THE PREDICTIVE CONTENT OF CLIMATE ANOMALIES FOR

AGRICULTURAL PRODUCTION: DOES ENSO REALLY MATTER?

Jan Alexander Kazimierz Orlowski
University of Sydney
jan.orlowski@sydney.edu.au

David Ubilava
University of Sydney
david.ubilava@sydney.edu.au

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ABSTRACT

While the production effect of El Niño and its counterpart – La Niña – is well documented, many of the previous studies apply binary variables (e.g., for El Niño and La Niña events) to analyze the relationship, and, moreover, much of their conclusions rely on in-sample fit and test statistics. In this study, we extend previous literature by examining the effect of El Niño Southern Oscillation (ENSO) on U.S. corn production in an out-of-sample setting. In so doing, we incorporate weather variables, such as degree days and precipitation in the analysis, to investigate the trade-off between model uncertainty and parameter uncertainty. We find that ENSO likely impacts U.S. corn production though extreme degree days. This is particularly true for Counties in the southern Corn Belt as well as corn-growing Counties in the Appalachian and Southeastern regions. In many instances, however, more accurate forecasts are obtained when the ENSO effect on corn yields is modeled directly.

Keywords: Climate Anomalies, El Niño Southern Oscillation, Forecast Evaluation, U.S. Corn Production

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[1] Preliminary and incomplete.

INTRODUCTION

A strong case of the 2015-2016 El Niño has generated turmoil in popular media and academic discussions. This reaction is not uncalled for, as the production effect of this climate phenomenon and its counterpart – La Niña – is well documented. A plethora of studies have analyzed the causal relationship between the cyclical re-occurrence of the aforementioned climate anomalies – a phenomenon known as El Niño Southern Oscillation (ENSO) – and production responses of major agricultural crops (e.g., Handler, 1990; Legler, 1999; Chen et al, 2001; Tack and Ubilava, 2013). Many of these studies apply binary variables (e.g., for El Niño and La Niña events) to analyze the relationship, and, moreover, much of their conclusions rely on in-sample fit and test statistics. The real potential benefit of measuring the relationship between the ENSO and agricultural production, however, is in an ability to facilitate improved out-of-sample prediction of the outcome variable. This is the focus of the current study.

While ENSO is no longer an obscure acronym in economic discussions, a brief description of this phenomenon is in order. The phenomenon originates in the tropical Pacific. Its intensity can be measured from both sea surface temperature (SST) and atmospheric pressure changes along the equatorial segment of the Pacific Ocean between the coast of Peru and Papa New Guinea. The "anomalous" deviations in this processes result in two extreme phases – the *warm phase*, or El Niño, and the *cool phase*, or La Niña. In absence of these anomalies the ENSO cycle is said to be in the *neutral phase*. These phases re-occur every three-to-seven years, and each results in divergent effects on weather conditions and crop yields throughout the world. However each phase does not signal one specific response, rather it alters probabilities of weather across geographical locations.

Over the past decade, there has been growing interest in the use of ENSO and their anomalies to forecast various weather conditions around the world (Aitsahlia et al, 2011; Mauget et al, 2009; Chen et al, 2002; Letson et al, 2002; Magrin et al, 1999). The economic importance of such analyses stems from a causal relationship between weather and production. Consequences of ENSO shocks, however, can extend beyond agricultural production. For example, studies have found linkages between this climate phenomenon and commodity prices, inflation, as well as social welfare, and political turmoil (e.g., Brunner, 2002; Ubilava and Holt, 2013; Hsiang et al, 2011).

The major channel, through which ENSO impacts agricultural production, is weather variables. While the weather is the most important factor in agricultural production, one cannot typically use temperature or precipitation to make forecasts throughout a growing season. This is because these high-frequency weather variables cannot be forecast with any degree of accuracy at long (more than several weeks ahead) horizons. They are, however, correlated and, in some respect, caused (at the very least, in Granger sense) by medium-frequency climate anomalies, such as the ENSO. This climate anomaly, in turn, can be forecast several months ahead. Therefore, ENSO can be used to facilitate prediction of agricultural production. The accuracy of such prediction, of course, relies on the degree of correlation between a global climate anomaly and local weather conditions.

The use of ENSO data in predicting agricultural production provides an avenue for mitigating impacts of adverse weather conditions – and also make the most of the positive weather conditions – before they occur, that is, prior to the planting season (Letson et al, 2005). The value of a "single source" forecasting mechanism with global relevance cannot be

understated, and therefore, a closer look at its potential for improved (or rather informed)

management practices is essential. This point is further amplified via ENSO volatility rising hand

in hand with climate volatility (e.g., Trenberth and Hoar, 1997; Zhang et al, 2012). A study by

Chen et al (2001), quantifies the damages occurring as a result of severe weather closely

related to ENSO fluctuations. The authors state that if the frequency of ENSO phases changes it

could costs 300-400 million USD annually, while if the events also intensify in strength these

damages could rise to 1 billion USD in the U.S. alone (Chen et al, 2001).

Adverse events can result in short-term damages, however through the use of forecasts

and long run planning perspective substantial risk can be avoided by altering management

techniques in response to anticipated (due to forecast) changes in weather (Tack and Ubilava,

2015). For example, one of the proxies for the reduction of such damages may be considered

via a forecasted drop in crop insurance indemnity payouts of 10-15% through the use of ENSO

forecast data (Tack and Ubilava, 2015). From the perspective of producers, various options

emerge in response to informative forecasts, these can range from changing planting date to

changing crop type or even adapting location of soil type.

Due to multiple weather links through which ENSO impacts agriculture, researchers may

need to consider the extent to which any given weather variable has the greatest influence over

crop yields. Recent studies have shown that when modeled "properly," temperature has

proven to carry the most detrimental impact (Schlenker and Roberts, 2009; Fisher et al, 2012).

This research is expanded on stating that in general crops have been observed to become less

prone to changes in precipitation (via technological advances and irrigation, for example), yet

more sensitive to significantly higher temperatures (Roberts and Schlenker, 2010; Lobell et al,

2013). The use of the degree day data has shown great statistical power in regression models, considering nonlinear effects of temperature on crop yields. See Schlenker and Roberts (2009) for a comprehensive discussion on this topic.

This study offers several contributions to the literature. First, it exploits the benefits of nonlinear temperature effect, and examines the role of ENSO in the U.S. corn production though the degree day data. Second, it assesses the predictive content of ENSO in the U.S. corn production in a pseudo-forecasting environment, by examining the out-of-sample performance of competing models in a framework equivalent to leave-one-out cross-validation. The findings of this study suggest that degree days, and in particular those capturing the extreme heat, indeed represent an important link through which ENSO affects U.S. corn yields.

LITERATURE REVIEW

Studies documented the ENSO impact on crop yields already in 1980s and early 1990s (Handler, 1984; Nicholls, 1985; Tziperman et al., 1994; Chen and McCarl, 2000). The turning point in ENSO analysis, however, was the 1997/1998 El Niño event, which caused several billion U.S. dollars' worth of damage in the U.S. alone (Adams et al., 1999) and worldwide. Since the late 1990s, a large body of literature has addressed ENSO impact on cereal production in different regions of the world, including Americas, Australia and Oceania, Southeast Asia, and Africa. Studies have addressed a variety of crops, with particular emphasis on grains, because of more direct links between weather extremes and yields, as well as the socio-economic importance of these crops in world nutrition.

A key aspect of establishing a causal relationship between yield and ENSO is understanding the interaction of ENSO fluctuations with weather variables. Interestingly some studies have found little influence over precipitation, sunshine hours, and annual mean temperatures, yet in some ways unexpectedly clear yield differences occur in La Niña and El Niño years compared to Neutral phase years (Liu et al, 2013). This was the case for U.S. winter wheat and summer maize, also confirming spatial variability in ENSO influence. Another study by Phillips et al (1997) finds a strong correlation between ENSO and rainfall in southern Africa, more specifically Zimbabwe, through considering ENSO influence on maize growth parameterized on soil conditions (Phillips et al, 1997).

Subsequently, studies discovered that the lower the water holding capacity of soil the greater is the influence of ENSO (Bartels et al, 2013). The four regions studied by Phillips et al (1997) in southern Africa – Karoi, Gweru, Masuingo, and Beitbridge – displayed the most significant decrease in rainfall as a result of ENSO during the El Niño phase compared to La Niña and the Neutral Phase. Although considering ENSO influence particularly for the US, a distinctive feature of ENSO is the heterogeneous influence it carries over regions and globally- hence considering the U.S. necessitates an awareness of El Niño's global characteristics.

The distinct impact of ENSO however does not imply an entirely direct relationship with agriculture. Podesta et al (2002) find four key issues with measuring ENSO impacts on agriculture: (i) crop records encompass only a limited number of ENSO events; (ii) it is difficult to assess current reaction to climate-induced vulnerability due to change in technology or other exogenous factors; (iii) it is difficult to separate various sources and origins of agriculture risk; and (iv) risk estimates from aggregate data may not be appropriate for farm level risk

management- spatial aggregation dulls year-to-year variability. Yet another caution lies with shifting yield response to weather types. That is, yield does not always behave similarly to comparable weather conditions. A papers discussing this aspect of yield forecasting place the reasons for this in new crop varieties, improved technologies and primarily soil type (Changnon and Winstanley, 2000). When aiming to establish these interconnections between climate and yield the caveats above must be kept under close consideration.

Legler et al (1999) tested the response of simulated agricultural productivity to ENSO related "climate-variability parameters." Findings include that cold ENSO events have greater impact on southern regions in the U.S., while warm ENSO events have larger impacts on the North. More specific results for Corn are found by Tack and Ubilava (2013). El Niño reduces an average production in the central Corn Belt, with positive yield impacts when moving east or west of the Corn Belt. While La Niña reduces corn yields in the west of central Corn Belt, with positive impacts when moving east or further west of the Corn Belt (Tack and Ubilava, 2013).

THE MODELING AND FORECASTING FRAMEWORKS

To begin, consider a basic econometric model given by a system of two equations:

$$y_{it} = \alpha(t) + \beta' w_{it} + \varepsilon_{it} \tag{1}$$

$$w_{it} = \delta' e_t + v_{it} \tag{2}$$

where y_{it} denotes crop yield for a County i in year t; w_{it} is a (vector of) weather variable(s) during the crop growing season; e_t denotes a measure of ENSO during its peak period (i.e., November-December-January) preceding the crop growing season of a given year; β and δ are

(vectors of) parameters to be estimated; ε_{it} and v_{it} are independent and identically distributed error terms.

The aforementioned specification should allow us to estimate the relationship between ENSO and crop yields through a predefined weather channel. Alternatively, one can directly estimate the effect of ENSO on crop yield as follows:

$$y_{it} = \alpha(t) + \eta' e_t + v_{it} \tag{3}$$

where η is a parameter (vector) to be estimated, v_{it} is independent and identically distributed error term, and the rest are as defined before. Here η represents a combined effect of every channel through which ENSO impacts production.

The aforementioned two specifications are not guaranteed to give similar results. To begin, correlation is not necessarily transitive. That is, if Y is correlated with X, and X is correlated with Z, it does not necessarily follow that Y is correlated with Z.[2] Specifically, while it is possible that ENSO is correlated with a weather variable, and the latter is correlated with yield, we may find no statistical linkage between ENSO and yield. In addition, there is a trade-off between model uncertainty and parameter uncertainty in the aforementioned two specifications. That is, a plausibly more accurate representation of ENSO–yield relationship through the weather channel, as given by equations (1) and (2), may not be efficient from the forecasting standpoint, due to estimation of a larger set of the parameters, as compared to the model represented by equation (3). The aforementioned implies that one or the other specification may result in the more accurate forecast of a variable of interest.

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[2] See a blog-post by Terrence Tao at: https://terrytao.wordpress.com/2014/06/05/when-is-correlation-transitive/ for a technical description, and Marc Bellemare's blog-post at: http://marcfbellemare.com/wordpress/11554 for an intuitive discussion of the matter.

DATA

Data is comprised of three main components – production, weather, and ENSO – spanning 59 years between 1961 and 2009. Production data, obtained from the USDA NASS QuickStats website, are represented by corn yields for every U.S. County containing complete time series. As such, this analysis applies a total of 911 Counties.

Weather data used in this analysis are similar to Schlenker and Roberts (2009), extended until 2009. As discussed above, degree day (DD) data is selected on a County level on a monthly basis. The monthly DD data are annualized based on crop growing seasons, wherein the latter is defined the season covering months between March and August. Perception data are aggregated over the growing season as well, with no further transformations.

Finally, ENSO data is derived from SST anomalies in the *Nino3.4* region, obtained from the Climate Prediction Center of the National Oceanic and Atmospheric Administration. The monthly series are transformed into an annual variable by averaging the observations of the peak period trimester – November through January – into a single observation, known as the Oceanic Nino Index. Thus, for a crop year t, the ENSO variable is obtained by averaging SST anomalies in November and December of year $t-1$, and January of year t.

ESTIMATION AND FORECAST EVALUATION

Two different weather vectors are assumed in equation (1). One of the scenarios uses degree days, where the latter are divided into normal degree days and extreme degree days. That is, this study assumes the "growth function" to be piece-wise linear (e.g., Schlenker and Roberts, 2009), with a kink about the temperature threshold, denoted by κ. These optimal thresholds

are selected by minimizing the sum of squared residuals across candidate thresholds, via regressing yield in a given County on a trend variable and the two-dimensional vector of degree days. The other scenario uses precipitation and its squared term as the weather variables. For each of the aforementioned two scenarios, the relationship between weather (i.e., normal and extreme degree days or precipitation) and ENSO is obtained using equation (2). Alternatively, we assess the effect of ENSO directly, using equation (3).

To perform forecasting exercise, we adopt the leave-one-out cross-validation method, which implies: (i) estimating the model of interest by omitting any one period, and using the rest of the observations; (ii) predicting the outcome variable for the omitted period, and comparing it with its actual realization; (iii) repeating steps (i) and (ii) for all observations, and collecting out-of-sample forecast errors for all periods in consideration and across all models of interest; (iv) examining forecast accuracy under the assumption of a quadratic loss function.

RESULTS AND DISCUSSION

Considering the ENSO effect, the results paint a spatially diverse picture with ENSO having varying influence over geographical locations. Such a relationship between ENSO and corn yields is particularly visible through clustering of ENSO intensity and significance over crop yields. Clustering can be thought of as regions of homogenous characteristics – at the least of homogenous behavior in response to ENSO. As one moves west horizontally across the Corn Belt the intensity of ENSO influence changes from roughly a ten percent decrease in corn yields to a six percent increase in corn yields further west. These results are aligned with previous studies considering the spatial nature of ENSO influence (e.g., Tack and Ubilava, 2013). In

summary, we see a degree of positive effect on the western Corn Belt and negative effect on the central and southern Corn Belt, where the transition is indisputably visible (see Figure 1).
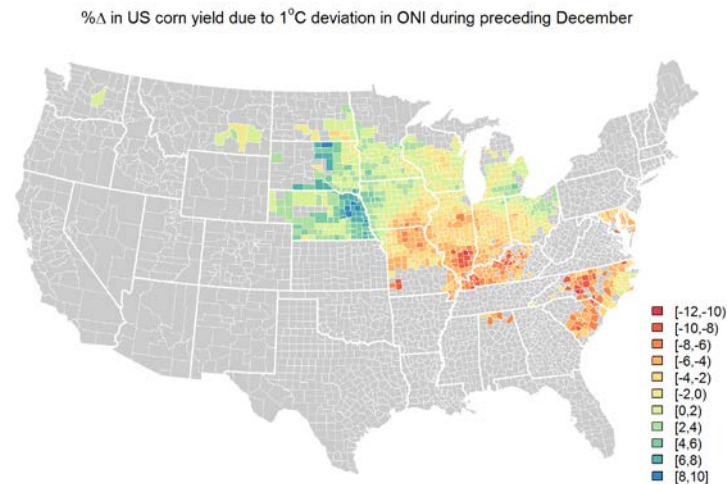

%Δ in US corn yield due to 1°C deviation in ONI during preceding December

Figure 1: The ENSO effect on U.S. corn yields

An El Niño-like event can have negative implications for corn producers in southern parts of Illinois and Indiana, as well as Kentucky, and the corn-producing Eastern States of the country. On the other hand, the same climate anomaly may result in higher-than-average corn yields in western parts of Iowa, as well as Nebraska and South Dakota. Reasons for the heterogeneity in ENSO effect can be numerous, ranging from soil type to interaction with local weather patterns.

The aforementioned relationship between ENSO and the U.S. corn yields appears to be driven by changes in extreme degree days (denotes by $DD > \kappa$) associated with ENSO anomalies, more so than changes in precipitation, as evidenced in Figures 2 and 3. While clustering, yet again, is visible when defining a relationship between ENSO and precipitation, its pattern is different from the one incorporating degree days.
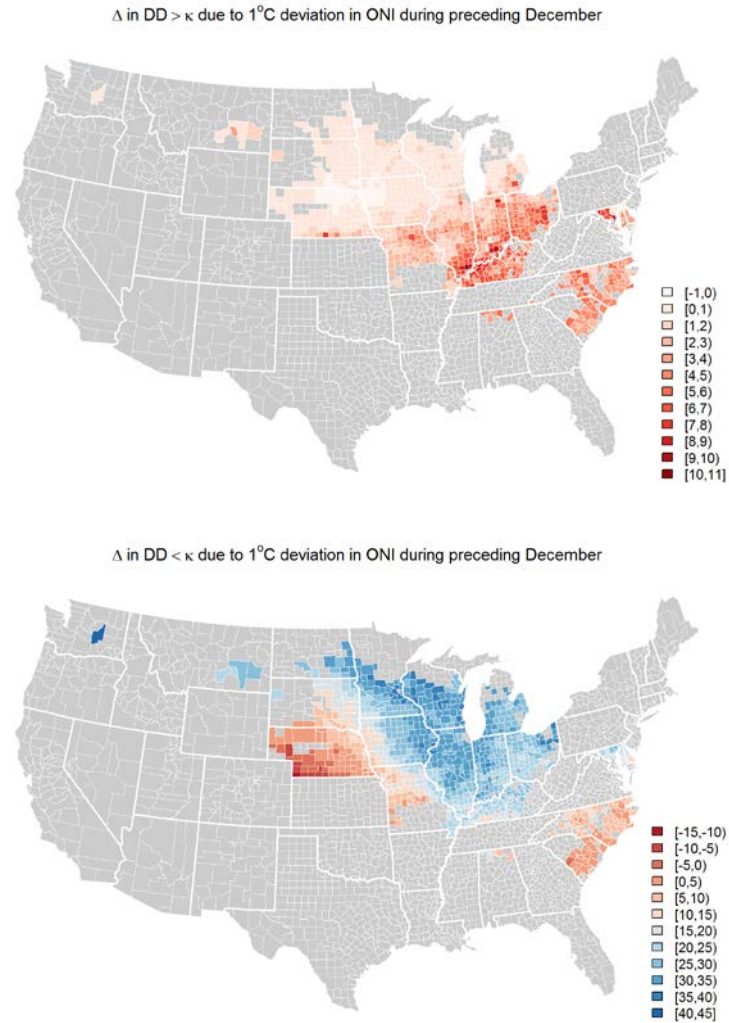
Figure 2: The ENSO effect on degree days in the U.S. corn-producing regions

To examine the predictive power of the models in consideration, we turn to the relative root mean squared forecast error (RMSFE) measures. We compare forecast accuracy from the base model that omits climate and weather variables (i.e., yield as a function of trend only), with those from the models that incorporate ENSO directly or through the two considered weather variables (i.e., degree days and precipitation). These RMSFE ratios (see Figure 4) are constructed so that values below one suggest that ENSO facilitates better prediction of yields.
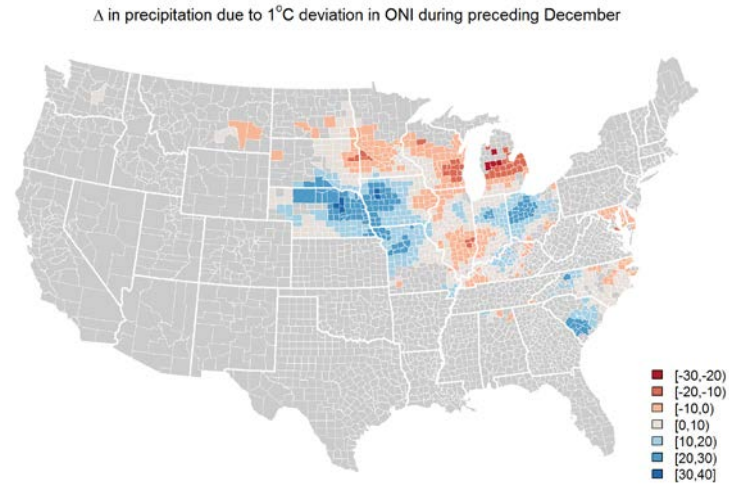
12

Δ in precipitation due to 1°C deviation in ONI during preceding December

Legend:
- [-30,-20)
- [-20,-10)
- [-10,0)
- [0,10)
- [10,20)
- [20,30)
- [30,40]

Figure 3: The ENSO effect on precipitation in the U.S. corn-producing regions

The results suggest that the inclusion of the degree day data can improve the predictive power of the model. The ENSO effect via precipitation, however, establishes a considerably weaker relationship, particular in the northern area of the Corn Belt. As for the direct ENSO effect vs the ENSO effect through degree days, different regions appear to favor one or the other specification. In particular, in several of the southern Corn Belt Counties, the specification as per equation (3) results in lower RMSFEs, while in the Appalachian and the Southeastern Counties, the specification that incorporates degree day data is preferred from the forecasting standpoint.
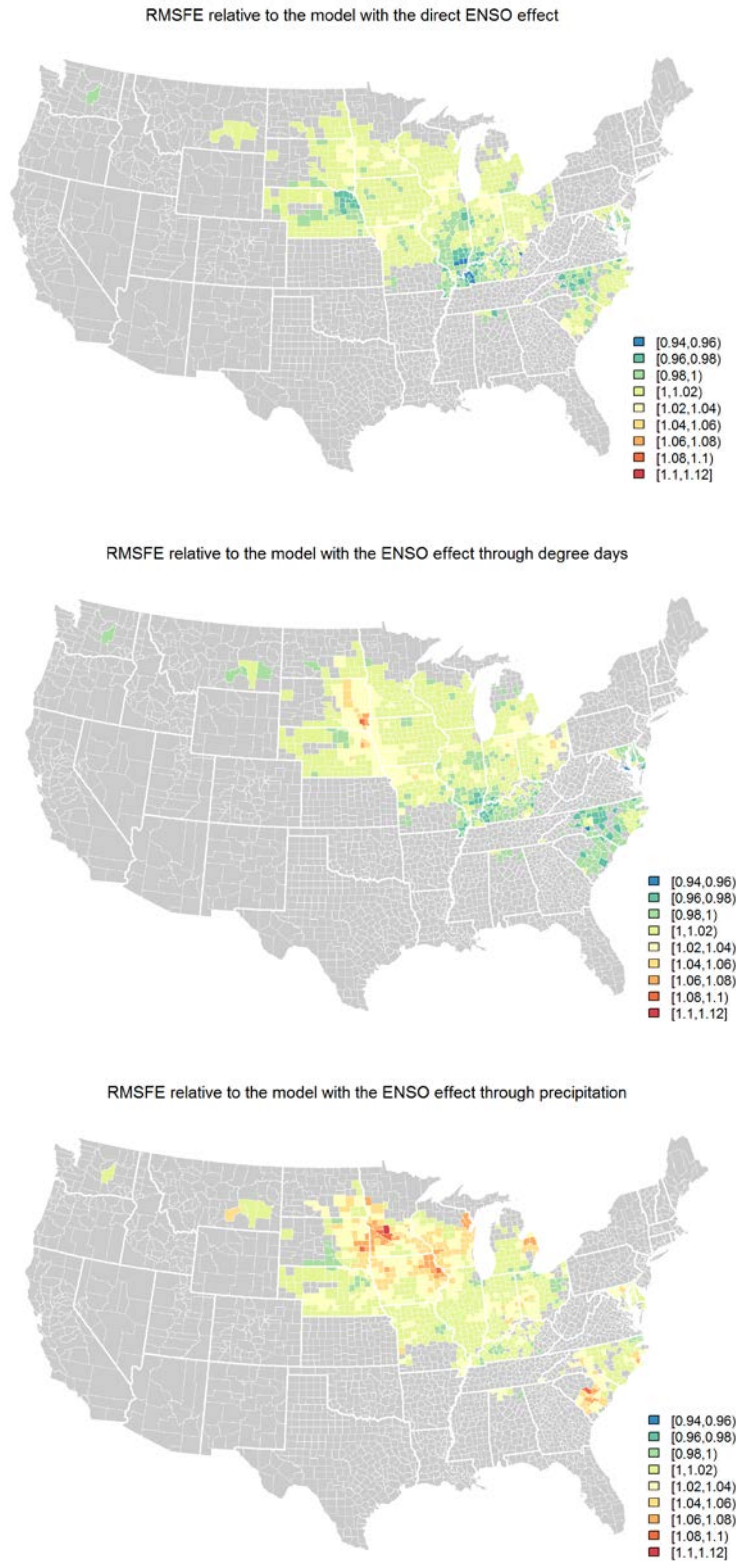
RMSFE relative to the model with the direct ENSO effect

[0.94,0.96)
[0.96,0.98)
[0.98,1)
[1,1.02)
[1.02,1.04)
[1.04,1.06)
[1.06,1.08)
[1.08,1.1)
[1.1,1.12]

RMSFE relative to the model with the ENSO effect through degree days

[0.94,0.96)
[0.96,0.98)
[0.98,1)
[1,1.02)
[1.02,1.04)
[1.04,1.06)
[1.06,1.08)
[1.08,1.1)
[1.1,1.12]

RMSFE relative to the model with the ENSO effect through precipitation

[0.94,0.96)
[0.96,0.98)
[0.98,1)
[1,1.02)
[1.02,1.04)
[1.04,1.06)
[1.06,1.08)
[1.08,1.1)
[1.1,1.12]

Figure 4: The information content of ENSO in U.S. corn yield forecasting

Several features of interest emerge from this analysis. First of all, the out-of-sample predictive accuracy is emphasized in regions where yields respond negatively to El Niño shocks. Second, note that in the current modeling approach, El Niño and La Niña are mirror images. That is, La Niña shocks result in higher-than-average yields in the southern Corn Belt as well as eastern States, while the yield reduction is expected in the western tier of the Corn Belt.

All the aforementioned also point to a couple of potential extensions from the current research. First, the effect of ENSO extremes can be asymmetric. That is, the El Niño and the La Niña effects need not be mirror images of each other. Second, some convex combination of yield forecasts from different models can result in more accurate forecasts. Both these points can add further insights to the current analysis.

CONCLUSION

With the U.S. being a major producer of caloric intake foods globally – which includes 40% of global corn market – responses of this crop yield to ENSO shocks should not be ignored. One can think of this problem from the perspective of increased weather variation due to the climate change and possible mechanisms of adaptation. The latter is not a trivial task. For example, while one of the simplest approaches may be shifting production to more suitable climates, studies have found that the highest quality soil types in the U.S. lie in moderate temperature regions (Roberts and Schlenker, 2010). Similar to the aforementioned, while the findings of this study offer additional knowledge to the U.S. farmers, there may be complexity in adjusting to the ENSO-related adverse weather occurrences across the United States. Nonetheless, we believe that building upon studies examining ENSO effect by measuring the

significance of the ENSO on yields from forecast evaluation may offer insights of particular

interest to the predictive power of such models.

The research establishes a clear link between yields, degree days, and most importantly

the ENSO cycle. The ENSO influence proves to be spatially varied, but best represented through

the use of degree days. The varied nature of ENSO can be summarized through clusters with a

clear trend of negative to positive yield influence as one moves from east to west, as well as

south to north when considering ENSO impact on particular weather variables of interest,

specifically precipitation. The particular contribution to the literature is through the use of

forecast evaluation or predicted values from the models discussed above.

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