Staff Paper

An Analysis of the Impact of ENSO
(El Niño/Southern Oscillation)
on Global Crop Yields

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Abstract:

Forecasts of global crop yields prior to planting have generally been single values, based entirely on past trends. Regression analysis testing a combination of data from ENSO (El Niño/Southern Oscillation) and ARMA models suggests that yield forecasting errors can be reduced, generating more normal distributions of these errors.

Key Words: El Niño, ENSO, forecasting crop yields, long range weather forecasting, agricultural modeling, food security, risk management.

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The greatest challenge in forecasting food production and agricultural prices year to year has been predicting crop yields. During the growing season, many resources are devoted to monitoring crop development in order to establish some parameters on the size of the prospective crops. The U.S. Department of Agriculture (USDA) publishes monthly estimates for production of major crops in the U.S. and throughout the world (U.S. Department of Agriculture, 1999). But until definitive information is available, crop production per acre or per hectare is routinely projected by past trends. These extrapolated estimates have been accepted as the best available well into the growing season. For U.S. corn and soybeans, for example, the USDA relies on trend yields until August 1, about two-thirds of the way in the development of these crops.

While yield forecasts are generated independently of and earlier than the USDA assessments, analysts have had little success in predicting yields even just prior to the normal planting season. This, of course, relates to the extreme difficulty in forecasting weather accurately for the upcoming growing season. Nevertheless, even marginal improvement in accuracy of weather forecasting six months to a year in advance of harvest would enhance planning and policy directives substantially.

An evaluation in 1984 of long-range weather forecasting by an Australian meteorologist was not highly optimistic about major improvements (Nicholls, 1985). Neville Nicholls made these observations and cited another analyst:

> "Unfortunately, the record of meteorological services and individuals who have attempted to predict climate variations is not very good (Nicholls, 1980). Such predictions are usually no more accurate than chance. Recent work (Madden) suggests that fluctuations of climate from year to year, in many parts of the world, are essentially random and inherently unpredictable. Thus, development of a successful and widely usable climate prediction technique seems unlikely."

Nicholls hastened to add:

> "There is, however, at least one exception to this bleak prospect: the El Niño-Southern Oscillation phenomenon......This relatively well-defined life cycle sometimes allows the prediction of anomalous meteorological and oceanic behavior associated with the phenomenon some months in advance."

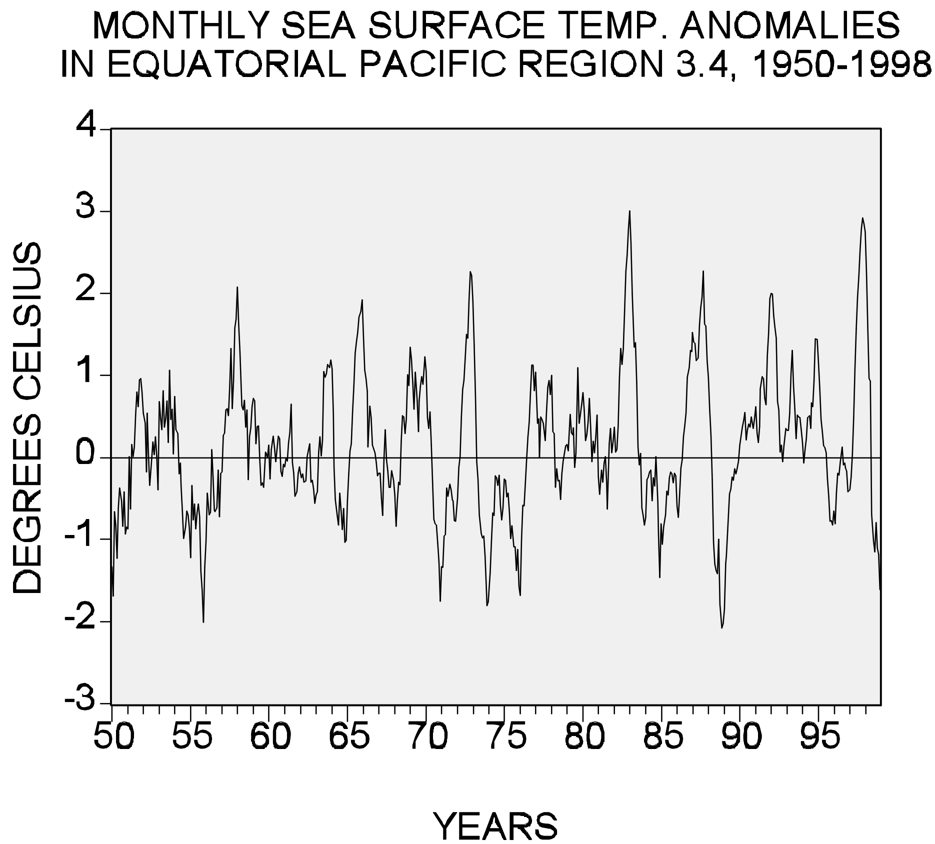
Popularly known as "El Niño", this cycle has been given increased attention in recent years as a means to forecast world weather patterns several months into the future. El Niño refers to abnormal warming of the sea surface in a large area of the equatorial Pacific ocean. This area about matches the size of the contiguous United States. "El Niño", Spanish name for "The Boy Child", refers to Jesus Christ, a label given to the warming by Peruvian fishermen who noted the phenomenon tended to develop around Christmas time. Fishermen were sensitive to El Niño because it affected their catch.

Just as there are warm anomalies in sea surface temperatures in the tropical Pacific, cold anomalies called "La Niña" (girl) are also observed. Both El Niño and La Niña affect weather patterns and are given the common name, "El Niño/Southern Oscillation" (ENSO).

Recognition of the importance of the effect of ENSO on crop yields and agricultural prices has been growing over the past quarter of a century. Early attention was triggered in the 1972-73 crop year as El Niño depleted the catch of anchovies off the coast of Peru. This reduced the production of fish meal for livestock feed in a year oilseed meal supplies were particularly tight. U.S. soybean meal prices reached a peak of $400 per ton (Decatur, IL) and averaged $229 per ton for the season. Weather problems in the U.S. Corn Belt in 1974, 1983 and 1988 followed strong El Niño years.

Current interest in ENSO can be traced to the observation that the intensity has increased over time. The El Niño which began in March 1997 reached a level exceeded in only one past month (January 1983) since detailed records have been compiled. This is illustrated in Figure 1 for sea surface temperatures in a combination of Regions 3 and 4 in the equatorial sector of the Pacific Ocean. The National Oceanic and Atmospheric Administration (NOAA) maintains detailed records of sea surface temperatures in four regions of the Pacific and calculates anomalies as shown in Figure 1 (NOAA, 5/8/99). These anomalies, which represent departures from monthly seasonal averages, are graphed as degrees Celsius. The combination of Regions 3 and 4, labeled 3.4 is preferred by NOAA for analyzing ENSO's impacts.

Figure 1



Major efforts have been directed by meteorologists in tying ENSO to current and future weather patterns around the world. Measurement of ENSO has concentrated on sea surface temperatures but also atmospheric pressure in the tropical Pacific has been monitored. A key series which has been tracked as early as the late 1800s is the difference in atmospheric pressure at sea level between Tahiti and Darwin, Australia, called "Southern Oscillation Index", (SOI). This data base was derived from the extensive records kept by ship captains over the years.

<u>References on Weather Patterns</u>

Many studies have been directed toward relating ENSO to weather patterns, both globally and to specific local areas and regions. Methodology has varied widely. Ropelewski and Halbert were not the first to examine global impacts but they did provide one of the more comprehensive analyses of recent years (Ropelewski and Halpert, 1986; 1987; 1989). They concluded that ENSO had significant effects on precipitation in 19 "core" regions around the world. These areas included the central and western tropical Pacific; northern, eastern and south eastern Australia; India; eastern equatorial and southeastern Africa; north Africa and western Mediterranean; north east South

America; Argentina; the Caribbean; the Gulf and Mexican region of North America; and the Great Basin of the U.S.

Kiladis and Diaz found similar sensitive regions for ENSO and added other areas including Southeast Asia, western Australia, far western and central Europe, western Africa, western South America, Brazil, Canada, eastern U.S. and east central U.S. (Kiladis and Diaz). Both of these studies related precipitation and temperature to specific years judged to be significant departures from normal. In other words, the relationship was not scaled to the level of departure of sea surface temperatures (SST) or the Southern Oscillation Index (SOI) from normal.

A global view of sensitive areas defined by the Climate Prediction Center on NOAA is described as follows (NOAA, 12/6/98):

> "Warm episodes (El Niño) result in abnormally dry conditions over northern Australia, Indonesia, and the Philippines in both (winter and summer) seasons. Drier than normal conditions are also observed over southeastern Africa and northern Brazil during the northern winter season. During the northern summer season, the Indian monsoon rainfall tends to be less than normal, especially in northwest India where crops are adversely affected. Wetter than normal conditions during warm episodes are observed along the west coast of tropical South America and at the subtropical latitudes of North America (Gulf Coast) and South American (southern Brazil to central Argentina).
>
> During cold episodes (La Niña) ......"wetter than normal conditions develop........over northern Australia and Indonesia during the northern winter and over the Philippines during the northern summer. Wetter than normal conditions are also observed over southeastern Africa and northern Brazil, during the northern winter season. During the northern summer season, the Indian monsoon rainfall tends to be greater than normal, especially in northwest India. Drier than normal conditions during cold episodes are observed along the west coast of tropical South America and at subtropical latitudes of North America (Gulf Coast) and South America (southern Brazil to central Argentina) during their respective winter seasons."
>
> A cold episode winter "favors the build-up of colder than normal air over Alaska and western Canada, which often penetrates into the northern Great Plains and the western U.S. The southeastern U.S., on the other hand, becomes warmer and drier than normal."

Other studies have focused on specific nations or regions of nations. An analysis of the contiguous U.S. found ENSO related to the frequency of occurrence of heavy rainfall in the Southeast, Gulf Coast, central Rockies and the general area of the Mississippi- Ohio river valleys (Gershinov and Barnett). Also, extreme warm temperature frequencies were associated with ENSO in southern and eastern U.S. Another study found significant precipitation anomalies in several regions of the central and eastern North America (Montroy, Richman and Lamb).

Several researchers have directed their efforts toward southern Africa, identified as a region especially susceptible to ENSO influences (Hastenrath, Greichar and Van Heerden; Jury). Other regions receiving attention include Australia (Evans and Allan; Stone and Auliciems) and India (International Research Institute for climate prediction). These studies confirm that ENSO related variables do impact weather patterns in those areas.

References on Crop Yields

Less numerous are studies which relate ENSO to crop yields, and, as with meteorological research, the methods have varied widely. Handler related El Niño to U.S. droughts and corn yields (Handler). He found no relationship in 1910 to 1950, but for the period of 1961 to 1988, corn yields in Illinois, Iowa and Indiana registered the strongest association with El Niño, with negative correlations throughout the six quarters prior to planting, but slightly positive during the growing season and strongly positive for a few months after harvest.

A 1992 study by the Economic Research Service of the U.S.D.A. found departures from a normal distribution on coarse grain yields in the Corn Belt and Great Plains in El Niño years, with evidence the departure was to the upside (Stephanski). For two years following El Niño, no significant departures could be discerned. El Niño years were defined as when El Niño began.

In another study, corn yields in Iowa, Illinois, Indiana, Missouri and Ohio were related to SOI for the period from 1900 to 1994 (Carlson, Todey, and Taylor). The analysts found a tendency for yields to be highest in the low phase of SOI which corresponds to El Niño and lowest during the high phase which corresponds to La Niña.

Mjelde, et. al. examined the lagged relationship between SOI in one year and rainfall in the fall of that year through the growing season of the next year in east-central Texas (Mjelde, et.al.,1997). Then, they applied this information to production functions on corn and sorghum which incorporated rainfall variables. Only in October of year t to March of year t+1 (preseason) were SOI variables significant in explaining rainfall. For the period of 1894 to 1992, 24 “ENSO event years” and 17 “cold event years” were identified. ENSO event years, captured by a zero-one dummy variable, tended to add to preseason rainfall while the cold event years tended to reduce preseason rainfall. They concluded that ENSO information could enhance profits somewhat on corn by modifying inputs, but not on sorghum.

Using a similar SOI model (zero-one variables lagged) to forecast *yields* directly, Mjelde and Keplinger found that warm events are correlated with increases in winter wheat yields in Texas and cold events are correlated with lower yields (Mjelde and Keplinger, 1998). For sorghum, the signs in most cases were correct (same as wheat) but the coefficients were not uniformly significant. They observed that significant correlations between SOI events and yields do not necessarily translate into more accurate forecasts. Including SOI events in forecasting yields decreased the forecast mean squared error for winter wheat, but had no significant impact on sorghum forecasts.

In a project to evaluate the potential economic gains from improved long range weather forecasting, analysts established that, for southern, central and southeastern U.S., non-irrigated crop yields were positively related to La Niña and negatively related to El Niño (Adams, et. al.) They defined ENSO anomaly years as beginning in October and ending in September of the following year. Their analysis covered 1948-1987. They assumed that the accuracy of yield forecasts from ENSO was about 60 percent. An improvement to 80 percent would add about $145 million to $265 million in social welfare (producer and consumer) in the area, equal to about 2-3 percent of the farm-gate value of total crop production.

In another study of ENSO effects on major crops in Southeast U.S. (Florida, Alabama, Georgia and South Carolina), University of Florida researchers examined not only yields but also areas harvested and prices (Hansen, Hodges and Jones). Little influence was detected on prices. Crop yields tended to be higher than trend in La Niña years and lower than trend in years immediately following La Niña events. The warm phase two years prior to harvest influenced areas of soybeans, cotton and peanuts harvested.

Relatively little research has been directed to associating ENSO with crop yields outside of the U.S. In a study of crop yields in Australia, Nicholls concluded that *changes* in sea-surface temperatures around northern Australia appear to offer a simple means for predicting crop fluctuations well in advance of harvest and even prior to the main planting season (Nicholls). These temperatures relate to ENSO.

A study of corn production in Zimbabwe found yields correlated more closely with ENSO than did rainfall (Cane, Eshel and Buckland). The researchers found more than 60 percent of the variance in yield correlated with ENSO. Their approach was to evaluate a model to predict ENSO and thereby forecast yields, a process they assessed as accurate.

Purpose and Relevance of This Study

The purpose of this study is to examine how ENSO/SOI have affected crop yields in a global perspective. The focal question is, "Can the information from ENSO/SOI improve the accuracy in forecasting crop production and prices in major segments of the world?" This includes the question of whether such information can provide an improved definition of the probability distribution on yields. An ancillary objective was to determine whether further research, especially in establishing meteorological linkages, is warranted.

For individual states and districts of nations, the possible impact of ENSO/SOI is, of course, important to those areas. Such research is imperative. However, in a broader sense, to producers and consumers alike around the world, a more relevant concern is the global impact. ENSO/SOI would be expected to have positive as well as negative effects on crop yields from region to region. What needs to be determined is the *net* impact on production and the implication to world agricultural and food prices. To make such an evaluation, crop production in ENSO/SOI sensitive areas must be aggregated into some type of global agricultural model which can generate price effects. Implications to prices depends on the world supply-demand situation, particularly as related to stock levels. When stocks of agricultural commodities are low, prices can be quite volatile in responding to variations in production or even changing forecasts of production.

Nations/Regions and Crops

Two sets of nations/regions were examined in this study. One set targeted the major agricultural nations and two aggregations of nations. The U.S. and four aggregations of nations comprised the second set designed to fit into the requirements for an econometric/simulation model of world agriculture, called AGMOD (Ferris, 1997). The first set was as follows:

United States	European Union
Canada	India
Argentina	China
Brazil	Republic of South Africa
Australia	Rest of the World

The second set included:

United States

Major grain exporters (Argentina, Australia, and Canada)

European Union

Major soybean and soybean product exporters (Argentina and Brazil)

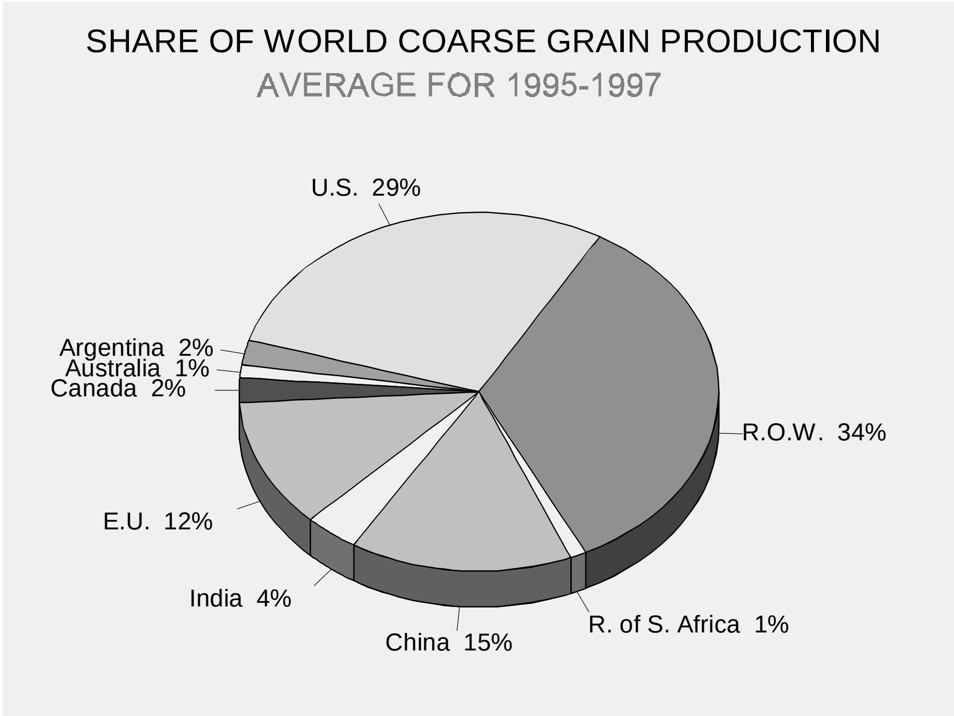
Rest of the World

A separate analysis was undertaken of grain yields in the Former Soviet Union but no linkages to ENSO could be established.

The crops selected were coarse grain, wheat, and oilseeds. Rice was not included since much of the production is under irrigation and less susceptible to variation in precipitation than are other crops. Coarse grain includes corn, sorghum grain, oats, barley, millet, and mixed grains. On coarse grain, corn was examined separately for the U.S. and the Republic of South Africa. On oilseeds, soybeans were analyzed for the U.S., Argentina, and Brazil. For the European Union (E.U.), oilseed yields were collectively tabulated. No analysis was directed toward oilseed yields outside of these nations.

The relative importance of these crops in the selected nations and regions is illustrated in Figures 2 to 4. On coarse grain production, the U.S. represented nearly 30% of the world's total in 1995-97 (Figure 2). This was followed by China (15%), E.U. (12%), and India (4%). Outside the U.S., the major exporting nations of Argentina, Australia , and Canada represented only about 5% of the total, with the Republic of South Africa about 1%. The rest of the world accounted for about a third of coarse grain production.

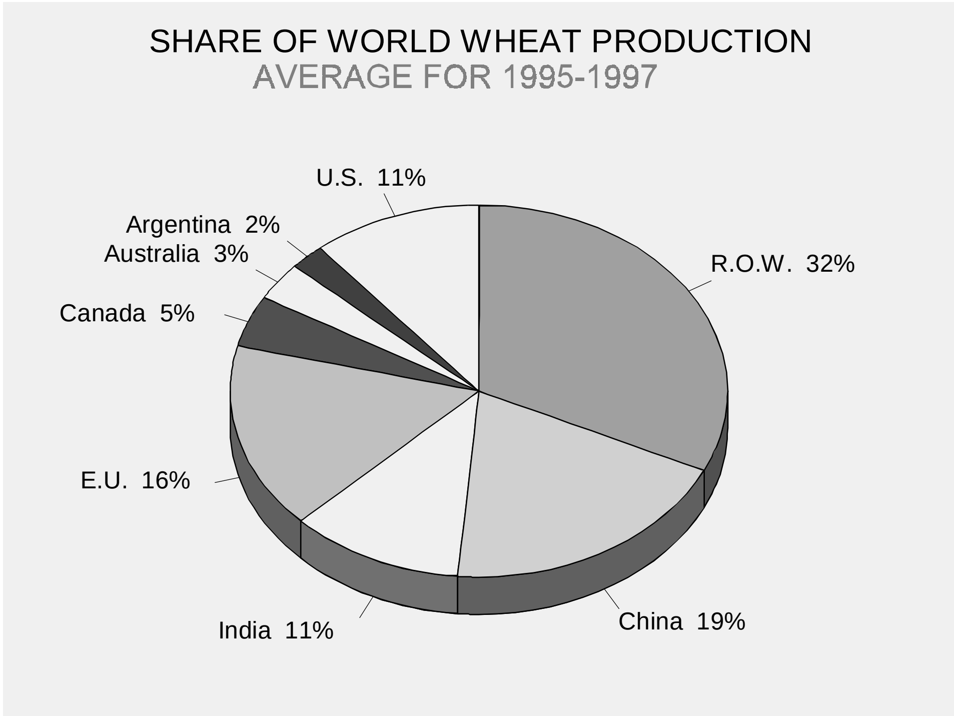
Figure 2



In the U.S., corn predominates coarse grain output at nearly 90% in 1995-97; sorghum production was about 7% in the same period. In Argentina, corn represented about 80% of the coarse grain output and in the Republic of South Africa, about 93% in 1995-97.

As shown in Figure 3, the U.S. produced only 11 percent of the world's wheat output in 1995-97, about the same as India, but less than China (19%) and the E.U. (16%). These nations were followed by Canada (5%), Australia (3%) and Argentina (2%). The rest of the world accounted for nearly a third of the global output.

Figure 3



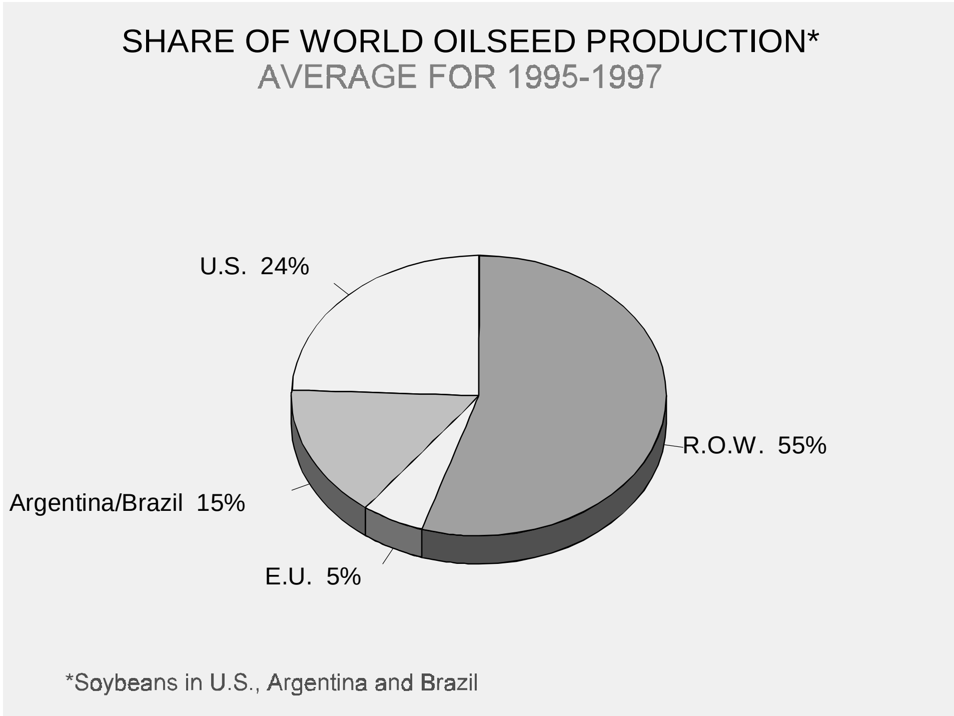
Soybean production in the U.S., Argentina, and Brazil coupled with oilseed production in the E.U. accounted for about 45% of the world's oilseed output in 1995-97 (Figure 4). The U.S. alone represented about a fourth of the global total.

Analytical Procedures

Several alternative formulations were explored in relating ENSO/SOI to crop yields. While the Southern Oscillation Index (SOI) has the advantage of a data base which extends back to the late 1800s, ENSO provided stronger statistical linkages to crop yields in the period since 1950. The ENSO data base begins in 1950. At the suggestion of NOAA, sea surface temperatures (SST) in the combination of Regions 3 and 4, labeled Region 3.4 were selected for the analysis. No further analysis of the effects of SOI was pursued. Since SST exhibit a seasonal pattern, the base data were the anomalies (departures) from the seasonal averages. The decision was made to incorporate both positive values (El Niño) and negative values (La Niña). For this reason, subsequent references will be to the entire cycle, that is ENSO.

The anomalies calculated by NOAA have been based on 30 year averages of SSTs for each month from 1950 to 1979. These averages were subtracted from the actual SSTs for each month to derive the anomalies.

Figure 4

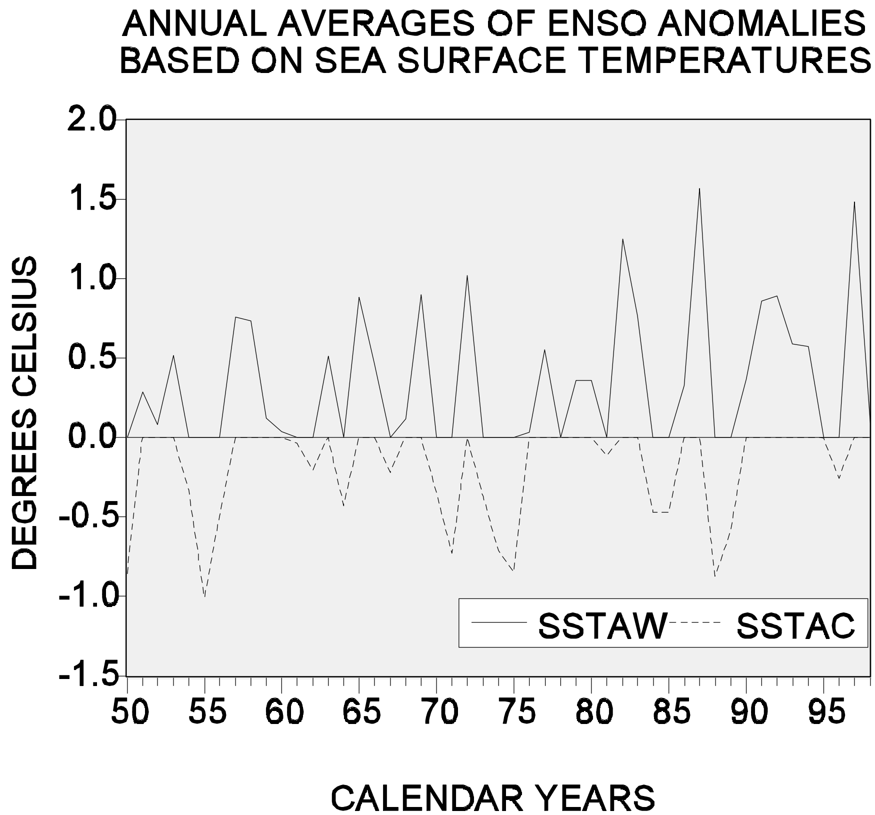


The SSTs have increased over the 1950 to 1998 period, significantly so since the late 1970s. For Region 3.4, the average across all months in 1980 through 1998 was 27.14 degrees Celsius compared to 26.84 degrees in 1950 to 1979, the base used by NOAA. Initial exploration with a 1950 to 1998 base revealed only minor differences in the results so the decision was made to incorporate NOAA's anomalies.

Observation of Figure 1 would reveal that the ENSO anomalies are not normally distributed. This was confirmed by a Jarque - Bera normality test which indicated a skewness of .403 and kurtosis of 3.425 (Bera and Jarque). These values portray a distribution in which the positive peaks of El Niño are greater than the negative peaks of La Niña and the tails are somewhat thicker than normal.

Alternative frequencies were explored before the decision was made to use calendar year averages. Two variables were constructed. The El Niño variable, SSTAW, is the calendar year average of the anomaly if positive and zero if negative. The La Niña variable, SSTAC, on the other hand, is the calendar year average of the anomaly if negative and zero if positive. These variables are plotted in Figure 5 for 1950 to 1998. Four ENSO variables were candidates as independent variables in linear regressions to forecast crop yields, SSTAW, SSTAC, SSTAW(-1), and SSTAC(-1). SSTAW(-1) and SSTAC(-1) represent one year lags of SSTAW and SSTAC.

Figure 5



A number of studies have used zero-one type variables, usually to designate which years can be defined as El Niño years. Normally, only those years in which the positive anomaly exceeds some prescribed level are analyzed relative to other years. Similar procedures were used to define La Niña years. Whether the procedure described above for this study is superior or not may be debatable but it does involve scaling, that is levels of departure from the norm are included in the measurement. Questions related to whether the warm and cold episodes are symmetric in their impacts on crop yields can be determined. Degrees of freedom are expanded in that all years are included in the measurement procedure. One of the limitations of ENSO research has been the limited number of observations when only clearly El Niño years or La Niña years are enumerated.

The formulation of the monthly data series into calendar year averages was somewhat arbitrary. The first approach was to: (1) separate *crop* year averages for the northern and southern hemispheres and (2) separate 6 month growing season averages for both hemispheres. The results were generally less satisfactory than with the calendar year averages even though conceptually such orientations seemed logical. For example, a current calendar year average in the northern hemisphere would include a period following harvest in which ENSO would not appear to be relevant to that year's yield. For consistency and to accommodate aggregations of nations across both hemispheres, only the results using calendar year averages for the anomalies are reported. Comments accompany the discussion where the alternative formulations provided the stronger relationship. Even in these cases, the results were similar to the application of calendar year averages.

The crop yield variable was the percent deviation of annual crop yields from trends based on double exponential smoothing (DES). Yield data were obtained from the USDA's "Production, Supply and Distribution" series (U.S. Department of Agriculture, 1998).

The formula for single exponential smoothing is:

$$F_t=\alpha A_{t-1}+(1-\alpha)F_{t-1}$$

where:

F=forecast

A=actual values

The value of α is usually small (less than .1) and indicates how much weight to give to the most recent actual observation versus the forecast for the previous period. In the software program, MicroTSP, the analyst can either set the value or have the program find the value that minimizes the sum of squared forecast errors within the sample (Hall, Jackson and Lilien). In double exponential smoothing, the single smoothed data is smoothed again, i.e.:

$$F'_t=\alpha F_{t-1}+(1-\alpha)F'_{t-1}$$

A trend is included in the forecast and is extended into the future beyond the sample period in line with the most recent past trend.

The application of double exponential smoothing to corn yields in the U.S. for 1950-97 is illustrated in Figure 6. The deviations of actual yields from the DES derived trends in terms of percentages were then calculated and plotted in Figure 7. The same procedure was applied to other crops to generate the dependent variables for the linear regression analysis. Attention was given to correlations between crops. If the correlation was relatively high, yield deviations for one crop were included, as an independent variable, in the equation for the second crop.

Figure 6

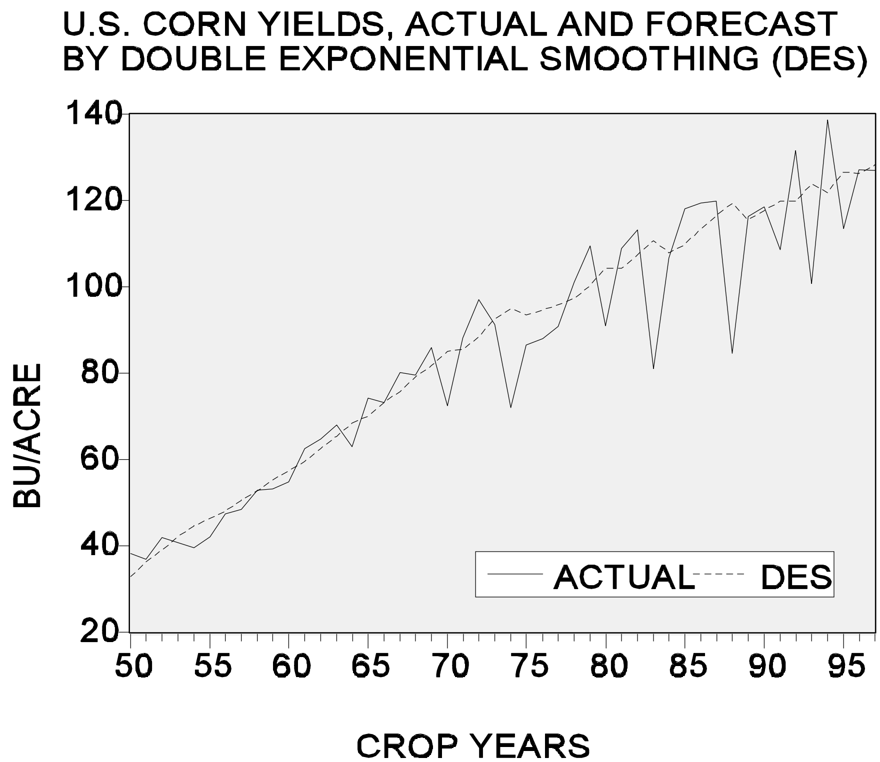
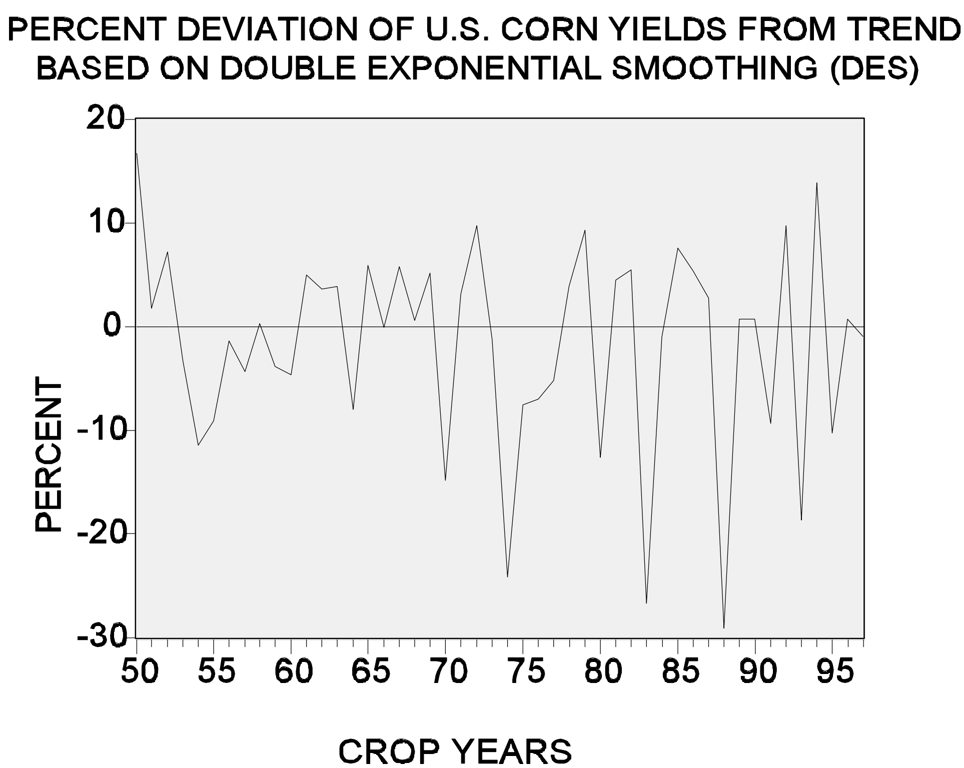


Figure 7



Standard ordinary least square procedures were employed in the analysis. Assumed was a linear relationship between the independent variables and the dependent variables. While not tested in this endeavor, future research should check for non-linearities which very well may be prevalent.

Routinely, all four ENSO anomalies were initially included as independent variables in the equations and then screened out based on statistical properties. In only a few cases were all four variables retained. While the lagged ENSO variables, SSTAW(-1) and SSTAC(-1), provided *direct* means to forecast yields, current ENSO variables, SSTAW and SSTAC would have to be forecast themselves, particularly for the northern hemisphere and fall planted crops in the southern hemisphere. Except for fall planted crops in the north, the anomalies for only part of the current year would need to be forecast *prior to planting*. Even so, this analysis over-estimates the forecasting accuracy of those equations which include the current averages. But in support of the rationale to incorporate current averages, the Climate Prediction Center of NOAA has been forecasting sea surface temperatures in the tropical Pacific experimentally since September 1992 and officially since December 1994 (NOAA, 5/1/99). As this program evolves and establishes a tracking record, their 15 month forecasts can be incorporated into the crop yield equations.

In the first step of the screening process, variables were eliminated if the coefficients were not significantly different from zero, that is their “t” values were less than an absolute value of “2.” However, in this process, it was noted that the residuals usually did not display “white noise”. This means that likely some weather cycle remained in explaining yield patterns not related to ENSO. For that reason, the procedure was changed in which time series analysis was combined with the standard statistical analysis to establish what independent variables should be incorporated. The criteria for inclusion were “t” values, R-squares and evidence of “white noise” in the residuals. However, a number of ENSO variables were retained for comparison purposes even though the absolute “t” values on their coefficients were less than two.

If the residuals appeared to lack “white noise,” some pattern remained unmeasured which could contribute to the explanation of yield deviations. For this reason, autoregressive (AR) and moving average (MA) procedures called ARMA were applied to the residuals. The assumption was made that weather cycles would not extend more than 5 or 6 years into the past. Empirical evidence indicates that deviations of yields from trends, with or without ENSO considerations, typically are not “white noise.”

Global Yield Equations

The results of the linear regression analysis are summarized in Table 1. The data period was from the mid 1950s to 1997 on U.S. crops and early 1960s to 1997 on crops outside the U.S. (The beginning crop years are indicated in Table 2.). For each crop, coefficient and "t" values are listed for the independent variables representing the ENSO anomalies and "t" values are listed for the ARMA terms. The numbers in parentheses ahead of the "t" values for the ARMA terms represent the number of previous years included in the formulations. Where yields were correlated with a second crop, footnotes indicate what crops were involved and what the coefficient and "t" values were on those variables. Negative signs on the SSTAW variables mean a negative effect on yields. A negative sign on the SSTAC variables indicates a *positive* effect since the SSTAC variable carries a *negative* sign. The "t" coefficients with absolute values greater than "2" were considered statistically significant. The Ljung-Box probability statistic listed for each equation is a measure of the presence of "white noise" in the residuals (Ljung and Box). The addition of the ARMA terms in each equation was conducted in such a way to provide reasonable assurance of "white noise" in the residuals, indicating that most predictive elements had been captured.

United States

El Niño lagged one year, i.e., SSTAW(-1), and SSTAC were particularly significant in cutting U.S. corn yields. One might attribute this to the tendency for a strong La Niña year to follow a strong El Niño year, which happened 4 times in 1951 to 1998. However, the correlations from year to year among the sea surface temperature anomalies were very small. Soybean yields were similarly affected by ENSO as were corn yields, considering the strong correlation with corn yields as noted in Footnote #5 in Table 1. On coarse grain other than corn, the correlation with corn yields made these crops in the aggregate also susceptible to lagged El Niño, current La Niña and also to lagged La Niña. Somewhat surprising is that SSTAC(-1) tended to affect U.S. crops other than corn negatively.

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In two years of the data base, corn yields were low for reasons other than dry weather — blight in 1970 and flooding in 1993. Using dummy variables for those years in the corn equation, no significant results emerged to indicate that these years should be eliminated.

Table 1. Results of Linear Regression Analysis on the Effect of ENSO Anomalies and ARMA Models on Percent Deviations of Crop Yields from Trends[1]

Nation/ Region and Crop	Coefficients and "t" Values[2]				"t" Values[3]		R^2 $\overline{R}^2$	Ljung-Box Probability
	SSTAW (-1)	SSTAW	SSTAC (-1)	SSTAC	AR	MA		
UNITED STATES								
Corn	-9.75 (-4.19)			11.51 (3.58)	(1)-3.16 (4)3.37	(4)25.86	.48 .41	.87
Coarse Grain[4]	1.74 (.85)		5.55 (2.12)			(4)-12.38 (5)17.32	.78 .75	.55
Wheat	1.53 (.78)		5.11 (1.79)		(4)-3.71	(2)5.25 (4)12.51 (5)-7.08	.48 .40	.54
Soybeans[5]	-.92 (-.57)		3.53 (1.61)		(2)2.76		.67 .63	.77
ARGENTINA								
Coarse Grain	-5.02 (-1.28)			25.08 (4.18)		(2)-4.28	.39 .33	.67
Wheat		7.16 (2.27)			(5)-4.53	(5)10.13	.32 .25	.92
Soybeans[6]	10.55 (2.50)		-38.36 (-5.50)	16.91 (2.90)	(3)-1.76		.76 .70	.90
BRAZIL								
Soybeans		3.88 (.81)		-8.38 (-.96)	(1)1.42		.12 .03	.82
AUSTRALIA								
Coarse Grain[7]				-7.20 (-1.88)		(3)-2.72	.84 .82	.81
Wheat	16.03 (2.10)	-13.14 (-1.85)				(2)-1.62	.29 .20	.97
CANADA								
Coarse Grain[8]					(1)3.06	(4)-10.53	.76 .74	.94
Wheat				17.46 (3.03)		(5)29.09	.54 .51	.48
EUROPEAN UNION								
Coarse Grain	-3.86 (-1.94)	4.10 (2.25)	9.39 (3.03)	-12.42 (-3.95)	(3)-2.55		.38 .27	.77
Wheat[9]		-2.59 (-2.22)			(2)2.85 (3)2.99	(1)5.11 (3)-13.43	.71 .65	.94
Oilseeds	-9.64 (-2.96)		9.86 (1.76)		(4)-2.03 (5)-3.38	(4)34.47	.63 .55	.79

Table 1. (Continued)

Nation/ Region and Crop	Coefficients and "t" Values[2]				"t" Values[3]		R^2 $\bar{R}^2$	Ljung- Box Probability
	SSTAW (-1)	SSTAW	SSTAC (-1)	SSTAC	AR	MA		
INDIA								
Coarse Grain	8.63 (2.97)					(5)-11.82	.47 .43	.95
Wheat	6.41 (4.10)		-13.65 (-4.60)	11.70 (4.49)	(5)-6.89	(4)-23.35	.74 . 69	.70
CHINA								
Coarse Grain	4.82 (2.04)	-3.87 (-1.75)			(2)-2.13		.32 .25	.60
Wheat	1.68 (.36)		-6.76 (-.93)				.02 -.03	.93
REPUBLIC OF SOUTH AFRICA								
Corn	13.27 (1.72)	-20.53 (-2.92)			(2)2.75	(2)-9.30	.38 .30	.9996
Coarse Grain[10]			34.88 (3.07)		(3)-2.20		.56 .52	.60
Wheat		10.70 (1.44)		-23.50 (-1.95)		(5)15.51	.29 .23	.42
REST OF THE WORLD								
Coarse Grain[11]		1.56 (1.44)		-2.40 (-1.37)	(3)-2.50	(4)-7.84	.78 .75	.84
Wheat	6.77 (2.03)		-18.82 (-3.49)			(2)3.03 (3)-4.81	.56 .48	.99

1 Trends in yields were derived from double exponential smoothing (DES). See Table 2 for the crop years involved.
2 SSTAW refers to the positive sea surface temperature anomaly in region 3.4 of the Pacific and SSTAC the negative anomaly, calculated as annual averages based on quarterly data. The (-1) refers to the previous year. "t" values are in parentheses..
3 The (i) for AR (auto-regressive) and MA (moving average) relates to lags in years.
4 Other than corn. Equation also included yield deviations on corn with a coefficient of .74 and a t value of 9.00.
5 Equation included yield deviations on corn with a coefficient of .49 and a t value of 6.25.
6 Equation also included yield deviations on coarse grain with a coefficient of .67 and a t value of 5.01.
7 Equation also included yield deviations on wheat with a coefficient of .61 and a t value of 10.85.
8 Equation also included yield deviations on wheat with a coefficient of .35 and a t value of 8.82.
9 Equation includes yield deviations on coarse grain with a coefficient of .92 and a t value of 9.07.
10 Other than corn. Equation also included yield deviations on corn with a coefficient of .61 and a t value of 5.12.
11 Equation also included yield deviations on wheat with a coefficient of .57 and a t value of 11.04.

The “t” values on the ARMA terms for U.S. crops provide strong indication of the lack of “white noise” in the residuals from the ENSO variables alone. The R2s and R-bar2s were relatively high on coarse grain other than corn and on soybeans because deviations from trend yields on corn were independent variables in those equations. The level of R2s and R-bar2s on corn and wheat (.40-.48) reflect that much of the variability in crop yields are due to factors outside ENSO and influences captured by ARMA techniques. The Ljung-Box statistic provided reasonable indications of “white noise.”

South America

The current year’s ENSO has had more impact on coarse grain, soybean and wheat yields in Argentina than in the U.S. as indicated in Table 1. Of course, the growing season in the southern hemisphere for corn and soybeans is mostly from October (t) to March (t+1), and partially lags the current ENSO variables. Soybean yields in Argentina were also affected adversely by current ENSO, particularly by SSTAC as related to the correlation with coarse grain yields and directly in addition. Also, soybean yields were positively enhanced by SSTAC(-1). The positive effect of SSTAW(-1) was diminished by the correlation with coarse grain yields.

In Brazil, neither the influence of ENSO nor ARMA appeared to be significant in explaining deviations of soybean yields from trends. Only current ENSO variables had some influence, with both SSTAW and SSTAC positive. When the data for the ENSO variables during the current growing season (quarter 4 of year t and quarter 1 of year t+1) were substituted for SSTAW and SSTAC, the t values and R-bar squares increased, but the t values remained insignificant and the R-bar squares remained low.

Australia

Both wheat yields and coarse grain yields (as a function of wheat yields) have been enhanced by El Niño in the previous year (Table 1). While not significant, El Niño in the current year has been a negative influence on wheat and coarse grain yields, and current La Niña has been a positive effect on coarse grain. Substituting the current growing season ENSO for the calendar year ENSO lowered the impact of lagged El Niño on wheat yields but increased the absolute value of the t statistic and R-bar square from current El Niño (to -2.95 on t and .29 on R-bar square). The coefficient on the warm episode was about the same as with the calendar year SSTAW. ARMA models contributed to the explanation of yield variability although not significantly on wheat.

Canada

In Canada, the strongest influence on coarse grain and wheat yields was La Niña in the current year, combined with ARMA models. On wheat, these influences generated a relatively high R-square of .54 and an R-bar square of .51. The R-squares on coarse grain are attributed to the correlation with wheat yields and an ARMA contribution.

European Union

In the E.U., both lagged El Niño and lagged La Niña tended to reduce coarse grain yields, and because of the strong correlation between coarse grain and wheat yields, wheat yields were similarly affected. On the other hand, current ENSO , both SSTAW and SSTAC, had positive effects on coarse grain yields — wheat also except that the effect of SSTAW was diminished.
Oilseed yields were depressed by both lagged El Niño and La Niña. ARMA models were significant in all the E.U. yield variations.

India

India's wheat yields were significantly and positively affected by lagged El Niño and La Niña and negatively affected by the current La Niña. In combination with MA(5) and AR(4), the ENSO variables "explained" about 74% of the variation in wheat yields, i.e., an R-square of .74 and an R-bar square of .69. The most significant impact on coarse grain yields was a positive effect of lagged El Niño.

China

The effect of ENSO in China was similar to that in India except that only lagged El Niño was significant in positively affecting coarse grain yields. Current El Niño had a negative impact on coarse grain yields. ARMA was not very helpful.

Republic of South Africa

The strongest influence on corn yields in the Republic of South Africa was a negative influence from El Niño in the current year. Lagged El Niño influenced yields positively but not significantly so. The most promising equation not shown in Table 1 included the current warm episode values in the growing season (October t to March t+1) and the ARMA variables in Table 1 (MA(2) and AR(2)). The coefficient on the ENSO variable was -22.3 and the t value was -4.26. The ARMA coefficients were significant at 23.1 and -5.1 respectively and the R-bar square was .33. Yields of coarse grains other than corn were significantly tied to corn yields and negatively affected by La Niña. Wheat yields were not significantly affected by ENSO but were responsive to MA(5).

Rest of the World

In the broad geographic and important sector of the "rest of the world", wheat yields were positively and significantly affected by lagged La Niña and lagged El Niño. MA(3) and MA(4) also contributed to the equation which was associated with 56% of the variation in wheat yields from trends (R-bar square at .48). Coarse grain yields were positively correlated with wheat yields. In combination with insignificant ENSO relationships and significant ARMA influences, the coarse grain equation "explained" about 78% of the variation in yields from trends (R-bar square at .75). Since the results from an analysis of the Former Soviet Union revealed no significant linkage to ENSO, this aggregation can be considered the rest of the world outside FSU.

Correspondence with Weather Linkages to ENSO

In comparing the results of the equations which significantly relate ENSO to crop yields and the past research linking weather patterns to ENSO, what conclusions might be reached? Based on meteorological research, the ENSO sensitive areas tend to be in the tropical and subtropical regions of the world. The U.S. Corn Belt, an important agricultural region, was not highlighted by a number of meteorological studies as an area susceptible to ENSO influences (although some did), yet significant relationships were detected on crop yields. Similar results were found in the E.U., not on every list of ENSO sensitive areas. Somewhat disappointing was that the target area of Australia did not reveal strong ties to ENSO related to crop yields. Neither did Brazilian soybeans.

On the other hand, results in other regions of the world backed the meteorological findings, with linkages in crop yields to ENSO in Argentina, India and the Republic of South Africa. The lack of effects can also be noted in China and the Former Soviet Union, consistent with meteorological research on ENSO.

Theil Evaluation

Traditional ways to forecast crop yields include extrapolation of linear trends and smoothing techniques such as the application of DES used in this analysis. With yield forecasts by DES as a standard, an evaluation of the performance of the *combination* of DES, ENSO variables, and ARMA was conducted. To generate yield forecasts by this *combination*, the forecast percentage deviations from trend were applied to yield trends based on DES. Following is an example on corn:

YCNF=YCNP*(DRYCNF+100)*.01

where:

YCNF is the forecast of corn yields

YCNP is the trend yield based on DES

DRYCNF is the forecast percentage deviation from trend

A method to evaluate forecasts developed by Henri Theil was applied to the crop yields (Theil). The formula, known as Theil's "Inequality Coefficient U_2", is:

$$U_2 = \left[\sqrt{\frac{1}{n-1} \sum_{t=2}^{n} \left[(F_t - A_{t-1}) - (A_t - A_{t-1}) \right]^2} \Big/ \sqrt{\frac{1}{n-1} \sum_{t=2}^{n} (A_t - A_{t-1})^2} \right]$$

where: F_t is the forecast value in year t

A_t is the actual value in year t

A feature of this formula is that an analyst can evaluate whether an equation can outperform a naive model in which the forecast is equal to the actual value in the most recent past period. A U_2 value of 0 represents perfect forecasts and 1 (or 100 percent) represents the equivalent of using the actual value in the previous period as a forecast.

The performance of the yield equations based on Theil's U_2 (in percent) is presented in Table 2. The yield equations essentially represent a combination of DES, ENSO, and ARMA variables. The DES equations generated the trends around which the percentage deviations were calculated for the ENSO and ARMA analysis. Since crop yields tend to trend upward over time, a stronger test for the yield equations would be a comparison with strictly DES forecasts. Theil coefficients for both the DES/ENSO/ARMA forecasts and the DES forecasts are tabulated. In the last column of Table 2 is the difference between the Theil coefficients from DES/ENSO/ARMA and the coefficients from DES.

Table 2. Performance of DES/ENSO/ARMA Yield Equations Based on Theil's U_2 Inequality Coefficients, Crop Years through 1997.

Nation/Region and Crop	Crop Years Beginning	Forecast Based On: DES/ENSO/ARMA	DES	Coefficient of DES/ENSO/ARMA less the DES Coefficient
U.S.		Coefficient	Coefficient	Difference
Corn	1955	45.5	68.4	-22.9
Coarse Grain other than corn	1955	53.9	78.2	-24.3
Wheat	1955	64.4	87.2	-22.8
Soybeans	1954	47.9	67.9	-20.0
ARGENTINA				
Coarse Grain	1960	69.9	88.4	-18.5
Wheat	1965	66.6	84.4	-17.8
Soybeans	1971	56.2	82.2	-26.0
BRAZIL				
Soybeans	1965	80.1	85.8	-5.7
AUSTRALIA				
Coarse Grain	1968	59.6	69.4	-9.8
Wheat	1968	60.2	71.4	-11.2
CANADA				
Coarse Grain	1961	68.3	78.1	-9.8
Wheat	1965	61.0	88.0	-27.0
E.U.				
Coarse Grain	1963	57.0	74.6	-17.6
Wheat	1965	60.6	77.8	-17.2
Oilseeds	1969	60.8	97.7	-36.9
INDIA				
Coarse Grain	1964	58.3	80.9	-22.6
Wheat	1965	46.6	78.8	-32.2
CHINA				
Coarse Grain	1962	71.6	84.4	-12.8
Wheat	1960	93.6	91.1	+2.5
REPUBLIC OF SOUTH AFRICA				
Corn	1962	56.4	73.7	-17.3
Coarse Grain other than corn	1963	79.2	92.0	-12.8
Wheat	1962	66.4	77.9	-11.5
REST OF THE WORLD				
Coarse Grain	1963	68.1	79.7	-11.6
Wheat	1963[1]	60.0	86.7	-26.7

[1] The 1975 crop year was excluded

The forecast evaluations in Table 2 represent the performance relative to a one year ahead time frame. That is, given what is known (or can be forecast, i.e. SSTAW and SSTAC) in year t-1, the evaluation is in terms of how close the forecasts are to the actual yields in year t. The equations in Table 1 which included yield deviations of other crops were give special treatment in Table 2. Rather than incorporating the *actual* values of the yield departures from trends, the *forecast* values of these other crops were employed in generating the yield forecasts for the indicated crops.

In all cases, the DES/ENSO/ARMA models and the strictly DES models outperformed the naive models (which forecast no change from year to year). That is indicated by the Theil coefficients all being less than 100 percent. Since crop yields almost universally trend upward with improved varieties and cultural practices, this was not much of a challenge for the two models. A more appropriate comparison is whether a combination of DES, ENSO, and ARMA can generate smaller errors than DES which does track upward trends closely.

The negative numbers in the last column of Table 2 indicate that the yield equations from a combination of DES/ENSO/ARMA generated smaller errors than did DES with one exception.. Only for wheat in China did the application of DES/ENSO/ARMA result in larger errors. The strongest case for DES/ENSO/ARMA was for oilseeds in the E.U.; wheat in India, Canada, and the Rest of the World; and soybeans in Argentina --- all with at least a 25 percentage point margin over DES. All of the crops in the U.S. registered at least a 20 percentage point margin from DES/ENSO/ARMA over DES alone. But as stated earlier in this paper, current ENSO variables in crop yield equations must be at least partially forecast. For this reason, the accuracy level of these equations is over-stated.

Selected Aggregates of Nations

Tables 3 and 4 present similar statistical data as in Tables 1 and 2, but for aggregates of nations which are compatible with the econometric/simulation model, AGMOD. Obviously, equations to predict crop yields in aggregations of nations will result in different statistical properties than for the component nations. The broader the geographic region being examined, the more offsetting weather factors tend to be. For both “Exporting Nations” and the “Rest of the World”, nations in the southern hemisphere are being combined with nations in the northern hemisphere, spanning a very wide area.

As indicated in Table 3, coarse grain and wheat yields in the Exporting Nations are clearly negatively related to the current La Niña and significantly related to weather cycles as captured by ARMA. Coarse grain and wheat yields are also correlated with each other.

Table 3. Results of Linear Regression Analysis on the Effect of ENSO Anomalies and ARMA Models on Percent Deviations of Crop Yields, from Trends in Selected Aggregates of Nations.[1]

Region and Crop	Coefficients and "t" Values[2]				"t" Values[3] ARMA Models		R2 $\overline{R}^2$	Ljung-Box Probability
	SSTAW (-1)	SSTAW	SSTAC (-1)	SSTAC	AR	MA		
EXPORTING NATIONS[4]								
Coarse Grain[5]				9.87 (3.74)		(4)3.97	.50 .45	.50
Wheat				13.54 (2.70)		(2)-2.70 (4)-3.83	.31 .24	.90
REST OF THE WORLD[6]								
Coarse Grain	2.36 (1.94)	-2.60 (-2.16)			(5)2.45	(5)- 22.53	.42 .34	.99
Wheat[7]	5.28 (2.99)		-8.24 (-3.02)	8.75 (4.00)		(5)- 22.55	.73 .68	.51
ARGENTINA AND BRAZIL								
Soybeans			-10.73 (-2.34)		(3)-1.98	(1)4.68	.37 .30	.96

1 Trends in yields were derived from double exponential smoothing (DES). Crop years were 1964-1997 for Exporting Nations, 1965-1997 for Rest of the World and 1967-1997 for soybeans in Argentina and Brazil.
2 See Footnote 2 in Table 1.
3 See Footnote 3 in Table 1.
4 Argentina, Australia and Canada
5 Equations included yield deviations on wheat in exporting nations with a coefficient of .25 and a t value of 3.09.
6 Nations except U.S., Exporting Nations and the European Union.
7 Equation included yield deviations on coarse grain with a coefficient of 1.06 and a t value of 6.25.

Table 4. Performance of DES/ENSO/ARMA Yield Equations Based on Theil's U_2 Inequality Coefficients, for Selected Aggregates of Nations, Crop Years through 1997.

Region and Crop	Crop Years Beginning	Forecast Based On: DES/ENSO/ARMA	DES	Coefficient of DES/ENSO/ARMA less the DES Coefficient
		Coefficient	Coefficient	Coefficient
Exporting Nations[1]				
Coarse Grain	1964	62.3	78.8	-16.5
Wheat	1964	58.5	71.5	-13.0
Rest of the World[2]				
Coarse Grain	1965	51.9	67.6	-15.7
Wheat	1965	51.9	75.1	-23.2
Argentina and Brazil				
Soybeans	1967	79.3	87.1	-7.8

1 Argentina, Australia and Canada

2 Nations except U.S., Exporting Nations and the European Union

For the "Rest of the World", both coarse grain and wheat yields were positively related to lagged El Niño and to each other. In addition, wheat yields were positively correlated with lagged El Niño and negatively related to the current La Niña. ARMA factors were important for both wheat and coarse grain.

On soybeans in Argentina and Brazil, the most notable relationship with ENSO was a positive tie with lagged La Niña but not a strong one with a t value of -2.34. ARMA techniques contributed bringing the R-square to .37 and the R-bar square to .30.

Performance of these equations relative to DES is indicated in Table 4. The equations on coarse grain in the Exporting Nations and wheat in the Rest of the World displayed the smallest errors relative to DES.

Normality Tests

One of the hopes in applying DES/ENSO/ARMA equations to crop yields was to generate residuals which were not only “white noise” but which also approached a normal distribution. This would facilitate use of existing software programs which routinely incorporate random number generators to produce normal distributions. Also, efforts to determine the appropriate distribution to represent yield variability would be simplified.

In Tables 5 to 7, statistics developed by Bera and Jarque evaluate how closely the residuals from the yield equations for the U.S. and E.U. in Table 1 and the aggregations in Table 3 approach a normal distribution (Bera and Jarque). Yield variations around DES derived trends tend to be skewed to the left indicated by the minus signs in Table 5. In other words, yields tend to be more negatively affected by unfavorable growing conditions than they are positively affected by favorable conditions. The addition of ENSO and ARMA reduced skewness in most cases, particularly for those crops with high skewness coefficients.

Table 5. Skewness Test for Percent Deviations of Crop Yields from Trends (DES) and for Residuals in DES/ENSO/ARMA Models of Yields in Selected Regions of the World.

Nation/Region and Crop	Skewness		
	DES	DES/ARMA	DES/ENSO/ARMA
U.S.			
Corn	-1.05	-.27	.20
Coarse Grain other than Corn	-.09	-.16	.49
Wheat	.68	.24	-.13
Soybeans	-.51	.20	-.25
Exporting Nations[1]			
Coarse Grain	-.41	-.21	.37
Wheat	-.20	-.40	.27
European Union			
Coarse Grain	-.40	-.13	.30
Wheat	1.24	.10	.12
Oilseeds	-.19	-.04	.20
Rest of World			
Coarse Grain	-.02	.37	.06
Wheat	-.33	-.67	.01
Argentina and Brazil			
Soybeans	-.39	-.58	-.34

[1] Argentina, Australia and Canada

Table 6. Kurtosis Test for Percent Deviations of Crop Yields from Trends (DES) and for Residuals in DES/ENSO/ARMA Models of Yields in Selected Regions of the World.

Nation/Region and Crop	Kurtosis	
	DES	DES/ENSO/ARMA
U.S.		
Corn	3.72	2.94
Coarse Grain other than Corn	2.93	2.89
Wheat	4.82	2.44
Soybeans	3.62	2.54
Exporting Nations[1]		
Coarse Grain	3.01	2.44
Wheat	2.43	2.44
European Union		
Coarse Grain	3.55	2.21
Wheat	6.12	2.29
Oilseeds	2.04	1.86
Rest of World		
Coarse Grain	2.09	2.42
Wheat	2.35	2.21
Argentina and Brazil		
Soybeans	3.13	2.57

[1] Argentina, Australia and Canada

Table 7. Normality Test for Percent Deviations of Crop Yields from Trends (DES) and for Residuals in DES/ENSO/ARMA Models of Yields in Selected Regions of the World.

	Jarque - Bera Normality Test Statistic	
Nation/Region and Crop	DES	DES/ENSO/ARMA
Percent		
U.S.		
Corn	1.3	86.8
Coarse Grain other than Corn	96.4	41.7
Wheat	0.1	71.1
Soybeans	27.2	65.3
Exporting Nations[1]		
Coarse Grain	61.7	54.1
Wheat	70.7	64.8
European Union		
Coarse Grain	50.3	49.0
Wheat	0.0	68.3
Oilseeds	52.9	41.2
Rest of the World		
Coarse Grain	56.7	78.4
Wheat	55.4	64.8
Argentina and Brazil		
Soybeans	66.5	65.6

[1] Argentina, Australia and Canada

Kurtosis relates to the thickness of tails in a distribution, with normalcy associated with a value of 3 based on Jarque-Bera measures. The crop yields tabulated in Table 6 did not display consistent tendencies above and below normal thickness of tails around DES trends. The addition of ARMA and ENSO brought kurtosis values closer to 3 in only about half of the cases.

The Jarque-Bera normality test was applied to the two yield models as shown in Table 7. Yield deviations around DES based trends were clearly not normal on corn and wheat in the U.S. and wheat in the E.U. — and possibly on soybeans in the U.S. For DES/ENSO/ARMA equations relative to DES, higher probabilities were registered on just half of the crops. Even so, the application of ENSO and ARMA consistently added to the normality scales on crops which scored low on the Jarque-Bera test statistic. Only on coarse grain other than corn in the U.S. did the residuals from the DES/ENSO/ARMA model rate appreciably lower than the residuals from the DES equations.

Concluding Comments

This very empirical analysis of the relationship of ENSO and weather cycles to crop yields around the world suggests further research is warranted, particularly in linking ENSO to climatic variation and, in turn, climatic variations to yields. Yield departures from trends typically do not exhibit "white noise". Patterns exist in the residuals which can be captured by the application of a combination of ENSO variables and ARMA techniques. The resulting residuals do score significantly higher on "white noise" tests. Yield variability around trends which are clearly not normal tend to approach normality after ENSO and weather cycle effects are introduced into yield equations.

However, ENSO/ARMA models can explain little more than about 40% of the variation in crop yields around trends for most of the crops analyzed. While many of the coefficients on ENSO variables were statistically significant, the lack of significance on some crops in nations which are identified as ENSO sensitive by meteorologists was somewhat puzzling. Also, to be noted is that response of crop yields to ENSO was found in regions not mapped as ENSO sensitive by meteorologists.

Regardless, long-range weather forecasting and the possible role of ENSO in this endeavor is so important to world food security and predicting agricultural commodity supplies and prices that increased resources toward that objective is justified. Such predictions will remain probabilistic but can be very useful information for risk management. The next step will be to integrate these stochastic yield forecasts into AGMOD, an econometric/simulation model of U.S. agriculture.

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