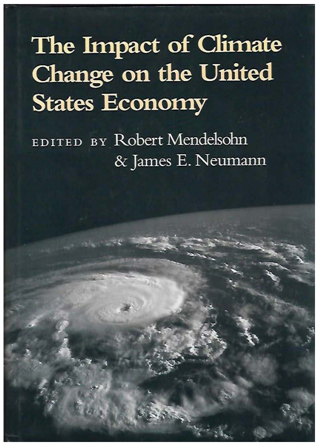
3 The impact of climate variation on US agriculture



in Robert Mendelsohn, James E. Neumann, eds,
The Impact of Climate Change on the United States Economy
1999

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This chapter explores the effect of climate on the value of US agricultural land using a Ricardian model. The research extends previous analyses by including both interseasonal and diurnal climate variation in addition to average temperature and precipitation variables. With these climate variation variables included, small increases in average temperature are predicted to be beneficial. Increases in interannual climate variation are predicted to be generally harmful to US agriculture but decreases in diurnal variation will be beneficial.

For centuries analysts have been interested in the impact of weather on crops in order to predict what crops to grow, when to plant and harvest, and what agricultural prices will be each year. With the growing likelihood that accumulating greenhouse gases will change the climate (IPCC, 1996), there has been growing interest in also measuring the impact of climate change on agriculture. Two distinct ways to measure the impacts of climate on agriculture have emerged in the literature: an agronomic approach and a Ricardian rent approach. The agronomic approach (Chapter 2; Adams *et al.*, 1989, 1990, 1995; Crosson and Katz, 1991; Rosenzweig and Parry, 1994) predicts changes in yield from crop simulation models such as CERES and SOYGRO and then enters these changes in mathematical models of agriculture production and consumption. The Ricardian approach (Johnson and Haigh, 1970; Mendelsohn *et al.*, 1994, 1996) uses an empirical cross-sectional approach and estimates the relationship between land prices and climatic, economic, and soil variables.

The agronomic approach, with its extensive reliance on specific crop models, has the advantage of being based directly on carefully controlled scientific experiments so that it can predict phenomena (such as carbon fertilization) that have not yet occurred in nature. The method is also capable of detailed displays of the links between climate, crop yields, and market equilibrium. The approach is popular among scientific analysts of climate impacts because it captures the tremendous detail of individual crop models. The approach, unfortunately, is somewhat mechanistic. The myriad adaptations that farmers might make to climate are difficult to model explicitly and so are often omitted, overestimating the damages from climate warming.

The Ricardian approach, by relying upon how farmers and ecosystems have actually adjusted to varying local conditions, incorporates adaptation readily. However, the Ricardian approach does not provide much information about the process of climate change or about conditions which are not evident in today's environment, such as carbon fertilization. The Ricardian approach has only recently been applied to climate change and so there is less experience of using this approach compared with the production function technique. Further, because it does not contain the minute detail captured in the crop response models, crop scientists have been slow to understand its merits. Each method has its own strengths and weaknesses and the two approaches complement each other.

This chapter begins by addressing several theoretical issues with the Ricardian model and specifically explores the bias introduced by assuming that prices remain constant (Section 3.1). The thrust of the chapter, however, lies in the extension of the empirical results to include the influence of climate variation (described in Section 3.2). Specifically, the study explores the impact of including interannual and diurnal variation in precipitation and temperature on US agricultural land values. The empirical study is described in detail in Section 3.3. These models are then used to assess the economic damages to US agriculture from several climate change scenarios in Section 3.4. The chapter concludes with some general observations.

3.1 Theory

This section summarizes the theoretical underpinnings of the Ricardian approach to climate modeling and explores a few extensions of this theory. We postulate a set of consumers with well-behaved utility functions (preferences for goods) and linear budget constraints. Assuming that consumers maximize their utility functions across available purchases and aggregating leads to a system of inverse demand functions for all goods and services:

$$\begin{aligned} P_1 &= D^{-1}(Q_1, Q_2, \ldots, Q_n, Y) \\ &\vdots \qquad \vdots \\ P_n &= D_n^{-1}(Q_1, Q_2, \ldots, Q_n, Y), \end{aligned} \tag{3.1}$$

where P_i and Q_i are respectively the price and quantity of goods i, $i = 1, \ldots, n$, and Y is the aggregate income. Inverse demand functions describe the prices at which consumers are willing to purchase specific bundles of goods. The Slutsky equation is assumed to apply, so that (3.1) is integrable.

We also assume that a set of well-behaved production functions exist which link purchased inputs and environmental inputs into the production of outputs by a firm on a certain site:

$$Q_i = Q_i(\boldsymbol{K}_i, \boldsymbol{E}), \qquad i = 1,\ldots,n. \tag{3.2}$$

In this equation, we use bold face to denote vectors or matrices. Q_i is the output of goods i, $\boldsymbol{K}_i = [K_{i1},\ldots,K_{ij},\ldots,K_{iJ}]$ where K_{ij} is the purchased input j ($j = 1,\ldots,J$) in the production of good i, and $\boldsymbol{E} = [E_1,\ldots,E_l,\ldots,E_L]$ where E_l is an exogenous environmental input l ($l = 1,\ldots,L$) into the production of goods, e.g. climate, soil quality, air quality, and water quality, which would be the same for different goods' production on a certain production site. Given a set of factor prices, R_j, for K_j, the exogenously determined level of environmental inputs, and the production function, cost minimization leads to a cost function:

$$C_i = C_i(Q_i, \boldsymbol{R}, \boldsymbol{E}). \tag{3.3}$$

Here, C_i is the cost of production of goods i, $\boldsymbol{R} = [R_1,\ldots,R_J]$, and $C_i(*)$ is the cost function. In this analysis, it is helpful to separate land from the vector of inputs, K. We assume that land, L_i, is heterogeneous with characteristics E and has an annual cost or rent of P_E. Companies are assumed to maximize profits given market prices:

$$\text{Max}\, P_i Q_i - C_i(Q_i, \boldsymbol{R}, \boldsymbol{E}) - P_E L_i \tag{3.4}$$

where P_i is the price of goods i. This maximization leads firms to equate prices and marginal costs as well as determine cost minimizing levels of production. We assume that there is perfect competition for land, which implies that entry and exit will drive pure profits to zero:

$$P_i Q_i - C_i(Q_i, \boldsymbol{R}, \boldsymbol{E}) - P_E L_i = 0. \tag{3.5}$$

If use i is the best use for the land given the environment E and factor prices R, the observed market rent on the land will be equal to the annual net profits from production of goods i_1. Solving for the value of land rent per acre yields:

$$P_E = [P_i Q_i - C_i(Q_i, \boldsymbol{R}, \boldsymbol{E})]/L_i. \tag{3.6}$$

The land rent should be equal to the net revenue from the land. Land value, V_E, is equal to the present value of the stream of future net revenue, which can be described by:

$$V_E = \int_0^\infty P_E\, e^{-rt}\, dt = \int_0^\infty [P_i Q_i - C_i(Q_i, \boldsymbol{R}, \boldsymbol{E})] e^{-rt}/L_i\, dt. \tag{3.7}$$

The discount rate is represented by r and time by t. By examining the relationship between land value and the environmental variable of interest, one can measure its

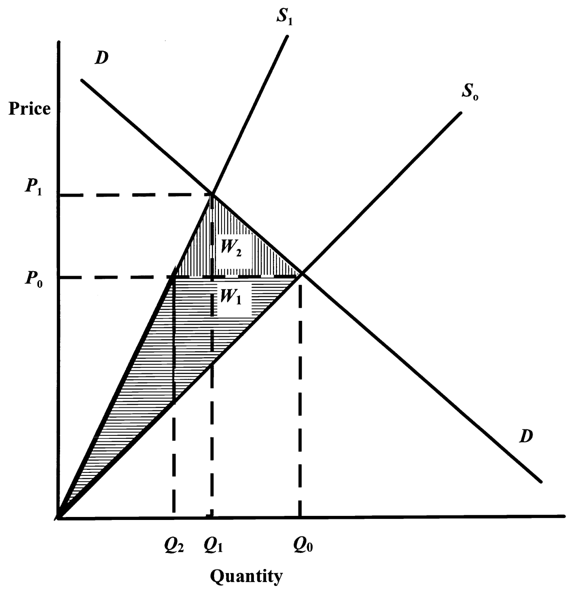

Figure 3.1 Welfare loss from supply reduction.

impact on the present value of net revenue. The essence of the Ricardian model is (3.7).

If an environmental factor reduces the stream of future land rents, land values will be reduced as well (note the similarity of this analysis and hedonic property studies, see Freeman (1979)). Reliance upon land values rather than land rents, however, introduces a potential source of additional problems. Land values will represent the present value of the rents using the parcel at its highest purpose. Although land may now be in agricultural use, it could be that its best future use may be industrial or urban. In order to control for nonagricultural influences, proxies for the development value of farmland must be included in the analysis.

Let us now examine the welfare value of an environmental change from an initial point E_A to a new point E_B. The change in annual welfare, W, from this environmental change is the change in net consumer surplus:

$$W(E_A - E_B) = \int_0^{Q_B} \sum D^{-1}(Q_i)\mathrm{d}Q_i - \sum C_i(Q_i,\boldsymbol{R},E_B) -$$

$$[\int_0^{Q_A} \sum D^{-1}(Q_i)\mathrm{d}Q_i - \sum C_i(Q_i,\boldsymbol{R},E_A)] \qquad (3.8)$$

where $\int\Sigma$ is the line integral evaluated between the initial vector of quantities and the zero vector, $\boldsymbol{Q}_A = [Q_1(K_1,E_A),\ldots,Q_i(K_i,E_A),\ldots,Q_n(K_n,E_A)]$, $\boldsymbol{Q}_B = [Q_1(K_1,E_B),\ldots,Q_i$

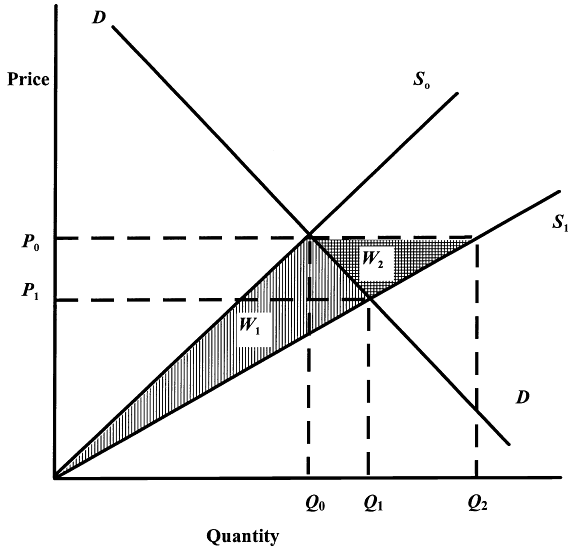

Figure 3.2 Welfare gain from supply expansion.

$(K_i, E_B),\ldots,Q_n(K_n,E_B)]$, $C_i(Q_i,\boldsymbol{R},E_A) = C_i(Q_i(K_i,E_A),\boldsymbol{R},E_A)$, and $C_i(Q_i,\boldsymbol{R},E_B) = C_i(Q_i(K_i, E_B),\boldsymbol{R},E_B)$. The above equation includes changes in both consumer and producer surplus. It is necessary to take this line integral as long as the environmental change affects more than one output. If only one output is affected, then (3.8) simplifies to the integral of the equation for a single item of goods. Note that as long as the Slutsky equation is satisfied, the solution to (3.8) is path-independent and unique.

If we assume that the changes in the environment will leave market prices unchanged,[1] then (3.8) can be expressed:

$$W(E_A - E_B) = \boldsymbol{P}\boldsymbol{Q}_B - \sum C_i(Q_i,\boldsymbol{R},E_B) - [\boldsymbol{P}Q_A - \sum C_i(Q_i,\boldsymbol{R},E_A)] \tag{3.9}$$

where $\boldsymbol{P} = [P_1,\ldots,P_i,\ldots,P_n]$. In this case, consumer surplus is not affected. Substituting (3.6) into (3.9) yields:

$$W(E_A - E_B) = \sum(P_{EB} \times L_{EB} - P_{EA} \times L_{EA}) \tag{3.10}$$

where P_{EA} is the value per acre of land area L_{EA} in environmental state A and P_{EB} is the value per acre of land area L_{EB} in environmental state B. The environmental state affects both the value per acre and the total number of acres in farmland. It follows that the present value of this welfare change is:

[1] If there is a nonmarginal change in market prices, one must also add changes in consumer surplus to find the total damages. The difficulty of including price changes should not be underestimated as it requires estimation of the international supply and demand for food.

Table 3.1. *Bias from holding prices constant*[a]

	Supply elasticity		
Demand elasticity	0.5	1.0	2.0
0.5	1.17	1.07	1.03
1.0	1.11	1.05	1.03
2.0	1.07	1.04	1.02

Notes:

[a] The table presents the ratio of the true welfare measure of damages from a 10% reduction in aggregate supply to the Ricardian welfare measure. The Ricardian method overestimates the benefits of a 10% increase in aggregate supply by a similar amount.

$$\int_0^\infty \sum W(\boldsymbol{E}_A - \boldsymbol{E}_B)\mathrm{e}^{-rt}\mathrm{d}t = \sum_i (V_{EA} - V_{EB}). \tag{3.11}$$

Equation (3.11) is the definition of the *Ricardian estimate of the value of environmental changes*. Under the assumptions used here, *the value of the change in the environment is captured exactly by the change in aggregate land values*.

The strongest assumption above is that output prices remain constant. Suppose that this assumption is relaxed. Climate change is expected to lead to increases in the supply of some crops and decreases in the supply of others. For example, crops which prefer cooler environments, such as apples and winter wheat, may not do as well with climate warming. In contrast, heat-loving plants, such as tomatoes and citrus fruit, should be able to grow in wider settings. As supply expands (contracts) for the warm-(cool-) loving plants, prices will fall (rise).

In a warming scenario, the crops which benefit will fall in price and crops which grow less well will rise in price. For example, the supply function for cool-loving crop A could shift from S_0 to S_1 in Figure 3.1. We measure the loss in net revenue holding prices constant as W_1. In fact, there is an additional consumer surplus loss of W_2. The model understates the damages from the change in supply. Similarly, if supply expands from S_0 to S_1 as in Figure 3.2, holding prices constant, we estimate a benefit of W_1. This overstates the benefits because prices fall to P_1 from P_0. The size of this over-estimate is equal to W_2.

Given that the welfare estimates of the Ricardian model are biased, it is important to estimate the size of this bias. Suppose that demand and supply price elasticities take on values within a plausible range for agriculture. What will be the size of

$W_1 + W_2$, the true measure of welfare, relative to W_1, the Ricardian measure? Mendelsohn and Nordhaus (1996) examine these ratios for a simple model with linear supply and demand functions. The results are given in Table 3.1. Assuming that global warming causes a 10 percent change in the aggregate supply of goods, the table estimates the error associated with the Ricardian measure of welfare. With typical unitary price-elasticities, the error is about 5 percent of the Ricardian measure. With price-inelastic demand and supply functions of 0.5, the error can be as large as 17 percent and with price-elastic demand and supply functions of 2.0, the error falls to 2 percent. With smaller changes in aggregate supply, the effect shrinks. Given that most models of aggregate supply predict very small changes in aggregate quantities of food as a result of warming,[2] the Ricardian measures of welfare should be accurate.

3.2 Data

In this section, we extend the Ricardian technique developed by Mendelsohn *et al.* (1994) to examine the impact of climate variation on US agriculture. We rely on data from the 1982 US Census of Agriculture to obtain much of the data on farm characteristics in each county. Although the analysis conducted in this study relies upon 1982 data, a similar analysis was conducted on 1978 data with similar results. The results appear to be robust over time. Nonetheless, it would be helpful if future analysts update the Ricardian estimate using more recent census data.

For the most part, the data reflects actual county averages, so that there are no major geographic issues involved in obtaining the census information on these variables. The *County and City Data Book*, and the computer tapes of that data, are the source for much of the agricultural data used here, including farmland and building values, and information on market inputs for farms in every county in the United States. In addition, we include social, demographic, and economic data on each of the counties drawn from the *County and City Data Book*.

Data about soils were extracted from the National Resource Inventory and other USDA surveys with the kind assistance of Daniel Hellerstein and Noel Gollehon of the US Department of Agriculture. For each county, we have average measures of salinity, clay content, sand content, soil permeability, available water capacity, flood probability, soil erosion, slope length, whether or not the land is a wetland, and numerous other variables that are not used in this analysis.

[2] See, for example, predictions in Chapter 2 which are only for the United States. Predictions for the world are even less severe because of trade between countries (Kane *et al.*, 1992).

Climatic data is available by weather stations rather than by county. The climate data was obtained from the National Climatic Data Center, which gathers data from 5511 meteorological stations throughout the United States. The data include information on precipitation and temperature for each month from 1951 to 1980. This analysis includes data on normal daily mean temperatures and normal monthly precipitation for January, April, July, and October, representing each season of the year. Interannual variation in precipitation and temperature in each of the four months is measured as the difference between the highest and lowest normal monthly precipitation and temperatures over the 30-year period. The variation variables measure the range of interannual variation.[3] We also measure the diurnal range (the difference between the average of the highest and lowest daily temperatures) for each of the four months. Altogether there are 12 variation measures in the study.

In order to link the agricultural data which is organized by county and the climate data which is organized by station, we conduct a spatial statistical analysis which examines the determinants of the climate of each county (see Mendelsohn *et al.*, 1994 for more details). The interpolation relies on a regression weighted by distance.

The next and crucial stage is to use the climate data to predict aggregate land values. Following Mendelsohn *et al.* (1996), we define the dependent variable as the aggregate value of farmland in each county rather than the farmland value per acre. This aggregate measure takes into account how the climate affects which land can be used for agriculture as well as how climate affects the value of the farmland that remains. In order to determine the marginal impact of each climate variable, we regress aggregate farm values on climate, soil, and economic variables. The soil and economic variables control for unwanted variation so that the climate variables are less likely to reflect correlated omitted variables. For example, the economic variables control for the effect of nearby local markets and speculative future land uses.

Alternative control variables in the theoretical model such as interest rates and farm input prices are not included in the empirical model because they are assumed to be the same for all counties. In a cross-sectional analysis, the capital market will equate interest rate expectations across parcels, so that this effect will be the same for all observations. Competitive market forces should also equate farm input prices for energy, labor, and equipment.[4]

In previous analyses, it was demonstrated that both precipitation and temperature

[3] An alternative formulation would have been to use the variance in monthly normals over the 30-year period. Our decision to rely upon the range is partially motivated by the availability of this measure and partially by a general concern about extreme events.

[4] To the extent that farm input and output prices vary because of proximity to an urban area, the urban variables used in the analysis would control for this effect.

have quadratic relationships with farm value (see Mendelsohn *et al.*, 1994, 1996). This same specification is used in this analysis:

$$V = a_o + \sum_{1}^{I} a_i E_i + \sum_{1}^{I} b_i E_i^2 + \sum_{1}^{12} c_i Q_i + \sum_{1}^{n} d_i Z_i + e, \tag{3.12}$$

where E_i represent the precipitation and temperature normals, Q_i represent the climate variation terms, Z_i represent the control variables and e is the error term. The climate variables have been de-meaned. The coefficients a_i can therefore be interpreted as the marginal effect of E_i on land values evaluated at the sample mean for the United States. The coefficients b_i measure the impact of the quadratic terms, the coefficients c_i measure the impact of the climate variation terms, and the coefficients d_i capture the impact of the control variables.

3.3 Empirical results

Following Mendelsohn *et al.* (1994) the empirical models are weighted regressions using either percent cropland or total crop revenue in the county. Weighting counties by total crop revenue makes sense if the focus of the study is on aggregate agricultural production since the counties with the highest valued production are more important. Weighting by percent cropland is justified if the focus is understanding what is happening to cropland. See Appendix A3 for a complete list of the variables used in the models and their definitions.

Columns 3 and 4 in Table 3.2 present the climate model without variation terms included. Some results are consistent across both weighting schemes. Higher average temperatures in January and July are harmful to farm values whereas higher temperatures in April and especially October increase values. Increased precipitation in July and especially October reduces farm values but more precipitation in January and April increases farm values. The coefficients of all the control variables exhibit consistent effects across the models (although magnitudes vary) with the exception of soil permeability.

The year-to-year and diurnal climate variation variables are introduced in the models in columns 1 and 2 of Table 3.2. F-tests of the variation terms as a group indicate that the variation coefficients are significantly different from zero in all regressions. All the individual coefficients of interannual climatic variation are significantly different from zero. The coefficients are all negative implying that increasing interannual variation reduces farm values with the exception of April temperatures and January precipitation. An increase in interannual variation in January precipitation and April

Table 3.2. *Regression models with and without climate variation*[a]

Variation	Climate variation		No climate variation	
Independent variables	Percent cropland	Crop revenue	Percent cropland	Crop revenue
January temp.	−120.0	−145.0	−86.7	−108.0
	(15.53)	(19.92)	(10.50)	(13.94)
January temp. sq.	−2.02	−2.71	−0.83	−0.93
	(11.11)	(16.87)	(4.04)	(5.25)
April temp.	21.9	49.6	59.6	65.0
	(2.20)	(6.20)	(4.83)	(6.06)
April temp sq.	−3.69	−3.76	−3.27	−1.36
	(6.46)	(8.97)	(5.65)	(3.09)
July temp.	−189.0	−182.	−117.0	−141.0
	(20.46)	(23.85)	(11.45)	(18.83)
July temp sq.	−5.63	−5.78	−1.90	−3.07
	(10.32)	(17.40)	(3.38)	(8.08)
October temp.	235.0	266.0	152.0	233.0
	(15.66)	(18.50)	(8.68)	(14.40)
October temp. sq.	7.81	10.1	3.00	2.87
	(9.65)	(17.24)	(3.50)	(4.49)
January rain	43.3	88.0	−131.0	−123.0
	(2.28)	(5.11)	(5.34)	(5.14)
January rain sq.	1.78	0.23	12.5	13.3
	(0.71)	(0.13)	(4.96)	(7.39)
April rain	110.0	36.3	117.0	99.0
	(5.40)	(1.74)	(4.24)	(3.31)
April rain sq.	−28.7	−14.5	−25.8	−40.6
	(3.92)	(2.19)	(3.59)	(5.87)
July rain	−53.4	−26.5	60.0	75.2
	(4.69)	(2.35)	(3.24)	(3.86)
July rain sq.	34.3	17.8	18.2	−6.7
	(7.18)	(4.33)	(3.50)	(1.46)
October rain	−188.0	−129.	−74.5	−7.9
	(9.70)	(6.66)	(2.40)	(0.26)
October rain sq.	−21.1	6.8	−24.5	−16.4
	(1.79)	(0.96)	(2.02)	(2.17)

Table 3.2. (*cont.*)

Variation	Climate variation		No climate variation	
Independent variables	Percent cropland	Crop revenue	Percent cropland	Crop revenue
Year-to-year variation				
January temp. Y-var.	−19.3	−19.1		
	(4.84)	(4.80)		
April temp. Y-var.	19.9	11.2		
	(3.01)	(1.76)		
July temp. Y-var.	−57.1	−63.9		
	(8.53)	(8.56)		
October temp. Y-var.	−27.6	−29.3		
	(4.61)	(4.46)		
January rain Y-var.	21.9	24.9		
	(2.89)	(4.05)		
April rain Y-var.	−19.5	−26.8		
	(2.85)	(3.42)		
July rain Y-var.	−29.1	−25.4		
	(6.39)	(4.74)		
October rain Y-var.	−13.2	−31.7		
	(2.09)	(5.15)		
Daily variation				
January daily var.	−61.7	−100.0		
	(7.19)	(13.13)		
April daily var.	−66.7	−4.4		
	(5.83)	(0.42)		
July daily var.	−10.6	−11.8		
	(1.00)	(1.43)		
October daily var.	59.8	73.8		
	(5.81)	(7.03)		

Table 3.2. (*cont.*)

Variation	Climate variation		No climate variation	
Independent variables	Percent cropland	Crop revenue	Percent cropland	Crop revenue
Control variables				
Constant	957.0	1060.0	870.0	945.0
	(49.96)	(57.31)	(37.44)	(47.08)
Income per capita	57.4	27.0	52.7	32.9
	(14.20)	(6.00)	(13.70)	(7.74)
Density	86.3	64.2	15.2	8.6
	(1.41)	(1.29)	(0.26)	(0.18)
Density sq.	−101.0	−68.6	−76.8	−44.7
	(3.60)	(4.24)	(2.92)	(3.00)
Solar radiation	−84.4	−38.6	−41.7	2.9
	(6.57)	(3.37)	(2.74)	(0.22)
Altitude	−121.0	92.9	54.9	90.4
	(5.10)	(4.53)	(2.19)	(4.20)
Salinity	−843.0	−467.0	−725.0	−715.0
	(4.74)	(3.51)	(4.30)	(5.73)
Flood prone	−136.0	−102.0	−185.0	−125.0
	(3.27)	(2.25)	(4.57)	(2.83)
Wetland	−509.0	−784.0	−656.0	−832.0
	(4.79)	(7.67)	(6.43)	(8.68)
Soil erosion	−799.0	−1480.0	−1050.0	−1420.0
	(4.54)	(7.64)	(6.14)	(7.65)
Slope length	24.6	73.1	29.0	64.1
	(4.76)	(14.29)	(5.94)	(13.42)
Sand	−86.1	−81.2	−21.2	−74.5
	(1.94)	(1.99)	(0.51)	(1.97)
Clay	91.6	21.5	86.6	49.4
	(5.00)	(1.03)	(4.97)	(2.52)
Water capacity	0.51	0.34	0.41	0.30
	(14.96)	(10.75)	(12.72)	(9.98)
Permeability	-0.70×10^{-3}	-598×10^{-3}	-0.37×10^{-3}	-8.42×10^{-3}
	(0.35)	(4.43)	(0.20)	(6.62)
Adjusted R^2	0.793	0.843	0.800	0.869
Number of observations	2938	2938	2938	2938

Notes:
[a] Dependent variable is aggregate farm value. All observations are weighted. Values in parenthesis are t-statistics.

temperatures may be beneficial because at least spring-planting farmers can adjust for the realized values before planting, thus permitting good years to outweigh bad years.

Increases in diurnal variation in January and April are harmful to farming. Increases in diurnal variation during the summer seem to have no effect on farm values. However, increases in diurnal variation in the autumn appear beneficial, possibly serving as a useful signal to plants to begin maturing and ripening fruit.

In order to understand the spatial implications of the climate model in Table 3.2, the climate coefficients from the regression using crop revenues as the weight (the second column) are used to predict the impact of current climate on the distribution of farm values in the United States. For each county, the deviation between that county's climate and the US mean climate is calculated. This deviation is then multiplied by the climate coefficient in column 3 of Table 3.2 and the effect is summed across the climate variables. The predicted effect of the range of climates observed in the United States on farm values is shown in Figure 3.3. All the climatic variables taken as a group predict that four areas of the country have climates which yield above average agricultural land values: the Gulf coast, the southern New England coast, the Pacific coast, and the Mississippi river valley. Climates which lead to below average land values include northern Maine, the western plains, and the Rocky Mountains.

This same process can isolate the spatial contribution of only the climatic variation. The parts of the country with the most stable climates include the Pacific coast, the southern Mississippi delta, and coastal New England. The part of the country most sensitive to climate variation lies near the dust bowl in Kansas, Missouri, and Oklahoma. Note that these were the states most devastated by the dust bowl in the 1930s. The range of values produced by climate variation across the United States is surprisingly large. The current spatial distribution of interannual and diurnal variation is quite important to crops.

Introducing climatic variation into the Ricardian model has important effects on the seasonal pattern of *mean* temperature and precipitation. Adding the climatic variation variables decreases the harmful effect of a warmer January or July, increases the benefits of a warmer April, and reduces the benefit of a warmer October. Adding the variation terms also alters the seasonal importance of increases in precipitation. January precipitation becomes harmful, July precipitation becomes beneficial, and October precipitation becomes less harmful. Overall, warmer temperatures and increased precipitation become more beneficial with the variation terms included in the model.

Adding the climate variation terms also affects two other control variables in the model. The effect of solar radiation is reduced with the variation terms in place. Altitude goes from being harmful to being beneficial. It is possible that the damaging influence of higher altitude is due to the increase in diurnal variation.

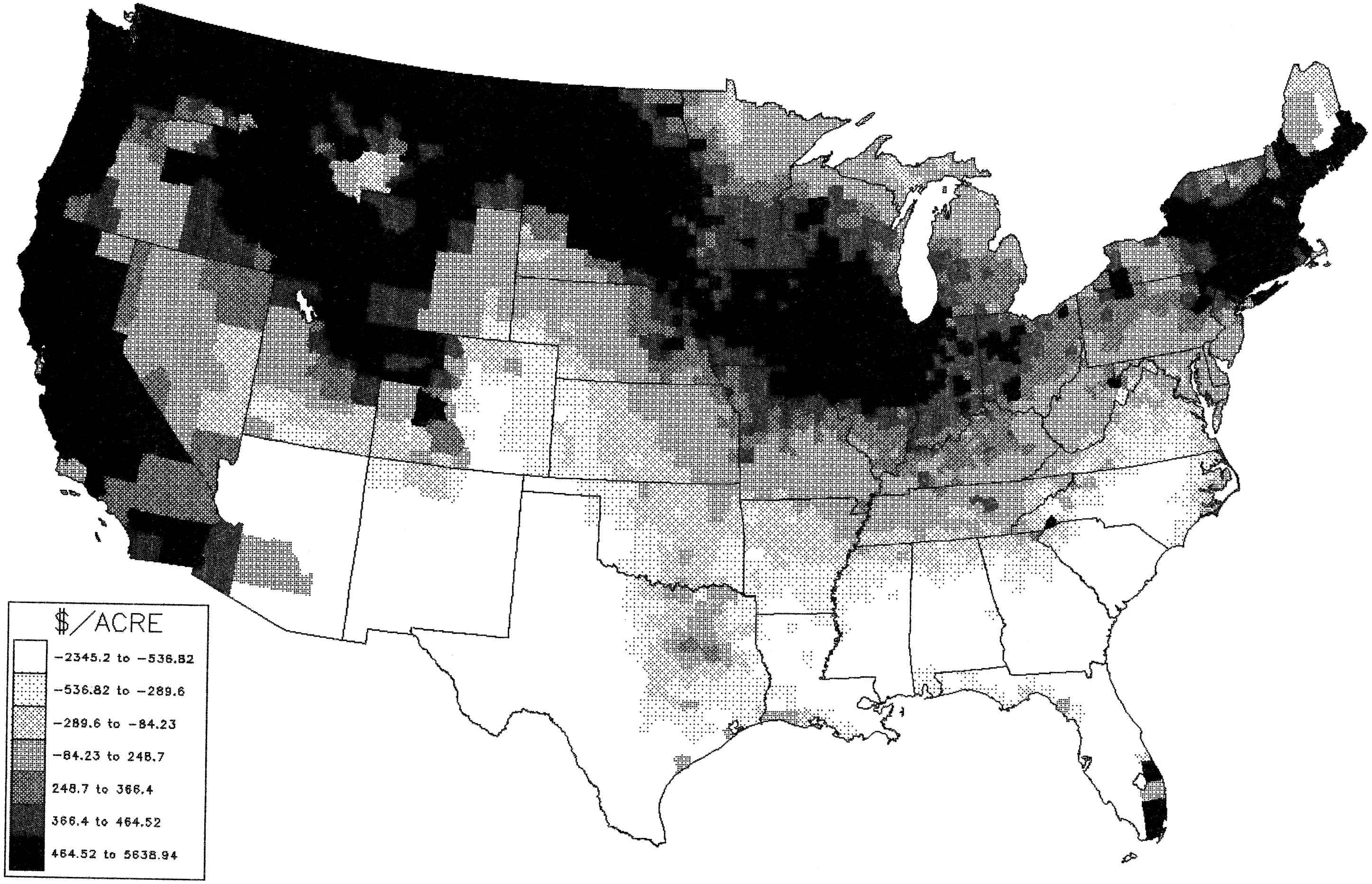

Figure 3.3 Farm values from current climate with crop revenue per county.

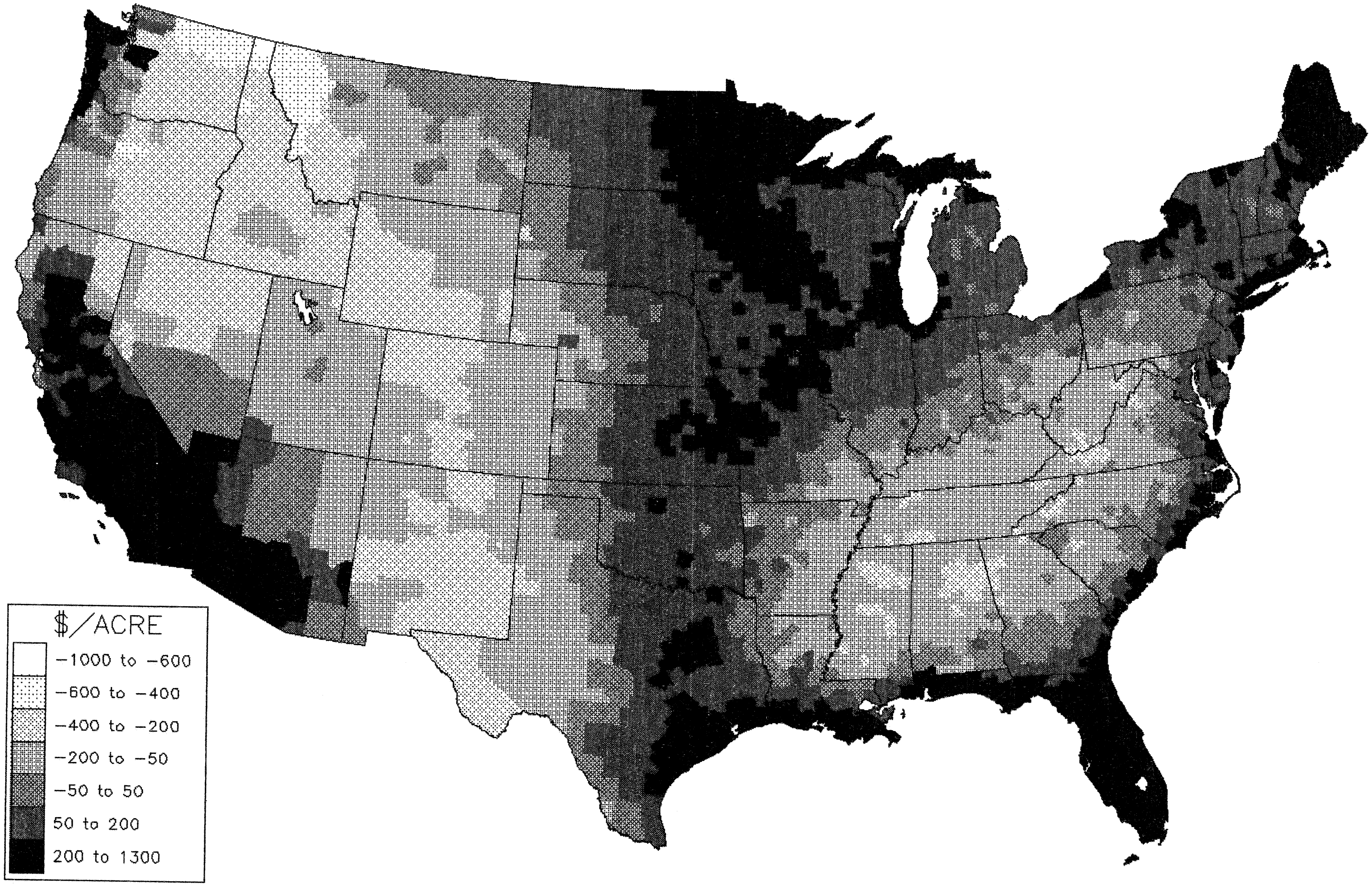

Figure 3.4 Change in value due to 5 °C uniform increase weighted by crop revenue/county.

Table 3.3. *Net agricultural effect of climate change without climate variation*[a]

Model: percent cropland – no climate variation

	Temperature change (°C)		
Precipitation change (%)	1.5	2.5	5.0
0	−11.9	−20.8	−39.1
7	−12.6	−21.3	−39.5
15	−13.4	−21.9	−39.8

Model: crop revenue – no climate variation

	Temperature change (°C)		
Precipitation change (%)	1.5	2.5	5.0
0	−2.6	−9.2	−15.7
7	−2.7	−5.7	−15.7
15	−2.7	−5.7	−15.6

Note:
[a] Change in annual net value to US agriculture in billions of dollars.

3.4 Climate simulations

In order to test what implications these models have for greenhouse warming, we simulate nine scenarios for each model. Following the protocol described in Chapter 1, we examine uniform temperature increases of 1.5, 2.5, and 5.0 °C for the entire United States under three precipitation scenarios of 0 percent, 7 percent, and 15 percent increases. Four impact models are explored: cropland weighted models and crop revenue weighted models with and without climate variation terms. The models without climate variations in columns 3 and 4 of Table 3.2 produce the results shown in Table 3.3. With both the cropland and crop revenue models, warming is increasingly harmful as one moves from 1.5 to 5 °C increases. Increased precipitation is also mildly harmful according to the cropland model and inconsequential according to the crop revenue model. Adding the climate variation terms (columns 1 and 2) changes these results dramatically, producing the results in Table 3.4. Gentle warming is strictly beneficial. As warming approaches 5 °C, however, the cropland model predicts that warming becomes harmful whereas the crop revenue model predicts even larger benefits. The regional impacts are shown in Figure 3.4.

Table 3.4. *Net agricultural effect of climate change with climate variation*[a]

Model: percent cropland – with climate variation

	Temperature change (°C)		
Precipitation change (%)	1.5	2.5	5.0
0	2.7	2.9	−3.7
7	3.3	3.1	−3.1
15	3.9	3.7	−2.5

Model: crop revenue – with climate variation

	Temperature change (°C)		
Precipitation change (%)	1.5	2.5	5.0
0	11.5	16.7	26.2
7	12.9	18.8	27.5
15	13.8	19.7	28.4

Note:
[a] Change in net annual income to US agriculture in billions of dollars.

3.5 Conclusion

This analysis examines the impact of climate variation on US farm values using the Ricardian approach developed by Mendelsohn *et al.* (1994). Three important results are developed. First, the assumption of constant output prices in the Ricardian model is shown to underestimate the damages and overestimate the benefits of climate change. However, these biases are very small, indicating the technique yields accurate estimates of welfare loss.

Second, climate variation (both diurnal and interannual) has important effects on farm values. In general, greater interannual variation is harmful to farm values. Variation in the beginning of the year, however, is less harmful than variation at the end of the year because farmers can more readily adjust to weather which occurs in winter and spring. Increases in diurnal variation are also important, generally reducing farm values in winter, spring, and summer. However, diurnal variation in the autumn appears to be beneficial, possibly because it serves as a useful signal to plants to begin ripening before dangerous frosts arrive.

Third, including climate variation in an empirical model is important because it is correlated with mean temperatures. Increases in mean temperatures can be harmful if climate variation terms are omitted from a model. However, when climate variation terms are included, increases in mean temperatures are strictly beneficial.

The marginal effect of temperature variation is large. If the interannual variation of temperature increases by 25 percent in every month, average farm values would fall by about one-third.[5] Similarly, if the diurnal range of temperature decreased in every month by 25 percent, farm values would double. In contrast, if the interannual variation of precipitation in every month increased by 25 percent, farm values would fall just 6 percent. What farmers should fear, apparently, is years with unusual temperatures, not years with unusual precipitation levels.

After estimating the effect of diurnal and interannual variations in temperature and precipitation on agricultural land values, we tested the implications of these models. Impacts from a total of nine climate scenarios were estimated using the four different impact models. The models that include climate variation variables in the estimate yield quite different results to those from the models which omit these variables. Including climate variation suggests that small amounts of warming are beneficial. Only when the temperature increase is above 2.5 °C does the cropland with the climate variation model suggest that increased warming is harmful.

An alternative perspective on the four models can be obtained by examining the overall response function of the four models. Each predicts a quadratic relationship with an optimal average temperature (given US seasonal variation). The cropland and crop revenue models without variation terms predict the optimal average temperature for agriculture is 4 and 1 °C, respectively, less than the US average. The cropland and revenue models with variation terms included predict that the optimal agricultural temperature is 1 and 6 °C, respectively, warmer than the US average. Thus, the results are generally in agreement among all four models and they suggest as a group that modest warming will have either a mildly harmful or mildly beneficial effect. The model predictions, however, diverge with more severe climate scenarios.

There are a number of improvements which could strengthen our understanding of climatic impacts on agriculture. The direct effect of carbon dioxide must also be included for an accurate assessment. According to the model presented in Chapter 2, including carbon fertilization effects could add another $50 billion of benefits, making global warming clearly beneficial. The analysis also needs to be extended to other countries, especially in subtropical and tropical settings. Finally, this chapter demonstrates that changes in climatic variation are important to agriculture. More precise

[5] Summing across months, the product of the coefficient in Table 3.2 multiplied by a change in that variable yields an estimate of the net effect of that change.

climate work quantifying changes in diurnal and interannual variation will be important to final damage estimates.

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Appendix A3. *Definition of major variables and terms used in this study*

Variable	Definition
Normal	As applied to temperature and precipitation refers to the value of that particular element averaged over the period from 1951–1980.
Temp	Normal daily mean temperature in the month, Fahrenheit. Computed as being the temperature one-half way between the normal daily maximum and normal daily minimum temperatures for the month.
Temp sq.	Temp for a month, squared.
Rain	Normal precipitation for the month, inches.
Rain sq.	Rain for a month, squared.
Daily var.	The difference between normal daily maximum and daily minimum temperatures in the month (diurnal cycle).
Temp y-var.	The range between the year with the highest and the year with the lowest mean monthly temperature over a 30-year period.
Rain y-var.	The range between the year with the greatest and the year with the least monthly precipitation over a 30-year period.
Income per capita	Annual personal income per person in $1000, 1984.
Density	Number of thousands of people per square mile, 1980.
Density sq.	Density, squared.
Solar radiation	Latitude measured in degrees from southern-most point in US.
Altitude	Height from sea level in feet.
Salinity	Percent of land which needs special treatment because of salt/alkaline in the soils.
Flood prone	Percent of cropland which is prone to flooding.
Irrigated	Percent of cropland with irrigation.
Water capacity	Ability of soil to hold water.
Permeability	Ability of water to pass through soil.
Wetland	Percent of land considered wetland.
Soil erosion	K factor–soil erodibility factor in hundredths of inches.
Slope length	Number of feet length of slope (not steepness).
Farm value	Estimate of the current market value of farmland including buildings for the county expressed in dollars per acre, 1982.
Sand	Mean surface layer texture of cropland from loamy sand to coarse sand.
Clay	Mean surface layer texture of cropland from sandy clay loam to clay.

4 Climate change and agriculture: the role of farmer adaptation

KATHLEEN SEGERSON AND BRUCE L. DIXON[1]

There has been considerable debate about the potential effect of emissions of "greenhouse gases" on climate change or "global warming" and its impact on economic and ecological systems (see Helms *et al.*, 1996). One sector thought to be sensitive to climate effects is the agricultural sector. The impact of global warming on the US agricultural sector has been studied by a number of previous authors (e.g. Adams *et al.*, 1988; Dudek, 1988; Adams, 1989; Crosson, 1993; Kaiser *et al.*, 1993; Mendelsohn *et al.*, 1994; Rosenzweig and Parry, 1994). However, most of these studies do not allow for the full range of adaptations that farmers could employ in response to climate change, such as changes in the crop/enterprise mix, input mix, and the timing of operations (with the exception of Mendelsohn *et al.*, 1994 which includes, but does not explicitly model adaptation). Those studies that do explicitly incorporate adaptation (e.g. Crosson, 1993; Kaiser *et al.*, 1993) base their estimates on simulated effects rather than actual evidence of adaptation that has occurred. Failure to reflect the full range of adaptation possibilities in estimates of impacts is likely to result in over-estimation of damages from climate change.

In order to assess the full range of adaptation possibilities, a study of the extent of farmer adaptations based on empirical adaptation data was undertaken. This chapter reports the results of that study. Some of the results reported here (specifically, the results from the estimated yield equations) were used in conjunction with other information on adaptation to generate "best guess" parameter adjustments for the Agricultural Sector Model (ASM). The ASM was then re-run with these adjustments to determine the effect of adaptation on the predicted aggregate welfare effects of climate change. Details regarding the parameter adjustments that were made and the resulting welfare impacts are reported in Chapter 2.

[1] We acknowledge the valuable research assistance of Susan Helms and Lih-Chyi Wen, as well as useful comments by Richard Adams, Robert Mendelsohn, James Neumann, and two reviewers.

4.1 Methodology

The basic approach used in this study was to estimate the adaptation possibilities by examining how farmers have responded to existing differences in climate across regions in the United States. The theoretical foundation for the approach is neoclassical duality theory. Duality theory suggests that farm-level production decisions depend on exogenous factors such as output prices, input prices, technological constraints, and environmental factors (Varian, 1992). Since environmental factors generally vary across regions, cross-sectional data can be used to estimate how production decisions (and the associated costs, revenues, and profits) have varied with these environmental factors. These estimated relationships reflect the adaptation possibilities, since in making the actual production decisions, farmers have taken advantage of all the mitigation or adaptation possibilities available to them. From the estimated relationships, we can then calculate how farm-level profits, for example, would change if an exogenous change in an environmental factor occurred and farmers adapted to that change.[2] The above approach could be applied in a number of different environmental contexts. For example, Garcia *et al.*, (1986) used cross-sectional data for farms in Illinois to estimate the impact of ground-level ozone changes on farm profitability.

The duality-based approach is related to the Ricardian approach used by Mendelsohn *et al.*, (1994, 1996) to estimate the impacts of global climate change (see also Chapter 3). Under the Ricardian approach, climate variables are assumed to affect farm-level profitability, which (among other things) determines land values. However, other factors affecting profitability, such as output prices, are not included. In addition, their methodology does not allow the estimation of yield changes that can be compared to yield change estimates based on crop simulation models to estimate the extent to which farmer adaptation can offset any negative impacts of climate change.

In this study, we take a two-pronged approach to estimating adaptation possibilities using duality theory. First, we directly estimate per-acre yield functions for corn, winter and spring wheat, and soybeans (the major field crops in the Midwest) that incorporate farmer adaptation to climate (temperature and precipitation). The yield equations are then used to predict the impact of alternative climate change scenarios on crop yields. Comparing these yield change estimates with the estimates obtained from crop simulation models that incorporate only modest adaptation allows the potential for adaptation to mitigate the yield losses to be measured. The yield effects,

[2] This approach does not incorporate input or output price changes that could occur if aggregate farmer responses are large. To incorporate price adjustments, the farm-level responses must be used in a market-level model in which prices are endogenous, such as the ASM model used in Chapter 2.