The Impact of Climatic Variation on Agriculture

Daigee Shaw, Robert Mendelsohn

ABSTRACT

This paper explores the effect of climatic variation on American agricultural land values. A Ricardian model of land value is estimated using data from over 3000 US counties. The model demonstrates that year-to-year climatic variation and diurnal temperature variation can substantially reduce the value of farmland. Further, including climatic variation along with average temperature and precipitation affects the net impact of monthly normals suggesting that some of the effects previously attributed to climate normals actually are variation impacts.

INTRODUCTION

Analysts have been interested in the impact of weather on crops for centuries in order to predict what crops to grow, when to plant and harvest, and what agricultural prices will be each year. With the accumulation of carbon dioxide (CO_2) and other greenhouse gases in the atmosphere (see National Research Council [1983], EPA [1989], and NAS [1991]), there has been growing interest in also measuring the impact of climate on agriculture. While weather is the day to day variation in temperature and precipitation, climate is the long run average of weather.

Two distinct ways to measure climate impacts on agriculture have emerged in the literature: a production function and a Ricardian rent approach. The production function approach (see Adams et al. [1988], Adams [1989], Adams et al. [1990], Callaway et al [1982], Decker [1986], Rosenzweig and Parry [1992], and USEPA [1989]) predicts changes in yield from crop simulation models such as CERES and SOYGRO and then enters these changes in mathematical progamming models of agriculture production and consumption. The Ricardian rent approach (see Johnson and Haigh [1970] and Mendelsohn, Nordhaus, and Shaw [1992], MNS) estimates the direct relationship between land prices and climatic, economic and soil variables.

The production function approach, with its extensive reliance on specific crop models, has the potential advantage of being based directly on carefully controlled scientific experiments. However, the Ricardian approach by relying upon how farmers have carefully adjusted to local conditions, does a much better job incorporating adaptation. Thus, each method has its own strengths and weaknesses and the two approaches complement each other.

The focus of this paper, however, is not to advocate the Ricardian approach but rather to examine a feature of climatic impacts which has been ignored in the literature to date. All the climatic impact studies listed above have focused upon mean climatic effects by season. For example, in the MNS study, the mean precipitation and temperature in January, April, July, and October over a 30 year period was used to represent climate. Climate variation, year to year changes in average monthly temperature and precipitation, however, has not been studied. This can be an important question with respect to greenhouse warming because there is tremendous uncertainty about how warming will affect local climates. We also examine the effect of diurnal (day-night) changes in temperature. Depending upon cloud cover, altitude, and winds, diurnal cycles vary across the country and potentially influence farm incomes.

In this study, we test whether climate variation has an impact on farmland values using the Ricardian approach developed in MNS. By including both the mean and the variation of climate variables, this study is able to measure the economic impacts of not only average seasonal temperature and precipitation but also the year-to-year and diurnal variation of these measures. In general, we expect to find that climate variation reduces land values. Year-to-year variation in monthly weather is difficult to predict and so farmers cannot perfectly adjust to the realized weather each year. They instead must plant for the possible distribution of weather outcomes. Climate variation prevents farmers from optimizing for one specific set of conditions. Although some climate fluctuations can be moderated with increased inputs such as irrigation and special breeding and some impacts may be moderated if climate could be more accurately forecasted, the net expected effect of variance is still to reduce agricultural rents and thus land values.

THEORY

This section summarizes the theoretical underpinnings of the Ricardian approach to climate modeling (for more details see Mendelsohn, Nordhaus and Shaw [1992]). We postulate a set of consumers with well behaved utility functions 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:

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

where P_i and Q_i are respectively the price and quantity of good i, $i=1, \ldots, n$, and Y is aggregate income. The Slutsky equation is assumed to apply, so that (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:

$$Q_i = Q_i(\mathbf{K}_i, \mathbf{E}),\ i = 1, \ldots, n. \tag{2}$$

In this equation, we use bold face to denote vectors or matrices. Q_i is the output of good i, $\mathbf{K}_i = [K_{i1}, \ldots, K_{ij}, \ldots, K_{iJ}]$ where K_{ij} is the purchased input j (j = 1, . . . , J) in the production of good i, and $\mathbf{E} = [E_1, \ldots, E_l, \ldots, E_L]$ where E_l is the exogenous environmental input 1 (1 = 1, . . . , 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:

$$C_i = C_i(Q_i, \mathbf{R}, \mathbf{E}). \tag{3}$$

Here, C_i is the cost of production of good i, $\mathbf{R} = [R_1, \ldots, R_j]$, 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_{LE}. Firms are assumed to maximize profits given market prices:

$$\max_{Q_i} \quad P_iQ_i - C_i(Q_i, \mathbf{R}, \mathbf{E}) - p_{LE}\, L_i, \tag{4}$$

where P_i is the price of good i. This maximization leads firms to equate prices and marginal cost 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:

$$P_iQ_i - C_i(Q_i, \mathbf{R}, \mathbf{E}) - p_{LE}\, L_i = 0. \tag{5}$$

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 good i.[1]

Next consider the impact of changes in the exogenous environmental variables. Assume that the environmental change is from initial point E_A to new point E_B. The change in value from changes in the environment are then given by:

$$V(E_A—E_B) = \int_0^{QB} \Sigma\, D^{-1}(Q_i)dQ_i - \Sigma\, C_i(Q_i, \mathbf{R}, E_B) -$$

[1]With imperfect competition, it is possible that a farmer could pay only as much as the next highest bidder for land and that this land payment would then be less than the productivity in the best use of the land. In addition, if the land is not put to the best use, the land payment may exceed the net productivity of the land.

$$[\int_{o}^{QA} \Sigma D_{-1}(Q_i)dQ_i - \Sigma C_i(Q_i, R, E_A)] \tag{6}$$

where $\int \Sigma$ is the line integral evaluated between the initial vector of quantities and the zero vector, $Q_A = [Q_1(K_1, E_A), \ldots, Q_i(K_i, E_A), \ldots, Q_n(K_n, E_A)]$, $Q_B = [Q_1(K_1, E_B), \ldots, Q_i(K_i, E_B), \ldots, Q_n(K_n, E_B)]$, $C_i(Q_i, R, E_A) = C_i(Q_i(K_i, E_A), R, E_A)$, and $C_i(Q_i, R, E_B) = C_i(O_i(K_i, E_B), R, E_B)$. 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 (6) simplifies to the integral of the equation for a single good. Note that as long as the Slutsky equation is satisfied, the solution to (6) is path-independent and unique.

If we assume that the changes in the environment will leave market prices unchanged[1], then (6) can be expressed:

$$V(E_A—E_B) = P\, Q_B - \Sigma C_i(Q_i, R, E_B) - [P\, Q_A - \Sigma C_i(Q_i, R, E_A)]. \tag{7}$$

where $P = [P_1, \ldots, P_i, \ldots, P_n]$. Substituting (5) into (7) yields:

$$V(E_A—E_B) = \Sigma_i(P_{LEB} - P_{LEA})\, L_i. \tag{8}$$

where P_{LEA} is P_{LE} at E_A and P_{LEB} is P_{LE} at E_B. Equation (8) 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 environmental value is captured exactly by the change in land rent.*

Land values are the present value of future rents. Thus, 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 probiems. 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 such potential sources of bias, proxies for the development value of farmland must be included in the analysis.

MEASURING CLIMATE VARIATION

In this section, we apply the Ricardian technique developed by MNS to value climate variation on U. S. agriculture. we rely on data from the 1982 U.S. Census of Agriculture to obtain much of the data on farm characteristics in each county. for the most part, the data are actual county averages, so that there are no major geographic issues involved in obtaining 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 farm land and building values[2], and information on market inputs for farms in every county in the United States. A map of farmland value is shown in Figure 1. In addition, in many of the equations, 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 (NRI) with the kind assistance of Drs. Daniel Hellerstein and Noel Gollehon of the U. S. Department of Agriculture. The NRI is an extensive survey of land characteristics in the United States. For each county, NRI has collected several soil samples, each providing a measure of salinity, clay content, sand content, soil permeability, available water capacity, flood probability, soil erosion (K factor), slope length, whether or not the land is a wetland, and numerous other variables that are not used in this analysis. Each sample also contains an expansion factor, which is an estimate of the amount of land the sample represents in that county. Using these expansion factors, we average this data to yield an overall county estimate for each soil variable.

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 through 1980. In this analysis, we begin with data on normal daily mean temperatures and normal monthly precipitations for January, April, July, and October. These months were chosen to represent each season: winter (December-February), spring (March-May), summer (June-August), and autumn (September-November)[2]. As demonstrated in MNS, these seasonal effects are quite important.

We then measure the effect of year to year variation in precipitation and temperature in each of the four months using the difference between the highest and lowest normal monthly precipitation and temperature over the 30 year period. The variation variables measure extreme months[3]. we also measure the average diurnal range: the difference between the average of the highest and lowest temperature each day in each month. 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 MNS for more details). A weighted regression is performed across all weather stations within 500 miles of the geographic center of the county for each climate variable. Each station is weighted by distance so that stations close to the county are given more weight than ones far away. Observed measures of climate are regressed on a second order polynomial based on latitude, longitude, altitude, and distance from large

[2]The definition and source of the farm value variable is critical to this study and its derivation is described in Appendix B.

water bodies. A separate regression is performed for each county center. This regression produces a surface which predicts each climate variable over space. The predicted value of climate at the center of each county is then used as the measure of climate for that county.

The next and crucial stage is to use the climate data to predict land values. In order to determine the marginal impact of each climate variable, we regress farmland 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 MNS, we explore introducing the climate variables in linear versus quadratic form. The results strongly support the quadratic form. This result is further supported by crop experiments which suggest nonlinear relationships between crops and climate.

The first regression in Table 1 reproduces the MNS model using mean climate variables. Controlling for soil and economic parameters, it is clear that climate does have an impact on farm values. Evaluating this impact at the US average (see Table 2) indicates that increased average temperatures in January and July are harmful to farm values whereas increased temperatures in October increase rents. In this model, an across the board increase in temperature of one degree Fahrenheit will decrease farm values by $70 per acre. Increased precipitation in October reduces farm rents but more precipitation in January and April increase farm values. An additional inch of rain spread evenly across the year would increase farm values by $35 per acre.

The year-to-year climatic variation variables are introduced in the second regression in Table 1. An F-test of the variation terms as a group, ($F(8,2988) = 851$), indicates that the year-to-year variation coefficients are significantly different from zero. All the individual coefficients of climatic variation are significantly different from zero with the exception of April temperatures. The significant coefficients tend to be negative implying variation reduces agricultural land values. The exception is variation in January precipitation which is beneficial. Variation in January precipitation may be helpful because at least spring-planting farmers can adjust to realized values before planting thus permitting good years to outweigh bad years.

The third regression in Table 1 adds the diurnal cycle temperature variables to the model.

The diurnal variables are statistically significant as a group ($F(4,2998) = 40$). Having greater spread between day and night temperatures reduces farm value in every season except October. Diurnal variation in the fall may be beneficial because some plants require cold frosts at night in order to mature their fruit.

In order to understand the spatial implications of this last model, the coefficients from the third model Table 1 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 Table 1 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 2. 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, Southern New England coast, Pacific coast, and Midwest centered around Illinois. Climates which lead to below average land values include northern Maine, the western Plains, and the Southwest deserts.

This same process can isolate the spatial contribution of just climatic variation. In Figure 3, the impact of climate variation alone is presented. The parts of the country with the most stable climates include the Pacific coast, southern Mississippi delta, and southern New England. The parts of the country where climate variation reduces land rents the most are near the dust bowl in Kansas, Missouri, and Oklahoma.

Breaking down these impacts further, the independent effect of year-to-year temperature and precipitation variation can also be examined[5]. Each variation term has a slightly different spatial impact. Being close to a large water body generally reduces temperature variation. Stable temperatures are beneficial to the lands along the coast. High temperature variation reduces land rents in the interior of the continent stretching from Montana to Missouri. One exception to this rule is the Southwest where despite the absence of nearby water bodies, there is little year-to-year temperature variation and this effect is beneficial to land rents. With precipitation variation, there is a different spatial pattern. The coasts benefit from the absence of precipitation variation and the interior suffers. However, with precipitation variation, farmland values in the northern Rocky Mountains do not fare as badly, the southern Rocky Mountains do more poorly, the Mississippi River delta improves, and Florida does much worse compared to the effects of temperature variation.

Introducing climatic variation to this model also has important effects on the seasonal pattern of mean temperature (see Table 2). Adding the climatic variation variables reduces the magnitude of marginal temperatures in January, July, and October and increases the effect of April temperatures. In each case, part of the effect that was attributed to monthly normals actually was a variation effect not a normal effect. The most important change from a policy perspective caused by adding the variation terms, however, is that the annual average impact of higher temperatures shifts from reducing farm values $70 per acre per degree to no net effect at all.

Adding the variation terms also affects the magnitude of monthly normal precipitation effects. the monthly normal marginal effects have all increased in magnitude with the variation terms included. January, April, and October precipitation effects have also changed signs. Curiously, despite these extensive seasonal adjustments, the beneficial annual impacts from more precipitation remain steady at $39 per acre per inch of annual rain.

These changes in the coefficients of mean climate variables suggest that there is some spatial correlation between mean temperatures and precipitation and their corresponding variation terms. The first model in Table 1, by omitting the variation terms, has biased the effects of the mean monthly normals.

Adding climate variation terms changes the spatial impact of mean precipitation and temperature[6]. With the variation terms, the best areas in the country for climate include the corn belt near Iowa and the Pacific coast, with the worst areas on the southern fringes of the country from California to Florida and the Intermountain deserts. The comparable result in MNS without any variation terms places the highest valued farmland from climate further north in Wisconsin. Further, the MNS results fail to pick up the drop in values associated with the Intermountain deserts.

In order to test whether the above results are robust, we have reproduced the analysis using 1978 data as well. The climate and soils data are identical in the 1982 and 1978 model, but the farm value and economic data are specific to 1978. Net migration was not available in the 1978 data set so that variable has been dropped from the regression in Table 1.

Comparing the results of the 1978 and 1982 regressions in Table 1, a formal F-test indicates that the climate coefficients are not significantly different across years ($F(28,5815) = 1.16$). Further, the coefficients in both years have similar patterns as can be seen in Tables 1 and 2. The variation terms all have the same sign in both years. The marginal effects from monthly normals are also the same sign. the magnitudes of some of the coefficients vary, for example with January temperature variation and April diurnal temperature variation. Examining the marginal effects in Table 2, higher mean temperatures result in larger impacts for every month except April in 1978 compared to 1982. Higher mean precipitation results in smaller impacts for every month except January in 1978 compared to 1982. The overall pattern of climate effects, however, remains stable across the two years.

CONCLUSION

This analysis examines the impact of climate variation on American farmland values using the Ricardian approach developed by Mendelsohn, Nordhaus, and Shaw [1992]. This focus on climatic variation is unique across greenhouse warming impact studies. Two important results are found. First, climate variation is significant and generally harmful as expected. Second, adding climate variation into a Ricardian model significantly changes the coefficients of mean climatic variables, yielding different policy conclusions.

Year-to-year variation of temperature and precipitation generally reduces farmland values (except for January precipitation and April temperatures) and these effects can be large. For example, if the year-to-year range of temperature increased by 50% in every month, average farm values would fall by almost $690 per acre (mean farm values are currently $1000 per acre)[7]. Similarly, if the range of precipitation in every month increased by 50%, farm values would fall $108 per acre. In contrast, if the diurnal range of temperature were to decrease in every month by 25%, farm values would increase by $1040 per acre.

In the MNS study, which only looked at mean climate effects in each season, the marginal effects of higher temperatures were harmful on average. An extra degree Fahrenheit spread over the year reduced farm values by $70 per acre. Including climate variation terms in the model, however, reduces the magnitude of temperature impacts so that higher annual temperatures no longer affect average farm values.

These results have major implications for greenhouse warming scenarios. First, with variation terms included, the results suggest that increases in mean global temperatures may not effect American agriculture[8]. The expected increase in precipitation, however, is likely to be beneficial. The reductions in the diurnal cycle predicted from greenhouse gases would also be beneficial. The results suggest that the major threat from global warming for American agriculture is from increased year-to-year variation in climate (particularly in temperature). If this variation increases significantly, American farm values may well decline.

Further research is clearly needed in this area to understand greenhouse gas impacts. Realistic spatially desegregated scenarios need to be developed to carefully measure greenhouse effects. Given that greenhouse gases have global effects, it is urgent that this analysis be extended to other countries. This is important for understanding the distribution of impacts around the earth as well as measuring global supply effects. Depending upon how climate change affects supplies of products across the world, agricultural prices may change thus adding additional consumer surplus effects not measured in this study. The direct effect of carbon dioxide must also be included for an accurate assessment.

Additional research also needs to be undertaken to further understand the Ricardian approach. Cross sectional analyses of crop productivity should be conducted to see to what extent climate affects individual products. Analyses of farm costs should be undertaken to begin to measure to what extent farmers adjust their behavior to compensate for local climate. Finally, farm level analyses should be conducted to make certain that aggregation effects are not distorting the results.

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Appendix A. 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 for a month — 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 for a month — TEMP for a month squared

RAIN for a month — Normal precipitation for the month, inches

RAIN SQ for a month — RAIN for a month squared

MONTH DAILY VAR — The range between normal daily maximum and daily minimum temperatures in the month

TEMP Y-VAR for a month — The range between the highest in a 30-year period and the lowest in a 30-year period of the daily mean temperature for the month, where daily mean temperature = (the average across each month of the highest temperature on each day + the average across each month of the lowest temperature on each day)/2.

RAIN Y-VAR for a month — The range in a 30-year period between the year with the greatest and the year for the least precipitation for that month

CONSTANT — a term equal to one.

INCOME PER CAPITA — annual personal income per person in the county, 1984

DENSITY — resident population per square mile, 1980

DENSITY SQ — DENSITY squared

LATITUDE — latitude measured in degrees from southern most point in U.S.

ALTITUDE — height from sea level in feet

MIGRATION — net of incoming people minus outgoing people from 1980 to 1986 for the county

SALINITY — percent of land which needs special treatment because of salt/alkaline in the soils

FLOOD PRONE — percent of crop land which is prone to flooding

IRRIGATED — percent of crop land with irrigation

WATER CAPACITY — ability of soil to hold water

SOIL 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 farm land including buildings for the county expressed in dollars per acre, 1982

SAND — mean surface layer texture of crop land from loamy sand to coarse sand

CLAY — mean surface layer texture of crop land from sandy clay loam to clay

Figure 1
TOTAL FARM VALUE IN 1982

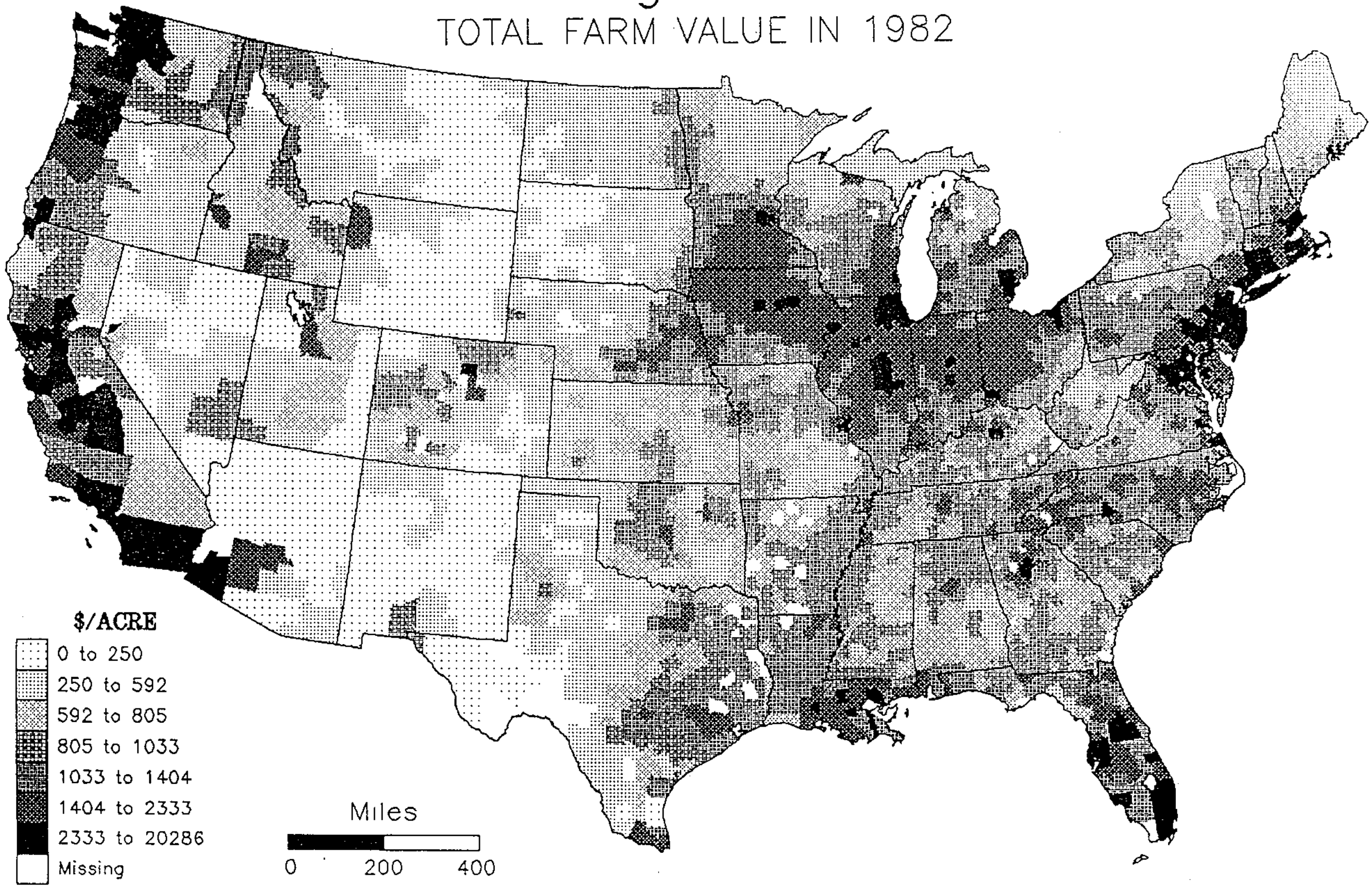

Figure 2
PREDICTED EFFECT OF ALL CLIMATE VARIABLES

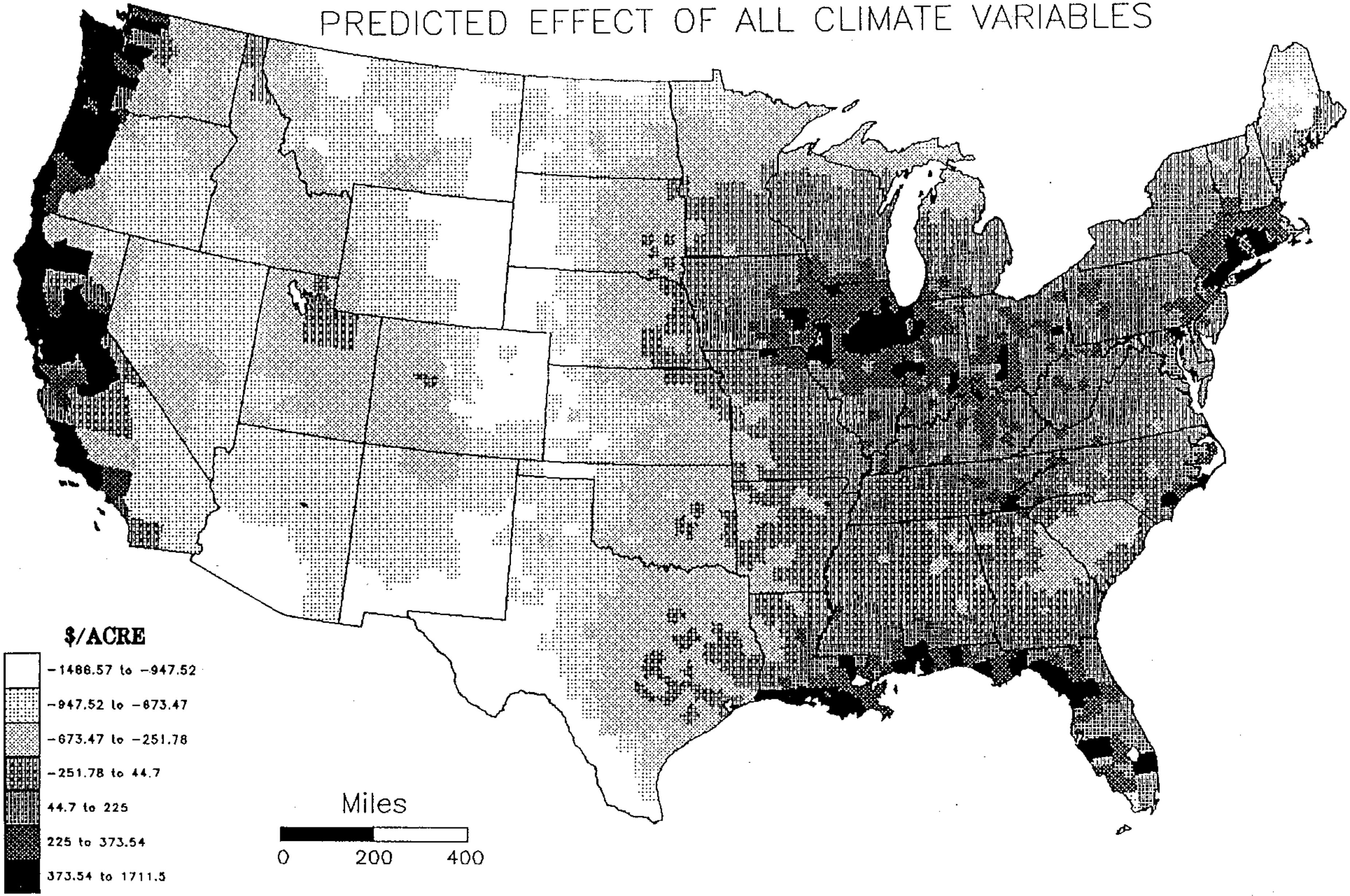

Figure 3

PREDICTED EFFECT OF CLIMATE VARIATION

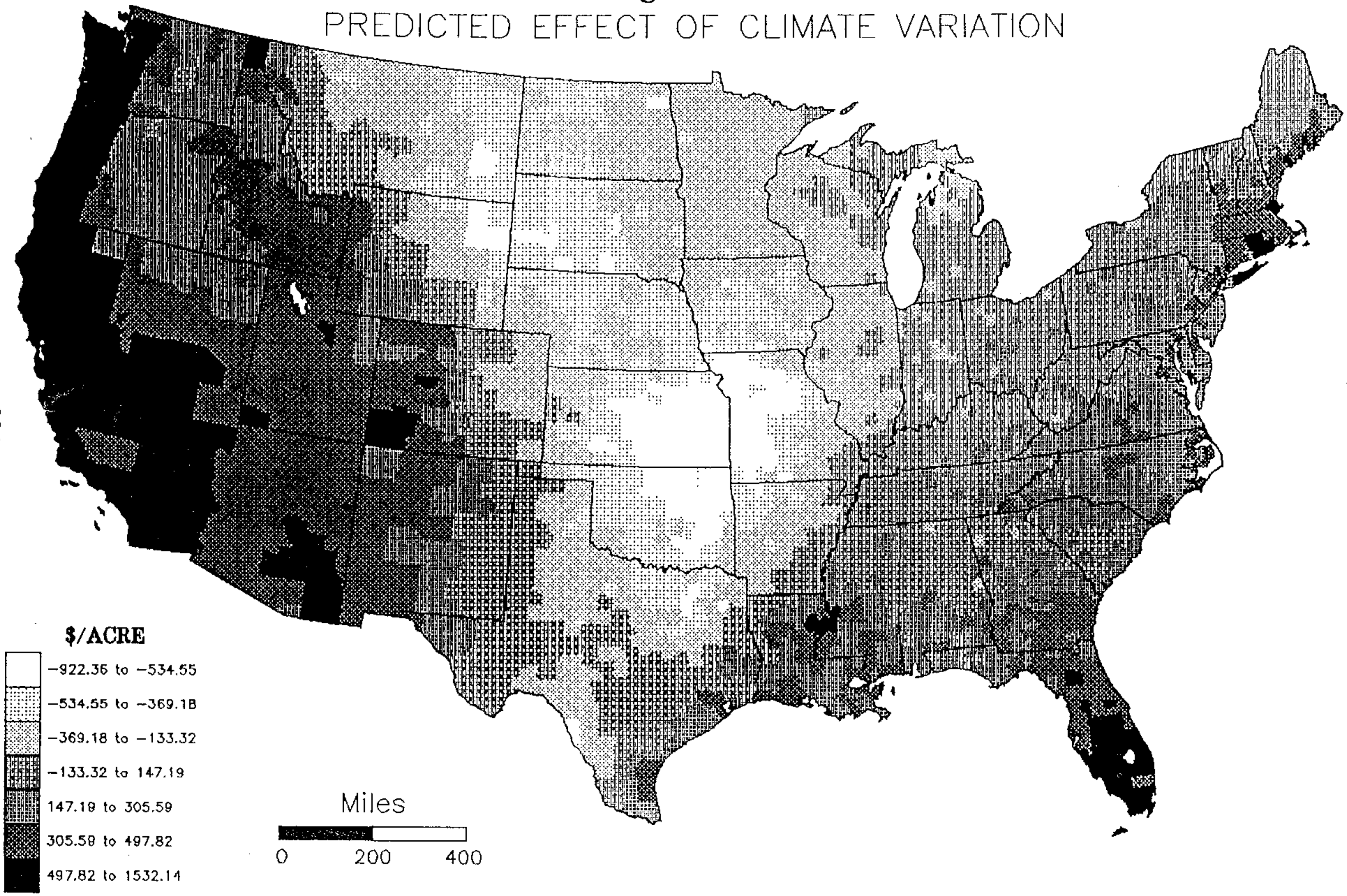

TABLE 1
REGRESSION MODELS EXPLAINING FARM VALUES
WITH AND WITHOUT CLIMATE VARIATION VARIABLES[a]

INDEPENDENT VARIABLES	1982 NO VAR	1982 NO DAILY VAR	1982 ALL VAR	1978 ALL VAR
NORMALS				
JANUARY TEMP	-3.11	-14.36	-46.39	-26.56
	(0.38)	(1.48)	(4.49)	(2.80)
JAN TEMP SQ	-1.22	-1.08	-0.03	-0.68
	(5.97)	(5.03)	(0.15)	(3.22)
APRIL TEMP	411.7	370.3	357.7	307.2
	(5.82)	(5.29)	(4.82)	(4.54)
APR TEMP SQ	-3.73	-3.04	-2.97	-2.54
	(5.67)	(4.73)	(4.46)	(4.20)
JULY TEMP	171.34	-65.97	341.3	-227.8
	(1.83)	(0.71)	(3.61)	(2.60)
JULY TEMP SQ	-2.08	-0.25	1.79	0.87
	(3.37)	(0.41)	(2.82)	(1.49)
OCTOBER TEMP	-396.2	-199.4	102.4	4.90
	(3.74)	(1.86)	(0.90)	(0.05)
OCT TEMP SQ	4.80	2.96	-0.11	1.00
	(5.18)	(3.19)	(0.11)	(1.11)
JANUARY RAIN	50.44	-164.1	-247.6	-271.6
	(1.58)	(4.45)	(6.65)	(7.91)
JAN RAIN SQ	2.53	9.85	13.14	13.30
	(0.90)	(3.46)	(4.62)	(5.04)
APRIL RAIN	293.1	454.5	310.4	210.2
	(4.50)	(6.60)	(4.53)	(3.34)
APR RAIN SQ	-26.85	-30.65	-23.20	-10.27
	(3.24)	(3.71)	(2.86)	(1.38)
JULY RAIN	-358.4	-277.0	-171.4	-114.7
	(8.21)	(6.04)	(3.12)	(2.28)
JULY RAIN SQ	47.64	41.92	33.97	23.56
	(8.83)	(7.86)	(5.80)	(4.41)
OCTOBER RAIN	3.41	85.21	190.4	148.2
	(0.04)	(1.00)	(2.10)	(1.76)
OCT RAIN SQ	-7.02	-8.35	-18.00	-14.23
	(0.53)	(0.62)	(1.31)	(1.15)

TABLE 1 (coun't 1)

INDEPENDENT VARIABLES	1982 NO VAR	1982 NO DAILY VAR	1982 ALL VAR	1978 ALL VAR
YEAR TO YEAR VARIATION				
JAN TEMP Y-VAR	...	-16.76	-21.05	-3.93
		(3.62)	(4.55)	(0.92)
APR TEMP Y-VAR	...	8.88	16.65	9.45
		(1.18)	(2.23)	(1.37)
JULY TEMP Y-VAR	...	-86.91	-69.98	-71.30
		(11.54)	(9.27)	(10.23)
OCT TEMP Y-VAR	...	-33.07	-41.02	-36.08
		(4.90)	(6.07)	(5.77)
JAN RAIN Y-VAR	...	54.86	57.49	57.34
		(6.42)	(6.75)	(7.28)
APR RAIN Y-VAR	...	-27.79	-24.38	-13.77
		(3.54)	(3.17)	(1.95)
JULY RAIN Y-VAR	...	-14.20	-24.55	-21.48
		(2.76)	(4.78)	(4.55)
OCT RAIN Y-VAR	...	-16.62	-17.48	-12.98
		(2.31)	(2.47)	(1.99)
DAILY VARIATION				
JAN DAILY VAR	...	...	-67.41	-91.84
			(6.97)	(10.26)
APR DAILY VAR	...	...	-45.40	-7.86
			(3.51)	(0.66)
JULY DAILY VAR	...	...	-39.34	-49.73
			(3.31)	(4.53)
OCT DAILY VAR	...	...	74.97	76.09
			(6.43)	(7.06)
CONTROL VARIABLES				
CONSTANT	-2302.0	370.7	-4346.0	4535.0
	(0.71)	(0.12)	(1.38)	(1.55)
INCOME PER	0.07	0.07	0.07	0.06
CAPITA	(15.84)	(15.81)	(15.24)	(15.31)
DENSITY	1.30	1.25	1.15	0.94
	(1.17)	(17.16)	(15.89)	(14.25)
DENSITY SQ	-1.50e-4	-1.34e-4	-1.10e-4	-6.96e-5
	(4.62)	(4.31)	(3.61)	(2.59)

TABLE 1 (coun't 2)

INDEPENDENT VARIABLES	1982 NO VAR	1982 NO DAILY VAR	1982 ALL VAR	1978 ALL VAR
SOLAR RADIATION	-75.38	-2.67	-0.95	-39.51
	(5.21)	(0.17)	(0.05)	(2.48)
ALTITUDE	-0.20	-0.09	0.02	0.01
	(7.56)	(3.36)	(0.81)	(0.51)
MIGRATION	1.90e-3	2.57e-3	3.54e-3	. . .
	(2.23)	(3.03)	(4.26)	
SALINITY	-506.8	-126.8	-306.3	-187.6
	(2.53)	(0.65)	(1.61)	(1.07)
FLOOD PRONE	-247.0	-274.6	-298.0	-369.6
	(5.22)	(5.90)	(6.51)	(8.74)
IRRIGATED	607.8	495.0	426.0	255.6
	(12.35)	(10.02)	(8.77)	(5.70)
WETLAND	-176.8	-299.7	-303.6	-191.3
	(1.47)	(2.58)	(2.64)	(1.80)
SOIL EROSION	-125.8	-1156.4	-1489.0	-1681.0
	(6.36)	(6.03)	(7.76)	(9.50)
SLOPE LENGTH	7.02	12.54	16.80	13.20
	(1.19)	(2.21)	(3.00)	(2.55)
SAND	-190.1	-143.0	-102.5	-12.43
	(3.80)	(2.93)	(2.15)	(0.28)
CLAY	87.98	85.83	77.84	54.96
	(4.27)	(4.29)	(3.97)	(3.04)
WATER CAPACITY	0.40	0.39	0.31	0.41
	(10.53)	(10.51)	(8.37)	(12.06)
PERMEABILITY	-4.96e-3	-4.96e-3	-4.29e-3	-5.07e-3
	(2.18)	(2.25)	(2.00)	(2.58)
ADJ R SQ	0.790	0.807	0.817	0.819
OBSERVATIONS	2935	2935	2935	2940

[a]Dependent variable is farm value in $/acre. All observations are weighted by percentage of county land covered by cropland. Values in parenthesis are t-statistics.

TABLE 2

MARGINAL EFFECTS OF TEMPERATURE ON FARM VALUE[a]

MEAN TEMPERATURE EFFECTS ($/degree Fahrenheit)

MONTH	1982 NO VAR	1982 NO DAILY	1982 ALL VAR	1978 ALL VAR
JANUARY	-80.20	-82.24	-48.62	-69.60
	(9.21)	(8.97)	(5.22)	(8.08)
APRIL	4.76	38.61	33.77	29.72
	(0.42)	(2.94)	(2.42)	(2.32)
JULY	-144.61	-104.27	-70.06	-95.37
	(13.86)	(9.60)	(6.06)	(8.97)
OCTOBER	149.69	137.47	90.00	118.8
	(8.71)	(7.62)	(4.53)	(6.49)
ANNUAL b	-70.35	-10.42	5.09	-16.50
	(2.85)	(0.39)	(0.18)	(0.63)

MEAN PRECIPITATION EFFECTS ($/monthly or annual inch)

MONTH	1982 NO VAR	1982 NO DAILY	1982 ALL VAR	1978 ALL VAR
JANUARY	63.72	-112.48	-178.7	-201.8
	(2.97)	(4.11)	(6.48)	(7.93)
APRIL	116.48	252.91	157.8	142.7
	(5.07)	(8.27)	(5.08)	(4.99)
JULY	-9.37	30.07	77.47	57.69
	(0.72)	(1.75)	(3.71)	(3.01)
OCTOBER	-31.65	43.50	100.5	77.13
	(1.45)	(1.36)	(2.87)	(2.39)
ANNUAL b	34.80	53.50	39.26	18.92
	(3.44)	(3.91)	(2.70)	(1.41)

[a]Marginal effects are calculated at the U.S. mean climate using Table 1 coefficients.

[b]The annual calculation assumes statistical independence across months and a uniform increase in rain or temperature across all four seasons. The t-statistics are in parenthesis.

ENDNOTES

1. If there is a nonmarginal change in market prices, one must also add changes in consumer surplus to measure total damages. The difficulty of including the effect of price changes should not be underestimated as it requires estimation of the international demand and supply for food.
2. Alternatively, we could have used the three month average for each season. However, climatic data is frequently available in a monthly form and we felt the results could be more easily interfaced with other models such as GCM's if kept in reference to specific months.
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 in the impacts community surrounding extreme events.
4. To the extent that farm input prices might vary because of transportation costs, it is likely that the urban variables used would capture these effects.
5. Figures for the distribution of precipitation and temperature are available from the authors upon request.
6. A figure of mean precipitation and temperature effects is available from the authors upon request.
7. Summing across months, the product of the coefficient in Table 1 times the mean of the variable yields an estimate of the net effect of that variable. Mean year-to-year variation in temperature yields a value of -$1380, precipitation yields a value of -$218 and diurnal temperature variation yields a value of $-4161.
8. If average farm values are not changed by an environmental impact, changes in food prices are also likely to be small.