Determinants of Agricultural Output: Degree Days, Yields and Implications for Climate Change

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Abstract

We link farmland values to climatic, soil, and socioeconomic variables for counties east of the 100th meridian, the historic boundary of agriculture not primarily dependent on irrigation. Degree days, a non-linear transformation of the climatic variables suggested by agronomic experiments as more relevant to crop yield gives an improved fit and increased robustness. Estimated coefficients are consistent with the experimental results. The model is employed to estimate the potential impacts on farmland values for a range of recent warming scenarios. The predictions are very robust and more than 75% of the counties in our sample show a statistically significant effect, ranging from moderate gains to large losses, with losses in the aggregate that can become quite large under scenarios involving sustained heavy use of fossil fuels (JEL Q1, Q2, C5)

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1 Introduction

A relationship between global warming and increased concentrations of greenhouse gases such as carbon dioxide (CO_2), produced by the burning of fossil fuels, is suggested by much accumulating evidence. As far back as 1992, more than 150 governments attending the Rio Earth Summit signed the Framework Convention on Global Climate change. Article 2 states that the "ultimate objective of this Convention ... is to achieve ... stabilization of greenhouse gas concentrations that would prevent dangerous anthropogenic interference with the climate system." More than ten years later, the questions remain: how "dangerous" are the consequences of anthropogenic interference, and how much "stabilization" is justified?

The economics literature so far has given mixed results with regards to the impact on agriculture.[1] In the remainder of this section we give a brief overview of previous approaches to set the stage for our study. These can be divided into three broad categories, beginning with the *agronomic* approach, based on the use of agronomic models that simulate crop growth over the life cycle of the plant and measure the effect of changed climate conditions on crop yield and input requirements. For example, Adams (1989) relies on crop simulation models to derive the predicted change for both irrigated and rainfed wheat, corn, and soybeans. The predicted changes in yields are then combined with economic models of farm level crop choice, using linear or nonlinear programming (Adams et al. 1995). The analysis, however, usually considers variable but not fixed costs of production. It often turns out to be necessary to add artificial constraints to make the programming model solution replicate actual farmer behavior in the baseline period. Moreover, the analysis focuses on the agricultural sector, and ignores the linkages with the remainder of the economy which would make the input prices and input allocations to agriculture endogenous.

This is remedied in the *computable general equilibrium* (CGE) approach, which models agriculture in relation to the other major sectors of the economy and allows resources to move between sectors in response to economic incentives. An example is FARM, the eight-region CGE model of the world agricultural economy by the United State Department of Agriculture. However, while a CGE model has the advantages of making prices endogenous and accounting for inter-sectoral linkages, these come at the cost of quite drastic aggregation in which spatially and economically diverse sectors are characterized by a representative farm or firm.

In summary, on the one hand the agronomic models do not fully capture the adaptation and mitigation strategies of farmers in the face of climate change, while on the other the

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[1]Major contributions include Smith and Tirpak (1989), Nordhaus (1991), Cline (1992), Fankhauser (1995), Tol (1995), Mendelsohn and Neumann (1999), and Reilly, ed (2002).

CGE models are only appropriate to highly aggregated sectors of the economy. Mendelsohn, Nordhaus and Shaw (1994) provide an interesting middle ground, proposing what they call a *Ricardian* approach, essentially a hedonic model of farmland pricing, based on the notion that the value of a tract of land capitalizes the discounted value of all future profits or rents that can be derived from the land. The advantage of the hedonic approach is that it relies on the cross-sectional variation to identify the implicit choices of landowners regarding the allocation of their land among competing uses instead of directly modeling their decision. Further, the hedonic function also allows one to calculate the direct impact on each farmer, county or state, in contrast to the highly aggregated structural CGE models. This is the approach we adopt, though with a number of innovations indicated below and explained in detail in succeeding sections.

In this paper we resolve some of the differences in previous studies by estimating a hedonic equation for farmland value east of the 100th meridian, the boundary of the region in the United States where farming is possible without irrigation. The main contributions of the paper are: First, we incorporate climate differently than previous studies, by using transformations of the climatic variables suggested by the agronomic literature. The relationship between climatic variables and plant growth is highly nonlinear and our approach yields results that are consistent with the agronomic evidence. Second, we develop a new data set that integrates the spatial distribution of soil and climatic variables within a county with the help of a Landsat satellite scan of the contiguous United States. Third, we allow the error terms to be spatially correlated to obtain a more efficient estimator and correct t-values (which would otherwise be overstated). Fourth, we present several sensitivity checks, and show that our results are robust to both different specifications and census years. We show that results remain similarly unchanged when we include state fixed effects to control for the influence of state-specific factors unrelated to climate, such as property taxes and crop subsidies. Finally, we evaluate potential impacts of warming using new climate projections from the most recent runs of two of the major global climate models.

The paper is organized as follows. Section 2 outlines a model of farmland value with attention to issues raised by irrigation. Section 3 addresses spatial issues that arise in the definition and measurement of climatic and soil variables and in the correlation of error terms. Section 4 presents our empirical results, including tests for spatial correlation and estimates of the hedonic regression coefficients and discusses a variety of tests of robustness of the results. Section 5 uses the results to generate estimates of regionally differentiated impacts of climate change on agriculture. Section 6 summarizes our conclusions.

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2 A Model of Farmland Value

The farmer's problem can be represented formally as follows. Let $\pi_{i,j,k}$ denote the profit associated with the kth potential use of a piece of land of farm i in county j, $k = 1...N_k$, $\boldsymbol{\omega}_{i,j}$ the vector of input prices, $\mathbf{C}_{i,j} = (C_{i,j,1}, \ldots, C_{i,j,N_k})$ the vector of fixed costs, and $\mathbf{p} = (p_1, \ldots, p_{N_k})$ the vector of output prices associated with that use of land. Let $\mathbf{z}_{i,j}$ denote the fixed inputs (including indicators of soil quality). Then the profit associated with the kth use of land can be represented by the function

$$\bar{\pi}_{i,j,k} = \pi_k(p_k, \boldsymbol{\omega}_{i,j}, \mathbf{z}_{i,j}) - C_{i,j,k} \tag{1}$$

Given a capitalization ratio θ, the corresponding value of land in farm i in county j in use k becomes $\theta\bar{\pi}_{i,j,k}$.

In an econometric context, the analysis includes an additive random error associated with the kth use of land, denoted $\xi_{i,j,k}$:

$$f\left(V_{i,j,k}\right) = f\left(\bar{V}_{i,j,k}\right) + \xi_{i,j,k} = f\left(\theta\bar{\pi}_k(p_k, \boldsymbol{\omega}_{i,j}, \mathbf{z}_{i,j}) - \theta C_{i,j,k}\right) + \xi_{i,j,k} \tag{2}$$

where f is a possible transformation of the dependent variable. The most common specifications in hedonic studies are the linear $f\left(V_{i,j,k}\right) = V_{i,j,k}$ and the semi-log $f\left(V_{i,j,k}\right) = ln\left(V_{i,j,k}\right)$.

The Ricardian approach is based on the observation that land is put to its most profitable use. The value of a piece of land is then given by the envelope

$$\begin{aligned} f\left(V(\mathbf{p}, \boldsymbol{\omega}_{i,j}, \mathbf{C}_{i,j}, \mathbf{z}_{i,j})\right) &= \max_k \left\{ f\left(\bar{V}_1(p_1, \boldsymbol{\omega}_{i,j}, C_{i,j,1}, \mathbf{z}_{i,j})\right) + \xi_{i,j,1}, \ldots, \right. \\ &\left. \qquad f\left(\bar{V}_{N_k}(p_{N_k}, \boldsymbol{\omega}_{i,j}, C_{i,j,N_k}, \mathbf{z}_{i,j})\right) + \xi_{i,j,N_k} \right\} \end{aligned} \tag{3}$$

We assume that the error $\xi_{i,j,k}$ can be decomposed into two components, i.e., $\xi_{i,j,k} = \nu_{i,j} + \varphi_k$, where $\nu_{i,j}$ is the error attributable to the location of farm i in county j and φ_k is the error attributable to the specific use of the land. For the particular case where the φ_k are i.i.d. extreme value with mean zero, there is a closed form expression for the expected value of the farmland value envelope (Johnson et al. 1994). If one had data on $(\mathbf{p}, \boldsymbol{\omega}_{i,j}, \mathbf{C}_{i,j}, \mathbf{z}_{i,j})$, the individual V_k functions could in principle be estimated from observed land value data.[2] In the general case where the φ_k are not extreme value distributed, there is no closed form expression for the expected value, and the conventional linear or semi-log hedonic equations

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[2]If one uses data on the shares of land in the farm, or the county, allocated to the different uses there would be a gain in efficiency by jointly estimating the logit share probabilities together with the land value envelope.

found in the literature may be regarded as an approximation to the land value envelope.

In this framework, climate variables play two different roles. Temperature is an exogenous shift variable in the production function; increases in temperature increase the demand for water as an input and they can raise or lower yield, depending on the size of the increase. Precipitation has a different role in irrigated areas than in dryland areas. In dryland areas, the water supply for crops comes from precipitation falling on the field before and during the growing season; in this case, the water supply is fixed by nature in any given year, and it comes with a price of zero. In irrigated areas, by contrast, the water supply is man-made, using local groundwater or surface water imported from somewhere else, it comes at a cost, and the quantity is endogenously determined. In terms of location, since the time of John Wesley Powell it has been common to take the 100th meridian as a rough approximation of the rainfall line in the US. To the east, rainfall generally exceeds 20 inches per year while, to the west, rainfall is generally less than 20 inches per year. Since virtually all traditional US crops require at least 20 inches of water to grow, the 100th meridian marks the boundary of the arid West, where farming is generally possible only with use of irrigation.[3] Thus the 17 western states account for about 88% of the 150 million acre feet of irrigation water used annually in the U.S.

The economic implications of the distinction between dryland and irrigated farming are discussed in detail by Cline (1996), Darwin (1999), and Schlenker et al. (2003), and will be summarized briefly here. In addition to the fact that precipitation does not measure water supply in the arid West, the other distinctive feature is that, in irrigated areas, future changes in water costs, unlike other input costs, are not likely to be capitalized in future land prices in the same way as past cost changes were capitalized in past land values. Many of the major surface water supply projects in the western United States were developed by the US Bureau of Reclamation or the Army Corps of Engineers and involved a substantial subsidy to farmers. Depending on the age of the project, there is substantial variation in federal irrigation charges across different projects, and these are clearly capitalized into farmland values. Failure to account for subsidies (some of which, on a per-acre basis, exceed farmland values in the eastern United States) could bias other regression coefficients, especially climatic coefficients that in turn are correlated with the access to irrigation.

Aside from the federal projects, the remainder of the irrigation supply in the western states comes from groundwater or from non-federal surface water storage projects. Neither of those sources of water is subsidized to any significant degree. Nevertheless, in the case of

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[3]Strikingly, among all of our exogenous variables the only one that is significantly different at the 5% level between the counties west and east of the 100th meridian is average precipitation between April and September.

irrigation with non-federal surface water it still would be misleading to predict the economic cost of a change in precipitation on the basis of a hedonic regression of current farmland values. This is because, although non-federal surface water is generally not subsidized, it is priced on the basis of historic cost, which is generally far below the current replacement cost of this capital.

In summary, the economic effects of climate change on agriculture need to be assessed differently for counties on either side of the 100th meridian, using different variables and different regression equations. Because of data constraints, our analysis here focuses on the effect of climate on farmland values in counties east of the 100th meridian. Our sample comprises approximately 80 percent of the counties and 72 percent of all farmland value in the United States.[4]

3   Spatial Dimensions of Variables and Error Terms

The dependent variable in our hedonic model is the county average value of land and buildings per acre as reported in the 1982, 1987, 1992, and 1997 Censuses of Agriculture. We have translated all numbers into 1997 dollars using the GDP implicit price deflator to make them comparable. It has been customary in the hedonic literature to use as explanatory variables soil and climatic variables evaluated at the *centroid* of a county. However, soils and climatic conditions can vary significantly within a county and the estimated value at the centroid might be quite different from what farmers experience. To more accurately reflect this reality, we therefore average the soil characteristics over all the farmland area in a county.[5] The agricultural area is used as a cookie-cutter for our exogenous variables, i.e., we average the climate and soil variables over all farmland areas in a county. All soil variables are taken from STATSGO, a country-wide soil database that aggregates similar soils to polygons.

The climatic variables are derived from the PRISM climate grid, a small-scale climate history developed by the Spatial Climate Analysis Service at Oregon State University and widely used by professional weather services. It provides the daily minimum and maximum

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[4]In section 5 on impacts of climate change, we offer some remarks on how results would be affected by adding in the impacts on irrigated farmland west of the 100th meridian, based on an ongoing study of California.

[5]Farmland area is derived from the 1992 National Land Cover Characterization by the United States Geological Survey. This land classification is based on Landsat satellite images and assigns each pixel to one of several land classifications, cropland and pasture being two of them. The pixel size is 30m in each direction, or approximately the length of a basketball court. This translates into approximately 8.5 billion pixels for the contiguous United States. All pixels classified as cropland and pasture are then aggregated to polygons, while federal land holdings and urban areas are excluded. Note that the agricultural area includes only cropland and pasture, not rangeland or woodland. It is difficult to determine from satellite images whether rangeland or forests are privately owned or belong to federal forests and grasslands.

temperature and precipitation averaged over a monthly time-scale for a 2.5 mile x 2.5 mile grid in the coterminous United States, i.e., more than 800,000 grid cells, for the years 1895 to 2003. The 2.5 mile x 2.5 mile climate polygons are intersected with the agricultural area to derive the agricultural area in each polygon. The climatic variables in a county are simply the area-weighted average of the variables for each climate grid. In this analysis we use the monthly average temperature and precipitation for the 30 years preceding each census year.[6]

The existing literature has generally represented the effect of climate on agriculture by using the monthly averages for January, April, July and October.[7] However, from an agronomic perspective, this approach is less than optimal. First, except for winter wheat, most field crops are not in the ground in January; most are planted in April or May and harvested in September or October (United States Department of Agriculture, NASS 1997). Second, plant growth depends on exposure to moisture and heat throughout the growing season, albeit in different ways at different periods in the plant's life cycle; therefore, including weather variables for April and July, but not May, June, August or September, can produce a distorted representation of how crops respond to ambient weather conditions. The agronomic literature typically represents the effects of temperature on plant growth in terms of cumulative exposure to heat, while recognizing that plant growth is partly nonlinear in temperature. Agronomists postulate that plant growth is linear in temperature only within a certain range, between specific lower and upper thresholds; there is a plateau at the upper threshold beyond which higher temperatures become harmful. This agronomic relationship is captured through the concept of degree days, defined as the sum of degrees above a lower baseline and below an upper threshold during the growing season. Here we follow the formulation of Ritchie and NeSmith (1991) and set the lower threshold equal to $8°C$ and the upper threshold to $32°C$. In other words, a day with a temperature below $8°C$ results in zero degree days; a day with a temperature between $8°C$ and $32°C$ contributes the number of degrees above $8°C$; and a day with a temperature above $32°C$ degrees contributes 24 degree days. Degree days are then summed over the growing period, represented here by the months from April through September.[8] Following Ritchie and NeSmith (1991), the level

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[6]For example, when the dependent variable is farmland value from the 1982 census we use the average climate over the period 1952-1981, and similarly with the other three censuses. The formal distinction between climate, which we use here, and weather is that weather refers to meteorological conditions at a particular point in time, while climate refers to the long-term average of weather over an extended period of time. The distinction is likely to make a difference from an economic perspective. Due to the inelasticity of short-run demand for many agricultural commodities, an adverse weather shock in a particular year can trigger an increase in price, thereby raising profit for the remaining producers. In the long-run, however, an adverse shift in climate is unambiguously likely to reduce the profits from farming in the region where the shift occurs.

[7]This approach was introduced into the economics literature by Mendelsohn et al. (1994).

[8]Different crops, and sometimes different varietals, have different temperature thresholds, but the values

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beyond which temperature increases become harmful is set at $34°C$.

A complication with degree days is that the concept is based on daily temperature while our climate records consist of monthly temperature averages. Thom (1966) develops the necessary relationship between daily and monthly temperature variables under the assumption of normality. This relationship is used to infer the standard deviation of daily temperature variables from monthly records. Degree days are then derived using the inverse Mills ratio to account for the truncation of the temperature variable.[9]

The spatial distribution of farmland within and between counties affects not only the exogenous variables, but also the error term structure. Neglecting the spatial correlation of the error terms can be expected to lead to an underestimate of the true variance-covariance matrix and therefore to an overestimate of t-values as the error terms are falsely assumed to be independent. Let $\mathbf{z}_j$ be the average of all farms i in county j. Assuming that the outer envelope of the average farmland value in county j can be approximated by a function that is linear in the variables $\mathbf{z}_j$, and adding a county-specific error term η_j we get

$$f(V_j) = f\left(\bar{V}_j\right) + \eta_j = \mathbf{z}_j'\boldsymbol{\beta} + \eta_j \tag{4}$$

Following the approach of Anselin (1988) and Griffith (1988), the spatial correlation of the error terms across counties can be modeled (in matrix notation) as $\boldsymbol{\eta} = \rho\mathbf{W}\boldsymbol{\eta} + \mathbf{u}$. Here, $\mathbf{u}$ is the vector of error terms that are independently normally distributed with $\mathbb{E}[u_j] = 0$ and $VAR[u_j] = \sigma_{u_j}^2$, ρ is the parameter of spatial correlation, and $\mathbf{W}$ is the spatial weighting or "contiguity" matrix which influences the form of the spatial dependence. We experiment with several matrices in the empirical section below. The product $\mathbf{W}\boldsymbol{\eta}$ is a vector with weighted averages of errors in contiguous counties, and ρ indicates the correlation between a county's error and the composite of the errors of its neighbors. In the standard applications of spatial correlation the variance $\sigma_{u_j}^2$ is assumed to be homoscedastic. However, in our case V_j is a county-wide average of the value of farmland and therefore the error terms u_j might be heteroscedastic as they are an average of the farm-specific white-noise error terms $\nu_{i,j}$. Researchers originally approached this via maximum likelihood (ML) estimation. However,

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given by Ritchie and NeSmith (1991) are broadly representative. Cool-season crops such as barley, oats and wheat have a slightly lower minimum threshold, while warm season crops such as cotton, corn and soybeans have a slightly higher minimum threshold. Different crops, and different varietals, also have different lengths of growing season. For example, many varieties of corn have a growing season in the range of 110-135 days, but some varietals and hybrids have a growing season of 80-110 days. Moreover, in many cases hybrids are rated by seed dealers specifically in terms of their growing degree day requirements, for example Pioneer 39K72 (2225) which requires 2225 degree days Fahrenheit, or 1,236 degree days Celsius.

[9]Some later studies have relaxed the normality assumption and compared monthly and daily observations at U.S. stations to generate better estimates. However, the predicted error is usually within 3-5%, which is rather low as compared to the cross-sectional variation in our data set.

we adopt the Generalized Method of Moments (GMM) estimator of Kelejian and Prucha (1999). Using Monte Carlo simulations, Kelejian and Prucha show that the GMM procedure yields results that are similar to ML but requires considerably less computer time and is far more stable.[10] The next section presents the results using the feasible GLS weights and GMM estimation.

4   Empirical Estimation

We turn now to the estimation of the hedonic farmland value equation(s). Before we present our regression results we first examine whether the spatial correlation of the error terms as described in the previous section is indeed present. We conduct three tests of spatial correlation for all counties east of the 100th meridian using the same set of exogenous variables as in the estimation of the hedonic equation in Table 3 below, including state fixed effects. One test is the Moran-I statistic (Anselin 1988). However, since this does not have a clear alternative hypothesis, we supplement it with two Lagrange-Multiplier tests involving an alternative of spatial dependence, the LM-ERR test and LM-EL test. The results are shown in the first three rows of Table 1. Note that they are rather insensitive to the chosen weighting matrix.[11]

The spatial correlation of the error terms is quite large and omitting it will seriously overstate the true t-values. For example, the t-values using standard OLS that does not correct for the spatial correlation or the heteroscedasticity of the error terms are up to nine times as large, with an average value of 2.2 for the model presented in the first column of Table 3. In the following we use a two stage procedure. In the first stage we estimate the parameter of spatial correlation and premultiply the data by $(\mathbf{I} - \hat{\rho}\mathbf{W})$. In the second stage we estimate the model and use White's heteroscedasticity consistent estimator to account for the heteroscedasticity of the error terms.

In previous climate assessments, it has been customary to estimate a linear regression model. Since farmland values have to remain non-negative, and given the highly skewed distribution of farmland values in Table 2 a semi-log model appears preferable. To determine which model better fits the data, we conduct a P_E-test (Davidson and MacKinnon 1981). We use 10,000 bootstrap simulations to get a better approximation of the finite sample

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[10]Bell and Bockstael (2000) use both GMM and ML estimation for a hedonic regression of urban home values and find that the results are very similar.

[11]Our data are county-averages and hence prone to heteroscedasticity. We also approximate distribution of farm sizes in each county by a log-normal distribution to derive the sum of squared farmland shares. However, our results are insensitive to the pre-multiplication of the data with a factor proportional to the inverse of the square root of the variance in each county.

Table 1: Test for Spatial Correlation in the Semi-Log Model

Model	Queen Standardized	Contiguity Matrix	Distance Weights
Tests for the Presence of Spatial Correlation			
Moran-I $N(0,1)$	41.8	42.9	40.1
LM-ERR $\chi^2(1)$	1551	1615	1435
LM-EL $\chi^2(1)$	1036	1114	1370
Parameter of Spatial Correlation			
ρ	0.71	0.72	0.69

We use three spatial weighting matrices to check the sensitivity of our results to the proposed structure of the employed weighting matrix. Under the contiguity matrix, the (i,j) element of **W** is positive if counties i and j have a common boundary, and zero otherwise. **W** is then normalized so that the elements in each row sum to unity, which implies an equal value for the non-zero elements in each row. The Queen standardized matrix is the same as the Contiguity Matrix except that to value the relative influence of each county, the non-zero elements for each pair of contiguous counties were multiplied by the inverse of the distance between the county centroids and then row-normalized (Kelejian and Prucha 1999). Finally, the distance weights use the same distance weights as the Queen standardized matrix, but the rows are no longer standardized to sum to one. (We normalized the entire matrix such that the average row sum is one).

distribution of the estimate. The t-value for rejecting the linear model in favor of the semi-log model is 873, while the t-value of rejecting the semi-log model in favor of the linear model is 0.01. We therefore focus the remainder of our analysis on the semi-log model.[12]

Results of the log-linear hedonic regression under the Queen standardized weighting matrix are displayed in the first two columns of Table 3. We present results with and without state fixed effects. The reason for including fixed effects is that this can control for the possibility that there are unobserved characteristics common to all farms within a state, such as state-specific taxes and uneven incidence of crop subsidies due to differences in cropping patterns across states. The concern is that the identification of the climate coefficients in the hedonic model might otherwise come primarily from variation in government programs that target specific crops. However, it should be noted that since we rely on a nonlinear functional form, the estimation procedure still uses variation between states in the identification of the coefficients. We find that inclusion of fixed effects does *not* reduce the significance level of the climatic variables. At the same time, the parameter of spatial correlation is virtually unchanged when we include fixed effects, suggesting that there are indeed spill-over effects that are based on spatial proximity rather than an administrative assignment to a particular

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[12]One might wonder whether the semi-log model performs better because it is superior at explaining the large farmland values close to urban areas. When we drop the 216 counties with a population density above 400 people per square mile or a combined population above 200,000, the test statistics remain comparable at 830 and 0.02, respectively.

Table 2: Descriptive Statistics for Counties East of the 100 Degree Meridian

Variable	Mean	Min	Max	σ
Farmland Value 1982 ($/acre)	1774	344	13748	1037
Farmland Value 1987 ($/acre)	1361	235	14050	1047
Farmland Value 1992 ($/acre)	1433	178	19622	1379
Farmland Value 1997 ($/acre)	1618	196	15558	1217
Farmland Value 1982-1997 ($/acre)	1546	252	14910	1113
Degree Days (8-32°C) April-September in Thousand	2.29	1.00	3.68	0.55
Degree Days (34°C) April-September	2.37	0.38	5.69	0.91
Precipitation April-September (cm)	59.51	33.23	98.21	9.66
Income Per Capita (Thousand $)	17.39	6.73	38.41	3.56
Population Density (Hundred People per Square Mile)	1.29	0.00	55.03	2.96
Latitude (degrees)	37.75	26.18	48.78	4.64
Water capacity (Inches / Inch)	8.92	3.48	17.17	1.88
Percent Clay (Percentage Points)	26.15	1.44	55.61	8.72
Minimum Permeability of All Layers (Inches/Hour)	1.24	0.05	11.65	1.24
K-factor of Top Soil	0.29	0.01	0.48	0.07
Best Soil Class (Percentage Points)	64.58	0.00	100.00	21.08
Number of observations	2398			

All dollar figures are in 1997 dollars. Exogenous variables are values from the regression averaging all census years. Climate variables are the average of all 30-year histories preceding each census.

state.

The estimated coefficients on the climatic variables are consistent with the agronomic literature. The optimal number of growing degree days in the $8°C - 32°C$ range peaks at 2400 degree days for the pooled model in column 1 of Table 3. This is close to the optimal growing condition for many agricultural commodities when one adjusts for the length of the growing season (Martin et al. 1976, Parker 2004).[13] Degree days above $34°C$ are always harmful.[14] Precipitation peaks at 79 cm or approximately 31 inches, which also is close to

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[13]We also examine the effect of yearly degree days variables on yearly corn yields for the years 1970-2003, with comparable optimal degree days numbers.

[14]We also experimented with a linear and quadratic specification on degree days above $34°C$, but the square root gives the best fit. An interpretation is that beyond some point, when crops are sufficiently adversely affected by the heat, the incremental damage from further increases is sharply reduced. The square root function is an approximation to this behavior. Note that degree days in the $(8 - 32°C)$ range are counted in thousands, while degree days with base $34°C$ are simply the total number of degree days. Table 2 reveals that the number of degree days above $34°C$ is currently quite limited. It should also be noted that the use of the degree days variable does *not* imply that changes in temperature in each month have the same effect on farmland value. July temperatures are much higher than, say April temperatures; thus a $1°C$ increase in average July temperature has a different effect than the same increase in average April temperature because it is more likely to raise the number of harmful degree days above $34°C$.

Table 3: Regression Results Explaining Log of Farmland Value per Acre Using Only Counties East of the 100 Degree Meridian

Variable	82-97 Census	82-97 Census	1982 Census	1987 Census	1992 Census	1997 Census
Constant	320	337	295	329	375	328
	(4.04)	(4.69)	(3.49)	(4.08)	(4.52)	(4.06)
Degree Days (8-32°C)	165	127	161	134	167	226
	(5.94)	(5.37)	(6.10)	(4.62)	(5.24)	(7.53)
Degree Days (8-32°C) Squared	-34.3	-24.9	-31.3	-26.9	-37.4	-51.4
	(5.34)	(4.58)	(5.09)	(4.04)	(5.04)	(7.56)
Square Root Degree Days (34°C)	-14.4	-25.2	-13.1	-15.5	-15.0	-14.2
	(4.80)	(9.76)	(4.70)	(4.91)	(4.34)	(4.31)
Precipitation	4.47	5.49	4.84	4.90	3.84	4.41
	(3.88)	(4.89)	(3.92)	(4.29)	(3.26)	(3.90)
Precipitation Squared	-0.0281	-0.0373	-0.0318	-0.0326	-0.0227	-0.0270
	(3.04)	(4.14)	(3.16)	(3.55)	(2.40)	(3.00)
Latitude	-0.582	0.0224	-0.403	-0.473	-1.33	-1.62
	(0.44)	(0.02)	(0.28)	(0.35)	(0.91)	(1.16)
Income per Capita	3.66	3.85	3.83	3.70	3.47	2.87
	(13.64)	(13.86)	(10.92)	(11.01)	(11.50)	(14.34)
Population Density	4.80	4.80	5.00	5.76	5.67	4.54
	(11.74)	(11.57)	(11.18)	(12.26)	(10.64)	(9.26)
Population Density Squared	-0.0639	-0.063	-0.0685	-0.0786	-0.0738	-0.0791
	(5.72)	(5.68)	(5.04)	(6.09)	(4.58)	(4.63)
Average water capacity	0.696	0.790	1.24	0.543	0.464	0.689
	(1.28)	(1.45)	(2.07)	(0.98)	(0.73)	(1.15)
Percent Clay	0.0905	0.0137	0.222	0.0968	0.0567	-0.0484
	(0.83)	(0.12)	(1.92)	(0.80)	(0.44)	(0.39)
Minimum Permeability	2.37	2.50	3.26	2.22	1.39	2.32
	(2.52)	(2.28)	(3.41)	(2.32)	(1.18)	(2.24)
K-factor of Top Soil	-29.0	-16.6	-38.1	-20.9	-39.9	-26.8
	(1.84)	(1.08)	(2.14)	(1.17)	(2.10)	(1.45)
Best Soil Class	0.298	0.289	0.417	0.255	0.294	0.269
	(6.51)	(6.05)	(7.82)	(5.28)	(5.64)	(5.64)
State Fixed Effects	Yes	No	Yes	Yes	Yes	Yes
Number of Observations	2398	2398	2398	2398	2398	2398
Spatial Correlation	0.71	0.74	0.65	0.67	0.68	0.64

Table lists coefficient estimates and t-values in parenthesis. For expositional purposes, the coefficients have been multiplied by 100. Variables in the first two columns are averages of the variables in each census year. Climate variables are constructed from the 30-year climate history preceding each census.

the water requirements of many crops, when adjusted for the length of the growing season.

Other variables have intuitive signs as well. Income per capita and population density are important and highly significant determinants of farmland value: higher population pressure translates into higher farmland values, albeit at a decreasing rate. Similarly, higher incomes drive up the price of farmland. Two soil variables are significant at the 5% level in the pooled model: better soils, as measured by a soil quality index, result in higher farmland values; and a lower minimum permeability, which indicates drainage problems, reduces farmland value. The effect of the former is quite large: farmland with 100% of soils in the best soil class categories are 35% more valuable compared to farmland with 0% in the top soil classes. The variable K-factor is significant at the 10% level in three out of the five regressions using state fixed effects. It indicates higher erodibility of the fertile top soil, which is harmful. Percent clay frequently switches sign and is not significant in most models; neither is the average water capacity of the soil.

We have suggested that degree days and precipitation over the growing season better represent the effect of climate on agriculture than the alternative specification of monthly averages of untransformed temperature and precipitation. To assess this claim, we conduct an encompassing test to determine which model is better at predicting the effects of climate change. In order to do so, we split the sample into two subsets: the northern-most 85% of the counties in our sample are used to estimate the parameters of both models in order to derive the prediction error for the southern-most 15%, i.e., we see which model calibrated on moderate temperatures is better at predicting the values for warmer temperatures. The results offer clear confirmation of the superiority of the degree days model. Even though this model has less than one third the number of climate variables included in the alternative, we can reject the null hypothesis of equal forecasting accuracy in favor of the degree days model with a t-statistic of 2.94 (Diebold and Mariano 1995, p.256).[15]

Kaufmann (1998) emphasizes that the parameter estimates in the model using undemeaned climate variables often vary between models. This is not surprising in light of the strong multicolinearity between the climate variables that leads to frequent switching of the parameter estimates, sometimes with large marginal effects. This can be seen in our data as well, as shown in an appendix available from the authors on request. Summarizing briefly, when the monthly climatic variables for January, April, July and October are included, the only variables which are significant in the pooled model between all census years are July temperature and April and October precipitation (including squared terms); none of the other 10 monthly climate variables in the pooled model is significant even at the 10% level.

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[15] We premultiply the forecasting errors by $(\mathbf{I} - \hat{\rho}\mathbf{W})$ to account for the spatial correlation of the error terms (otherwise the test statistic would have been 8.31). The results remain comparable when we change the percentage of data in the south that is excluded.

Further, the coefficients on July temperature imply that farmland value peaks at an average temperature of $22°C \approx 72°F$, which seems rather low given agronomic research showing that plant growth is linear in temperature up to about $32°C$. There are other anomalous results, but as the coefficients are not significant, we do not discuss them further here.

The results of the degree days model are very reasonable in the light of the agronomic literature. But how robust are they across plausible alternative specifications of variables and data? Here we briefly describe several sensitivity tests. A more complete discussion is given in the appendix available on request.

We test the stability of the five climatic coefficients across the several census years in our pooled model. During this period there were some significant changes in farmland values east of the 100th meridian; the overall farmland value in this region declined by 32% between 1982 and 1987 in real terms, and increased by 13% between 1987 and 1992, and 14% between 1992 and 1997. A decline in some commodity markets and a shift in federal crop subsidy programs in the mid 1980s affected different growing regions in different ways. Under these circumstances it would not be surprising if the coefficients on the climate variables varied somewhat over time. In fact, however, they are very robust. Pair-wise Chow tests between the pooled model and the four individual census years in Table 3 reveal that the five climatic variables are not significantly different at the 10 percent level in any of the ten tests.

Although we have excluded western counties because their agriculture is dependent on irrigation, what about irrigated areas east of the 100th meridian? To test whether these are affecting our results, we repeat the estimation excluding counties (i) where more than 5% of farmland area is irrigated, and (ii) where more than 15% of the harvested cropland is irrigated[16] We also examine further the influence of population, excluding counties with a population density above 400 people per square mile or a population total above 200,000. The exclusion of the three sets of counties leaves the coefficient estimates virtually unchanged, and the lowest of the three p-values for the test of whether the five climate variables have the same coefficients is 0.85. It is not surprising that excluding irrigated counties east of the 100th meridian has little effect on our regression results, since very few are highly irrigated, and all receive a substantial amount of natural rainfall. Under these circumstances, irrigation is a much smaller supplement to local precipitation, small enough to have little effect on regression results.[17] By contrast, the p-value for the test of whether the five climate

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[16]One possible concern is that pasture and woodland are rarely irrigated. Since cropland accounts for only about one third of farmland area, it is possible in principle that a large fraction of the cropland area in a county might be irrigated, but there is sufficient unirrigated pasture that the combined irrigation percentage is relatively low. To guard against this, we re-estimate the degree day model excluding counties where more than 15% of the harvested cropland is irrigated.

[17]On average, 55% of all harvested cropland west of the 100th meridian was irrigated in the years 1982,

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coefficients are the same in counties west of the 100th meridian is 10^{-11}. Including western counties that depend crucially on large-scale irrigation significantly (and inappropriately) alters the equation.

To test whether the time period over which the climate variables are calculated makes any difference, we replicate the analysis using as alternatives to the 30-year histories on which the estimates reported in Table 3 are based, 10- and 50-year averages. Neither of the alternatives yields climate coefficients significantly different from the pooled regression results based on the 30-year histories.

These tests suggest that our model is stable for various census years, data subsets, and climate histories. Nevertheless, one might wonder whether there could be problems with outliers or an incorrect parametrization. We briefly address these concerns.

In a test of the robustness of our results to outliers, the analysis is replicated using median regression, where the sum of absolute errors is minimized both in the first-stage derivation of the parameter of spatial correlation and in the second stage estimation of the coefficients. Again, the climatic variables remain robust and are not significantly different. To test the influence of our covariates on the results we follow the idea of Leamer's extreme bound analysis and take permutations of our model by including or excluding each of 14 variables for a total of 16,384 regressions.[18] No sign switches are observed in any of the five climatic variables, again suggesting that our results are very stable. Further, the peak-level of degree days $(8 - 32°C)$ is limited to a relatively narrow range. We check sensitivity to the assumed length of the growing season by allowing the season to begin in either March, April, or May and end in either August, September, or October. The estimated impact of warming remains robust across all possible combinations. Finally, in order to examine whether the quadratic specification for degree days in our model is unduly restrictive, we estimate a penalized regression spline for degree days $8°C - 32°C$ and find that the quadratic approximation is consistent with the data.

5   Climate Change Impacts

Before turning to the determination of the potential impacts of global warming on the agricultural sector of the U.S. economy as measured by predicted changes in farmland values we briefly consider whether farmers' expectations have changed over the period covered by

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1987, 1992, and 1997 and the average precipitation between the months of April and September was 23 cm or 9 inches. In sharp contrast, only 8% of all harvested cropland was irrigated east of the 100th meridian and farms there still received 59 cms or 23 inches of rain between April and September.

[18]We take permutations over the 5 soil variables, latitude (including squared terms), and the squared terms on income per capita and population density.

our study, and whether this may affect our estimates. In the previous section we regressed farmland values on past climate averages, even though farmland values are determined using forward-looking expectations about future climate. The weather in the U.S. over the past century was viewed as a random drawing from what until recently was thought to be a stationary climate distribution. Our own data are consistent with this: the correlation coefficients between the 30-year average in 1968-1997 and the two previous 30-year averages of the century, i.e., for 1908-1937, and 1938-1967, are 0.998 and 0.996 for degree days ($8 - 32°C$), 0.91 and 0.88 for degree days ($34°C$), and 0.93 and 0.93 for precipitation variable. Accordingly, when we use the error terms from our regression and regress them on past values of the three climate averages, none of the coefficients is statistically significant. The same result holds if we move to the shorter 10-year climate averages. This suggests that past climate variables are not a predictor of farmland values once we condition on current climate.

As pointed out above, consecutive census years give comparable estimates of the climate coefficients in our hedonic equation and none of them are significantly different.[19] Similarly, we check whether the aggregate climate impacts for the four emission scenarios in Table 5 change if we use the 1982 census instead of the pooled model. Even though the standard deviations are fairly narrow, t-tests reveal that none of the eight mean impact estimates are significantly different (the largest t-value is 1.09). We conclude that our results are not affected by any significant change in expectations over the study period.[20]

In the calculations which follow we use the regression coefficients from the semi-log model, which we have shown to be both plausible and robust, along with predictions from a general circulation model to evaluate the impacts of climate change. The climate model we use for this analysis is the most recent version of the UK Met Office Hadley Model, HadCM3, recently prepared for use in the next (fourth) IPCC Assessment Report. Specifically, we use the model's predicted changes in minimum and maximum average monthly temperatures and precipitation for four standard emissions scenarios identified in the IPCC Special Report on Emissions Scenarios (SRES) (Nakicenovic, ed 2000). The chosen scenarios span the range

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[19]We use 10,000 bootstrap simulations to repeatedly derive the optimal number of degree days $8 - 32°C$, but can not detect any significant change.

[20]Weart (2003) observes that, until 1988, global warming was generally below the threshold of public opinion in the United States. It began to receive some attention that year, but in the United States, unlike in Europe, this was soon followed by an organized campaign of skepticism about global warming which appears to have influenced public opinion. According to Immerwahr (1999), only 24% of Americans said they worry a great deal about global warming and the greenhouse effect in 1997, and even then this was seen as a very long-run phenomenon. Subsequently, the Kyoto Protocol, signed in December 1997, has raised the visibility of the issue. There is no evidence that for the period covered by this study - 1982 through 1997 - the market for farmland in the US was affected by significant change in the expectations regarding future climate in relation to farm asset values.

from the slowest increase in greenhouse gas concentrations (B1), which would imply a little less than a doubling of the pre-industrial level by the end of the century, to the fastest (A1FI), associated with between a tripling and a quadrupling, and include two intermediate scenarios (A2 and B2). We use the 1960-1989 climate history as the baseline and calculate average predicted degree days and precipitation for the years 2020-2049 and 2070-2099. The former captures impacts in the near to medium term, while the latter predicts impacts over the longer term, all the way to the end of the century, the usual benchmark in recent analyses of the nature and impacts of climate change.[21] Predicted changes in the climatic variables are given in Table 4.

Impacts of these changes on farmland values are presented in Table 5 for both the 2020-2049 and 2070-2099 climate averages under all four emissions scenarios. Not surprisingly, results for the near-term 2020-2049 climate averages are similar under all four scenarios. The relative impact ranges from a 10% to a 25% decline in farmland value, which translates into an area-weighted aggregate impact of -\$3.1 billion to -\$7.2 billion on an annual basis.[22] Although the aggregate impact is perhaps not dramatic, there are large regional differences. Northern counties, that currently experience cold climates, benefit by as much as 34% from the predicted warming, while others in the hotter southern states face declines in farmland value as high as 69%. Similarly, average relative impacts are comparable across scenarios for the individual variables degree days $(8 - 32°C)$ and degree days (above $34°C$), but again there are large regional differences. The effect of an increase in the latter variable is always negative because increases in temperature above $34°C$ are always harmful, while the effect of the former variable depends on whether a county currently experiences growing conditions above or below the optimal number of degree days in the $8 - 32°C$ range.[23]

The impact estimates for the longer-term 2070-2099 climate average become much more uncertain as the range of predicted greenhouse gas emission scenarios widens. Predicted

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[21]Changes in climatic conditions are calculated separately for each PRISM grid cell. We use the inverse of the squared distance between each of the PRISM grids and the four surrounding grid nodes of the climate change model to weight the influence of each of the four grid nodes. Note that the change in degree days captures the increase in both the mean and the standard deviation of temperature, since the predicted change in the variance of monthly temperatures is used in the inverted Mills ratio.

[22]We use the ratio of net cash income to farmland values for counties in our sample as proxy for the implicit discount rate. Unfortunately, the variable "net cash income" is not reported in the 1982 census and we therefore use observations from just the 1987, 1992, and 1997 censuses. The implicit discount rate is 4.65%.

[23]Note that the variable degree days $8 - 32°C$ has a bounded range of possible values, and even the largest temperature increases result in prediction currently observed in the sample for most counties. On the other hand, degree days above $34°C$ under the A1FI scenario results in values well outside the currently observed range, and should therefore be treated with some caution. As a sensitivity check we truncate temperature increases such that all future variables are in the range of currently observed values. The predicted total impact for the B2 scenario changes from a 20.6% and 31.6% decline to a 19.2% and 27.2% decline.

Table 4: Predicted Changes in Climatic Variables for Counties East of the 100 Degree Meridian Under Different Emission Scenarios for the Hadley HadCM3 model

	2020-2049 Average				2070-2099 Average			
Variable	Mean	Min	Max	σ	Mean	Min	Max	σ
Hadley HadCM3 - Scenario B1								
Average Temperature ($^\circ C$)	1.98	1.01	2.49	0.26	3.58	2.03	4.24	0.36
Degree Days (8-32$^\circ C$)	0.34	0.18	0.43	0.05	0.61	0.36	0.71	0.05
Degree Days (34$^\circ C$)	4.94	-0.62	40.60	4.51	15.98	0.44	108.91	13.31
Precipitation (cm)	2.45	-9.39	10.19	3.94	2.72	-10.61	18.28	4.37
Hadley HadCM3 - Scenario B2								
Average Temperature ($^\circ C$)	2.22	1.00	3.07	0.36	4.17	2.26	4.84	0.42
Degree Days (8-32$^\circ C$)	0.38	0.18	0.50	0.06	0.70	0.40	0.81	0.06
Degree Days (34$^\circ C$)	11.12	0.23	56.36	8.78	22.11	1.23	188.23	22.46
Precipitation (cm)	0.29	-15.28	10.73	4.44	2.21	-18.84	11.14	4.58
Hadley HadCM3 - Scenario A2								
Average Temperature ($^\circ C$)	2.41	0.99	3.00	0.34	5.98	3.02	6.98	0.63
Degree Days (8-32$^\circ C$)	0.41	0.17	0.51	0.06	0.95	0.52	1.11	0.10
Degree Days (34$^\circ C$)	11.93	0.45	75.67	8.92	67.56	5.89	319.81	42.16
Precipitation (cm)	0.16	-14.24	6.52	2.73	-0.45	-21.00	11.10	6.21
Hadley HadCM3 - Scenario A1FI								
Average Temperature ($^\circ C$)	2.28	1.05	2.97	0.31	7.44	3.83	8.70	0.74
Degree Days (8-32$^\circ C$)	0.38	0.19	0.47	0.05	1.15	0.61	1.34	0.14
Degree Days (34$^\circ C$)	15.76	-0.13	69.34	12.63	97.27	7.02	468.96	69.16
Precipitation (cm)	1.10	-7.27	9.92	3.76	2.34	-21.89	20.73	7.67

Table lists changes in degree days and precipitation during the major growing season, April through September, as well as changes in average temperature for the months April-September. The above emissions scenarios are taken out of the Special Report on Emissions Scenarios (SRES) for the IPCC 3rd Assessment Report (Nakicenovic, ed 2000). The chosen scenarios span the range from the slowest increase in greenhouse gas concentrations (B1), which would imply a little less than a doubling of the pre-industrial level by the end of the century, to the fastest (A1FI), associated with more than a tripling, as well as two intermediate scenarios (A2 and B2).

emissions over the course of the century are largely driven by assumptions about technological change, population growth, and economic development, and compounding over time leads to increasingly divergent predictions. The distribution of impacts now ranges from a average decline of 27% under the B1 scenario to 69% under the A1FI scenario. At the same time, the sharp regional differences observed already in the near to medium term persist, and indeed increase: northern counties generally benefit, while southern counties generally suffer. An exception is found in Appalachia, characterized by a colder climate than other counties at a similar latitude. Regional differences widen as counties with a very cold climate can

Table 5: Decomposition of Relative Changes in Farmland Value Due to Each Individual Climatic Variable (Percent)

Variable	2020-2049 Average				2070-2099 Average			
	Mean	Min	Max	σ	Mean	Min	Max	σ
Hadley HadCM3 - Scenario B1								
Degree Days (8-32°C)	-0.96	-26.83	24.33	12.11	-4.44	-41.73	49.83	20.13
Degree Days (34°C)	-11.17	-33.66	2.75	4.82	-26.21	-59.01	-1.86	9.57
Precipitation	1.02	-19.51	13.26	4.99	1.11	-21.31	11.33	4.35
Total Impact	-10.46	-58.58	28.02	16.21	-27.37	-78.77	44.15	22.58
Std. Error Total Impact	(2.89)	(4.85)	(4.51)		(4.90)	(4.83)	(8.93)	
Hadley HadCM3 - Scenario B2								
Degree Days (8-32°C)	-1.38	-31.50	30.37	14.02	-6.79	-45.71	60.91	22.40
Degree Days (34°C)	-19.77	-42.84	-2.09	7.35	-29.79	-73.26	-8.20	12.73
Precipitation	-1.22	-30.61	13.42	5.44	0.18	-37.45	13.70	5.84
Total Impact	-20.57	-67.67	34.41	18.66	-31.61	-88.28	52.37	26.57
Std. Error Total Impact	(3.44)	(4.75)	(5.70)		(5.17)	(3.66)	(11.20)	
Hadley HadCM3 - Scenario A2								
Degree Days (8-32°C)	-1.44	-30.12	30.11	14.19	-14.90	-52.76	80.70	26.54
Degree Days (34°C)	-20.12	-49.19	-3.96	8.12	-56.53	-84.78	-23.59	10.85
Precipitation	-0.32	-28.56	8.94	3.83	-2.70	-41.48	15.83	7.62
Total Impact	-20.21	-69.31	29.70	19.72	-61.64	-94.72	27.87	20.25
Std. Error Total Impact	(3.58)	(4.86)	(5.22)		(6.01)	(2.44)	(11.48)	
Hadley HadCM3 - Scenario A1FI								
Degree Days (8-32°C)	-0.54	-28.82	31.07	13.28	-23.29	-56.83	91.38	27.10
Degree Days (34°C)	-24.99	-50.49	1.04	9.42	-63.16	-90.97	-20.08	13.39
Precipitation	-0.22	-15.15	13.28	4.39	-0.80	-41.66	18.74	9.20
Total Impact	-24.50	-60.38	23.83	18.68	-68.54	-96.95	39.61	21.79
Std. Error Total Impact	(4.00)	(5.61)	(4.65)		(5.90)	(1.86)	(13.85)	

Table decomposes total impacts into contribution of each of the three climatic variables for four emission scenarios. The last line for each scenario reports the standard error for the mean, minimum, and maximum of the total impact.

benefit from continued warming: the maximum positive relative impact now ranges from 29% to 52%. However, the total number of counties with significant gains decreases in most scenarios. For the 2020-2049 time span, 446, 126, 269, and 167 counties, respectively, show statistically significant gains at the 95% level for the scenarios given in Table 4. These numbers change to 244, 202, 4, and 26 for the 2070-2099 time span. By the same token, the number of counties with statistically significant loses increases from 1291, 1748, 1762, and 1873 for the 2020-2049 time span to 1805, 1803, 2234, and 2236 for the 2070-2099 time span.

The regional distribution of impacts is shown in Figure 1 for counties with significant

Figure 1: Counties with Statistically Significant Gains and Losses East of the 100 Degree Meridian under the Hadley HadCM3 - B2 Scenario.
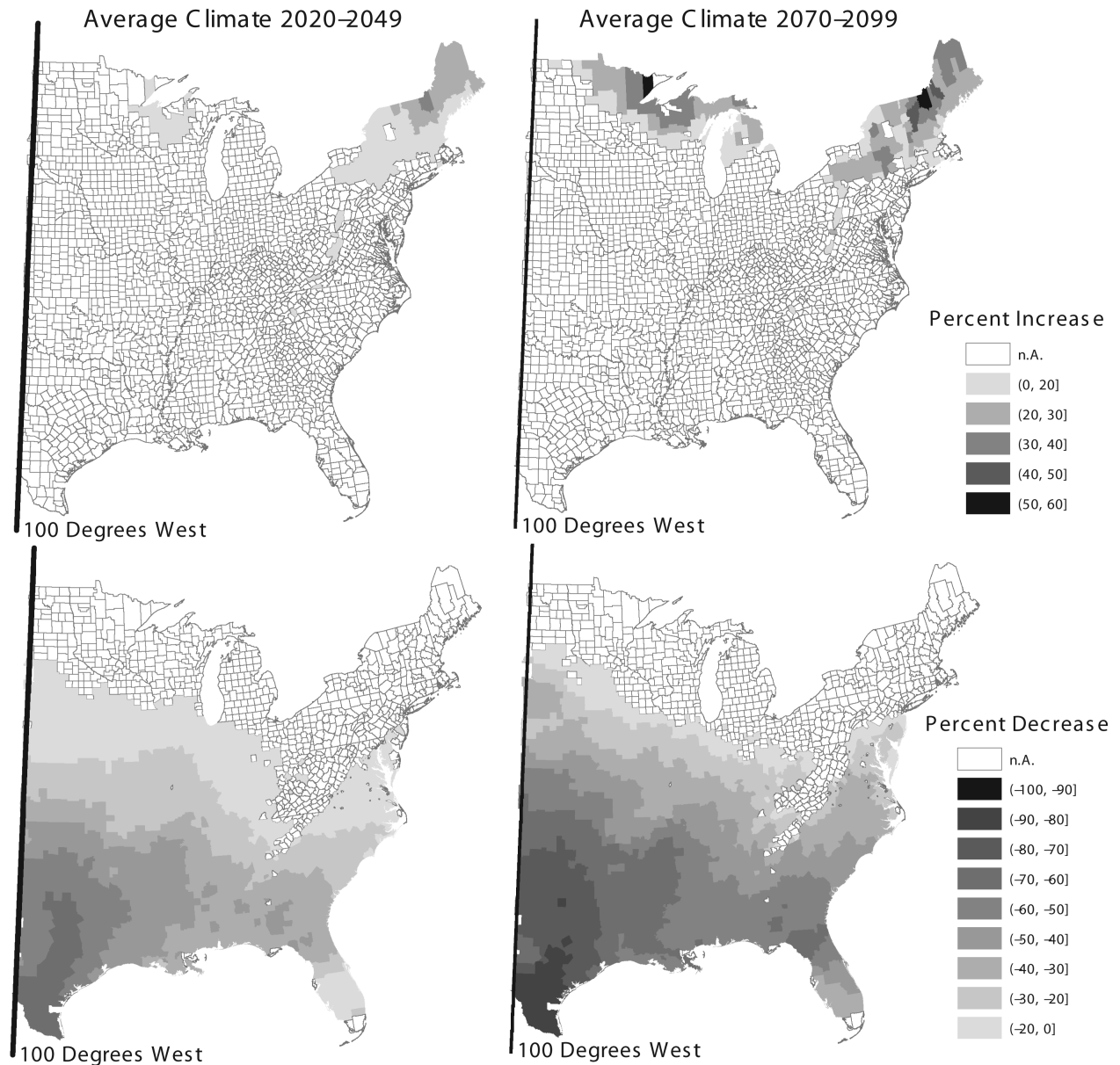

Figure displays counties with statistically significant gains (95% level) in the top row and losses in the bottom row for the Hadley HCM3 - B2 scenario. The left column compares climate average in 2020-2049 to the base period 1960-1989, while the right column uses the 2070-2099 forecast.

gains and loses under the intermediate $B2$-scenario. The predicted changes are also closer to those in another general circulation model, the DOE/NCAR Parallel Climate Model (PCM), which we use as an alternative because it is considered a low-sensitivity model, as opposed

to the mid-sensitivity HadCM3; for a given CO_2 scenario the temperature changes are lower under the PCM than under the Hadley model. We replicated the impact analysis using the PCM climate forecasts in the appendix available on request. Not surprisingly, the predicted area-weighted aggregate damages are lower. However, the regional pattern remains the same: out of the 73% of counties that have statistically significant declines in farmland values under all four Hadley scenarios by the end of the century, 73% (55%) still have significant losses under the PCM A1FI (B1) model and 0.7% (12%) switch to having significant gains. The magnitude of temperature changes simply shifts the border between gainers and losers.

Some of the predicted potential losses, in particular for the high emissions scenario in the later period toward the end of the century, are quite large. However, average temperature increases of $7°C$ $(13°F)$ would lead to the desertification of large parts of the South. A way of interpreting the results that places them in the context of other studies and also highlights the role for policy, is that if emissions are fairly stringently controlled over the course of the coming century, as in B1, such that atmospheric concentrations of greenhouse gases remain a little below double the pre-industrial level, predicted losses to agriculture, though not trivial, are within the range of the historically wide cyclical variations in this sector. If on the other hand concentrations climb beyond three times the pre-industrial level, as in A1F1, losses go well beyond this range. This suggests a meaningful role for policy involving energy sources and technologies, since choices among feasible options can make a major difference.

A complete impact analysis of climate change on U.S. agriculture would require a separate analysis for counties west of the 100th meridian. Based on the information presently available, we do not believe the impact will be favorable. A recently published study downscales the HadCM3 and PCM predictions to California and finds that, by the end of the century, average winter temperatures in California are projected to rise statewide by about $2.2°C$ under the B1 scenario and $3.0-4.0°C$ under the A1FI scenario (Katherine Hayhoe et al. 2004). Summer temperatures are projected to rise even more sharply, by about $2.2-4.6°C$ under the B1 scenario and $4.1-8.3°C$ under the A1FI scenario. Winter precipitation, which accounts for most of California's water supply either stays about the same or decreases by 15-30% before the end of the century. The rising temperature will severely reduce the snowpack in the Sierra Nevada, which currently provides almost as much storage at the beginning of the irrigation season as the state's man-made reservoirs. By the end of the century, the spring snow pack is projected to decline by 30-70% under the B1 scenario, and by 70-90% under the A1FI scenario. This would drastically reduce water supply available in the late-spring and summer, when roughly 75% of all water use in California occurs. Moreover, the rise in summer-time temperatures will cause an increase in the water demand during this period both in agriculture and for urban uses The result is likely to be an increased scarcity

of water in California.[24] Obviously, this can be dealt with in a variety of ways, including water marketing, increased conservation, water rights re-allocation, the improved operation of existing reservoirs, the construction of new reservoirs, and the development of conjunctive use schemes. The likely mix of solutions and their potential cost are being assessed in a case study now being conducted for the State of California. Although we do not cite quantitative results here because the work is still in progress, it seems likely that economic losses could be quite substantial in the aggregate.

6 Summary and Conclusions

In this paper we sketch a model of farmland value that forms the basis for a hedonic, or Ricardian, regression analysis. The study area of this paper is the predominantly dryland farming area east of the 100th meridian in the United States, a very large area that includes approximately four fifths of the counties (our units of observation) in the country and 72 percent of all farmland value. The independent variables include measures of climatic, soil, and socio-economic conditions.

For the empirical estimation, we use data on farmland values from four agricultural censuses over the past two decades to determine how climatic variables in particular capitalize into farmland values. Although aggregate farmland values have gone through some ups and downs over this period, our estimates remain remarkably robust. To get the climatic variables, we construct non-linear transformations of raw temperature variables suggested by agronomic findings that plant growth is only indirectly linked to temperature through the transformed variables, known as degree days. Our statistical results are consistent with these findings. The optimal number of growing degree days in the range $8 - 32°C$ in the preferred model peaks at levels consistent with field experiments for several crops. Other variables have intuitive signs and magnitudes as well. For example, degree days above $34°C$ are always harmful, and precipitation during the growing season is beneficial up to a point, peaking at a level close to the water requirements for many crops. Results remain robust to various changes in specification.

One other feature of the paper worth noting here is the development of an improved data set that specifically incorporates the spatial distribution of variables within a county. We use the agricultural area obtained from fine-scale satellite images as a cookie-cutter to derive both soil and climatic variables by averaging all observations in a county that constitute cropland or pasture. Another spatial issue is correlation of the error terms in our

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[24]A preliminary analysis suggests a similar pattern of impacts in the Pacific Northwest.

county-level observations. The analysis takes this into account and utilizes an appropriate Generalized Method of Moments estimator for the coefficient of spatial correlation. Results remain significant after adjusting for spatial correlation, as they do when we introduce fixed effects to allow for differences across states.

The estimated coefficients from the preferred hedonic equation are used, along with regionally disaggregated climate scenarios, to predict the impact of global warming on farmland values for counties east of the 100th meridian. The aggregate impact for these counties in the near to medium term (2020-2049) is a 10%-25% decrease in aggregate value, depending on the climate scenario chosen. In the longer run, to the end of the century (2070-2099), the distribution of predicted impacts substantially widens across scenarios, as varying assumptions about technological change, population growth, energy sources, and environmental policies lead to diverging paths of predicted greenhouse gas concentrations and hence changes in climatic conditions. Predicted average impacts range from -27% all the way to -69%. To put this decline into perspective, recall that average farmland value in our sample declined by one third between the 1982 and 1987. Another way of thinking about the results is that fairly stringent controls on greenhouse gas emissions, keeping atmospheric concentrations a bit below twice the pre-industrial level, lead to losses within the (wide) range of cyclical variation in this sector, whereas if concentrations are allowed to exceed three times the pre-industrial level, losses go well beyond this range. Perhaps the most striking and robust result is that in all scenarios, over both time frames, we observe strong regional differences ranging from statistically significant gains to statistically significant loses, with the number of counties experiencing losses exceeding the number experiencing gains (and as noted, losses in the aggregate). Adding in the impact on farmland values west of the 100th meridian would likely increase losses, as suggested by preliminary results from a study of the potential impact in California, the richest agricultural region in the West.

Several caveats apply. The hedonic approach is a partial-equilibrium analysis and assumes that prices remain constant. This assumption can perhaps be justified on the grounds that the aggregate effect will be limited, as other areas further north, especially in Canada, are predicted to increase yields and benefit from global warming. Our approach also does not specifically model the effects of changes in government involvement and transfer programs on farm prices. However, our data set covers observations from two decades with three farm bills that substantially changed government involvement, yet the results are remarkably robust: the fundamental dependence of agricultural yields on climatic conditions is independent of government programs. Finally, our analysis focuses on the impact of changes in temperature and precipitation, and not other things that might be affected by climate change, in particular CO_2 fertilization. Reilly, ed (2002) and others suggest that increased CO_2 fertilization can

offset reduction in yield. However, there may be a tradeoff between quantity and quality, as the projected increase in crop growth is offset by a decline in nutritional value (Jablonski et al. 2002), and the impact of increased CO_2 fertilization on yields is in any event believed to be minimal beyond a doubling of the preindustrial concentration.[25]

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[25]Under the A1FI scenario, the CO_2 concentration more than triples towards the end of this century.

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Appendix 1   Data Description

All agricultural data are taken from the county-level geographic area series of the Census of Agriculture for the years 1982, 1987, 1992, and 1997. All numbers are translated into 1997 dollars using the GDP implicit price deflator.

We merge the agricultural data from the Census of Agriculture with soil data from the State Soil Geographic (STATSGO) Data Base. We average all variables over the agricultural area obtained from Landsat satellite images.

Soil characteristics are area-weighted averages of the characteristic under consideration. The minimum permeability of all vertical soil layers in inches per hour hour specifies at what rate water passes through the soil; the average water capacity indicates how much water the soil can absorb; the unitless K-factor indicates how susceptible the soil is to soil erosion, i.e., the loss of fertile top soil; a higher clay content in percentage points indicates lower soil quality; and the variable percent high class top soil is the percentage points of soils in the top three soil categories classes of an eight-class soil classification system.

The climatic variables are derived from the PRISM climate grid developed by the Spatial Climate Analysis Service at Oregon State University. It lists minimum and maximum temperature as well as precipitation on a monthly time-scale for a 2.5 mile x 2.5 mile grid in the coterminous United States for the years 1895 to 2003. We use the agricultural area in each 2.5mile x 2.5 mile grid and calculate the area-weighted average of the climatic variables at each grid point. Longitude and latitude are area-weighted averages of the longitude/latitude combinations of all agricultural areas in a county.

Finally, the socio-economic variables population density and income per capita are derived from the 1988, 1994, and 2000 County and City Data Book.