Impacts of Increased Climate Variability on the Profitability of Midwest Agriculture

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ABSTRACT

Approximate profit functions are estimated using time-series, cross-sectional, county level data for 12 midwest states. Measures of climate variability are included in the profit functions. Simulated impacts of climate changes on profits are derived. Results show that inclusion of measures of climate variation are important for measuring the impact of changes in mean temperature and precipitation levels. Failure to account for the impact of differences in variability leads to an overestimate of damages. If global warming increases diurnal variation, such increases would have negative impacts on the profitability of midwest agriculture.

Key Words: *climate change, climate variability, midwest, profit function.*

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.*). One sector thought to be sensitive to climate effects is the agricultural sector. The impact of global warming on the United States agricultural sector has been studied by a number of authors (e.g., Adams *et al.* 1988; Adams *et al.* 1999; Dudek; Adams; Adams *et al.* 1995; Crosson;

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Kaiser *et al.*; Mendelsohn, Nordhaus, and Shaw 1994, 1999; Rosenzweig and Parry; Dalton). The typical approach is to assume some level of change in the prevailing climate and then deduce the crop yields that would be associated with that climate regime. Different climate scenarios lead to different expected yields and, therefore, different economic impacts.

Unpredictable variability in both economic and non-economic factors usually affects producer decisions such as the quantity produced (Chavas and Holt). Thus an accurate assessment of the impact of climate change on some sector of the economy, such as agriculture, requires explicit consideration of the impact of changes in climate variability. Among the global warming studies listed above, only Dalton and Mendelsohn, Nordhaus, and Shaw (1999) address changing climate variability explicitly, the latter by using a Ricardian model.

The present study uses an approximate profit function, which is a variant of the Ricardian method, to evaluate the impact of increased

climate variability on midwest farm profitability. This approach allows projected changes in net returns due to hypothesized climate changes to be estimated using observed (i.e., actual) farmer adaptation to geographical climate variation, assuming such adaptation will persist under the projected climate change scenarios. In contrast, most previous studies that incorporate adaptation (e.g., Adams *et al.* 1988; Kaiser *et al.*; Lambert *et al.*) are based on hypothesized adaptation patterns.

The results of the present analysis suggest two important conclusions. First, models that fail to account for differences in variability across the sample are likely to overstate the damages resulting from climate change. In other words, losses attributable to a given increase in mean temperature will be over-estimated if the model used for the estimation does not control for differences in climate variability across regions. Second, if global warming induces not only increases in mean temperature and precipitation but also increased variability, the economic impacts of warming could be considerably larger. We find, in particular, that in our sample region increased diurnal (within-day temperature) variation can generate significant losses.

Methodology

The theoretical basis for the estimated models, a profit function, is a variant of the Ricardian method. The Ricardian approach assumes that climate changes cause farmers to adapt to the most profitable alternative by switching enterprises, seed varieties, technology, etc., and that markets are functioning efficiently so that the land rents reflect land's best use and the associated profitability. With well-functioning markets, net profits should be equal to the rental value of land. In this study net profits are used as the Ricardian measure instead of land values. One advantage of net profits over land value is that land values may include a speculative component that is most likely not a function of climate. In addition, use of net profits does not require an assumption about the efficiency of the land market.

An advantage of the Ricardian approach is that it does not require direct observation of the impact of climate change on crop yields. Instead, it makes use of the fact that climate varies considerably across large regions of the U.S., and that farmers have adapted to the different climates (and would presumably also adapt to future climate changes in like patterns). Profit-maximizing farmers should organize crop selection, input intensity, etc. in concert with the expected climate. Thus, two farmers facing identical situations except for climate would likely organize their operations differently because of adapting to climate differences. The resulting differences in net profits would then reflect the direct cost of climate differences without having to use intervening yield functions to estimate the effect of climate change on output levels. In addition, by including climate variation variables directly into the regression model, there is no need to make specific assumptions about farmers' risk aversion since the direct relationship of this variation to profits reveals producers reaction to climate risk. Moreover, use of observed data in estimation reflects real-world adaption whereas models such as Adams *et al.* (1988), Kaiser *et al.*, or Lambert *et al.* rely primarily on assumptions about producer behavior.

A weakness of the Ricardian or profit function approach is that prices are held constant under the environmental change so profit losses are likely to be overestimated.[1] Mendelsohn, Nordhaus, and Shaw (1999) address this problem by examining the error in using the Ricardian measure as a measure of change in the sum of consumer and producer surplus. Using plausible values of elasticities of supply and demand for agricultural goods, they conclude that for the modest changes in supply due to changing climate the Ricardian welfare measures are reliable for modest supply shifts. Simulations using the Ricardian approach are also premised on the assumption that technology and policy are held constant.

A second limitation is that our methodology does not allow for movements of land in

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[1] Price increases triggered by large reductions in supply would offset some of the losses in profit due to those reductions.

and out of agriculture, i.e., the simulated impacts are predicated on the land base remaining constant after climate change.[2] To the extent that climate change induces the land base to change, the methodology used here does not capture the full impact of adaptation to climate change. Assuming the land base is constant almost certainly provides conservative estimates of loss due to negative climate change impacts.[3] The potential effects of carbon dioxide fertilization are also not included in our analysis. Including such effects is desirable, but the lack of a consistent data set on observed carbon dioxide levels precludes such an analysis.

In the present study four regression models are estimated with observed profits per acre as the dependent variables and climate, intra-annual weather, edaphic and price variables along with time and regional binaries as independent variables. A listing of the variables is provided in the Appendix. Effects of changes in the climate distribution are determined by simulating total profits within the midwest before the climate change and subtracting the simulated total profits after the climate change.

Data and Model Specification

County-level data for the four agricultural census years of 1978, 1982, 1987, and 1992 are used to estimate approximate profit functions.[4] By using four years of data as opposed to one year, the peculiar effects of any one year biasing adaptation patterns are more likely to be

averaged out. The sample consists of 981 counties in a 12-state region, consisting of the 12 Midwest states in the USDA farm production regions of the Lake States, Northern Plains, and Corn belt. Only this 12-state region is used because of its relatively homogenous technology.[5]

Cost and revenue data were taken directly from the Census of Agriculture.[6] Profit (or more precisely, net revenue) per acre was defined as the market value of agricultural products sold minus the sum of variable farm production expenses and machinery and equipment costs, divided by the sum of cropland and pastureland for all farms. This is an approximate computation of profit because it ignores inventory shifts, and input costs were limited to those items available in all four census years. Because the actual revenues and costs are used, the net revenues are ex-post.

A proper profit function has output and input prices in its domain, as well as other fixed or uncontrollable factors—in this case climate and weather measures and edaphic variables. The particular Ricardian approach by Mendelsohn, Nordhaus, and Shaw (1994, 1999) has no price variables because the data were purely cross sectional and price variations would be due primarily to transportation costs and be reflected in the land values. However, because the sample used here spans four years, price variables are necessary. The use of observed profits also necessitates the inclusion of variables measuring observed weather in a given year. Thus, profit variations due to deviations in a given year's weather from long-term trends in climate are explained by the weather variables.

Output price data come from Agricultural Statistics and are state-level, market year prices rather than expected prices.[7] The included

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[2] This assumption is necessitated by a practical consideration. If land base is used as an explanatory variable for county level profits, it overwhelms all other variables in explaining total county profit variation.

[3] Suppose profitability per acre decreases due to a climate change. In this case some land would likely be drawn into alternative non-agricultural uses with a higher return than that reflected in the diminished profitability. Thus by holding the land base constant in predicting aggregate profits, the net returns under the less profitable scenario would be underestimated, implying the overall losses due to the adverse climate event are overestimated.

[4] The applications in Mendelsohn, Nordhaus, and Shaw (1994, 1999) are limited to one year of cross-sectional data. In addition, the dependent variables are gross revenue and farm value per acre.

[5] These consist of counties for which at least 20% of the land was in agriculture and complete observations were available. See Segerson and Dixon for full details on sample selection.

[6] Nominal values of all prices, revenues, and costs were converted into 1987 dollars using the GNP deflator.

[7] Use of output prices lagged one year did not change parameter estimates substantially because prices turn out not to be very important, probably due to having only four different years.

price variables are the market year prices received for the major field crops (corn, soybeans, wheat, and hay) and the mean per-capita value of inventory for the major livestock animals (cattle and swine). The latter two variables performed better than beef and pork prices and the per-capita cattle value also reflects the value of beef and dairy cattle.

Since county or state-level data on input prices are not available for all the inputs listed in the census, regional input price variation was captured by two regional dummy variables, one for the Northern Plains states and one for states in the Lake States region. The three binary variables capturing year effects also represent time series effects in input price shifts, as well as technology trends and variation in farm policies. For moderate input price variations, the comparative advantages and biological imperatives of various enterprises likely outweigh the effect of input price fluctuations. Thus, the results reported here should be reasonably accurate for the input prices in effect during the study period.

The climate data (seasonal temperature and precipitation) and the data on soil and site characteristics are identical to the variables used in Mendelsohn, Nordhaus, and Shaw (1999). Intra-year weather data were provided by USDA/ERS.[8] The climate variables, observed by county, are as follows: 30-year (1951–1980) mean seasonal temperature levels (January, April, July, and October), 30-year mean seasonal precipitation levels (same four months), the observed range of each of the prior eight variables (maximum annual value observed over 30 years for a county less the minimum annual observation) and 30-year mean diurnal temperature variation for each of the four months.[9] Four months of these data are used to capture major climate variations within a year and seasons important in agriculture. Spring, summer, and fall are clearly important for much of the planting, growing,

and harvesting and winter is important for livestock and winter wheat. Two weather variables representing deviations of actual summer (June, July, and August) temperature and precipitation from their respective thirty year climate for July are also included.[10]

Because of the potential sensitivity of the simulation results to the specification of the profit function, results from four different models are discussed. The first model, A, is additive and is thus similar to Mendelsohn, Nordhaus, and Shaw (1999) except for the deletion of some site characteristics not found to be relevant, addition of the two weather variables and the interaction terms. Model A is linear in the dependent variable (per-acre net revenue) and all the independent variables except the eight climate level variables and the interaction terms. Quadratic terms were included in addition to linear terms for the mean seasonal temperatures and precipitation. Twelve interaction terms were included for the interactions of mean seasonal temperature with observed temperature range and diurnal variation, and mean seasonal precipitation with the observed precipitation range as described in more detail in Table A1. Model A1 is similar to Model A except that the range and diurnal variation variables and their associated interaction terms are deleted. Model L regresses per-acre profits on the logs of all the regressors in Model A except the binary variables for time and region (which remain as binaries) and includes quadratic log terms for output prices to allow for proper curvature of the profit function in prices.[11] Model L1 is the same as L except the range and diurnal variables and their interaction terms are deleted.

Estimated Models and Elasticities

Since each of the four models has a large number of coefficients, they are not presented here

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[8] The data were provided by David Westenbarger of the Economic Research Service, U.S. Department of Agriculture.

[9] Note that a given climate variable is the same for each of the four years for a given county.

[10] The weather variables temperature and precipitation are observed at NOAA regional levels where each region consists of several counties within a state.

[11] To get logarithms of the two weather variables, logs were taken of the ratio of the mean of the observed three months to the thirty year averages. The quadratic terms are the logs of the relevant variables squared.

Table 1. Summary Regression Statistics for the Estimated Models

	Model			
Statistic	A	A1	L	L1
R^2	0.6571	0.6231	0.6623	0.6289
$\bar{R}^2$	0.6516	0.6195	0.6564	0.6248
Maximum Condition Index	43624	24835	.76784E+6	.49562E+6
B-P-G Test for Heteroscedasticity[a]	332	269	419	333

[a] This is the Breusch-Pagan-Godfrey test for heteroscedasticity where the variance is a function of all the regressors as discussed in Judge *et al.*

but are available upon request from the senior author. Summary regression statistics are presented in Table 1. All models were estimated by least squares and were characterized by high levels of multicollinearity and heteroscedasticity. Coefficient standard errors were estimated by White's method. This implies that the ratios of coefficients to their standard errors are asymptotically, normally distributed. The high levels of multicollinearity suggest difficulty in identifying significant climate effects of individual climate variables.[12] Much of this collinearity is associated with the linear and quadratic climate variables. Indeed, the re-

[12] The condition indexes displayed in Table 1 for each of the four models indicate extraordinarily high levels of collinearity so that indications of coefficient statistical insignificance are suspect.

Table 2. Seasonal Temperature and Precipitation Elasticities For the Four Alternative Models[a]

	Model			
Month	A	A1	L	L1
Seasonal Temperature Elasticities				
Jan	−2.87	−3.51	−1.49	−1.11
Apr	5.31	−2.33	3.37	−3.45
Jul	−15.47	−18.88	−12.26	−13.50
Oct	7.97	19.13	4.82	12.01
Seasonal Precipitation Elasticities				
Jan	0.291	0.129	−0.341	−0.295
Apr	−0.001	0.097	0.779	0.702
Jul	−0.084	0.025	−1.498	0.490
Oct	−0.476	−0.408	−0.491	−0.512

[a] Elasticities are evaluated at the sample means of the appropriate dependent and independent variables.

sulting imprecision motivates the use of simulation in which all the temperature or precipitation variables are varied simultaneously to identify climate impacts.

Models A and L fit the cross-sectional data well with Model A having an R^2 of .657 and Model L an R^2 of .662. By the adjusted R^2 criterion, inclusion of the variation variables with their interaction terms (by comparison with Models A1 and L1, respectively) is justified. Omitting these variables results in some noticeable differences in the climate variable elasticities, as verified in Table 2.[13] A majority of the climate variable coefficients are statistically significant in both models.[14]

Models A and L do not totally agree on the signs and significance of the various climate variables. The impacts of the various climate variables between models can be compared by computing elasticities. The elasticities for the temperature and precipitation seasonal variables computed at sample means are presented in Table 2. Temperature has substantially larger elasticities than precipitation. July and Oc-

[13] The extent to which omitting climate variation and interactions matters in valuing climate change is estimated in the simulation section.

[14] Model A has three of the eight (four linear and four quadratic) seasonal temperature variables significant at .05, and four of the eight seasonal temperature variables are significant at .05 in Model L. Two of the eight seasonal precipitation level variables in Model A are significant at .05, and all eight seasonal precipitation level variables are significant in Model L. Both models have 12 interaction terms. Ten of these terms are significant in Model A and seven are significant in Model L. In Models A and L, nine and seven of the 12 range and diurnal variation variables, in each model respectively, are significant at .05.

tober temperatures have the largest elasticities. Model A has July and October temperature elasticities of −15.5 and 7.97 while Model L has corresponding elasticities of −12.3 and 4.82.

It is clear that increased July temperatures reduced profits, whereas higher temperatures in October increased profit. For crops both effects on profits are plausible since higher summer temperatures can exacerbate moisture stress and higher fall temperatures can lower grain drying costs. All models imply that winter temperature increases would be profit decreasing.[15] The elasticity signs for spring temperature increases are mixed and show the inclusion of the interaction and variation terms change signs in both the additive and logarithmic models.

In general, the precipitation effects are much smaller in elasticity terms than temperature effects. Models A and L only agree in the signs of precipitation effects in summer and fall. The negative signs in summer are surprising although too much moisture can hinder some field operations. The negative fall effect is expected since rain can delay harvests and increase drying costs. Thus the impact of precipitation on profits is somewhat ambiguous for two of the seasons in contrast to the agreement between the models for temperature effects.

In terms of intra-annual weather effects, the models are in agreement that higher-than-average temperatures for a given summer are detrimental and higher-than-average precipitation is profitable. These results are not surprising given the sparse use of irrigation in the midwest. However, the significance of the variables is not consistent across models. The weather variable for temperature deviation is significant in Model A but not in Model L, and precipitation deviation variable is significant in Model L but not in Model A.

The importance and impact of the variational variables is evident from the elasticities in Table 3. Signs of the various elasticities for a given climate effect and season are consis-

tent between the two models except for diurnal variation in April. However, signs of the variational variable elasticities differ by season. For example, increased temperature variability is beneficial in the winter and summer but detrimental in the spring and fall. Increased precipitation variability is detrimental in the winter and spring but beneficial in the summer and fall. Note that in Table 3, for a given model, the sum of either the temperature or precipitation elasticities is within −.2 of zero. This implies that a uniform increase in inter-year variability is somewhat insensitive to profits, suggesting that farmers might be offsetting production risk with input mix and marketing strategies.

Diurnal variation has elasticities on a comparable magnitude with those of temperature variability, which implies diurnal variation effects are substantially greater than inter-year precipitation variation. In both models greater diurnal variation in January and July is estimated to be detrimental whereas increased October diurnal variation is beneficial. The impacts of greater April diurnal variation differ between models. Unlike the precipitation and temperature, there is a net negative effect on profits from increased diurnal variation.[16]

Simulation Results

Simulating profits under alternative climate scenarios measures climate change impacts on net revenues. In the simulations, climate variables for seasonal temperature were set at observed levels, then at observed levels plus 1.5°C, 2.5°C, and 5.0°C in successive simulations. Seasonal precipitation was set at 90 percent, 100 percent, 107 percent, and 115 percent of observed levels. The variables representing long-term climate variation—the ranges of the seasonal temperature and precipitation variables observed over the 30-year interval and the 30-year diurnal variations—

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[15] Warmer winters could be conducive to greater pathogen growth for corn and soybeans (Takle).

[16] In communication with agronomists, a comprehensive rationale for increased diurnal variation causing a decrease in yield could not be established. Egli and Wardlaw find empirical support for decreased summer diurnal variation increasing soybean yields.

Table 3. Elasticities of Variational Variables[a]

Month	Model A	Model L
Seasonal Temperature Range Elasticities		
Jan	0.454	0.471
Apr	−0.474	−0.605
Jul	0.548	0.453
Oct	−0.496	−0.503
Seasonal Precipitation Range Elasticities		
Jan	−0.123	−0.026
Apr	−.177	−.167
Jul	0.007	0.032
Oct	0.299	0.169
Seasonal Diurnal Variation Elasticities		
Jan	−1.121	−1.609
Apr	−0.122	0.032
Jul	−2.610	−2.633
Oct	1.101	1.333

[a] Elasticities are evaluated at the sample means of the appropriate dependent and independent variables.

were set at observed levels and then increased by 10 percent and 25 percent. These levels of range variation were chosen to represent approximately a 10-percent to 25-percent increase in the standard deviations of the range variables. The two weather deviation variables were set to zero in all simulations to give all counties average weather. The simulation results are for 1992 so all other variables are set at their 1992 levels. Changes in aggregate profits relative to the baseline scenario of all variables at their 1992 levels, except for the two weather deviation variables, are presented in Table 4 (in 1987 dollars). The simulations implicitly hold technology constant. If climate change occurs, it would do so over a long period and technology would probably change accordingly. Thus, the loss estimates are biased upwards by holding technology constant.

Differences in profit changes between Models A and L are not large. Both models show that moderate temperature increases result in net revenue losses to midwest agriculture.[17] However, as the temperatures increase

from the 2.5°C increment to the 5.0°C increment, the losses level off and start to decrease. In models estimated without the interaction terms (not shown here) the losses increase monotonically with temperature. Thus, the inclusion of the interaction terms affects the qualitative nature of the simulation results. In general, Model A predicts larger losses from increasing temperatures than Model L. These differences do not exceed $2 billion for any scenario except where there is a 25 percent increase in the variational variables and a 5.0°C increase in temperature. Here, Model L shows a $3.7 billion greater loss of net revenues. In percentage terms, the losses in Table 4 are substantial in some cases since the model predicts midwest net returns for 1992 of $16.5 billion in 1987 dollars for Model A and $21.7 billion for Model L.

Precipitation level impacts are similar in the two models. Profits are highest when precipitation is at 90 percent of historical levels for a given temperature. This is somewhat counterintuitive and contrary to results in Adams *et al.* (1988, 1999) but consistent with Kaiser *et al.* and with preliminary results when the interaction terms were not included in Models A and L. Maximum dollar losses from increased rainfall for a given temperature level are modest, about $2.1 billion for a given temperature in Model A and $1.4 billion for Model L.[18]

Although not strictly comparable, our results show some distinct departures from those in Mendelsohn, Nordhaus, and Shaw (1999) for changes in the levels of the climate variables.[19] They find benefits from some temperature increases, while our findings show declines in profits for all temperature increases modeled. For example, for both the 1.5°C and

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[17] In the simulations the net revenue per acre for a given county is predicted using the regression model and this figure is multiplied by the number of acres in crops and pasture in that county in 1992. These county

level figures are aggregated over the 12 state regions to get total net revenues for the midwest.

[18] These are the maximum differences between the profit changes with the scenarios having precipitation at 90 percent of observed for a given temperature level less profits in scenarios at higher levels of precipitation.

[19] All our comparisons are with those models in Mendelsohn, Nordhaus, and Shaw (1999) that weight the Midwest more heavily, i.e., the cropland models.

Table 4. Predicted Changes in Aggregate Profit for Various Climate Change Scenarios[a]

Hypothesized Changes in Climate Variables[a]			Change in Aggregate Profit (1987 $s)			
ΔT(°C)	ΔP	ΔV	$ bil. Model *A*	$ bil. Model *A1*	$ bil. Model *L*	$ bil. Model *L1*
0.00	−10%	0.00	+1.41	0.851	1.20	−.487
0.00	+7%	0.00	−.701	−.400	−.241	.751
0.00	+15%	0.00	−1.21	−.661	−.043	1.93
1.5	−10%	0.00	−2.56	−7.42	−2.31	−5.96
1.5	0.00	0.00	−3.97	−8.28	−3.51	−5.48
1.5	+7%	0.00	−4.67	−8.68	−3.75	−4.73
1.5	+15%	0.00	−5.19	−8.94	−3.55	−3.55
2.5	−10%	0.00	−3.96	−14.1	−3.65	−11.3
2.5	0.00	0.00	−5.37	−15.0	−4.85	−10.8
2.5	+7%	0.00	−6.07	−15.4	−5.09	−10.0
2.5	+15%	0.00	−6.59	−15.6	−4.89	−8.85
5.0	−10%	0.00	−3.09	−35.0	−3.52	−29.0
5.0	0.00	0.00	−4.50	−35.9	−4.73	−28.5
5.0	+7%	0.00	−5.20	−36.3	−4.97	−27.7
5.0	+15%	0.00	−5.71	−36.5	−4.77	−26.6
0.00	+7%	10%	−10.3 (−.964)[a]	NA	−9.99 (−1.07)	NA
0.00	+7%	25%	−24.7 (−1.36)	NA	−23.1 (−2.17)	NA
1.5	+7%	10%	−12.4 (−5.58)	NA	−12.0 (−4.94)	NA
1.5	+7%	25%	−24.0 (−6.93)	NA	−23.0 (−6.52)	NA
2.5	+7%	10%	−12.6 (−7.40)	NA	−12.4 (−6.53)	NA
2.5	+7%	25%	−22.3 (−9.40)	NA	−22.2 (−8.44)	NA
5.0	+7%	10%	−8.58 (−7.59)	NA	−10.3 (−7.03)	NA
5.0	+7%	25%	−13.7 (−11.2)	NA	−17.4 (−9.80)	NA

[a] Figures in parentheses represent the loss from an increase in the ranges of seasonal temperature and precipitation with diurnal variation held at its observed values.
[b] ΔT, ΔP and ΔV indicate the change from historical values of temperature, precipitation and the variational variables, respectively. The change in temperature is measured in °C and the changes in precipitation and variational variables are in percentage change from observed.

2.5°C increases, Mendelsohn, Nordhaus, and Shaw (1999) show net benefits to U.S. agriculture as a whole whereas our results show a decline for the midwest. Only at the 5.0°C temperature level do they find negative benefits to agriculture. Precipitation effects in our models are contrary to predictions in the Mendelsohn, Nordhaus, and Shaw (1999) models that include the climate variation variables, which find additional precipitation to be beneficial. A possible explanation for the differences is that the present models are only for the midwest where precipitation is generally adequate and excessive precipitation can hin-

der field operations in both the spring, summer, and fall.[20]

We also simulated the impact of a simultaneous increase in all of the variation variables.[21] As displayed in Table 4, increasing climate variation has a large impact on profit losses. This result holds regardless of whether Model A or Model L is used, although Model A shows slightly higher losses unless the temperature increase is 5.0°C. The marginal impact of increasing climate variability is obtained by subtracting the change in profits of the increased variability scenarios from the change in profits for corresponding scenarios where variability is at observed levels. For example, with climate variation increased by 10 percent, temperature unchanged, and precipitation increased by 7 percent, losses are $10.3 billion compared with $.701 billion for no climate variation change. This gives a marginal loss of $9.6 billion due to increased climate variation.

Table 5 shows the marginal losses due to increased climate variability range widely as a function of the variation assumed and the temperature level. In both Model A and Model L, the marginal losses of increased variation are

Table 5. Marginal Losses Due to Increased Climate Variability for Various Climate Change Scenarios[a]

Hypothesized Changes in Climate Variables[b]			Marginal Change in Aggregate Profit $ bil	
ΔT(°C)	ΔP	ΔV	Model A	Model L
0.0	7%	10%	9.60	9.75
0.0	7%	25%	24.0	22.9
1.5	7%	10%	7.73	8.25
1.5	7%	25%	19.3	19.2
2.5	7%	10%	6.53	7.31
2.5	7%	25%	16.2	17.1
5.0	7%	10%	3.38	5.33
5.0	7%	25%	8.50	12.4

[a] The marginal loss due to increased climate variability is the change in profit for a given ΔT and ΔP with $\Delta V = 0$, less the corresponding change in profit for a given ΔT, ΔP, and ΔV.

[b] DT, DP and DV indicate the change from historical values of temperature, precipitation and the variational variables, respectively. The change in temperature is measured in °C and the changes in precipitation and variational variables are in percentage change from observed.

highest with no temperature change and then diminish monotonically as temperatures increase over the scenarios. With no change in temperatures, profits decline about $1 billion for each percentage increase in variation. The decrease in dollar losses as temperatures rise reflects the interaction effects of the level and variation variables. However, even in the 5.0°C temperature increase scenario, a 10-percent variation increase results in additional losses of $3.38 billion for Model A and $5.33 billion for Model L.

The figures in parentheses in Table 4 below the profit changes associated with increases in all variational variables are the profit changes if only the range variables are varied, i.e., if diurnal variation is held constant. For both Models A and L, diurnal variation accounts for a large portion of the losses due to all forms of increased climate variation except in the 5.0°C temperature increase scenarios.

Because of collinearity in the data, the specific numbers that result from the simulations must be interpreted with caution. Nonetheless, two important conclusions emerge from the

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[20] Results in Adams *et al.* (1999) indicate somewhat more favorable climate change impacts for U.S. agriculture than our results. There are a number of possible reasons for the differences. First, Adams *et al.* (1999) cover the nation and our results pertain only to the midwest. Table 2.4 of Adams *et al.* (1999) suggests that impacts vary regionally. Second, Adams *et al.* (1999) include regions with heat-tolerant crops which ours does not. Inclusion of these crops mitigates or offsets losses due to heat-sensitive crops, which are the primary crops in our study region. Third, Adams *et al.* (1999) include a carbon dioxide fertilization effect, which boosts yields under climate change. Fourth, they allow for price endogeneity. As noted earlier, because our analysis does not account for price effects, it is likely to lead to higher estimated damages. Finally, our methodology treats the agricultural land base as fixed, while Adams *et al.* (1999) do not. The ability of land to move out of agriculture in response to reduced profits would tend to reduce any negative impacts of climate change.

[21] For consistency, we simulate an increase in diurnal variation (along with the other variation variables) although it is possible that climate change would actually lead to a reduction in diurnal variation. The role of diurnal variation in the impacts of overall increases in variation is discussed below.

analysis. The first relates to the importance of including climate variation measures in models to obtain better specified models. As noted earlier, the magnitudes of the temperature and precipitation elasticities vary substantially in some cases as a function of whether variational variables are excluded from the model. The net effects of such exclusions in the simulations are substantial. Omitting the variational variables and their interactions generally increases the loss estimates from temperature increases. The differences are most apparent at the higher levels of temperature increases. For example, at a 5.0°C temperature and 15-percent precipitation increase, the model without variation (A1) predicts a loss of $36.5 billion compared with $5.71 billion for the model with variation (A). Given that predicted profits for 1992 for the midwest were $16.2 billion, the change in specification yields a very different conclusion about the impacts of climate change and indicates that specification is a very important feature of measuring the impacts of climate change. Mendelsohn, Nordhaus, and Shaw (1999) found a similar result when including variation variables in their models. However, in their sample, inclusion of the variation variables in the regression had not only a quantitative but also a qualitative effect on the simulated impact of changes in mean temperature. In particular, when these variables were included, moderate increases in mean temperature were beneficial to agriculture, rather than detrimental as predicted with a model that excluded the variation variables. Our results suggest that inclusion of the variation variables would reduce but not eliminate the negative impacts of changes in mean temperature.

Second, the simulation results show clearly that for the changes in climate variables hypothesized, changes in variation are potentially very costly to midwestern agriculture. Of course, the magnitude of the impact depends on the hypothesized change in variation that would result from climate change. However, the elasticities corroborate the results of the simulations. Of the variation variables, our analysis suggests that diurnal variation is potentially the most important. The importance

of potential increases in variability is consistent with the results in Mendelsohn, Nordhaus, and Shaw (1999). In addition, using a stochastic growth model that incorporates a link between changes in the mean and variance of climate variables, Dalton shows that damages from climate change are likely to be underestimated in analyses that fail to account for changes in climate variability. Thus, to predict the impact of climate change accurately, future studies should include not only changes in mean temperature and precipitation but also the impact of climate change on the variability of these variables.

Summary

While several previous studies have estimated the impact of climate change on U.S. agriculture, for the most part these studies have not considered the impact of climate variability. A few recent studies (Mendelsohn, Nordhaus, and Shaw 1999; Dalton) have begun to incorporate climate variability into their analyses and have shown that variability is potentially important. This study contributes to this recent literature, using a variant of the Ricardian methodology introduced by Mendelsohn, Nordhaus, and Shaw (1994).

Four approximate profit function models were estimated and used to simulate the impact of long-run climate change on agricultural net revenues in the midwest. Models were estimated both with and without variables reflecting climate variability and for the two different functional forms. Choice of functional form was of minor consequence. The simulation results were very sensitive to the inclusion of climate variability variables and their associated interaction terms. Perhaps the most important aspect of this sensitivity is in measuring the impact of changes in mean temperature and precipitation. When the variation variables are excluded from the estimated models, the net revenue losses due to changes in mean temperature are estimated to be much higher. In other words, accounting for differences in climate variability across the sample reduces the estimated damages. However, in contrast to the results in Mendelsohn, Nord-

haus, and Shaw (1999), in our study incorporating these variables does not eliminate losses or make moderate mean temperature increases beneficial. Nonetheless, if the impact of changes in the levels of climate variables are to be estimated accurately, the analysis must control for the impact of climate variability.

In addition, the estimated elasticities and simulations suggest that damages from global warming could be substantially higher if warming leads to greater climate variability. In our analysis, damages were particularly sensitive to increases in diurnal variation, a result that is consistent with other studies (Mendelsohn, Nordhaus, and Shaw 1999; Dalton). This suggests that meteorologists predicting climate change effects should focus their attention not only on changes in the mean values but also on any impact that global warming is likely to have on climate variability.

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Table A1. Definition of Variables

Variable	Definition
PROFIT/ACRE	Market revenue less variable costs and machinery costs divided by sum of cropland and pastureland. ($)
TEMP1, TEMP4, TEMP7 and TEMP10	Mean daily mean temperature in the month from 1951–1980, Fahrenheit +3°. Computed as being the temperature one-half way between the mean daily maximum and mean daily minimum temperatures for the month. Number indicates month, where 1 = January, 4 = April, 7 = July, 10 = October.
TEMP12, TEMP42, TEMP72 and TEMP102	Square of TEMP1, TEMP4, TEMP7 and TEMP10, respectively.
PRE1, PRE4, PRE7 and PRE10	Mean precipitation for the month, in inches averaged from 1951–1980.
PRE12, PRE42, PRE72 and PRE102	Square of PRE1, PRE4, PRE7 and PRE 10, respectively.
DIURN1, DIRUN4, DIURN7, and DIURN10.	The difference between mean daily maximum and daily minimum temperatures in the month, Fahrenheit (diurnal cycle).
TEMP1R, TEMP4R, TEMP7R, TEMP10R	The range between the year with the highest and the year with the lowest mean monthly temperature over 1951–1980, Fahrenheit.
PRE1R, PRE4R, PRE7R, PRE10R	The range between the year with the greatest and the year with the least monthly precipitation over 1951-1980, inclusive in inches.
T1R1, T4R4, T7R7, and T10R10	Interaction of temperature and temperature range so that T1R1 = TEMP1 · TEMP1R, etc.
P1R1, P4R4, P7R7, and P10T10	Interaction of precipitation and precipitation range so that P1R1 = PRE1 · PRE1R, etc.
T1DI1, T2DI2, T7DI7, and T10DI10	Interaction of temperature with diurnal variation so that T1D1 = TEMP1 · DIURN1, etc.
WTD	Mean of June, July and August mean temperatures for observation year less TEMP7, Fahrenheit.
WPD	Mean of June, July and August precipitation for observation year less PRE7, inches.
LATITUDE	Latitude measured in degrees from southern most point in U. S.
ALTITUDE	Height of county from sea level in feet.
SALINITY	Percent of land which needs special treatment because of salt/alkaline in the soils.
WATER CAP	Water capacity-Ability of soil to hold water (inches per pound).
PERMEA	Permeability-Ability of water to pass through soil (inches per hours).
WET	Percent of land considered wetland.
KFAC	K factor-soil erodibility factor in hundredths of inches.
SLOPE	Number of feet length of slope (not steepness).
PCORN	Market price of corn ($/bu.).
PWHEAT	Market price of wheat ($/bu.).
PSOY	Market price of soybeans ($/bu.).
HAYPRICE	Market price of hay ($/ton.).
PBEEF	Per capita inventory value of cattle ($/head).
PPORK	Per capita inventory value of pork ($/head).
LAKEST, NORPLA	Lake states (MI, WI, MN) binary; Northern Plains States (ND, SD, NE, KA) binary.
D1978, D1982 and D1992	Annual binary variables taking on the value of 1 for the indicated year, 0 otherwise