How does temperature affect land values in the East of the US?

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PRELIMINARY DRAFT – PLEASE DO NOT CIRCULATE NOR QUOTE

Abstract

We test three functional forms that relate land values and temperatures in a Ricardian model of US agriculture: a quadratic relationship based on average seasonal temperature and precipitations, a non-linear relationship based on degree days and a flexible functional form in which average seasonal temperatures are interacted with dummies. Results obtained using growing season average temperature and degree days are not significantly different. We do not find evidence of a threshold if we include degree days above 34 °C. Cold degree days instead matter and should not be omitted. Models that use a quadratic specification of average temperatures perform better than models that use degree days. This is in line with the agronomic literature. Degree days should be used to estimate the duration of phenological events rather than yields. Estimates of uniform +2 °C and +4 °C warming indicate that warming is significantly harmful for agriculture in the East of the US. The use of a more flexible functional form reveals that the relationship between temperatures and land values is flatter than in the quadratic. Seasons, within and outside the growing season, significantly affect land values and allow separating beneficial and harmful effects of warming more effectively.

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1 Introduction

A large literature uses agro-economic models to examine the relationship between crop yields, crop profitability and climate (Adams et al. 1990; Rosenzweig and Parry 1994; Adams et al. 1995; Reilly et al. 2003). A problem with agro-economic models is that farmers' decisions are poorly modeled, adaptation is limited and they only cover major crops.

Mendelsohn, Nordhaus, and Shaw 1994 (MNS) argue that a cross-section analysis of farmers that operate under different climates is able to provide a more accurate description of the relationship between climate and long-run agricultural profitability. MNS use a hedonic econometric model in which land values – a measure of long-term farm profitability – are regressed on climatic and other control variables. The method has been used to study impacts on US agriculture by Mendelsohn and Dinar (2003), Schlenker, Hanemann, and Fisher (2005; 2006), Massetti and Mendelsohn (2011; 2012). The hedonic method has been applied in many countries.

One area of disagreement in the literature concerns the functional form used to introduce climate variables in the hedonic model.

MNS use January, April, July and October climatologies (i.e. 30-year averages) of mean monthly temperature and precipitation data to characterize a quadratic climate surface at county-level. They argue that the quadratic functional form is sufficient to capture a non-linear response of land values to temperatures and precipitations.

The use of monthly mean quadratic temperature variables is instead criticized by Schlenker, Hanemann, and Fisher 2006 (SHF). SHF argue that a quadratic function does not capture severe impacts of abnormally high temperatures on crop yields, and thus on profits and land values. SHF suggest using climatologies of growing season degree days (DD) between 8 and 32 °C and above 34 °C instead of monthly temperatures in the four seasons. Growing season DD are calculated by summing daily mean temperatures that fall within a given interval over the whole growing season (from April 1st to September 30th in SHF study). For example, 8-32 °C DD are computed as follows: days with mean temperature *t* below 8 °C contribute with zero DD, days with temperature between 8-32°C contribute with *t*-8 DD. Analogously, a day with mean temperature above 34 C contributes with *t*-34 DD to the definition of 34 °C DD. By separating days with temperatures that are beneficial (between 8 and 32°C) from days with temperatures that are harmful (above 34°C) SHF try to capture the different effect of warming at different temperature levels.

SHF show that the model that uses a quadratic function of 8-32 °C DD during the growing season and controls for the number of degree days above 34 °C performs better than the model that uses monthly temperatures. In particular, counties that record days with mean temperature above 34 °C have significantly lower land values, *ceteris paribus*. This implies that global warming, especially if concentrated during summer time and in counties where temperatures are already close to 34 °C may be very harmful to US agriculture.

The work by SHF raises three intriguing questions. First is the quadratic functional form capable of reproducing the relationship between climate and yields that emerges in the agronomic literature? Second, is the quadratic able to capture “threshold” effects of heat on crop yields and on land values? Third, does climate outside the growing season – both temperature and precipitations - matter or is irrelevant, as postulated by SHF?

In this paper we address those three questions. We test three functional forms: a quadratic relationship based on average seasonal temperature and precipitations, a non-linear relationship based on degree days and a flexible functional form in which average seasonal temperatures are interacted with dummies to allow a different response of land values at different climates. We assess strengths and weaknesses of these models in light of the econometric evidence and in light of the agronomic literature. We also test if climate outside the growing season matters and what are the implications of not including it in the hedonic model.

We closely follow SHF in setting up our model. We pool together county-level land values, county-level climate variable and other control variables over four US Agricultural Census years (1982-2002). As SHF we focus on counties east of the 100th meridian in the US. We use instead different climate data.

We build a unique climate dataset for US counties using the North American Regional Reanalysis (NARR) “Merge” dataset prepared for the National Climatic Data Center.[1] The NARR dataset provides a high spatial (32 km) and temporal (3 hour) analyses of North America and adjacent oceans and land masses from October 1978 to December 2011. With this data we can compute degree days using actual mean daily temperatures instead of deriving them from mean monthly temperatures using smoothing techniques, as in SHF. Our data is therefore qualitatively superior to that used by SHF.

The rest of the paper is structured as follows. Section 2 surveys the agronomic literature that estimates the relationship between temperature and crop yields and presents descriptive statistics of climate data to assess the merits of using degree days instead of average seasonal temperatures. Section 3 illustrates the models that are empirically tested and data. Section 4 presents and discusses results. Conclusions follow.

2 Climate and land values

Mendelsohn, Nordhaus, and Shaw (1994) (MNS) is the first study that uses the variation of climate and of land values to estimate the welfare impact of climate change on agriculture.[2] They use a hedonic method that is often called “Ricardian” because it relies on the fact that land values reflect the long-

[1] See http://nomads.ncdc.noaa.gov/docs/ncdc-narrdsi-6175-final.pdf for further information.

[2] Johnson (1970) used a similar method to study how climate affects the productivity of land in the United States. Johnson was not interested in climate change because at the time it was not yet a concern. Johnson was rather interested in finding the value of methods to change weather, which apparently were attracting a lot of interest at the end of the ‘60s.

term profitability of land as first suggested by Ricardo.[3] MNS regress US agricultural land values on climate, soil, geographic characteristics and other socio-economic variables. A general Ricardian equation is built as follows:

$$Y_{i,t} = \boldsymbol{\beta}\, h(C_i) + \boldsymbol{\gamma} X_{i,t} + \boldsymbol{\theta} Z_i + \epsilon_{i,t}\ . \tag{1}$$

Where Y is the land value per hectare at time t for observation i, $h(\cdot)$ is a generic function of the vector of climate variables, X is a set of socio-economic variables that vary over time, Z is a set of geographic and soil characteristics and ε is assumed to be a random component. The long-run relationship between climate (a long-run average of weather) and land values is captured by the coefficient $\boldsymbol{\beta}$. Estimates of $\boldsymbol{\beta}$ provide information on the sensitivity of land values to climate and can be used to estimate the welfare impact of climate change.

MNS describe climate using a quadratic functional form for average temperature and precipitations in four representative months:

$$Y_{i,t} = \beta_0 + \sum_k \beta_{1,k} T_{i,k} + \sum_k \beta_{2,k} T_{i,k}^2 + \sum_k \beta_{3,k} P_{i,k} + \sum_k \beta_{4,k} P_{i,k}^2 + \boldsymbol{\gamma} X_{i,t} + \boldsymbol{\theta} Z_i + \epsilon_{i,t}\ , \tag{2}$$

where $k = \{\,\text{January}, \text{April}, \text{July}, \text{October}\,\}$. Other Ricardian analysis of US agriculture use average temperature and precipitations over the four seasons (Massetti and Mendelsohn 2011; 2012).

Ricardian studies that use a seasonal characterization of climate find that warming in spring and in autumn is beneficial for farmers because they have a longer growing season. Warming in winters and in summers lowers instead land values. Cold winter days kill bugs. If winter becomes warmer, farmers must spend more in pesticides to protect their crops, lowering profits and land values. Hot summer days are harmful for crops because they suffer from heat stress.

Schlenker, Hanemann, and Fisher (2006) (SHF) claim that a quadratic, seasonal model does not characterize well the agronomic relationship between heat and crop growth. SHF argue that crops respond to the overall amount of heat they receive during the growing season, no matter when. In

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[3] In a more formal language, the Ricardian method assumes that the value per hectare of farmland in location i (V_i) is equal to the discounted value of future profits from farm operations:

$$Y_{i,t} = \int_{s=t}^{\infty} \left(\sum P_{i,s} Q_{i,s}\left(I_{i,s}, C_i, X_{i,s}, Z_i\right) - R_{i,s} I_{i,t} \right) e^{rs} ds$$

where $P_{i,s}$ denotes the set of farm output prices. $Q_{i,s}$ denotes farm output, which is a function of a set of inputs $I_{i,s}$, of climate conditions C_i, of a set $X_{i,s}$ of socio-economic drivers that might change over time – e.g. density of population and income per capita – and a set of variables that do not change over time – e.g. elevation, soil characteristics, distance from metropolitan areas. $R_{i,s}$ collects input prices. e^{rs} is the discount factor.
Profit maximizing farmers will chose the vector of inputs $I_{i,s}$ to maximize the expected value of farmland per hectare. The choice of inputs should be considered here in a broad sense: farmers can choose what farm type they have, whether to irrigate or not and, what crops to grow and the amount of fertilizers and other inputs. It is possible to solve the maximization problem of the farmer and show that land values ultimately depend on a set of exogenous variables:

$$Y_{i,t} = f\left(C_i, X_{i,t}, Z_i\right)$$

particular, they argue that crops grow well when temperatures are within a mild range. Within this interval plant growth is linear in temperature. Outside of this mild temperature interval the effect of temperature on crop growth is strongly non-linear. Crops do not grow at all if it is too cold and they grow much less if it is too hot because they suffer from heat stress.

In order to capture these relationships SHF suggest replacing seasonal temperatures with climatologies of *degree days* over the growing season. Degree days (DD) are equal to the sum of daily mean temperatures within a given time interval *R* during the growing season. There are several ways to calculate DD. SHF do not include days with mean temperature below 8 °C and cap DD at 32 °C (see Figure 1). Denoting with $dd8\text{-}32_{i,r}$ the contribution of day $r \in R$ in location *i* to 8-32 °C DD ($\mathrm{DD8\text{-}32_i}$) they calculate degree days as follows:

$$dd8\text{-}32_{i,r} = \begin{cases} 0 \text{ if } & t_{i,r} \leq 8 \\ t_i - 8 \text{ if } & 8 < t_{i,r} \leq 32 \\ 24 \text{ if } & t_{i,r} > 32 \end{cases} \qquad DD8\text{-}32_i = \sum\nolimits_{r \in R} dd_{i,r} \tag{3}$$

where we omitted the time subscript for ease of notation. In order to capture the effect of very hot days on land values SHF also use degree days above 34 °C (DD34), calculated as follows:

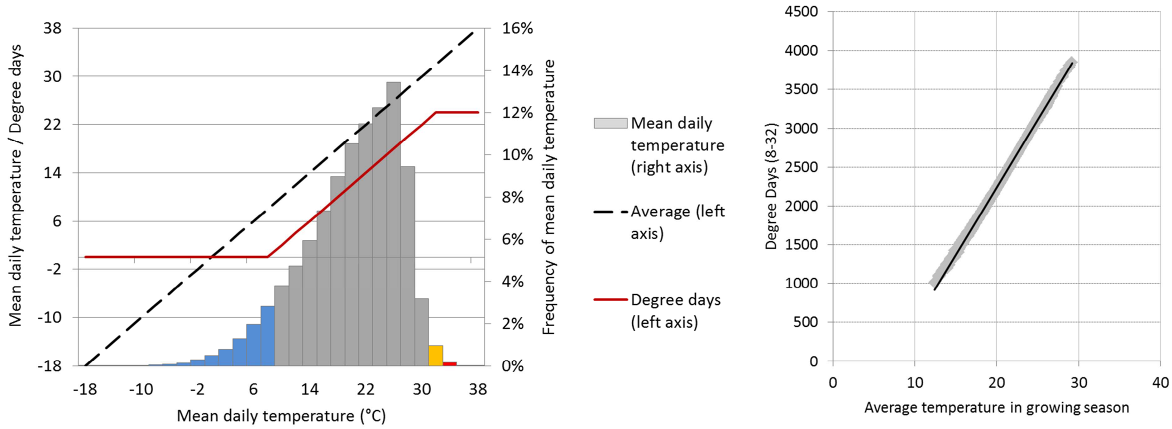
$$dd34_{i,r} = \begin{cases} 0 & \text{if } t_{i,r} \leq 34 \\ t_i - 34 & \text{if } t_{i,r} > 34 \end{cases} \qquad DD34_i = \sum\nolimits_{r \in R} dd34_{i,r} \tag{4}$$

DD are calculated for all years during a 30-year time period and then averaged to obtain climatologies. SHF transform the Ricardian model described in Equation (1) using climatologies of DD8-32 and DD34 together with total growing season mean precipitations:

$$Y_{i,t} = \beta_0 + \beta_1 DD8\text{-}32_i + \beta_2 DD8\text{-}32_i^2 + \beta_3 DD34_i + \beta_4 P_i + \beta_4 P_i^2 + \boldsymbol{\gamma} X_{i,t} + \boldsymbol{\theta} Z_i + \epsilon_{i,t} \tag{5}$$

In summary, SHF argue that: (1) degree days between 8 and 32 °C are better than average temperature; (2) degree days should be capped at 32 °C; (3) the effect of degree days rises linearly from 8 to 32 °C and then falls precipitously after 34 °C; (4) cold degree days do not matter; (5) seasons (spring summer fall) within the growing season do not matter; (6) all that matters is degree days over a fixed growing season (winter or non-growing season does not matter).

The model used by SHF is certainly attractive and raises legitimate doubts on the ability of a simple quadratic functional form to describe the relationship between climate and land values. It also raises the question of whether seasons within the growing season matter and if climate outside the growing season affects or not agricultural productivity.



Notes. Left panel: the solid red line indicates the contribution of mean daily temperature to the total sum of degree days; the dashed black line indicates how each day contributes to the standard seasonal average. The underlying distribution of mean daily temperatures from 1981 to 2010 from April 1st to September 31st is from the NARR dataset. Only grid-points east of the 100th meridian (22,300,380 data points). Blue bars indicate days with temperature below 8°C (5% of total); yellow bars indicate days above 32°C and below 34°C (1% of total); red bars indicate days above 34°C (0.18% of total). Range: from -17.4 to 39.3°C; mean: 20.9°C; median: 22.2°C. Right panel: scatter plot of mean temperature between April and September and degree days calculated at counties' centroids for 2351 US counties east of the 100th meridian. The R-squared of the linear fit is in excess of 0.999.

Figure 1. Degree days and distribution of mean daily temperatures east of the 100th meridian in the US.

Before testing the degree days model against the quadratic model using our climate dataset we highlight several problems of the model used by SHF. First, we raise doubts on the relevance of DD compared to average seasonal temperature and we highlight several problems that emerge when using DD. Second, using evidence from agronomic studies we question the validity of assuming that heat affects crop yields linearly between 8 and 32 °C and then precipitously reduces yields when temperature is above 34 °C. Third, using data on present planting and harvesting dates, we argue that a rigid definition of the growing season is problematic and climate outside the growing season matters.

2.1 Are degree days better than average temperature?

Despite looking a sophisticated measure of temperature, degree days, as used by SHF, have a lot in common with mean seasonal temperatures. Let us consider for example the case in which daily mean temperatures are always between 8 and 32 °C during the growing season.[4] In this case, the estimated coefficient of degree days in a Ricardian model would be equal to the coefficient of mean growing season temperature, after one subtracts 8 from average temperature and multiply by 183 (the number of days between April 1st and September 30th) with a correction term in the intercept.[5]

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[4] The same would apply to other temperature thresholds. The wider is the temperature interval, the closer degree days are to mean seasonal temperature.

[5] If daily mean temperature is always between 8 and 32 °C during the growing season we have:

$$DD_i = \sum_{r \in R} d_{i,r} = \sum_{r \in R} (t_{i,r} - 8) = \sum_{r \in R} t_{i,r} - R8 = R(\bar{t}_i - 8)$$

where $\bar{t}_i$ is the average temperature during season R.

If there are many days below 8°C or above 32°C degree days and average seasonal temperature diverge. However, this happens under fairly rare circumstances in the East of the US, as illustrated by Figure 1. Even rarer is the case in which counties east of the 100th meridian have mean (over 1981-2010) daily temperatures outside the 8-32 °C interval. The 30-year average mean daily temperature in Iowa City, Iowa, USA, at the center of the "corn belt" is always between 8°C and 32°C from the beginning of April to October.

It should therefore be of no surprise that the correlation between 8-32 °C degree days and mean growing season temperature is in excess of 0.999, as shown in the right panel of Figure 1. Thus, using 8-32 °C degree days or average seasonal temperature is expected to make little difference in Ricardian models.

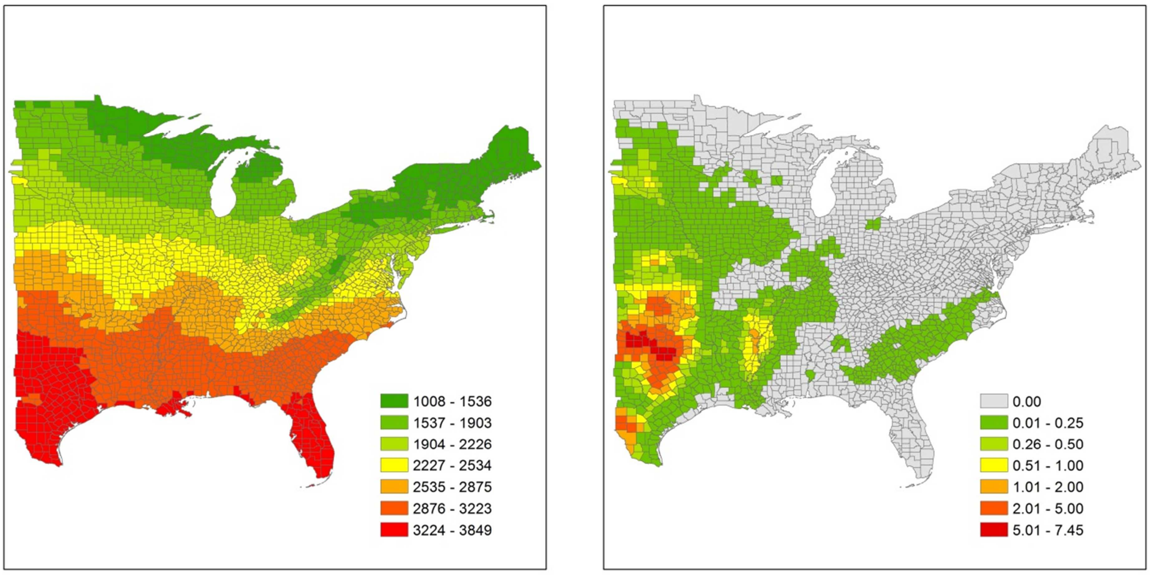
The only advantage of using degree days seems to be the possibility to control for days with abnormally high temperatures. Extremely high temperatures, especially if unexpected, clearly damage crops. It is therefore legitimate to understand how relevant this phenomenon is.

Our data shows that the number of degree days in the East of the US is extremely limited. 54% of counties never experience mean daily temperatures above 34 °C (Figure 1 and Figure 2). If they record mean daily temperatures above 34 °C it is only for brief intervals of time. The 90th percentile of the distribution is equal to 0.31. Only a handful of counties (2%) has more than one day during the growing season with temperature equal or higher than 35 °C. It is important to stress that we are considering climatologies over thirty years. Therefore it is highly probable that for the vast majority of counties degree days above 34 °C appear as a result of a heat wave occurring once or twice from 1981 to 2010. It is very likely that degree days capture inter-annual variance rather than average conditions. However, if variance is the variable of interest, more appropriate measurements of inter-annual variation should be used instead of degree days.

It is also questionable if a very brief exposition to high temperatures is sufficient to determine a sudden drop of productivity. Experiments cited in Section 2.2 use constantly high temperatures over weeks to assess the impact of extreme heat on crop yields. Field observations suggest that crop yields drop due to prolonged heat waves and droughts, rather than as a consequence of one single very hot day in which temperature may be only a fraction of a degree above the 34 °C threshold.

It seems that there are no apparent benefits of using degree days instead of average seasonal temperatures. Quite the opposite, there are several disadvantages, especially in the specific formulation of degree days used by SHF.

First, the influence of days with temperature below 8 °C within the growing season – much more frequent (30 times more) than days with temperatures above 34 °C (see Figure 1) – is lost. Agronomic studies clearly show that cold days are harmful because they shorten the growing season and sudden freezing temperatures kill crops.



Notes. 1981-2010 climatologies of degree days for US counties east of the 100th meridian. Source: own calculations based on the NARR Merge dataset. Degree days calculated for all grid-points of the NARR Merge dataset. County-level degree days obtained using a weighted average of the four closest grid-points to counties' centroids.

Figure 2. The spatial distribution of 8-32 ° degree days (left panel) and of 34 °C degree days (right panel).

			Usual Planting dates			Usual Harvesting dates		
Crop	State	% of total harvest acres	Begin	Peak	End	Begin	Peak	End
Corn	Iowa	17%	19-Apr	Apr 25 - May 18	26-May	21-Sep	Oct 5 - Nov 9	21-Nov
	Illinois	15%	14-Apr	Apr 21 - May 23	5-Jun	14-Sep	Sep 23 - Nov 5	20-Nov
Cotton	Texas	47%	22-Mar	Apr 8 - Jun 7	20-Jun	10-Aug	Sep 13 - Dec 21	11-Jan
	Georgia	13%	23-Apr	May 2 - May 31	11-Jun	23-Sep	Oct 10 - Dec 2	18-Dec
Sorghum	Kansas	46%	22-Mar	Apr 8 - Jun 7	20-Jun	10-Aug	Sep 13 - Dec 21	11-Jan
	Texas	37%	23-Apr	May 2 - May 31	11-Jun	23-Sep	Oct 10 - Dec 2	18-Dec
Soybeans	Iowa	12%	2-May	May 8 - Jun 2	16-Jun	21-Sep	Sep 28 - Oct 20	31-Oct
	Illinois	12%	2-May	May 8 - Jun 12	24-Jun	19-Sep	Sep 26 - Oct 26	7-Nov
Spring Wheat	North Dakota	49%	16-Apr	Apr 24 - May 25	3-Jun	1-Aug	Aug 8 - Sep 13	25-Sep
	Montana	18%	6-Apr	Apr 14 - May 12	18-May	30-Jul	Aug 7 - Sep 6	13-Sep
Winter Wheat	Kansas	26%	10-Sep	Sep 15 - Oct 20	1-Nov	15-Jun	Jun 20 - Jul 5	15-Jul
	Oklahoma	10%	3-Sep	Sep 15 - Oct 22	6-Nov	1-Jun	Jun 6 - Jun 27	3-Jul

Source: (USDA 2010).

Table 1. Planting and harvesting dates for major crops in the East of the US.

Second, the choice to truncate degree days at 32 °C is questionable and has some unintended consequences: days with temperature in excess of 32 °C – supposedly harmful for agriculture – contribute with 24 °C to DD8-32 – supposedly beneficial for agriculture. This also leads to some double counting: days with temperature above 34 °C contribute with 24 °C to DD8-32 and also to DD34.

Third, calculating degree days as in SHF requires many arbitrary choices. The upper and lower thresholds are crop-specific and the length of the growing season is fixed. It is then difficult to use degree days in studies that span a large number of crops and climate regions (Kurukulasuriya et al. 2006).

Finally, a major obstacle towards using degree days is the large amount of weather observations needed: in order to get climatologies of degree days daily mean temperature for 30 years are needed, for each observation. Computing degree days from raw data is clearly a cumbersome task, if possible at all.

In fact SHF do not use a dataset with daily mean temperatures. They estimate mean temperatures using a smoothing technique based on monthly maximum and minimum temperatures, borrowed from Thom (1966). One potential problem with this method is that it relies on the assumption that daily temperatures are normally distributed within the maximum and minimum monthly temperature corridor. The analysis of the NARR Merge dataset reveals instead that temperatures are not distributed normally within days nor they are within the growing season. The temperature distribution is positively skewed. Assuming a symmetric distribution leads to overestimate the number of hot days. This might explain why the number of DD34 in SHF is equal to 2.37, much higher than the value of 0.17 that we find in the NARR Merge dataset. Interestingly, SHF do not find any county with zero DD34 (compared to 54% counties with zero DD34 in the NARR Merge dataset). Normality assumptions used by SHF might also explain why we find that the highest number of DD34 is equal to 7.5 while in SHF is equal to 5.7.

2.2 Is the effect of temperature on crops positive and largely linear up to 34 °C and then precipitously negative?

DHF's claim that DD8-32 are better than average seasonal temperatures and that a quadratic functional form does not represent well the relationship between climate and crop development rests on the assumption that warming is largely time-separable, it improves yields linearly until 32 °C and then precipitously reduces yields. These assumptions are derived from several agronomic studies but mainly from an interpretation of data from agronomic experiments by Grobellaar (1963) summarized in Ritchie and NeSmith (1991, Fig. 2-3 and Fig. 2-4, pp. 9-13). We argue that the interpretation that SHF give to Ritchie and NeSmiths' data is incorrect.

Fig- 2-3 in Ritchie and NeSmith (1991) illustrates the inverse duration of appearance of the fifth leaf of maize. The agronomic literature pays great attention to leaves development because leaves affect the amount of energy that the plant captures through photosynthesis, ultimately determining plant growth.

Maize plants were grown in an artificial environment with identical temperature until the appearance of the fourth leaf and then placed in environments with constant temperature ranging from 5 to 40 °C. With temperatures below 8 °C the fifth leaf did not appear. With temperatures between 8 °C and 33 °C the number of days needed for the fifth leaf to appear decreases linearly. With temperature higher than 33 °C the number of days for leaf appearance starts increasing quickly and when temperature is approximately equal to 40 °C the plant does not develop the fifth leaf.

At first sight, panel (a) of Figure 2-3 confirms the intuition of SHF that very high temperatures have a sharp negative effect on plants. However, this interpretation is only partially correct. Panel (a) of Figure 2-3 describes the relationship between temperature and the *inverse duration* of leaf growth rather than the relationship between temperature and the *size* of the leaf, a better indicator of the effect of temperature on plant development, described by panel (c) of Figure 2-3. Development is jointly determined by the growth rate and by the duration of growth.

Experimental data reveals that the *growth rate* of the leaf peaks when temperature is between 22 and 32 °C, as described in panel (b) of Figure 2-3. At low temperatures a low growth rate is compensated by a long duration. At medium temperatures the growth rate increases but the duration decreases. At very high temperatures both the growth rate and the duration decrease. Thus:

> *As with individual leaf sizes, the product of the rate and duration usually leads to larger leaf size, grain size, or grain number when the temperature at which the crop is growing are considerably below [33 °C]. Respiration rate is often given as the reason for low yields at high temperatures without any consideration being given to how high temperatures reduce growth duration.* (Ritchie and NeSmith 1991, p. 11)

Panel (c) illustrates the joint effect of growth rate and duration on leaf development. The relationship between temperature and leaf development is approximately quadratic, with a maximum at around 13 °C. As temperature increases beyond 33 °C, the marginal impact on leaf development is expected to increase because both the growth rate and the duration of growth decrease. Data reported by Ritchie and NeSmith (1991) clearly indicate that heat affects plant development gradually.

The existence of a quadratic relationship between heat and plant development is somehow confirmed by SHF. While saying that temperatures between 8 and 32 °C are equally beneficial to plant growth, SHF in fact use a quadratic functional form to describe the relationship between degree days and land values. They find a significant hill-shaped relationship indicating that too much heat during the growing season is harmful, even without accounting for extreme temperatures.

Farmers and agronomists use degree days, but not to predict yields. They use degree days to predict the timing of different stages of plants growth in order to schedule agricultural management activities (Swan et al. 1987; McMaster and Wilhelm 1997; Miller, Lanier, and Brandt 2001):

> *Particularly in the areas of crop phenology and development, the concept of heat units, measured in growing degree-days (GDD, °C-day), has vastly improved description and prediction of phenological events compared to other approaches such as time of year or number of days.* (McMaster and Wilhelm 1997)

Degree days predict the actual stage of development of the plant more accurately that average temperature:

> *It's tough to predict plant growth based on the calendar because temperatures can vary greatly from year to year. Instead, growing degree days, which are based on actual temperatures, are a simple and accurate way to predict when a certain plant stage will occur.* (Miller, Lanier, and Brandt 2001)

2.3 Do seasons matter?

By using degree days over April-September SHF assume that the time sequence with which crops receive heat does not matter. What matters is the total amount of heat received during the growing season. The same applies to rainfall. Furthermore, temperatures and precipitations from October to March are assumed to be irrelevant for explaining land values.

This is a strong assumption and is at odds with the preoccupation of farmers to obtain the right amount of heat and moisture at particular moments of plants growth. For example, dry conditions during harvest are highly desirable. Too much rainfall in spring creates problems for planting summer crops.

By fixing the length of the growing season SHF are not able to capture the beneficial effect of warming in spring and fall. By fixing the end of the growing season in September, they do not recognize that usual harvesting dates for many important crops fall in October and November (**Errore. L'origine riferimento non è stata trovata.**).

The notion that winter temperatures and rainfall do not affect land values is also not supported by facts. For example, winter wheat is planted in the fall, goes into dormancy during the winter, and is harvested for grain the following spring.[6] Under optimal weather condition, winter wheat in the Southern Great Plains is harvested in fall and again in late winter and early spring (USDA 2010). Rainfall in winter is important because it replenishes aquifers and builds soil moisture.

Therefore, a functional form based on degree days does not seem to be the best alternative to a quadratic formulation. Of course, this does not mean that the quadratic is the best functional shape. In the next section we introduce a more flexible functional form that we use to test the quadratic model.

3 Models and data

3.1 Models

We test three broad families of models. The first class of models uses degree days, the second uses average temperatures using a quadratic specification and the third uses a flexible functional form obtained by interacting dummies with average temperatures and precipitations.

[6] In 2009, winter wheat accounted for 69% of all wheat produced in the US (USDA 2010).

The dependent variable is always the logarithm of the value of land and buildings per hectare in county *i* at time *t:* $y_{i,t}$.

The first model that we test uses only DD8-32 and a quadratic functional form and average growing season precipitations (P) (model 1):

$$y_{i,t} = \beta_0 + \beta_1 DD8\text{-}32_i + \beta_2 DD8\text{-}32_i^2 + \beta_4 P_i + \beta_4 P_i^2 + \boldsymbol{\gamma} X_{i,t} + \boldsymbol{\theta} Z_i + \epsilon_{i,t} \tag{6}$$

We then add DD34 (model 3) and then using the squared root (model 4). Models 9 and 10 use degree days and average monthly precipitations in April-June and July-September.[7]

A further robustness test considers warm and cold degree days, respectively above and below 8 °C, without any truncation:

$$\begin{aligned} cdd8_{i,r} &= \begin{cases} 8 - t_i & \text{if} \quad t_{i,r} \leq 8 \\ 0 & \text{if} \quad t_{i,r} > 8 \end{cases} \\ CDD8_i &= \sum_{r \in R} cdd8_{i,r} \end{aligned} \tag{7}$$

$$\begin{aligned} dd8_{i,r} &= \begin{cases} \mathrm{t_i} - 8 & \text{if} \quad \mathrm{t_{i,r}} > 8 \\ 0 & \text{if} \quad \mathrm{t_{i,r}} \leq 8 \end{cases} \\ DD8_i &= \sum_{\mathrm{r \in R}} dd8_{i,r} \end{aligned} \tag{8}$$

The models that use average temperatures follow the standard Ricardian formulation as in equation 2. In order to allow comparison with coefficients of DD8-32 we subtract 8 °C from average temperature and we multiply by 183, the number of days between April 1st and September 30th:

$$y_{i,t} = \beta_0 + \beta_1[(T_i - 8)183] + \beta_2[(T_i - 8)183]^2 + \boldsymbol{\gamma} X_{i,t} + \boldsymbol{\theta} Z_i + \epsilon_{i,t} \tag{9}$$

where $T_i = \sum_{m=4}^{9} t_m / 6$, being t_m the average monthly temperature climatology for month *m* during 1981-2010. We build analogously monthly means over different seasonal intervals.

In models 5 and 6 we introduce DD34 linearly and then using the squared root. When then include seasonal detail to the models and we converge to the model illustrated in Equation 2.

In the flexible models we interact dummies with temperatures. We use 1 °C temperature interval dummies for the models that focus only on April-September and 2 °C interval dummies for the models that consider the four seasons.[8] We use 1 cm interval dummies for the models that include the flexible specification also for rainfall. The model with temperature and precipitation dummies during April-September reads as follows:

[7] We indicate the number of months over degree days and temperatures are calculated using calendar numbers 1, 2, … , 12.

[8] Robustness tests that use different temperature intervals show that results with 1 °C and 2 °C temperature intervals are preferable because allow for sufficiently high flexibility while still preserving sufficient variance across counties with similar temperatures. Within seasons, especially in Summer, there is less variance across counties and therefore the wider temperature interval is preferable.

$$y_{i,t} = \beta_0 + \sum\nolimits_k \beta_k dt_{k,i} T_i + \sum\nolimits_j \beta_j dp_{j,i} P_i + \boldsymbol{\gamma} X_{i,t} + \boldsymbol{\theta} Z_i + \epsilon_{i,t} \tag{10}$$

where $dt_{k,i} = 1$ if $T \quad \leq T_i < T_{k+1}$, otherwise $dt_{k,i} = 0$, with $k = 1, \dots, K$ (the same holds for precipitations). The models with four seasons are built analogously.

We estimate a semi-log pooled model with year fixed effects and weights equal to farmland, as in Massetti and Mendelsohn (2011).[9] We estimate all models with and without state fixed effects.

We estimate percentage impacts from climate change using two representative uniform warming scenarios of +2 °C and +4 °C. For simplicity, precipitations are assumed not to change. This is clearly not realistic and spatially and temporally detailed scenarios generated General Circulation Models could provide a more accurate estimate of the expected impact of climate change. However, this goes beyond the scope of this paper. While losing detail and realism, the analysis gains in transparency.

The transformation of temperature variables with climate change is straightforward for the models that use mean seasonal temperatures. In order to calculate degree days with the new climate we start from raw data, augment it by 2 or 4 °C and recalculate degree days for each grid-point, in each year from 1981 to 2010 and then we average over years. The percentage change of land values in the East is obtained by subtracting the predicted value of land using transformed temperature variables in each county from the predicted value of land using 1981-2010 climate, by summing over all counties and by dividing by the sum over all counties of the predicted value of land calculated with 1981-2000 temperature.[10] For the model with growing season mean temperature dummies the percentage impact of temperature change *tc* in county *i* is equal to:

$$\begin{aligned} \frac{\Delta Y_i}{Y_i} &= \sum\nolimits_{s=k}^{k+(tc-1)} \beta_s dt_{k,i} \quad \text{for } k = 1, \dots, K - (tc - 1) \\ \frac{\Delta Y_i}{Y_i} &= tc\, \beta_k dt_{k,i} \quad \text{for } k > \; K - (tc - 1) \end{aligned} \tag{11}$$

We then use the percentage impact at county level and sum over all counties with weights equal to farmland in each county. We proceed analogously for the model with seasonal temperature dummies.

3.2 Data

We build a balanced panel using US Agricultural Census data for 1982, 1987, 1992, 1997 and 2002. We use time varying socio-economic variables: income per capita, population density, population density squared, residential house price index. We control for a set of geographic, time invariant characteristics at counties centroids: latitude, elevation, and distance from major metropolitan areas. We use USGS data to estimate the average annual surface and ground water use per hectare of farmland during 1982-2002. Finally, we control for some important soil characteristics: salinity, percentage of soil subject to flooding, percentage of land with low drainage, soil erodibility, and average slope length factor,

[9] SHF estimate a model without year dummies.

[10] We multiply the exponential of predicted log land values by $exp\{0.5\ (\hat{y}_i - y_i)^2\}$ as in Cameron and Trivedi (2009, p. 108).

percentage of sand and of clay, minimum available water capacity, and permeability.[11] Climate data is from the NARR Merge dataset. We compute degree days at grid level, then calculate climatologies by averaging over 1981-2010 and then we attribute degree days to counties by interpolating the four closest grid points to each county's centroid.[12] We cover 2,351 out of 2,471 counties east of the 100th meridian.

4 Results

4.1 8-32 °C degree days vs mean seasonal temperature

We start by comparing a model in which DD8-32 and average temperature (modified as discussed above), both over April-September, enter with a quadratic functional form. Monthly mean precipitations over April-September also enter following a quadratic specification. Table 2 reveals that all climate coefficients are highly significant. The relationship between temperature and land values is concave as expected. Also the relationship between precipitations and land values is solidly concave. Coefficients of DD8-32 and of modified average temperature are almost identical, as all other climate coefficients. This provides additional evidence of the strong similarity between DD8-32 and mean temperatures in the east of the US.

Estimates of both +2°C and +4°C warming are almost identical using degree days or average temperatures. Warming is significantly harmful for agricultural land east of the 100th meridian. A scenario of uniform 4°C warming – close to what predicted at global level by many long-term baseline emission scenarios – reduces land values by roughly 50%.

It is legitimate to be concerned about the possibility that land values are affected by state-specific policies and factors not included within the set of regressors. For this reason we estimate all models with and without state fixed effects. Table 1 reveals that fixed effects move the optimal temperature level to the right. Warming is less harmful in the models that use fixed effects.

As in SHF we use the Morgan-Granger-Newbold (MGN) significance test to assess the forecasting accuracy of the models (Diebold and Mariano 1995). We use the coldest 80% of counties to estimate the Ricardian function and we forecast land values of the remaining counties included in our panel. We reject the null hypothesis of equal forecasting accuracy in favor of the model that uses mean seasonal temperature with a t-statistic equal to 9.9.

Overall, our results indicate that there is no advantage from using DD8-32 instead than average growing season temperature. The fine and costly high temporal resolution detail is lost when all degree days are lumped together.

[11] All signs of control variables behaves as expected. A full set of regression results is available from the authors.
[12] Robustness tests done averaging all grid points that fall within a county confirm our results.

	DD8-32 (1)	AV TEMP (2)	DD8-32 (1-FE)	AV TEMP (2-FE)
$DD8\text{-}32_{4\text{-}9}$	0.000283***		0.000283***	
	[6.22e-05]		[0.000104]	
$DD8\text{-}32_{4\text{-}9}$ sq.	-2.26e-07***		-1.87e-07***	
	[1.41e-08]		[2.27e-08]	
$T_{4\text{-}9}$		0.000300***		0.000298***
		[5.34e-05]		[8.75e-05]
$T_{4\text{-}9}$ sq.		-2.21e-07***		-1.80e-07***
		[1.26e-08]		[1.98e-08]
$P_{4\text{-}9}$	0.240***	0.252***	0.335***	0.341***
	[0.0296]	[0.0294]	[0.0337]	[0.0338]
$P_{4\text{-}9}$ sq	-0.0135***	-0.0141***	-0.0179***	-0.0180***
	[0.00156]	[0.00155]	[0.00177]	[0.00178]
State fixed effects	No	No	Yes	Yes
Adjusted R^2	0.777	0.776	0.827	0.827
Impact of +2°C	-26.4%	-26.2%	-20.7%	-20.0%
	[-30% , -23%]	[-29.8% , -23%]	[-26.1% , -15.4%]	[-25.4% , -14.6%]
Impact of +4°C	-46.9%	-47.8%	-38.6%	-38.6%
	[-51.3% , -42%]	[-52.3% , -42.7%]	[-46.3% , -29.8%]	[-46.8% , -30.2%]

Notes: Robust standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1; 95% bootstrap confidence intervals for climate change impacts in brackets. All climate variables from April to September. DD8-32 in °C. We subtract 8 °C to average seasonal temperature and multiply by 183. Precipitations in cm/month.

Table 2. Degree days 8-32 and average seasonal temperature.

4.2 Degree days above 34 °C

The next set of models that we assess (3 through 6) tests the importance of including DD34. In models 3 and 4 DD34 enters first linearly and then with the square root, as in SHF. Model 5 uses DD8 and a linear specification for DD34. Model 6 uses average temperatures and DD8.

We find that the variable DD34 is significant but positive when it enters with a linear specification while it is negative, but not significant, when it enters with the squared root. These results raise doubts about the validity of using DD34 as a cut-off point beyond which land values decline precipitously.

What are the implications of adding DD34 for aggregate impacts of +2 °C and +4 °C warming? Impacts of +2 °C warming do not significantly change when we include the variable DD34. With +4 °C impacts are lower when DD34 enters linearly and slightly higher when it enters as squared root. However, bootstrap confidence intervals of +4 °C warming show that the models become unstable because they generate some very high positive impacts.

With fixed effects the variable DD34 is never significant. This means that the fixed effect absorbs the impact of the variable, which has a very clear regional distribution (Figure 2). For this reason state fixed effects also make the models more stable.

	DD8-32 & DD34	DD8-32 & DD34 SQRT	DD>8 & DD34	AV TEMP & DD34	DD8-32 & DD34	DD8-32 & DD34 SQRT	DD>8 & DD34	AV TEMP & DD34
	(3)	(4)	(5)	(6)	(3-FE)	(4-FE)	(5-FE)	(6-FE)
$DD8\text{-}32_{4\text{-}9}$	0.000305***	0.000273***			0.000269**	0.000290***		
	[6.44e-05]	[6.38e-05]			[0.000106]	[0.000106]		
$DD8\text{-}32_{4\text{-}9}$ sq.	-2.38e-07***	-2.18e-07***			-1.77e-07***	-1.94e-07***		
	[1.56e-08]	[1.59e-08]			[2.44e-08]	[2.45e-08]		
$T_{4\text{-}9}$				0.000338***				0.000289***
				[5.56e-05]				[9.03e-05]
$T_{4\text{-}9}$ sq.				-2.41e-07***				-1.74e-07***
				[1.42e-08]				[2.17e-08]
$DD34_{4\text{-}9}$	0.0116*		0.0183**	0.0190***	-0.00918		-0.00480	-0.00511
	[0.00697]		[0.00717]	[0.00716]	[0.00732]		[0.00756]	[0.00755]
$DD34_{4\text{-}9}$ sq. root		-0.0172				0.0124		
		[0.0151]				[0.0167]		
$DD32\text{-}34_{4\text{-}9}$								
$DD8_{4\text{-}9}$			0.000268***				0.000233**	
			[6.40e-05]				[0.000105]	
$DD8_{4\text{-}9}$ sq			-2.27e-07***				-1.65e-07***	
			[1.55e-08]				[2.39e-08]	
$P_{4\text{-}9}$	0.231***	0.248***	0.236***	0.236***	0.343***	0.330***	0.347***	0.346***
	[0.0302]	[0.0305]	[0.0303]	[0.0301]	[0.0340]	[0.0341]	[0.0342]	[0.0342]
$P_{4\text{-}9}$ sq	-0.0131***	-0.0139***	-0.0133***	-0.0133***	-0.0182***	-0.0177***	-0.0183***	-0.0182***
	[0.00159]	[0.00160]	[0.00159]	[0.00158]	[0.00179]	[0.00180]	[0.00179]	[0.00179]
State fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Adjusted R^2	0.777	0.777	0.777	0.777	0.827	0.827	0.827	0.827
Impact of +2°C	-25.7%	-26.4%	-25.0%	-25.1%	-20.8%	-20.8%	-20.1%	-20.0%
	[-29.8% , -20.1%]	[-29.9% , -23.1%]	[-29.3% , -19.5%]	[-29.6% , -19.5%]	[-26.2% , -14.7%]	[-25.8% , -15.8%]	[-25.3% , -14%]	[-25.4% , -14.1%]
Impact of +4°C	-40.6%	-47.3%	-37.1%	-36.9%	-41.1%	-38.4%	-39.8%	-39.8%
	[-52.6% , 145.1%]	[-52.2% , -41.7%]	[-51.4% , 259%]	[-51.5% , 277.1%]	[-49.6% , -7%]	[-46.6% , -29%]	[-48.8% , -4%]	[-48.3% , -8.5%]

Notes: Robust standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1; 95% bootstrap confidence intervals for climate change impacts in brackets. All climate variables from April to September. DD8-32 and DD34 in °C. We subtract 8 °C to average seasonal temperature and multiply by 183. Precipitations in cm/month.

Table 3. Degree days above 34°C.

	DD8-32 & CDD8 (7)	AV TEMP & CDD8 (8)	DD8-32 & CDD8 (7-FE)	AV TEMP & CDD8 (8-FE)
$DD8\text{-}32_{4\text{-}9}$	-0.00119***		-0.000769***	
	[0.000161]		[0.000203]	
$DD8\text{-}32_{4\text{-}9}$ sq.	4.12e-08		-1.20e-08	
	[3.13e-08]		[3.91e-08]	
$T_{4\text{-}9}$		-0.00128***		-0.000876***
		[0.000153]		[0.000197]
$T_{4\text{-}9}$ sq.		6.31e-08**		1.28e-08
		[2.95e-08]		[3.72e-08]
$CDD8_{4\text{-}9}$	-0.00669***	-0.00815***	-0.00469***	-0.00588***
	[0.000637]	[0.000709]	[0.000728]	[0.000836]
$P_{4\text{-}9}$	0.213***	0.216***	0.314***	0.318***
	[0.0297]	[0.0296]	[0.0342]	[0.0343]
$P_{4\text{-}9}$ sq	-0.0119***	-0.0120***	-0.0169***	-0.0170***
	[0.00157]	[0.00156]	[0.00180]	[0.00180]
State fixed effects	No	No	Yes	Yes
Adjusted R^2	0.777	0.781	0.828	0.828
Impact of +2°C	-22.5%	-22.2%	-20.3%	-19.9%
	[-26.7% , -18.6%]	[-26.6% , -17.8%]	[-25.3% , -14.6%]	[-25.2% , -14.9%]
Impact of +4°C	-40.5%	-40.7%	-37.3%	-37.4%
	[-46.5% , -34%]	[-47.3% , -33.9%]	[-45.3% , -28.4%]	[-45.5% , -28.5%]

Notes: Robust standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1; 95% bootstrap confidence intervals for climate change impacts in brackets. DD8-32 and DD34 in °C. We subtract 8 °C to average seasonal temperature and multiply by 183. Precipitations in cm/month.

Table 4. Degree days below 8°C.

The MGN forecasting test reveals that model 2 (average seasonal temperature) has greater forecasting accuracy of all models that use DD34. Therefore, we find no evidence of a temperature threshold at 34 °C beyond which land values in the East start declining precipitously. Our results are in accordance with the agronomic literature and with many other Ricardian studies: high temperatures are harmful, but there are no threshold effects.

4.3 Cold degree days

So far we have not controlled for the effect on land values of cold days during the growing season. However, if abnormally high warm days are expected to be harmful, so should be abnormally cold days. Cold days reduce the length of the growing season and freezing temperatures kill crops. For this reason we add degree days below 8 °C (CDD8) to models 3 and 6. We find that cold degree days significantly and consistently reduce land values, with or without state fixed effects.

Including cold degree days reduces the negative impact of warming in models that use DD8-32 and average growing season temperature (models 1 and 2), more markedly when state fixed effects are not included.

The MGN forecasting test reveals that model 1, without including cold degree days, has greater forecasting accuracy than model 7, which includes CDD8. Interestingly we find that model 8, in which we include both the quadratic of average seasonal temperature and CDD8 has greater forecasting accuracy than model 1. This means that the quadratic may underestimate the benefits of warming counties with many cold degree days.

4.4 Flexible functional form during April-September

One problem with the construction of degree days as in SHF is the arbitrariness of different cut-off points. Crops have different sensitivities to temperature. Some are more resistant than others to high or low temperatures. It is hard to motivate the decision of using a curt-off point instead of another. If one wants to test the robustness of the quadratic functional form it is better to reduce the structure imposed on the data rather than increasing it. The model in which we interact average seasonal temperatures with dummies for each 1 °C temperature interval (equation 10) allows full flexibility and reveals important insights.

The growing season temperature dummies model reveals that the marginal impact of warming is negative, as in the quadratic formulation, but the relationship is less concave, almost linear. This resembles the functional form of panel *c* of Figure 2-3 in Ritchie and NeSmith (1991). This functional shape does not change whether we include state fixed effects or not (top row of Figure 3). The functional shape is confirmed if we include dummies also for precipitations or not (bottom row of Figure 3). The impact of uniform warming is still significantly negative, but is lower than in the quadratic model (Table 5).[13]

The flexible models have greater forecasting accuracy than the quadratic models and the flexible model with both temperature and precipitation dummies has the greatest accuracy of all.

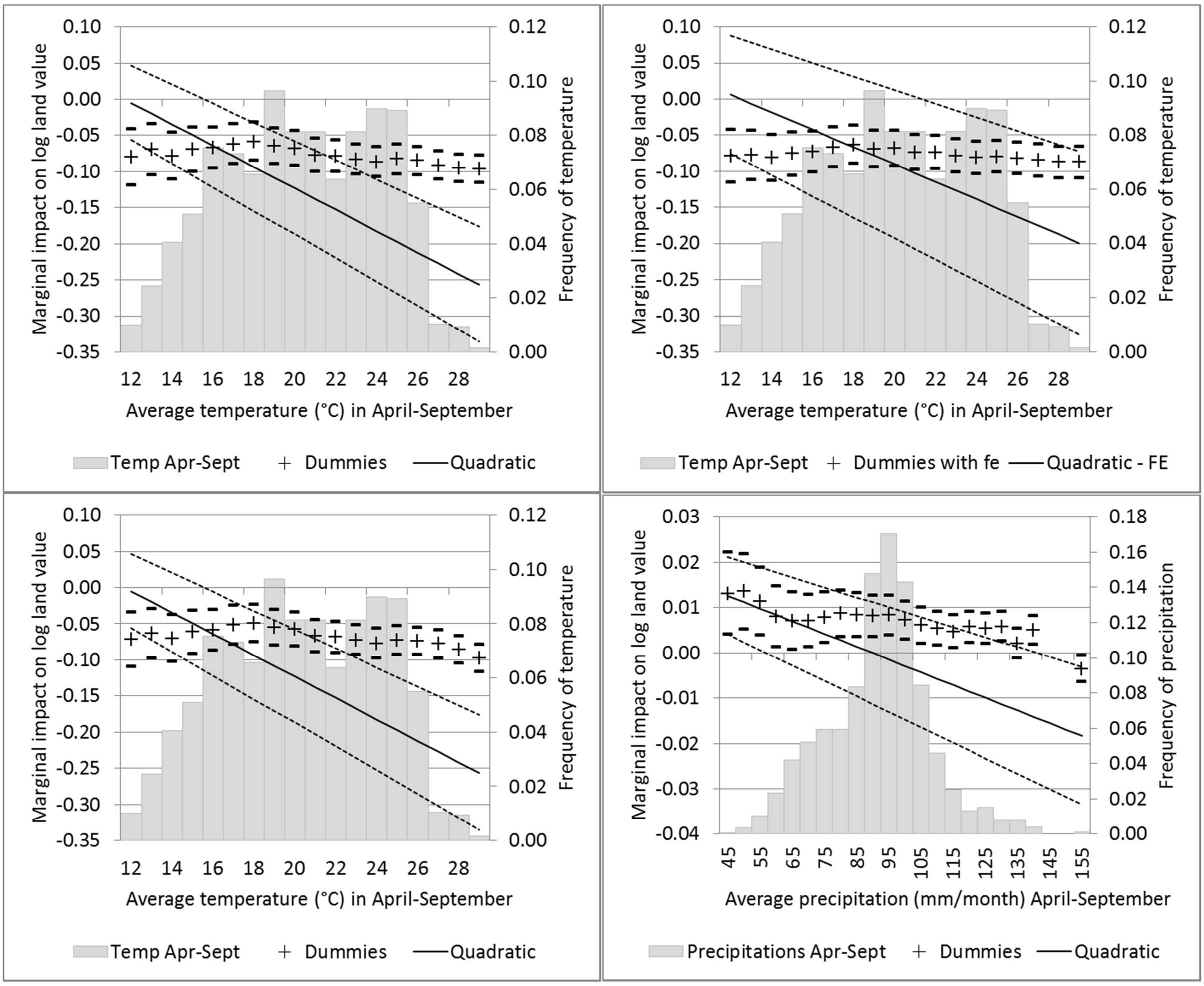
4.5 Seasons

The last question that we address is if seasons, within and outside the growing season, starting in April and ending in September, matter or not.

We find that seasons are significantly different within the growing season, both when we use degree days and seasonal average temperatures, with or without sate fixed effects (Table 6). Warming in spring is beneficial while it is harmful in summer. Also precipitations have marked seasonal patterns. Higher rainfall in spring is beneficial while in summer it is harmful. Summer is usually the wettest season in most regions in the East (see Figure 4). Impacts of warming are significantly negative, but lower than in the models that do not separate spring from summer.

According to the MGN forecasting test the models with spring and summer temperature and precipitations have greatest forecasting accuracy than the relative counterparts in which the growing season is not split in two (model 10 against model 1 and model 12 against model 2). We reject the hypothesis of equal forecasting in favor of the model that uses seasonal average temperatures with a t-statistic equal to 8.69.

[13] We use the coefficient of the dummy associated to the highest temperature level to forecast climate change for the hottest counties.



Notes. Top row: average April-September temperatures interacted with dummies for 1°C intervals, with (left) and without (right) state fixed effects. Bottom row: average April-September temperatures interacted with dummies for 1°C intervals and average April-September precipitations interacted with dummies for 1 cm intervals, without state fixed effects. Temperature and precipitations distribution of grid-points east of the 100th meridian from the NARR Merge model. Tick dashed lines limit the 95% confidence interval. The figures also display the marginal impact of 1°C warming and of 1 cm of additional precipitations using the quadratic models 13, 13-FE and 14 illustrated in Table 6.

Figure 3. Flexible models with distinct spring and summer seasons.

	No state fixed effects		State fixed effects	
	+2°C	+4°C	+2°C	+4°C
April-September				
Temperature only	-14.9%	-30.6%	-14.8%	-29.8%
	[-19.6% , -10.3%]	[-39.4% , -21.7%]	[-19.7% , -9.9%]	[-39.3% , -20.4%]
Temp. and precip.	-14.4%	-29.6%	-14.9%	-30.1%
	[-19% , -9.8%]	[-38.4% , -20.8%]	[-19.8% , -10.1%]	[-39.5% , -20.7%]
4 seasons (DJF)				
Temperature only	-17.0%	-31.3%	-13.5%	-24.8%
	[-24.1% , -10%]	[-44.8% , -17.7%]	[-20.2% , -6.8%]	[-37.5% , -12%]

Notes: 95% robust confidence intervals for climate change impacts in brackets

Table 5. Impact of +2° and +4°C uniform warming in the flexible models.

	DD 2 SEAS. T	DD 2 SEAS. T&P	DD 2 SEAS. T	DD 2 SEAS. T&P	DD 2 SEAS. T	DD 2 SEAS. T&P	DD 2 SEAS. T	DD 2 SEAS. T&P
	(9)	(10)	(11)	(12)	(9-FE)	(10-FE)	(11-FE)	(12-FE)
$DD8\text{-}32_{4\text{-}6}$	0.00721***	0.00608***			0.00685***	0.00589***		
	[0.000310]	[0.000300]			[0.000433]	[0.000441]		
$DD8\text{-}32_{4\text{-}6}$ sq.	-2.53e-06***	-1.91e-06***			-2.65e-06***	-2.10e-06***		
	[1.34e-07]	[1.24e-07]			[1.72e-07]	[1.79e-07]		
$DD8\text{-}32_{7\text{-}9}$	-0.00569***	-0.00368***			-0.00642***	-0.00512***		
	[0.000409]	[0.000384]			[0.000529]	[0.000530]		
$DD8\text{-}32_{7\text{-}9}$ sq.	8.00e-07***	3.88e-08			1.24e-06***	7.01e-07***		
	[1.35e-07]	[1.24e-07]			[1.68e-07]	[1.73e-07]		
$T_{4\text{-}6}$			0.00747***	0.00633***			0.00643***	0.00567***
			[0.000281]	[0.000285]			[0.000368]	[0.000398]
$T_{4\text{-}6}$ sq.			-2.72e-06***	-2.11e-06***			-2.56e-06***	-2.10e-06***
			[1.22e-07]	[1.19e-07]			[1.49e-07]	[1.66e-07]
$T_{7\text{-}9}$			-0.00936***	-0.00708***			-0.00873***	-0.00747***
			[0.000467]	[0.000464]			[0.000589]	[0.000625]
$T_{7\text{-}9}$ sq.			2.00e-06***	1.18e-06***			2.00e-06***	1.49e-06***
			[1.49e-07]	[1.47e-07]			[1.82e-07]	[1.98e-07]
$P_{4\text{-}9}$	0.0270		-0.0716*		0.0662		0.00546	
	[0.0363]		[0.0369]		[0.0413]		[0.0428]	
$P_{4\text{-}9}$ sq	-0.00321*		0.00182		-0.00578***		-0.00286	
	[0.00188]		[0.00192]		[0.00209]		[0.00217]	
$P_{4\text{-}6}$		0.358***		0.262***		0.213***		0.153***
		[0.0298]		[0.0309]		[0.0367]		[0.0389]
$P_{4\text{-}6}$ sq.		-0.0170***		-0.0125***		-0.0102***		-0.00734***
		[0.00141]		[0.00146]		[0.00168]		[0.00178]
$P_{7\text{-}9}$		-0.157***		-0.163***		-0.102***		-0.110***
		[0.0182]		[0.0179]		[0.0253]		[0.0256]
$P_{7\text{-}9}$ sq.		0.00548***		0.00610***		0.00240**		0.00287**
		[0.000904]		[0.000890]		[0.00122]		[0.00123]
State fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Adjusted R^2	0.803	0.812	0.808	0.814	0.835	0.837	0.836	0.838
Impact of +2°C	-23.2%	-24.0%	-21.7%	-22.7%	-21.2%	-23.3%	-21.8%	-23.6%
	[-26.7% , -19.6%]	[-27.4% , -20.7%]	[-25.4% , -17.9%]	[-26.7% , -19.2%]	[-26.1% , -16%]	[-28.2% , -18.3%]	[-27% , -16.9%]	[-28.9% , -18.3%]
Impact of +4°C	-41.4%	-43.4%	-39.5%	-42.5%	-39.3%	-42.5%	-40.2%	-43.3%
	[-46.5% , -36.4%]	[-48.4% , -38.8%]	[-44.7% , -34%]	[-47.6% , -37.6%]	[-47.2% , -31.2%]	[-49.6% , -34.1%]	[-47.5% , -31.6%]	[-50.8% , -35.4%]

Notes: Robust standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1; 95% bootstrap confidence intervals for climate change impacts in brackets. Degree days in °C. We subtract 8 °C to average seasonal temperature and multiply by 91 (months 4-6) or 92 (months 7-9). Precipitations in cm/month.

Table 6. Spring and summer.

Also climate outside the growing seasons significantly affects land values. Table 7 reports results of a standard Ricardian model with four seasons and shows that virtually all temperature and precipitation coefficients are highly significant. We find that warming in spring and in summer is beneficial because it extends the growing season while warming in summer is harmful because increases heat stress while warming in winter is harmful because increases expenditures for pests control. The model with the subdivision in seasons starting in December explains a higher fraction of the variance in land value and has a higher number of significant climate coefficients. Impacts from 2 °C and +4 °C of warming are significantly negative but lower than in the models with only two seasons.

All models with four seasons have greater forecasting accuracy than model 15, with two seasons. However, the model in which winter is January-February-March has greater forecasting accuracy than the model in which winter is December-January-February (we reject the null hypothesis of equality in favor of model 15 with a t-statistic equal to 2.26).

We also test a model with seasonal dummies interacted with temperature and precipitations, in this case only without fixed effects. Figure 4 reports the marginal impact of temperature and precipitation separately for the four seasons. Also in this case we find that the flexible model confirms the sign of the seasonal marginal impacts found with the quadratic model but at the same time indicates that the functional form might be flatter than what implied by the quadratic. Impacts of warming are however higher than what predicted by the quadratic model with four seasons and very similar to what found using the flexible model without separating Spring and Summer during the growing season.

4.6 Aggregate and regional impacts of warming

The right panel of Figure 6 shows that warming from +2 to + 4 °C has generally a lower marginal impact on land values than warming from the present climate to + 2 °C. Interestingly, the models with DD34 do not make the aggregate response of land values to warming convex (models 5 and 6). In general, we find that the relationship between US land value in the East and temperatures is concave. The only models that show a convex response are those that separate among seasons (models 16-20).

Figure 6 and Figure 5 summarize predicted impacts for +2 and +4 °C across all models, for six regions. Warming is significantly harmful for all regions, with the highest negative impacts in the South.

5 Conclusions

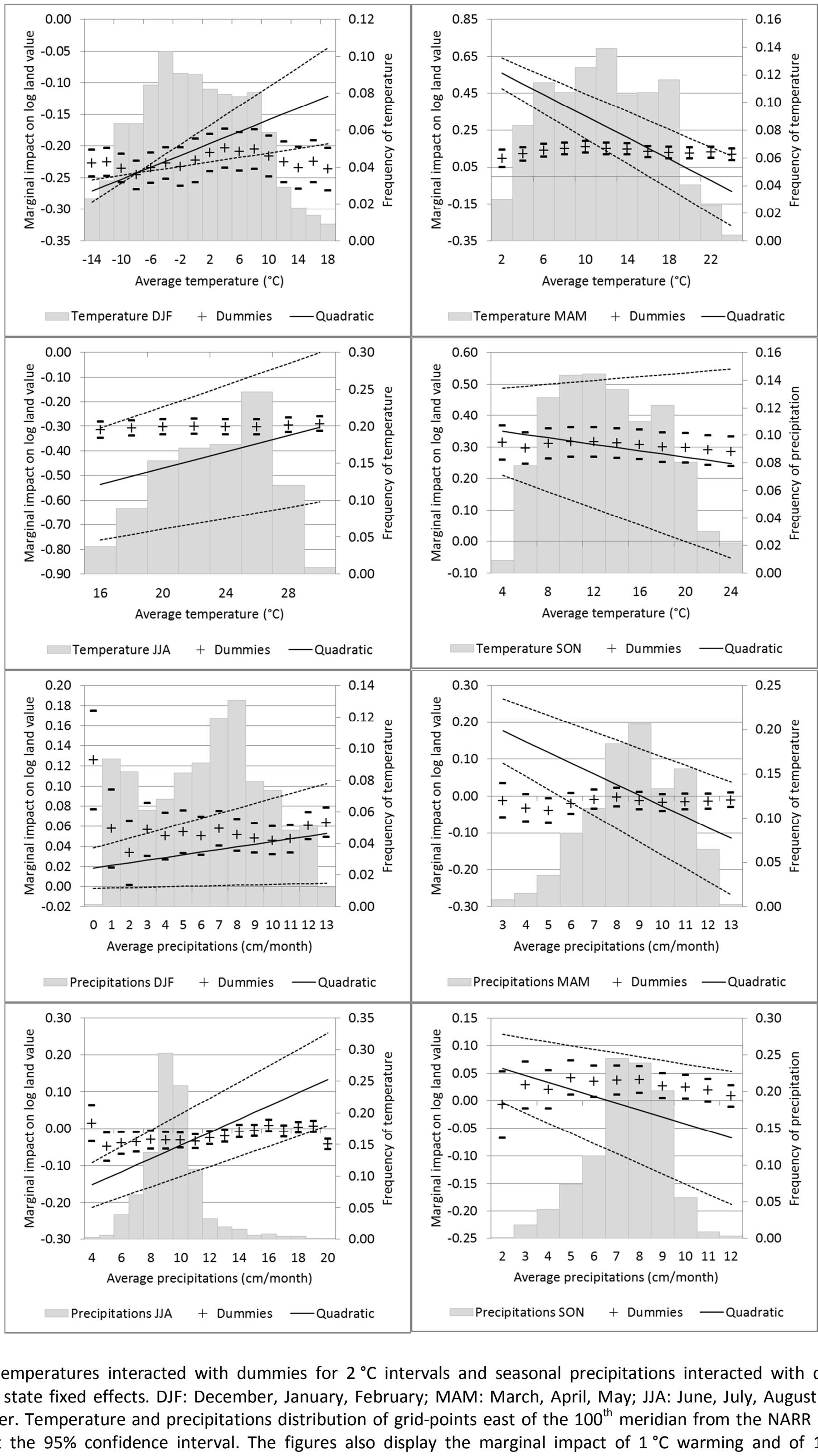
Ricardian models have traditionally used a quadratic specification of temperature and precipitations for the four seasons to estimate the impact of climate change on agricultural land values.

Schlenker, Hanemann, and Fisher (2006) (SHF) argued that the quadratic functional form does not reflect well sharp non-linear responses of crop yields to very high temperatures. They suggest using degree days instead than average temperatures in order to separate the beneficial and the harmful effect of warming more effectively. They also argue that climate outside the growing season – defined as April-September in the East of the US – does not affect land values.

	AV TEMP 4 SEAS. T (13)	AV TEMP 4 SEAS. T&P (14)	AV TEMP 4 SEAS. T (13-FE)	AV TEMP 4 SEAS. T&P (13-FE)		AV TEMP 4 SEAS. DJF (15)	AV TEMP 4 SEAS. DJF (15-FE)
T_{1-3}	-0.00328***	-0.00304***	-0.00200***	-0.00257***	T_{12-2}	-0.00186***	-0.00170***
	[0.000244]	[0.000272]	[0.000294]	[0.000297]		[0.000237]	[0.000266]
T_{1-3} sq.	-2.63e-07**	-8.41e-08	5.05e-07***	4.88e-07***	T_{12-2} sq.	2.89e-07***	5.16e-07***
	[1.05e-07]	[1.24e-07]	[1.37e-07]	[1.40e-07]		[9.20e-08]	[9.56e-08]
T_{4-6}	0.00287***	0.00309***	0.00582***	0.00524***	T_{3-5}	0.00422***	0.00242***
	[0.000185]	[0.000193]	[0.000400]	[0.000405]		[0.000220]	[0.000246]
T_{4-6} sq.	2.24e-07*	2.47e-08	-2.34e-06***	-1.96e-06***	T_{3-5} sq.	-1.75e-06***	-1.20e-06***
	[1.35e-07]	[1.56e-07]	[1.81e-07]	[1.87e-07]		[1.51e-07]	[1.62e-07]
T_{7-9}	-0.00718***	-0.00554***	-0.00708***	-0.00587***	T_{6-8}	-0.00726***	-0.00648***
	[0.000519]	[0.000585]	[0.000630]	[0.000644]		[0.000547]	[0.000629]
T_{7-9} sq.	1.44e-06***	8.03e-07***	1.60e-06***	1.11e-06***	T_{6-8} sq.	9.76e-07***	1.01e-06***
	[1.64e-07]	[1.78e-07]	[1.91e-07]	[1.98e-07]		[1.63e-07]	[1.93e-07]
T_{10-12}	0.00287***	0.00309***	0.00249***	0.00332***	T_{9-11}	0.00358***	0.00465***
	[0.000185]	[0.000193]	[0.000203]	[0.000209]		[0.000287]	[0.000283]
T_{10-12} sq.	2.24e-07*	2.47e-08	-7.49e-07***	-5.77e-07***	T_{9-11} sq.	-3.01e-07	-8.22e-07***
	[1.35e-07]	[1.56e-07]	[1.76e-07]	[1.80e-07]		[2.45e-07]	[2.60e-07]
p. Apr-Sept	-0.0390		0.0557				
	[0.0386]		[0.0419]				
P. Apr-Sept sq	0.00108		-0.00464**				
	[0.00199]		[0.00213]				
p_{1-3}		-0.0137		0.0934***	P_{12-2}	0.00183*	0.00174
		[0.0192]		[0.0242]		[0.00102]	[0.00151]
P_{1-3} sq.		0.00144		-0.00247**	P_{12-2} sq.	1.33e-05**	1.79e-05**
		[0.000989]		[0.00121]		[5.79e-06]	[8.43e-06]
P_{4-6}		0.261***		0.213***	P_{3-5}	0.0264***	0.0300***
		[0.0338]		[0.0406]		[0.00343]	[0.00403]
P_{4-6} sq.		-0.0111***		-0.00860***	P_{3-5} sq.	-0.000145***	-0.000148***
		[0.00157]		[0.00184]		[1.68e-05]	[1.99e-05]
P_{7-9}		-0.146***		-0.104***	P_{6-8}	-0.0224***	-0.0173***
		[0.0198]		[0.0264]		[0.00223]	[0.00318]
P_{7-9} sq.		0.00505***		0.00223*	P_{6-8} sq.	8.93e-05***	6.00e-05***
		[0.00102]		[0.00129]		[1.04e-05]	[1.44e-05]
P_{10-12}		-0.0149		-0.123***	P_{9-11}	0.00832***	-0.00165
		[0.0210]		[0.0273]		[0.00255]	[0.00288]
P_{10-12} sq.		-3.72e-05		0.00471***	P_{9-11} sq.	-6.29e-05***	-8.71e-06
		[0.00109]		[0.00136]		[1.50e-05]	[1.69e-05]
State FE	No	No	Yes	Yes	State FE	No	Yes
Adjusted R^2	0.815	0.821	0.841	0.845	Adjusted R^2	0.824	0.847
Impact of +2°C	-13.2%	-13.2%	-16.1%	-13.5%	Impact of +2°C	-10.7%	-11.5%
	[-19.8% , -6.4%]	[-20.7% , -5.4%]	[-22.9% , -9%]	[-19.8% , -5.6%]		[-17.9% , -3%]	[-17.6% , -4.3%]
Impact of +4°C	-27.1%	-28.8%	-33.3%	-29.3%	Impact of +4°C	-22.9%	-24.2%
	[-38.2% , -14.7%]	[-40.1% , -15.8%]	[-43.6% , -22.4%]	[-39.8% , -16.4%]		[-34.5% , -9.4%]	[-35.1% , -10.2%]

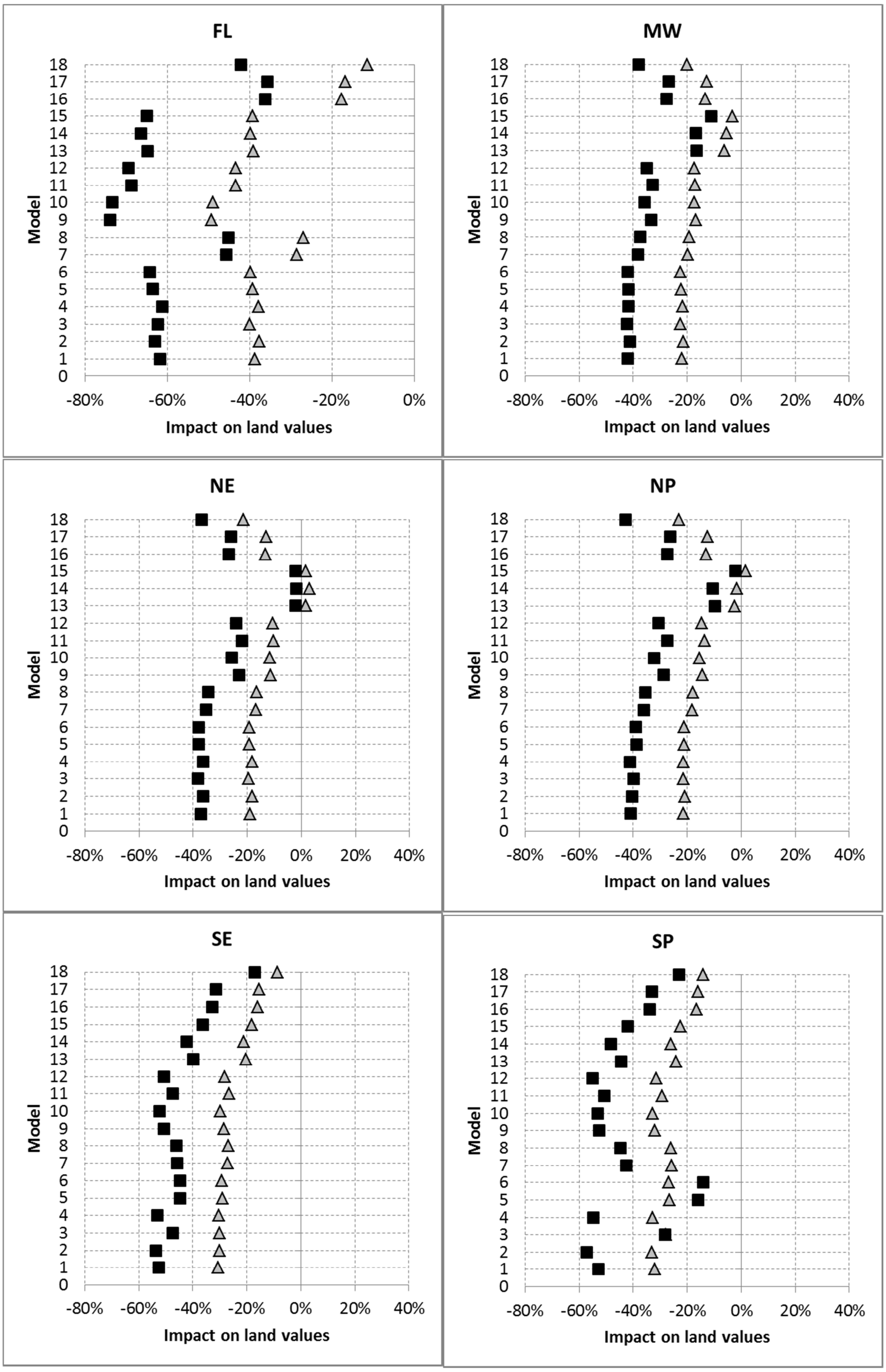
Notes: Robust standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1; 95% bootstrap confidence intervals for climate change impacts in brackets. We subtract 8 °C to average seasonal temperature and multiply by 91 (months 3-5 and 4-6), by 92 (months 6-8, 7-9, 9-11, 10-12) or by 90 (months 12-2, 1-3). Precipitations in cm/month.

Table 7. Four seasons.



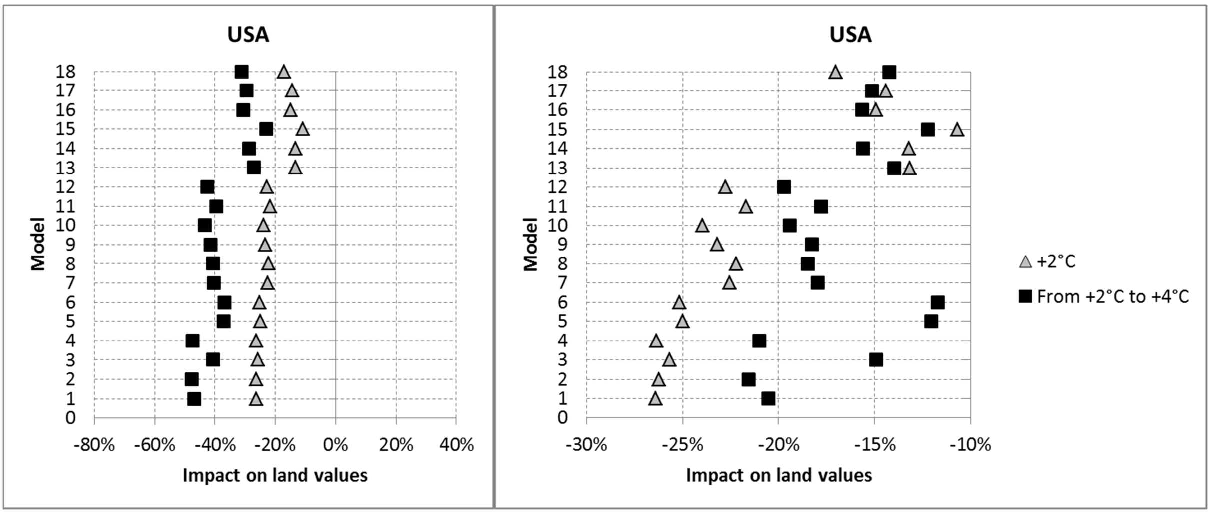
Notes. Seasonal temperatures interacted with dummies for 2 °C intervals and seasonal precipitations interacted with dummies for 1 cm intervals, without state fixed effects. DJF: December, January, February; MAM: March, April, May; JJA: June, July, August; SON: September, October, November. Temperature and precipitations distribution of grid-points east of the 100th meridian from the NARR Merge model. Tick dashed lines limit the 95% confidence interval. The figures also display the marginal impact of 1 °C warming and of 1 cm of additional precipitations using the quadratic models 10 and 10-FE and 11 illustrated in Table 6.

Figure 4. Flexible models with four seasons.



Notes. Left panel: models 1-12 as in Table 2, Table 3, Table 4 and Table 6. Model 13: Spring and summer temperature flexible model (Figure 3, top row). Model 14: Spring and summer temperature and precipitations flexible model (Figure 3, bottom row). Model 15: four seasons flexible model (Figure 4).

Figure 5. Summary of impacts on regional land values of uniform +2°C and +4°C warming.



Notes. Left panel: models 1-12 as in Table 2, Table 3, Table 4 and Table 6. Model 13: Spring and summer temperature flexible model (Figure 3, top row). Model 14: Spring and summer temperature and precipitations flexible model (Figure 3, bottom row). Model 15: four seasons flexible model (Figure 4). Right panel: impact of +2°C warming from 1981-2010 climatologies and impact of additional 2°C uniform warming (from +2°C to +4°C with respect to 1981-2010 climatologies).

Figure 6. Summary of impacts of uniform +2°C and +4°C warming on land values in the East.

We show that SHF model has several weaknesses by using a more accurate weather dataset, by using evidence from the agronomic literature and by testing several competing models econometrically.

First, the fact that degree days between 8 and 32 °C appear to significantly affect land values in SHF work is due to the fact that they are highly correlated with mean seasonal temperature (in excess of .999). However, several tests show that models that use a quadratic specification of the mean temperature over the growing season are more accurate than models that use degree days. Using average seasonal temperatures is a win-win solution: more accuracy at lower cost.

Second, evidence on the importance of controlling for degree days above 34 °C is mixed and fragile at best. We use the Morgan-Granger-Newbold a significance test to assess the forecast accuracy of the model with degree days against the model with seasonal climate. We find that the model with seasonal average temperature performs better than the model with degree days, even after accounting for very hot days.

These results are in accordance with the agronomic literature, which suggests that heat affects yields gradually. Controlled laboratory experiments that assess the impact of constant and prolonged exposure to temperatures show that the duration of growth is linearly affected by temperatures until 30-34 °C. After that the duration declines precipitously. However, the relationship between temperatures and plant development is rather quadratic. In fact, degree days are used by farmers to estimate different stages of plant growth, in order to plan management activities rather than forecasting yields. Degree days are appropriate to assess the duration of different stages of plant growth not yields.

Third, cold degree days are important because they reduce the length of the growing season and unexpected freezing temperatures may kill crops. Therefore they should be included in the analysis.

Fourth, seasons within and outside the growing season significantly affect land values. Furthermore, fixing the growing season is arbitrary because different crops have different planting and harvesting dates. Winter wheat, for example, grows in fall and in early spring. Our econometric estimates confirm this intuition. Virtually all seasonal coefficients are significant, with the expected signs: warming is beneficial in spring and fall because it extends the growing season; warming is harmful in summer and in winter because it increases heat stress and it requires higher use of pesticides to control for bugs, respectively.

Despite these shortcomings, SHF raise an important question: what is the best functional form to describe the relationship between land values and temperatures? We answer this question by estimating a set of flexible models in which we interact mean seasonal temperatures with dummies for 1 °C and 2 °C temperature intervals.

Our results show that the flexible models generate marginal effects with the same sign of the quadratic model although the relationship between temperatures and land values appears to be flatter than in the quadratic model.

We estimate impacts of climate change using two representative uniform warming scenarios of +2 °C and +4 °C, with no precipitation change. We find that the use of degree days does not explain high negative impacts in the East; impacts estimated using mean seasonal temperatures are virtually identical. We also find that the relationship between uniform warming and land values in the East appears to be concave, or at most linear, in all the models that we test.

Our analysis consistently shows that the cost of dealing with data necessary to generate degree days is not motivated by any benefit. Quite the opposite, we find a number of flaws in the degree days model that discourage its use. This is particularly important for those that want to study impacts of climate change on agriculture in areas of the world in which daily temperatures are not easily available or not available at all.

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