

WILL U.S. AGRICULTURE REALLY BENEFIT FROM GLOBAL WARMING? ACCOUNTING FOR IRRIGATION IN THE HEDONIC APPROACH.

Wolfram Schlenker, W. Michael Hanemann, and Anthony C. Fisher*

There has been a lively debate about the potential impact of global climate change on U.S. agriculture. Most of the early agro-economic studies predict large damages (see, for example, Richard M. Adams, 1989; Harry M. Kaiser et al., 1993; and Adams et al., 1995). In an innovative paper Robert Mendelsohn, William D. Nordhaus and Daigee Shaw (1994) - hereafter MNS - propose a new approach: using the variation in temperature and precipitation across U.S. counties to estimate a reduced form hedonic equation with the value of farmland as the dependent variable. A change in temperature and/or precipitation is then associated with a change in farmland value which can be interpreted as the impact of climate change. Adams et al. (1998) characterize the hedonic approach as a spatial analogue approach, and acknowledge that "the strength of the spatial analogue approach is that structural changes and farm responses are implicit in the analysis, freeing the analyst from the burden of estimating the effects of climate change on particular region-specific crops and farmer responses." On the other hand, one of the potential disadvantages of the hedonic approach is that it is a partial equilibrium analysis, i.e., agricultural prices are assumed to remain constant.¹ While year-to-year fluctuations in annual weather conditions certainly have the potential to impact current commodity prices, especially for crops produced only in a relatively localized area, (such as citrus fruits which are grown mainly in California and Florida), changes in long-run weather patterns (i.e., changes in climate) might have a smaller effect on commodity prices because of the greater potential for economic adaptation, particularly shifts in growing regions.² The hedonic approach as implemented by MNS predicts that existing agricultural land on average might be more productive and hence result in benefits for U.S. farmers.³ The hedonic approach has received considerable attention in our judgment in part because the conclusions are at variance with those of some other studies

that suggest warming will lead to damages and in part because of the new methodology. Although the approach is appealing, it is at the same time vulnerable to problems related to misspecification.

Several authors have questioned the particular implementation in MNS (William R. Cline, 1996; Robert K. Kaufmann, 1998; Darwin (1999b); and John Quiggin and John K. Horowitz, 1999). Specifically, they suggest that (i) the hedonic approach cannot be used to estimate dynamic adjustment costs; (ii) the results are not robust across different weighting schemes; and (iii) the inadequate treatment of irrigation in the analysis might bias the results. The first criticism alludes to the fact that some farmers might not find it profitable to switch to new cropping patterns given their existing crop-specific fixed capital. However, climate change will occur only gradually and most costs can thus be seen as variable. In this paper we focus on the latter two points, especially the role of irrigation. Previous comments have raised theoretical concerns about potential sources of misspecification related to irrigation. We provide an empirical test. Once irrigation is accounted for, we show that results also become robust across weighting schemes or models. Elsewhere we extend the analysis in various directions: construction and use of climate variables tied more closely to agronomic findings; development of more accurate measures of both climate and soil conditions; adjustment for spatial correlation of the error terms in a hedonic regression; and use of recent climate scenarios that go beyond the traditional assumption of uniform impacts across regions of a doubling of greenhouse gas concentrations in the atmosphere (Wolfram Schlenker et al., 2004). We note here that none of the implied changes in the analysis affects the arguments concerning irrigation discussed in this paper.

I Irrigation and Impact Assessment

As implemented by MNS, the hedonic approach to estimating the impact of climate change on agriculture relies on two key assumptions: (1) the precipitation variable measures the

water supply for crops grown on the farmland, and (2) future changes in production costs, including those associated with water supply, will be capitalized in future land values in the same way as past production costs were capitalized in past land values. However, both assumptions are problematic in the case of irrigated agriculture in the US.

Water is an essential input for all plant life.⁴ In humid areas, the water input is provided, at zero cost, by precipitation falling on the field during and immediately prior to the period when the plant is in the ground. In arid areas, however, the precipitation that occurs during the growing season is inadequate for the plant's needs, and these must be met by a supplementary supply either from local groundwater or from surface water imported from elsewhere. Hence, irrigation breaks the link between the growth of a plant and the climate at the farm where the plant is grown. By way of illustration, the major crop grown in Iowa is corn. Corn grown in Iowa has an ET of about 22 inches. All of this is supplied by local precipitation: about 2 inches is supplied by available soil moisture at the time of planting at the end of April, and 20 inches is supplied by precipitation occurring during the growing season between May and August. In California, by contrast, the major crop is cotton. Cotton grown in California has an ET of about 31.5 inches. Only about 5 percent of this is supplied by local precipitation: the available soil moisture at the time of planting in April is less than an inch, and the precipitation occurring during the growing season of May through September is also less than an inch. About 30 inches (95 percent of crop ET) has to be supplied by irrigation water obtained from either local groundwater or surface water imported from up to 500 miles away. Thus, in irrigated areas, local precipitation is an inaccurate measure of crop water supply.

In terms of the supply curve of water, one can say that, in dryland farming areas such as Iowa, water is a (naturally occurring) fixed input available at a price of zero; in irrigated areas such as California, water is a variable but costly input with a supply curve that varies with the supply source.⁵

In irrigated areas, the second assumption used by MNS is also problematic. A national

hedonic study such as theirs which relies on cross-sectional variation to measure the impact of climate change on U.S. agriculture implicitly assumes that if Iowa were to have the same climate as California, it would have the same arrangement for water supply. This is not plausible for the reason just noted.

Moreover, it is likely that a hedonic cost function estimated for current farmland values in irrigated areas could fail to predict the costs of future changes in the availability of irrigation supply, for two reasons. About 19 percent of the irrigation water in the western states is supplied by the US Bureau of Reclamation, which heavily subsidizes this water. Richard W. Wahl (1989) estimates that the Bureau charges only about 14 cents per dollar of true supply cost, but this is based on an optimistic estimate of the length of the repayment period. He translates the subsidy into an average of about \$1,900 per acre of farmland served by the Bureau.⁶ The subsidy is capitalized into current farmland values (Ray G. Huffaker and B. Delworth Gardner, 1986). But it should not be counted as a net social benefit because it is simply a transfer from taxpayers to farmers. Moreover, it would be inaccurate to extrapolate from current land values in areas served by the Bureau to other areas that might require irrigation in the future because it is highly unlikely that the federal government will subsidize new water projects in the future as extensively as it did in the past.

Even in irrigated areas not served by the Bureau of Reclamation, if these involve surface water (which accounts for 63 percent of the water used for irrigation in the U.S.), it would be inaccurate to extrapolate from current land values to other areas that might in the future require irrigation due to climate change. This is because, although non-Bureau surface water is not generally subsidized, it is still priced far below replacement cost. The general practice of water districts in the western states is to set prices so as to just cover historical construction costs plus current operating costs. Surface water storage and conveyance systems are highly capital intensive and the capital is extremely long-lived. Moreover, construction costs have appreciated considerably over time in real terms (Kenneth D. Frederick and Gregory E. Schwarz, 2000). Consequently, the cost of new surface water systems substantially exceeds

the cost of existing systems. For example, the California State Water Project (SWP), constructed between 1961 and 1973, supplies (unsubsidized) water to irrigation districts in Kern County at a wholesale cost of about \$70 acre foot (AF). However, the SWP has only about 60 percent of the supply capacity that was originally planned in 1960 - the completion of the remainder has been blocked since the defeat of Proposition 9 in 1982.⁷ If the system were now to be built out, current estimates are that the new water storage facilities would cost on the order of \$500-\$1,000/AF (California Department of Water Resources, 1998; Frederick and Schwarz, 2000). The price that farmers in Kern County pay for SWP water reflects what it cost to construct the SWP in the 1960s, not what it would cost to complete the SWP: it is the historical cost that is capitalized in current land value there, not the future cost of expansion.

In short, for both hydrological and economic reasons, we believe that the economic effects of climate change on agriculture need to be assessed differently in dryland and irrigated areas. Using a hedonic model fitted to a national data set of farmland values that combines both dryland and irrigated farming counties is likely to be questionable both on econometric grounds, because it combines what we expect to be two heterogeneous equations with different variables and different coefficients into a single regression, and also on economic grounds, since we expect it to understate future capital costs, especially those borne by farmers, in the areas that will need additional surface water irrigation due to the effects of climate change.

II Model

Following the standard assumption of many agro-economic studies, profit π is modeled as a quadratic function of the inputs. This seems reasonable since many inputs like pesticides, water, and fertilizer initially have positive marginal products that diminish and eventually turn negative; too much will kill the plant. We can approximate the *outer envelope* of the various production functions by a quadratic function of the exogenous inputs \mathbf{x} (e.g. climatic

variables or soil type) as well as endogenous inputs \mathbf{z} (e.g. the amount of fertilizer applied).⁸ In symbols,

$$(1) \quad \pi = [\mathbf{x}' \quad \mathbf{z}'] \begin{pmatrix} \mathbf{A}_{xx} & \mathbf{A}_{xz} \\ \mathbf{A}_{zx} & \mathbf{A}_{zz} \end{pmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{z} \end{bmatrix} - \boldsymbol{\omega}'\mathbf{z} - C$$

where \mathbf{A}_{xx} , \mathbf{A}_{xz} , \mathbf{A}_{zx} , and \mathbf{A}_{zz} are the coefficients of the quadratic production function, $\boldsymbol{\omega}$ are the variable costs associated with \mathbf{z} and C are the fixed costs. A rational farmer will maximize profit by choosing the optimal inputs \mathbf{z}^* :

$$(2) \quad \mathbf{z}^* = \mathbf{A}_{zz}^{-1} \left(\frac{\boldsymbol{\omega}}{2} - \mathbf{A}_{zx}\mathbf{x} \right)$$

The optimal profit hence becomes

$$(3) \quad \pi = \mathbf{x}' \underbrace{[\mathbf{A}_{xx} - \mathbf{A}_{xz}\mathbf{A}_{zz}^{-1}\mathbf{A}_{zx}]}_{\mathbf{A}_1} \mathbf{x} + \boldsymbol{\omega}' \underbrace{\mathbf{A}_{zz}^{-1}\mathbf{A}_{zx}}_{\mathbf{A}_2} \mathbf{x} - \boldsymbol{\omega}' \underbrace{\frac{1}{4}\mathbf{A}_{zz}^{-1}\boldsymbol{\omega}}_{\mathbf{A}_3} - C$$

In equilibrium the price of farmland V will equal the discounted sum of future profits, i.e. $V = \theta\pi$ where θ is the capitalization ratio.

$$(4) \quad V = \theta [\mathbf{x}'\mathbf{A}_1\mathbf{x} + \boldsymbol{\omega}'\mathbf{A}_2\mathbf{x} - \boldsymbol{\omega}'\mathbf{A}_3\boldsymbol{\omega} - C]$$

where \mathbf{A}_1 , \mathbf{A}_2 , and \mathbf{A}_3 are the coefficients associated with the reduced form equation.

While it might be reasonable to assume that certain input prices, $\boldsymbol{\omega}$, such as the price of fertilizer, are fairly uniform across different parts of the country, the price of water is likely to vary from region to region. In dryland farming areas, the price is zero while, as noted above, in areas irrigated from surface water supplies, the price typically reflects the historical cost of constructing the water supply system or the pattern of subsidy. The variation in the price of water affects not only the constant term in the hedonic farmland value regression

equation but also the coefficients associated with some of the variables in \mathbf{x} through \mathbf{A}_2 . For example, if rainfall and irrigation are substitutes, the coefficient on rainfall will be shifted by the varying input prices of irrigation water.

One way to deal with the fact that the hedonic farmland value equation for irrigated areas may be different than that for dryland areas is to explicitly control for irrigation in some fashion; another is to run separate hedonic regressions for irrigated and dryland counties using the separate regressors appropriate to each group. In fact, we cannot employ either approach because they both require data on the availability of irrigation water in irrigated counties which do not exist in national-level data sources. When water is provided from surface water storage systems, quantity restrictions are often imposed on the deliveries to farmers, reflecting both seniority of water rights (both legal and contractual) and also year-to-year variation in runoff and carry-over storage. In these systems, one needs not only a measure of the average quantity of water available per acre in the service area, as well as its cost, but also a measure of the reliability (uncertainty) of this supply. These differ from system to system and have to be measured on a case by case basis. Thus, while we have the data required to estimate a hedonic farmland value regression for dryland counties, we do not possess the data we believe are required for irrigated counties.⁹ Nevertheless, we can test whether or not it is appropriate to pool irrigated and dryland counties by estimating the same equation separately for dryland versus irrigated counties and testing whether or not the two equations have the same coefficients on \mathbf{x} . If the coefficients turn out to be different, this would support our contention that there are separate hedonic equations for the two types of agriculture.

III Empirical Estimation

In this section we examine empirically whether the hedonic farmland value equation is different for dryland versus irrigated counties. In making this comparison, we omit all urban

counties because the strong influence of urbanization on farmland values in these counties could cause bias.¹⁰ The non-urban counties are divided into two groups. The first group consists of non-urban counties with purely dryland farming: we define this as having less than 20 percent of the harvested cropland that is irrigated;¹¹ with more than 20 percent of the harvested cropland irrigated form the second group ("irrigated counties").¹²

Our data contain 2203 dryland, non-urban counties, 508 irrigated non-urban counties, and 227 urban counties. We conduct a Chow test to determine whether all coefficients for the two groups of dryland, non-urban and irrigated, non-urban counties are jointly the same. The $F_{(31,2649)}$ -statistic is 17.5 for the cropland model and 25.0 for the crop revenue model. The p-value of rejecting a true null hypothesis that the coefficients for the two subgroups are equal is less than 10^{-16} . Since the cropland and crop revenue models use weights that might not correctly adjust for the true variance-covariance matrix, the test statistics could be biased. Accordingly, we replicate the Chow test by utilizing White's heteroscedasticity consistent estimator of the variance-covariance matrix for an unweighted regression.¹³ The test statistic changes to 10.1, which is still significant at a p-value less than 10^{-16} .

Mendelsohn and Nordhaus (1999) fit a version of the MNS model that includes as an additional regressor the predicted percent of farmland irrigated, derived from a prior auxiliary regression. This is equivalent to allowing the percent of farmland irrigated to shift the constant term in the hedonic regression, while leaving the slope coefficients unchanged. We believe that irrigation is likely to change some of the slope coefficients because, as equation (4) shows, the regression coefficient on \mathbf{x} consists of a combination of water prices and \mathbf{A}_2 . Furthermore, the auxiliary regression uses the same dependent variables which will lead to perfect multicollinearity unless the predicted share of farmland that is irrigated is truncated.

To test whether the coefficients of climate variables are unchanged by irrigation, we allow the constant term and the non-climate (i.e., socio-economic and soil) variables to vary between dryland and irrigated counties and perform a Chow test to determine whether the 16 climatic coefficients are the same. For the crop revenue model, the $F_{(16,2649)}$ statistic is 18.1

while it is 7.0 for the cropland weights and 4.2 using White's heteroscedasticity consistent estimator.¹⁴ We also test whether each of the 16 climatic variables *individually* is the same in dryland, non-urban counties as in irrigated, non-urban counties. For the crop revenue weights 11 coefficients are significantly different at the 5 percent level, while the number reduces to 7 under the cropland weights and 4 under White's heteroscedasticity consistent estimator. The Chow tests are summarized in Table 1.

Two variables in particular illustrate how the pooling of dryland and irrigated counties can produce bias in the coefficient estimates. The pooled data generate coefficients on precipitation in July which entail that this has a negative marginal value at the sample mean, implying that a decrease in July precipitation would be beneficial. But, July is the height of the growing season for most crops in the US and the time of the highest ET requirement, making it unlikely that a reduction in precipitation would be beneficial at the average climate. Instead, we believe that the negative marginal value is an artifact of the failure to control for irrigation. Some of the most profitable farming counties in the US are to be found in California and Arizona; these are also some of the driest counties. But the profitability of farming occurs despite the lack of rainfall, not because of it.

The sign of the coefficient of the variable "slope length" is also counterintuitive. Higher values of this variable indicate a larger loss of fertile soil due to erosion. In both the cropland and crop revenue models the sign is positive, suggesting that loss of fertile soil is beneficial. Again, this variable is strongly correlated with irrigation. Slope length measures the distance to the nearest river. In the arid and generally irrigated western states, the distance to the nearest river is large. Hence, slope length picks up the benefits of irrigation which is not adequately controlled for in the pooled regression.¹⁵ When we limit the analysis to dryland, non-urban areas, both signs reverse. The selected regression coefficients are listed in Table 2.¹⁶

The MNS estimates of the impact of global warming on US agriculture are shown in Table 3. These estimates are based on the regression coefficients from their regression pooling

all counties, both dryland and irrigated. However, we have disaggregated their impact estimates by (i) dryland, non-urban counties, (ii) irrigated, non-urban counties, and (iii) urban counties. Note that both of their models predict some damages for irrigated, non-urban counties. For dryland, non-urban counties, while their cropland model predicts large damages, their crop revenue model shows modest benefits.

In order to examine the variability underlying these point estimates, we use bootstrap simulations to develop a probability distribution of the impact on farmland value.¹⁷ As can be seen from Figure 1, the distribution is very disperse, especially with the crop revenue weights. This makes any inference from the point estimates questionable, in our judgement. We develop a second estimate of the variability of the estimated impact using the OLS variance-covariance matrix that should be identical to the bootstrap distribution for a correctly specified model with i.i.d. normal error terms.¹⁸ Both the OLS distribution and the bootstrap distribution are calculated using the Epanechnikov Kernel estimator.¹⁹ The bootstrap and OLS distributions of the estimated impacts on farmland value are exhibited in Figure 1. If the regression model were well specified, the predicted probability distributions for the impact of climate change should be about the same, but they clearly diverge. Notice that for the crop revenue weights, the OLS distribution is significantly tighter than the bootstrap distribution. A possible explanation for the difference is irrigation. As indicated in equation (4), the omission of the varying prices and access to irrigation will result in a misspecified equation with large error terms. The crop revenue weights aggravate the problem because, unlike the cropland weights, these are relatively highly correlated with irrigation.²⁰ The bootstrap method repeatedly samples from these outliers and results in a very disperse distribution.

We turn next to the estimates of the impact of global warming on agriculture in the dryland, non-urban counties, using only these counties to estimate the hedonic farmland value regression equation. The truncated impact estimates for these counties are displayed in Table 4 and Figure 2. When the data used in estimation are confined to dryland, non-urban

counties, the impact estimates under the different weighting models converge dramatically, as do the OLS and bootstrap distributions. This robustness with respect to alternative weighting schemes is consistent with our surmise that separating observations on dryland from irrigated counties eliminates a specification error that arises when they are pooled.²¹

For dryland, non-urban counties, under all models, agriculture is predicted to suffer from the benchmark climate change scenario associated with a doubling of greenhouse gas concentrations.²² The estimated loss in annual profit comes to about \$5.3-5.4 billion; this result is significant at the 1 percent level.²³

The estimates of climate change impacts in Table 4 and Figure 2 account only for dryland, non-urban counties. Climate change will also affect irrigated and urban counties but, because of the data problems discussed above, our present analysis cannot quantify this impact. Instead, we offer a few general observations. As noted in Table 3, both the cropland and the crop revenue models estimated by MNS using all counties combined lead to the conclusion that climate change will harm counties with irrigated agriculture. Although we believe these estimates are not reliable, the direction of the impact, at least, is plausible. This is because it appears that climate change will cause an increased water shortage in a number of these counties. On the one hand, higher temperatures significantly raise crop ET, which has two effects. First, it is likely to lead to a switch to irrigated farming in some dryland areas if the increase in ET cannot be met by natural rainfall. Second, it will increase the amount of water applied per acre in irrigated areas. On the other hand, hydrological studies suggest that climate change will lead to a reduction in the effective supply of surface water in some of these areas, including the Columbia River Basin and the Sacramento-San Joaquin River Basin.²⁴ Thus, the overall effect is likely to be increased water shortage. This could be met in various ways - by developing new surface water storage and conveyance facilities, through water rights reallocation and water marketing, through increased conservation, or through land retirement. However, these solutions are likely to entail economic costs that are not fully reflected in the hedonic farmland value regression equation estimated by MNS. Some

of the costs will be borne by urban water users and, because of the way surface water is priced in most of the U.S. West, the full cost of supplying agricultural users is generally not completely capitalized in current farmland values. The bottom line is that the economic cost of climate change in irrigated areas could be substantial. A region-specific analysis accounting for the relevant hydrology and institutional framework of water deliveries will be required to evaluate these costs in more detail.

IV Conclusions

We estimate the potential impact on farmland value in the U.S. of a climate change scenario of a five degree Fahrenheit increase in temperature and an eight percent increase in precipitation, associated with the benchmark doubling of pre-industrial concentrations of greenhouse gases. We find that irrigated and dryland counties cannot be pooled in a single regression equation. The evidence suggests that the economic effects of climate change on agriculture need to be assessed differently in dryland and irrigated areas. Local climate variables fail to measure water supply in irrigated areas, and the pricing of irrigation water can cause a hedonic regression for these areas to misstate the economic cost of a future water shortage. Consequently, a hedonic farmland value regression for irrigated areas requires different variables than for dryland areas. If, despite this, dryland and irrigated counties are pooled using the same regressors for both, we find that this biases coefficients on climate-related variables.

Since the necessary data are not currently available for irrigated areas, we have confined our analysis to dryland areas. When the model is estimated for dryland, non-urban counties alone we find that the estimates are unambiguously negative and converge to an annual loss of about \$5.3-\$5.4 billion. This is comparable to some of the earlier estimates of potential losses to U.S. agriculture in the literature. It is likely that adding in the impact on irrigated areas will result in still greater losses, but a more precise estimate will depend on analyses

specific to the separate hydrological regimes in the arid West.

Several caveats apply to our analysis, along with much of the rest of the literature here. Our impact estimates depend upon the specific hypothesized scenario of climate change, which may well turn out to be oversimplified both spatially and temporally. Further we do not allow for changes in input and output prices beyond what is reflected in the existing cross-section equilibrium of land values nor for changes in technology or market structure.

Our analysis focuses on the impact of changes in temperature and precipitation, and not other things that might be affected by climate change, in particular CO_2 fertilization. The effects of CO_2 fertilization are still controversial. The existing empirical data are based mainly on controlled agronomic experiments; other factors may be limiting in the field, and weeds may also be fertilized. Moreover, it now appears there may be a tradeoff between quantity and quality, as the projected increase in crop growth is offset by a decline in nutritional value (Leanne M. Jablonski et al., 2002). Finally, it appears that fertilization exhibits strong decreasing marginal productivity, with little to no benefit above twice the pre-industrial level ($2XCO_2$).

References

- Adams, Richard M.**, “Global Climate Change and Agriculture: An Economic Perspective,” *American Journal of Agricultural Economics*, December 1989, *71* (5), 1272–1279.
- , **Brian H. Hurd, Stephanie Lenhart, and Neil Leary**, “Effects of Global Climate Change on Agriculture: An Interpretative Review,” *Climate Research*, December 1998, *11* (1), 19–30.
- , **Ronald A. Flemming, Ching-Chang Chang, Bruce A. McCarl, and Cynthia Rosenzweig**, “A Reassessment of the Economic Effects of Global Climate Change on U.S. Agriculture,” *Climatic Change*, June 1995, *30* (2), 147–167.
- California Department of Water Resources**, *California Water Plan Update, Bulletin 160-98*, 1998.
- Cline, William R.**, “The Impact of Global Warming on Agriculture: Comment,” *American Economic Review*, December 1996, *86* (5), 1309–1311.
- Darwin, Roy**, “A Farmers view of the ricardian approach to measuring agricultural effects of climate change,” *Climatic Change*, August 1999, *41*, 371–411.
- , “The Impact of Global Warming on Agriculture: A Ricardian Analysis: Comment,” *American Economic Review*, September 1999, *89* (4), 1049–1052.
- , **Marinos Tsigas, Jan Lewandrowski, and Anton Raneses**, *World Agriculture and Climate Change: Economic Adaptations. Agricultural Economic Report Number 703*, June 1995.
- Frederick, Kenneth D. and Gregory E. Schwarz**, “Socioeconomic Impacts of Climate Variability and Changes on U.S. Water Resources,” Resources for the Future Discussion Paper 00-21, May 2000.

- Gleick, Peter H. and Elizabeth L. Chalecki**, “The Impacts of Climatic Changes for Water Resources of the Colorado and Sacramento-San Juaquin River Basins,” *Journal of the American Water Resources Association*, December 1999, *35* (6), 1429–1441.
- Hamlet, Alan F. and Dennis P. Lettenmaier**, “Effects of Climate Change on Hydrology and Water Resources in the Columbia River Basin,” *Journal of the American Water Resources Association*, December 1999, *35* (6), 1597–1623.
- Huffaker, Ray G. and B. Delworth Gardner**, “The Distribution of Economic Rents Arising from Subsidized Water When Land Is Leased,” *American Journal of Agricultural Economics*, May 1986, *68* (2), 306–312.
- Jablonski, Leanne M., Xianzhong Wang, and Peter S. Curtis**, “Plant Reproduction under Elevated CO₂ Conditions: A Meta-Analysis of Reports on 79 Crop and Wild Species,” *New Phytologist*, 2002, *156*, 9–26.
- Jetton, Anne E., Michael D. Dettinger, and J. LaRue Smith**, *Potential Effects of Climate Change on Streamflow of Eastern and Western Slopes of the Sierra Nevada, California and Nevada*, Denver, CO: U.S. Geological Survey WRI Report 95-4260, 1996.
- Kaiser, Harry M., Susan J. Riha, Daniel S. Wilks, David G. Rossiter, and Radha Sampath**, “A Farm-Level Analysis of Economic and Agronomic Impacts of Gradual Climate Warming,” *American Journal of Agricultural Economics*, May 1993, *75*, 387–398.
- Kaufmann, Robert K.**, “The Impact of Climate Change on US Agriculture: A Response to Mendelsohn et Al. (1994),” *Ecological Economics*, August 1998, *26*, 113–119.
- Lettenmaier, Dennis P. and Thian Yew Gan**, “Hydrologic Sensitivities of the Sacramento-San Juaquin River Basin, California, to Global Warming,” *Water Resources Research*, January 1990, *26* (1), 69–86.

- Leung, L. Ruby and Mark S. Wigmosta**, “Potential Climate Change Impacts on Mountain Watersheds in the Pacific Northwest,” *Journal of the American Water Resources Association*, December 1999, 35 (6), 1463–1471.
- Mendelsohn, Robert and Ariel Dinar**, “Climate, Water, and Agriculture,” *Land Economics*, August 2003, 79 (3), 328–341.
- and **William D. Nordhaus**, “The Impact of Global Warming on Agriculture: A Ricardian Analysis: Reply,” *American Economic Review*, September 1999, 89 (4), 1053–1055.
- , — , and **Daigee Shaw**, “The Impact of Global Warming on Agriculture: A Ricardian Analysis,” *American Economic Review*, September 1994, 84 (4), 753–771.
- Plantinga, Andrew J., Ruben N. Lubowski, and Robert N. Stavins**, “The Effects of Potential Land Development on Agricultural Land Prices,” *Journal of Urban Economics*, November 2002, 52 (3), 561–581.
- Quiggin, John and John K. Horowitz**, “The Impact of Global Warming on Agriculture: A Ricardian Analysis: Comment,” *American Economic Review*, September 1999, 89 (4), 1044–45.
- Rosenzweig, Cynthia and Daniel Hillel**, *Climate Change and the Global Harvest*, New York: Oxford University Press, 1998.
- Schlenker, Wolfram, W. Michael Hanemann, and Anthony C. Fisher**, “The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions,” *Mimeo. University of California, San Diego*, 2004.
- Segerson, Kathleen and Bruce L. Dixon**, “Climate Change and Agriculture: The Role of Farm Adaptation,” in Robert Mendelsohn and James E. Neumann, eds., *The Impact*

of Climate Change on the United States Economy, Cambridge University Press, 1999, pp. 75–93.

Smith, Joel B. and Dennis A. Tirpak, *The Potential Effects of Global Climate Change on the United States : Report to Congress*, Washington, D.C.: U.S. Environmental Protection Agency, Office of Policy, Planning, and Evaluation, Office of Research and Development, December 1989.

Wahl, Richard W., *Markets for Federal Water: Subsidies, Property Rights, and the Bureau of Reclamation*, Resources for the Future, 1989.

Notes

*Schlenker: Department of Economics, University of California at San Diego, La Jolla, CA 92093 (e-mail: wschlenker@ucsd.edu). Hanemann: Department of Agricultural and Resource Economics, University of California at Berkeley, Berkeley, CA 94720 (e-mail: hanemann@are.berkeley.edu). Fisher: Department of Agricultural and Resource Economics, University of California at Berkeley, Berkeley, CA 94720 (e-mail: fisher@are.berkeley.edu).

We gratefully acknowledge comments on an earlier draft by three anonymous reviewers, John (Mac) Callaway, Olivier Deschenes, Michael Greenstone, Guido Imbens, George Judge, Robert Mendelsohn, William Nordhaus, and Arnold Zellner and participants at the National Bureau of Economic Research Summer Institute in Environmental Economics. We also wish to thank Robert Mendelsohn for providing us with data used in the estimations. Partial financial support was received from the Institute for Business and Economic Research at the University of California at Berkeley and the Giannini Foundation of Agricultural Economics.

¹Roy Darwin (1999a) compares the hedonic approach to other modeling techniques. He emphasizes that "changes in agricultural land rents reflect exactly the annual value of climatic change to agriculture if output and other input prices remain constant," but are inappropriate if there are endogenous price changes.

²Thus, some recent agricultural yield studies find that world agricultural productivity might change only slightly, even though there are strong regional impacts. For example, Cynthia Rosenzweig and Daniel Hillel (1998, p. 233) find that "Global agricultural production appears to be sustainable in the face of climate change as predicted by GCMs for doubled CO_2 equilibrium scenarios. However, crop yields and productivity changes will vary considerably across regions." This might indicate limited effects on long-run world prices.

³Early studies by Joel B. Smith and Dennis A. Tirpark (1989) and Darwin et al. (1995) also find benefits for U.S. farmers. However, this result is not a consequence of increased agricultural productivity, but instead caused by an increase in prices that outweighed the reduction in productivity.

⁴Water is used up in plant growth through evaporation from the soil surface and through transpiration by the plant; together these are known as evapotranspiration (ET).

⁵With groundwater, the quantity of water applied is determined typically by the individual farmer. However, the provision of surface water for irrigation is typically determined through some type of collective action.

⁶For comparison, the average value of farmland was \$784 per acre in 1982.

⁷Proposition 9 proposed the construction of a peripheral canal to transport additional water diversions from Northern California rivers to Southern California *around* the San Francisco Delta rather than transporting water through the Delta using the natural river channels, which was environmentally damaging. The proposition's defeat killed prospects for additional water transfers.

⁸Darwin (1999b) shows how the omission of the endogenous variable irrigation, which itself is a function of climatic variables, might bias the results.

⁹The United States Geological Service (USGS) provides estimates of the amounts of surface and ground water used for irrigation in each county. However, these data are problematic and incomplete in several respects. First, the estimates are often based on theoretical estimates of crop water requirements rather than on direct observation and measurement of water application on-farm; this is the case in California, for example. Secondly, there generally are multiple irrigation districts within a county, and these are likely to have different water rights, different water allocations, and different water prices. Because of the differences among irrigation districts even within a single

county, we believe that the appropriate aggregate unit of analysis in irrigated areas is the irrigation district. Any analysis using more aggregated data is likely to be confounded by measurement error. Thirdly, the USGS provides no information on the cost or reliability (uncertainty) of irrigation water supply.

¹⁰For example, Andrew J. Plantinga et al. (2002) find that more than 80 percent of farmland value close to New York City is attributable to the option value of developing the land for urban uses. We define urban as having a population density of more than 400 people per square mile, which corresponds to the five percentile of the distribution of population densities. Since counties in the Western United States are very large, the variable population density alone might not pick up the presence of urban centers and we hence also excluded all counties with a total population above 200,000 people.

¹¹Whenever the amount of irrigated harvested cropland is missing in the 1982 census, we fill the missing observations from consecutive census years, or by using the upper bound given by the variable harvested cropland in irrigated farms, which includes all harvested cropland in a farm that irrigates at least one acre.

¹²Kathleen Segerson and Bruce L. Dixon (1999) suggest using 10 percent of the acreage (as opposed to harvested cropland) irrigated as a criterion for defining an irrigated county. As indicated below, we tried a range of cutoff levels for defining irrigated versus dryland counties and found that this did not affect our results.

¹³When we apply White's correction to the weighted regressions we obtain comparable results.

¹⁴We repeat the Chow test and it fails for every observed irrigation percentage between 5 percent and 47.5 percent in the data set at the 1 percent level, indicating that our results are insensitive to the chosen cutoff level. For irrigation percentages above 47.5 percent the dryland sample includes

sufficiently many irrigated counties that the test for equal coefficients sometimes does not fail.

¹⁵Mendelsohn and Ariel Dinar (2003) have recently published a new version of their hedonic model which includes the USGS estimate of surface water deliveries in each county as an additional exogenous variable; this still pools all dryland and irrigated counties in a single regression, which we believe to be a misspecification. The estimated coefficient on slope length continues counterintuitively to be positive.

¹⁶Since the weighting matrices under the cropland and crop revenue model do not equal the inverse of the variance-covariance matrix of the error terms, the OLS t-statistic might be biased.

¹⁷We use 100,000 paired bootstrap simulations. In each simulation we randomly draw 2938 counties with replacement and estimate the coefficients.

¹⁸Note that for the case of a diffuse prior and normally distributed error terms, the Bayesian posterior of the coefficients will be distributed multivariate student-t and the derived 95 percent confidence interval will be identical to the OLS confidence interval, even though the interpretations are very different. Following MNS we *truncate* possible damages from above as the value of farmland has to remain non-zero. We therefore first sample the variance s^2 from the inverted gamma distribution and then take a draw from the multivariate normal distribution of the regression parameters. Again, we utilize 100,000 draws.

¹⁹The untruncated impact estimator would be distributed univariate student-t as it is a linear function of the coefficients. We draw another 100,000 samples and derive the *untruncated* impacts. The smoothed Epanechnikov Kernel distribution is indistinguishable from the closed form univariate student-t distribution of the untruncated impact estimator.

²⁰The correlation coefficient between the crop revenue weights and the percent of farmland that is irrigated is 0.39; with the cropland weights, the correlation is only 0.05.

²¹Moreover, when we confine the data used in estimation to irrigated and non-urban counties and use the MNS variables to predict the effects of climate change on those counties, the impact estimates are noticeable less precise than for the dryland, non-urban counties.

²²There is some controversy about the predicted change in climatic conditions. Here we follow MNS and use the scenario of the first report by the Intergovernmental Panel on Climate Change. As noted earlier, in (Schlenker et al., 2004) we explore the implications of more recent and sophisticated climate scenarios.

²³The main result that predicted impacts under both models converge and become unambiguously negative when the data is limited to dryland, non-urban counties is confirmed in other census years. When we pair the same independent variables with farmland values from the 1987, 1992, and 1997 census, the estimated impacts on yearly profits change to -4.84, -6.46, -8.78 billion under the cropland model and -4.90, -6.47, and -10.24 billion dollars under the crop revenue model, respectively. All numbers are adjusted to 1982 prices using the GDP implicit price deflator. Furthermore, we obtain comparable results when we use yearly "net cash income" as the dependent variable, which is given in the 1987, 1992, and 1997 census.

²⁴The impact of increased temperature on the timing of snowmelt together with the increased ET of watershed vegetation and increased evaporation from stored surface water appear likely to outweigh the benefits of increased precipitation in these regions (Dennis P. Lettenmaier and Thian Yew Gan, 1990; Anne E. Jetton et al., 1996; Peter H. Gleick and Elizabeth L. Chalecki, 1999; Alan F. Hamlet and Lettenmaier, 1999; and Ruby L. Leung and Mark S. Wigmosta, 1999).

Table 1: Chow Tests Whether Dryland, Non-urban and Irrigated and/or Urban Counties Can be Pooled

	Crop Revenue Weights	Cropland Weights	White's Estimator
P-value for the test that			
all 31 coefficients are the same	$< 10^{-16}$	$< 10^{-16}$	$< 10^{-16}$
P-value for the test that			
the 16 climatic variables are the same	$< 10^{-16}$	$4.4 * 10^{-16}$	$3.4 * 10^{-8}$
Number of climatic variables that are			
individually different at the 5 percent level	11	7	4

Notes: All tests examine whether the coefficients are the same for the 2203 dryland, non-urban counties and the 508 irrigated, non-urban counties. Both the crop revenue and cropland model are weighted regressions. White's estimator is an unweighted regression that utilizes White's heteroscedasticity consistent estimate of the variance-covariance matrix.

Table 2: Selected Regression Coefficients

Variable	Crop Revenue Weights	Cropland Weights	White's Estimator
All Observations in the Estimation			
July Precipitation	-116	-34.5	-24.9
t-statistic	(6.06)	(2.63)	(1.27)
July Precipitation Squared	57.0	52.0	25.8
t-statistic	(8.20)	(9.43)	(3.66)
Slope length	54.0	17.4	23.3
t-statistic	(6.24)	(2.91)	(2.38)
Dryland, Non-urban Counties			
July Precipitation	52.5	2.46	8.26
t-statistic	(3.48)	(0.16)	(0.52)
July Precipitation Squared	27.1	18.7	16.8
t-statistic	(4.32)	(2.71)	(2.67)
Slope length	-33.3	-20.6	-9.82
t-statistic	(4.74)	(3.05)	(1.24)

Notes: Both the crop revenue and cropland model are weighted regressions. White's estimator is an un-weighted regression that utilizes White's heteroscedasticity consistent estimate of the variance-covariance matrix.

Table 3: Change in Farmland Value from Global Warming, Using All Counties in the Estimation (\$ billion, 1982)

Model	Change in Farm Value (\$ billion)	Change in Annual Profit (\$ billion)	Change in Profit per Acre (\$ per acre)
Cropland Weights			
Dryland, Non-urban Counties	-175.4	-5.12	-8.69
Irrigated, Non-urban Counties	-64.0	-1.87	-6.49
Urban Counties	-15.8	-0.46	-9.32
All Counties Combined	-255.2	-7.45	-8.04
Crop Revenue Weights			
Dryland, Non-urban Counties	35.7	1.04	1.77
Irrigated, Non-Urban Counties	-11.6	-0.34	-1.17
Urban Counties	8.8	0.26	5.23
All Counties Combined	32.9	0.96	1.04

Notes: MNS assume a climate change scenario consisting of a uniform 5 degree Fahrenheit increase in temperature and a uniform 8 percent increase in precipitation. The estimates presented here use the same regression coefficients as MNS but we correct what we believe is an error in their calculations. Since the dependent variable in their regression is value per *acre of farmland* one should multiply the predicted change in farmland value per acre by the acreage of farmland. It appears that MNS multiplied by the acreage of cropland, which on average is about one third of the farmland area.

We use the ratio of net farm income to aggregate farm value in 1982 as the conversion factor to translate the capitalized value into an annual impact. The ratio is 2.92 percent in 1982.

Table 4: Change in Annual Profits in Dryland, Non-urban Counties from Global Warming, Using Only Dryland, Non-urban Counties in the Estimation (\$ billion, 1982)

Model	Point Estimate	95 Percent Bootstrap Confidence Interval	95 Percent OLS Confidence Interval
Cropland Weights	-5.38	(-6.88; -3.77)	(-6.62; -3.99)
Crop Revenue Weights	-5.28	(-7.45; -2.93)	(-6.81; -3.64)

Titles of Figures

Figure 1: Change in Annual Profits from Global Warming using All Observations in the Estimation of the Coefficients. Impacts are Evaluated for Dryland and Non-urban Counties (\$ billion)

Figure 2: Change in Annual Profits from Global Warming. Dryland, Non-urban Counties Only (\$ billion)

Figure 1:

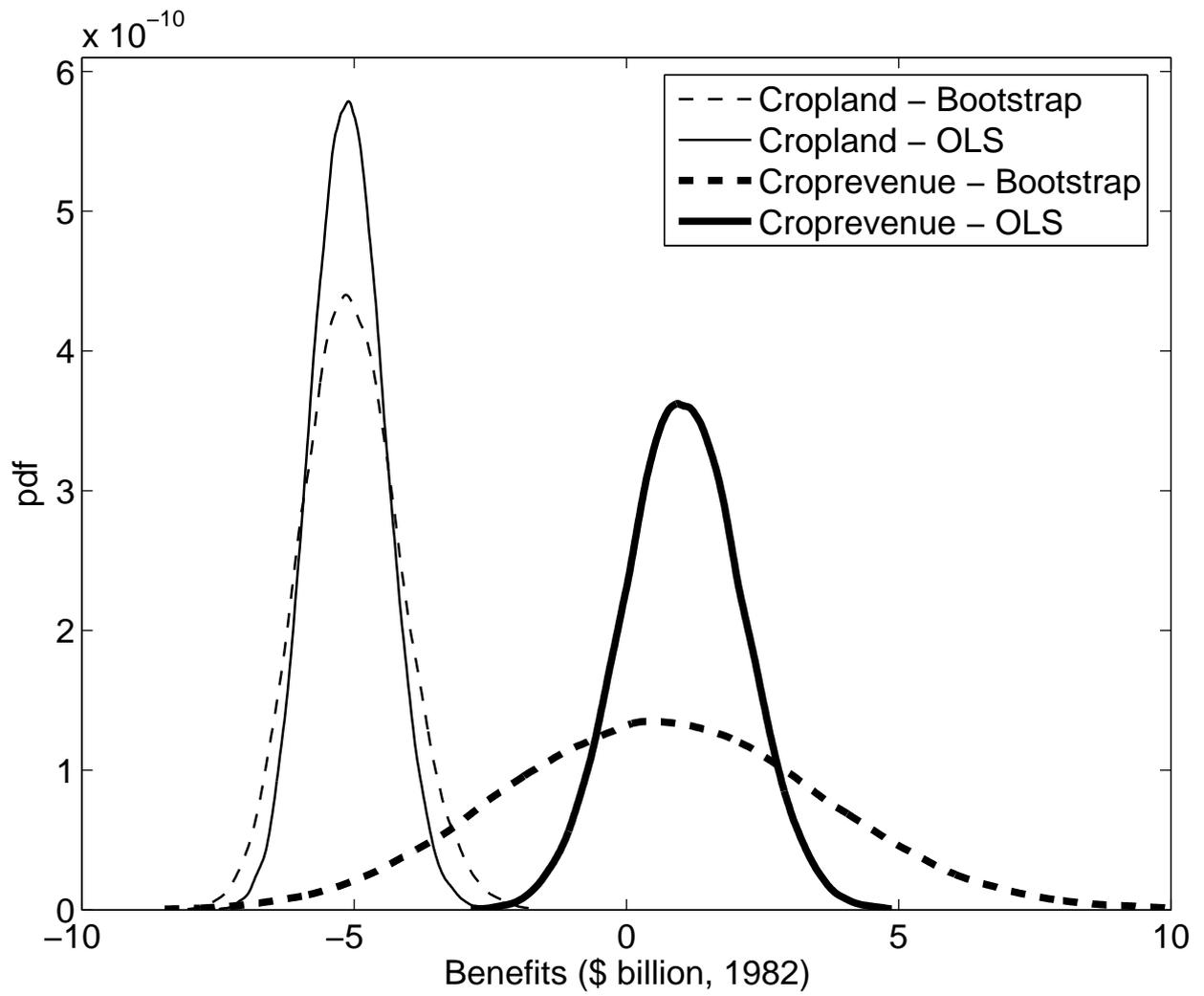


Figure 2:

