El Niño/Southern Oscillation Effects on Farmland Values in the United States

by

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Abstract: This paper evaluates the impact of the El Niño/Southern Oscillation (ENSO) on U.S. farmland values. Fourier series analysis decomposes climatological variation into ENSO and non-ENSO components. Farmland values, regressed against ENSO variation and other variables, are negatively affected by ENSO related weather variability in about 90% of U.S. climatological regions.

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In May of 1997 scientists observed changes in the atmospheric pressures in the Pacific Ocean that indicated the upcoming of yet another El Niño cycle. The 1997 El Niño event was one of the strongest on record and, in conjunction with the 1998 La Niña event, was responsible for causing extensive economic damage due to heavy rains, snow, and floods throughout the world. The agricultural sector is especially sensitive to the extreme weather events attributed to the El Niño/La Niña cycle. The effects of this cycle, also called the El Niño/Southern Oscillation cycle, or ENSO cycle, on specific crops and on prices of agricultural commodities has been well-documented in the past few years. Handler (1984) studied corn yields in the mid-western United States and found that there is a relationship between warm sea surface temperatures in the Pacific and high yields in the corn-belt region. Thompson (1990; 1992; 1993) also found a relationship between crops and ENSO cycles: corn yields in the mid-western U.S. were greater during El Niño years and lower than normal during La Niña years, whereas the opposite effects were found for wheat yields in the Dakotas and winter wheat in Kansas and Oklahoma. Tiller and Ugarte (1998) found that prices of simulated yields for eight crops were lower under during ENSO cycles, which they attributed to yield increases. Brunner (1998) found that El Niño years cause commodity price inflation of about 3.5-4 %.

Most of this research has been focused on one crop, or just a small number of crops, with little attention paid to how ENSO cycles affect the agricultural sector as a whole. We deviate from the traditional crop yield/price approach and instead examine the impact of ENSO related weather variation and its impact on farm values. The analysis rests on “Ricardian” rent theory, which suggests that weather induced changes in land productivity are capitalized into farmland values.

ENSO Cycles and Farmland Values

Our model adapts the two-stage approach used by Mendelsohn et al. (1994) to evaluate the impact on agriculture due to global warming. Mendelsohn et al. developed an empirical model for climate changes based on Ricardian land value theory. In the Ricardian theory, land rent in agriculture is simply the difference between revenues and production costs. Revenues are a function of quantity produced and the market price. Research has shown the quantity produced will depend upon weather related variables (e.g., precipitation and temperature), as will prices for agricultural commodities. Indeed, the literature cited in the introduction has found a link between ENSO cycles and agricultural output and agricultural prices.

A simple model will show that land rents are also a function of ENSO related weather variability. For any given agricultural market, let aggregate supply be described as a function of output price (P), a measure of ENSO related weather variability ($ENSO$), and other climatological variables (W), so that the supply curve is given by $Q^S=Q^S(P,W, ENSO)$. Further, the aggregate demand for the commodity is also a function of the market price. Assuming the demand for the commodity is a derived demand, other arguments of the demand function are the price of the final output (P_{Out}) and the price of substitute inputs (P_{Sub}), so that aggregate demand is given by $Q^D=Q^D(P, P_{Out}, P_{Sub})$. Equating aggregate supply and aggregate demand, and solving for the equilibrium market price shows that market price is also a function of ENSO related weather variation, $P=P(P_{Out}, P_{Sub}, W, ENSO)$.

Now let an individual producer's supply curve be denoted by a lower case *q(.)*, where the arguments of individual producer supply are the same as the aggregate supply. Producer rent in any time period *t* is then given by, $R_t = [P_t(P_{Out}, P_{Sub,} W, ENSO) * q_t(P,W, ENSO) - Costs_t]$, where costs are simply the sum of factor prices times factor quantities. Farmers will attempt to maximize rents at any time period *t*. Ricardian theory views the value of farmland as the capitalized value of the future stream of benefits from farmland, in perpetuity. Thus we obtain an expression for farmland values by taking the sum of rents over time, where the term in the denominator is the discount factor reflecting an interest rate, *i*,

$$\text{Farmland Value} = \sum R_t(ENSO, \textit{other variables}) / (1+i)^t$$

Mendelsohn et al argued that:

> *…with farms, land rents tend to be a large fraction of total costs and can be estimated with reasonable precision. Farm value is the present value of future rents, so if the interest rate, rate of capital gains and capital per acre are equal for all parcels, then farm value will be proportional to the land rent.*

The Expected Effect of ENSO Cycles on Farmland Value

The impact of ENSO-related weather variation on rents and farmland values is unclear. The producer observes ENSO effects as extreme weather conditions; depending on the geographic location of the producer ENSO effects may be manifested, for example, as either increased or decreased precipitation. Consider the producer's rent maximization problem at any time *t*. Rent (profit) maximization requires the producer to equate the value of the marginal product (VMP) for any input, say fertilizer, equal to its factor cost. Ex ante, the farmer will apply fertilizer in accord with his or her expectation with respect to exogenous factors of production such as precipitation, the outcome of which is unknown at the time the fertilizer input decision is made. Assuming output price is known and the farmer's expectation is that precipitation will be some amount μ, the farmer chooses fertilizer level $X(\mu)$ as the profit maximizing level (Figure 1, top). But precipitation is not known with certainty, instead following a probability distribution (Figure 1, bottom). If precipitation is some amount greater than normal, $\mu+\sigma$, fertilizer is more productive, shifting the VMP schedule to the right. While the producer benefits from the increased productivity (area ACHG), the producer would have liked to apply amount $X(\mu+\sigma)$ of fertilizer to maximize profits. Area ACE represents the loss due to uncertainty. Now consider precipitation outcome $\mu-\sigma$. Fertilizer is not as productive under low levels of precipitation, so the VMP schedule shifts left. The producer suffers losses given by area ABFG. Of this portion, area ABD represents losses due to overuse of fertilizer.

In either case, uncertainty is the driving force that makes it unlikely that farmers actually achieve the profit maximizing levels of input use. Thus, rent and farmland value are not maximized. We hypothesize that ENSO cycles represent added variation in weather variables, thus causing deviations from profit maximizing input use. The impact on farm values in any given geographic region will depend on whether ENSO-related climate variation skews the weather distribution to increase rents (on average, VMP shifts to the right) or skews the distribution to decrease rents (on average, VMP shifts to the left).

An Empirical Model

Obtaining a Measure of ENSO-Related Weather Variation

The National Oceanic and Atmospheric Administration (NOAA) has divided the contiguous U.S. into 344 climatological divisions called CLIMVIS regions. Monthly historical temperature and precipitation data are available for each region; previous research (Kappene and Ghil) has shown that the 1941-1991 time series for precipitation and temperature were stationary. Fourier series analysis (FSA) was used to separate the ENSO related variability from the other variability inherent in the time series of temperature and precipitation (DeLurgio 1998; Hamilton 1994). FSA separates variation in these series into cyclical components and white noise. ENSO is not a neatly cyclical phenomena and atmospheric scientists have described ENSO events with cycles of different periods, but the most common assumption is that ENSO events appear at 4-5 year intervals. FSA was applied to the monthly time series for each CLIMVIS division, yielding the *portion* of total variance in the series due to ENSO under the assumption of a 4-5 year cycle. All variance remaining in the time series was attributed to other cycles (e.g., the 18.5 year wet/dry cycle) and white noise.

Other Factors Influencing Land Values

Farmland values were available from the Agricultural Census for each county in the contiguous U.S. The data set represented a cross-section of data at a given point in time, so that no variation in the price terms influencing rents (output prices, input prices) was observed. These terms, therefore, did not appear in the estimation model. Other factors do influence the value of land, however, and data were gathered from a variety of sources. The National Resources Inventory (NRI) provided data for agricultural land class, soil pH, bulk density, salinity, clay content and permeability, the degree to which land was flood prone, and land elevation. County level data were also available from other Census sources for income and population density. For each type of variable, the data were scaled up from point level (NRI) or county level (Census) to match the CLIMVIS region level. Additional data for the model included mean monthly precipitation and temperature data. Following Mendelsohn et al., precipitation and temperature for the months of January, April, July, and October were included in the model, as proxy variables for winter, planting, growing, and harvesting conditions.

Empirical Results

Due to missing data, 338 usable observations (out of 344 CLIMVIS regions) were included in the analysis. To gauge the effect of ENSO cycles over time, the farmland value model was estimated for 1982 land values (using 1941-1981 precipitation and temperature data) and for 1992 land values (using 1941-1991 precipitation and temperature data). Farmland values and median regional income were converted to constant 1984 dollars. For each year specification #1 separates variation in monthly precipitation and temperature into ENSO and non-ENSO components, while specification #2 uses total variation (ENSO + non-ENSO variation). All models were estimated using OLS, and were weighted by total cropland in the region.

In the model for 1982, most of the variables had the expected sign and were statistically significant (Table 1). Increases in income and population density, indicating proximity to urban areas (i.e., alternative land uses), raise farmland values. Increasing salinity decreases the value of land, as does lower soil pH (more acidic land). The highest land class (Class I, the omitted category) was worth more than all lower quality land (classes II through VIII). Farmland at higher elevations was also worth less. Mean precipitation and temperature for the key months showed results broadly similar to those found by Mendelsohn et al.

In specification #1 for 1982 land values, five of the eight ENSO related variation measures for precipitation and temperature were statistically significant. Four variables showed that ENSO related variance had a negative effect on farmland value (April, July, and October precipitation) whereas July temperature variation had a positive effect. Five of the eight non-

ENSO related variation measures were statistically significant, of which four were negative. Specification #2 combined the ENSO and non-ENSO variation into a single measure of total variation without regard to ENSO cycles. Only three of the eight variation measures were statistically significant (January and July temperature, and October precipitation).

We can test whether separating precipitation and temperature variation into ENSO and non-ENSO components was worthwhile by using an F-test to compare the coefficients across the two models. Specification #1 was the unrestricted model with the following general form,

$$\ln(value) = a + b'\tilde{X} + g'EN + d'NEN$$

where *EN* is the vector of eight ENSO variation measures, *NEN* is a vector of eight non-ENSO variation measures, and *X* is a vector of all other variables. Specification #2 was the restricted model with the following general form,

$$\ln(value) = a \quad + b'X + w'TV = a + b'X + w'(EN + NEN)$$

where the elements of *TV* are the total variation for each monthly measure of precipitation and temperature, which are equal to the ENSO-related component plus its non-ENSO component. The test, therefore, has 16 restrictions (γ=ω and δ=ω, for all eight variation measures) across specifications #1 and #2. The F-statistic for the restrictions had a value of 2.18 whereas the critical value was 1.67; the null hypothesis was rejected, suggesting that ENSO- and non-ENSO related weather variation affect farmland values in different magnitudes.

With the exception of the population density variables, results for specification #1 of the 1992 land value model were broadly comparable to the 1982 results. For the variables of interest, however, the 1992 land value model changed considerably. Of the eight ENSO-related variation measures, only two (April precipitation and October temperature) were statistically significant. Both variable coefficients were negative. Four of the eight non-ENSO variation measures had statistically significant coefficients. Conducting the F-test across specifications #1 and #2, the null hypothesis that the coefficients across the two models were equal was not rejected ($F=1.09$; $F_{cv}=1.67$). For 1992 land values, decomposing precipitation and temperature variation into ENSO and non-ENSO components did not improve the model. This suggests that ENSO-related variation in precipitation and temperature do not affect farmland values differently.

The Impact of ENSO-Related Weather Variation on Farmland Value

The last three ENSO cycles (corresponding to the 1982, 1987, and 1992 El Niños) have been more severe than past ENSO cycles. This raises the question of whether ENSO-related variation in the precipitation and temperature time series is becoming larger relative to non-ENSO variation. For relatively small increases in ENSO variation, the effect on farmland values can be calculated by examining the total derivative of the model,

$$dValue = b \exp(.)dX + g \exp(.)dEN + d \exp(.)dNEN$$

where exp(.) is the exponential of the empirical model. If the change in the ENSO vector (d*EN*) is small, then d*X* and d*NEN* can be set equal to zero. Assuming a 10% increase in all components of the ENSO variation vector, the 1982 model predicts that farmland values across the U.S. would, on average, decrease by $30.62 per acre (with a 95% confidence interval of $2.74 - $57.05). This represents, on average, about a 4% loss in value. Agricultural land values in the mountain west were not affected substantially, but land values in the midwest, southeast, northeast, and Pacific northwest experienced declines in value (Figure 2).

As might be expected, the 1992 results were mixed. The model predicted an average loss of \$12.68 per acre, but the 95% confidence interval includes the value of \$0, ranging from a loss of \$34.81 per acre to a gain of \$7.59 per acre. Thus, despite the predicted loss of about \$13 per acre, it cannot be stated that ENSO-related weather variation influenced agricultural land values in 1992. The average loss was about 2% of land value. Again much of the mountain west experience little change in farmland value, as did the northeastern U.S. (Figure 2). Losses in land value were concentrated in the midwest and southeast, with gains in northern California.

Conclusions/Future Research

The analysis suggests that ENSO-related weather variation may have influenced farmland values in 1982, but in 1992 farmland values did not respond to ENSO variation any differently than non-ENSO variation. Did this result occur because the measure of ENSO variation was inadequate, or because farmers now receive advanced warning about ENSO cycles and engage in "defensive" farming practices? With respect to the first question, the FSA approach limits the ENSO effect to a harmonic 4-5 cycle. Alternative variance decomposition techniques, such a singular spectrum analysis, allow one to identify and extract variation due to anharmonic cycles such as the ENSO phenomena (Kappene). This line of research should clearly be pursued.

With respect to farmer adjustments to ENSO warnings, Costello et al. recently developed a model linking ENSO forecasts to management of salmon fisheries. Under different ENSO forecast scenarios, salmon harvesting can be managed to maximize producer and consumer surplus in commercial and recreational fishing. It is possible that, given ENSO forecasts in recent years, farmers might have managed farm enterprises to limit rent losses. This response should also be investigated.

Table 1. Farm Value Model: Dependent variable is ln(value per acre)

Independent variable	**1982**		**1992**	
	Model 1	**Model 2**	**Model 3**	**Model 4**
Constant	19.28 (0.0001)	23.47 (0.0001)	23.715 (0.0001)	23.755 (0.0001)
Income	3.09E-5 (0.0553)	2.7E-5 (0.0874)	6.6E-5 (0.0001)	5.2E-5 (0.0001)
Population Density	8.24E-5 (0.0539)	5.5E-5 (0.2020)	4.5E-5 (0.3507)	4.6E-5 (0.3346)
Population Density^2	-2.82E-9 (0.0964)	-1.93E-9 (0.2663)	-2.1E-9 (0.2737)	-1.91E-9 (0.3248)
Salinity	-0.149 (0.0001)	-0.169 (0.0001)	-0.075 (0.0607)	-0.085 (0.0312)
pH	-0.165 (0.0010)	-0.190 (0.0001)	-0.197 (0.0002)	-0.215 (0.0001)
Bulk Density	0.007 (0.8780)	0.007 (0.8687)	0.035 (0.4547)	0.040 (0.3827)
Land Class II	-2.755 (0.0001)	-2.825 (0.0001)	-2.736 (0.0001)	-2.763 (0.0001)
Land Class III	-3.228 (0.0001)	-3.262 (0.0001)	3.084 (0.0001)	-3.090 (0.0001)
Land Class IV	-3.619 (0.0001)	-3.600 (0.0001)	-5.718 (0.0001)	-3.256 (0.0001)
Land Class V	-4.796 (0.0001)	-4.292 (0.0001)	-5.718 (0.0001)	-5.359 (0.0001)
Land Class VI	-3.870 (0.0001)	-4.020 (0.0001)	-3.713 (0.0001)	-3.756 (0.0001)
Land Class VII	-4.16 (0.0001)	-4.307 (0.0001)	-3.959 (0.0001)	-3.898 (0.0001)
Land Class VIII	-1.680 (0.0175)	-2.207 (0.0024)	-1.087 (0.1796)	-1.494 (0.0514)
Clay	0.064 (0.3652)	0.078 (0.2646)	0.076 (0.2881)	0.072 (0.3036)
Permeability	0.027 (0.3652)	-0.028 (0.5831)	-0.012 (0.8187)	-3.4E-4 (0.9948)
Flood Prone	-0.692 (0.1682)	-0.916 (0.0673)	-1.600 (0.0035)	-1.827 (0.0005)
Elevation	-9.62E-5 (0.0001)	-0.0001 (0.0001)	-1.07E-4 (0.0001)	-1.1E-4 (0.0001)
Moisture quarter 1	0.310 (0.2322)	0.173 (0.5017)	0.842 (0.0073)	0.801 (0.0098)
Moisture quarter 2	0.108 (0.6660)	-0.053 (0.8320)	0.543 (0.0578)	0.635 (0.0245)
Moisture quarter 3	-0.242 (0.1817)	-0.058 (0.7489)	-0.467 (0.0695)	-0.398 (0.1016)
Moisture quarter 4	-0.271 (0.2586)	-0.186 (0.4463)	-0.224 (0.5766)	-0.361 (0.3561)
Temperature January	-0.018 (0.3430)	-0.006 (0.7406)	-0.03 (0.1819)	-0.033 (0.1245)
Temp January ^2	-0.001 (0.0338)	-0.001 (0.0037)	-5.6E-4 (0.3031)	-7.5E-4 (0.1520)
Temperature April	0.664 (0.0001)	0.550 (0.0001)	0.626 (0.0001)	0.553 (0.0001)
Temp April ^2	-0.005 (0.0001)	-0.004 (0.0001)	-0.005 (0.0001)	-0.004 (0.0001)
Temperature July	0.050 (0.7370)	-0.117 (0.4123)	-0.270 (0.0968)	-0.329 (0.0335)
Temp July ^2	-0.0007 (0.4487)	-0.0003 (0.7302)	0.001 (0.1652)	0.001 (0.0851)
Temperature October	-0.963 (0.0001)	-0.770 (0.0001)	-0.682 (0.0005)	-0.514 (0.0074)
Temp October ^2	0.009 (0.0001)	0.007 (0.0001)	0.006 (0.0002)	0.005 (0.0018)
Precipitation January	0.020 (0.8105)	0.042 (0.5947)	0.238 (0.0092	0.182 (0.0181)
Prec January ^2	0.007 (0.3887)	0.006 (0.4489)	-0.017 (0.0914)	-0.011 (0.1996)
Precipitation April	0.626 (0.0001)	0.444 (0.0002)	0.139 (0.2605)	0.247 (0.0335)
Prec April ^2	-0.043 (0.0202)	-0.051 (0.0061)	2.98 E-4 (0.9881)	-0.026 (0.1411)
Precipitation July	-0.348 (0.0001)	-0.443 (0.0001)	-0.411 (0.0001)	-0.406 (0.0001)
Prec July ^2	0.033 (0.0005)	0.044 (0.0001)	0.043 (0.0001)	0.041 (0.0001)
Precipitation October	-0.290 (0.0529)	-0.286 (0.0578)	-0.091 (0.5653)	-0.065 (0.6739)
Prec October ^2	0.042 (0.0839)	0.042 (0.0876)	0.059 (0.0361)	0.046 (0.0887)
EN Prec Jan	0.140 (0.4421)		0.117 (0.2323)	
EN Prec Apr	-0.355 (0.0241)		-0.264 (0.0976)	
EN Prec Jul	-0.299 (0.0718)		-0.049 (0.6032)	
EN Prec Oct	-0.384 (0.0989)		0.052 (0.5341)	
EN Temp Jan	-0.114 (0.0053)		0.012 (0.6192)	
EN Temp Apr	-0.178 (0.2741)		0.055 (0.5066)	
EN Temp Jul	0.331 (0.0010)		-0.100 (0.2938)	
EN Temp Oct	-0.039 (0.7437)		-0.147 (0.0177)	
Non EN Prec Jan	-0.003 (0.8849)		-9.4E-4 (0.9765)	
Non EN Prec Apr	-0.091 (0.0146)		-0.046 (0.1969)	
Non EN Prec Jul	0.042 (0.0718)		-0.013 (0.6455)	
Non EN Prec Oct	-0.060 (0.0153)		-0.120 (0.0003)	
Non EN Temp Jan	-0.012 (0.0001)		-0.015 (0.0069)	
Non EN Temp Apr	0.008 (0.6116)		0.008 (0.6563)	
Non EN Temp Jul	-0.177 (0.0001)		-0.189 (0.0001)	

Non En Temp Oct	0.011 (0.4902)		0.042 (0.0339)	
Total Temp Jan		-0.013 (0.0001)		-0.014 (0.0001)
Total Temp April		0.007 (0.6397)		0.013 (0.4698)
Total Temp July		-0.136 (0.0001)		-0.174 (0.0001)
Total Temp October		-0.004 (0.7877)		-7.46E-4 (0.9601)
Total Prec Jan		-0.005 (0.8108)		-0.006 (0.7895)
Total Prec April		-0.032 (0.3665)		-0.021 (0.5315)
Total Prec July		0.031 (0.1473)		-0.015 (0.5444)
Total Prec October		-0.048 (0.0490)		-0.085 (0.0008)
F-test	61.528 (0.0001)	65.594 (0.0001)	64.824 (0.0001)	73.577 (0.0001)
Adjusted R^2	0.9052	0.8964	0.9094	0.9065
Error Sum of Squares	50059542.196	56256818.437	51380597.741	54539239.467

p-values in parenthesis

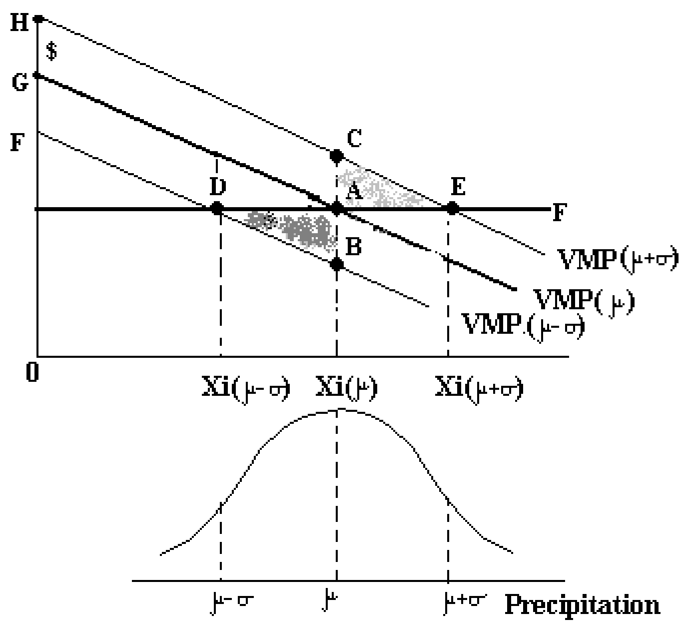
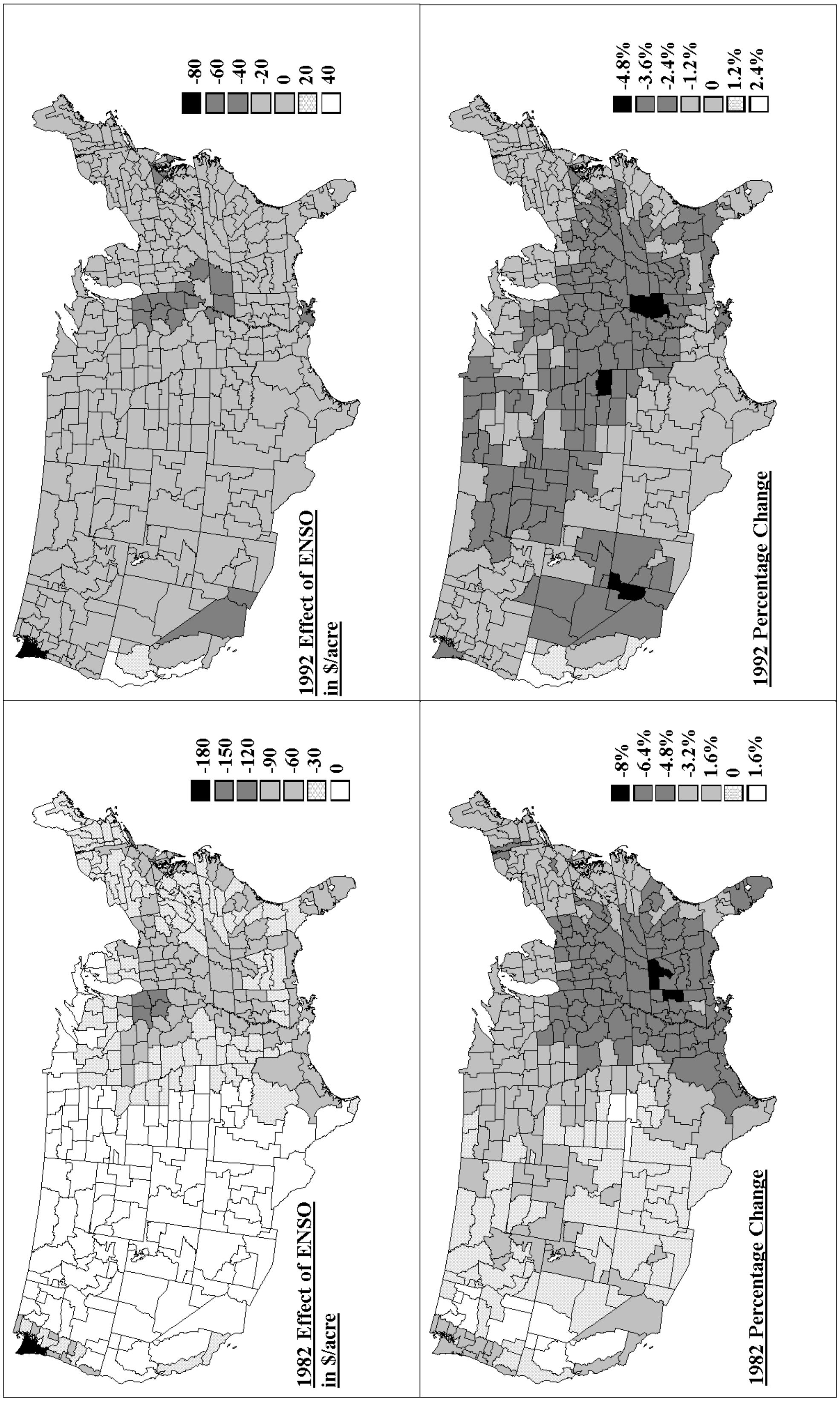


Figure 1. Rent Maximizing Conditions with Uncertainty


1982 Effect of ENSO
in $/acre
-180
-150
-120
-90
-60
-30
0
1992 Effect of ENSO
in $/acre
-80
-60
-40
-20
0
20
40
1982 Percentage Change
-8%
-6.4%
-4.8%
-3.2%
1.6%
0
1.6%
1992 Percentage Change
-4.8%
-3.6%
-2.4%
-1.2%
0
1.2%
2.4%

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