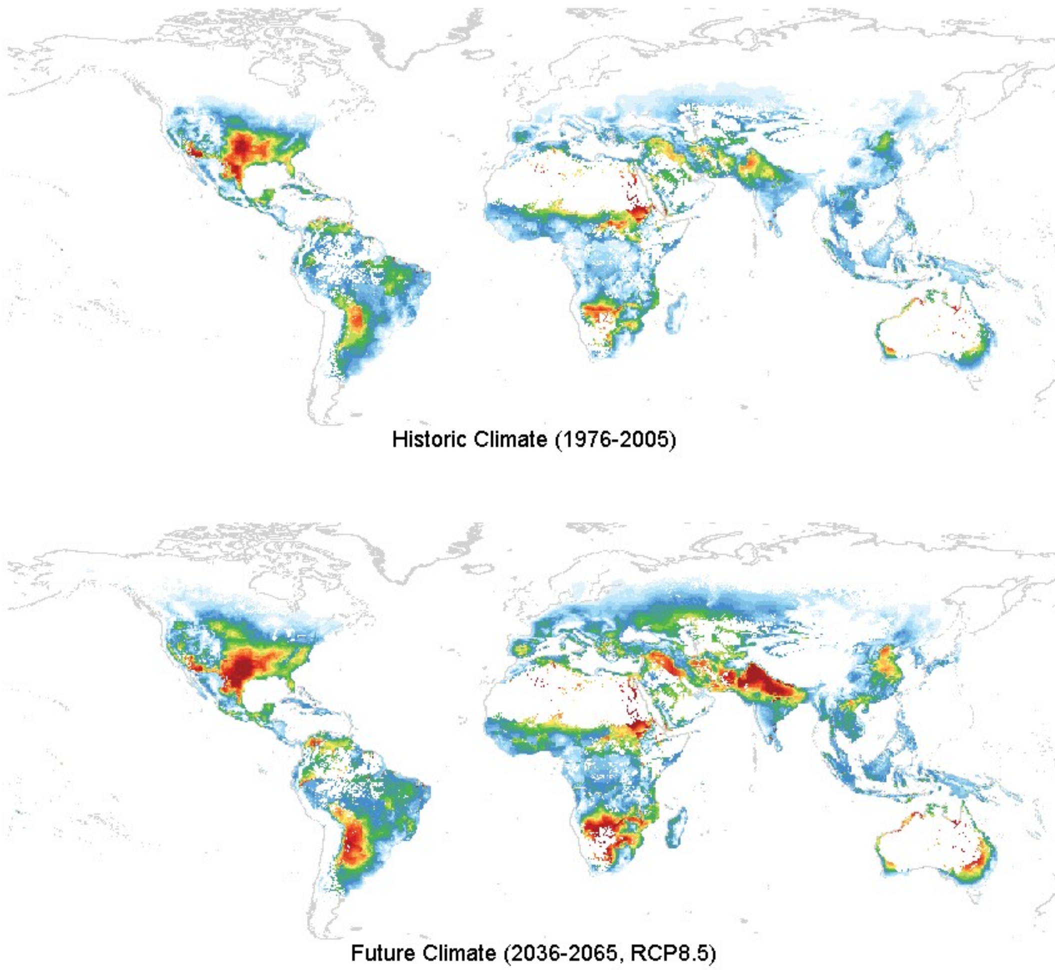


Figure A-4. Standard deviation of degree days above 29C illustrated for NEX-GDDP CCSM4 model.

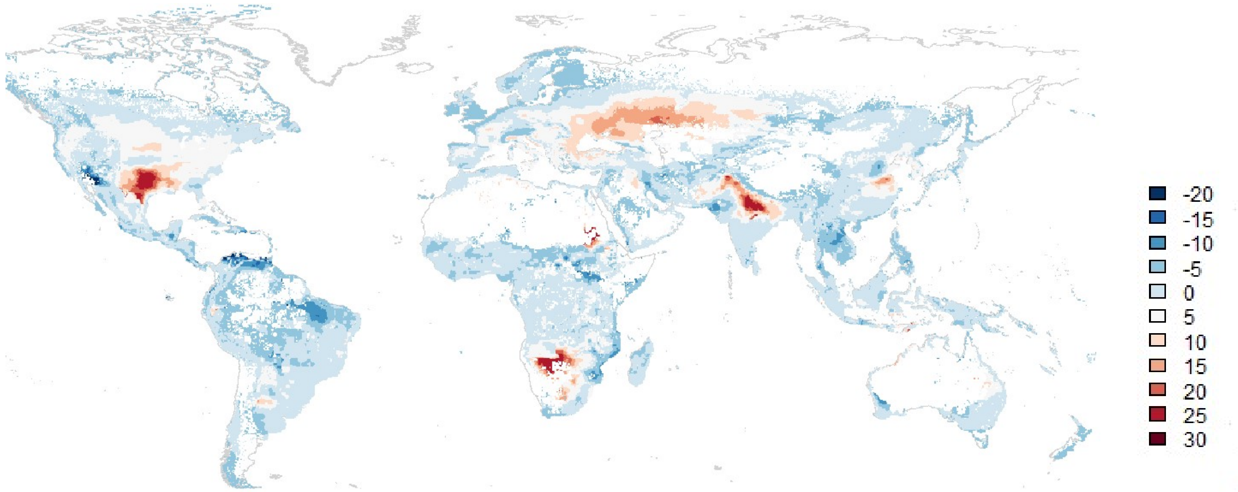


Figure A-5. Change in standard deviation gap defined as:
$GAP_{sd}^{1976-2005} - GAP_{sd}^{1976-2005}, GAP_{sd}^{t} = sd_{non}^{t} - sd_{irr}^{t}$.

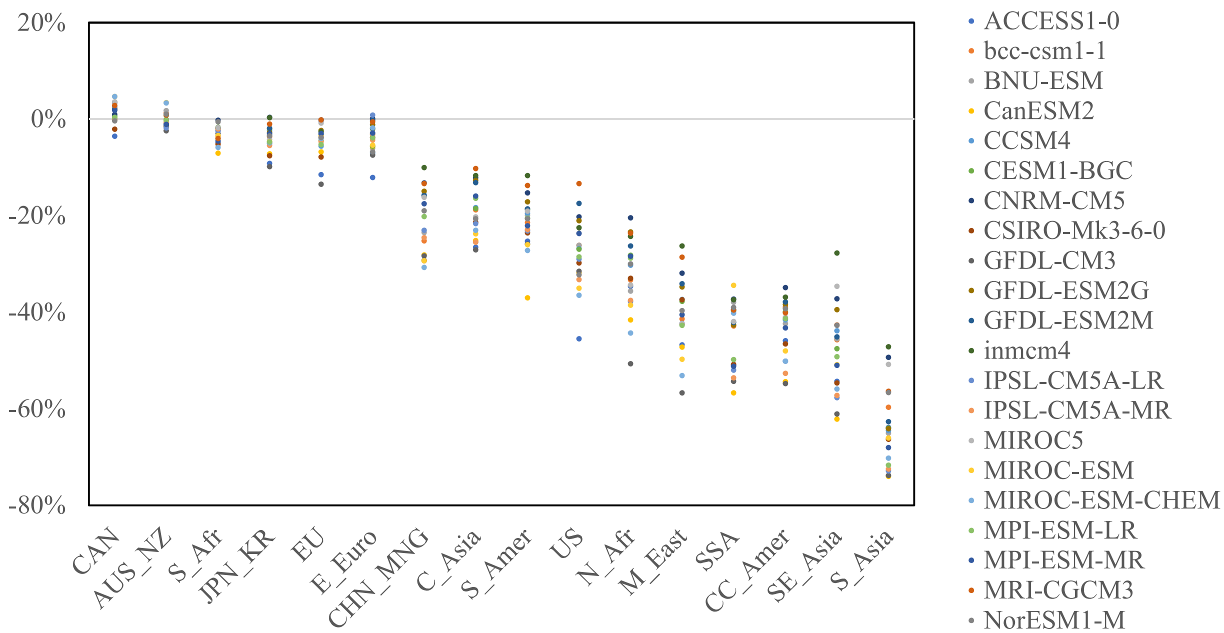


Figure A-6. Climate impacts on corn yields by region 1976-2005 to 2036-2065, averages with no change in area.

APPENDIX B

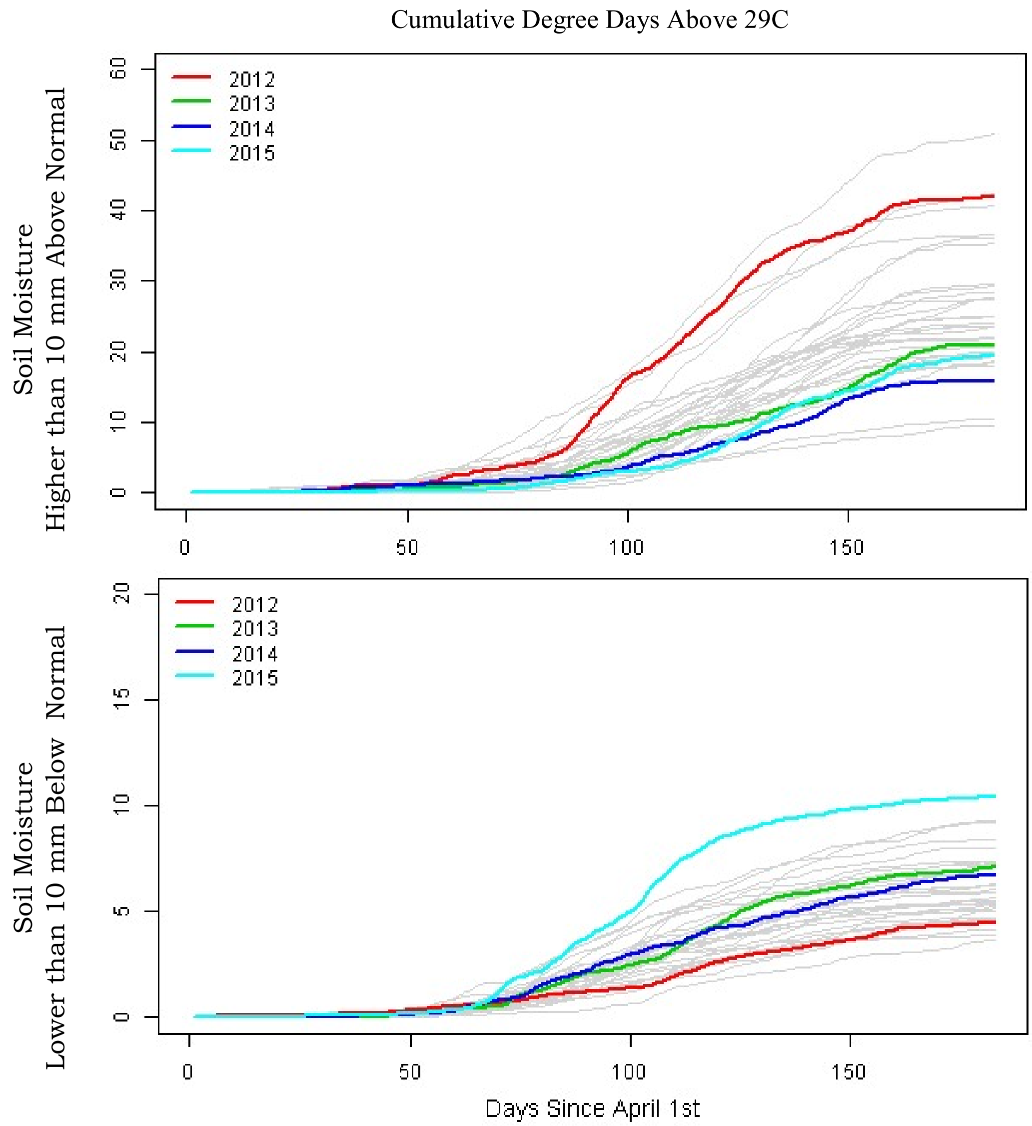


Figure B-1. Figures illustrate cumulative degree days above 29C. The degree days are measured based on daily soil moisture level considering for soil moisture levels.

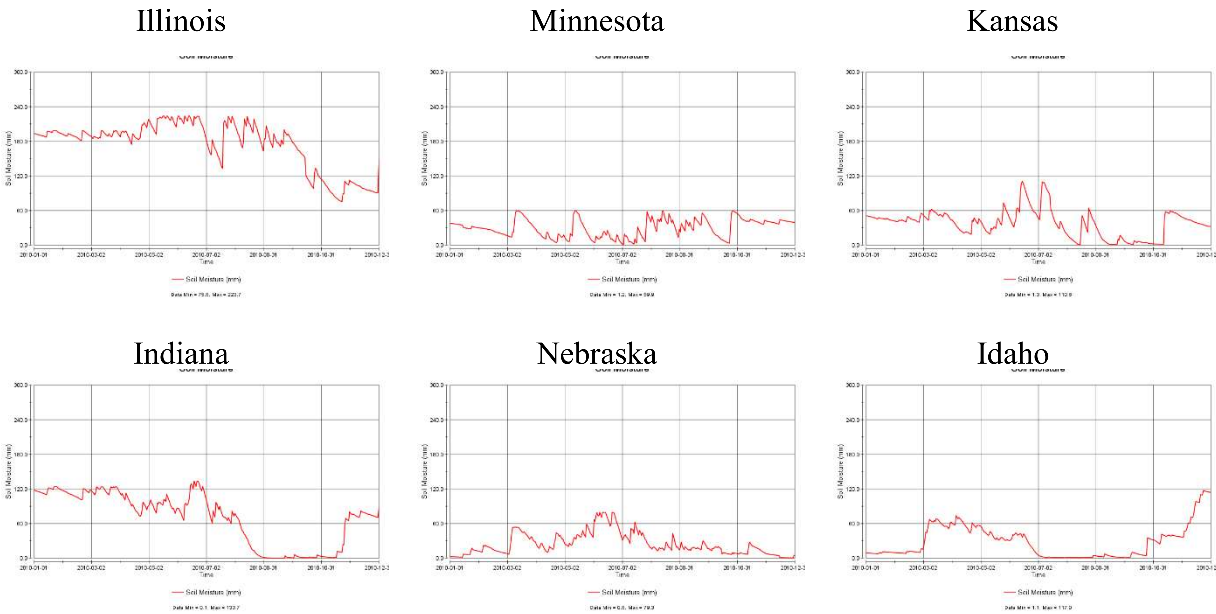


Figure B-2. Soil moisture content variation during 2010 in randomly selected grid cells in major corn producing states. The vertical axis shows soil moisture ranging from 0 to 300 mm. The horizontal axis shows the date. The plots show an example of differences among soil moisture regimes in different regions.

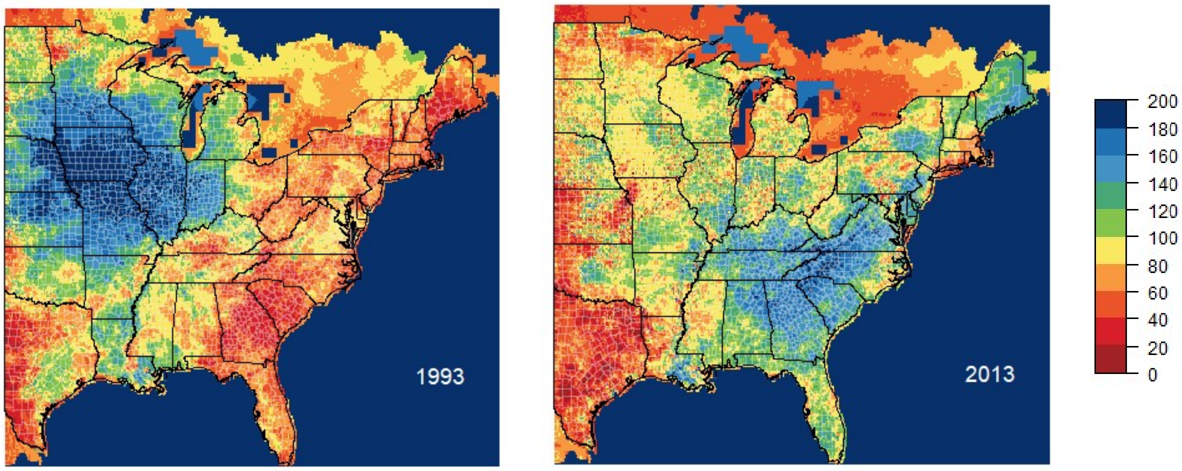
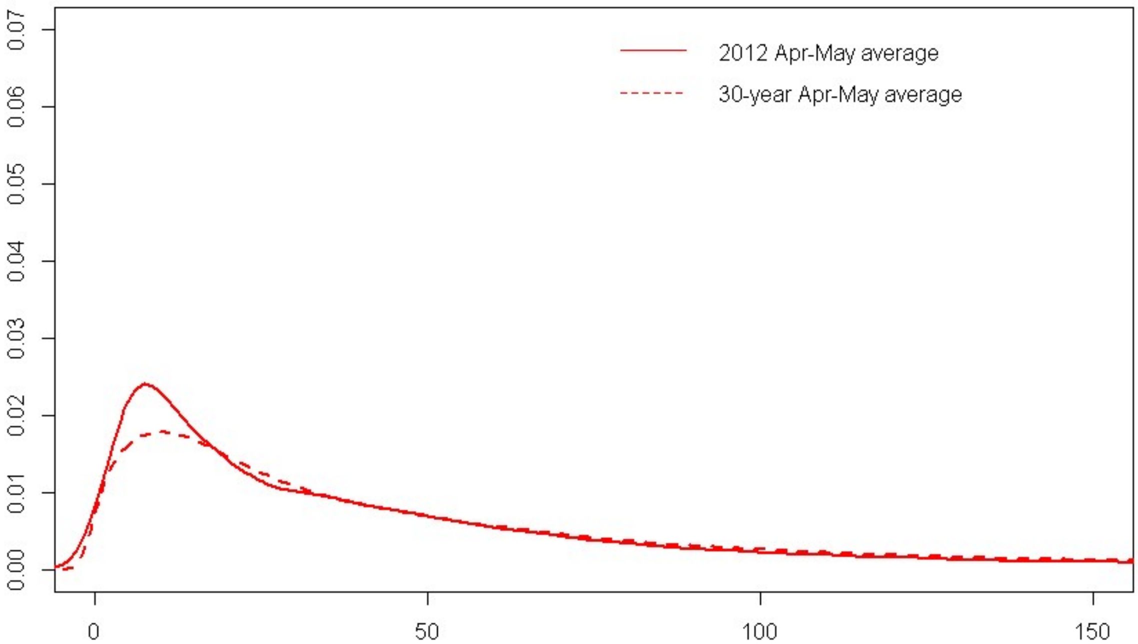


Figure B-3. Maps show the number of days that soil moisture is at least at historic monthly average. The historic average is calculated based on WBM soil moisture level from Apr-Sep for 1981-2015. The plots show an example of soil moisture metrics calculated in this study.

Apr-May



Aug-Sep

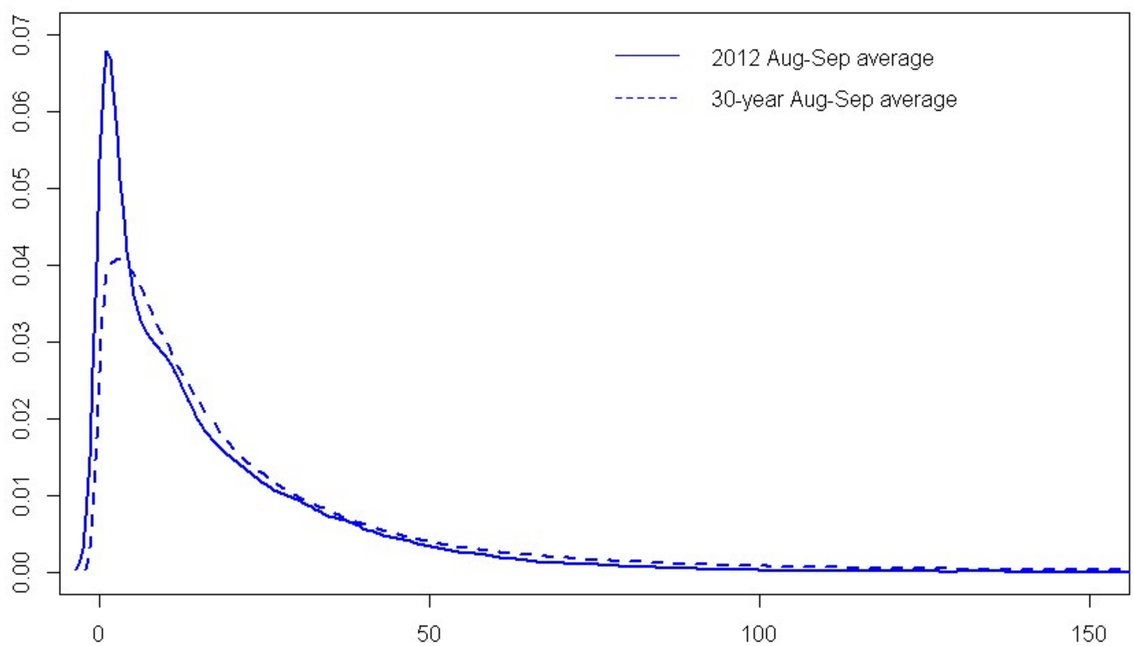


Figure B-4. The distribution of US croplands in terms of average soil moisture for 2012 compared to historical average. This map shows how a drought year like 2012 affects the distribution of lands in terms of average soil moisture. It also shows that soil moisture content is generally lower at Jun-Jul and Aug-Sep compared to Apr-May.

Mean of daily deviations

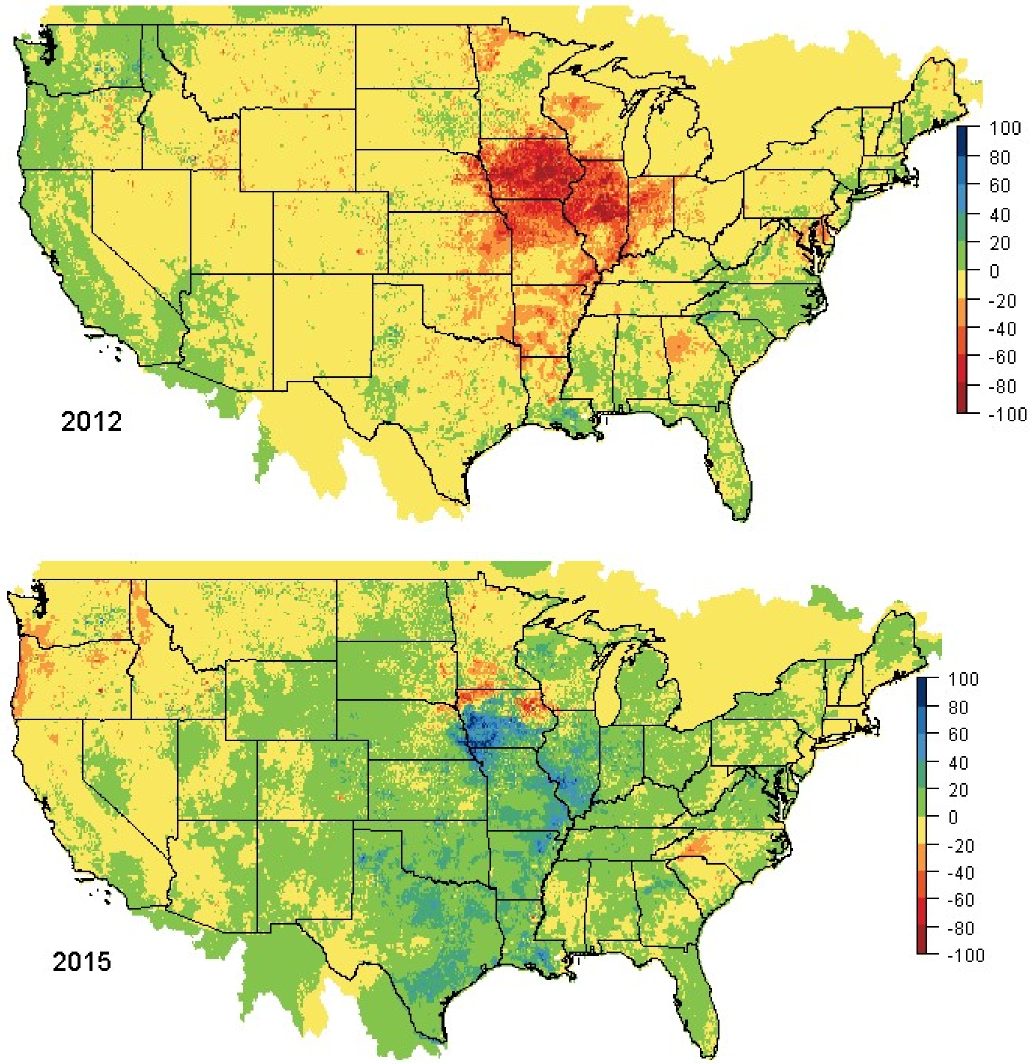


Figure B-5. Soil moisture anomaly. mean of daily deviation from the historical mean.

Table B-1. Estimating corn yield with evapotranspiration and soil moisture fraction

	(1) Log CornYield	(2a) Log CornYield	(2b) Log CornYield	(2-etr) Log CornYield	(2-frc) Log CornYield	(2-alt) Log CornYield
dday10_29C	0.00034***	0.00036***	0.00034***	0.00032***	0.00036***	0.00036***
	(0.00009)	(0.00008)	(0.00008)	(0.00008)	(0.00008)	(0.00009)
dday29C	-0.00531***	-0.00521***	-0.00512***	-0.00519***	-0.00532***	-0.00521***
	(0.00067)	(0.00068)	(0.00069)	(0.00065)	(0.00066)	(0.00068)
prec	0.00066**	0.00028		0.00023	0.00051*	0.00026
	(0.00025)	(0.00026)		(0.00025)	(0.00030)	(0.00026)
prec2	-0.00000**	-0.00000*		-0.00000	-0.00000*	-0.00000
	(0.00000)	(0.00000)		(0.00000)	(0.00000)	(0.00000)
sMoit		0.00440***	0.00364***			
		(0.00093)	(0.00068)			
sMoit2		-0.00002***	-0.00002***			
		(0.00000)	(0.00000)			
etRfd				0.51410***		
				(0.07304)		
etRfd2				-0.08746***		
				(0.02234)		
SMf					0.10893	
					(0.11225)	
SMf2					0.04099	
					(0.08595)	
smoit						0.00444***
						(0.00092)
smoit2						-0.00002***
						(0.00000)
_cons	3.71461***	3.65382***	3.76748***	3.63989***	3.64296***	3.65090***
	(0.17304)	(0.16026)	(0.10831)	(0.15606)	(0.15195)	(0.16145)
Obs.	69923	69923	69923	69923	69923	69923
R-squared	0.46856	0.47485	0.47132	0.47851	0.47051	0.47510

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

Notes: Table lists regression coefficients and shows standard errors in brackets. Temperature is in degree Celsius, soil moisture in mm in 1000 mm topsoil. Soil moisture volume, soil moisture fraction, and evapotranspiration are obtained from WBM at 6 arcmin output while degree days calculated based on temperatures from PRISM at 2.5 arcmin. Soil moisture from WBM is interpolated to PRISM grids with smoit showing the nearest neighbor method and sMoit showing bilinear method. They are aggregated from grid cells to counties based on crop area weight. Yield data is acquired from USDA.

Table B-2. Estimating corn yield including SD of water related indicators

	(1-sd) Log CornYield	(2-sd) Log CornYield	(2-etr-sd) Log CornYield	(2-frc-sd) Log CornYield
dday10_29C	0.00034***	0.00035***	0.00035***	0.00036***
	(0.00008)	(0.00008)	(0.00008)	(0.00008)
dday29C	-0.00523***	-0.00476***	-0.00502***	-0.00520***
	(0.00068)	(0.00063)	(0.00064)	(0.00065)
prec	0.00077***	0.00054***	0.00028	0.00076***
	(0.00022)	(0.00019)	(0.00021)	(0.00027)
prec2	-0.00000**	-0.00000***	-0.00000	-0.00000**
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
precip_SD	-0.00742**	-0.00239	-0.00627*	-0.00710**
	(0.00348)	(0.00260)	(0.00320)	(0.00309)
sMoit		0.00804***		
		(0.00100)		
sMoit2		-0.00003***		
		(0.00000)		
sMoit_SD		-0.00646***		
		(0.00097)		
etRfd			0.73509***	
			(0.09823)	
etRfd2			-0.13448***	
			(0.02341)	
etRfd_SD			-0.35001***	
			(0.09418)	
SMf				0.86690***
				(0.19533)
SMf2				-0.69268***
				(0.17862)
SMf_corn_SD				-0.54312***
				(0.10420)
_cons	3.70454***	3.64349***	3.67527***	3.57464***
	(0.16718)	(0.14075)	(0.15832)	(0.14514)
Obs.	69923	69923	69923	69923
R-squared	0.46938	0.49509	0.48204	0.47591

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

Notes: *Table lists regression coefficients and shows standard errors in brackets. Temperature is in degree Celsius, soil moisture in mm in 1000 mm top soil. Soil moisture volume, soil moisture fraction, and evapotranspiration are obtained from WBM at 6 arc min output while degree days calculated based on temperatures from PRISM at 2.5 arc min. Soil moisture from WBM is interpolated to PRISM grids with smoit showing nearest neighbor method and sMoit showing bilinear method. They are aggregated from grid cells to counties based on crop area weight. Yield data is acquired from USDA.*

Table B-3. Estimating corn yield assuming three growth stages

	(1-bimo) Log CornYield	(2-bimo) Log CornYield	(2-etr-bimo) Log CornYield	(2-smf-bimo) Log CornYield
dday10_29C	0.00032***	0.00032***	0.00032***	0.00035***
	(0.00009)	(0.00008)	(0.00008)	(0.00007)
dday29C	-0.00488***	-0.00469***	-0.00498***	-0.00496***
	(0.00064)	(0.00063)	(0.00064)	(0.00066)
precip_SUM Apr-May	0.00051**			
	(0.00021)			
precip_SUM Jun-Jul	0.00099***			
	(0.00021)			
precip_SUM Aug-Sep	0.00051**			
	(0.00025)			
precip2	-0.01713***			
	(0.00593)			
sMoit_AVG Apr-May		-0.00018		
		(0.00023)		
sMoit_AVG Jun-Jul		0.00276***		
		(0.00045)		
sMoit_AVG Aug-Sep		0.00148***		
		(0.00036)		
sMoit2		-0.00002***		
		(0.00000)		
etRfd_AVG Apr-May			0.07141**	
			(0.03269)	
etRfd_AVG Jun-Jul			0.24134***	
			(0.03645)	
etRfd_AVG Aug-Sep			0.11654***	
			(0.02818)	
etRfd2			-0.08517***	
			(0.02697)	
SMf_corn_AVG Apr-May				-0.22313***
				(0.07582)
SMf_corn_AVG Jun-Jul				0.22494***
				(0.04077)
SMf_corn_AVG Aug-Sep				-0.11954*
				(0.06855)
SMf2				0.22370
				(0.15146)
_cons	3.70157***	3.75821***	3.66784***	3.78214***
	(0.16001)	(0.10819)	(0.11584)	(0.11544)
Obs.	69923	69923	69923	69923
R-squared	0.47682	0.48093	0.47835	0.47498

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

Notes: *Table lists regression coefficients and shows standard errors in brackets. Temperature is in degree Celsius, soil moisture in mm in 1000 mm top soil. Soil moisture volume, soil moisture fraction, and evapotranspiration are obtained from WBM at 6 arc min output while degree days calculated based on temperatures from PRISM at 2.5 arc min. Soil moisture from WBM is interpolated to PRISM grids with smoit showing nearest neighbor method and sMoit showing bilinear method. They are aggregated from grid cells to counties based on crop area weight. Yield data is acquired from USDA.*

Table B-4. Regression results for model 4 including extremes

	(4) Log CornYield
Mean of Moisture Apr-Sep	0.00333** (0.00147)
Mean of Moisture Apr-Sep Squared	-0.00002*** (0.00000)
Within Season SD of Degree Days 10-29℃ Apr-Sep	-0.00355*** (0.00100)
Mean of Negative Deviations from Normal Moisture Apr-Sep	-0.00421*** (0.00137)
Largest Negative Deviation from Normal Moisture Apr-Sep	-0.00135** (0.00052)
Degree Days from 10C to 27C with Soil Moisture Lower than 25 mm Below Normal	0.00045*** (0.00012)
Degree Days from 10C to 27C with Soil Moisture within ±25 mm around Normal	0.00055*** (0.00007)
Degree Days from 10C to 27C with Soil Moisture Higher than 25 mm Above Normal	0.00038*** (0.00006)
Degree Days above 27C with Soil Moisture Lower than 25 mm Below Normal	-0.00399*** (0.00068)
Degree Days above 27C with Soil Moisture within ±25 mm Around Normal	**-0.00321*** (0.00028)**
Degree Days above 27C with Soil Moisture Higher than 25 mm Above Normal	-0.00255*** (0.00063)
_cons	3.68037*** (0.12468)
Obs.	69753
R-squared	0.51581

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Notes: *Table lists regression coefficients and shows standard errors in brackets. Temperature is in degree Celsius, soil moisture in mm in 1000 mm top soil. Soil moisture is obtained from WBM at 6 arc min output while degree days calculated based on temperatures from PRISM at 2.5 arc min. They are aggregated from grid cells to counties based on crop area weight. Yield data is acquired from USDA.*

APPENDIX C

Validation for SIMPLE-G

The SIMPLE model has been validated (Baldos & Hertel, 2014) to replicate the observed history. I am interested to evaluate the ability of the model in replicating the pattern of changes in water and land use. To validate the SIMPLE-G-W, here I show a primary but helpful exercise. I calculated the changes in aggregate yields of irrigated and non-irrigated crops as reported by USDA from ~2002 to ~2007. I also calculated the change in the irrigation costs from USDA FRIS.

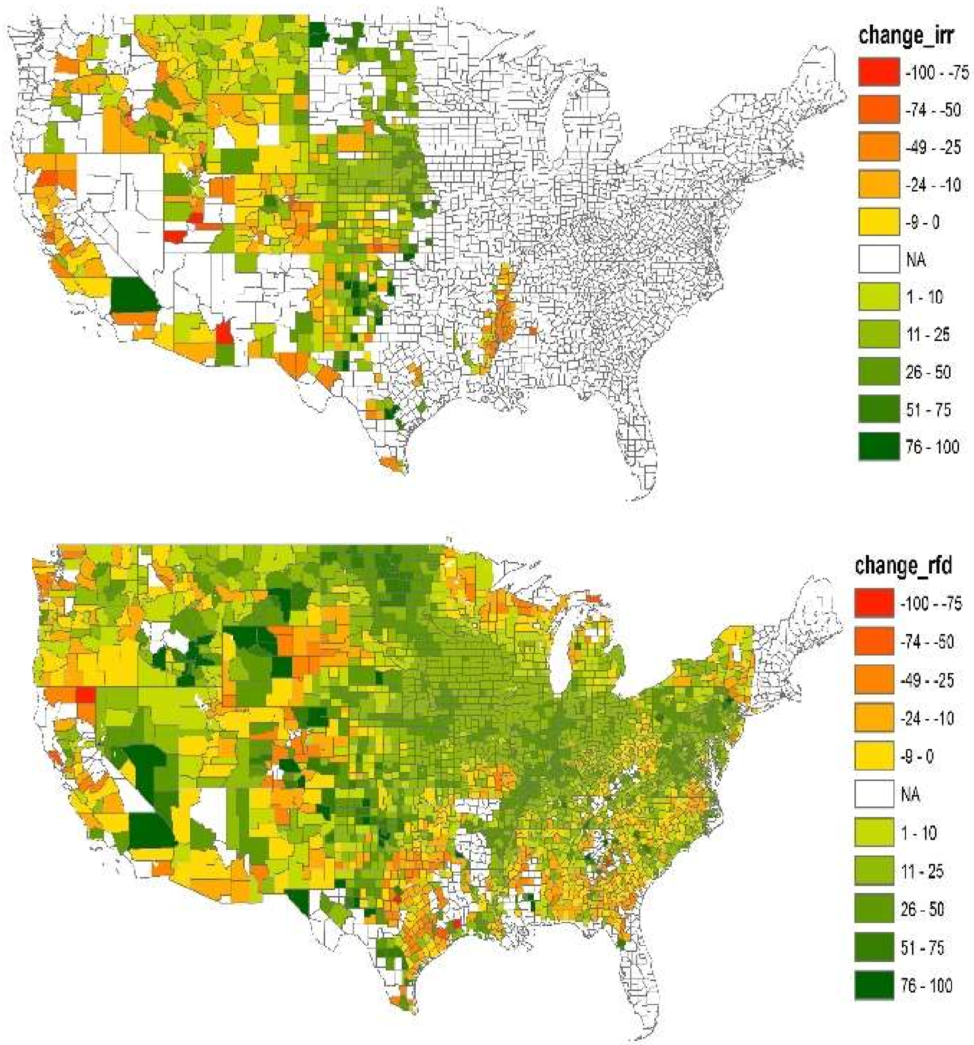


Figure C-1. Percentage change in yields of aggregate irrigated crops (top) and non-irrigated crops (down).

I apply these change in the model to see the direction of changes in irrigation. Figure C-2 compares the projected change in irrigated area (left) and reported change in irrigated area from

USDA (right). While USDA does not provide the gridded data source of the right panel, I find that direction of the projected changes is in line with USDA. However, further attempts are required for validation of the model and estimation of reallocation parameters.

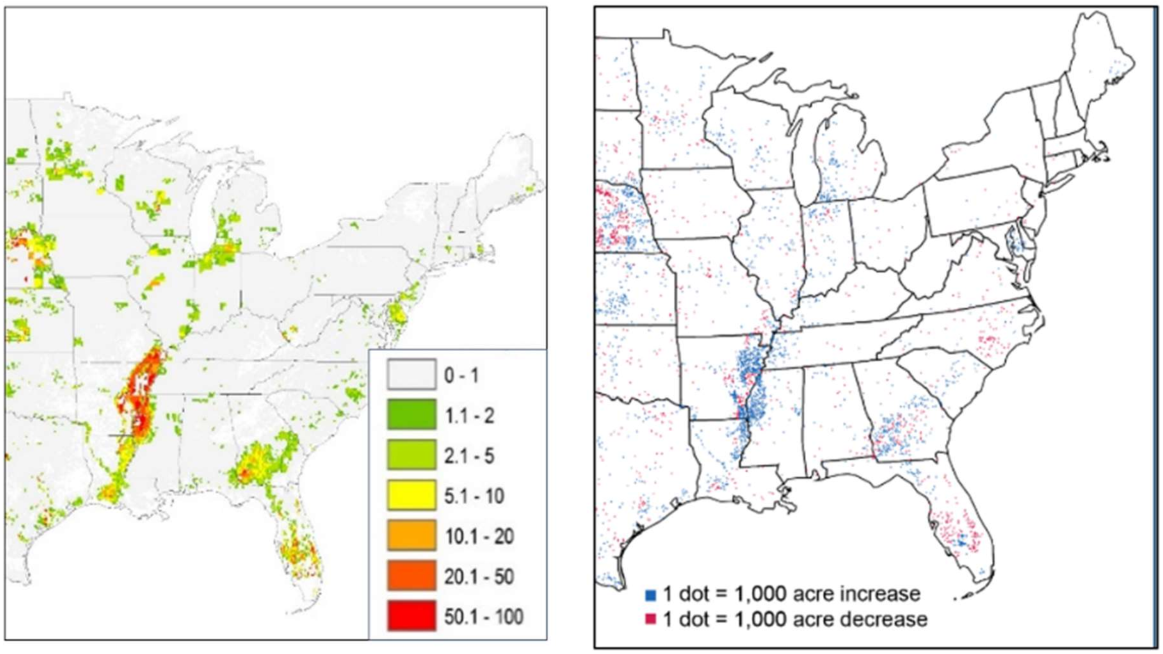


Figure C-2. Change in irrigated area as projected by SIMPLE-G-W (left, in 1000 ha) and as reported by USDA (right).

Figures C-3 illustrated the Farm Resource Regions used in the model. Also, Figure C-4 shows the extent of irrigation areas in the SIMPLE-G-W.

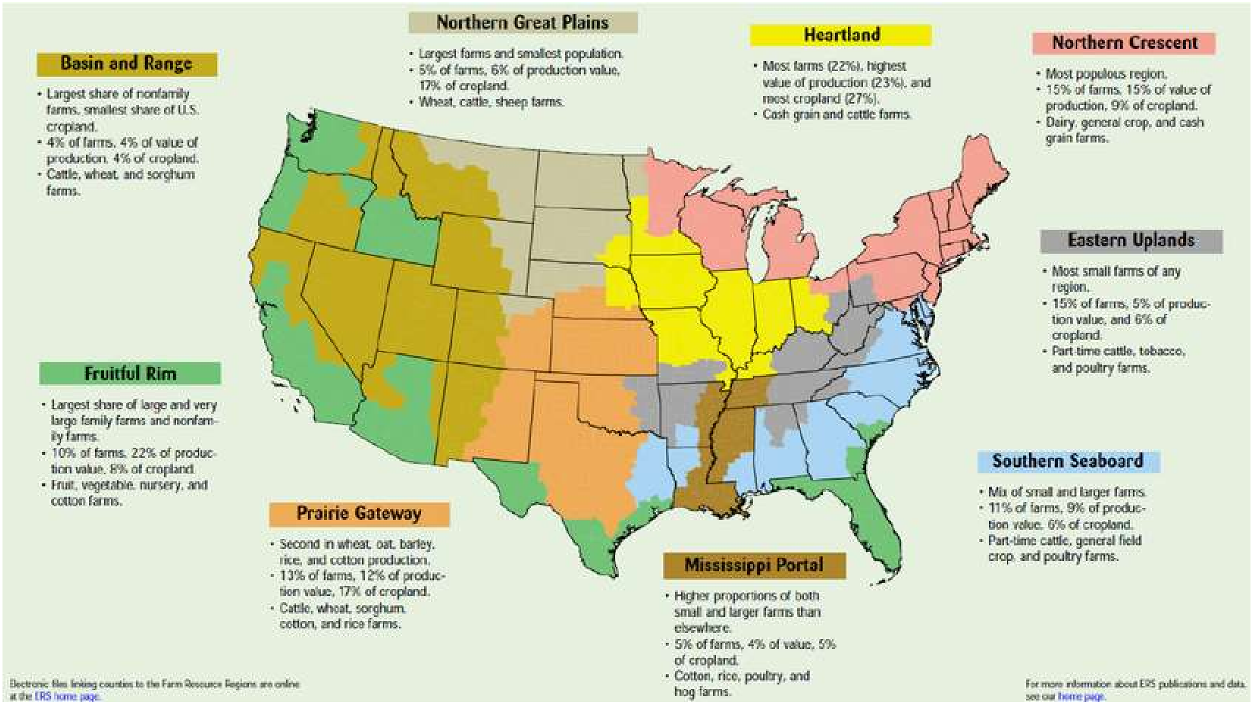


Figure C-3. USDA Farm Resource Regions provided by USDA-ERS.

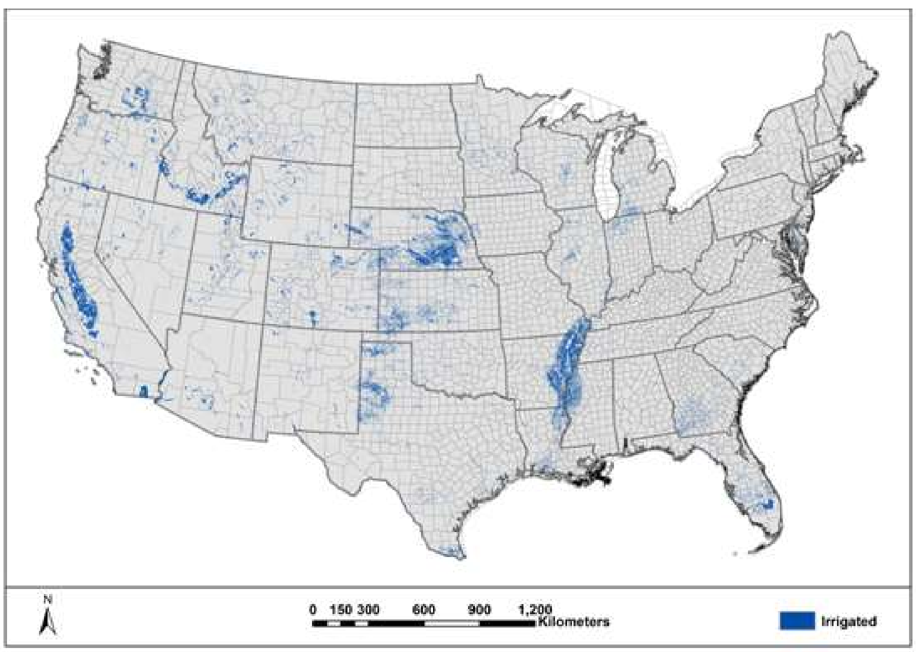


Figure C-4. Moderate Resolution Imaging Spectroradiometer (MODIS) Irrigated Agriculture Dataset for the United States (MIrAD-US) provided by USGS (Brown & Pervez, 2014)