

**ENSO Effects on United States Farmland Values: A Ricardian
Approach**

**A Thesis
Presented for the
Master of Science Degree
The University of Tennessee, Knoxville**

**Dimitrios Dadakas
May 1999**

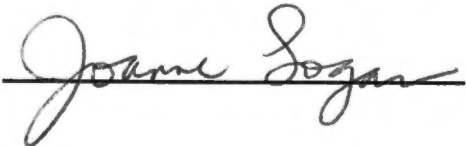
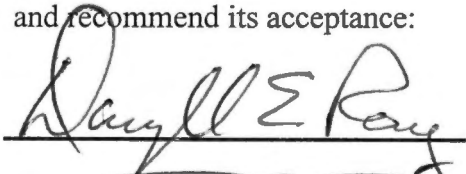
To the Graduate Council:

I am submitting herewith a thesis written by Dimitrios Dadakas entitled "El Niño/Southern Oscillation Effects on United States Farmland Values: A Ricardian Approach." I have examined the final copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Agricultural Economics.



Paul Jakus, Major Professor

We have read this thesis
and recommend its acceptance:



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Associate Vice Chancellor and
Dean of The Graduate School

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Πατερα-μητερα θελω να σας ευχαριστησω για οτι δυσκολια χρειαστηκε να περασετε για να βοηθησετε το γαιδαρο γιο σας να σπουδασει. Σας αγαπω πολυ.
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Abstract

This research examines the effects that El Niño and La Niña events have on agriculture in the United States. The procession of an El Niño and a La Niña event is referred to in this research as an ENSO. ENSO cycles cause weather anomalies that can significantly affect farmer income. In this research we are interested in determining what the effect of ENSO is on farmland values in the United States.

Previous research that has estimated the impact of ENSO on agriculture has been crop and region specific. We deviate from the traditional crop yield model approach that may provide biased results. To estimate the impacts the “*Ricardian Approach*”, developed by Mendelsohn, Nordhaus and Shaw is used, which allows us to model farmland values as functions of land characteristics, climate and an ENSO measure.

The model consists of two stages. In the first stage we obtain an ENSO variability measure of precipitation and temperature, which is extracted through Fourier Series Decomposition on the time series of precipitation and temperature. The results are then used as independent variables in a second stage cross-sectional data set regression conducted for the years 1982 and 1992, which estimates predicted values of farmland.

Results suggest that US agriculture may have adapted to weather variability caused by ENSO cycles by 1992. The phenomenon reduces farmland values mostly in the Midwest and in the Western regions of the US by an average of \$148 per acre. Most of the effects are caused by temperature related variability. Effects from precipitation related variability on farmland values are minimal.

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I. Introduction

In May of 1997 scientists observed changes in the atmospheric pressures in the Pacific Ocean that indicated an upcoming El Niño year. The 1997 El Niño was one of the strongest events that has developed thus far and was responsible for a number of weather abnormalities that triggered a chain of events such as heavy rain, snow and floods causing damages all over the world. The 1997 event was immediately followed by the 1998 La Niña event, which did not receive as much attention. During La Niña years weather abnormalities are seen as enhanced normal climate patterns¹. Although it is wrong to attribute individual storms to either El Niño or La Niña, history shows us that during La Niña years the US Atlantic coast sees a very strong hurricane season. During the 1998 La Niña event Hurricanes Georges and Mitch caused extensive damage in the southern United States and in Latin America. La Niña years can be as damaging as El Niño years. It is important to assess the damage that these two events cause.

The El Niño and the subsequent La Niña event, was first observed by fishermen in the coast of South America. Fishermen saw unusually warm waters on the Pacific after the period of Christmas several centuries ago, which would indicate an El Niño year (Glantz, 1991). (The name El Niño means “the boy” but it has come to mean the “Child Christ” a name given because the warm waters were observed near Christmas [Thompson, 1990]). The warm waters would signal “*years of abundance*” for the local people, who saw increases in crop yields from the heavy rainfall. The El Niño

¹ http://www.elniño.noaa.gov/laniña_new_faq.html (4-99)

phenomenon was recognized by scientists as early as 1932, by Sir Gilbert Walker who observed changes in water temperatures and atmospheric pressures. In 1960 oceanographers realized that the warm waters extended for thousands of kilometers westwards to the upper part of the tropical pacific. The warm waters were soon connected to global anomalies in the weather patterns and the large-scale atmospheric teleconnections² to the phenomenon El Niño/Southern Oscillation (ENSO).

The ENSO cycle has been blamed not only for droughts and floods, but also for outbreaks of encephalitis, plague and various diseases in the US, in South America, Australia and other regions of the world (Glantz, 1991). The economic consequences from ENSO related weather abnormalities can be enormous, both in aggregate levels and for households. Previous research has looked into the economic consequences of ENSO events such as the effects on corn yields and how commodity prices are affected from El Niño weather abnormalities. Most of this past research however, has been crop specific. It has not allowed farmers and consumers to look at how the agricultural sector in the whole United States is affected by the El Niño cycle. The agricultural sector depends on normal weather patterns in order to produce with little risk and few economic losses due to unexpected climate anomalies. The increased weather variability during El Niños and La Niñas introduces more risk in an already risky industry. Farmer income can significantly decline if those effects are not accurately predicted so that experts can make site and crop specific suggestions for production and policy makers can come up with programs to protect farmer income. The additional ENSO related weather variability

² The linkages over great distance of seemingly disconnected weather anomalies (Glantz, 1991).

affects agricultural practices all over the United States so it is important to determine and quantify the effect of ENSO induced weather variation on agriculture. This research adds to the existing literature by looking at how the agricultural sector of the United States is affected by El Niño cycles. We deviate from the traditional crop yield model that is crop and area specific and focus on the effect that the El Niño cycle has on the US agriculture, and specifically on the value of farmland throughout the United States.

The analysis rests on Ricardian rent theory, which suggests that weather induced changes in land productivity are capitalized into farmland values. As land becomes either more or less productive in response to ENSO weather effects individuals are willing to pay more or less for a parcel respectively, thus affecting the price of farmland.

II. Review of Literature

II-1. The Dynamics El Niño and La Niña

El Niños have occurred since the early times. It is not a phenomenon that appeared in the early 20th century and, unlike common belief, it is not related to global warming. Before proceeding with any discussion on the El Niño phenomenon a number of clarifications must be made about the terminology that is used throughout this thesis regarding the use of the terms El Niño, ENSO event, La Niña and El Niño cycle. This research is concerned with the effect that both El Niño (warm event) and La Niña (cold event) have on US farmland values. Most of the discussion will be for the El Niño phenomenon as it has received more attention in previous literature. However, we are interested in the effect of both events as most of the time a cold La Niña event follows immediately after a warm El Niño event. In some of the previous literature the term ENSO has been used to refer to the biannual cycle of a warm (El Niño) event and a cold (La Niña) event. This biannual cycle will most frequently be called the *ENSO event*, although the authors may have used the terms the *El Niño cycle* or the *4-5 year cycle*.

The reason the 4-5 year cycle was chosen to describe the El Niño phenomenon can be better understood by looking at past literature. On average El Niños are described to occur irregularly every 4 to 5 years. Lockyer and Lockyer (1902) confirmed the existence of an atmospheric pressure oscillation in the Pacific and estimated the period of the oscillation to be 3.8 years. Thompson (1993) described the El Niño as a 3-5 year

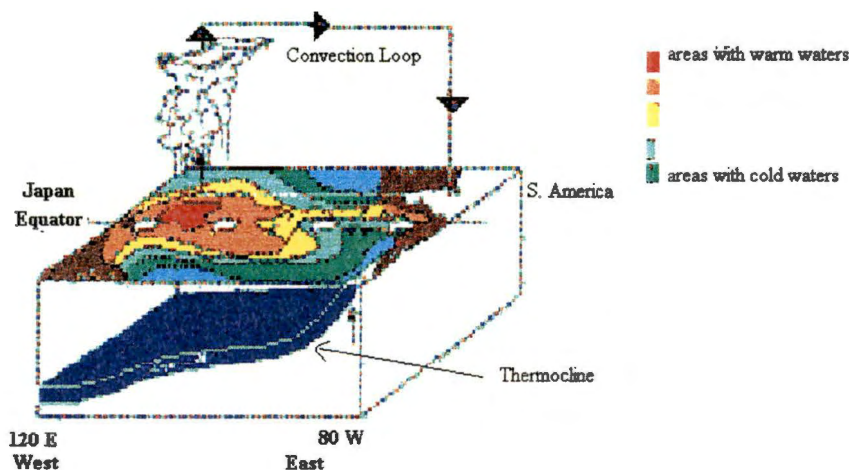
cycle. Kappenne, on the other hand used a lower 2-3 year high frequency and a 4-6 year low frequency component to capture El Niño variability in a principal component analysis. Trenberth (Trenberth in Glantz, 1991) suggested that the average time between two events is 4 years, however observations of two sequential El Niños can vary from 2 to 10 years. Jordan (Jordan in Glantz, 1991), on the other hand, examined the last 450 years in which 79 El Niño events were observed. Jordan separated those events into very strong, strong and moderate events. Very strong events are expected every 14 to 63 years, strong ones every 6 to 18 years and moderate every 2 to 11 years. While the question of what period identifies an ENSO event is debated by atmospheric scientists, the model used in this research will assume that an ENSO event is sufficiently described by a 4-5 year cycle, the average suggested by previous research.

During an ENSO cycle the ocean atmospheric system of winds is disrupted on the tropical Pacific. Normally, the ‘tradewinds’³ on the surface of the Pacific Ocean blow from east to west (figure II.1.1). The tradewinds cause a flow of warm surface water in the same direction, which piles up in the western part of the Pacific along the equator. As the water moves towards the west it creates a “warm pool” near the equator that extends approximately 100 meters in depth. Large amounts of water evaporate which cause low atmospheric pressures in the western part of the tropical Pacific. On the eastern side of the Pacific the warm water extends only down to 50 meters. The warm water is separated

³ The name tradewinds was given because these winds blow so regularly that trade ships could depend on them.

from colder waters by the “thermocline”, which can be seen in the lower (blue) part of figure II.1.1. The sea surface temperature is usually 8 C° higher in the west.

During an El Niño year the tongue of warm water reaching 28-28.5 C° (red area on figure II.1.2.) normally observed only in the western Pacific extends to the eastern side, causing a disruption in the winds that now blow from east to west. At the same time atmospheric pressure in the west Pacific increases. The change in the winds moves warm water from the west to the east and the thermocline is flattened. The warm ocean during El Niño years covers 5-10% of the earth’s surface. The change in pressure between two points on the two sides of the Pacific, specifically between Darwin, Australia and Tahiti, defines the Southern Oscillation Index (SOI), which is based on deviations from the normal sea level pressures

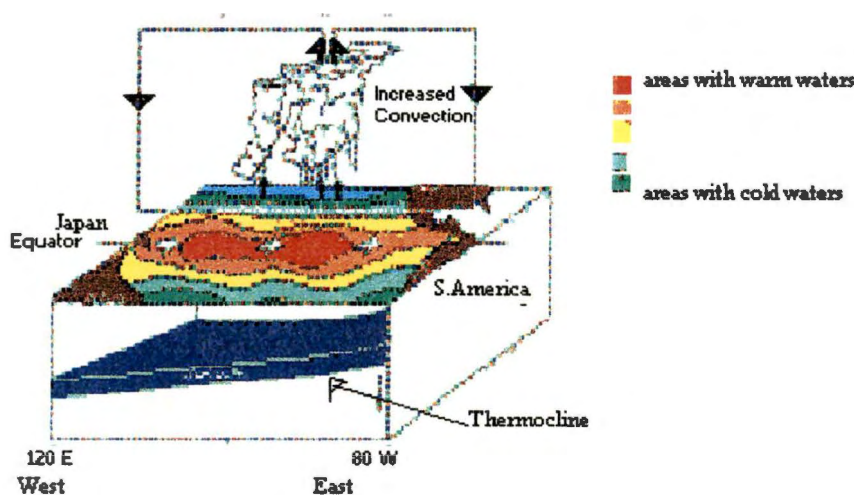


Graph taken from the NOAA web site (<http://www.pmel.noaa.gov/toga-tao/el-niflo-story.html>) (4-99)

Figure II.1.1. Water Temperatures in the Pacific during “Normal” non-ENSO Years

between Tahiti and Australia. High negative values of SOI describe a flatter thermocline, which means a collection of warm sea-surface temperatures in the east, indicating a warm El Niño event. High positive SOI, on the other hand describe a steeper thermocline (steeper than that seen under normal non-El Niño years in figure II.1.1) and warm waters extending only on the west-side of the pacific indicating a cold (La Niña) event. Cold La Niña events usually follow immediately after an El Niño event.

The combination of occurrence of the two events define an ENSO event. Although the term ENSO refers to the occurrence of both an EN and a SO event there is not a one-to-one relationship between the occurrence of Southern Oscillation events and El Niño events (Glantz, 1991). Southern Oscillation Index (SOI) changes usually indicate El Niño events but a change in the thermocline “seesaw” (SO change) can occur without observing the warm waters in the east Pacific and vice versa.



Graph taken from the NOAA web site (<http://www.pmel.noaa.gov/toga-tao/el-niño-story.html>) (4-99)
Figure II.1.2. Water Temperatures in the Pacific during El-Niño Years

The most intense phase of each event lasts approximately one year. An El Niño event usually starts as early as March and it starts fading out by March in the following year. Warm sea surface temperatures will develop during the period of March through early May (Diaz , 1992). The effects of El Niños are stronger during the winter of each hemisphere (Trenberth & Paolino, 1981). El Niños are categorized into strong, moderate, weak and very weak events as they are measured through the SO index.

During an El Niño event both the ITCZ (Inter Tropical Convergence Zone) and the (SPCZ) South Pacific Convergence Zone merge over the western portions of the Pacific. The ITCZ is a west to east oriented band of convective rainfall extending across the Pacific from the Philippines to the Central American Zone and the SPCZ is a broader region of rains extending southeastward from New Guinea to the Polynesian region (Diaz, 1992). Those zones merge over the western portions of the Pacific causing drier conditions over India and Australia during the monsoon season. Wetter conditions along the equator are found only in few regions of Asia such as Sri Lanka during the normal September through November rain season (Kiladis, 1989). Precipitation is increased in the southeastern regions of Africa during southern summer and fall. High precipitation is found over South America to the eastern part of the Andes and from Chile to Argentina during the winter until the following summer, as well as in the Gulf coast region, in parts of northern Mexico and in the Caribbean islands during winter.

Drier than normal conditions are found in areas of the western Pacific, the South Pacific islands, the Indian Ocean, Australia, Indonesia, and the Asian Monsoon. In Africa drier than normal conditions are found over Ethiopia, Egypt and the Sahel. Over the

Americas dry conditions are found throughout Brazil northward to the Caribbean islands through the fourth quarter of the year (Diaz, 1992). One of the most important consequences of the increased sea-surface temperatures can be found in the coast of Peru. Warm water prevents the upwelling of nutrient-rich cold water. As a result during El Niño years the low level of nutrients cannot support the diverse marine ecosystems and the fisheries of the region.

In the United States we can observe a number of diverse effects. El Niño warm events have been linked to suppressed Atlantic hurricane seasonal activity (Glantz, 1991). Although this is one of the positive effects of El Niños we must note that in 1992, the La Niña year that followed the 1991 El Niño, the US saw some of the strongest and most damaging hurricanes in its history including Andrew. During the 1998 La Niña year, Hurricane Georges caused extensive damage in the Southern US, while Hurricane Mitch caused 13,000 deaths in Nicaragua and the Honduras.

During El Niño years temperatures over the southeast United States are below normal in the summer and colder than normal during the winter. On the other hand, the northern parts of the US sees warmer than normal temperatures during the winter. In terms of precipitation the southern part of the US next to the Gulf region suffers wetter than normal conditions during the winter. Heavy rainfall is also found in Texas. These areas see heavier than normal precipitation from October, after the warm temperatures are observed in the coast of Peru, until the March of the next year. The area of California and the South-west sees higher than normal precipitation from April until October of the year El Niño is observed (Philander, 1990). It is necessary to note, however, that there is

variability over each El Niño event so that different effects can be found for the same regions each time.

In most El Niños a warm event is immediately followed by a cold La Niña event. The change in the phase from an El Niño to a La Niña event usually occurs between March and April. During La Niña events the tongue of warm water with temperatures higher than 27.5 C° recedes to the western part of the pacific and the thermocline becomes steeper. La Niña cold events have been linked to persistent summer time drought in North America during 1988 (Trenberth, 1988), heavy rainfall over the monsoon regions and increased hurricane activity in the west Atlantic coast.

II-2. Agricultural Crop Yields and General Climate Data

A number of researchers examined the effect that changes in global temperatures and precipitation have on crop yields. Although most of this research is not directly linked to ENSO weather anomalies, it is still useful for our purposes because ENSO cycles affect annual precipitation and temperature rates, which in turn affect crop yields. By examining how temperature and precipitation extremes and anomalies affect crops in the United States we can infer some expectations about the likely effect that El Niño related weather anomalies will have on US agricultural yields.

Arthur and Abizadeh (1988) found that while temperatures rise under different climate change scenarios, those increases vary from region to region. In areas with small

temperature increases, slight rises in precipitation levels can offset increased evapotranspiration and can lead to increased production volumes. For most crops initial moisture stress resulted in increased yields for the early stages of crop growth. Yields declined for further moisture stress. Since changes in temperature and precipitation affect crop yield levels, ENSO cycle variation in temperature and precipitation might affect crop yield levels differently across different regions in the US.

Dixon, Hollinger, Garcia and Tirupattur (1994) added to the existing literature on yield estimation by separating the stages of crop growth. They suggest that the three most important weather-related factors for plant growth are soil moisture, ambient air temperature and solar radiation. Their approach included weather variables measured at different times of crop growth, which allowed the use of the model if climate change were to shift the dates of the crop growing seasons. They measured the effects of climate variables during four stages of plant growth: early vegetative growth, development, pollination and grain fill. This research shows that it may be important to consider 'timing' in ENSO related weather variability to months of the year that are representative of growth stages.

Offut, Garcia and Pinar (1987) explored how US corn yields respond to advances in technology and changes in weather. They explored whether changes in technology have accentuated or moderated the impact of weather on corn yields. Among other results, they suggested that variability of yields has increased over time and that there is no evidence that yields have reached an upper bound. They attributed the increased yield

variability to either weather variability or to the increased sensitivity of new technologies to weather variables. The literature on global climate change is summarized in table II.1.

II-3-A. ENSO and Agricultural Crop Yields

Having examined some of the literature relating temperature and precipitation anomalies to crop yields, we now turn to the literature examining the impact that El Niño and La Niña events have on crop yields and prices. One of the first studies to examine El Niño effects on agriculture was by Handler (1984), who studied the impacts of Pacific temperature anomalies on US corn yields. Corn yield levels for 50 El Niños from 1868 to 1982 were examined. Corn yields were classified as “normal” if the yield was within 3% of the trend line. In Illinois yields in 30 out of 50 El Niño years were above the trend line 11/50 on the trend line and 9/50 below the trend line. Results were similar for Iowa where yields in 30 out of 50 El Niño years were above the trend line as well. Handler suggested that higher sea surface temperatures were likely to displace storms southwards, from Canada towards the northern United States during the growing season. The resulting moist climate was able to produce corn yields above average.

Nicholls (1986) used the Southern Oscillation Index to predict sorghum yield in Australia. He investigated the relationship of yields and the SO index to show that a lagged relationship between the index and yields allows early prediction of sorghum yields. The technique involved correlating average sorghum yields with a three-month

Table II-1. Global Climate Change/Agricultural Yield Literature

Author	Pub. Date	Region/ Crops or Variable studied	Method Used	Results
Arthur M.L. <i>et al</i>	1988	Northern Prairie regions of Canada	General Circulation Models	Small temperature increases can result in increased yields.
Dixon L.B. <i>et al</i>	1994	Illinois, corn	Corn yield response model. Separated crop growth stages	Increased temperature during last three stages of growth had a negative effect on yields. Precipitation was insignificant in explaining yield variation.
Offut E.S. <i>et al</i>	1987	US corn yields	Pre and post 1950's yields were examined to determine ag. response to changes in technology and weather	Increased yield variability can be attributed to either weather variability or to increased sensitivity that new technologies have to weather variables.

average SO index from before and during the growing season. Results suggested that yields were correlated to the SO index and were predictable during the pre-planting season from observations of the SO index. Yields were negatively correlated with Darwin pressures during and before the growing season. Sorghum yields were lower than normal during El Niño years and higher during La Niña years.

Cane, Eshel and Buckland (1994) examined the effects of El Niño in Zimbabwe of South Africa for the 1991-92 warm event. They found that there is a very strong correlation between an El Niño index⁴ and both rainfall and the yield of maize in Zimbabwe. Results indicated that the correlation of an El Niño event is stronger with maize yields than with rain. The correlation of an El Niño event to maize yield was found to be 0.57 and it was significant at the 0.01 a level.

Thompson (1993) approached the weather-yield relationship by looking at the global warming and cooling cycle. He notes that corn production was stable from 1957 to 1973, after which corn production was low for three years in a row, which he attributed to dry phase of the 20-year weather cycle (1990). A general pattern seemed to emerge when he observed that El Niño years were accompanied by high corn yields in the Midwest, whereas the following year corn yields were reaching record lows. Furthermore, El Niño's impact seemed to be more severe in the dry part of the 18.5-year cycle and in the warming phase of the global 100-year temperature cycle. In view of this, the year 1993

⁴ The Pacific Ocean is divided into four Niño regions. Cane et al. use the sea surface temperature of the Niño3 region because the series is less noisy.

was expected to be a very bad year for corn yields as it was following an El Niño event and at the same time it was at the dry part of the 18.5-year wet-dry cycle⁵.

Thompson's results also suggested that normal preseason precipitation and June temperatures with cooler and wetter weather during July and August could be associated with increased yields during the 1992-93 El Niño.

Thompson (1992) also looked at the effect of El Niño on simulated wheat yields in South and North Dakota and winter wheat yields in Kansas and Oklahoma. Results for spring wheat showed that yields for El Niño years were normally distributed above and below the yield with normal weather. Winter wheat yields on the other hand seemed to be lower than normal for El Niño years and higher the year after.

The literature suggests that ENSO definitively affects crop yields. ENSO has a positive effect on the production of some crops and a negative on others. However, this effect that we observe on crop yields is ambiguous. Some crops benefit, whereas others don't. ENSO causes uncertainty in the production of agricultural commodities for farmers. The literature on ENSO effects on yields is summarized in table II.2.

II-3-B. ENSO and Market Prices

Another way in which ENSO may affect agriculture is through impacts on commodity prices. If the El Niño cycle affects prices then it will also affect farmer

⁵ The 1993 eruption of Mt. Pinatubo caused global cooling resulting in record high corn yields.

Table II-2. El Niño/La Niña Effect on Yields Literature

Thompson L.M.	1992,1993	Midwest, SD, Kansas, Oklahoma. Corn, Wheat.	Looked at deviations from the yield distribution.	El Niños are associated with increased corn yields and La Niñas with decreased corn yields. Opposite results were found for winter wheat.
Handler P.	1984	Iowa, Illinois, Corn	Compared yield deviations for 50 EN from 19868 to 1982	For 30 out of 50 EN yields were above the trend line. During EN years sorms were likely to be displaced southwards from Canada to the northern US favoring corn yields.
Nicholls N.	1986	Australia, Sorghum yields	Yield simulation. Correlated average sorghum yields with SO index.	Simulated yields were lower during El Niño years and higher during La Niña years.
Cane M.A. <i>et al</i>	1994	Zimbabwe, Maize	Examined correlation of El Niño index with rain and yields.	El Niño correlation with yields was 0.57 and significant.

profits by changing the value of land productivity. Tiller and De La Torre Ugarte (1998) linked probabilities of current El Niño strength to historical crop yield deviations to estimate the likely impacts of the 1997 event on crop yield, acreage and income. Their method utilized a stochastic version of the Policy Analysis System (POLYSYS) national agriculture simulation model. POLYSYS allowed for the development of a probability distribution for the yields of eight crops through an iterative random draw from annual crop yield deviations for the years 1972-1996. The random draw was then weighted by the probability of the event developing into a strong, moderate or weak event. Simulated yields of corn, cotton, soybean, rice and sorghum were higher while yields for oats and barley declined. Harvested acreage in the Southeast was lower under the ENSO simulation with the largest acreage reductions in Georgia, South Carolina and the smallest in Tennessee and Kentucky. Prices of all eight crops were lower, which was attributed to increased supply due to yield increases. Furthermore, net returns under the ENSO simulation were greater for cotton, grain sorghum and wheat, and smaller for corn, oats, barley, soybeans and rice.

Another study examining the effect of El Niño on commodity prices was conducted by Brunner (1998), who used vector autoregression to examine the historical effects of El Niño on world prices and on economic activity. Brunner's analysis indicated that El Niño has a significant effect on world real commodity prices and that a one standard deviation from normal sea level pressures (the El Niño signal) could cause real commodity price inflation of about 3.5-4%. Brunner also found that El Niño accounts for 20% of commodity price inflation movements and for about 10-12.5% of

world consumer price inflation and world economic activity. Prices for food commodities and agricultural raw materials are the ones most affected by El Niño, although the effect can also be seen on prices of beverages and metals.

An FAO report (The Possible Impact of El Niño on Agricultural Commodity Prices, December 1997) on the possible impacts of El Niño indicated that for commodities with low levels of stock any declines in production, or even any speculation about shortfalls, might have a significant impact on demand with potential for rising prices in many markets. In mid-1998 prices of protein substitutes were expected to increase because South-American fishmeal production was expected to decrease by 15-20%, which would cause an increase in the demand for protein substitutes. Higher international rice prices were expected due to decreases in the production of rice in Brazil and India, which resulted in an increase in import demand.

In the July 14, 1998 USDA International Agricultural Trade Report⁶ it was reported that strong international prices of rice lured 5% more acreage in the United States in the production of rice, supporting the FAO report. USDA suggests that the lingering effects of El Niño will keep the US exports moving to Latin America until the end of the 1999 calendar year, thus keeping prices high. Wheat production was not expected to be significantly affected by the 1997 El Niño, however the authors suggest that the wheat market was reacting nervously to weather reports because low levels of wheat stocks and possible spillovers from other commodity markets can cause higher wheat prices. The cotton market was not expected to be significantly affected as the

⁶ (http://www.fas.usda.gov/grain/highlights/1998/98-07/rice_out.pdf) (4-99)

countries likely to be affected by El Niño were likely to balance out with countries such as the United States where cotton production during El Niño was expected to increase due to increased precipitation and temperatures. Drought conditions brought about by El Niño were also expected to damage the livestock sector and meat production either by deteriorating pastures and meadows or by reducing the output of basic feedstuff. High heat could also cause a reduction in animal fertility and an increase in the mortality rate. El Niño was expected to result in an increase in meat output and falling prices in 1998, followed by a reduced meat production and a price recovery in the succeeding years. The pig industry did see in late 1998 the lowest prices for hogs for the last 26 years⁷. The reduction in the availability of coarse grains and the projected higher feed prices was also expected to have negative consequences in the production of poultry and pig meat during the second half of 1998.

Although some of these expected price changes in agricultural commodities occurred while others did not the important conclusion for this study is that economic research suggested that we should expect to see some effect of ENSO events on commodity prices. We conclude that El Niño cycle events can also affect prices of agricultural commodities. These changes in output and prices of commodities represent a change in return to land and thus an increase or decrease in the rent and the value of the land. The literature on ENSO effects on agricultural commodity prices is summarized in table II.3.

⁷

(<http://www.showmenews.com/archive/1998/Oct/29/Business%20Finance/1998102908.html>).(3-99)

Table II-3. El Niño/La Niña Effects on Prices Literature

Tiller H.K. <i>et al</i>	1998	Southeast United States. Corn, cotton, soybeans, rice, sorghum, oats, barley.	POLYSYS simulation model.	Corn, cotton, soybean, rice and sorghum yields increased whereas oats and barley yields decreased. Large acreage reductions occurred in GA, SC and smaller in TN and KY. Prices for all crops were lower.
Brunner D.A.	1998	World commodity prices.	Vector autoregression.	El Niño has a significant effect on commodity prices. A one standard deviation from SO pressures could cause real commodity price inflation of 3-4%. El Niño Granger causes commodity prices.
Prepared by the FAO committee and trade commission	1997	World agricultural commodity prices.		Prices for protein substitutes, rice, soybeans and wheat are expected to increase due to the El Niño. Effects will also be felt in the livestock sector and on maize production and prices.

III. Theory

III-1-A The Ricardian Model

The model used to estimate the effect of ENSO events on the value of land is the “Ricardian” approach introduced by Mendelsohn, Nordhaus and Shaw (1994).

Mendelsohn *et al* suggested that research using production-function and crop yield models to examine the impact of climate on land values has a tendency to overestimate the damages to farming. Crop yield models overestimate the damage due to an inherent bias that Mendelsohn calls the “dumb-farmer scenario”. The dumb farmer scenario can be seen in figure III.1, adapted from Mendelsohn et al.

That inherent bias lies in that production yield models do not account for farmer’s ability to adapt to the changing climate by shifting production towards a more profitable activity. For example, if the value of wheat production decreases as climate temperature increases, then once the value of the activity decreases from π_b to π_c the farmer will shift production from wheat towards more profitable corn. The traditional production function approach does not permit farmers to adjust production in response to changing climatic conditions. Instead it overestimates the damage by suggesting that by the time temperature increases to T_f the value of the production activity will be as low as π_f . However, before temperature reaches those levels farmers will have shifted production towards corn, which has a value of π_d . In this simple example wheat production declines

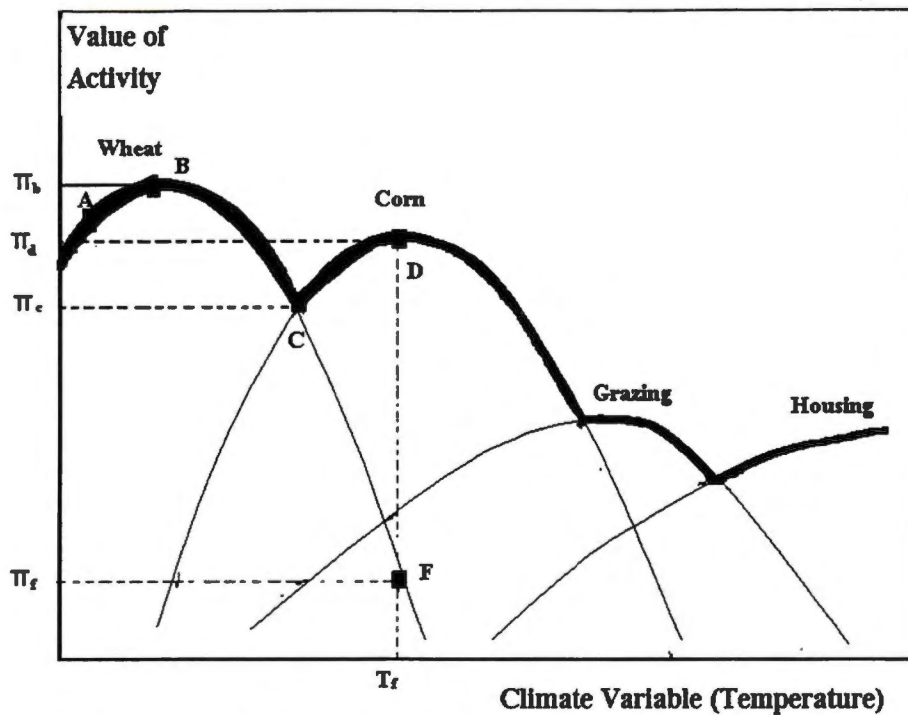


Figure III.1. Dumb Farmer Scenario

as farmers shift to corn. If a production-function approach were used to estimate damage due to increasing temperatures, the model could overestimate the damage to farmers by $\pi_d - \pi_f$. The “Ricardian” approach attempts to recognize this bias and estimates the value of land as a function of the climate variables and land characteristics, tracing the heavy line in figure III.1, which Mendelsohn calls “*best-use value function*”.

Mendelsohn et al measured the best-use value function for global climate variables on US agriculture. They measured the economic impact of climate on land prices using cross-sectional data on climate, farmland prices and other economic and geophysical data for 3,000 counties in the US. The approach consisted of two stages. The first stage estimated mean climate for each one of the counties in the United States

from time series data. The predicted values of mean temperature and precipitation for each county for January, April, July and October were then used as independent variables in a second-stage model. The second stage estimated the value of land as a function of climate, land characteristics and socioeconomic characteristics in each county.

The Mendelsohn et al model rests on Ricardian rent theory, which considers the value of land as the present value of the future stream of rents or

$$(3.1) \quad PV(land) = \sum_{t=1}^{\infty} \frac{rent_t}{(1+r)^t}$$

where PV represents the present value of land, $rent_t$ is the rent received from a parcel of land at time period t , and r is the discount rate, which is assumed to be constant over time. Rents are defined as:

$$(3.2) \quad Rents_t = P_t * q_t - C_t$$

where rent received at time t is equal to quantity produced by individual producers (q_t) times the market price (P_t) less input costs (C_t) at time t .

With this definition of rent in mind, we proceed to include an ENSO effect in the Ricardian rent theory using a simple supply-demand relationship for an agricultural commodity. The literature previously reviewed revealed that the quantity produced of an agricultural commodity is affected by ENSO events. A simple aggregate supply function for an agricultural commodity, for example sorghum, will depend on the prices of the output, weather variables and an ENSO effect such that:

$$(3.3) \quad Q^s = S(P_{\text{sorghum}}, W, \text{ENSO})$$

with Q^s representing the quantity supplied of sorghum, P_{sorghum} the market price of sorghum, W the weather and ENSO a measurement of the effect of ENSO events. The derived demand for sorghum, say for animal feed, is given by :

$$(3.4) \quad Q^d = D(P_{\text{beef}}, P_{\text{sorghum}}, P_{\text{corn}})$$

with Q^d representing derived demand for sorghum, P_{beef} the market price of the output commodity that uses sorghum as an input, P_{sorghum} the price of sorghum and P_{corn} the price of substitute input such as corn. At equilibrium, quantity supplied is equal to quantity demanded and thus:

$$(3.5) \quad S(P_{\text{sorghum}}, W, \text{ENSO}) = D(P_{\text{beef}}, P_{\text{sorghum}}, P_{\text{corn}})$$

By inverting equation 3.5 we can get an expression for the market price of sorghum such that:

$$(3.6) \quad P_{\text{sorghum}} = P(P_{\text{beef}}, P_{\text{corn}}, W, \text{ENSO})$$

Equation 3.6 demonstrates how the market price of the agricultural commodity will depend on ENSO related weather variation.

To illustrate this point graphically, figure III.2. shows how the interaction of the supply and demand, with ENSO effects, determines market price and aggregate supply. The supply S_1 of sorghum can shift up to S_3 or down to S_2 due to ENSO events, following equation 3.3. Changes in the equilibrium price of sorghum represent movements along the demand curve. So a supply shift might move the equilibrium price from P_A to either P_C or P_B .

At the same time the derived demand for sorghum might also shift due weather changes caused by ENSO events. In terms of equation 3.4, the demand for sorghum is also a function of the price of corn.

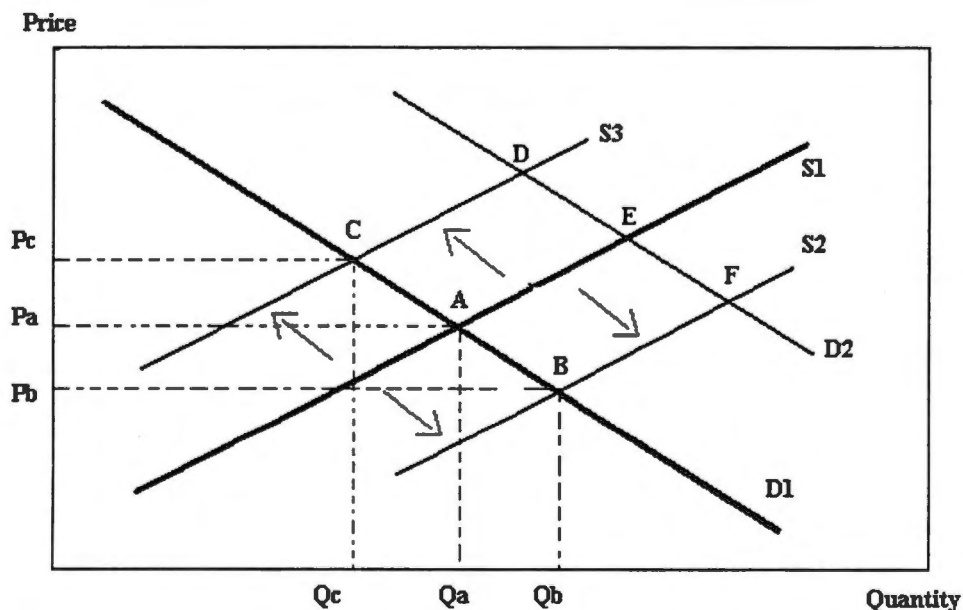


Figure III.2. ENSO Induced Shifts in Derived Demand and Aggregate Supply of Sorghum

Because the supply of corn is also subject to ENSO effects, the price of corn may change (equation 3.6), thus shifting the derived demand for sorghum. Thus, for a rise in the price of corn, the demand for sorghum shifts right to D_2 . Depending on the supply of sorghum (curves S_1 , S_2 , or S_3) equilibrium price and quantity may be characterized by the points D, E, or F. From this simple example, it can be seen that ENSO events affect the output price and the quantity of an agricultural commodity.

Increased weather variability may also increase the costs of production, as the farmer must deal with averting potential losses due to weather extremes either through insurance or through practices such as irrigation. For example, some of the costs that farmers incur are labor and capital costs,

$$(3.7) \quad C = r \cdot l + v \cdot k$$

where C is total costs, r is the cost of labor, l is the quantity of labor, v is the cost of capital and k is the quantity of capital.

Equations 3.3 and 3.6 show that ENSO is a factor in determining quantity produced and the equilibrium price. Substituting 3.3, 3.6, and 3.7 into equation 3.2 we obtain a Ricardian rent model with ENSO effects,

$$(3.8) \quad \text{Rents} = [p(P_{\text{beef}}, P_{\text{com}}, W, \text{ENSO}) * q(P_{\text{sorg}}, \text{labor}, W, \text{ENSO}) - (r \cdot l + v \cdot k)]$$

Ricardian rent theory views the value of farmland as the capitalized value of the future stream of benefits from farmland from year $t=1$ to $T=\infty$. Thus, by substituting 3.8 in 3.1 we obtain a general expression for farmland values that reflects an ENSO effect:

$$(3.9) \quad PV = \sum_{t=1}^{\infty} \frac{R_t(ENSO, P_{out}, P_{sub}, W, P_{inputs})}{(1+r)^t}$$

where PV is the present value of the land, or the discounted sum of Ricardian rent. P_{out} represents the price of the output product (equivalent to the P_{beef} in the example), P_{sub} represents prices of substitute products (equivalent to the price of corn in the example), and P_{inputs} represents costs for inputs to production. Because the Ricardian value of land is a function of rent, farmland values are also a function of El Niño cycles.

III-1-B. Developing an Empirical Version of the Rent Model

Rents and Prices

Although we usually cannot observe rents because they are a small portion of profits, Mendelsohn et al argue 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. Therefore, by observing the relationship of farm values to climatic and other variables, we can infer the shape of the best use value function...

Prices of output products, prices of inputs and prices of substitute products that are seen in equation 3.9 are not included in the empirical estimation because the available data are a cross section of observations, where prices are held constant⁸. However, some *other* variables that affect the productivity of land might also be considered.

Plant Growth

Literature reviewed in chapter II showed that temperature and precipitation affect the productivity of land. Dixon (1994) argues that temperature and precipitation variables should reflect the different stages of plant growth. In this study we follow Mendelsohn by choosing temperature and precipitation for the months of January, April, July and October; the first month of every season. However, Arthur et al (1988) also suggested that increased precipitation might offset the effect of increased evapotraspiration. Since evapotranspiration and precipitation are capturing different effects we also include a “moisture anomaly index”, which is defined as a measure of departure from normal moisture climate. We tie the moisture data to the same months as the rest of the climate variables.

Soil Characteristics

Soil characteristics affect the productivity of land. The quality of the land across the United States is vastly different, which imply different productivities. A number of

⁸ Technology is also held constant as we are looking at cross-sectional United States data for one year.

variables that describe the characteristics of the soil are also included. These variables include salinity, permeability, land class, slope and elevation.

Urban Influences

Phipps (1984) explored the theoretical and empirical relationships between farm based residual returns, rents and farmland prices. Phipps suggests that agricultural land does not have a nonzero opportunity cost, since land can be put in alternative uses such as non-farm or development use. For land that is located in agricultural regions farmland prices should follow farm based returns whereas for parcels of land that are located on the rural-urban fringe farmland price would be influenced by non-farm based returns. Shi, Phipps and Colyer (1997) hypothesized that the price differential between use value and market values is directly related to the population of urban areas.

Adjusting for these additional factors, the model of equation 3.9 becomes

$$(3.10) \text{ Rent} = R(\text{Alternative Use, Land characteristics, Plant Growth Phase, W, ENSO})$$

We use population density and income as an indicator of alternative uses of land. As agricultural areas are less densely populated than urban areas, areas with low population density are expected to be primarily agricultural land whereas areas where the population density is higher are expected to put land into alternative uses. Higher median income also proxies urban areas.

III-2. The Expected Effect of ENSO

We have developed a model showing that ENSO related variability should affect the value of land. We now rely on microeconomic theory to examine testable hypothesis regarding ENSO events. We want to determine whether increased variability will have a negative effect on farmland values, a positive effect or whether the effect of ENSO variability on land values is ambiguous.

First consider optimal production decisions with certainty, where weather related conditions are perfectly known in advance by farmers. Let quantity produced be a simple function of precipitation and a vector of other production factors, $\tilde{X}$, such as labor, capital and other inputs. For simplicity also assume that precipitation is simply an annual total and this is all that a producer needs to know. Finally, assume that output price is constant from the farmer's perspective. The farmer's profit maximizing problem is given by

$$(3.11) \quad \text{Max} \pi = P * q(\tilde{X}, \text{precipitation}, \text{temperature}) - \tilde{F}' \tilde{X}$$

with $\tilde{X}$ representing a vector of i factors of input into production and $\tilde{F}$ a vector of the factor cost of each input i . With precipitation and temperature levels known in advance, the first order condition gives us

$$(3.12) \quad \frac{\partial \pi}{\partial \tilde{X}_i} = P * \frac{\partial Q}{\partial \tilde{X}_i} - F_i$$

Depending on the functional form of the production function, the derivative $\frac{\partial Q}{\partial \tilde{X}_i}$ will have the climate variables either as shifters of the value of the marginal product or it might affect the slope of the MP curve. In its general form $\frac{\partial \pi}{\partial \tilde{X}_i}$ will give us the profit maximizing conditions:

$$(3.13) \quad VMP_i(X_i, precipitation, temprature) = F_i$$

where VMP_i is the value of the marginal product. Equation 3.14 tells us that under certainty farmers maximize profits by setting the value of the marginal product of each input of production i equal to its factor cost F_i . In this case temperature and precipitation affect the value of the marginal product but they only act as shifters. We can see this in figure III.3.

When we produce under certainty the precipitation and temperature levels are known and we know the position of the value of the marginal product. The density function for precipitation is a spike because it has a known outcome, μ_0 . We also know the wage rates, which allows us to produce optimally by equating the value of the marginal product for each resource X_i to its factor cost. The profit maximizing level of input X_i is then $X_i(\mu)$. In this case the density of quantity produced of the agricultural commodity is also a spike, i.e. there is no variance in output.

Now let us introduce uncertainty regarding weather extremes. Let precipitation for example be a normally distributed random variable with mean μ and variance σ^2 . Farmers still attempt to maximize equation 3.11, only now the level of precipitation is not known. The farmer tries to set the value of the marginal product of factor i equal to its factor cost, but uncertainty resulting from ENSO events shift the VMP either to the left or right making it difficult for the farmer to set $VMP_i = W_i$. Consequently the farmer is unlikely to be able to maximize profits for any given precipitation outcome. We can see the above results clearer in figure III.4 (reproduced and adapted from Howitt, 1993). In this case the random variable precipitation can affect the marginal product and thus the value of the marginal product by shifting the VMP function to the left or right. The farmer may form an expectation of total precipitation, say μ , and aims to use $X_i(\mu)$ of the

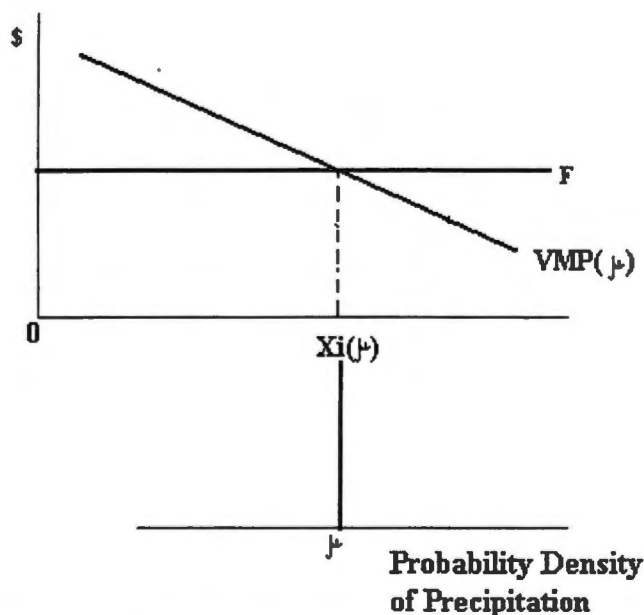


Figure III.3. Production Under Certainty for Annual Precipitation Levels

resource and produce $Q(\mu)$. However, as precipitation deviates from μ , shifting the VMP curve left or right the farmer might end up overusing or underusing resource X_i . As a result of precipitation being a random variable the farmer is unlikely to set the value of the marginal product equal to its factor cost and thus is unlikely to maximize profits. If for example the farmer estimates that he needs to use input amount $X_i(\mu)$ but precipitation is greater than expectations, then the VMP shifts to the right to $VMP(\mu+\sigma)$. The farmer's income now increases as he is producing at point C where returns are higher. Note that the farmer is not maximizing profits because for the actual level of precipitation he should have used $X_i(\mu+\sigma)$ amount of resource input. Instead X_i was underused, ending up at point C. However, if precipitation levels are beneficial and increase the VMP then the farmer still increases his profits although he is not maximizing

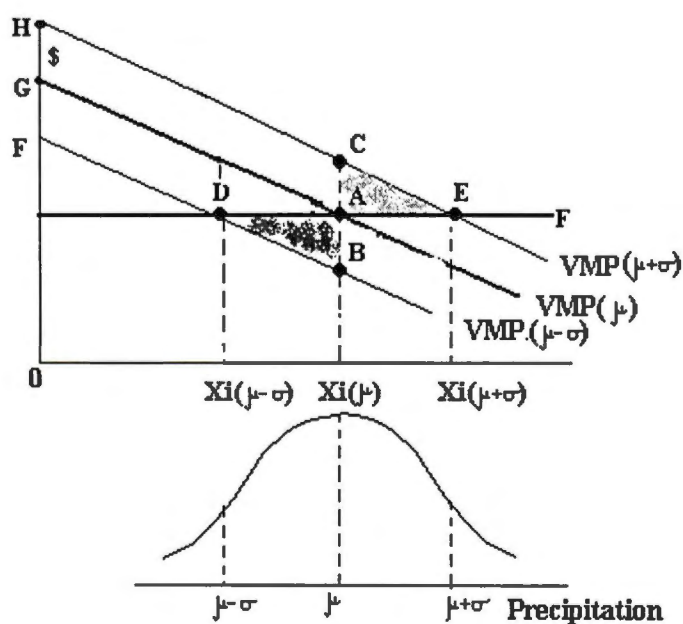


Figure III.4. Production Under Uncertainty for Annual Precipitation Levels

them. In this case beneficial precipitation can increase the farmer's rents by the amount ACHG. The "loss" due to imperfect knowledge is ACE (loss due to input underuse).

On the other hand, if precipitation levels are such that the VMP shifts to $VMP(\mu - \sigma)$ then by using $X_i(\mu)$ the farmer ends up at point B, whereas the profit maximizing level should have been at point D. In this case the farmer overuses resource X_i . The lower precipitation level, $\mu - \sigma$, causes losses to farmers of ABFG, where area ABD is the loss due to input overuse.

In either of the two cases, uncertainty is the driving force that does not allow farmers to achieve the profit maximizing level of resource input X_i . Weather variation clearly makes profit maximization a challenging task.

We hypothesize that weather variation is composed of two parts: variability from ENSO events and variability from all other sources. The combination of ENSO variability and other variation makes the probability density of weather flatter relative to the weather distribution if ENSO variation were not present. That is, the variance in precipitation with ENSO $\sigma_{w/o}^2$, is greater than the variance in precipitation without ENSO, $\sigma_{w/o}^2$. This point can be illustrated in figure III.5. Without ENSO variability, a one standard deviation range of precipitation is in the light gray shaded area $(\mu - \sigma_{w/o})'$ to $(\mu + \sigma_{w/o})'$. When we account for ENSO variability that area increases to $(\mu - \sigma_w)$ to $(\mu + \sigma_w)$, which includes the dark gray shaded area. In terms of figure III.4., this implies that the density function for precipitation will be even flatter causing the one deviation level of precipitation $(\mu - \sigma)$ and $(\mu + \sigma)$ to be even further away from the mean. This, in turn,

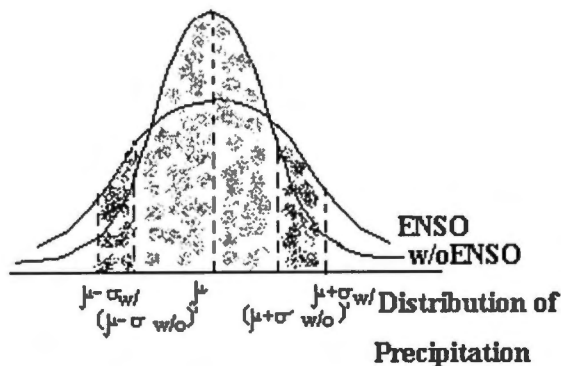


Figure III.5. Weather Variability with and without ENSO

causes even greater fluctuations in farmer's overuse or underuse of inputs. Thus ENSO events can cause farmers to deviate from the profit maximizing levels of resource use.

The distribution of precipitation may not be symmetric as shown in the previous graphs. Even if the “with ENSO” and “without ENSO” distributions have the same mean, the distributions may be skewed. We can see this case in figure III.6. In this case the left tail of the skewed distribution may extend for a long way, pulling the mean μ to the left. The median and mode of the ^{w/}ENSO distribution may be greater than the mean. ENSO related variability might have an outcome more likely to end up greater than the mean, so that farmers may actually be able to increase production during ENSO events. This is the case that we showed earlier where the skewed precipitation distribution causes the VMP to shift to the right every time an ENSO event is observed. A good example was mentioned in the introduction. The warm waters that are found during El Niño years in the coast of Peru signal “*years of abundance*” for the local people, who see increases in the crop yields from the heavy rainfall. So ENSO events might have a positive effect

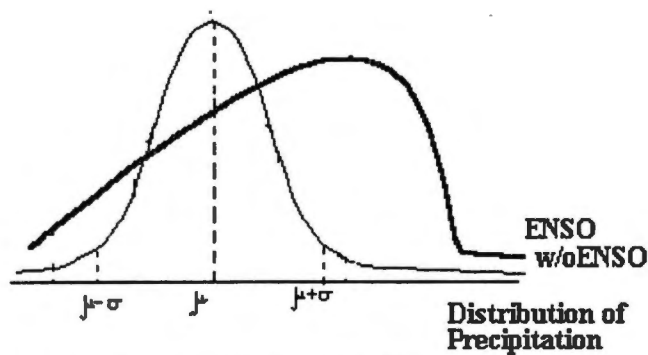


Figure III.6. Weather Variability with Skewed Distributions

on farmland if the distribution of the climate variables is negatively skewed. By the same token, ENSO events may have an outcome more likely to end up less than the mean if the distribution of the climate variables is positively skewed, implying that some producers may have production decreasing during ENSO events. The impact of ENSO on rents can be positive or negative, so the expected sign on the ENSO variables is ambiguous.

IV. Methods and Data

It has been argued that farmland values in the United States are a function of climate, ENSO, plant growth phase, urban influences and land characteristics. Before this equation can be estimated we need to obtain measures for each of the above variables. ENSO and the climate data need to be extracted from time series data of precipitation and temperature. This time series data will allow us to obtain mean values of climate and estimates of weather variability for the US, which we then use as arguments in the land value regression. The data for land characteristics is available from the National Resource Inventory (NRI). The data for urban influences was taken from the US census and the agricultural census.

IV-1. Climate, Moisture and ENSO Variables

In chapter II it was suggested by Arthur et al (1994) that climatological effects can vary from region to region. We are thus interested in separating the contiguous United States into regions that have approximately the same climate. We obtained data on precipitation and temperature from the WWW site for the National Oceanic and Atmospheric Administration (NOAA)⁹. Monthly climate data from 1941 to 1991 were available for 344 “CLIMVIS” regions throughout the contiguous United States. NOAA

⁹ (<http://www.ncdc.noaa.gov/onlineprod/drought/ftppag.html#da>) (3-98)

devised each CLIMVIS region because the area within each region has a similar climate pattern. CLIMVIS boundaries often coincide with county lines, but a few overlapped county lines. For approximately 75 out of 344 regions the CLIMVIS region borders were slightly redefined to follow county lines because farm value data were available only at the county level. The division in which the majority of the county was located or in which the majority of the agricultural land of the county was located was the CLIMVIS region to which the county was assigned.

Monthly temperature and precipitation means were calculated for each CLIMVIS region for the years 1941-1991. Kappene (1992) notes that temperature and precipitation were relatively stationary time series during this period. The CLIMVIS data set also contained soil moisture variables. Moisture levels indicate the extend to which there is naturally available water in the soil depth of the root, with higher levels of moisture being beneficial for crops. The “Moisture Anomaly Index” is defined by its departure from the normal levels for that month. Monthly moisture means were calculated for the years 1941-1991.

The CLIMVIS data on temperature and precipitation were manipulated to obtain a measure of the degree to which ENSO events influence climate within the region. The literature reviewed suggests that El Niños and La Niñas cause weather anomalies in the form of increased variability of precipitation and temperatures. We hypothesized in chapter III that ENSO variability flattens and widens the probability density of weather variables. In order to measure this additional variability caused by the El Niño cycle, a variance decomposition technique known as “Fourier Series Analysis” (FSA) was used.

FSA was developed in 1822 by Joseph Fourier, who showed that any periodic observation can be represented by a series of harmonic trigonometric functions of sines and cosines. FSA can be used to identify the contributions to the variance of the observed data of any components that exhibit a cyclical pattern. Because an El Niño cycle is described in most of the previous literature as a 4-5 year cycle we will observe the total variance in precipitation and temperature and attempt to attribute a portion of that variance to the 4-5 year cycle, separating this ENSO variation from the remainder inherent in the data. We assume that the 4-5 year cycle adequately defines ENSO. The remaining variation includes what Thompson (1992) calls the 18.5 year wet-dry cycle, the 100 year temperature cycle and any other cycles that are found in the time series.

One of the assumptions of FSA is that the time a series is mean and covariance-stationary¹⁰. In order to assure that the observations of the data on temperature and precipitation are stationary we limited the data obtained from CLIMVIS to the years 1941 to 1991¹¹. Kappenne and Ghil (1992) ignored data prior to 1941 because of problems with the stationarity of the data.

A number of terms must first be defined. We intend to use FSA to separate the 4-5 year periodic component from the rest of the variability in a time series. Figure IV.1.1. shows *one* periodic component of a time series that is described through a combination of sines and cosines. The term frequency, is the number of peaks or troughs in a series (figure IV.1.1.). Frequencies are denoted by the letter ω . The periodic component that

¹⁰ A *weakly stationary* series is one where neither the mean nor the autocovariances depend on the date t .

¹¹ Data was available since 1895

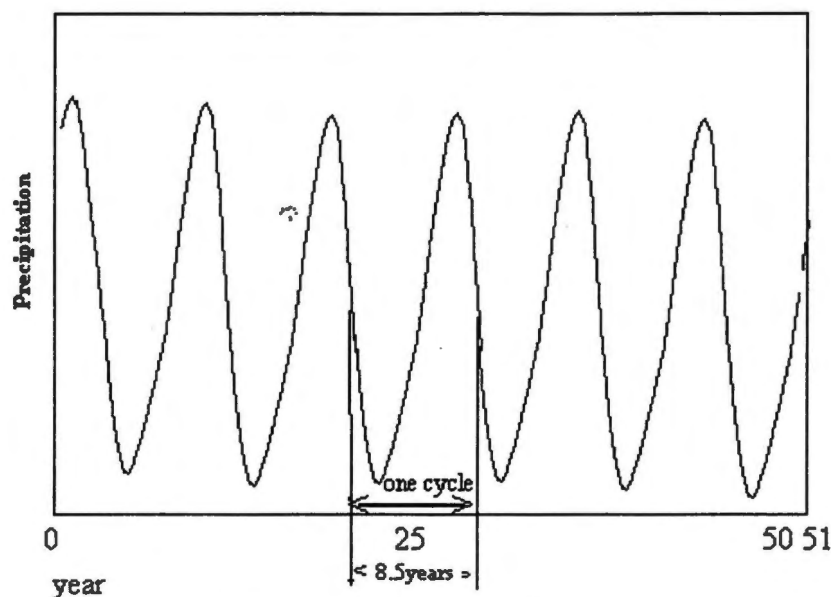


Figure IV.1.1. FSA Frequency and Cycle¹²

we observe in figure IV.1.1. has 6 peaks it therefore has a frequency of 6, or ω_6 . But for any time series with $T=51$ years of observations, we will observe a number of different frequencies. Frequency ω_{25} will complete 25 peaks and 25 troughs in the same 50 years. We observe a total of $M=(T-1)/2$ different frequencies, with T representing the total number of observations available. Thus for $T=51$ years of data we observe 25 different frequencies. We also observe cycles. A cycle is the number of years it takes to go from one trough or peak to the next. Frequency ω_6 completes a cycle in 8.5 years for 51 years of data. On the other hand frequency ω_{25} will complete one cycle every two years.

The basic function of FSA is to *take us from the time domain to the frequency domain*. This means that any time series data that is graphed with *time* on the horizontal

¹² Figure reproduced and adapted from DeLurgio (1998)

axis (time domain) can now be represented with *frequencies* on the horizontal axis (frequency domain). Figure IV.1.2.A. graphs data from a time series of precipitation. We see that in this specific example we have 51 years of precipitation available and they have an increasing trend. From the data we can calculate the variability of precipitation, say the variance is equal to k . Figure B represents the frequency domain, where we construct what is called the *sample periodogram*. The light gray area under the sample periodogram is equal to the variance of the time series equal to k^{13} . The sample periodogram is used to separate variance k into its components, and calculate the

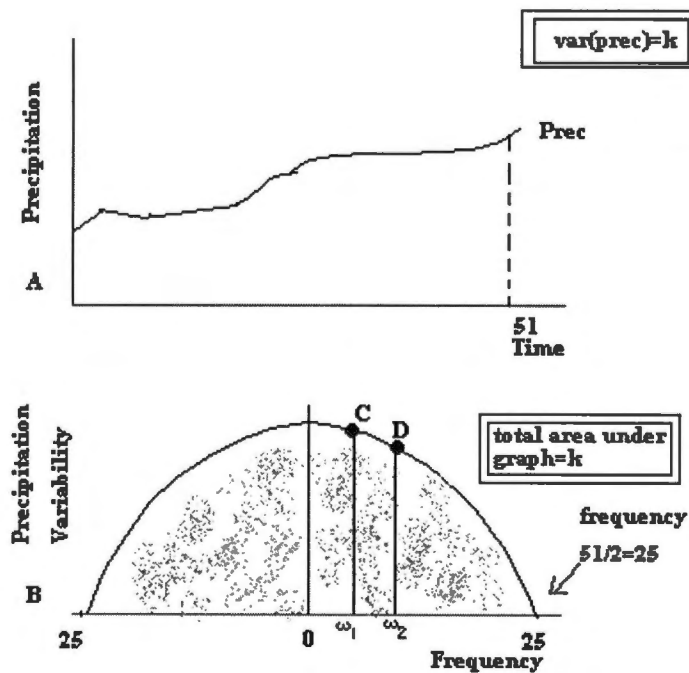


Figure IV.1.2. Time to Frequency

¹³ In a sense, the sample periodogram is analogous to a probability density function, where

variability due to frequencies $\omega_1, \omega_2, \dots, \omega_{25}$ by looking at the area between points C, D and so forth. The frequency domain will be symmetric around frequency zero.

Any time series will consist of frequencies (cycle attributed variation) and some leftover white noise (variation inherent in the time series that cannot be attributed to cycles). Separating a time series into all its cyclical components yields the sample periodogram (figure IV.1.3.), under which its total area is equal to the variance of the time series. Therefore the sample periodogram *describes the portion of sample variance of the time series data that can be attributed to all the frequencies $\omega_1, \omega_2, \dots, \omega_M$* (Hamilton,

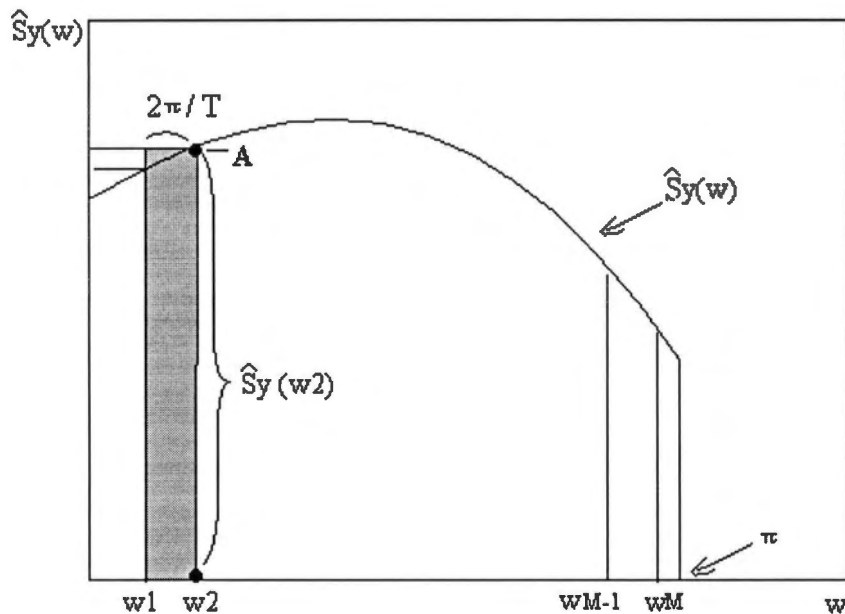


Figure IV.1.3. Sample Periodogram

integrating from $-\infty$ to $+\infty$ gives a total probability of 1.

1994). The formula to calculate the sample periodogram is:

$$(4.1) \quad S_y(\omega_j) = \frac{1}{2\pi T} * \left\{ \left[\sum_{t=1}^T y_t \cos[\omega_j(t-1)] \right]^2 + \left[\sum_{t=1}^T y_t \sin[\omega_j(t-1)] \right]^2 \right\}$$

where y_t represents observations from the time series data at year t . ω_j is the frequency for which the periodogram is calculated, and T is the number of years in the time series.

$S_y(\omega_j)$ is the value of the sample periodogram. Once the sample periodogram is calculated, the proportion of total variance that can be attributed to frequency ω_j is determined by multiplying $S_y(\omega_j)$ by $(4\pi/T)$. To better understand the multiplication, consider figure IV.I.3 with the example of frequency ω_2 (a 25 year cycle). $S_y(\omega_2)$ is the vertical distance from ω_2 to the sample periodogram function at point A. If we multiply this by $\frac{2\pi}{T}$, which is the horizontal distance from one frequency to the other, we obtain the gray shaded area. But the sample periodogram is symmetrical around frequency $\omega=0$. In order to get the sample variance that is attributed to frequency ω_2 we need to multiply the shaded area by two. So the proportion of sample variance that can be attributed to cycle of frequency ω_j can be expressed as¹⁴

$$(4.2) \quad \text{Sample variance due to cycle of frequency } \omega_j = S_y(\omega_j) * \frac{4\pi}{T}$$

¹⁴ The periodogram is not necessarily smooth as in figure IV.I.3.

An example of Fourier Decomposition is shown in Figure IV.1.4. Precipitation observations for the period 1941 to 1991 were available, for a total of 51 observations. With $T=51$ observations we get a total of $(T-1)/2$ different frequencies, or 25 different cycles. The horizontal axis measures the frequencies and the vertical axis the value of the sample periodogram. The upper line represents the value of the sample periodogram for each frequency as calculated using equation 4.1. The lower line represents the proportion of variance that can be attributed to each frequency as calculated using equation 4.2. It is the lower line is most important for our purposes. The cycle that can be seen every four years is observed 12.75 times in 51 ($51/4$) years ($\omega_{12.75}$).

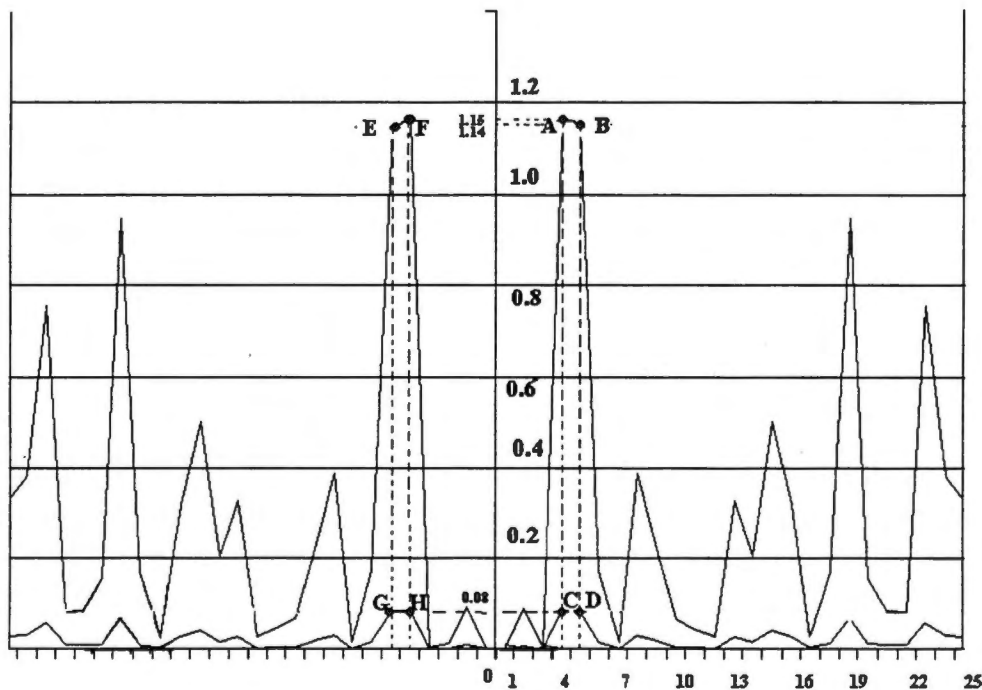


Figure IV.1.4. Spectrum for 51 Years of Data

Figure IV.1.4 indicates that the percentage variability attributed to the 4-year cycle is equal to approximately 0.16 at point C and H (add C+H)¹⁵. The 5-year cycle can be observed 10.2 times within a period of 51 years. The percentage variability of the 5 year cycle can be seen at point D and G is also approximately 0.16. So if we would like to capture the four and five year cycle we need to add the variance that is attributed to the frequencies [(points [C+D]*2)] j=4 and j=5. This amount of variability is 0.32 or 32% of the variability in this precipitation time series is due to 4-5 year cycles, or ENSO cycles. After filtering out the variability that is due to the 4 and 5 year ENSO cycle what is left is either white noise or variability due to other cycles inherent in the time series. This leftover variability we call *Non-El Niño* variability and it also enters the equation explaining farmland values since it is also affecting the productivity of land.

FSA was done for all CLIMVIS regions for the periods 1941-1981 and 1941-1991¹⁶. The SAS/ETS econometrics package was used to conduct the spectral analysis on the temperature and precipitation time series in each region. Variation was decomposed into 4-5 year cycle for the periods 1941-1981 and 1941-1991. The analysis was done for the months of January, April, July and October. The outcome of these calculations expressed ENSO cycle variability as a *proportion* of total variability of the series.

Using an example, total variance in precipitation is 7.56 in the CLIMVIS division

¹⁵ Recall that it is symmetrical around 25 so we need to add variability from both ends.

¹⁶ These two periods were used because the farmland value model is tested for 1982 values and 1992 values.

01001 (first division of Alabama). Spectral analysis indicates that 12.5% of total variability can be attributed to ENSO cycles in this division. The *proportion* of variability due to the ENSO cycle and the *proportion* due to other cycles non-El Niño variability (1-0.125) were then multiplied with the total variance of the series to express it in terms of a *portion* of total variance. Thus 12.5 % of 7.56 is equal to 0.95 units of variability that are due to El Niño cycle events. The remaining 6.62 units are due to other cycles that or inherent in the series, which is the non-ENSO component. The results from the complete data set (1941-1991) were put in SAS/GIS to produce maps that describe what percentage of the precipitation and temperature variability is attributable to the 4 and 5-year cycle for each month of the year. Appendix I shows these results from the spectral analysis for the 4 and 5-year cycle for all 12 months for the United States.

IV-2. National Resource Inventory (NRI) Data

The second set of variables was obtained from the 1992 National Resources Inventory (NRI). The NRI data set provided 1982 and 1992 data on soil characteristics such as permeability of the land, salinity, percentage of land that is flood prone etc. Appendix II contains a brief definition of NRI variables. NRI contains data on approximately 1.3 million points over the contiguous United States. Data were scaled up to the divisions as defined by CLIMVIS. For example, the proportion land in a CLIMVIS region defined as land class I was calculated as:

$$(4.3) \quad \frac{\sum_{i=1}^n LCI_i * EF_i}{Total \cdot Land \cdot in \cdot CLIMVIS \cdot division} = \% \text{ of land in } LCI_i$$

where $i=1 \dots n$ is the total number of points in a CLIMVIS division, LCI_i is a dummy variable (1= land class I , 0= any other land class). EF_i is the “expansion factor” that tells us the number of acres of land that each point represents. The numerator, which sums all points defined as land class I times the expansion factor, gives us the total land in the CLIMVIS division classified as land class I. This is then divided by the total land in a CLIMVIS division to get an expression of the percentage of land that is classified as land class I within the CLIMVIS division. The same method was applied to all NRI variables used in this analysis.

The NRI data set reports eight land capability classes. Classes 1-4 can be used for cultivation, and classes 5-8 cannot be cultivated under normal management. Class I soils can be used continuously for intensive crop production with minimum attention. Class II soils have some limitations such as moderate slopes of 2-5%. Class III soils have severe limitations such as shallow soil, steep slopes of 6-10% or shallow water tables and they require conservation practices to allow them to be continuously productive. Class IV soils have greater limitations and need more conservation practices. Most of the time class IV soils are pastures. Class V soils do not have erodibility problems but they are limited to pasture, range, woodland or wildlife habitat because of boulders or wetness that make the land unsuitable for cultivation. Class VI soils have a few more conservation practices needs than Class V because of steeper slopes and shallow soils.

Class VII soils require extreme care to protect the soil and Class VIII have also extreme limitations such as steep slopes, rock lands swamps which make them useful only for wildlife or recreation. For each class this variable will be expressed as percentage of land in each subclass within each CLIMVIS region, with land class I (best land) being left out as a control variable and with land classes II-VIII carrying an expected negative sign – with respect to the control variable land class I.

In addition to the land class variables, the NRI data contains other land characteristics that influence land productivity. For example an excessive concentration of soluble salts suppresses plant growth (Plaster 1992) because plants have difficulty absorbing water from the soil. Accumulation of soluble salts is mostly a problem in the arid regions in the United States such as in the San Joaquin Valley in California, the lower Rio Grande Valley in Texas, Arizona, New Mexico, Utah and others. Soil salinity is measured by the electrical conductivity of the soil by passing an electrical current through a solution extracted from a soil sample. Salinity is measured in millimhos per centimeter (mmhos/cm), with soil defined as saline when the electrical conductivity is higher than 4 mmhos/cm with some crops being sensitive to levels as low as 2. Increased levels of salinity are expected to have a negative effect on land productivity and land values, with the salinity variable carrying a negative sign.

Bulk density is the density of a volume of soil as it exists naturally, including air space and organic material in the soil volume (Miller 1995). Depending on soil texture and humus content different bulk densities may be suitable for plant growth. For good plant growth bulk density should be between 1.1-1.4 g/cm³. Any values within this range

will be considered as “suitable” for plant growth. The variable used in the model takes the form of a dummy with 1 indicating values in the range of 1.1-1.4 g/cm³ and 0 values out of that range. A positive sign on the bulk density variable is expected.

Permeability is the ease with which water, air and roots travel through the soil (Plaster 1992). High levels of permeability allow aeration and supply plant roots with high levels of oxygen. Permeability is measured using hydraulic conductivity, the rate at which water moves through a soil. Soils with soil permeability rates less than 0.014 in/hr are considered to have slow permeability rates. Soils with permeability between 0.014-1.44 in/hr are considered to have moderate permeability rates and any soils with rates more than 1.44 have rapid rates. In this study we expect soils with rates of permeability between 0.014 and 1.44 to have a positive effect on plant growth. Values less than 0.014 will not allow oxygenation of the roots whereas values higher than 1.44 will allow water to pass through at a very fast rate lowering the ability of the soil to retain nutrients and causing erosion. This variable also takes the form of a dummy variable with 1 representing beneficial levels of permeability within the range of 0.014-1.44 in/hr and 0 values other than that. A positive sign is expected for the soil permeability variable.

Clay content of the soil is related to the soil texture. Soils consist of mineral particles defined as sand for the largest size particles, silt for the medium sized particles and clay for smallest soil separates (Plaster 1992). Sand grains are visible to the eye and improve water infiltration and aeration. Silt particles are silky or powdery; like sand they do not stick together and they also have the ability to hold water. Because permeability is used as the measure of the infiltration rate, silt and sand content will not be used to

avoid possible problems of collinearity. The smallest soil separate is clay, which results from chemical reactions between weathered minerals in order to form new small particles of size less than 0.002mm in diameter. These new minerals have the ability to chemically bond nutrients to their surfaces and help plants hold nutrients in the soil. Soils with clay content between 35-40% are expected to have a positive effect on soil productivity. Soils with less than 35% clay content cannot hold nutrients whereas soils with clay content more than 40% are difficult to wet, drain and till. Values between 35-40% are considered beneficial, and the dummy variable [for clay content in this range] is expected to have a positive sign.

Soil pH is an indication of soil acidity. The pH scale is logarithmic and ranges from 0 to 14, with values above 7 being basic and below 7 being acidic. Soil pH can influence plant growth as it affects the activity of some beneficial microorganisms (Miller 1995). Different plants have different levels of optimal pH. For tobacco the optimal range is 5-6, for cotton 5.5-6.5, oats and rye 5.5-7.5, soybeans 5.5-7, corn, sorghum and wheat 6-7.5, barley 6.5-7.5, alfalfa 7-8, blackberry 6.5-8.0 (Plaster 225). All values of pH in the data set fall between 4.6 and 8.3 with approximately 91% of the values within 5.0 and 8.0. Therefore the pH variable will be left as a continuous variable. As some soils perform better under lower levels of pH and others under slightly higher levels the expected sign of pH is ambiguous.

The last variable measures how prone a parcel of land is to flooding, where flooding class code measures the duration of annual flooding in a normal year. Very brief flooding is less than 2 days, brief flood duration is 2-7 days, long is 7 days to 1

month and very long flooding is more than 1 month. The variable used in this model combines the first two flooding class codes and the last two. Land that is flooded less than 7 days per year is coded as 0, whereas flooding longer than 7 days is coded as 1. The reason the dummy variable was redefined is that only 7% of the land in the US has flooding larger than 7 days. The variable is expected to have a negative sign because flooding reduces crop output.

IV-3. Data from Censuses and other Sources

The final data sets used came from the US Bureau of Census reports for agriculture (1982 and 1992) and population. The agricultural census provided us with county level values for farmland and total land in farm measures. A population density measure and the mean elevation of the county was also used obtained from Burton C. English (personal communication, 1998). The higher a parcel of land is located the lower the value of land should be. Income per capita and a population density measure were obtained from the 1980 and 1990 US census.

Census county level data were scaled to CLIMVIS divisions. The scaling from county level data to CLIMVIS divisions was done by weighting by total land in the county. Equation 4.3 was modified such that i indexed counties in a CLIMVIS region. Table IV.I. summarizes the variables used to explain variation in farmland values and their expected signs.

Table IV.1. Expected Signs for Regression

Dependent Variable – Farmland Values			
Component of Equation 3.10		Variable	Expected Sign
1 Alternative Uses	Income	β_1	+
	Density	β_2 - β_3	+
2 Land characteristics	Elevation	β_4	-
	Permeability	β_5	+ (as defined)
	Clay	β_6	+ (as defined)
	Ph	β_7	?
	Salinity	β_8	-
	Flood Prone	β_9	- (as defined)
	Bulk Density	β_{10}	+ (as defined)
	Land Class	β_{11} - β_{17}	+ (as defined)
3 Climate	Temperature and Precipitation means and squares for respective months	$(\beta_{18}$ - $\beta_{33})$	?
	Moisture for each quarter	$(\beta_{34}$ - $\beta_{37})$	+
4 El Niño	Non El Niño Temperature and Precip. Variability for respective months	$(\beta_{38}$ - $\beta_{45})$	?
	El Niño Temperature and Precipitation Variability for respective months	$+(\beta_{46}$ - $\beta_{54})^*$	?

V. Results

There were 338 usable observations out of 344 CLIMVIS divisions in the data. We first present the results from the 1982 farm value model and then the results from the 1992 farm value model, followed by a comparison of the two models. Farmland values and income are in constant 1984 dollars for both models. Each model is estimated with four specifications. The first specification does not use any variability measures. It estimates farmland values as a function of urban influences, land characteristics and the mean climate variables. This model resembles the model that was used by Mendelsohn et al (1994). The second specification adds ENSO variability to the model. The third includes both ENSO and non-ENSO variability and the fourth replaces the ENSO and non-ENSO variability measures with a measure of total variability (ENSO+non-ENSO). We compare the models by testing the sum of squared errors for the restrictions. As an example of one of these tests, consider the model that uses both ENSO and non-ENSO variability in comparison to the model that uses total variability instead (Model 3 vs. Model 4).

The unrestricted model in this test takes the following form:

$$(5.1) \ln(\text{farmland values/acre}) = \alpha + \beta \tilde{X} + \sum_{i=1}^8 \beta_i^E EN_i + \sum_{j=1}^8 \beta_j^N NEN_j$$

where $\tilde{X}$ is a vector representing alternative use, land characteristics, and average climate variables, EN is a vector of eight ENSO variability measures (Jan, Apr, Jul, Oct precipitation variability and Jan, Apr, Jul, Oct temperature variability) and NEN is a vector of eight non-ENSO variation measures (Jan, Apr, Jul, Oct precipitation variability and Jan, Apr, Jul, Oct temperature variability). The restricted model, uses total variation instead of ENSO and non-ENSO components, where $TV_i = EN_i + NEN_j$, $i=j$, $i=1 \dots 8$.

The restricted model took the form:

$$(5.2) \quad \ln(\text{farmland values/acre}) = \alpha + \gamma \tilde{X} + \sum_{i=1}^8 \gamma_i (TV_i) = \alpha + \gamma \tilde{X} + \sum_{i=1}^8 \gamma_i^v (EN_i + NEN_i)$$

Using equations 5.1 and 5.2 the restrictions take the following form:

$$(5.3) \quad \begin{aligned} \gamma_{i=1-8}^v &= \beta_i^E \text{ for } i=1-8 \\ \text{and } \gamma_{i=1-8}^v &= \beta_j^N \text{ for } i=1-8 \text{ and } j=1-8 \end{aligned}$$

The null hypothesis is:

$$(5.4) \quad H_0 : \gamma_{i=1-8}^v = \beta_{i=1-8}^E = \beta_{j=1-8}^N$$

We have a total of 8 such equations, which means we have a total of 16 restrictions. The alternative hypothesis H_A is that at least one of the equations does not hold.

The F test that we use to test the restriction is given by equation 5.5:

$$(5.5) \quad F_{r,n-k} = \frac{(SSE_R - SSE_U)/r}{SSE_U/(n-k)_U}$$

where r is the number of restrictions, k is the number of independent variables without the constant, SSE_R and SSE_U are the sum of squared errors for the restricted and the unrestricted model, respectively, and $n-k$ is the degrees of freedom from the unrestricted model.

If the two models are significantly different that would suggest that there is a reason to separate total variability to ENSO and non-ENSO components. That is, the test would suggest choosing the unrestricted model. On the other hand, if they are not significantly different, that would suggest ENSO related variation and is no different than non-ENSO variability, so there is no ENSO effect to which farm values respond.

V-1. Results for 1982 Farmland Values

For 1982, specification #1¹⁷, where none of the variability measures are included, the regression model explains approximately 86% of the variability in the farmland values, which is very good for cross-sectional data (table V.1). The null hypothesis is

¹⁷ All models were weighted by the land in farms in each CLIMVIS region

Table V.1. Semi-log model. Dependent variable log of farmland values for 1982 model

Independent variable	Model 1	Model 2	Model 3	Model 4
Constant	21.56 (0.0001)***	21.913 (0.0001)***	19.28 (0.0001)***	23.47 (0.0001)***
Income	1.54E-5 (0.3766)	9.1E-6 (0.6049)	3.09E-5 (0.0553)*	2.7E-5 (0.0874)*
Population Density	9E-5 (0.0624)*	1.1E-4 (0.0173)**	8.24E-5 (0.0539)*	5.5E-5 (0.2020)
Population Density Squared	-3.18E-9 (0.1012)	-3.9E-9 (0.0418)*	-2.82E-9 (0.0964)*	-1.93E-9 (0.2663)
Salinity	-0.248 (0.0001)***	-0.235 (0.0001)***	-0.149 (0.0001)***	-0.169 (0.0001)***
Ph	-0.224 (0.0001)***	-0.197 (0.0005)***	-0.165 (0.0010)**	-0.190 (0.0001)***
Bulk Density	0.1 (0.0487)*	0.126 (0.0137)**	0.007 (0.8780)	0.007 (0.8687)
Land Class II	-3.343 (0.0001)***	-2.795 (0.0001)***	-2.755 (0.0001)***	-2.825 (0.0001)***
Land Class III	-4.287 (0.0001)***	-3.666 (0.0001)***	-3.228 (0.0001)***	-3.262 (0.0001)***
Land Class IV	-4.355 (0.0001)***	-3.820 (0.0001)***	-3.619 (0.0001)***	-3.600 (0.0001)***
Land Class V	-5.16 (0.0001)***	-4.981 (0.0001)***	-4.796 (0.0001)***	-4.292 (0.0001)***
Land Class VI	-5.0663 (0.0001)***	-4.392 (0.0001)***	-3.870 (0.0001)***	-4.020 (0.0001)***
Land Class VII	-5.099 (0.0001)***	-4.385 (0.0001)***	-4.16 (0.0001)***	-4.307 (0.0001)***
Land Class VIII	-2.631 (0.0012)***	-2.091 (0.0094)**	-1.680 (0.0175)**	-2.207 (0.0024)**
Clay	0.055 (0.4570)	0.042 (0.5933)	0.064 (0.3652)	0.078 (0.2646)
Permeability	-0.061 (0.2903)	-0.030 (0.5935)	0.027 (0.3652)	-0.028 (0.5831)
Flood Prone	-0.795 (0.1258)	-0.558 (0.3031)	-0.692 (0.1682)	-0.916 (0.0673)
Elevation	-4.6E-5 (0.0488)**	1.1E-5 (0.6325)	-9.62E-5 (0.0001)***	-0.0001 (0.0001)***
Moisture quarter 1	0.704 (0.0079)**	0.679 (0.0137)**	0.310 (0.2322)	0.173 (0.5017)
Moisture quarter 2	-0.328 (0.1750)	-0.409 (0.1043)	0.108 (0.6660)	-0.053 (0.8320)
Moisture quarter 3	-0.363 (0.0578)*	-0.387 (0.051)*	-0.242 (0.1817)	-0.058 (0.7489)
Moisture quarter 4	-0.332 (0.1856)	-0.201 (0.4312)	-0.271 (0.2586)	-0.186 (0.4463)
Temperature January	0.009 (0.5235)	0.003 (0.8245)	-0.018 (0.3430)	-0.006 (0.7406)
Temp January Squared	-0.001 (0.0125)**	-8.8E-4 (0.0537)*	-0.001 (0.0338)*	-0.001 (0.0037)**
Temperature April	0.348 (0.0052)**	0.497 (0.0001)***	0.664 (0.0001)***	0.550 (0.0001)***
Temp April Squared	-0.003 (0.0034)**	-0.004 (0.0002)***	-0.005 (0.0001)***	-0.004 (0.0001)***
Temperature July	-0.027 (0.8599)	-0.064 (0.7017)	0.050 (0.7370)	-0.117 (0.4123)

Table V.1. Semi-log model. Dependent variable log of farmland values for 1982 model

Temp July Squared	-2.9E-4 (0.7827)	7.9E-5 (0.9455)	-0.0007 (0.4487)	-0.0003 (0.7302)
Temperature October	-0.624 (0.0005)***	-0.773 (0.0001)***	-0.963 (0.0001)***	-0.770 (0.0001)***
Temp October Squared	0.006 (0.0001)***	0.007 (0.0001)***	0.009 (0.0001)***	0.007 (0.0001)***
Precipitation January	0.168 (0.0334)*	0.222 (0.0106)**	0.020 (0.8105)	0.042 (0.5947)
Prec January Squared	-0.007 (0.3588)	-0.011 (0.1676)	0.007 (0.3887)	0.006 (0.4489)
Precipitation April	0.350 (0.0031)**	0.541 (0.0001)***	0.626 (0.0001)***	0.444 (0.0002)***
Prec April Squared	-0.058 (0.0014)***	-0.078 (0.0001)***	-0.043 (0.0202)*	-0.051 (0.0061)**
Precipitation July	-0.369 (0.0001)***	-0.369 (0.0001)***	-0.348 (0.0001)***	-0.443 (0.0001)***
Prec July Squared	0.034 (0.0004)***	0.036 (0.0006)**	0.033 (0.0005)***	0.044 (0.0001)***
Precipitation October	-0.247 (0.1079)	-0.328 (0.0346)*	-0.290 (0.0529)*	-0.286 (0.0578)*
Prec October Squared	0.036 (0.1678)	0.056 (0.0358)*	0.042 (0.0839)*	0.042 (0.0876)*
EN Prec var Jan		-0.043 (0.8263)	0.140 (0.4421)	
EN Prec var Apr		-0.432 (0.0117)**	-0.355 (0.0241)*	
EN Prec var Jul		-0.522 (0.0030)**	-0.299 (0.0718)*	
EN Prec var Oct		-0.305 (0.2325)	-0.384 (0.0989)*	
EN Temp var Jan		-0.041 (0.3458)	-0.114 (0.0053)**	
EN Temp var Apr		-0.469 (0.0042)**	-0.178 (0.2741)	
EN Temp var Jul		-0.007 (0.9423)	0.331 (0.0010)***	
EN Temp var Oct		0.317 (0.0117)**	-0.039 (0.7437)	
Non EN Prec var Jan			-0.003 (0.8849)	
Non EN Prec var Apr			-0.091 (0.0146)**	
Non EN Prec var Jul			0.042 (0.0718)*	
Non EN Prec var Oct			-0.060 (0.0153)**	
Non EN Temp var Jan			-0.012 (0.0001)***	
Non EN Temp var Apr			0.008 (0.6116)	
Non EN Temp var Jul			-0.177 (0.0001)***	
Non En Temp var Oct			0.011 (0.4902)	
Total Temp var Jan				-0.013 (0.0001)*
Total Temp var April				0.007 (0.6397)
Total Temp var July				-0.136 (0.0001)*
Total Temp var October				-0.004 (0.7877)

Table V.1. Semi-log model. Dependent variable log of farmland values for 1982 model

Total Prec var Jan				-0.005 (0.8108)
Total Prec var April				-0.032 (0.3665)
Total Prec var July				0.031 (0.1473)
Total Prec var October				-0.048 (0.0490)*
F-test	59.728 (0.0001)***	52.889 (0.0001)***	61.528 (0.0001)***	65.594 (0.0001)***
Adjusted R ²	0.8661	0.8742	0.9052	0.8964
Error Sum of Squares	74708018.612	68299167.512	50059542.196	56256818.437

p-values in parenthesis

* significant at the $\alpha=0.1$ level

** significant at the $\alpha=0.01$ level

*** significant at the $\alpha=0.001$ level

that all coefficients are equal to zero and it is rejected at the $\alpha=0.001$ with an $F=61.53$ ¹⁸.

The independent variables in the first model all carry the expected sign. Increases in income and population density, which signify the influence of urban areas on farm value, are accompanied by higher land values. Salinity has a negative effect on the value of farmland. Clay content, soil permeability and flood prone land are not significant factors in determining farmland values. Optimal values for bulk density also carry the expected positive sign. The negative sign on the elevation variable indicates that the higher a parcel is located above sea level the lower the value of the land. The land class variables indicate that, everything else constant, class I land is worth more than the less productive land class II through VIII. The pH variable indicates that high pH values in the land decrease the value of land suggesting that “basic” land parcels are less valuable. Moisture in the first and third quarter seem to have a significant effect on farmland values with a positive and negative sign respectively. Ten of the sixteen the mean climate variables for temperature and precipitation are significant.

Specification #2 included the ENSO variability measures. In this model none of the land characteristic or urban influence variables changed in any meaningful way. The standard errors of the coefficients were relatively constant across the two model specifications. The only observed difference between models 1 and 2 were some changes

¹⁸ In all four model specifications some problems with multicollinearity were observed on two of the mean temperature variables and on two of the land class variables. We are not interested in making statistical inference from those results and since the regression still produces BLUE estimates, the variables are included for theoretical reasons.

in the magnitudes of the coefficients of the first moment variables, i.e., mean climate variables. This suggests that the coefficients of the climate variables in model #1 may have captured some of the effect that should have been attributed to ENSO variability. Four of the eight ENSO measures were significant with three of them carrying a negative sign. The effect ENSO precipitation variability on farmland is negative for April and July precipitation, and April temperature. The only positive effect comes from ENSO related October temperatures. In sum, ENSO related variation seems to decrease farmland values. We tested the restrictions between the first and the second model to see whether adding ENSO improved the model or not. The test had a total of eight restrictions, testing the null hypothesis that the coefficients on the ENSO variability measures are jointly equal to zero. The critical value at the $\alpha=0.05$ level for eight restrictions is 1.94, but the calculated F-statistic was 3.41 indicating that adding the ENSO variability measure was an improvement in the model.

Specification #3 included both ENSO and non-ENSO variability measures. Again most of the variables in the equation remained fairly constant, as did their standard errors. Some changes were again observed in the mean climate coefficients when compared to the first model. This model yielded the highest value for adjusted R^2 , explaining 90.52% of the variation in the dependent variable. Again we tested for the restrictions between the first and the third model. In this specification we have 16 restrictions testing that the coefficients of all the ENSO and the non-ENSO variability measures are jointly equal to zero. The critical F-value was 1.67, but the calculated F-statistic was 8.71 suggesting that the model specification that includes both the ENSO

and non-ENSO variability measures is better than the model not including any measure of weather variability.

The final step was to estimate a fourth model using total variability instead of separating this variation into ENSO and non-ENSO components. Again all the coefficients other than the mean climate coefficients were constant across the two models. The restrictions between the first and the fourth model tested whether the model that includes the total variability measures is better than the model that does not include any variability measures. There were 8 restrictions testing the null hypothesis that the coefficients of the total variability measures are equal to zero. The F-critical was equal to 1.94 and the calculated $F=11.93$. Again the better model seems to be the one where total variability measures are used.

Models including the weather variability measures better explain variation in farmland values than the model not including any variability measures. Next we want to compare specifications 3 and 4 where we can directly test the decomposition of total variation into ENSO and non-ENSO components (This test has the 16 restrictions given in equation 5.4). The critical F-value for $\alpha=0.05$ is 1.67 but the restrictions calculated F-statistic is 2.18, suggesting the null hypothesis be rejected. The test suggests that 1982 farmland values are best modeled by separating climate variability into its ENSO and non-ENSO components.

The test indicates that ENSO variation may be different from other variation in impacting farmland values. ENSO events represent the extremes of the distribution of the climate variables. Those extremes prevent farmers from finding the optimal levels of

resource inputs that maximize profits. The negative values on ENSO related variation, with the exception of July temperature, indicates just this. ENSO variability causes the values of farmland to decrease as it causes reductions in farmer rents, due to the loss in land productivity. The results are in accordance to the Ricardian land value model, which suggests that less productive land will be worth less.

Two methods were used to estimate the impact on the value of farmland due to ENSO cycles. The first method used the predicted values of farmland with ENSO events, subtracting from that the predicted values of farmland when the ENSO variation is set equal to zero. Land values with ENSO are given by equation 5.6, while values without ENSO are given by equation 5.7. and the effect from ENSO events in equation 5.8:

$$(5.6) \quad \hat{Y}_i^{wEN} = \exp[\hat{\beta}X_i + \sum_{i=1}^8 \hat{\beta}_i^E EN + \sum_{j=1}^8 \hat{\beta}_j^N NEN]$$

$$(5.7) \quad \hat{Y}_i^{w/oEN} = \exp[\hat{\beta}X_i + \sum_{j=1}^8 \hat{\beta}_j^N NEN]$$

$$(5.8) \quad ENeffect = \hat{Y}_i^{wEN} - \hat{Y}_i^{w/oEN}$$

where the notation follows that of equation 5.1.

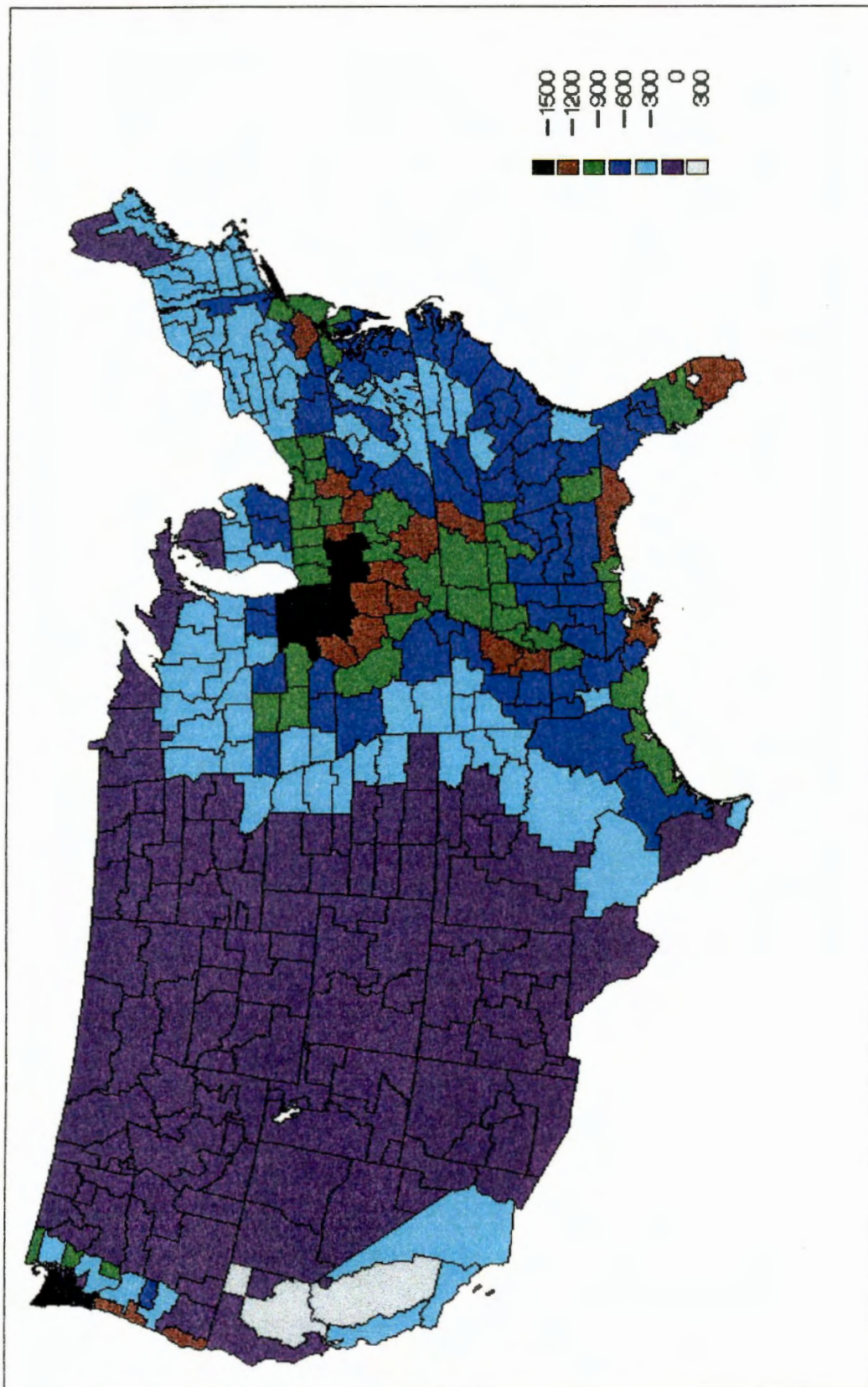
Equation 5.8 was calculated for every division in the United States and the results were put into SAS/GIS to produce maps illustrating ENSO effects in the United States. The problem with this method of estimating the effect of ENSO lies in that we have to make the assumption that the covariance and correlation between ENSO and non-ENSO

variables is zero, or that ENSO is orthogonal to all other variables in vector $\tilde{X}$. For 312 out of 338 divisions El Niño cycles decreased the value of land whereas the model predicted that farmland values increase in 26 divisions. The model overestimated the damage on farmland values by more than its actual value for only 9 out of 338 divisions. Figure V.1. shows the effect of ENSO cycles on 1982 farmland values.

The bulk of the negative effects are concentrated in the mid-western and the Atlantic region. Illinois, Indiana, Ohio, Kentucky and Tennessee saw the largest decreases in farmland values reaching in value up to \$1500/acre with most around \$1000/acre. The areas around the Gulf of Mexico also saw major reductions in farmland values that ranged from \$900 to \$1200/acre. In contrast, some parts of California saw decreases in farmland values of up to \$300/acre whereas others saw increases in the value of land of up to \$300/acre. California is the only area in the United States where increases in farmland values are observed. The average reduction of farmland values for the United States as a whole was \$320/acre. From this reduction we observed \$241 decrease in farmland values due to temperature variability and \$80 decrease due to precipitation variability. The total decrease in farmland values amounted to \$272 billion.

The second method of estimating the effect of ENSO on farmland values was to look at the change in the predicted value of farmland in the United States between models 3 and 1. By looking at models 3 and 1 we estimate the predicted change in through the following equation:

$$(5.9) \quad ENeffect = \hat{Y}_i^3 - \hat{Y}_i^1$$



V.1. Effect of ENSO Variation on Farmland Values/acre in 1982

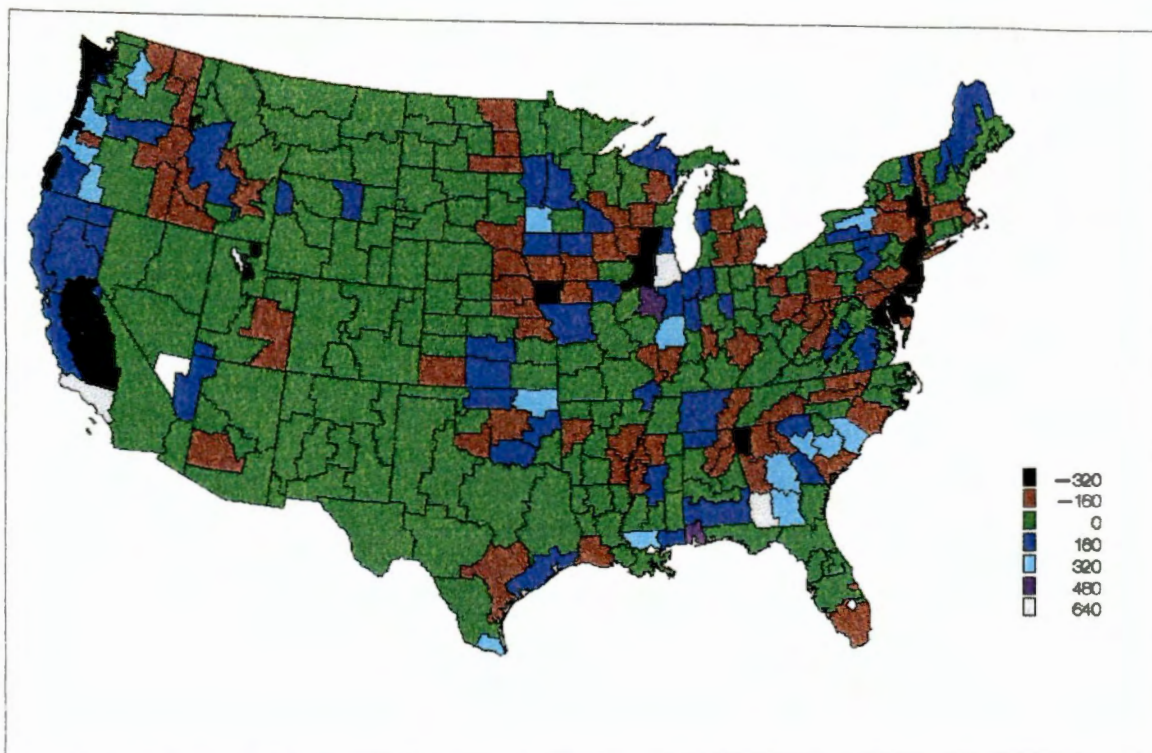


Figure V.2. Effect of ENSO on Farmland Values in 1982. Estimated by Looking at Differences in Predicted Values of Farmland per Acre

where the 3 and 1 superscripts indicate the model specification. This difference looks at how farmland value changes when we add an ENSO effect to the simplest specification in model 1. The results can be seen in figure V.2.

As we can see this method shows very different results. Most of the effects are concentrated on the Mid-West and the Pacific coast, however now, the effect is much more variable throughout the United States and the size of the effect is much smaller. The problem with this second method of estimating the effect of ENSO is that we are forcing the mean effect on the United States to be roughly equal to zero with half of the regions approximately having a positive effect and the other half a negative effect because both regression planes go through the point $\{\bar{X}, \bar{Y}\}$.

V-2. Results for 1992 Farmland Values

Turning to the 1992 models, spectral analysis was conducted for 1941 through 1991, and the mean climate and moisture variables were obtained for the same years. The ten additional years in the FSA may improve the reliability of the ENSO and non-ENSO measures. On the other hand, one of the problems of FSA is that additional terms that increase the historical fit might not improve accuracy, a situation called overfitting, as the model might now include more outliers (DeLurgio, 1998). We estimated the same four model specifications in 1992 that were estimated for 1982 farm values. The results for the four models can be seen in table V.2.

The first specification that does not include any variability measures explains 86.55% of the variability in farmland values. The F-test for the overall model gives a value of 59.59 suggesting the coefficients are jointly significantly different from zero at the 99% confidence level. All non-weather variables were broadly similar to the 1982 model. Income is again positive and significant, however, population density is no longer a significant factor in explaining variation in farmland values. Flood prone land is significant and negative, indicating that floods negatively affect land values. Soil moisture also became a significant factor during the last three quarters of the year with the second and fourth quarter carrying a positive sign and the third quarter a negative sign. The land class variables still indicate that high quality class I land is valued greater than land classified as land II-land VIII. Salinity is still negative and significant indicating that the presence of soluble salts is bad for the value of land. The pH of the

Table V.2. Semi-log model. Dependent variable log of farmland values for 1992 model

Independent variable	Model 1	Model 2	Model 3	Model 4
Constant	18.783 (0.0001)***	25.217 (0.0001)***	23.715 (0.0001)***	23.755 (0.0001)***
Income	7.0E-5 (0.0001)***	6.2E-5 (0.0003)***	6.6E-5 (0.0001)***	5.2E-5 (0.0001)***
Population Density	8.23E-5 (0.1492)	9.1E-5 (0.0925)*	4.5E-5 (0.3507)	4.6E-5 (0.3346)
Population Density Squared	-2.88E-9 (0.2120)	-3.3E-9 (0.1221)	-2.1E-9 (0.2737)	-1.91E-9 (0.3248)
Salinity	-0.194 (0.0001)***	-0.102 (0.0226)*	-0.075 (0.0607)*	-0.085 (0.0312)*
Ph	-0.275 (0.0001)***	-0.261 (0.0001)***	-0.197 (0.0002)***	-0.215 (0.0001)***
Bulk Density	0.133 (0.0116)**	0.125 (0.0139)**	0.035 (0.4547)	0.040 (0.3827)
Land Class II	-3.016 (0.0001)***	-2.575 (0.0001)***	-2.736 (0.0001)***	-2.763 (0.0001)***
Land Class III	-3.837 (0.0001)***	-3.184 (0.0001)***	3.084 (0.0001)***	-3.090 (0.0001)***
Land Class IV	-3.678 (0.0001)***	-3.005 (0.0001)***	-5.718 (0.0001)**	-3.256 (0.0001)***
Land Class V	-5.825 (0.0001)***	-5.344 (0.0001)***	-5.718 (0.0001)***	-5.359 (0.0001)***
Land Class VI	-4.664 (0.0001)***	-3.987 (0.0001)***	-3.713 (0.0001)***	-3.756 (0.0001)***
Land Class VII	-4.258 (0.0001)***	-3.636 (0.0001)***	-3.959 (0.0001)***	-3.898 (0.0001)***
Land Class VIII	-1.141 (0.2046)	-0.707 (0.4301)	-1.087 (0.1796)	-1.494 (0.0514)*
Clay	-0.045 (0.5610)	0.077 (0.3368)	0.076 (0.2881)	0.072 (0.3036)
Permeability	-0.006 (0.9092)	0.031 (0.5866)	-0.012 (0.8187)	-3.4E-4 (0.9948)
Flood Prone	-2.069 (0.0004)***	-1.740 (0.0038)**	-1.600 (0.0035)**	-1.827 (0.0005)***
Elevation	-6.0E-5 (0.0122)**	-5.3E-5 (0.0375)*	-1.07E-4 (0.0001)***	-1.1E-4 (0.0001)***
Moisture quarter 1	0.542 (0.1285)	0.700 (0.0421)*	0.842 (0.0073)**	0.801 (0.0098)**
Moisture quarter 2	0.5455 (0.0883)*	0.678 (0.0326)*	0.543 (0.0578)*	0.635 (0.0245)*
Moisture quarter 3	-1.065 (0.0001)***	-1.009 (0.0003)***	-0.467 (0.0695)*	-0.398 (0.1016)
Moisture quarter 4	1.391 (0.0012)***	0.945 (0.0244)*	-0.224 (0.5766)	-0.361 (0.3561)
Temperature January	0.004 (0.7830)	-0.011 (0.5593)	-0.03 (0.1819)	-0.033 (0.1245)
Temp January Squared	7.7E-4 (0.1016)	-5E-4 (0.2885)	-5.6E-4 (0.3031)	-7.5E-4 (0.1520)
Temperature April	0.242 (0.0825)*	0.418 (0.0019)**	0.626 (0.0001)***	0.553 (0.0001)***
Temp April Squared	-0.002 (0.041)*	-0.004 (0.0010)***	-0.005 (0.0001)***	-0.004 (0.0001)***
Temperature July	-0.074 (0.661)	-0.336 (0.0540)*	-0.270 (0.0968)*	-0.329 (0.0335)*
Temp July Squared	8.9E-5 (0.9388)	0.002 (0.0911)*	0.001 (0.1652)	0.001 (0.0851)*
Temperature October	-0.408 (0.0480)*	-0.475 (0.0181)**	-0.682 (0.0005)***	-0.514 (0.0074)**
Temp October Squared	0.004 (0.0090)**	0.005 (0.0067)**	0.006 (0.0002)***	0.005 (0.0018)***

Table V.2. Semi-log model. Dependent variable log of farmland values for 1992 model

Precipitation January	0.252 (0.0023)**	0.218 (0.0186)**	0.238 (0.0092)**	0.182 (0.0181)*
Prec January Squared	-0.014 (0.0780)*	-0.021 (0.0106)**	-0.017 (0.0914)*	-0.011 (0.1996)
Precipitation April	-0.001 (0.9926)	0.141 (0.2887)	0.139 (0.2605)	0.247 (0.0335)*
Prec April Squared	-0.011 (0.5443)	-0.020 (0.2949)	2.98 E-4 (0.9881)	-0.026 (0.1411)
Precipitation July	-0.253 (0.0004)***	-0.213 (0.0045)**	-0.411 (0.0001)***	-0.406 (0.0001)***
Prec July Squared	0.019 (0.0511)*	0.020 (0.0442)*	0.043 (0.0001)***	0.041 (0.0001)***
Precipitation October	0.064 (0.6953)	-0.146 (0.3941)	-0.091 (0.5653)	-0.065 (0.6739)
Prec October Squared	9E-4 (0.9749)	0.054 (0.0583)*	0.059 (0.0361)*	0.046 (0.0887)*
EN Prec var Jan		0.180 (0.0668)*	0.117 (0.2323)	
EN Prec var Apr		-0.225 (0.1900)	-0.264 (0.0976)	
EN Prec var Jul		-0.156 (0.1260)	-0.049 (0.6032)	
EN Prec var Oct		-0.225 (0.0055)**	0.052 (0.5341)	
EN Temp var Jan		-0.050 (0.0017)***	0.012 (0.6192)	
EN Temp var Apr		0.174 (0.0563)*	0.055 (0.5066)	
EN Temp var Jul		-0.268 (0.0065)**	-0.100 (0.2938)	
EN Temp var Oct		-0.179 (0.0019)***	-0.147 (0.0177)**	
Non EN Prec var Jan			-9.4E-4 (0.9765)	
Non EN Prec var Apr			-0.046 (0.1969)	
Non EN Prec var Jul			-0.013 (0.6455)	
Non EN Prec var Oct			-0.120 (0.0003)***	
Non EN Temp var Jan			-0.015 (0.0069)**	
Non EN Temp var Apr			0.008 (0.6563)	
Non EN Temp var Jul			-0.189 (0.0001)***	
Non En Temp var Oct			0.042 (0.0339)*	
Total Temp var Jan				-0.014 (0.0001)***
Total Temp var April				0.013 (0.4698)
Total Temp var July				-0.174 (0.0001)***
Total Temp var October				-7.46E-4 (0.9601)
Total Prec var Jan				-0.006 (0.7895)
Total Prec var April				-0.021 (0.5315)
Total Prec var July				-0.015 (0.5444)

Table V.2. Semi-log model. Dependent variable log of farmland values for 1992 model

Total Prec var October				-0.085 (0.0008)*
F-test	59.591 (0.0001)***	57.605 (0.0001)***	64.824 (0.0001)***	73.577 (0.0001)
Adjusted R ²	0.8655	0.8832	0.9094	0.9065
Error Sum of Squares	80597773.28	68130190.582	51380597.741	54539239.467

p-values in parenthesis

* significant at the $\alpha=0.1$ level

** significant at the $\alpha=0.01$ level

*** significant at the $\alpha=0.001$ level

land is again negative indicating that “basic” land is not suitable for plant growth.

Optimal values of Bulk density have a positive effect on farmland values. Clay content and permeability were insignificant in explaining farmland values. Elevation was also negative, with parcels of land that are in higher elevations being worth less than parcels in lower ones.

No major changes occurred in the second model specification. Again all the coefficients and their standard errors were in the majority constant for all model specifications. The second model, including ENSO variability measures increased the R^2 to 88.32%. Comparing models #1 and #2, there were 8 restrictions for the ENSO variables, and we tested the null hypothesis that ENSO coefficients are equal to zero. The F-critical was equal to 1.94 and the calculated $F=6.65$. Adding ENSO variability improves the overall performance of the model.

The third model included both ENSO and non-ENSO variability measures. The model again was a good fit with an F-test of 64.824 which is significant at the $\alpha=0.001$ level. The third model also has the highest adjusted R^2 explaining 90.94% of the variability in the dependent variable. Comparing the first and the third model, the restrictions tested the 16 restrictions that would set the ENSO and non-ENSO coefficients jointly equal to zero. The F-critical was 1.67 and the F-test from the model was 10.05, which allowed us to reject the null hypothesis. Again we found that adding ENSO and non-ENSO variability to the model improves the performance of the model.

The final model was the specification including total variation instead of its ENSO and non-ENSO components. Adding total variability to the model also seems to

be an improvement over the first model. Testing for the restrictions we find that we reject the null hypothesis at 95% level with calculated $F=17.37$. The model that includes total variability is better than the model that does not include any variability measures.

Again we found that adding weather variability to our models improves the overall performance of the model. The last question is whether or not the total variability should be separated into its two components, that is ENSO and non-ENSO variability. In the 1982 models we found that the model that separates total variability into its ENSO and non-ENSO component performs better than the model that uses total variability. In the 1992 models, testing the restricted model specification 4 against the unrestricted model specification 3, we find that critical F value for the 16 restrictions defined by equation 5.4 to be equal to 1.67 for a 95% level of α . The calculated F was equal to 1.08 so in this case we fail to reject the null hypothesis. At least one of the 16 equations in 5.4 is not true at the 95% confidence level. Unlike the 1982 model adding ENSO cycles as explanatory variables do not seem to improve the performance of the model relative to the model that combines all variation in a single measure.

Again we can estimate and map the effects of ENSO effects with the same two methods that were used for 1982. Figure V.3. shows the results from the first method as it is given by equation 5.9. Recall that this model specification assumes the covariance and correlation of the ENSO and the non-ENSO variables is equal to zero. We assume that all the ENSO coefficients are orthogonal to all other variables. As we can see even in the Midwest, which sustains the most of the damage in terms of farmland value decreases, the largest decrease is now \$800 per acre instead of \$2000 per acre, which was

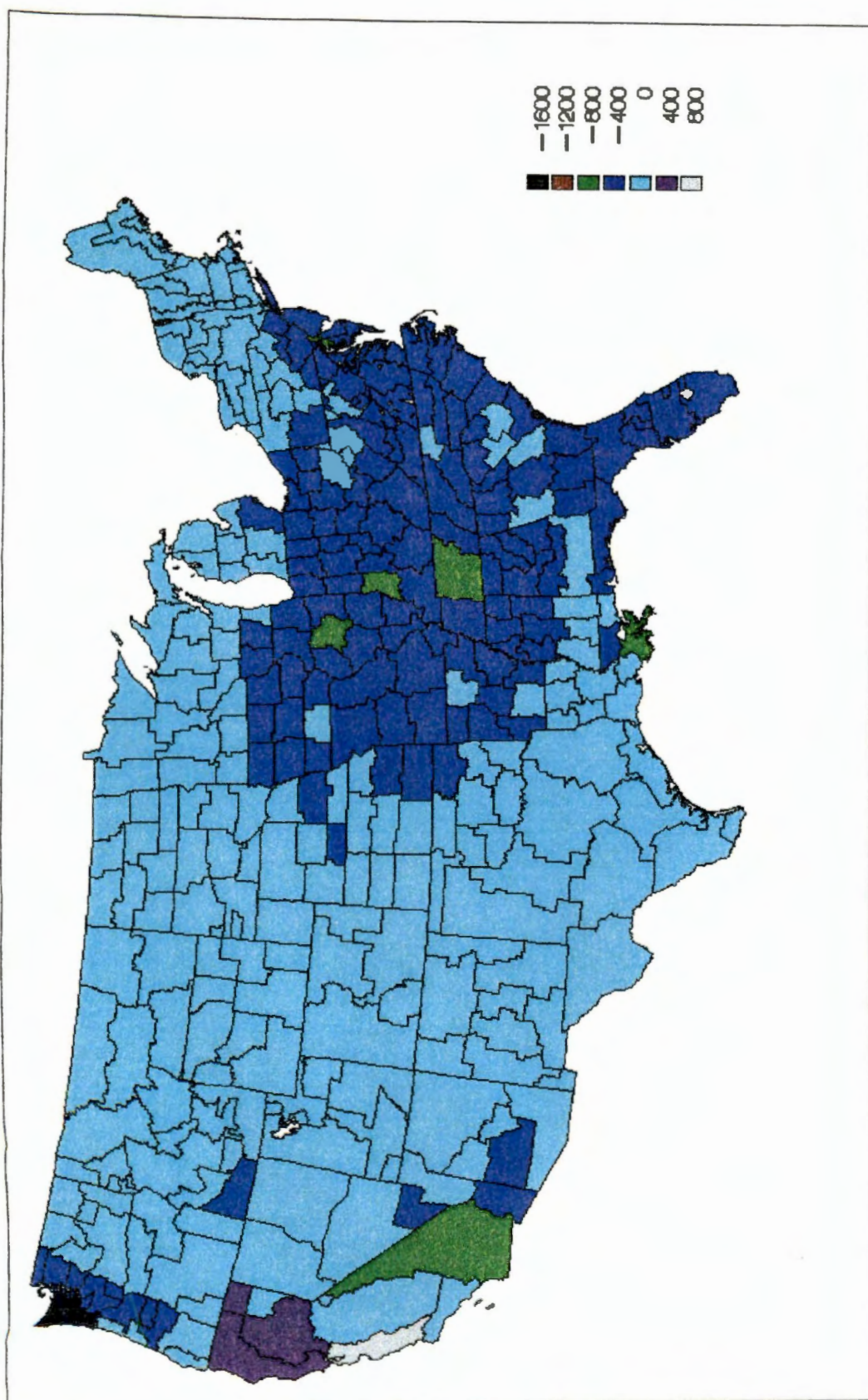


Figure V.3. Effect of ENSO on Farmland Values/acre in 1992

the case in 1982. Most of the damage is in the area of \$400 at maximum. Interestingly enough, the only areas where positive effects from ENSO are observed are still in California.

By 1992 the average decrease per acre in the United States from the 4 and 5 year cycle decreased from \$320 to \$148 /acre. Of those \$126 /acre are related to temperature variability and \$25 /acre are related to precipitation variability. 85% of the total reduction in farmland values was due to temperature variability and 15% due to precipitation variability. The damage from precipitation seems to be much lower than temperature. Total decrease in farmland values decreased from \$272 billion to \$131 billion.

The results from the second method of estimating the predicted change in farmland values due to ENSO events as they are given by equation 5.9. and can be seen in figure V.4. Recall that the problem with this method is that we are forcing the average effect of ENSO events in US farmland values to be roughly zero. We observe again more variability in the results and smaller effects.

One more set of results was generated and put into maps. We took the results from the first method of estimating the effect of ENSO events and we separated the effects of variability into the effect from temperature and precipitation. We also estimated the effect in terms of percentage changes. We then put all of the results together for 1982 and 1992 and produced figure V.5. that summarizes those results and allows the reader to compare the effect of ENSO on farmland values in 1982 and 1992.

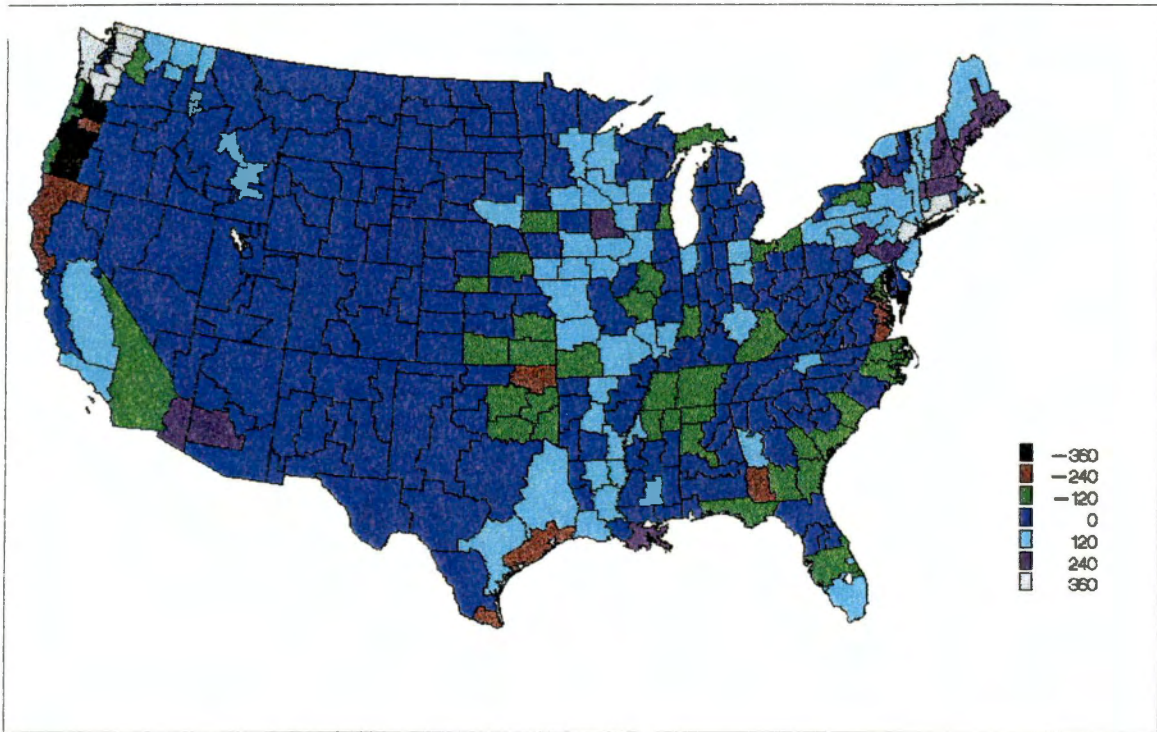


Figure V.4. Effect of ENSO on Farmland Values in 1982. Estimated by Looking at Differences in Predicted Values of Farmland per Acre

The results from those figures are also summarized in table V.3., which shows what the predicted effect is from the two models in terms of average decrease in farmland values and average percentage decrease.

By comparing the effects of ENSO cycles in 1982 and in 1992 we find that the total effect decreased by 1992. We also see that most of the effects come from ENSO related temperature variability. Precipitation variability seems to have a minimal effect on farmland values, especially in 1992.

Table V.3. Summary of Results for both Models

	1982	1992
Average Decrease in Farmland Values	\$ 320/acre	\$ 148/acre
Due to Temperature	\$ 241/acre (75%)	\$ 126/acre (85%)
Due to Precipitation	\$ 80/acre (25%)	\$ 25/acre (15%)
Average Percentage Decrease in Farmland Values	30.8%	20.99%
Due to Temperature	21.2%	17.8%
Due to Precipitation	9.6%	4%
Total Decrease in Farmland Values	\$ 272 billion	\$ 131 billion

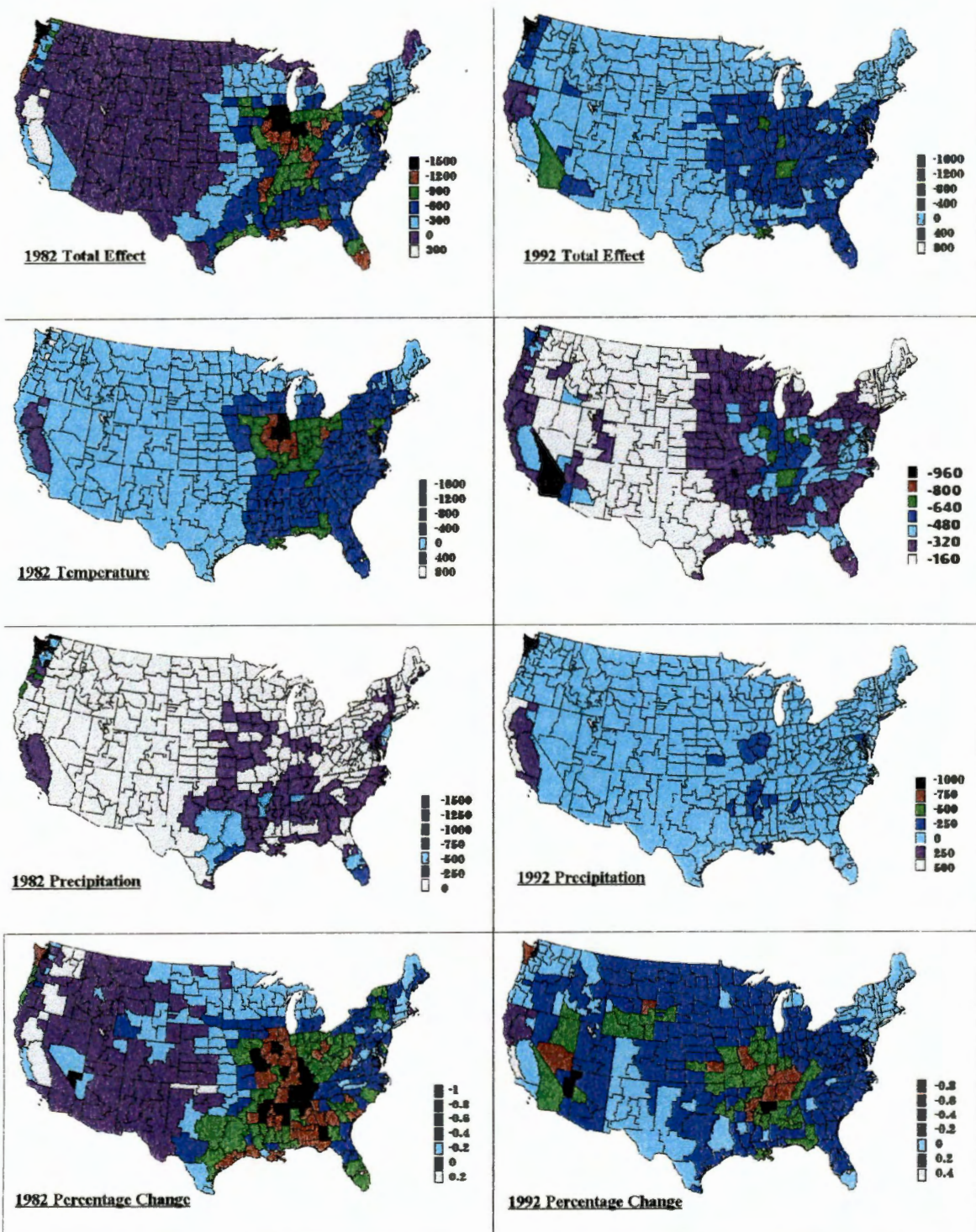


Figure V.5. Comparing Absolute Decreases in Farmland Values for 1982 and 1992

VI. Summary and Conclusions

This research examined how the El Niño and the La Niña weather phenomenon affects farmland values in the United States. To estimate the damage caused by the ENSO cycle we employed a method that was initially developed by Mendelsohn et al. The method estimated farmland value as a function of land characteristics, weather and an ENSO variability measure that was obtained through Fourier Series Analysis. FSA captured the effect from the 4-5 year cycle, which we assumed adequately describes ENSO cycles.

Results suggested that for both the 1982 and 1992 models the performance of the models improved when weather variability measures were added. We tested whether ENSO variability is an important factor in explaining variation in farmland values. Testing the restrictions we found that ENSO events seemed to matter in 1982 but not in 1992. We saw that for 1982 we need to separate total variability into its two components, ENSO and non-ENSO variability, whereas for 1992 separating total variability does not add anything significant to the model.

The total effect from the El Niño and the La Niña events on land decreased in 1992 as compared to the earlier 1982 event from \$272 billion to \$131 billion. The average decrease in farmland values decreased from \$320/acre (30% decrease) in 1982 to \$148/acre (21% decrease) in 1992. This set of results suggests that the majority of the effects from ENSO event comes from ENSO related temperature variability. The effect of ENSO related precipitation variability is minimal. Despite this decrease the effect of

ENSO on farm values was still very large. However, we have to keep in mind that ENSO effect was estimated under some very restrictive assumptions regarding ENSO variation and other variables. We assumed that the covariance and correlation of ENSO to all the other variables is equal to zero. If these assumption do not hold we might be overstating the impact of ENSO.

The results suggest that by 1992 ENSO events might not be differentiated from other variation in weather. Improved information regarding ENSO may be an explanation. Alternatively, improvements in agricultural production technologies may have mitigated the influence of ENSO events. Following the 1982 event, research examining the causes of ENSO events and their effects on US climate was readily available. This information might have been used by farmers as an input so that given an ENSO warning, farmers may have adjusted crop production and input use.

Although this research provided interesting results and conclusions, one of the basic shortcomings is the method used to extract the variability from El Niño. Fourier series decomposition captures variability from times series with harmonic cycles that can be described as a function of sines and cosines. Although the El Niño cycle has been described as a 4-5 year cycle, the problem that is created is that El Niño might actually be an anharmonic cycle as it is observed sometimes every two years and others after a period of ten years. An improvement would be to use a different method to extract the variability described by Kappenne (1994). The method is called Principal Component Analysis (PCA) and it allows capturing the variability from a time series with anharmonic cycles.

Another problem associated with the theory of Ricardian rent is that it assumes a constant discount rate. Falk (1991) studied farmland prices and tested the validity of the constant discount rate version of the Present Value model of farmland prices. His results indicated that the present value model failed. The author attributed this to economic factors and suggested that one possible explanation is that the discount rate in the present value model is time varying. This is a problem that might be addressed in future research.

This research provided results that estimate the effect of ENSO cycles in the United States that should be of help in terms of protecting farmer income through government programs. Knowing where the effect of the next El Niño will be felt the most will allow policy makers to produce programs to protect farmer income in those regions by adjusting production practices and through direct government help. However, more research is still needed to fully understand and predict the effect that ENSO cycles have on the United States.

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Appendices

Appendix I. Variability Charts from Spectral Analysis

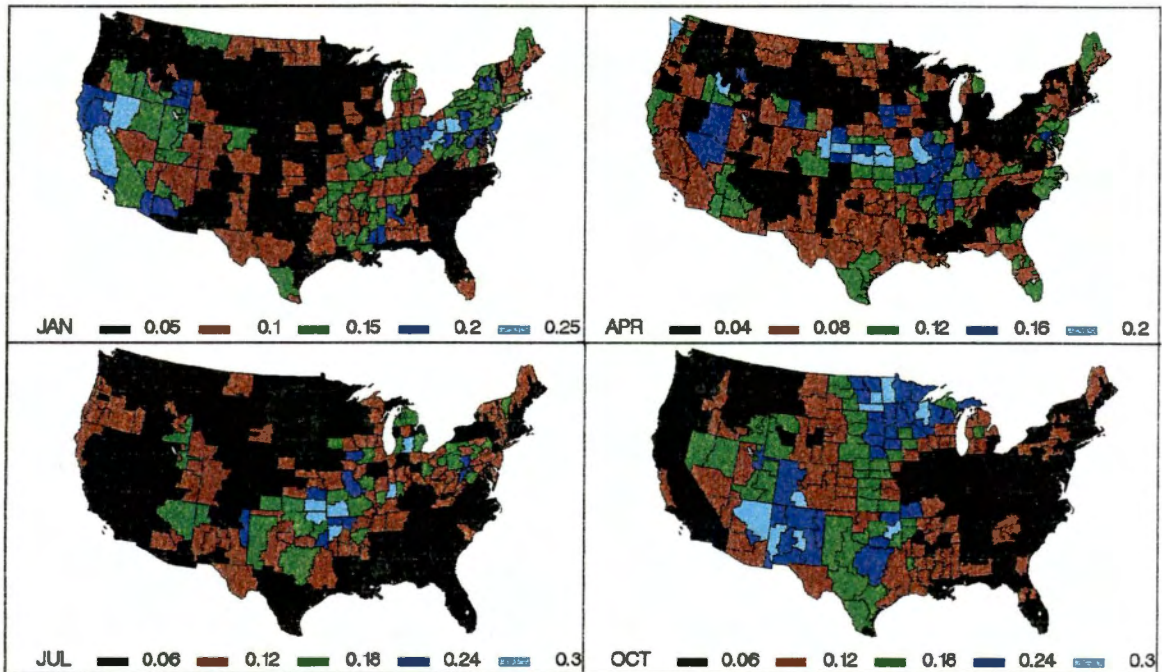


Figure AII.1. US El Niño Precipitation Variability for Jan., Apr, July, October.

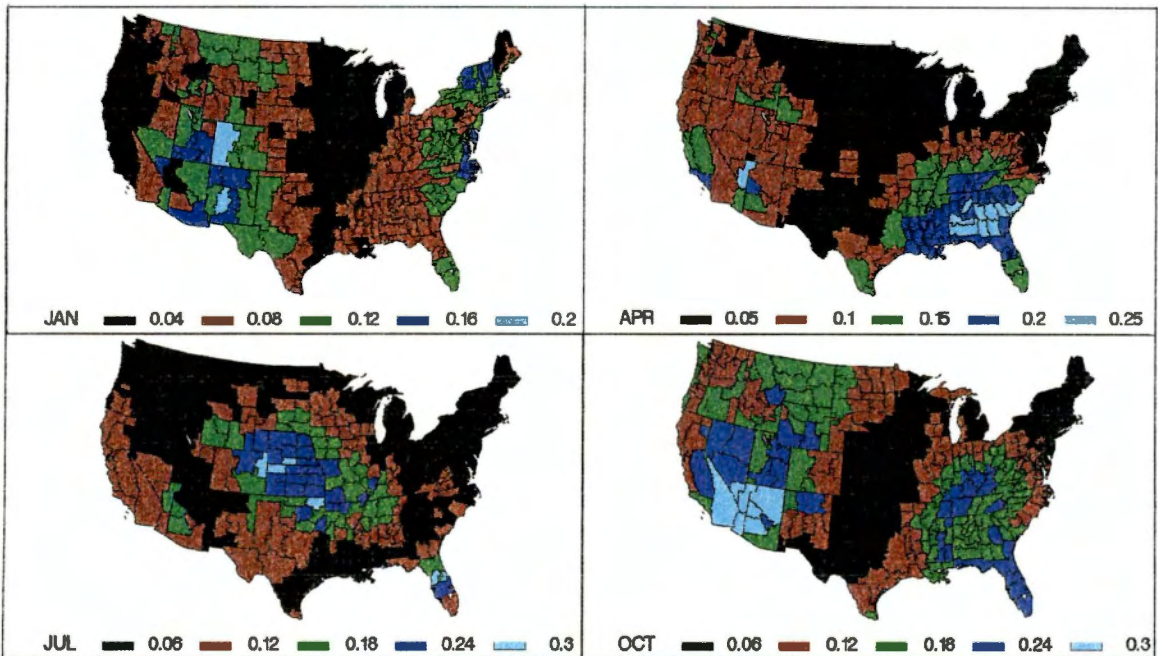


Figure AII.2. US El Niño Temperature Variability for Jan., Apr, July, October

Appendix II. Variable definitions

Temperature (month): Mean temperature for respective month measured in degrees Fahrenheit.

Precipitation (month): Mean precipitation for respective month measured in inches.

Moisture: Moisture Anomaly Index, given by monthly Z-values defined as a measure of departure from normal of the climate for that month measured as quarterly averages.

El Niño temperature variability (month): Portion of temperature variability of respective month that is attributable to El Niño.

El Niño precipitation variability (month): Portion of precipitation variability of respective month that is attributable to El Niño.

Non El Niño temperature variability (month): Portion of temperature variability of respective month that belongs to factors other than El Niño.

Non El Niño precipitation variability (month): Portion of precipitation variability of respective month that belongs to factors other than El Niño.

Landclass: Land capability class and sub class for 1992. Class I have soils have few limitations that restrict their use, class II have some limitations that reduce the choice of plants or require moderate conservation practices, class III and IV have severe limitations, class V have little erosion hazards but have other limitations impractical to remove that limit their use, class VI are limited to pasture use, class VII have very severe limitations that limit their use to grazing and class VIII have limitations that preclude their use for commercial plant production and restrict their use. Landclass variables are measured as percentage of land in each land class in each CLIMVIS division.

Salinity: Average value for the range in soil salinity of the soil layer or horizon measured as electrical conductivity of the soil in a saturated paste, expressed as mmhos/cm. (presence of an excessive amount of soluble salts that suppresses plant growth).

Bulk Density: Average value for the range in moist bulk density of the soil layer or horizon, expressed as grams per cubic centimeter.

Permeability: Average rate for the range in permeability for the soil layer or horizon, expressed as inches/ hour (permeate =to spread or follow through).

Clay: Average value for the range of clay content of the soil layer or horizon, expressed as a percentage of the material less than 2mm in size. (amorphous gel-like material likely to generate high proportions of runoff and suspended sediment, liable to mudflows once water saturated. Non-extreme contents of clay provide structural stability).

Ph: The average value in soil reaction (ph) for the soil layer or horizon, expressed in values from 0-7, with values less than 5.5 being acidic and more than 5.5 being basic.

Flood Prone: Soil flooding class code. The duration of annual flooding in a normal year. Very brief flooding is less than 2 days, brief flood duration is 2-7 days, long is 7 days to 1 month and very long flooding is more than 1 month.

Density: Density of population per square mile for 1990.

Elevation: Elevation of the centroid point in a division expressed in feet.

Landvalue: Estimated market value of land and buildings measured in average dollars per acre (1984 dollars).

Income: Money income per capita (1984 dollars).

Vita

Dimitrios Dadakas was born in June 23, 1975 in Alexandroupolis, Greece. He initially attended public elementary school in Lubeck, Germany and later in Alexandroupolis, Greece. In 1987 he enrolled with a scholarship at Anatolia High School in Thessaloniki, Greece. After finishing high school he enrolled in 1993 in Illinois Wesleyan University in Bloomington, Illinois. He graduated in May of 1997 with a degree in Economics and a minor in Mathematics. In August of 1997 he started a Masters of Science in the Agricultural Economics department of the University of Tennessee, where he worked as a research assistant. Dimitrios will continue his studies pursuing a Ph.D. in Environmental Economics at North Carolina State University in Raleigh, North Carolina.

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