

## THE IMPACT OF CLIMATE CHANGE ON US AGRICULTURE

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### **Key words**

climate change, marginal impacts, Ricardian method, long-run adjustment, farmland value, functional form, loglinear model

### **Abstract**

This study relies on the Ricardian method to estimate the damages of climate change to US agriculture. The study uses repeated cross sectional analyses of US Census data collected at the county level from 1978-2002. Regressions of farmland value on climate and other control variables reveal that climate consistently affects farmland values across the US. The 1978 and 1982 data imply that warming is beneficial to farming whereas the data from more recent years implies warming is harmful. Linear, enhanced linear and log linear regressions all confirm these results. With the linear and enhanced linear models, projections of future impacts from climate models lead to similar findings. With the Hadley and uniform climate scenarios, coefficients from the 1978 and 1982 data generally imply benefits whereas the coefficients from the later data imply damages. The loglinear model leads to different results. The loglinear model implies that these climate scenarios will generally be beneficial, although the benefits do vary across years. All the regression models suggest the mild PCM scenarios will generally be beneficial. The climate results are mixed. They generally imply that mild warming is beneficial but more extensive warming is harmful to the US. However, the results are not stable across time, suggesting the repeated cross sections are still not capturing all the important factors that change annually in the farmland market.

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## I. Introduction

With the mounting evidence that climate is changing because of manmade emissions of greenhouse gases (IPCC 2007a), it is increasingly important to understand the impacts of climate change. Perhaps the most important economic sector that is sensitive to climate is agriculture (Pearce 1996; Tol 2002; Mendelsohn and Williams 2004). As climates warm, damages to the agricultural sector could be amongst the largest economic impacts of climate change. It is critical to develop methods and estimates of the size of damages in this sector.

Many methods have been developed to date to measure climate impacts. Agronomists have conducted laboratory experiments to see how plants will respond to temperature and moisture in controlled settings (Reilly et al. 1996). These results have been incorporated into crop simulation models that in turn predict changes in yields of major grains (Rosenzweig and Parry 1994; Iglesias and Minguez 1996; Parry et al.; 2004 Kim et al. 2010). Although rooted in solid science, there are several important limitations to these estimates. First, the crop simulation analyses fail to capture endogenous adaptation to climate. Second, the analyses are limited to major grains and do not capture many crops that are more suited for warmer climates. Third, the analyses do not reflect livestock which are also well suited for warmer and dryer climates. Fourth, the crop simulation models focus on gross revenue and not net revenue.

Economists have developed some methods that overcome at least some of the deficiencies of the crop simulation models. Agronomic-economic mathematical programming models have been developed to simulate how farmers would react if climate caused the yields of crops to change (Adams et al. 1990; 1994). These models predict that farmers would shift crops in response to climate change. Crop prices would also change if supplies changed. More recent models also capture livestock responses (Adams et al. 1999). In the US, livestock responses are expected to be small because most animals are sheltered and fed from feedstock and not pasture (Adams et al. 1999).

An alternative empirical method has also been developed called the Ricardian method (Mendelsohn, Nordhaus, and Shaw 1994). The Ricardian method is a comparative static analysis that captures long-run equilibrium adjustments (adaptation) to climate. Farm values are regressed on climate and other control variables to understand how the locus of net revenues is shaped by

exogenous factors. The method has now been applied to 31 countries around the world (Kurukulasuriya et al. 2005; Mendelsohn and Dinar 2008; Seo and Mendelsohn 2008).

This study examines the US. It follows research recently conducted by Deschenes and Greenstone (2007) using panel data from 1978 through 2002. The analysis corrects a number of errors in Deschenes and Greenstone (2007) in order to get more accurate Ricardian estimates of climate impacts.

## II. Theory

Following MNS (Mendelsohn Nordhaus and Shaw 1994), we assume that each farmer maximizes income subject to the exogenous conditions of their farm. Specifically, the farmer chooses the crop or livestock or some mix of them and inputs for each unit of land that maximizes net revenue:

$$Max \pi_i = \sum_{j \in J} P_{ij} R_{ij}(X_{ij} | C_i, W_i, S_i) - \sum_{j \in J} P_{ij} X_{ij} \quad (1)$$

where  $\pi_i$  is the net revenue of farm  $i$ ,  $P_{ij}$  is a vector of input and output prices  $R_{ij}$  is the production function for each crop or livestock  $j$ ,  $X_{ij}$  is a vector of endogenous input choices such as seeds, fertilizer, irrigation, pesticides, hired labor, and capital,  $C_i$  is a vector of climate variables,  $W_i$  is a vector of economic control variables, and  $S_i$  is a vector of soil characteristics. Note that  $j$  denotes a choice set of outputs which includes any combination of crops and livestock.

Differentiating (1) with respect to each input identifies the set of inputs that maximize net revenue. The resulting locus of net revenues for each set of exogenous variables is the Ricardian function. It describes how net revenue will change as exogenous variables change:

$$\pi^* = \pi(C, W, S | P_v) \quad (2)$$

Assuming perfect competition for land, the land value will be equal to the present value of the net revenue of each farm:

$$V_{land} = \int_0^{\infty} \pi_t^* \cdot e^{-rt} dt \quad (3)$$

where  $r$  is the market interest rate.

The literature concerning the climate sensitivity of individual crops and livestock suggest a concave relationship between yield and temperature (see Reilly et al. 1996). One would consequently expect a concave relationship between annual temperature and net revenue as well. With crop and livestock switching, farmers can make their choice set less concave by moving to more advantageous combinations of outputs as well as inputs as climate changes (MNS). It follows that the more limited the set of choices available to a farmer, the more concave the climate response function. Of course, the concavity of the response function can be quite different depending on the set of choices that a farmer is restricted to.

We estimate two functional forms in this paper. The linear form looks like the following:

$$V_i = A + BT_i + CT_i^2 + DP_i + EP_i^2 + FX_i + \varepsilon_i \quad (4)$$

where the dependent variable,  $V$ , is land value per hectare of land,  $T$  and  $P$  represent a vector of seasonal temperature and precipitation variables,  $X$  represents a vector of relevant control variables,  $\varepsilon$  is an error term, and the other parameters are coefficients. In this analysis, we rely on winter and summer seasonal temperature and precipitation variables.

The log linear form looks like:

$$\ln V_i = a + b \ln T_i + 2c \ln T_i + d \ln P_i + 2e \ln P_i + f \ln X_i + v_i \quad (5)$$

With the linear form, the effect of climate is additive. For example, the marginal effect of an increase in temperature,  $T_{i,j}$ , evaluated in season  $j$  at farm  $i$  is

$$dV_i / dT_{i,j} = b_j + 2 * c_j * T_{i,j} \quad (6)$$

Similarly, the marginal impact of precipitation in season  $j$  for farm  $i$  is

$$dV_i / dP_{i,j} = d_j + 2 * e_j * P_{i,j} \quad (7)$$

The annual marginal impact is the sum of the seasonal impacts. The marginal impact depends on the temperature and precipitation of each farmer. Consequently, marginal impacts may vary across the country.

With the loglinear form, the effect of climate is proportional. For example, the marginal effect of a change in temperature is

$$dV_i / dT_{i,j} = V_i(b_j + 2 * c_j T_{i,j}) \quad (8)$$

And the effect of precipitation is:

$$dV_i / dP_{i,j} = V_i(d_j + 2 * e_j * P_{i,j}) \quad (9)$$

Again the effect on a farm depends on the local temperature and precipitation so that impacts will vary across the country. With the log-linear functional form, the coefficients determine a percentage change in land value.

In this study, we estimate the Ricardian functions using cross-sectional data from each census year between 1978 and 2002. This will lead to 7 equations for each functional form. In each case, we will estimate a weighted least squares regression using the square root of farmland in a county as the weight. One question that has been raised by Deschenes and Greenstone (2007) is whether these coefficient estimates are the same over time. We will examine this by comparing the coefficients directly, comparing the marginal impacts of climate, and comparing the predicted impacts of selected climate scenarios. For these marginal and welfare comparisons, we will use the expected quantity of farmland  $E[F_i]$  in each county over the 1978-2002 period.

The impacts of climate change are measured by the difference in land value before and after climate change. The change in land value per hectare,  $\Delta V$ , resulting from a climate change from  $C_0$  to  $C_1$  can be measured as follows:

$$\Delta V_{land} = V_{land} (C_1) - V_{land} (C_0) \quad (10)$$

The welfare change,  $\Delta W_i$ , for a county is therefore:

$$\Delta W_i = \Delta V_i * F_i \quad (11)$$

where  $F_i$  is the hectares of land in farmland in county  $i$ . Summing the welfare change across counties yields the welfare change in a state, region, or country. In this particular study, we calculate the welfare effect of three climate scenarios.

Because the Ricardian models allow farmers to switch across all endogenous choices (crop species, livestock species, irrigation, fertilizer, etc), it fully captures adaptation. Farmers can endogenously adjust all their choices as conditions change. This is a great strength of the Ricardian method. The model also captures long-run adjustments made by the ecosystem. Changes in pests, weeds, and insects due to climate are all captured in the analysis. Because the model does capture these long-run adaptations, it is less suitable for modeling short-run changes in weather. Farmers have much less opportunity to adapt to short-run weather fluctuations. Short-run studies of intertemporal weather (Deschenes and Greenstone, 2007) are good measures of acute effects but are less appropriate measures of the long-run impacts of climate change.

The analysis assumes that prices remain unchanged (Cline 1996). Although changes in local supply might be dramatic, prices of food crops are determined by global markets. With the expansion of crop production in some parts of the world and the contraction in others, the changes in the price of crops from global warming are expected to be small (IPCC 2007b). The analysis also does not take into account carbon fertilization from the higher CO<sub>2</sub> concentrations. The omission of price effects implies that the Ricardian method will overestimate both damages and benefits. The omission of CO<sub>2</sub> effects suggests that the estimates will overestimate damages and underestimate benefits.

### III. Data

Following Deschenes and Greenstone (2007), we have constructed a balanced panel with observations for 2,814 counties in the contiguous 48 States over the U.S. Agricultural Census years of 1978, 1982, 1987, 1992, 1997 and 2002. Units of measurement follow the metric system; economic variables have all been converted to constant 2000 USD using the GDP deflator.

We rely on the 1971-2000 monthly precipitations and mean temperature normals computed by the National Climatic Data Center for 7,467 weather stations in the contiguous 48 States. Following MNS, we estimate a quadratic climate surface as a function of longitude, latitude, elevation and distance from coastline for the contiguous 48 States. A separate surface is estimated using weather stations within 500 miles of each county. The data is weighted to give nearby stations more weight. The predicted values from that surface are used to yield monthly climate variables for each county. Seasonal climate is the arithmetic average of climate variables in winter (December, January, February), spring (March, April, May), summer (June, July, August) and autumn (September, October, November).

For farmland value, land in farms, and other agricultural data, we rely on the U.S. Census of Agriculture (USDA 1978, 1982, 1987, 1992, 1997, 2002). The dependent variable in our panel is the average estimated value of land and buildings per hectare of land in farm.

We include several variables not used in Deschenes and Greenstone (2007). We measure the long-term availability of water to farmers using the average over time of fresh surface water used at the county level (United States Geological Survey, 1988, 1993, 1998, 2004). Access to surface water can be largely considered as exogenous, depending on annual surface flows and historical rights for water use rather than on markets (Mendelsohn and Dinar, 2003). We combine survey years from 1985, 1990, 1995 and 2000 to compute the long-run availability of surface water. Data about greenhouses and subsidies to farmers by county are included from the Census of Agriculture.

We use as a proxy of the opportunity cost of keeping land in farms the median value of owner-occupied housing in each county. These data are available at the county level from the US Census of Population and Housing every ten years. We construct estimates of house values extrapolating linear

trends from the three census years of 1980, 1990 and 2000.

#### IV. Analytical Results

The first regression results, presented in Table 1, rely on a linear functional form and the set of independent variables from Deschenes and Greenstone (2007). The climate coefficients are statistically significant in all the regressions. Comparing the coefficients across regressions reveals that there is consistency across years. The signs of the climate coefficients are generally the same every year. For example, the squared terms for winter, spring, and summer temperature are negative implying a hill-shaped function. The squared term for autumn precipitation is positive implying a U-shape. However, as found by Deschenes and Greenstone (2007), the magnitudes of the coefficients vary across years. For example the coefficient on the linear summer term ranges from -1800 in 1982 to -200 in 1987. The linear summer precipitation term varies from 3.5 in 1978 to -20 in 1982. The climate coefficients are not stable over time.

Table 1 also presents results of the control variables. Many of the soil variables are significant including flooding, wet factor, k factor, slope length, sand, and moisture level. The three economic variables, income per capita, population density, and density squared are also very significant. The control variables have their expected sign. Flooding, k factor, and sand are all negative implying they are harmful. Wet factor, slope length, and soil moisture are all positive implying they are helpful variables. The coefficients of the economic variables are all positive as they are all beneficial characteristics. The two geographic variables, altitude and latitude, are not significant. As with the climate coefficients, the coefficients of the control variables are also not stable, and their magnitude also varies over time.

The lack of stability in the coefficients in Table 1 implies that there may be some missing variables in the regression that change over time. Some additional control variables are included in Table 2. The table includes distance from nearest metropolitan area, surface water, greenhouses, subsidies, and residential housing values. The coefficients of each of these variables are highly significant implying that they belong in the regression. The adjusted R squared



of the regression is higher in Table 2 than in Table 1.

TABLE 1. Linear Ricardian Model

	1978	1982	1987	1992	1997	2002
Winter Temp	-1797.2 (-20.91)	-1232.5 (-15.75)	-471.8 (-8.51)	-526.8 (-7.73)	-851.1 (-12.38)	-929.3 (-9.8)
Winter Temp Sq	-42.22 (-11.71)	-11.56 (-3.51)	-10.49 (-4.46)	-7.87 (-2.73)	-18.20 (-6.27)	-18.88 (-4.74)
Spring Temp	1171.2 (5.56)	890.5 (4.65)	549.9 (4.00)	644.6 (3.81)	691.7 (4.05)	473.6 (2.01)
Spring Temp Sq	-30.27 (-3.42)	-27.78 (-3.45)	-29.21 (-5.05)	-37.25 (-5.24)	-29.60 (-4.10)	-25.18 (-2.52)
Summer Temp	-1434.3 (-5.3)	-1787.8 (-7.27)	-176.3 (-1.00)	-756.2 (-3.49)	-558.2 (-2.54)	-654.2 (-2.15)
Summer Temp Sq	-12.28 (-2.12)	6.74 (1.27)	-11.55 (-3.03)	-0.14 (-0.03)	-11.796 (-2.48)	-16.02 (-2.44)
Autumn Temp	1942.0 (4.76)	2208.8 (5.95)	132.2 (0.50)	531.8 (1.64)	861.9 (2.61)	1483.0 (3.27)
Autumn Temp Sq	67.59 (5.20)	20.24 (1.71)	44.05 (5.23)	36.32 (3.52)	44.02 (4.20)	35.58 (2.47)
Winter Prec	41.37 (7.83)	29.49 (6.07)	20.51 (5.93)	20.53 (4.83)	28.71 (6.71)	26.06 (4.44)
Winter Prec Sq	-0.052 (-2.61)	-0.066 (-3.61)	-0.059 (-4.58)	-0.04 (-2.53)	-0.034 (-2.13)	-0.008 (-0.34)
Spring Prec	29.81 (3.12)	64.98 (7.35)	17.90 (2.83)	20.34 (2.06)	18.60 (2.32)	19.41 (1.74)
Spring Prec Sq	-0.225 (-4.08)	-0.32 (-6.28)	-0.134 (-3.63)	-0.134 (-2.92)	-0.124 (-2.66)	-0.129 (-2.02)
Summer Prec	3.54 (0.53)	-20.39 (-3.34)	-6.54 (-1.53)	-13.16 (-2.50)	-16.68 (-3.11)	-13.79 (-1.85)
Summer Prec Sq	0.053 (1.43)	0.119 (3.53)	0.021 (0.88)	0.066 (2.23)	0.092 (3.08)	0.072 (1.75)
Autumn Prec	-102.07 (-8.93)	-99.70 (-9.56)	-44.44 (-5.95)	-50.67 (-5.51)	-54.03 (-5.79)	-45.65 (-3.6)

Autumn Prec Sq	0.443 (6.65)	0.488 (8.04)	0.325 (7.45)	0.306 (5.68)	0.279 (5.11)	0.214 (2.92)
Salinity	-100.4 (-0.45)	181.4 (0.89)	3.7 (0.03)	-31.2 (-0.18)	-125.2 (-0.70)	-128.6 (-0.52)
Flooding	-1050.9 (-4.92)	-709.4 (-3.67)	-434.1 (-3.16)	-517.0 (-3.06)	-548.1 (-3.11)	-643.5 (-2.68)
Wet Factor	2826.6 (12.03)	2017.0 (9.44)	419.5 (2.74)	639.4 (3.40)	726.2 (3.85)	340.6 (1.32)
Kfactor	-7903.3 (-9.00)	-5524.7 (-6.88)	-3980.3 (-6.92)	-4605.5 (-6.53)	-5688.6 (-7.90)	-6331.0 (-6.39)
Slope Length	1.626 (7.74)	1.809 (9.48)	1.161 (8.53)	1.332 (7.97)	1.660 (9.64)	1.471 (6.09)
Sand	-41.1 (-0.10)	95.7 (0.25)	-780.4 (-2.80)	-1240.0 (-3.64)	-959.1 (-2.79)	-1441.2 (-3.05)
Clay	-381.5 (-1.57)	-214.3 (-0.97)	38.2 (0.24)	-583.0 (-3.04)	-594.8 (-3.07)	-676.1 (-2.55)
Moisture Level	16356.4 (10.05)	11413.8 (7.70)	2683.7 (2.54)	521.4 (0.40)	3158.7 (2.39)	595.3 (0.33)
Permeability	-39.5 (-0.50)	-92.9 (-1.29)	34.4 (0.66)	33.1 (0.52)	29.4 (0.45)	86.3 (0.97)
Income per Capita	158.06 (12.64)	72.20 (6.89)	91.25 (12.01)	82.05 (9.8)	86.88 (11.42)	92.33 (9.72)
Density	20.49 (15.65)	22.88 (19.3)	17.43 (20.25)	20.21 (19.44)	21.15 (21.53)	25.60 (19.81)
Density Sq	-0.015 (-7.03)	-0.019 (-10.52)	-0.011 (-8.46)	-0.013 (-7.97)	-0.019 (-13.14)	-0.017 (-9.55)
Latitude	81.556 (1.23)	109.497 (1.81)	-66.327 (-1.55)	-63.322 (-1.20)	-0.513 (-0.01)	2.289 (0.03)
Altitude	0.712 (1.59)	0.719 (1.77)	-0.59 (-2.04)	-0.663 (-1.86)	-0.192 (-0.53)	-0.549 (-1.10)
Constant	-5644.2 (-1.06)	-1695.9 (-0.35)	3745.3 (1.08)	8216.7 (1.92)	527.4 (0.12)	1164.1 (0.19)
Adjusted R <sup>2</sup>	0.707	0.68	0.705	0.664	0.704	0.672

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t-statistics in parenthesis

TABLE 2. Extended Ricardian Model

	1978	1982	1987	1992	1997	2002
Winter Temp	-1695.6 (-20.89)	-1042.1 (-14.73)	-202.7 (-3.76)	-333.7 (-5.2)	-590.9 (-8.89)	-710.7 (-7.83)
Winter Temp Sq	-49.64 (-14.11)	-26.08 (-8.23)	-14.72 (-6.67)	-18.51 (-6.67)	-24.81 (-9.06)	-24.26 (-6.34)
Spring Temp	1128.5 (5.58)	1155.0 (6.59)	573.1 (4.46)	688.2 (4.28)	790.9 (4.90)	565.4 (2.47)
Spring Temp Sq	-24.46 (-2.95)	-33.94 (-4.66)	-26.78 (-5.01)	-32.06 (-4.76)	-31.32 (-4.65)	-26.13 (-2.72)
Summer Temp	-872.1 (-3.39)	-709.8 (-3.14)	505.7 (3.08)	243.9 (1.18)	334.0 (1.61)	154.0 (0.53)
Summer Temp Sq	-24.77 (-4.44)	-13.05 (-2.67)	-19.30 (-5.53)	-14.67 (-3.35)	-23.73 (-5.42)	-26.18 (-4.23)
Autumn Temp	1451.6 (3.72)	631.6 (1.82)	-873.7 (-3.46)	-738.2 (-2.32)	-459.8 (-1.44)	290.1 (0.66)
Autumn Temp Sq	80.84 (6.47)	61.66 (5.49)	56.42 (7.15)	59.55 (5.92)	67.86 (6.82)	56.11 (4)
Winter Prec	35.91 (7.24)	22.17 (5.08)	11.36 (3.58)	10.29 (2.60)	17.25 (4.36)	9.56 (1.66)
Winter Prec Sq	-0.021 (-1.14)	-0.012 (-0.76)	-0.017 (-1.47)	0.015 (0.99)	0.023 (1.55)	0.057 (2.72)
Spring Prec	3.95 (0.43)	34.59 (4.31)	2.86 (0.49)	1.90 (0.26)	2.71 (0.37)	5.57 (0.53)
Spring Prec Sq	-0.116 (-2.23)	-0.258 (-5.67)	-0.097 (-2.88)	-0.099 (-2.35)	-0.1 (-2.35)	-0.095 (-1.57)
Summer Prec	45.29 (6.78)	28.92 (5.00)	23.51 (5.67)	19.38 (3.81)	11.10 (2.16)	14.40 (1.96)
Summer Prec Sq	-0.125 (-3.47)	-0.066 (-2.12)	-0.098 (-4.38)	-0.055 (-1.97)	-0.018 (-0.64)	-0.043 (-1.08)
Autumn Prec	-96.50 (-9.02)	-82.02 (-8.77)	-25.97 (-3.77)	-27.02 (-3.12)	-32.71 (-3.75)	-24.09 (-1.97)
Autumn Prec Sq	0.371 (5.94)	0.371 (6.85)	0.224 (5.60)	0.169 (3.40)	0.154 (3.06)	0.082 (1.18)
Salinity	38.6 (0.19)	355.5 (1.96)	159.9 (1.21)	172.8 (1.06)	-6.1 (-0.04)	121.1 (0.52)
Flooding	-861.1 (-4.30)	-446.2 (-2.58)	-218.5 (-1.73)	-264.8 (-1.70)	-419.3 (-2.58)	-606.6 (-2.66)

Wet Factor	2972.0 (13.52)	1756.1 (9.16)	351.5 (2.47)	801.7 (4.52)	674.9 (3.78)	590.6 (2.38)
Kfactor	-5359.9 (-6.42)	-4460.8 (-6.24)	-2963.0 (-5.59)	-4195.9 (-6.47)	-4560.9 (-6.88)	-5146.8 (-5.51)
Slope Length	0.711 (3.51)	0.87 (4.96)	0.612 (4.78)	0.876 (5.55)	0.966 (5.93)	0.895 (3.81)
Sand	-272.1 (-0.69)	-414.0 (-1.19)	-950.1 (-3.72)	-1461.6 (-4.63)	-1441.9 (-4.55)	-1616.9 (-3.64)
Clay	-471.1 (-2.09)	-570.7 (-2.89)	-127.2 (-0.89)	-814.7 (-4.62)	-808.0 (-4.55)	-887.1 (-3.55)
Moisture Level	8134.5 (5.06)	3211.7 (2.32)	-1514.4 (-1.47)	-1933.2 (-1.55)	-2774.7 (-2.12)	-2527.8 (-1.44)
Permeability	-110.8 (-1.50)	-159.0 (-2.48)	-21.7 (-0.46)	-2.1 (-0.04)	-4.9 (-0.08)	51.8 (0.62)
Income per Capita	93.36 (6.8)	13.55 (1.23)	46.09 (5.97)	25.39 (2.98)	38.75 (4.82)	24.14 (2.3)
Density	14.14 (10.39)	14.83 (12.53)	10.64 (12.01)	10.81 (9.97)	13.98 (13.89)	18.66 (14.29)
Density Sq	-0.009 (-4.35)	-0.012 (-6.88)	-0.005 (-4.35)	-0.005 (-3.43)	-0.013 (-9.59)	-0.011 (-6.15)
Latitude	141.8 (2.27)	127.2 (2.35)	-58.9 (-1.5)	-50.9 (-1.04)	-35.5 (-0.71)	-44.0 (-0.62)
Altitude	0.373 (0.88)	-0.023 (-0.06)	-1.118 (-4.23)	-1.248 (-3.80)	-0.941 (-2.80)	-1.397 (-2.93)
Dist from Met Areas	-1.373 (-5.36)	-1.886 (-8.50)	-0.838 (-5.27)	-0.935 (-4.79)	-1.027 (-5.15)	-0.685 (-2.38)
Surface Water	160.2 (12.05)	196.0 (17.25)	128.5 (15.58)	129.4 (12.67)	150.4 (14.41)	155.6 (10.29)
Greenhouses	2921.1 (3.23)	2318.0 (3.22)	2337.6 (5.61)	3179.0 (6.66)	2841.4 (7.18)	1558.2 (5.85)
Subsidies	33.7 (8.40)	43.8 (10.35)	4.6 (7.54)	6.7 (3.41)	19.5 (7.36)	6.2 (3.04)
House Value	19.88 (10.58)	23.33 (13.03)	17.00 (14.1)	22.18 (16.12)	14.91 (11.26)	19.62 (11.71)
Constant	-10797.4 (-2.15)	-5760.4 (-1.33)	1328.4 (0.42)	2846.0 (0.72)	-307.5 (-0.08)	348.1 (0.06)
Adjusted R <sup>2</sup>	0.746	0.748	0.757	0.717	0.752	0.71

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t-statistics in parenthesis

The signs of the climate coefficients in Table 2 are generally stable across time. However, the magnitudes of the coefficients still vary. It is difficult to know whether the coefficients are more or less stable than in Table 1 because of the complex shape of the Ricardian function.

Table 3 presents the results of the loglinear model using the same variables as in Table 2. The coefficients are not the same because they now reflect percentage differences rather than absolute differences. In general, the loglinear model fits the data more closely. The errors are more lognormally distributed than normal, making this functional form more appropriate than the linear model. The adjusted R squared of the model is significantly higher in Table 3 than either Table 1 or 2.

TABLE 3. Extended Loglinear Ricardian Model

	1978	1982	1987	1992	1997	2002
Winter Temp	-0.341 (-18.75)	-0.270 (-15.27)	-0.155 (-8.56)	-0.251 (-13.38)	-0.236 (-12.27)	-0.302 (-16.19)
Winter Temp Sq	-0.00639 (-8.11)	-0.00583 (-7.36)	-0.00254 (-3.43)	-0.00556 (-6.86)	-0.00502 (-6.33)	-0.00577 (-7.35)
Spring Temp	0.396 (8.74)	0.468 (10.69)	0.322 (7.47)	0.500 (10.62)	0.403 (8.62)	0.355 (7.56)
Spring Temp Sq	-0.0125 (-6.73)	-0.016 (-8.78)	-0.0116 (-6.48)	-0.0183 (-9.31)	-0.0126 (-6.48)	-0.01 (-5.09)
Summer Temp	-0.682 (-11.85)	-0.549 (-9.7)	-0.402 (-7.31)	-0.532 (-8.83)	-0.454 (-7.56)	-0.546 (-9.2)
Summer Temp Sq	0.00576 (4.61)	0.005 (4.09)	0.004 (3.42)	0.00521 (4.07)	0.00349 (2.75)	0.00338 (2.66)
Autumn Temp	0.336 (3.85)	0.0134 (0.16)	-0.0362 (-0.43)	-0.108 (-1.16)	-0.0037 (-0.04)	0.214 (2.35)
Autumn Temp Sq	0.0142 (5.09)	0.0195 (6.96)	0.0136 (5.12)	0.0226 (7.67)	0.0166 (5.77)	0.0146 (5.07)
Winter Prec	0.00968 (8.71)	0.00855 (7.84)	0.00869 (8.16)	0.00955 (8.25)	0.01 (8.73)	0.00598 (5.06)
Winter Prec Sq	-0.0000223 (-5.32)	-0.0000186 (-4.55)	-0.0000255 (-6.38)	-0.0000195 (-4.46)	-0.000024 (-5.51)	-0.0000172 (-3.98)
Spring Prec	0.00837 (4.12)	0.0166 (8.27)	0.0113 (5.82)	0.00972 (4.58)	0.0121 (5.63)	0.0162 (7.45)
Spring Prec Sq	-0.0000431 (-3.70)	-0.000101 (-8.90)	-0.0000734 (-6.50)	-0.0000761 (-6.17)	-0.0000702 (-5.67)	-0.0000725 (-5.86)

Summer Prec	0.011 (7.37)	0.00688 (4.76)	0.00851 (6.12)	0.00541 (3.63)	0.00335 (2.24)	0.00389 (2.58)
Summer Prec Sq	-0.0000305 (-3.78)	-0.0000118 (-1.51)	-0.000035 (-4.65)	-9.23E-06 (-1.14)	2.02E-06 (0.25)	-7.81E-07 (-0.1)
Autumn Prec	-0.0224 (-9.36)	-0.020 (-8.57)	-0.014 (-6.05)	-0.0125 (-4.93)	-0.0156 (-6.19)	-0.0159 (-6.34)
Autumn Prec Sq	0.000091 (6.52)	0.000091 (6.72)	0.0000897 (6.70)	0.0000686 (4.71)	0.00008 (5.48)	0.0000738 (5.17)
Salinity	-0.0754 (-1.62)	-0.0938 (-2.07)	-0.0423 (-0.95)	-0.0346 (-0.73)	-0.0909 (-1.90)	-0.0459 (-0.96)
Flooding	-0.362 (-8.07)	-0.272 (-6.29)	-0.187 (-4.42)	-0.214 (-4.69)	-0.217 (-4.61)	-0.267 (-5.7)
Wet Factor	0.406 (8.25)	0.24 (5)	-0.0605 (-1.27)	0.0185 (0.36)	-0.0236 (-0.46)	-0.0000 (0.00)
Kfactor	-0.48 (-2.57)	-1.06 (-5.96)	-0.793 (-4.46)	-1.36 (-7.17)	-1.32 (-6.90)	-1.27 (-6.60)
Slope Length	0.00007 (1.54)	0.000138 (3.14)	0.000153 (3.56)	0.000198 (4.29)	0.000198 (4.20)	0.00021 (4.36)
Sand	0.175 (1.97)	0.092 (1.05)	-0.0458 (-0.54)	-0.176 (-1.91)	-0.169 (-1.84)	-0.113 (-1.24)
Clay	-0.124 (-2.45)	-0.2 (-4.05)	-0.00176 (-0.04)	-0.202 (-3.92)	-0.244 (-4.75)	-0.223 (-4.36)
Moisture Level	1.18 (3.27)	0.613 (1.77)	-0.501 (-1.45)	0.148 (0.40)	-0.753 (-1.98)	0.514 (1.43)
Permeability	-0.0531 (-3.22)	-0.0515 (-3.21)	-0.0371 (-2.34)	-0.0275 (-1.62)	-0.0397 (-2.30)	-0.0209 (-1.22)
Income per Capita	0.00986 (3.21)	-0.00186 (-0.68)	0.0205 (7.91)	0.0161 (6.44)	0.0182 (7.80)	0.00268 (1.24)
Density	0.0026 (8.54)	0.00266 (8.99)	0.0027 (9.09)	0.00266 (8.37)	0.00214 (7.35)	0.00191 (7.11)
Density Sq	-2.55E-06 (-5.73)	-2.87E-06 (-6.88)	-2.87E-06 (-6.94)	-3.09E-06 (-7.05)	-2.69E-06 (-6.92)	-2.01E-06 (-5.70)
Latitude	0.0108 (0.77)	0.00857 (0.63)	-0.014 (-1.06)	-0.00939 (-0.66)	-0.000326 (-0.02)	0.0181 (1.25)
Altitude	-0.00022 (-2.33)	-0.000296 (-3.24)	-0.000379 (-4.27)	-0.000354 (-3.68)	-0.000304 (-3.13)	-0.000297 (-3.04)
Dist from Met Areas	-0.000658 (-11.48)	-0.000838 (-15.13)	-0.000692 (-12.98)	-0.000957 (-16.75)	-0.00089 (-15.40)	-0.000822 (-13.93)
Surface Water	0.0644 (21.62)	0.0677 (23.85)	0.066 (23.87)	0.0663 (22.19)	0.0738 (24.41)	0.0703 (22.64)
Greenhouses	0.298 (1.47)	0.382 (2.12)	0.476 (3.40)	0.509 (3.64)	0.586 (5.11)	0.46 (8.42)

Subsidies	0.0154 (17.17)	0.0196 (18.51)	0.00289 (14.15)	0.00595 (10.33)	0.0104 (13.56)	0.00366 (8.80)
House Value	0.0059 (14.00)	0.00603 (13.48)	0.00368 (9.09)	0.00445 (11.06)	0.00423 (11.04)	0.00632 (18.39)
Constant	10 (8.92)	10.5 (9.73)	10.6 (9.96)	11.4 (9.86)	10.2 (8.78)	9.51 (8.16)
Adjusted R <sup>2</sup>	0.844	0.841	0.843	0.846	0.855	0.869

t-statistics in parenthesis

The climate coefficients appear to be more stable in Table 3 than in the previous two tables. The magnitudes of the coefficients do not vary as much across years. However, the functional form of this model is different making comparisons across coefficients unclear. The control variables have very similar signs in Table 2 and 3. Two noticeable differences, however, are that permeability and altitude are negative and significant in the loglinear model but not significant in the linear model.

In order to compare the impact of climate across years, we need to turn to more comprehensive measures of climate sensitivity that measure effects across coefficients. In Table 4, we examine the marginal temperature and precipitation effects across the three models estimated in Tables 1, 2 and 3. The results reveal that the marginal impacts of temperature and precipitation are not constant across either the intertemporal data sets or the three models.

The average of the temperature marginals across time in the linear model is +\$65/°C and in the extended linear model, it is +\$47/°C. The average percentage change in the loglinear model is +0.7 percent. However, these average effects are the result of the marginal impact of temperature having a large positive value in the first two census years. With the linear models, the marginal temperature effect is negative though insignificant in the later years. The results are more mixed with the loglinear model.

The averages of the precipitation marginals are \$7.8/mm and \$3.6/mm for the linear and extended linear models respectively. The loglinear model predicts that precipitation has a +0.5% effect/mm. These results are significant only for the linear regression. Unlike the temperature effects, the marginal precipitation effects are more consistent across the years.

TABLE 4. The Marginal Value of Temperature, Precipitation and Water

	Linear Model	Extended Linear Model	Extended Loglinear Model
Temperature (°C)	(2000\$ per hectare)	(2000\$ per hectare)	(% of land value per hectare)
1978	296.88*	324.46*	3.83%*
1982	241.69*	198.74*	1.42%
1987	-55.34	-70.19	-1.33%
1992	-58.96	-48.64	-0.69%
1997	22.34	-26.60	-0.38%
2002	-59.32	-96.49	1.09%
Average	64.5	46.9	0.66%
Precipitations (mm)	(2000\$ per hectare)	(2000\$ per hectare)	(% of land value per hectare)
1978	4.20	-0.25	0.45%*
1982	6.34	1.81	0.35%*
1987	9.82*	8.81*	0.55%*
1992	7.33*	5.23	0.50%*
1997	10.17*	4.43	0.69%*
2002	8.68*	1.32	0.62%*
Average	7.76*	3.56	0.53%*
Surface water (tons per day / hectare)		(2000\$ per hectare)	(% of land value per hectare)
1978		160.2*	6.44%*
1982		196.0*	6.77%*
1987		128.5*	6.60%*
1992		129.4*	6.63%*
1997		150.4*	7.38%*
2002		155.6*	7.03%*
Average		153.4*	6.81%*

Note: \* is significant at 95% level



Although it is helpful to understand the average marginal impact of temperature and precipitation on US farms, it is important to recognize that the country is large enough to have varying effects across the landscape. Figure 1 presents a map of the marginal impacts of temperature using the loglinear model and data from 2002. As one can see from the map, increasing temperature is beneficial to farms in the northeastern and north central regions of the country. However, higher temperatures are harmful to the southern and western regions of the US. This range of effects is due to the hill-shaped relationship between land value and annual temperature. Places that are cold will rise up the hill when it warms. Places that are already warm will fall down the hill as it warms. Figure 2 presents the marginal impacts of precipitation. In general, more precipitation is beneficial across the US, especially in the west. However, there are wet regions in the southeast where additional precipitation is likely to be harmful.

FIGURE 1. The Marginal Impact of Temperature ( $^{\circ}\text{C}$ ) on Land Value in the United States (2000\$ per hectare): Extended Loglinear Ricardian Model - 2002

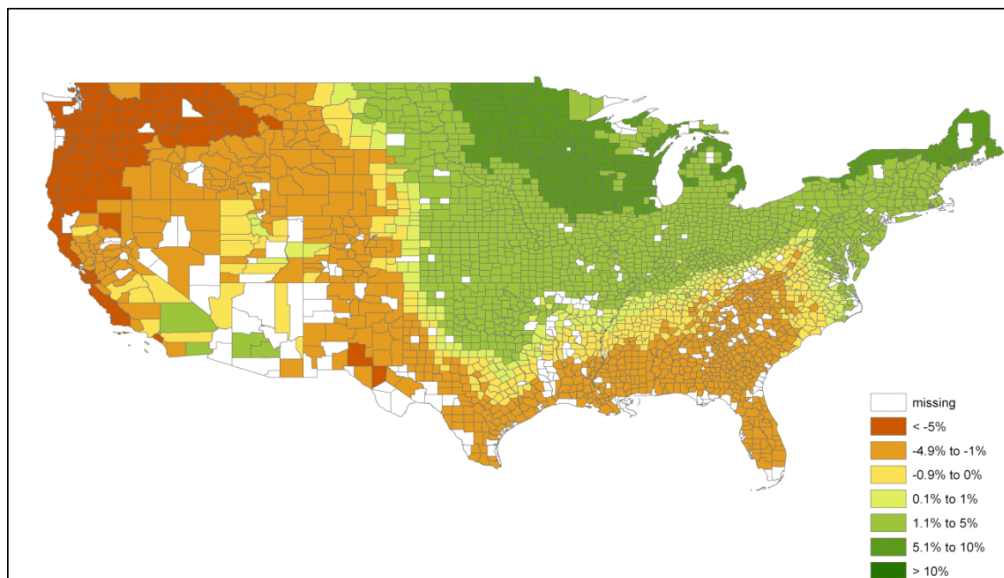
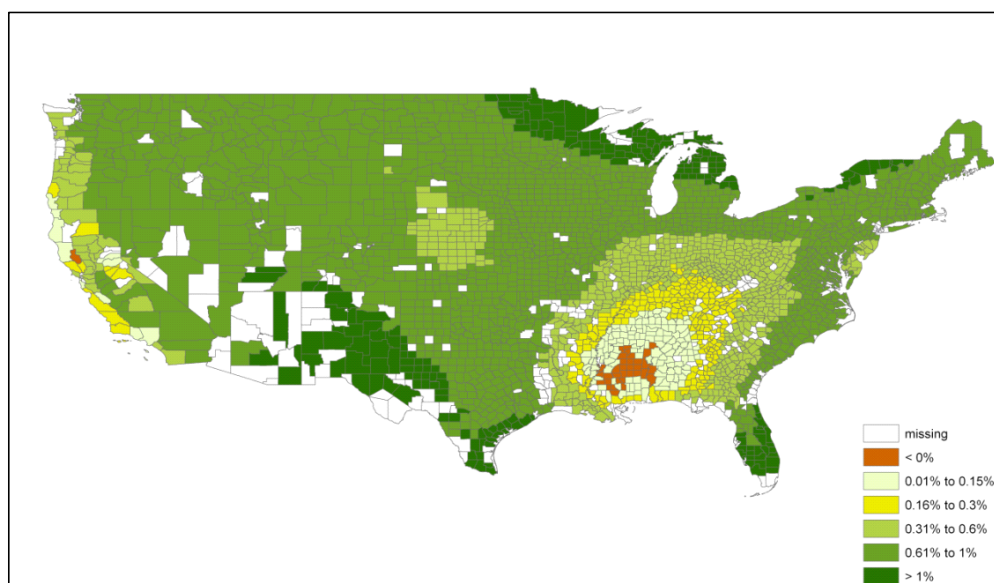


FIGURE 2. The Marginal Impact of Precipitations (mm) on Land Value in the United States (2000\$ per hectare): Extended Loglinear Ricardian Model - 2002



In the final analysis, we compare the agricultural impacts of three different climate scenarios. The uniform scenario assumes that temperature increases by  $2.3^{\circ}\text{C}$  and that precipitation increases by 7% for every county in the US. The other two scenarios are products of climate models where effects vary across the US. These are 2100 climate scenarios associated with a rapid emissions trajectory. The Parallel Climate Model (PCM) climate scenario is generally mild with warming of around  $2.5^{\circ}\text{C}$  and increased rainfall.<sup>1</sup> The HAD3CM (Atmosphere-Ocean coupled Global Circulation Model) scenario is harsher with warming closer to  $4^{\circ}\text{C}$  without any increase in precipitation. The climate model scenarios are not uniform across all counties and have some regional variation within the US.

<sup>1</sup> The Parallel Climate Model (PCM) is developed and managed by Warren Washington's group at the National Center for Atmospheric Research (NCAR). This model is used to simulate the earth's climate system and has been used to study the climate of the 20th century and to project possible climate changes into the 21st century and beyond. It was designed for use on distributed memory, highly parallel, architectures.

The results for the 3 climate scenarios and the three regression models are shown in Table 5 and Table 6. The percentage change in land value is shown in Table 5 and the aggregate welfare effect is shown in Table 6. With the uniform climate scenario, the linear model predicts benefits using the coefficients estimated from 1978 and 1982 data but damages using the coefficients estimated from the remaining years. One gets similar results with the enhanced linear model. In contrast, the loglinear model predicts benefits from the uniform climate scenario using data from every year. However, the predictions are not significant and they still vary a great deal from year to year.

TABLE 5. Percentage Changes in Agricultural Value from Climate Change

	Climate Scenario		
	Uniform	HADCM3	PCM
<b>Linear Model</b>			
1978	26.2%*	20.0%	72.7%*
1982	23.5%*	25.7%	54.8%*
1987	-7.7%	-19.8%	10.8%
1992	-7.5%	-12.2%	14.1%
1997	-0.5%	-16.3%	26.9%*
2002	-9.8%	-47.8%*	24.0%*
Average	4.0%	-8.4%	33.9%*
<b>Linear Extended Model</b>			
1978	27.4%*	1.1%	70.1%*
1982	16.7%*	-6.8%	41.1%*
1987	-9.4%	-30.7%*	-0.6%
1992	-7.4%	-21.1%	5.6%
1997	-7.0%	-34.2%*	11.9%
2002	-14.8%	-60.6%*	11.1%
Average	0.9%	-25.4%	23.2%*
<b>Loglinear Extended Model</b>			
1978	30.6%	56.4%*	137.7%*
1982	18.5%	40.2%	86.0%*
1987	0.8%	10.5%	11.7%
1992	2.9%	22.1%	28.5%*
1997	4.3%	9.2%	29.5%*
2002	8.4%	11.9%	46.5%*
Average	10.9%	25.1%	56.7%*

TABLE 6. Change in Total Agricultural Value from Climate Change

	Climate Scenario		
	Uniform	HADCM3	PCM
<b>Linear Model</b>			
Billions, 2000\$			
1978	261.4*	199.8	725.4*
1982	235.1*	256.9	546.8*
1987	-76.7	-198.1	108.0
1992	-75.0	-122.1	141.2
1997	-5.0	-163.2	268.8*
2002	-97.5	-477.2*	239.2*
Average	40.4	-5.3	338.2
<b>Extended Linear Model</b>			
Billions, 2000\$			
1978	273.4*	11.1	699.9*
1982	166.6*	-67.4	410.3*
1987	-94.0	-306.3*	-6.3
1992	-73.8	-211.1	56.0
1997	-69.9	-341.7*	118.7
2002	-148.3	-605.0*	110.7
Average	9.0	-253.4	231.6
<b>Loglinear Extended Model</b>			
1978	305.8	563.0*	1374.4*
1982	184.5	401.4	858.9*
1987	8.1	105.2	117.2
1992	29.4	220.4	284.6*
1997	43.0	91.4	294.0*
2002	83.9	118.5	464.1*
Average	109.1	250.0	565.5

With the PCM climate scenario, the linear model predicts benefits in every year although the estimates for 1982 and 1987 are smaller and insignificant. The enhanced linear model makes similar estimates for the first two years but much lower estimates for the remaining years. The new variables in the enhanced regression appear to lead to less optimistic predictions in later years. The loglinear results are noticeably more positive leading to large predicted gains in every year but 1987.

With the HADCM3 climate scenario, the linear model predicts benefits of 20% to 25% for US agriculture using the data from 1978 and 1982 but losses using the data from the later years. However, only the 2002 data predicts statistically significant losses of almost -50%. The enhanced linear model predicts more negative results. The 1978 changes are virtually zero and the remaining predictions are harmful. The 1987, 1997, and 2002 values are statistically significant. The 2002 prediction is a loss of -60% of farmland value.

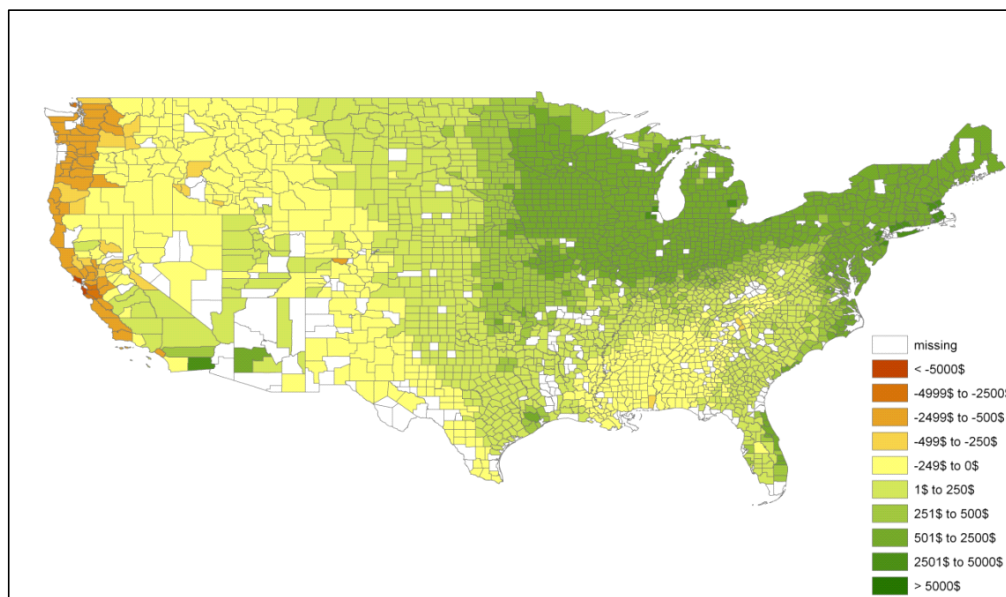
The Table 6 reports the same results but expresses them in terms of the total magnitude of the welfare effect rather than in percentage terms. Using the data in 2002, the uniform climate scenario leads to a loss of -\$97 billion/year, with the linear model, a loss of -\$148 billion according to the enhanced linear model, and a gain of \$109 billion according to the loglinear model. Using the 2002 data, the PCM climate scenario leads to a gain of \$338 billion, \$232 billion, and \$565 billion across the three Ricardian models. The HADCM3 climate scenario leads to a loss of -\$5 billion, a loss of -\$253 billion, and a gain of \$250 billion across the three models. The effects in each year vary considerably more. The annual impacts vary from a loss of -\$148 billion to a gain of \$306 billion in the uniform climate scenario, from a loss of -\$6 billion to a gain of \$1.4 trillion in the PCM climate scenario, and from a loss of -\$605 billion/year to a possible gain of \$563 billion in the HAD3CM climate scenario. There is considerable variation remaining in the repeated cross sections using different models.

In addition to knowing the aggregate impacts of climate change, it is also useful to see how the effects vary across the country. Figure 3 displays the impacts of the uniform climate change scenario. Although the change in climate is the same for every county in this scenario, the agricultural impacts are not the same. The northeast and north-central regions are predicted to have large gains. Most of the Great Plains and southeast will have small benefits. The western regions will experience small damages and the Pacific coast will experience large damages.

Figure 4 displays the results of the PCM climate scenario. The entire eastern and central regions of the US benefit in this scenario. The damages are limited to the west and in particular the northwest. Figure 5 displays the results of the HAD3CM climate scenario. The HAD3CM model predicts benefits in the eastern US including the southeastern US. There are also benefits in the northern states of Minnesota and North Dakota. However, there are strong damages

stretching from Indiana west. The entire western region of the US is damaged. The spatial pattern of damages is therefore quite different compared with the other climate scenarios.

FIGURE 3. The Impact of Climate Change on Land Value in the United States (2000\$ per hectare): Extended Loglinear Ricardian Model - Uniform Climate Scenario - 2002



## V. Summary and Conclusion

This analysis measures the impact of climate change on US farmland. The Ricardian method is used to compute the sensitivity of American farms to climate. Farmland value is regressed on climate and other control variables using a repeat cross-sectional method. The resulting empirical relationship is then used to estimate the marginal impact of climate change and to evaluate the impact of future climate scenarios. The analysis consistently finds that climate affects farmland value. Whether the empirical model is a basic linear model, an enhanced linear model, or a loglinear model, the climate coefficients are significant. However, the climate coefficients are sensitive to the inclusion of

additional control variables (enhanced model). The climate coefficients are also sensitive to the functional form, comparing linear versus loglinear. The analysis was repeated for different census years from 1978 through 2002. As found by Deschenes and Greenstone (2007), the results do vary across years. In the first two periods of data (1978, 1982), the analyses suggest that the marginal effect of temperature is positive but in the remaining four periods (1987-2002), it is negative. In contrast, the marginal effect of precipitation was generally positive across every year.

Examining future climate scenarios reveals that the results vary by scenario and econometric model. For the linear and enhanced linear models, the uniform and Hadley climate scenarios are predicted to be harmful using data from 1987 onward but beneficial using data from 1978 and 1982. In contrast, with the loglinear model, these climate scenarios were predicted to generate small benefits. With the PCM climate scenario, all models and almost all years predict a beneficial outcome for the US.

Because the magnitude of impacts varies depending on technical choices of how to model impacts, it is important that more research be done to measure the impacts carefully. The results depend upon the functional form. The Ricardian literature needs to be more careful on deciding what functional form to choose. Analysts should determine which functional form most closely fits the data. The results also vary depending on the control variables. Analysts must include more of the relevant control variables. Underspecified models can lead to seriously biased estimates. Finally, the year of data also matters. These results imply that there are still missing variables that explain why farmland prices vary across time and that these variables affect the climate coefficients. More research is clearly needed to try to reduce the range of results across years.

Finally, the results suggest that if climate change is mild, it will likely be beneficial to US farmers. However, if climate change turns out to be harsh, US farmers may well be large losers. The small changes in temperature expected over the next few decades will not likely threaten US agricultural production. However, if very little is done about mitigation over the century and there are large change in temperature, US agricultural production will be far more vulnerable. It is likely that large changes in temperature will cause a reduction in US agricultural output by the end of the century.

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Date Submitted: Jun. 2, 2011

Period of Review: Jun. 3~Jun. 13, 2011