IMPACT OF THE ENSO CLIMATE PHENOMENON ON FLORIDA FRESH TOMATOES

By

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This document is dedicated with love to my parents, Peter and Maria Hildebrand.

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The ENSO phenomenon, more popularly known as El Niño and La Niña, has an effect on agricultural production, particularly in Florida. Knowledge of the impact of ENSO on tomatoes is important because the fresh market tomato industry has a farm value of more than $1 billion in the United States. Florida produces the majority of the nation's fresh tomatoes, accounting for one third of the state's approximate $1.33 billion in cash receipts for vegetables. The effects of seasonal climate variation resulting from ENSO on Florida tomato prices have not been quantitatively measured.

The overall objective of this research is to determine if ENSO seasonal climate variation has an impact on Florida tomato prices. Because scientists are better able to predict ENSO, growers could use this information to modify their practices to maximize profit. An empirical model composed of four simultaneous equations is used to determine the significance ENSO phases have on tomato yield and price. The empirical results indicate that the El Niño and La Niña variables are not significantly different from

zero. Therefore it can be concluded that ENSO has no impact on yield which indicates that prices are not affected by ENSO. This research found no relationship of El Niño and La Niña phases on Florida tomato prices indicating that improved forecasts of ENSO would have no value to farmers.

CHAPTER 1
INTRODUCTION

1.1 Introduction

Seasonal climate variations can have a global impact from agricultural production to the electric bill. Strong effects from seasonal climate variations are very noticeable in the southeastern United States, especially in Florida (Hansen et al. 1998). In 1997, North Central Florida farmers fought flood-ridden fields causing much devastation to their crops. Instead of getting relief from the rains the following year, these same farmers fought drought and warmer than average temperatures (Arndorfer 1998). These farmers were facing the El Niño and La Niña phases of the seasonal climate variation phenomenon known as the El Niño Southern Oscillation or ENSO.

Changes in the sea surface temperature of the equatorial Pacific Ocean affect the atmosphere and cause seasonal climate variations. These variations came to be known as ENSO. ENSO is a system of interactions between the Pacific Ocean and the atmosphere around it (Soreide and McPhaden 2005). There are three ENSO phases known as El Niño, La Niña and Neutral. ENSO effects are noticeable in the southeast United States, though its impacts are most prominent in Peninsular Florida. During the winter months, January, February, and March (Table 1-1) ENSO effects are most noticeable, though the effects can be noticed during the months of both spring (April, May, June), and fall (October, November, December). During an El Niño year, Florida faces wetter and cooler fall and winter conditions than during a Neutral year. Increased rainfall during an El Niño can damage root systems resulting in reduced yields, while the lower daytime temperature can slow crop development (Hansen et al. 1998). Generally, opposite effects such as dryer and warmer fall and winter conditions than an El Niño are felt during La Niña years.

Table 1-1. ENSO impacts across the southeast United States.

El Niño/La Niña Impacts Across the Southeast U.S.					
Phase	**Region**	**Seasons**			
		Oct-Dec	Jan-Mar	Apr-Jun	Jul-Sep
El Niño	Peninsular Florida	Wet & cool	Very wet & cool	Slightly dry	Slightly dry to no impact
	Tri-State Region	Wet	Wet	Slightly wet	No impact
	Western Panhandle	No impact	Wet	Slightly dry	No impact
	Central and North Ala. & Ga.	No impact	No impact	No impact	Slightly dry
La Niña	Peninsular Florida	Dry & slightly warm	Very dry & warm	Slightly wet	Slightly cool
	Tri-State Region	Slightly dry	Dry	Dry	No impact
	Western Panhandle	Slightly dry	Dry	Dry	No impact
	Central and North Ala. & Ga.	Dry	Dry in the south, wet in NW Ala.	No impact	Wet in NW Ala.
Neutral	All Regions	No impact	No impact	No impact	No impact

(Source: Southeast Climate Consortium http://www.agclimate.org/Development/apps/agClimate/controller/perl/agClimate.pl, last accessed April 30, 2006)

Planting dates for fresh tomatoes in Florida range from mid-July through mid-March, and harvesting dates range from mid-October through mid-June. The largest production occurs from November through January (Lucier 2004). The Florida fresh tomato industry is affected by variations in temperature and precipitation. Fresh tomatoes require specific variations in temperature and precipitation to be of optimum quality.

Florida fresh tomatoes are grown across the state, though the planting and harvesting dates varies by season. During the summer months (July, August, September) the planting of fresh Florida tomatoes occurs in north Florida and progresses southwards as temperatures decrease into the months of both fall (October, November, December) and winter (January, February, March). Fresh tomatoes in Florida are generally not planted during spring months because conditions are not favorable (Table 1-2).

Table 1-2. Planting dates in months for Florida fresh tomatoes by region.

	J	F	M	A	M	J	J	A	S	O	N	D
NORTH FLORIDA												
CENTRAL FLORIDA												
SOUTH FLORIDA												

Past research has determined that weather and climate have an economic impact on agriculture. More recent research has shown that the economic value of ENSO on the U.S. agriculture, forestry, and fishery sectors at $200 million per year with the majority going towards agriculture (Adams et al. 1995). To determine whether ENSO seasonal climate variations affect specific crops, researchers including Solow et al. (1998) and Adams et al. (1995) used plant biophysical simulation models and included crops in Florida in their data. Both studies found that ENSO impacted crop production, though both models assumed perfect forecasts, an unlikely scenario. Hansen et al. (1998) also analyzed the response of specific crops to ENSO in several states including Florida. Breuer et al. (2004) examined the use crop models by other researchers to determine the effects of planting dates on tomato yield when influenced by ENSO. As technology and knowledge of ENSO seasonal climate variation improves, researchers are better able to predict ENSO events. By being able to more accurately forecast ENSO events, it has been thought that farmers would be able to adjust input costs and vary growing decisions that impact yield.

Knowledge of the impact of ENSO on tomatoes is important because the fresh market tomato industry has a farm value of more than $1 billion in the United States. Florida produces the majority of the nation's fresh tomatoes making tomatoes one of the highest valued crops in Florida, accounting for one third of the state's approximate $1.33 billion cash receipts for vegetables (Lucier 2004 and Mongiovi 2005). Fresh tomatoes in Florida are harvested when they are fully grown and still green (Sargent 1998). The majority of Florida tomatoes are grown for the fresh market. Fresh market tomatoes are generally sold on the open market and therefore are not under contract (Lucier 2004). Because of this, fresh market tomatoes have more variation in price than contract vegetables. Though much research has been done showing the effects of ENSO on yield and overall economic value, no significant research has been done to study the impacts of ENSO on Florida tomato prices.

1.2 Researchable Problem

The effects of seasonal climate variation resulting from ENSO on Florida tomato prices have not been quantitatively measured. This study will measure the effect of ENSO seasonal climate variation on Florida fresh tomato prices. Because scientists are better able to predict ENSO, growers could use this information to modify their practices in order to maximize profit.

1.3 Objectives

Past research has indicated that an economic value can be assigned to ENSO and its impact on agriculture. The overall objective of this research is to determine if ENSO seasonal climate variation has an impact on Florida tomato prices. The specific objectives are to

- Complete a literature review on ENSO and its effects on crop production and value to agriculture.
- Build an econometric supply and demand model of Florida fresh tomatoes.
- Obtain supply and demand data for the supply and demand model of Florida tomatoes.
- Determine if a relationship exists between ENSO events and Florida tomato prices.
- Determine the impact of ENSO on Florida tomato prices.

CHAPTER 2
SEASONAL CLIMATE VARIATION

2.1 Weather and Climate

For this study it is important to distinguish between weather and seasonal climate. Weather is the day to day variation in temperature, humidity, wind speed, and precipitation. It affects daily activities from what clothes will be worn to whether or not to irrigate. Using computer models, weather forecasters use the atmospheric behavior to determine weather patterns for no more than 2 weeks into the future (Mjelde et al. 1998). Seasonal climate on the other hand, is the variation of average weather patterns over time due to global conditions including ocean temperatures (O'Brien et al. 1999). Seasonal climate can be forecasted four to six months ahead with improved technology (Green 1997). Besides having an impact on human comfort levels, climate fluctuations can influence productivity, particularly on the agricultural and forestry industries (O'Brien et al. 1999).

2.2 El Niño Southern Oscillation (ENSO)

ENSO or the El Niño Southern Oscillation is a system of interactions between the equatorial Pacific Ocean and the atmosphere around it (Soreide and McPhaden 2005). In the 1500s fisherman off the coast of Peru and Ecuador began to notice unusually warm water pooling occasionally around the winter months (O'Brien et al. 1999). Usually winter months were a vacation period for the fisherman because the waters would warm to a temperature unfavorable for fish. Fisherman noticed unusually warm waters during certain years which caused the warm periods to extend into early summer. Because this unusually warm water began around Christmas time, the fisherman named the phenomenon “El Niño” or the Christ child (Wallace and Vogel 1994).

In the 1920s Sir Gilbert Walker, a British scientist, studied the Asian monsoons in India. He wanted to determine a method to predict the monsoons. After reviewing world weather records, he noticed a connection between barometer readings in the eastern and western sides of the Pacific Ocean (Wallace and Vogel 1994). When pressure rose in the east, he observed that pressure fell in the west, and when pressure fell in the east it rose in the west (Wallace and Vogel 1994). Sir Gilbert Walker bestowed the phenomenon with the title Southern Oscillation because of its seesaw-like characteristic.

Walker also noticed that monsoon seasons occurred at the same time as severe droughts in Australia, Indonesia, and parts of Africa (Wallace and Vogel 1994). Though many of his colleagues were skeptical of Walker’s findings, he predicted that an explanation could be found with an understanding of wind patterns. In the 1960s, Jacob Bjerknes, a professor at the University of California, was the first researcher to notice a correlation between the unusually warm sea surface temperatures and unusual rainfall associated with weak easterlies (Wallace and Vogel 1994). This information provided the key to relate these warm waters and Walker’s Southern Oscillation pressure changes. ENSO became the name for the disruption of the normal atmospheric and oceanic systems in the Pacific Ocean which could have impact on weather around the world (Soreide and McPhaden 2005). The warm phase of ENSO is named El Niño while the cool phase of ENSO is named La Niña.

The Pacific Ocean waters associated with ENSO are measured by a system of buoys and satellites that measure temperatures, currents, and winds in the equatorial band off the coast of Peru and Ecuador and extend to Indonesia and Australia in the southern hemisphere (Soreide and McPhaden 2005). The Japan Meteorological Agency has an index which shows monthly sea surface temperature anomalies (JMA 1991). This index is used by many researchers to classify what ENSO phase is occurring, i.e., El Niño, La Niña, or Neutral. El Niño and La Niña occur approximately every 2 to 7 years. The duration of the phase is generally one year and defined as beginning in October and ending in September. This definition is intentionally created to seize the peak months of the phase which occur during December and January (O'Brien et al. 1999).

2.3 Neutral

Walker was correct in his prediction that wind patterns would play a vital role in his Southern Oscillation theory. During a normal or Neutral year (Figure 2-1), tropical trade winds blow from east to west pooling warm water in the western Pacific Ocean off the coast of Indonesia and Australia (O'Brien et al. 1999). Figure 2-1 shows the Pacific Ocean water temperature in degrees Celsius during a given day in December of 1993.

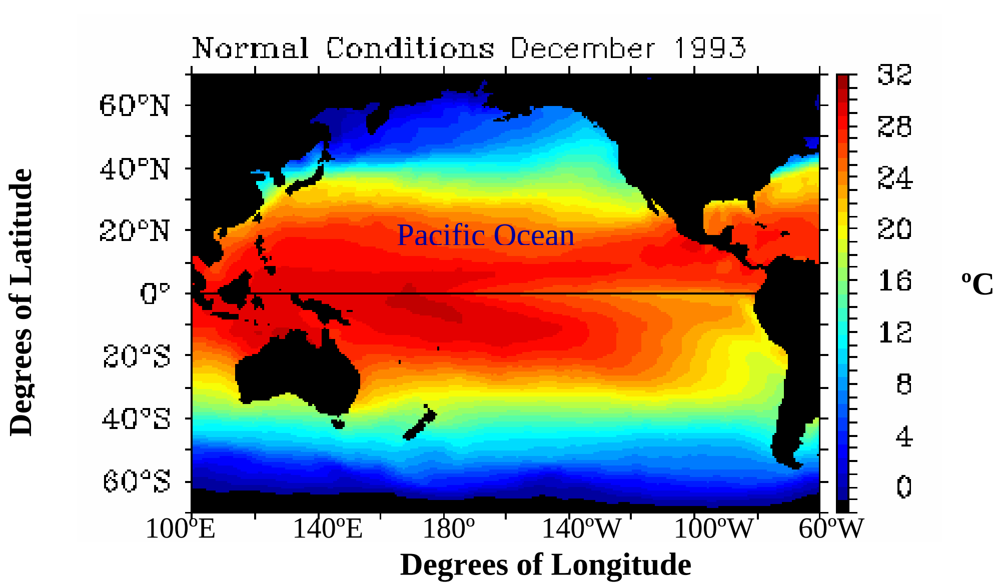

Figure 2-1. Sea surface temperatures during a Neutral year in the Pacific Ocean. Source: NOAA (http://www.pmel.noaa.gov/tao/elnino/el-nino-story.html , Last accessed October 12th, 2005)

The eastern winds stir up cool and nutrient rich water towards the surface in the eastern equatorial Pacific Ocean off the coasts of Peru and Ecuador. The warm water from the western Pacific Ocean creates a vigorous hydrological cycle with tropical storms that send atmospheric waves and disturbances around the globe. These disturbances are evenly distributed by high altitude winds.

2.4 El Niño

During an El Niño year, the tropical trade winds slowly die down in the central and western Pacific causing the warm water to move back towards the South American coast(Figure 2-2), resulting in sea surface temperatures that are much warmer than usual, (O'Brien et al. 1999).

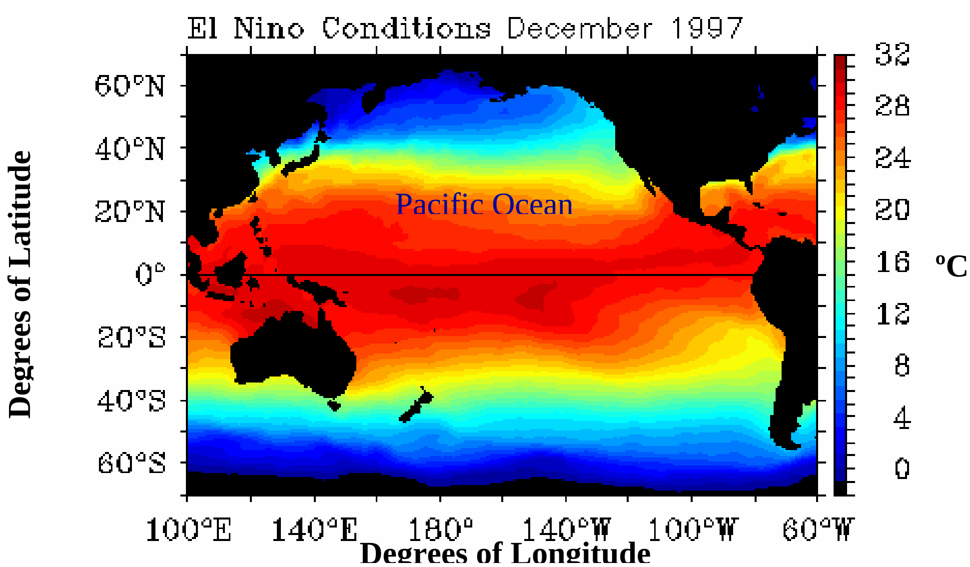

Figure 2-2. Monthly sea surface temperatures during an El Niño year in the Pacific Ocean. Source: NOAA (http://www.pmel.noaa.gov/tao/elnino/el-nino-story.html , Last accessed October 12th, 2005)

This unusual increase in water temperature must occur for a minimum of six months with an average sea surface temperature of 0.5ºC higher than normal for the Japan Meteorological Agency or JMA to classify the disturbance as El Niño in their index (O'Brien et al. 1999). Because trade winds are weaker than usual, the cold nutrient rich water is unable to surface. Storms follow the warm waters in the east which result in flooding in areas of Peru and Ecuador while Indonesia and Australia experience droughts. In addition, the warm waters in the Pacific disturb the global atmospheric circulation which alters weather in regions around the globe (Soreide and McPhaden 2005). In the United States, the warm waters of the Pacific Ocean strengthen the jet stream and pull it further south guiding storms from California into Florida (Figure 2-3). This causes cooler and wetter winters in Florida. Greater than average rainfall amounts and cooler than average temperature are seen in Florida.

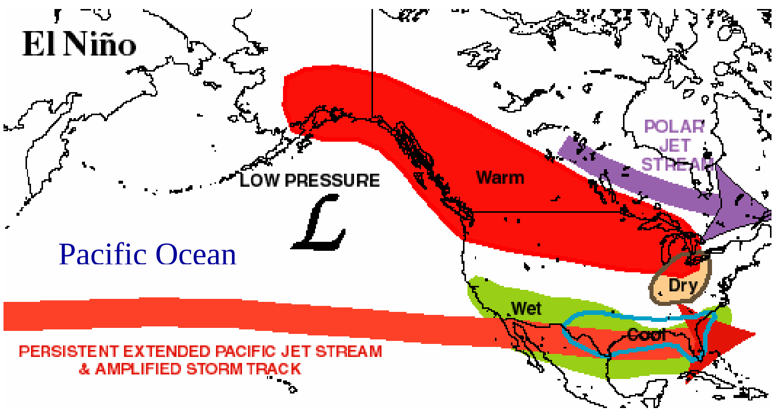

Figure 2-3. Typical weather patterns observed in North America in January, February, and March during an El Niño year. Source: NOAA (http://www.pmel.noaa.gov/tao/elnino/el-nino-story.html , Last accessed October 12th, 2005)

During an El Niño phase, the average winter rainfall in Florida increases by more than 30% compared to a Neutral year. Winter temperatures during an El Niño in Florida are on average 2ºF to 3ºF cooler than Neutral winter temperatures (O'Brien et al. 1999).

2.5 La Niña

During a La Niña year stronger than normal trade winds occur (Figure 2-4), stirring up the cold water below the sea resulting in cooler than normal sea temperatures in the eastern Pacific Ocean (O'Brien et al. 1999).

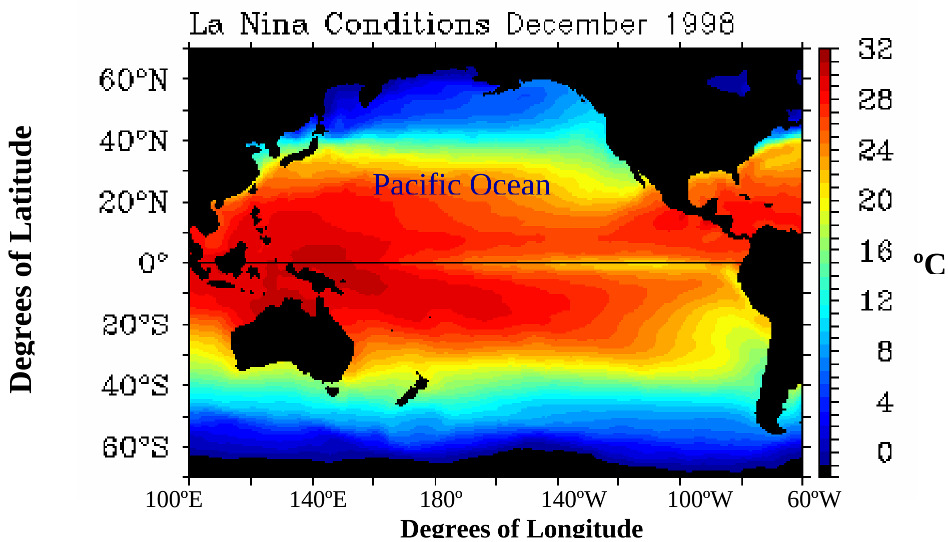

Figure 2-4. Monthly sea surface temperatures (ºC) during a La Niña year in the Pacific Ocean. Source: NOAA (http://www.pmel.noaa.gov/tao/elnino/el-nino-story.html , Last accessed October 12th, 2005)

This unusual decrease in water temperature must occur for a minimum of six months with an average sea surface temperature of 0.5ºC lower than normal for the Japan Meteorological Agency (JMA) to classify the disturbance as La Niña in their index (O'Brien et al. 1999). Because trade winds are stronger than usual, the cold and nutrient rich water is able to rise to the surface of the Pacific Ocean. This causes Indonesia and Australia to experience increased rainfall while the western coast of South America experiences dryer than normal conditions (Soreide and McPhaden 2005), exactly opposite effects of El Niño conditions.

The cooler water from the Pacific Ocean weakens the jet stream and pulls it northward over the United States (Figure 2-5). This northward movement prevents storms from easily moving into Florida. This causes warmer and dryer winters in Florida. Less than average rainfall amounts and warmer than average temperatures are seen in Florida (O'Brien et al. 1999). During a La Niña phase, the average fall, winter, and spring rainfall in Florida decreases by 10% to 30% compared to a Neutral year.

Winter temperatures in Florida during a La Niña are on average 2ºF to 4ºF warmer than a Neutral winter (O'Brien 1999).

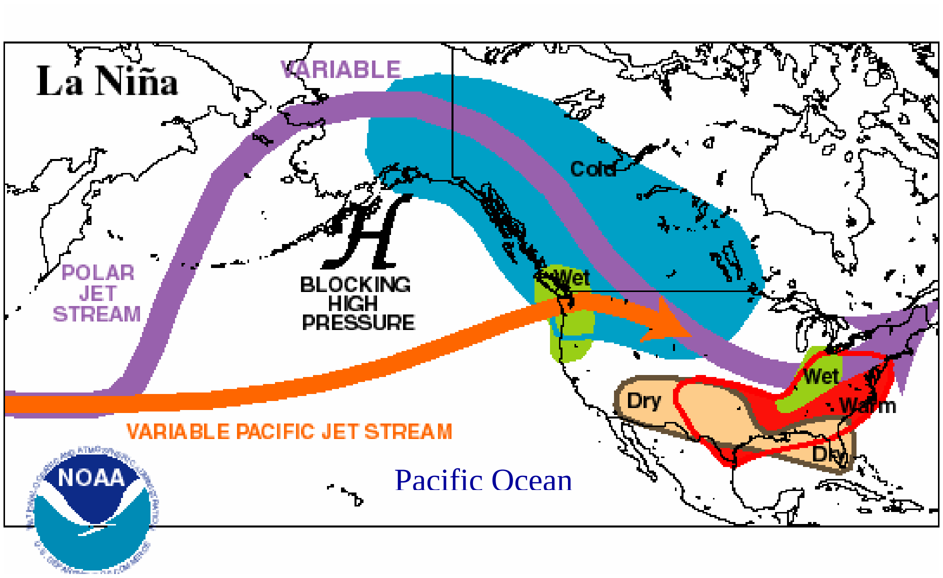

Figure 2-5. Typical weather patterns observed in North America in January, February, and March during a La Niña year. (Source: NOAA http://www.pmel.noaa.gov/tao/elnino/el-nino-story.html, Last accessed October 12th, 2005)

2.6 Summary

El Niño and La Niña have vital roles in determining climate variations around the globe. These climate variations have an effect on weather that varies in strength by regions. Strong relationships have been seen in the southeastern United States (Mjelde et al. 1998). In Florida, average precipitation and temperature vary significantly depending on the ENSO phase. Though average winter temperature decreases in Florida during an El Niño, 11 out of 12 major freezes in the last century in central Florida occurred during a Neutral phase (Jagtap et al. 2002). El Niño and La Niña phases are not identical in strength year to year. Most of the climate effects caused by El Niño and La Niña are strongest during the winter season but are also noticed in other months.

CHAPTER 3
REVIEW OF LITERATURE

3.1 Introduction

This chapter presents a summary of the major topics taken into consideration for this study. Past research has determined an economic value exists between agriculture and weather forecasts while other research has attempted to establish an exact value. More advanced research has begun to examine not just weather forecasts, but has ventured into seasonal climate forecasts and more specifically, the ENSO phenomenon. Researchers have begun to explore the ENSO signal and strength and its relevance to agriculture production and price.

3.2 Weather Forecasts and Input Decisions

3.2.1 Value of Weather Forecasts to a Crop

In theory, perfectly forecast weather would greatly aid growers allowing them to optimize crop output and ultimately profit. Unfortunately, meteorologists are unable to perfectly forecast weather. This has led researchers to question if significantly more accurate weather forecasts would help growers.

Raisin growers in California place significant value on weather forecasts during the months of September and October when their crop is particularly vulnerable to rain. They require dry conditions during these months to dry the grapes. In 1963, Lave wanted to determine whether more accurate weather forecasts would prove to be beneficial to California raisin growers, both on a microeconomic and a macroeconomic level. On the microeconomic level, Lave (1963) analyzed information relating to a single grower and examined the entire raisin industry on the macroeconomic level.

In order to determine the quantitative effect of weather on raisin production, Lave (1963) fitted a supply curve for the raisin industry. He then created a relationship between the quantity of raisins dried in any given year, the number of degree days in any given growing season, the price of raisins two and three seasons before and a random error term. The number of degree days is a measure to determine the best use of grapes in a region during a growing season. A degree day for raisin grapes is the mean temperature in a day minus 50ºF. Raisin grapes require 3,000 degree days to be of optimal quality. The sum of degree days within an ideal season would be 3,000 degrees. Lave (1963) used the prices two and three seasons before because a new grapevine takes two to three years to mature. Lave (1963) then fitted the equation by least squares and ran a Durbin-Watson test. He found the data to be consistent with the hypothesis and noted a strong dependence on weather. Lave's (1963) supply equation showed that an additional degree day would result in the production of a statistically significant increase in pounds of raisins. Thus, Lave (1963) concluded that a grower could increase profits if weather could accurately be forecast. With a perfect forecast, a grower could optimize yield and maximize profit.

Because weather cannot be controlled nor accurately predicted, growers must gamble. Individual growers must decide when and how much to plant, when to harvest, and whether to sell fresh or dried grapes. Using a component of game theory, Lave (1963) used a decision matrix which relates the grower's actions to the related payoff to that action. Thus, each grower is playing a game with nature. Growers are given two main options of either fully cropping or under cropping and then must decide whether to pick their grapes to dry for raisins, sell the grapes to wineries for crushing, or pick the grapes when ripe regardless of weather forecasts. The decision matrix shows that growers will always have an advantage if they fully crop and prepare to pick the grapes for crushing. In addition, the matrix shows that an advanced forecast of three weeks holds greater value to growers than no forecast, but does not provide an exact value. To further investigate his conclusions, Lave (1963) used a game tree based on the growers' need to make significant decisions once the grapes are planted. The game tree branches out with various paths the grower may take and assigns an expected value to the grower based on rain probabilities. Lave (1963) concluded that with a three week advanced forecast of rain, growers could optimize their profit thus placing a significant value on more accurate weather forecasts.

Now that Lave (1963) had established that weather had a value for a single raisin grower, he wanted to see if improved weather forecast information could benefit the entire raisin industry. If weather conditions were poor and all farmers chose to sell their grapes for crushing, the drastic supply increase to wineries would result in a significant decrease in price. Because production costs in grapes have minimal variability and are not affected by the weather, profit must be determined by changes in revenue. Lave (1963) estimated a demand curve to determine the elasticity of demand. The inelasticity of the demand showed that an increase in supply (i.e., a shift to the right) would decrease profits to the growers.

Lave (1963) concluded that while improved weather forecasts benefit an exclusive grower, it does not necessarily benefit a collection of growers. Significantly improved weather forecasts and the addition of government intervention could possibly allow farmers to grow alternate crops on the grape land and attempt to increase profits.

3.2.2 Weather Forecasts and Markets

Lave (1963) concluded that while improved weather forecasts could increase raisin supply, it would subsequently decrease raisin price, showing that the raisin industry as a whole would not benefit from improved weather forecasts. Lave (1963) did not discuss the actions producers would follow with this dilemma caused by improved forecasts. In 1990, Babcock wanted to determine how the value of more accurate forecasts changed when farmers acted independently. Babcock (1990) assumed each farmer's output would be small enough as to not influence market price. By assuming rational expectations of an individual farmer, he hypothesized that individual farmers would not stray from what was beneficial to all farmers, meaning no farmer would produce sub optimally (Babcock 1990). To test his hypothesis, Babcock (1990) created the following production function

(3.1) $y = f(x, w)$

where *y* represented the yield per acre; *x* is a variable input; and *w* as a stochastic weather input that can assume the values w_g or w_b, where the variable w_g is future weather and w_b is weather that actually happens. He assumed that a "forecaster is 'correct' in that w_g occurs 60% of the time when the forecaster says that the probability of receiving w_g is 60%" (Babcock 1990, p.64). He then set up an objective function and first order condition for a specific forecasted probability and assumed that farmers would not focus on the change in output price that could occur as a result of their input decisions because farmers have a perfectly elastic demand curve.

To determine the input use and resulting supply changes with more accurate forecasts, Babcock (1990) examined the production and demand functions and expected profit effects. When demand is elastic, expected revenue for farmers is greater with a large supply at a lower price than that of a low supply with high prices. For an inelastic demand, expected revenue is less for a large supply at a lower price than a smaller supply with a high price.

Babcock (1990) then determined the marginal value of information based on both elastic and inelastic demands. He concluded that improved forecast accuracy in an elastic demand curve increases the marginal value of information while an inelastic demand curve actually results in a decrease in the marginal value of information (Babcock 1990). Babcock (1990) concluded that individual farmers are better off using all available weather forecasts, while collectively farmers may be worse off due to declining prices caused by higher supplies. Based on his conclusions, Babcock (1990) assumed that if farmers in an industry discussed whether or not to use improved forecasts they would choose against it (Babcock 1990).

3.2.3 Variable Input Application and Weather

Though Babcock (1990) concluded that farmers in an industry would not use improved forecasts, Roberts et al. (2002), among other objectives, wanted to determine if a financial benefit existed whether expected rainfall equaled actual rainfall or not when using variable rate input application technology for applying nitrogen to corn fields. They also wanted to determine if a difference in net revenue existed between variable and uniform input application rate technology when actual rainfall was different from expected rainfall. Several studies have been done in the past assessing the value of both precision farming and of variable rate input application technology, but none have examined the effects of weather patterns on the two. Weather patterns can greatly affect yield in rain fed agriculture. For example, rainfall affects the yield response to nitrogen. Based on expected rainfall, farmers could potentially optimize not only nitrogen application costs, but could potentially increase profit, and decrease nitrogen lost to the environment. In this case, expected rainfall is referring to what farmers expect will happen based on past average history.

Roberts et al. (2002) used two profit functions to determine the optimal return when applying nitrogen for both variable and uniform input application rate technology. Using the Environmental Policy Integrated Climate crop growth model, data for corn yields and nitrogen loss were created for a time span of 20 years over three management zones. Three weather scenarios were created for the model using monthly rainfall and temperature data from a weather station. The first rainfall scenario used average monthly rainfall measures, the second scenario decreased average monthly rainfall measures by a 0.5 standard deviation, and the third scenario decreased average monthly rainfall measures by one standard deviation. Roberts et al. (2002) did not find it necessary to include a scenario for above average rainfall measures because they found an increase in rainfall did not significantly impact yields.

The results showed that the lower average rainfall in scenario two compared to scenario one did not significantly decrease corn yields. The lowest average rainfall of scenario three decreased corn yields more than scenario two. When expected rainfall equaled the actual rainfall, variable rate input application technology was more profitable than uniform rate technology. More nitrogen was applied with variable rate input application technology than with uniform rate technology, but the nitrogen was more efficiently utilized by the crops, resulting in less nitrogen being lost to the environment. When less than average rainfall occurred, returns on variable rate input application technology was greater than when average rainfall was expected and actually occurred. Less nitrogen was lost while using variable rate technology, showing that as in the first scenario, nitrogen was more efficiently used. The results also showed that while yield levels did not significantly increase or decrease, a difference in nitrogen cost was observed. If rainfall scenario one was expected and actually occurred, growers would be better off to use variable rate input application technology due to its more efficient use.

Overall, Roberts et al. (2002) concluded that farmers would be better off using variable rate input application technology. Less nitrogen is lost, reducing input costs which aids in increasing profit. Roberts et al. (2002) did not specifically examine ENSO climate effects; they introduced the idea by investigating rainfall expectations.

3.2.4 Economics and Weather Forecast

Though predated from the now current distinction between seasonal climate variability and weather, Sonka et al. (1986) wanted to determine whether unusual weather occurrences were a factor in economic uncertainty during the past two decades. Recognizing the arguments that improved weather forecasts were necessary, they wanted to determine if decision makers would use this improved information making it economically valuable. To determine whether economic performance would in fact increase with more accurately forecasted weather information, they examined corn production in Illinois.

In order for an improvement in weather forecasting to be beneficial to any sector, the sector must be able to accommodate any changes in the weather with production alternatives. When dealing with the agricultural sector this would imply the ability to either vary inputs to optimize yield for any given crop for specific weather forecasts or substitute crops. Generally, inputs for production are fixed assuming average weather conditions. If producers used weather forecasts to their advantage, they could more accurately use inputs, possibly minimizing production costs. If so, then there is value to improved weather forecasts.

Using the corn data from Illinois, Sonka et al. (1986) examined the bushels per acre and the level of nitrogen applied from 1971 until 1983. They noticed a significant difference of approximately 115 bushels per acre of corn in 1982 compared to approximately 80 bushels in 1983. Analyzing past weather data indicated favorable weather conditions for corn in 1982 and poor weather conditions in 1983. Sonka et al. (1986) analyzed the amount of fertilizer applied during both the 1982 and 1983 growing seasons, and found a positive relationship between additional fertilizer and yield in 1982, but not in 1983. They concluded that farmers would have made more efficient use of fertilizer if forecasts had been used (Sonka et al. 1986).

To determine the usefulness of weather information using the corn industry, Sonka et al. (1986) followed three steps. To begin, they identified the most weather sensitive periods during corn production. They then wanted to determine if growers would adjust input decisions more efficiently if more accurate forecasts were known at these sensitive growing stages. This was followed by creating and testing their hypotheses on factors that affected production decisions (Sonka et al. 1986). Important weather parameters for growers including rainfall, temperature, evapotransporation, solar radiation, and wind speed for each growth stage during specific time periods were listed. In a separate table the decision time period and production choices were shown. By comparing the two tables, Sonka et al. (1986) thought decision makers would be able to use forecasts to efficiently and continually make production input decisions to maximize yield (Sonka et al. 1986).

Sonka et al. (1986) stressed the need for further research to be conducted including finding correlations between the value of weather forecasts and economic conditions. They concluded that for weather and climate information to be useful, it must be presented in a manner that decision makers will both understand and have the ability to implement the changes to their advantage.

3.2.5 Production Functions and Perfect Weather Forecasts

Cotton yields in the Texas High Plains are influenced by many factors including irrigation rates, fertilization methods and climate variability (Britt et al. 2002). In order to maximize profit, it is necessary for growers to obtain and utilize all available information concerning these factors. Britt et al. (2002) were interested in determining the possibility of increasing profits and decreasing risk to growers by evaluating six equations that would simultaneously show any relationships between input decisions and cotton output in the Texas High Plains categorized within three temperature and rainfall patterns (Britt et al. 2002).

To begin, they set up a simple theoretical model

(3.2) $Y = F(R, HU, X_1, X_2)$,

(3.3) $PR = PR(Q)$, and

(3.4) $Q = Q(R, HU, X_1 X_2)$

where Y is lint yield; R is a function of rainfall; HU is heat units; X_1 and X_2 are two variable inputs; PR is the quality premium per unit of lint yield; and Q is quality. They then set up a profit function per unit of lint yield

(3.5) $\Pi = (P + PR)Y - R_1 X_1 - R_2 X_2 - FC$,

where P is the price per unit of lint; PR is the quality premium per unit of lint; R_1 is the cost per unit of X_1 which is irrigation water. R_2 is the cost per unit of X_2 which is fertilizer use, and FC is the fixed costs. To obtain the maximum profit, first order conditions were taken. The resulting equation showed that input use decisions resulted in equal or higher profits and would probably cause an increase in the use of both irrigation water and fertilizer use. Several inputs can affect the quality of cotton including climatic conditions. The accuracy of weather conditions can be factored into the original theoretical model as

(3.6) $R^* = AR + \delta_R (R - AR)$

(3.7) $HU^* = AHU + \delta_{HU} (HU - AHU)$,

where R^* is assumed rainfall; AR is long term average rainfall; δ_R is the rainfall information availability coefficient; and R is actual rainfall. HU^* is assumed heat unit amounts; AHU is heat units; δ_{HU} is the heat unit information availability coefficient; and HU is the heat unit amount. Perfect climate information would give δ a value of one, meaning that management decisions would be made on the basis of actual rainfall and heat unit accumulation which would result in higher profits than a simple average of rainfall and heat accumulation.

To conduct their research, Britt et al. (2002) collected data from three field experiments over a time frame of three consecutive years. The data included information on lint yield, seed yield, turnout, staple length, and fiber length The three fields were subjected to different irrigation water and fertilizer application rates and weather conditions. Using the following hedonic profit equation allowed Britt et al. (2002) to account for multiple quality features as

(3.8) $\Pi = TR(MD, W) - TC(MD, W)$

where Π is profit; *TR* is total revenue; *MD* is management decisions; *W* is prevailing weather; and *TC* is total cost. Using this equation, Britt et al. wanted to determine the extent of the effect and risk of using more reliable climate and weather information on management decisions and profitability (Britt et al. 2002).

Using equation (3.8), Britt et al. created four scenarios to determine whether management decisions under improved weather forecasts would improve profitability and/or reduce risk. The first scenario assumed perfect weather forecasts with decision makers wanting to maximize profit considering both quality and quantity. The second scenario assumed the decision maker wanted to maximize profit under perfect weather forecasts while only considering quantity. The third scenario only based decisions on past average weather history while maximizing profit considering both quality and quantity while the fourth, also using past average weather history maximizes profit only considering quantity.

The results showed that maximizing quality and quantity require very different input combinations. A perfect forecast slightly increases overall price when quality is considered but also reduces overall yield. Though there is reduced yield at higher quality, profit still increases because irrigation costs are reduced. When quality is dismissed, perfect weather forecasts barely increase overall average lint yields. Britt et al. concluded that while it is seen that input use decisions based on quality considerations and the availability of improved forecasts can increase profits and reduce risk, it is not known if the benefits are enough for growers to practice.

3.2.6 Planting Decisions and Rational Expectations

In 1982, Shonkwiler and Emerson created a model of the Florida tomato industry which included factors that influenced the production decisions of growers. In this study, the main factor considered was the competition provided by Mexican tomato growers. They knew that many Florida growers were upset by the overwhelming tomato supply Mexican growers were exporting to the United States. They hypothesized that growers would vary planting decisions based on information available at planting time. If farmers had a realistic expected price of a crop, determined by predictions from supply and demand models, then they would plant accordingly (Shonkwiler and Emerson 1982).

To create their model, Shonkwiler and Emerson (1982) followed the concept of rational expectations as defined by Muth, who said that "rational expectations are essentially the same as predictions of the relevant theory" (Shonkwiler and Emerson 1982). Shonkwiler and Emerson (1982) created a system of four equations specifying the supply of Florida tomatoes in both acreage and yield equations as

(3.9) $$A_t = \alpha_o + \alpha_1 P^*{}_t + \alpha_2 C^*{}_t + \alpha_3 R_t + \alpha_4 A_{t-1} + \mu_{1t}$$

and

(3.10) $$Y_t = \beta_o + \beta_1 (P_t - L_t) + \beta_2 W_t + \beta_3 X_t + \mu_{2t},$$

where A_t is the acreage of planted tomatoes in time t; $P^*{}_t$ is the expected price of tomatoes in time t; $C^*{}_t$ is the expected cost of production in time t; R_t is the prime interest rate during the planting decision phase in time t; A_{t-1} is the partial acreage adjustment factor; μ_{1t} is the error term; Y_t is the yield of thirty pound cartons per planted acre in time t; P_t is the season average price per carton of tomatoes in time t;. L_t is the wage per carton for farm workers in time t; W_t is the weather index in time t; X_t is the adoption of new technology in time t; and μ_{2t} is the error term in time t. The third equation shows the demand equation for Florida tomatoes as

(3.11) $P_t - D_t = \gamma_o + \gamma_t Q_t + \gamma_2 M_t + \gamma_3 I_t + \mu_{3t}$,

where P_t is the season average price per carton of tomatoes in time t; D_t is the consumer price deflator in time t; Q_t is the quantity of shipped tomatoes in time t; M_t is the quantity of imported tomatoes from Mexico in time t; I_t is the total consumer disposable income in time t; and μ_{3t} is the error term in time t. The fourth equation the researchers included finalized the system of equations:

(3.12) $Q_t \equiv A_t \times Y_t$

where Q_t is the quantity of shipped tomatoes in time t; A_t is the acreage planted in time t; and Y_t is the yield per acre in time t. In the creation of this system of equations the researchers assumed that planting decisions were made based on expected price and cost, farmers rent the land and therefore are less interested in planting alternate crops, and only partial adjustments may be made in acreage from one year to the next, A_{t-1}. To simplify the system of equations used for this study, Shonkwiler and Emerson (1982) hypothesized that Mexican tomato imports were exogenous.

The data used for past tomato prices and acreage planted were from the *Florida Vegetable Summary* and included data from nineteen winter seasons from 1961 through 1980. Using this information, Shonkwiler and Emerson (1982) constructed an economic model to determine expected prices as

$$(3.13)\quad P^*_t = \left(\gamma_1^{-1} - \alpha_1 - \beta_1\right)^{-1} \begin{bmatrix} \alpha_0 + \beta_0 + \alpha_2 C^*_t + \alpha_3 R_t + \alpha_4 A_{t-1} - \beta_1 L^*_t + \beta_2 W^*_t + \\ \beta_3 X_t + \gamma_1^{-1}\left(\gamma_0 + \gamma_2 M^*_t + \gamma_3 I^*_t + D^*_t\right) \end{bmatrix}$$

where the asterisks indicate the expected values of the current exogenous variables (Shonkwiler and Emerson 1982). They found that expected prices are dependent on expected imports M_t^* and the exogenous variables C_t, L_t, D_t, and I_t. Substituting the expected values for the exogenous variables into an expected price equation and acreage equation, Shonkwiler and Emerson (1982) found that a 10% increase in imports would decrease Florida tomato prices by 2.68% and quantity by 5.91% (Shonkwiler and Emerson 1982). They concluded that imported Mexican tomatoes impact the Florida tomato supply. Florida tomato acreage was adjusted 42% in the time period due to changes in expected Mexican imports (Shonkwiler and Emerson 1982). They concluded that Florida tomato growers adjust their planting acreage based on expected Mexican tomato imports.

3.2.7 Supply Response and Weather

Florida and Mexican tomato growers have been in turmoil since the United States trade embargo with Cuba in 1961 (Thompson et al. 2005). Florida growers blamed Mexican growers of dumping fresh tomatoes in the United States market. In November 1996 a suspension agreement was established in an attempt to resolve tomato importing issues between Mexico and Florida (Thompson et al. 2005). The suspension agreement was designed to minimize Mexican tomato imports by assigning a reference price. Thompson et al. (2005) wanted to determine if the reference price affected the supply response for Florida fresh tomatoes.

With an empirical supply-response model and using growing degree days from daily weather observations, Thompson et al. (2005) were able to determine timing and size of upcoming tomato harvests. This also allowed them to determine specific measures for lags between planting and harvesting. Thompson et al. (2005) noted that Florida's fresh tomatoes are shipped in the winter from mid-October to late June. They are transplanted beginning in August until mid-March. If the fresh tomato market has a high price, many growers will harvest only the highest quality tomatoes. If the fresh tomato market has low prices many growers will harvest all tomatoes as long as they are still able to cover costs (Thompson et al. 2005). Growing degree days can help determine the moment of harvesting and potential quantity of tomatoes. Using this information, Thompson et al. (2005) modeled current shipments of round tomatoes

(3.14) $q_t = q(p_t, x_t, A_{i,t-h(GDD_t)},) \quad i = 1,\ldots,4;\ t = 1,\ldots,T$

where q_t is the quantity of round tomatoes shipped in a given week in a particular season, p_t is the weighted average price of mature green and vine ripe tomatoes in week t, x_t is the vector of exogenous shipment shifters including wages and other input prices, and $A_{i-h(GDD_t)}$ is the corresponding total acreage from all i regions "harvestable in week t as determined by matching cumulative degree days (GDD_t) with acreage planted in prior weeks of $t-h$ (Thompson et al. 2005). The weekly planted acreage for the counties used was only available for eight growing seasons from 1993-2001. These data capture the necessary information before and after the suspension agreement was implemented in November 1996.

Thompson et al. (2005) found that changes in prices, shipments and acreages occurred during the eight seasons. Shipments from Florida have increased with a significant increase noted during the first reference price period. Florida average prices have not decreased during the suspension agreement. In the first reference period, Mexican tomato shipments increased by 11% in the first reference period, but declined in the second period by 38%.

3.3 Seasonal Climate Variations and Agriculture

3.3.1 ENSO Signal and Soybean Futures Prices

Keppenne (1995) determined the existence of a correlation between soybean futures prices and the ENSO signal. Because ENSO effects are heavily noticed around the world in various ways, Keppenne (1995) rationalized that these effects would have an influence on an economic time series. The soybean was the perfect candidate to test his theory due to their dramatic response to climate effects. Another characteristic of soybean conducive to the study was their presence in the futures market. Since soybean supply is affected by climate, futures prices could theoretically be more accurately predicted using ENSO forecasting.

To test this theory, Keppenne (1995) used a normalized detrended time series of monthly average closing prices of soybean futures contracts and normalized southern oscillation index (SOI) data. SOI is calculated by the monthly fluctuations in air pressure between Tahiti and Darwin. Identical normalization processes were applied to both the soybean prices and the SOI data. Keppenne (1995) decided to use average monthly soybean prices despite much concern. He believed that through averaging, most discontinuities in the data could be removed. To account for noise in the data, Keppenne (1995) subjected the data to singular spectrum analysis (SSA) which aides in removing high frequency noise in the data. He then subjected the data to multichannel SSA (M-SSA) which provided for a more distinct separation of the interannual components. His results showed that 40.3% of the variance of the SOI data and 44.7% of the variance in the soybean price data were captured, suggesting that a relationship existed between soybean prices and the interannual climate.

In his discussion, Keppenne (1995) pointed out other ENSO factors that could influence the results in his study or studies similar to his. Warm conditions over the Pacific Ocean cause poor fishing conditions, increasing the demand for soy, a protein substitute. In addition, El Niño generally causes very rainy weather over the Midwestern United States, reducing harvest expectations of soy grown in the area. During his study, Keppenne (1995) also tested the impact of ENSO on wheat and corn future prices, and found no significant correlation. Keppenne (1995) believed this lack of correlation was due to government programs in the corn and wheat markets.

3.3.2 ENSO and Soybeans

Letson and McCullough (2001) decided to test Keppenne's (1995) findings further by determining if it was possible to describe the strength of the relationship between ENSO and soybean prices. They believed that in order for soybean producers, distributors, and consumers to benefit from ENSO forecasts it was necessary to know the strength and timing of ENSO occurrences. Letson and McCullough (2001) also wanted to account for the effect of ENSO on both the demand and supply for soy. Because supply and demand affect the spot price of a commodity, they wanted to see if the ENSO signal could be seen in the spot price of soy. To further test Keppenne's (1995) methods and results, Letson and McCullough (2001) chose to use a different set of data to account for ENSO and used sea surface temperature anomalies (SST) instead of the SOI data.

Using price data provided by the USDA/NASS, Letson and McCullough (2001) analyzed the relationship between soy price per bushel and the SST data. Using spectral analysis on the data from 1974-2000, Letson and McCullough (2001) regressed soy prices on a constant, linear time trend. The time trend was found to be statistically significant. To test their findings further, they ran autocorrelation and partial autocorrelation on the two series together. They found that with the soy price data, partial autocorrelation stops after two lags while the autocorrelation decreases as the lags increase, indicating a weak 12 month cycle. The SST data showed that both partial autocorrelation and autocorrelation were no more significant than the spectral analysis conclusion.

Letson and McCullough (2001) also tested cross spectral analysis, finding no coherence at the 48 month cycle or at any cycle that could be caused by the ENSO signal. Letson and McCullough (2001) concluded because of Keppenne's results and their own that ENSO and soybean prices are highly correlated and nearly in phase only in relation to SOI signal. The SST signal was found only to be in phase at the annual cycle, though they could not conclude that SST affects soy prices.

Because Letson and McCullough (2001) found some correlation between soy prices and the SST data, they wanted to test whether the correlation satisfied the economic concept of causality. Using the Granger Causality with a maximum lag of 18 months for soy and SST, they ran regressions with 2 to 16 lags for soy and 13 to 17 lags for SST for a total of 75 regressions. After running a t-test on the lags, no evidence of instantaneous causality was found. They also found that after running F-tests, not one of the 75 regressions resulted in SST having a direct effect on soy prices. Letson and McCullough (2001) found that the relationship between ENSO and soybean prices found by Keppenne has no practical economic content.

3.3.3 Value of Improved ENSO Forecasts

In 1998, Solow et al. assessed the return to investment in improving climate forecasts in regards to agricultural production. The three ENSO phases affect various regions around the United States in different ways. If farmers knew which of the ENSO phases were to come in the future, arrangements could be made to select appropriate and profitable cropping patterns that would optimize yield. Solow et al. (1998) stated that the economic effect of improved ENSO prediction is equivalent to that of a technological improvement. The increase in supply resulting from input adjustments leads to economic surplus. Solow et al. (1998) defined the economic effect of ENSO phase prediction as the expected change in economic surplus due to changes in cropping patterns from ENSO predictions. In order to estimate the value of improved ENSO prediction, Solow et al. (1998) modeled the climatic differences of the ENSO phases, the differences in yield related to the climate effects, planting decisions, and the way farmer behavior affected the market of agricultural products.

Solow et al. (1998) used the ENSO phase classifications of El Niño, La Niña, and Neutral compiled by the Japan Meteorological Index (JMI) over a 40 year period from 1947- 1986. The JMI is based on a five month moving average of the average sea surface temperature anomaly in the equatorial Pacific Ocean (Solow et al. 1998). If the index was greater than 0.5ºC for six consecutive months then the ENSO was classified as El Niño phase, if less than -0.5ºC then the ENSO was classified as La Niña. All other indexes were calculated as Neutral (Solow et al. 1998). Next, they calculated monthly climate statistics in 54 locations across the United States associated with agriculture. Data used included the mean and standard deviation of daily minimum and maximum temperature, skewness of daily precipitation, the number of wet days, and the transition probabilities between wet and dry days. From these data, they concluded that the difference in ENSO phases was greatest during winter months. Solow et al. (1998) concluded that ENSO was most pronounced in the southeastern United States where El Niño years are colder and wetter than normal in fall and winter, and warmer and dryer than normal in spring and summer. La Niña was found to affect climate opposite to El Niño although at a lesser strength.

To determine effects on yield, Solow et al. (1998) used a plant biophysical simulation model similar to Adams et al. (1995). The crops used in their study included barley, corn, cotton, hay, potatoes, rice, sorghum, soybeans, tomatoes and wheat. The yield results indicated differences in summer crops due to water stress while winter crops were mostly affected by temperature stress.

The way in which farmers could use the simulated crop yields to optimize their cropping patterns can be seen with the Bayesian decision theory. The expected economic surplus T_1 can be found with a probability of a specific ENSO phase given

(3.15) $T_1 = \sum_s T_1(s)\pi(s)$

where s designates the realization of an ENSO phase; $T_1(s)$ is the economic surplus from aggregate supply curves; and $\pi(s)$ equals the probability of each phase based on past history divided by the total number of observations. If an ENSO phase is forecasted prior to a planting season, then the farmer could use predictions to update the probability distribution for $\pi(s)$ using Bayes' theorem. In order to create realistic probabilities to test Bayes' theorem, Solow et al. used known ENSO phases from 1947-1986 and divided the total number of each phase occurring over the time span of 40 years by the total number of observations. Yield data from 1992 were used to solve for price and quantity data. Solow et al. (1998) found that over a 10 year period, well predicted ENSO phases presented a net present value of approximately $2 billion to the agricultural sector.

Solow et al. (1998) determined that while their study shows a significant value to the agricultural sector from correct ENSO predictions, they realized their unrealistic assumption that all farmers would respond optimally to ENSO predictions. They also noted that there is a significant difference between perfect ENSO predictions and perfect climate prediction due to climate variability within ENSO phases, which would have a direct impact on individual regions. Despite this, the Solow et al. (1998) study corroborates with others that ENSO forecasts can have an economic impact on the agricultural sector.

3.3.4 ENSO and Other Commodities

In 1998, Hansen et al. evaluated both ENSO phases and SST anomalies in reference to their influence on crop production in Alabama, Florida, Georgia, and South Carolina. This southeast region of the United States, between October and April, generally has cooler temperatures and wetter conditions during El Niño phases and warmer temperatures and dryer conditions during La Niña phases. Six crops including peanut, tomato, cotton, tobacco, corn, and soybean were examined and ranked relative to the economic impact of ENSO (Hansen et al. 1998).

They gathered historical data from 1960-1995 provided by the USDA/NASS for the six crops. Using an analysis of variance test (ANOVA), they tested their hypothesis that ENSO influences the value of crops in these four states. They found that crop yield showed a significant response to ENSO, though corn and tobacco showed the most significant response. They also noticed high yields seen during a La Niña year were lower the following year. The ANOVA results implied that ENSO does in fact play a role in crop yield. Hansen et al. (1998) realized from their results that SST had a strong influence on the yields of all six crops in Florida, making it the most susceptible state in their study to ENSO effects. Similar to Letson and McCullough (2001), Hansen et al. (1998) found no ENSO influence on prices. They attributed this to the methods of their study which made it difficult to identify an ENSO influence on an individual crop price. They concluded that if ENSO phases were forecast, farmers could adjust their strategies to prevent losses and increase revenue.

3.4 Improved Climate Predictions and ENSO

3.4.1 Value of Forecasting

Seasonal climate variation plays a large role in many aspects around the globe from severe drought to devastating floods. While extreme weather conditions do occur, even moderate changes in temperature and precipitation can be important especially when it comes to agriculture. Interannual variation in both precipitation and temperature affects agriculture on many levels including production, prices and profits. One study estimated the economic value of ENSO on the U.S. agriculture, forestry and fishery sectors at $200 million per year with the greatest percentage going to agriculture (Adams et al. 1995). This study was based on several subjective findings regarding avoidable losses due to ENSO (Adams et al. 1995). Adams et al. (1995) determined there was a need for an objective assessment of the value of improved ENSO forecasting on several levels involved in agricultural decision making, including agronomic, economic and meteorological. Their primary focus was in the southeastern United States due to the strong and diverse agricultural production in that region and the significant impact the ENSO phenomenon presents.

The framework used in the Adams et al. (1995) study is Bayesian decision theory combining data and models from meteorology, plant science, and economics. Their economic model showed the impact of crop production in the southeastern United States on the welfare of the United States as a whole. The value of ENSO forecasts to agriculture can be measured by the expected increase in economic benefits that result in the use of forecast information to make decisions. If farmers alter their decisions due to forecasts provided by ENSO, then it can be said that economic value of ENSO forecasting exists. Adams et al. (1995) used the assumption that farmers will use planting and harvesting strategies that maximize profits under their current beliefs about the ENSO phases. They summarized these beliefs in the form of a probability distribution over the three ENSO phases. Calculating the value of an ENSO forecast requires the knowledge to determine a farmer’s optimal strategy and total economic welfare under each of the three possible distributions. Using Bayes’ theorem, farmers can make decisions based on ENSO phase predictions. Using updated distributions, farmers can use strategies that maximize expected profits.

In order to assess the value of ENSO forecasts, Adams et al. (1995) used a three stage process. The first stage estimated the average seasonal minimum and maximum daily temperatures and monthly precipitation. They then categorized each year between

1948 and 1987 to be El Niño, La Niña or Neutral according to the Japan Meteorological Index (JMI). In the second stage they used the Erosion Productivity Impact Calculator, a mathematical model, to estimate the yield implications of various weather events on particular crops. The data set used for the Erosion Productivity Impact Calculator consisted of weather, wind, soil, and crop management data within a specific location in the southeast United States. Adams et al. simulated yields for a 10 year period for four major crops considering individual weather scenarios and locations. They then averaged each of the yield observations, to calculate the percent change in crop yield, climate conditions and location. The results indicated, in practically every scenario, that La Niña produced the highest crop yields; El Niño produced the lowest crop yields and a Neutral year produced yields in between the two.

The percentage changes found using the Erosion Productivity Impact Calculator were then used for economic modeling. Economic modeling allowed the physical yield effects to be converted into economic effects on both producers and consumers. The results showed a gain to producers and consumers with *perfect forecasting,* with or without government involvement in farm programs. Adams et al. (1995) concluded that the agricultural sector can acclimatize to climate variation.

3.4.2 Seasonal Climate Forecasts and the Economy

Hill and Mjelde (2002) wanted 1) to determine if improved seasonal climate forecasts are possible, 2) what would be the value to society and more importantly, 3) if decision makers would use this improved information, and finally, 4) how would decision makers use this improved information.

While there are other ocean phenomena around the world, ENSO is the most widely studied. Sea surface temperature anomalies in the equatorial Pacific ocean affect trade wind circulation in both the northern and southern hemisphere. The sea surface temperature changes cause a disturbance to the jet stream, which in turn affects storm patterns. Hill and Mjelde (2002) found that the temperature changes between El Niño and La Niña are not proportional, meaning that “the climate variability associated with the La Niña event is not a linear image of the El Niño event in terms of magnitude or regional association” (Hill and Mjelde 2002, p.607).

From their research of past studies, Hill and Mjelde (2002) found a correlation between the ENSO climate phenomenon and crop output. One study determined that 25% of the value of corn in the United States could be related to ENSO. If forecasts were accurate, farmers could capture some of the value by changing input practices. In the United States, the strongest correlations between climate effects on agriculture and ENSO have been found on the Gulf Coast and in the northeast, southwest and northwest regions. Unfortunately, it is difficult to perfectly forecast how an ENSO phase will affect each region. ENSO phases not only have different strengths, but also affect the various areas differently at different times of the year (Hill and Mjelde 2002).

For a seasonal climate forecast to be valuable, it has to help individuals or groups to significantly improve their utility more than without a forecast and be able to influence decision makers’ actions (Hill and Mjelde 2002). If decision makers are able to change regular decisions to improve their economic outcomes, then forecasts are valuable. Some studies have shown that lead time is a very important factor with forecasting. At times, a less accurate forecast that decision makers receive early enough to alter decisions can be more valuable than more accurate forecasts given at a later date (Hill and Mjelde 2002).

To determine how to place a monetary value on ENSO forecasts, researchers have used the Bayesian approach combined with decision theory. This method uses updated seasonal forecasts and the decision makers' knowledge of past or historical climate conditions. Other researchers have determined ways to account for risk attitude or use crop simulation models to attempt to determine how climate would affect yield.

Improved seasonal climate forecasts can help decision makers be more efficient; however it is difficult to determine the best way to publicize the knowledge that decision makers face risk when adopting new technologies and may not be open to new ideas. Hill and Mjelde (2002) concluded that if only a few decision makers choose to utilize climate forecasts, their actions will slightly impact the crop price, reducing the rate of acceptance by others.

3.5 Summary

Previous studies show that weather and climate can influence agriculture. Many of these studies looked into the value of forecasting weather and climate. Generally, they observed weather and climate as equal entities because many of the studies were completed before the distinction between seasonal climate variability and weather discussed in Chapter 2. All of the studies determined an economic value existed for forecasts though many of them assumed perfect forecasts, a near impossible reality at this time. Input use and costs could be most affected by improved forecasts.

Keppenne (1995) found a relationship between soybean prices and interannual climate using SOI data, but Letson and McCullough (2001) determined that Keppenne's (1995) results had no practical economic content. Hansen et al. (1998) found that crop yield showed a significant response to ENSO. They also found that SST had the most influence on all crops, including tomato yields in Florida. They found no evidence of

ENSO influence on prices, though they attributed this to their methods of study. Shonkwiler and Emerson (1982) provided the framework for the economic model for this present study while the other studies helped to provide a larger range of knowledge to produce an ideal model.

CHAPTER 4
EMPIRICAL MODEL

4.1 Background

The framework for the empirical model used in this research is based on Shonkwiler and Emerson (1982). Shonkwiler and Emerson (1982) wanted to determine if Florida tomato growers adjusted planted acreage based on the expected winter Mexican tomato imports and their impact on the price of tomatoes. In their supply and demand model, Shonkwiler and Emerson use the rational expectations hypothesis based on the idea that expected price will determine expected acreage. They created a four equation system for their supply and demand model for Florida tomatoes with the supply side consisting of acreage and yield equations (Shonkwiler and Emerson 1982).

4.2 The Model

Similar to Shonkwiler and Emerson (1982), the empirical model used in this study consists of four equations. Slight alterations have been made in equations (4.1) and (4.2). In equation (4.1) Shonkwiler and Emerson solved for planted acreage, but this model will solve for harvested acreage due to data limitations. Because harvested acreage is being used, the interest rate variable is removed, and the price and cost data have been deflated. In equation (4.2), Shonkwiler and Emerson (1982) consider the hourly labor wage rate, while this model simply examines deflated harvest costs, which also include the hourly wage rate. Shonkwiler and Emerson's (1982) weather index is substituted with two variables indicting the presence of either El Niño or La Niña climate phases. The technology improvement, methyl bromide, has been added to the model. The empirical model (Appendix A) used in this study consists of the following four equation system:

(4.1) $A_t = \alpha_o + \alpha_1 P_t + \alpha_2 C_t + \mu_{1t}$,

(4.2) $Y_t = \beta_o + \beta_1 (\frac{P_t}{C_t}) + \beta_2 D_1 + \beta_3 D_2 + \beta_4 X_t + \beta_5 L_t + \mu_{2t}$,

(4.3) $\frac{P_t}{F_t} = \gamma_o + \gamma_1 Q_t + \gamma_2 M_t + \gamma_3 \frac{I_t}{F_t} + \mu_{3t}$,

(4.4) $Q_t \equiv A_t * Y_t$,

where A_t is the acreage of harvested tomatoes in time t and has been adjusted to thousands of acres; P_t is the price per 25 pound carton of tomatoes in time t, and is expected to have a positive impact on acres harvested; C_t is the harvest cost per 25 pound carton of tomatoes in time t, and is expected to have a negative impact on acres harvested; μ_{1t} is the error term; Y_t is the yield of 25 pound cartons per harvested acre in time t and has been adjusted to tens of cartons; D_1 =1 for the El Niño climate effect, zero otherwise, and is expected to have a negative impact on yield; D_2 =1 for the La Niña climate effect, zero otherwise, and is expected to have a slightly positive impact on yield; D_3 =1 for the Neutral climate, zero otherwise, but was eliminated because it would have caused a singular matrix; X_t =1 for the adoption of plastic mulch in time t, zero otherwise, and is expected to have a positive impact on yield; L_t =1 for the adoption of methyl bromide in time t, zero otherwise, and is expected to have a positive impact on yield; μ_{2t} is the error term in time t; F_t is the consumer price deflator (October-June) in time t; Q_t is the production of Florida fresh tomatoes in 1,000 cartons in time t, adjusted to thousands of 25 pound cartons, and is expected to have a negative impact on price; M_t is the quantity of imported tomatoes (October-June) from Mexico in time t, adjusted to ten thousands of pounds, and is expected to have a negative impact on price; I_t is the total consumer disposable income (October-June) in time t adjusted to hundreds of billions of dollars, and is expected to have a positive impact on price; and μ_{3t} is the error term in time t.

4.3 Data Values and Sources

Collecting data for the model was an intricate and detailed process. The time frame for the data is from 1959-2003 due to limited data available for the quantity of imported Mexican tomatoes. All data are representative of the fresh Florida tomato industry (Appendix B). In addition, data concerning tomato crate weight in pounds have been converted from 60, 40, and 30 pound crates to the current standard of 25 pound crates.

The focus for this research centered on the fresh Florida tomato industry. Florida has a relatively small number of processed tomato growers. Due to legality issues, data for planted acreage of either fresh or processed tomatoes cannot be individually reported because of the small number of processed tomato growers. The Florida Agricultural Statistics Service who provides data for the *Vegetable Summary* does not individually provide data exclusively for fresh tomatoes planted or harvested acreage. They do provide fresh tomato data for Y_t the yield of 25 pound cartons per harvested acre in time t, and for Q_t, production of Florida fresh tomatoes in 1,000 cartons in time t.

(4.5) $$A_t \equiv \frac{Q_t}{Y_t}.$$

Using equation (4.5) the acreage harvested, A_t, could be determined. The time frame used for the fresh tomato harvest season is from October through June. For example, the 1959 season begins in October 1959 and ends June 1960. Data for P_t were found in the Florida Statistical Services *Vegetable Summary*.

The data for C_t were found using various issues of a cost and returns publication provided by the University of Florida's Food and Resource Economics Department (Brooke 1950-1979), (Bean 1981), (Smith and Taylor 1986-2004), (Taylor 1981-1986). The cost data had to be modified. The original formatting of the data provided only a small sampling of farms in 4 specific areas in Florida. Data from the Dade, Ft. Pierce, Immokalee and Manatee/Ruskin area, were weighted using acreage data from the Florida Agricultural Statistical Service's *Vegetable Summary*. To begin, the sum of the cost times the acreage for each county were totaled then divided by the sum of the acreage per county to provide the weighted average. This final number, depending on the year, had to then be converted from 60, 40, or 30 pound cartons to 25 pound cartons.

Data for Y_t were gathered from the *Vegetable Summary* which provided data for fresh tomatoes. Certain years had to be converted from 60, 40, or 30 pound cartons to the now standard 25 pound cartons.

Data for D_1 and D_2 were found through the Center for Ocean-Atmospheric Prediction Studies (Legler 2005). A value of one was assigned to the years when either an El Niño or a La Niña phase occurred. A value of zero was used for Neutral phase years. El Niño is expected to have a negative impact on yield because the greater than average precipitation associated with El Niño can damage root systems. Also, the lower than average temperatures associated with El Niño can delay crop development. Though

La Niña is associated with lower than average rainfall amounts, irrigation can be used to adjust any deficit in precipitation.

Data for X_t were based on Shonkwiler and Emerson's (1982) model. They assigned a value of one each year after 1973, when the use of plastic mulch was adopted, and a value of zero prior to 1974. Data for L_t were found in Carpenter et al. (2000). A value of one was assigned to each year after 1977 when methyl bromide was widely used in Florida, and a value of zero was used prior to 1978.

Data for F_t were found from the United States Department of Labor. The sum of the monthly values from October through June was averaged to assign a value to the year. For example, the monthly average from October 1964 through June 1965 was used as the value for F_t during the year 1964. Data for Q_t were obtained from the Florida Statistical Services *Vegetable Summary*. These data were provided in 1000 bushel units for fresh tomatoes. Data for M_t were provide by the United States Department of Agriculture (Lucier 2004). The data provided were in 1000 pound cartons and were only available as far back as 1956. These data limited the time frame for this study. Finally, the data for I_t were found using the United States Department of Commerce. The data were not deflated and were provided quarterly where data from the fourth quarter (October-December), first quarter (January-March) and the second quarter (April-June) were used. An average of the three quarters provided the final value for the year. For example, the average of the data from the fourth quarter (October-December) of 1978 through the second quarter (April-June) of 1979 was used as the value for I_t during the year 1978 in 100 billion dollars.

CHAPTER 5
RESULTS

5.1 Model Results

Using the data collected, the four equations (4.1), (4.2), (4.3), and (4.4) were estimated using the TSP statistical program (Appendix C). The Full Information Maximum Likelihood Statistical Estimator was used. The Durbin-Watson test showed there was serial correlation present in the model. Therefore the first order serial correlation was corrected. Both linear and logarithm models were run. Though neither run showed either El Niño or La Niña to be significantly different than zero, the logarithm results were preferred. Table 5-1 shows the results for the linear models while Table 5-2 shows the results in logarithm form.

For the linear model the parameters $\alpha_1, \alpha_2, \beta_2, \beta_3, \beta_4, \beta_5, \gamma_2, \gamma_3$ all had p-values that were greater than [0.1] indicating that the estimates were not significantly different from zero at the [0.1] level (Table 5.1). The parameters $\alpha_0, \rho_A, \beta_0, \beta_1, \rho_Y, \gamma_0, \gamma_1, \rho_D$ all had p-values that were less than [0.1] indicating that the estimates are significantly different from zero at the [0.1] level. The negative sign on the estimate for price (P_t) indicates that a decrease in price would increase harvested acreage which is incorrect, as is the sign for P_t/C_t. The negative sign on the estimate for El Niño (D_1) is as expected. The positive sign on the estimate for La Niña (D_2) is also as expected. The negative sign on the estimate for income (I_t/F_t) is incorrect (Table 5.1).

Table 5-1. Empirical results from the linear model.

Equation	Parameter	Variable	Estimate	Standard Error
Acreage	α_0		71.729***	24.781
	α_1	P_t	-1.3387	1.1604
	α_2	C_t	-5.6651	3.7179
	ρ_A	e_{t-1}	0.92385***	0.06645
Yield	β_0		163.53***	51.941
	β_1	$\frac{P_t}{C_t}$	-18.817**	7.9692
	β_2	D_1	-2.3421	2.9120
	β_3	D_2	0.40675	1.9452
	β_4	X_t	9.8803	20.787
	β_5	L_t	0.57862	19.489
	ρ_Y	e_{t-1}	0.92663***	0.09226
Demand	γ_0		22.164***	8.3541
	$\gamma_1$8	Q_t	-0.28252***	0.10240
	γ_2	M_t	0.77623E-03	0.79980E-02
	γ_3	$\frac{I_t}{F_t}$	-0.3349	0.17459
	ρ_D	e_{t-1}	0.87404***	0.07193

*Significant at the [0.1] level
**Significant at the [0.05] level
***Significant at the [0.01] level

The estimated signs on the parameters for the linear model are different than what is normally expected, with the exception of El Niño and La Niña. The signs on the ENSO parameters were exactly as was expected. It was thought that El Niño would have a negative effect on yield, while La Niña would have a positive effect on yield. As an alternative, the model was run on TSP with all variables in logarithm form. The results are shown on Table 5-2.

Table 5-2. Empirical results from the logarithm model.

Equation	Parameter	Variable	Estimate	Standard Error
Acreage	α_0		3.5246***	0.37382
	α_1	P_t	0.2163	0.33068
	α_2	C_t	-0.11983	0.29512
	ρ_A	e_{t-1}	0.68256***	0.13483
Yield	β_0		3.7673***	0.34533
	β_1	$P_t - C_t$	0.33200	0.34259
	β_2	D_1	0.07587	0.09018
	β_3	D_2	-0.41208E-02	0.05769
	β_4	X_t	0.42737**	0.19589
	β_5	L_t	0.37125*	0.19102
	ρ_Y	e_{t-1}	0.45319**	0.21258
Demand	γ_0		-0.91663	0.95164
	γ_1	Q_t	-0.49458	0.51765
	γ_2	M_t	-0.14933	0.13705
	γ_3	$I_t - F_t$	0.21137	0.67801
	ρ_D	e_{t-1}	0.62520***	0.14438

*Significant at the [0.1] level
**Significant at the [0.05] level
***Significant at the [0.01] level

For the logarithmic model the parameters $\alpha_1, \alpha_2, \beta_1, \beta_2, \beta_3, \gamma_0, \gamma_1, \gamma_2, \gamma_3$ all had p-values that were greater than [0.1] indicating that the estimates were not significantly different from zero at the [0.1] level (Table 5.2). The parameters $\alpha_0, \rho_A, \beta_0, \beta_4, \beta_5, \rho_Y, \rho_D$ all had p-values that were less than [0.1] indicating that the estimates are significantly different from zero at least at the [0.1] level.

The estimated signs on the parameters for the logarithm model are as expected with the exception of El Niño and La Niña. The positive sign on the estimate for P_t indicates that an increase in price would increase the acreage harvested, as expected. The negative sign on the estimate for C_t indicates that a decrease in the harvest cost would result in an increase in acres harvested, as expected. The positive sign on the estimate for D_1 shows that El Niño positively impacts tomato yield compared with a Neutral year, which is not as expected. The negative sign on the estimate for D_2 shows that La Niña negatively impacts tomato yield compared with a Neutral year, which is not as expected. The estimate value for El Niño indicates it has a larger impact on yield than the value for La Niña. This could be explained due to the fact that El Niño years are generally wetter and cooler, while La Niña years are generally dryer which can be corrected through irrigation. The positive signs on the estimates for X_t and L_t indicate that an increase in technology would increase yield, both of which are expected impacts and are significantly different than zero. The negative sign on the estimate for quantity produced indicates that as production decreases, the price increases, as expected. The positive sign on the estimate for income indicates that as income increases, price increases, as expected.

5.2 ENSO Impact on Price

In order to determine the impact of ENSO on fresh tomato price, the four equation model would have to be solved simultaneously for the four unknown endogenous variables, A_t, Y_t, P_t, Q_t. This would solve for the price variable which would show the impact of ENSO on price. In addition, the empirical results indicate that the El Niño and La Niña variables are not significantly different from zero. This shows that there is no impact on yield, and therefore no impact on price.

ENSO effects are strongest in Florida during the winter months. Ideally, the model would have been run using seasonal data, specifically winter, rather than annual data.

Due to data limitations this was not possible. This limitation could partially account for the results obtained. Irrigation can be used to correct drought conditions faced during La Niña phases which could also account for some of the results. In addition, the effects of ENSO could be too small, preventing a regression to detect it.

A simple regression of actual tomato price over a period of years incorporating ENSO phases, Figure 5-1, is a way to see if ENSO phases are correlated with tomato price. The graph in Figure 5-1 shows the correlation each ENSO phase has on tomato price. Neutral years have a greater correlation with tomato price than El Niño or La Niña years. El Niño years seem to have a lower correlation with price. La Niña years have lower tomato prices than Neutral years. It is interesting to note that a change in the relationship of ENSO phases to prices occurs around 1980. Further research could be done to determine the reason.

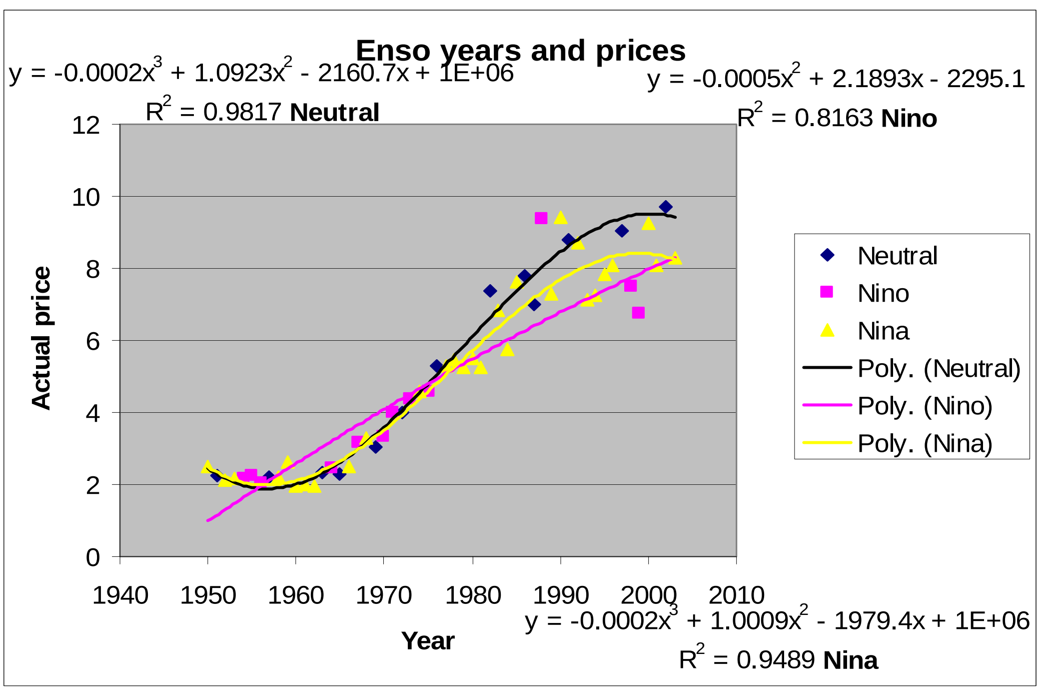

Figure 5-1. ENSO phases over time and price.

5.3 Summary

The linear model had the incorrect sign on every estimate except for D_1, D_2, X_t and L_t. Neither El Niño nor La Niña had p-values that were significantly different from zero in the linear model. The logarithm model had the correct signs on every parameter, with the exception of D_1 and D_2. Neither El Niño nor La Niña had p-values that were significantly different from zero in the logarithm model. These results indicated that neither ENSO phase had an impact on fresh Florida tomato yield. Because the system of equations could not be solved for price as a function of ENSO, ENSO has zero effect. ENSO phases had no impact on the price of tomatoes.

If ENSO phases do influence tomato prices, it may be on a scale that is too small for the method used in this study. If historical, seasonal tomato data were available; this study could be replicated, replacing annual data with seasonal data, possibly resulting in significant findings.

CHAPTER 6
CONCLUSIONS AND IMPLICATIONS

6.1 Summary

This study centered on determining if fresh Florida tomato prices were impacted by the ENSO phenomenon. ENSO is a seasonal climate variation caused by interactions between the Pacific Ocean and the atmosphere (Soreide and McPhaden 2005). The three phases of ENSO are known as El Niño, La Niña, and Neutral. The variations in climate among the three phases are noticeable around the world. In the United States, the effects are most prominent in Florida during the winter months.

The majority of fresh tomatoes produced in the United States are grown in Florida. A large portion of fresh tomatoes in Florida are planted during the winter months. Researchers have assigned monetary values to ENSO forecasting using subjective findings (Adams et al. 1995). Other research has shown relationships exist between futures prices and SOI data. Overall, past research has indicated that climate has an economic impact on agriculture. Among other factors, the fresh tomato industry in Florida depends on the high quality of their tomatoes to determine price. Fresh tomatoes in Florida are sold on the open market allowing for more variation in price than processed tomatoes. It is thought that ENSO phases could impact Florida's fresh tomato prices.

The fresh market tomato industry has a farm value of more than $1 billion in the United States with Florida holding the largest share. Fresh tomatoes in Florida account for approximately one third of the state's vegetable cash receipts (Lucier 2004 and Mongiovi 2005). Much research has been done showing the effects of ENSO on yield, though no significant research has been done studying the impacts of ENSO on Florida tomato prices. Thus, the primary objective of this research was to determine if ENSO seasonal climate variation has an impact on Florida tomato prices. An empirical model composed of four simultaneous equations with all variables in logarithms, similar to those of Shonkwiler and Emerson (1982), was used for this research.

6.2 Conclusions

The empirical results indicated that the El Niño and La Niña variables are not significantly different from zero, meaning they have no significant impact on yield fluctuations. Therefore it can be concluded that ENSO has no impact on price because it had no impact on yield. The model used in this study was run using annual data from 1959-2003. Data for ENSO phases are available as far back as 1868 (Legler 2005). Ideally, a longer time frame would have been used in the model to capture as many ENSO phases as possible; however, data availability was a problem.

6.3 Implications

Based on this model, ENSO has no impact on price. Improved forecasts of ENSO would have no value to farmers as ENSO would not influence their decision making process. Though this study found no ENSO impact on yield, this study can be used as a baseline for researchers to further determine the impact ENSO may have for tomato growers. If more historic detailed data could be gathered or future data gathering techniques improve, further research regarding ENSO and its impact on tomato or other crop prices could more accurately reflect the value of ENSO forecasts to farmers.

APPENDIX A
EMPIRICAL MODEL

(4.1) $A_t = \alpha_o + \alpha_1 P_t + \alpha_2 C_t + \mu_{1t}$,

(4.2) $Y_t = \beta_o + \beta_1 (\frac{P_t}{C_t}) + \beta_2 D_1 + \beta_3 D_2 + \beta_4 X_t + \beta_5 L_t + \mu_{2t}$,

(4.3) $\frac{P_t}{F_t} = \gamma_o + \gamma_1 Q_t + \gamma_2 M_t + \gamma_3 \frac{I_t}{F_t} + \mu_{3t}$,

(4.4) $Q_t \equiv A_t * Y_t$,

APPENDIX B
DATA SET

Year	A_t	P_t	C_t	R_t	Y_t	W	D_1	D_2	D3	T	X_t	L_t	F_t	Q_t	M_t	I_t
1956	36202	2.03	0.71	4.00	367	31.15	1	0	0	33.26	0	0	27.74	13286	69,005	314.97
1957	29631	2.19	0.75	4.07	271	23.17	0	0	1	24.51	0	0	28.64	8030	100,430	324.37
1958	46396	2.21	0.73	4.08	414	35.09	0	1	0	37.51	0	0	28.97	19208	226,241	343.77
1959	38315	2.61	0.73	5.00	464	39.36	0	1	0	42.03	0	0	29.43	17778	240,355	361.07
1960	41286	1.97	0.83	4.50	616	51.94	0	1	0	55.75	0	0	29.80	25432	251,822	372.83
1961	42188	2.00	0.86	4.50	649	54.70	0	1	0	58.72	0	0	30.09	27380	156,070	398.10
1962	44314	1.97	0.94	4.50	612	51.62	0	1	0	55.38	0	0	30.64	27120	233,216	416.13
1963	43685	2.34	0.90	4.50	673	56.73	0	0	1	60.81	0	0	30.89	29400	239,965	447.83
1964	50472	2.47	0.92	4.50	576	48.66	1	0	0	52.14	0	0	31.29	29072	246,122	481.97
1965	51400	2.29	0.97	5.09	593	50.11	0	0	1	53.59	0	0	32.01	30480	265,459	524.23
1966	46613	2.48	0.99	5.77	626	52.94	0	1	0	56.66	0	0	33.01	29180	358,743	561.30
1967	47043	3.16	1.09	6.04	606	51.36	1	0	0	54.86	0	0	34.14	28508	362,354	606.07
1968	47465	3.31	1.27	7.06	516	43.97	0	1	0	46.75	0	0	35.89	24492	378,401	651.13
1969	47448	3.06	1.35	8.32	391	33.64	0	0	1	35.39	0	0	38.04	18552	446,239	713.00
1970	40634	3.34	1.42	6.17	574	48.74	1	0	0	51.98	0	0	39.94	23324	641,015	776.77
1971	43532	4.01	1.48	5.18	598	50.72	1	0	0	54.14	0	0	41.28	26032	570,287	835.93
1972	45812	4.02	1.29	6.30	605	51.38	0	0	1	54.70	0	0	43.08	27716	582,284	940.17
1973	34704	4.39	1.78	10.00	796	67.68	1	0	0	72.06	0	0	47.21	27624	749,121	1037.00
1974	31497	4.57	1.87	9.10	1026	86.80	0	1	0	92.82	1	0	52.39	32316	590,601	1142.90
1975	38292	4.59	1.94	7.11	918	77.64	1	0	0	83.05	1	0	55.79	35152	559,095	1259.83
1976	34019	5.30	1.98	6.42	854	72.31	0	0	1	77.19	1	0	59.13	29052	648,584	1376.63
1977	41477	5.28	2.13	7.98	826	70.12	0	1	0	74.76	1	0	69.93	34260	785,386	1544.17
1978	40824	5.47	2.23	11.43	980	83.26	0	1	0	88.69	1	1	69.31	40008	814,116	1720.27
1979	42189	5.23	2.10	15.93	1102	93.77	0	1	0	99.73	1	1	78.90	46492	710,250	1924.47
1980	46293	5.49	2.72	18.29	1003	85.79	0	1	0	90.82	1	1	87.72	46432	649,473	2160.07
1981	40506	5.23	3.05	16.59	1250	106.24	0	1	0	113.10	1	1	94.69	50632	521,597	2362.97
1982	45615	7.39	3.17	11.11	1154	97.97	0	0	1	104.33	1	1	98.30	52640	589,119	2521.40
1983	47138	6.83	3.18	11.46	1128	95.79	0	1	0	102.07	1	1	102.29	53172	733,254	2801.20
1984	47405	5.74	3.71	10.85	1223	103.61	0	1	0	110.63	1	1	106.18	57976	814,810	3050.70
1985	48193	7.62	3.17	9.16	1243	105.25	0	1	0	112.44	1	1	109.08	59904	838,415	3224.90
1986	53282	7.78	3.05	7.68	1241	104.96	0	0	1	112.16	1	1	111.71	66123	950,918	3372.40

Year	A_t	P_t	C_t	R_t	Y_t	W	D_1	D_2	D3	T	X_t	L_t	F_t	Q_t	M_t	I_t
1987	56795	7.00	3.02	8.74	1344	113.56	0	0	1	121.46	1	1	116.32	76333	896,775	3637.30
1988	60719	9.37	3.26	10.84	1207	102.54	1	0	0	109.21	1	1	121.89	73288	799,676	3935.50
1989	51613	7.29	3.23	10.18	1169	99.14	0	1	0	105.76	1	1	127.74	60336	850,796	4188.60
1990	50415	9.40	3.24	9.29	1278	108.33	0	1	0	115.61	1	1	134.70	64430	776,715	4393.40
1991	52003	8.81	3.57	6.87	1591	134.19	0	0	1	143.77	1	1	138.72	82736	779,504	4637.33
1992	48393	8.70	3.43	6.00	1483	125.09	0	1	0	134.09	1	1	143.07	71767	403,702	4857.43
1993	50605	7.14	3.45	6.31	1294	109.24	0	1	0	117.02	1	1	146.70	65483	882,938	5045.87
1994	49010	7.25	3.47	8.66	1330	112.45	0	1	0	120.29	1	1	150.90	65183	829,007	5340.10
1995	45493	7.82	3.54	8.43	1250	105.82	0	1	0	113.07	1	1	159.42	56866	1,307,479	5569.90
1996	37296	8.08	3.54	8.34	1468	124.00	0	1	0	177.00	1	1	162.04	54750	1,511,659	5869.80
1997	39307	9.05	3.53	8.50	1427	120.67	0	0	1	171.96	1	1	164.92	56091	1,456,391	6244.70
1998	43393	7.50	3.61	7.81	1427	120.49	1	0	0	154.85	1	1	169.98	61922	1,618,308	6582.47
1999	43214	6.73	3.54	8.77	1439	121.50	1	0	0	130.13	1	1	175.76	62185	1,356,162	7015.53
2000	43811	9.26	3.51	8.49	1373	116.19	0	1	0	124.18	1	1	178.33	60152	1,300,466	7369.67
2001	43486	8.07	3.35	4.89	1351	113.94	0	1	0	122.16	1	1	182.61	58750	1,497,419	7706.00
2002	43000	9.70	3.50	4.31	1320	111.46	0	0	1	119.29	1	1	186.60	56760	1,594,876	7987.60
2003	42000	8.28	3.54	4.00	1440	121.32	0	1	0	130.19	1	1	192.39	60480	1,731,002	8458.87

APPENDIX C
TSP PROGRAM

```
OPTIONS MEMORY=175 LIMWARN=2 SIGNIF=4 LIMPRN=95 LINLIM=1500
LEFTMG=0;

READ (FILE='a:TomARDat.XLS' FORMAT=EXCEL);

SMPL 2,48;

? The columns in TomARDat.XLS are:
? Year = Years 1956-2004 (49 obs) CT missing for 2004 (48 obs)
? At = the acreage of harvested tomatoes
? Pt = the price per 25 pound carton of tomatoes
? Ct = the harvest cost per 25 pound carton of tomatoes
? Rt = the prime interest rate during the harvest decision phase (October-June)
? Yt = the yield of 25 pound cartons per harvested acre
? Wt = precipitation
? D1 = dummy, 1 for the El Ni?o climate effect, zero otherwise
? D2 = dummy, 1 for the La Ni?a climate effect, zero otherwise
? Tt = the temperature
? Xt = dummy, the adoption of plastic mulch
? Lt = dummy, the adoption of methyl bromide
? Ft = the consumer price deflator (October-June)
? Qt = the quantity of shipped Florida tomatoes
? Mt = the quantity of imported tomatoes (October-June) from Mexico
? It = the total consumer disposable income (October-June)
? D3 = dummy, for neutral climate effect, 0 otherwise

At = At/1000;
Yt = Yt/10;
Qt = Qt/1000;
Mt = Mt/10000;
It = It/100;

?print YEAR AT PT CT RT YT WT D1 D2 TT XT LT FT QT MT IT D3;


tp = year;
ltp = log(tp);

TREND TIME;
```

```
LAt = LOG(At);
LPt = LOG(Pt);
LCt = LOG(Ct);
LRt = LOG(Rt);
LYt = LOG(Yt);
LWt = LOG(Wt);
LTt = LOG(Tt);
LFt = LOG(Ft);
LQt = LOG(Qt);
LMt = LOG(Mt);
LIt = LOG(It);


ft = ft/100;
PF  = (PT/FT);   ? Deflated price
PC  = PT/CT;     ? Price per carton/Harvest cost per carton
CF  = (CT/FT);   ? Deflated cost
PCF = (PF/CF);
IF  = (IT/FT);   ? Deflated income

LPF  = LOG(PF);
LPC  = LOG(PT/CT);
LCF  = LOG(CF);
LPCF = LOG(PF/CF);
LIF  = LOG(IF);


? MSD(TERSE,CORR) YEAR AT PT CT RT YT WT D1 D2 TT XT LT FT QT MT IT;
? HIST(DISCRETE) D1 D2 XT LT;


PROC LIN;

frml acres, AT = a + apt*pt + act*ct + arho*(AT(-1) - a - apt*pt(-1) - act*ct(-1));
frml yield, YT = y + yptct*(pt/ct) + yd1*d1 + yd2*d2 + yxt*xt + ylt*lt + yrho*(YT(-1) -
y - yptct*(pt(-1)/ct(-1))
               - yd1*d1(-1) - yd2*d2(-1) - yxt*xt(-1) - ylt*lt(-1));
frml demand,(pt/ft) - (d + dqt*qt + dmt*mt + dif*if
           + drho*((pt(-1)/ft(-1)) - (d + dqt*qt(-1) + dmt*mt(-1) + dif*if(-1))));
IDENT QUANT  QT = AT * YT;


SMPL 4,48; ?obs was an outlier;
param a apt act arho y yptct yd1 yd2 yxt ylt yrho d dqt dmt dif drho;
FIML (ENDOG = (AT YT Pt QT),maxit=500) acres yield demand quant;
```

```
ENDPROC LIN;

PROC aLOG;

frml acres, lAT - (la + lapt*lpt + lact*lct);
frml yield, lYT - (ly + lyptct*(lpt - lct) + lyd1*d1 + lyd2*d2 + lyxt*xt + lylt*lt);
frml demand,(lpt-lft) - (ld + ldqt*lQT + ldmt*lmt + ldif*lif);
IDENT QUANT  lQT = lAT + lYT;

SMPL 4,48; ?obs was an outlier;
param la lapt lact ly lyptct lyd1 lyd2 lyxt lylt ld ldqt ldmt ldif;
FIML (ENDOG = (lAT lYT lPt lQT),maxit=500) acres yield demand quant;


ENDPROC aLOG;

PROC lfinal;

frml acres, lAT - (la + lapt*lpt + lact*lct
            + arho*(lAT(-1) - (la + lapt*lpt(-1) + lact*lct(-1))));
frml yield, lYT - (ly + lyptct*(lpt - lct) + lyd1*d1 + lyd2*d2 + lyxt*xt + lylt*lt
            + yrho*(lYT(-1) - (ly + lyptct*(lpt(-1) - lct(-1)) + lyd1*d1(-1)
            + lyd2*d2(-1) + lyxt*xt(-1) + lylt*lt(-1))));
frml demand,(lpt-lft) - (ld + ldqt*lQT + ldmt*lmt + ldif*lif
                 + drho*((lpt(-1)-lft(-1)) - (ld + ldqt*lQT(-1) + ldmt*lmt(-1) + ldif*lif(-
1))));
IDENT QUANT  lQT = lAT + lYT;

SMPL 4,48; ?obs 2 was an outlier;
param la lapt lact arho ly lyptct lyd1 lyd2 lyxt lylt yrho ld ldqt ldmt ldif drho;
FIML (ENDOG = (lAT lYT lPt lQT),maxit=500) acres yield demand quant;

ENDPROC lfinal;

lin;
alog;
lfinal;


END
```

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BIOGRAPHICAL SKETCH

Ann Hildebrand was born in Gainesville, Florida, in 1980. After graduating from Oak Hall School, she earned her bachelor's degree in food and resource economics with a specialization in agribusiness management at the University of Florida in 2002. In August of 2003, Ann began the food and resource economics Master of Science program.