The Effect of El Niño Southern Oscillation on U.S. Corn Production and Downside Risk*

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Abstract

ENSO teleconnections imply anomalous weather conditions, causing yield shortages, price fluctuations, and civil unrest. We estimate ENSO's effect on U.S. county-level corn yield distributions and find that temperature and precipitation alone are not sufficient to summarize the effect of global climate on agriculture. We find that acreage-weighted aggregate impacts mask considerable spatial heterogeneity at the county-level for the mean, variance, and downside risk of corn yields. Impacts for mean yields range from −24 to 33 percent for El Niño and −25 to 36 percent for La Niña, with the geographical center of losses shifting from the Eastern to Western corn belt. ENSO's effect on the variance of crop yields is highly localized and is not representative of a variance-preserving shift. We also find that downside risk impacts are large and spatially correlated across counties.

1 Introduction

El Niño Southern Oscillation (ENSO) is a climatic phenomenon that takes place in the tropical Pacific and has global weather implications (Ropelewski and Halpert, 1987; Rasmusson, 1991; Adams et al, 1999; Zhang et al, 2012). ENSO can affect world economies, amplify social instabilities, and may induce civil wars (Solow et al, 1998; Brunner, 2002; Hsiang et al, 2011). Research suggests that ENSO is at least partly responsible for such historically documented events as the biblical droughts in Egypt (Eltahir, 1996), the demise of ancient civilizations (Haug et al, 2003; Tsonis et al, 2010), and the most devastating famines in recent history (Davis, 2002). While research linking climatic anomalies to social unrests is not widely established, much research has focused on the effect of climatic anomalies on various measures of economic performance (Brunner, 2002; Kim and McCarl, 2005), with particular attention paid to the relationship of ENSO with agricultural and aquacultural production (e.g. Handler, 1990; Hansen et al, 1998; Adams et al, 1999; Dalton, 2001).

Understanding these effects is increasingly important as some studies have conjectured that the frequency and intensity of ENSO events will increase parallel to climate change (Trenberth and Hoar, 1997; Timmermann et al, 1999; Chen et al, 2008; Zhang et al, 2012).[1] In the short run, ENSO

*The final publication is available at http://link.springer.com/article/10.1007/s10584-013-0918-x

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[1]The literature on this topic is still evolving, with some studies questioning whether the observed change in ENSO activities during the past several decades is statically significant (Rajagopalan et al, 1997). The general conclusion being that none of the competing hypotheses can be rejected at this time (Fedorov and Philander, 2000).

effects on agricultural productivity can be measured through immediate impacts on crop yields. Several papers have found that both El Niño and La Niña have potentially damaging implications for U.S. agriculture (Solow et al, 1998; Adams et al, 1999; Chen et al, 2002). In the intermediate run, amplified ENSO conditions associated with climate change may call for adaptive actions by producers. Thus, a better understanding of ENSO effects can help mitigate losses associated with climate change, and could result in annual welfare gains of several hundred million U.S. dollars (Chen et al, 2001).

The research presented here extends our understanding of climate impacts by examining the historic effect of ENSO on U.S. corn yields in a regression-based framework. We focus on the U.S. as it is the global leader in corn production and exportation, and recent interest in corn-based ethanol production has further amplified the importance of this crop. Previous regression-based studies linking climate to crop yields typically involve one of two approaches: the inclusion of temperature and precipitation measures as explanatory variables (e.g. Schlenker and Roberts, 2009), or the inclusion of climate dummy variables (e.g. Carlson et al, 1996; Hansen et al, 1998). Interestingly, recent research analyzing the determinants of civil conflict found that an ENSO-related effect was identified even after controlling for temperature and rainfall (Hsiang et al, 2011), which suggests that combining the above approaches could aid in identifying ENSO's impacts on corn yields. This is the approach taken here, and we estimate the impact of both El Niño and La Niña on average corn yields using a county level panel spanning 55 years.

Additional reasons exist for generalizing the regression-based approach, all based on the assumption that *ENSO impacts crop production through multiple vectors* (e.g. Cane et al, 1994; Phillips et al, 1998). First, linkages with precipitation and temperature provide a straightforward causal connection (Stone et al, 1996; Barlow et al, 2001). Second, ENSO events can amplify hazardous weather conditions resulting in damaging storms, drought, flooding, and wildfires (Handler, 1990; Bove et al, 1998; Saunders et al, 2000; Swetnam and Betancourt, 1990; Brenner, 1991). Third, ENSO events are correlated with pest damage as they can generate large changes in development rates for insects and germination rates for bacteria, fungi, and nematodes (Rosenzweig et al, 2000; Iglesias and Rosenzweig, 2007). The second and third points justify inclusion of ENSO dummy variables to proxy for complex factors not captured by temperature and precipitation alone, as it essentially controls for the "extreme" events not captured by conventional weather variables.

Previous research typically focuses on linking ENSO events to average (i.e. mean) crop yields. This approach is potentially limiting in that it does not take into account ENSO's effect on the overall shape of the yield distribution (Chen et al, 2004), and the literature examining higher-order effects is rather thin (exceptions include Legler et al (1999); Nadolnyak et al (2008)) even though the importance of the yield distribution's shape for production and downside risk management is well established (Chavas and Holt, 1996; Moschini and Hennessy, 2001; Di Falco and Chavas, 2006, 2009; Antle, 2010; Du et al, 2012). In this paper, we measure downside risk as the probability of a yield outcome from the lower tail of the distribution, which essentially captures the probability of a "below average" crop yield. This measure is closely related to crop yield skewness, since an increase in skewness generates a reduction in downside risk (Di Falco and Chavas, 2009); thus, existing empirical evidence and theoretical support in favor of a risk management preference for positive skewness (Du et al, 2012) naturally extends to a preference for the reduction of downside risk.[2]

[2]A strength of our empirical approach is that we estimate the entire distribution of yields. As such, one can calculate a large variety of risk measures including variance, coefficient of variation, upside and/or downside risk,

We leverage regression model parameter estimates to construct a set of conditional yield distributions for each county in the data using a novel application of the Moment Based Maximum Entropy (MBME) model. We find that acreage-weighted aggregate impacts mask a considerable amount of regional heterogeneity for the mean, variance, and downside risk of corn yields. El Niño reduces mean yields throughout the central corn belt region, however impacts turn positive as one migrates both East and West. The same pattern holds for La Niña, however the geographical center of losses shifts West. We decompose mean yield impacts into temperature/precipitation versus "other" channels and find that neither impact dominates the other across all regions of the sample, and that each impact in isolation can generate misleading results. This suggests that temperature and precipitation alone are not sufficient to summarize the effect of the global climate on corn yields. Furthermore, we find that variance effects are highly localized and that ENSO does not generate a variance-preserving shift of the distribution. We also find that downside risk impacts are spatially heterogeneous, and that mean impacts are a leading (but not perfect) indicator of downside risk impacts.

In what follows, we first present the empirical framework for this research. Next, we describe the data and then discuss the empirical results and implications. The final section concludes and suggests avenues for future research.

2 Empirical Framework

Yield distributions vary both spatially and temporally due to localized growing conditions and the evolution of production technology over time. This implies that historical yield data alone are not sufficient to analyze ENSO impacts as there is no single "original" distribution from which all data are sampled; rather, each historical observation is drawn from a specific location-year distribution. To overcome this limitation, yields are often regressed on location-specific dummy variables and a trend variable, which allows the mean of the distribution to vary over space and time. In a similar manner, the shape of distribution likely changes as well.

Our empirical approach addresses these data limitations and has two components. First, we extend the fixed effects model of Schlenker and Roberts (2009) by directly controlling for El Niño and La Niña events, which provides additional vectors beyond temperature and precipitation for ENSO events to affect corn yield outcomes. This is an important extension as it permits a decomposition of the ENSO effects into temperature, precipitation, and other more nuanced vectors such as hazardous weather conditions and environmental pests. This model is used to measure changes in mean crop yields across three ENSO regimes: El Niño, La Niña, and Neutral.

The other component utilizes the MBME framework of Tack et al (2012), which extended the moments-based approach of Antle (1983, 2010). Whereas moments-based models are capable of identifying effects on specific moments of the distribution, the MBME approach permits identification of effects on the entire distribution of yields. This admits the usage of a much broader range of risk measures, such as the probability of a lower tail outcome used here. We use the MBME model to estimate yield distributions conditional on the above ENSO regimes, which permits quantification of the downside risk effects. A detailed description of the modeling approach is provided in the Empirical Framework section in the Supplementary Material.

partial moments, Value at Risk, etc. We focus on downside risk because of its established role in production decision-making.

3 Data

We combine three different data sources to construct a county-level panel of yield, temperature, precipitation, and ENSO data that spans 55 years. The limiting factor for this data is the temperature and precipitation data, which is only available from 1950-2005. County-level yield data are collected from the National Agricultural Statistics Service and are measured in bushels per acre. We include counties that have a complete 55 year yield history, and there are a total of 54,395 observations representing 989 counties spanning 16 states.

We use a monthly time series of the ENSO anomaly, *Niño 3.4*, derived from the index tabulated by the Climate Prediction Center at the National Oceanic and Atmospheric Administration. This index measures the difference in Sea Surface Temperature (SST) in the area of the Pacific Ocean between $5°N - 5°S$ and $170°W - 120°W$, and is a strong indicator of ENSO occurrence. The anomaly is the deviation of the *Niño 3.4* monthly measure from the average historic measure for that particular month from the period 1971–2000.

We use the same weather data as in Schlenker and Roberts (2009), which is based on the rectangular grid system underlying PRISM that covers the contiguous United States. The authors construct a distribution of temperatures within each day using a sinusoidal curve between minimum and maximum temperatures. They then estimate time in each $1°C$ temperature interval between $-5°C$ and $50°C$. The area-weighted average time at each degree over all PRISM grid cells within a county is constructed, and are then summed over the six month corn growing season from April through September. More details regarding the data can be found in the Yield and Weather Data section in the Supplementary Material.

4 Results

The first subsection presents results for mean yields, while the second subsection presents results for yield variance and downside risk.

4.1 El Niño and La Niña Mean Effects

Table S1 in the Supplementary Material reports parameter estimates for the mean equation. We allow the trend parameters to vary across states to control for differential technological change, and the El Niño and La Niña parameters to vary across counties to control for highly localized ENSO effects. We estimate the parameters using pooled OLS with dummy variables included to account for county-level heterogeneity, and cluster standard errors by state to control for arbitrary patterns of spatial and serial correlation. Although spatial correlation does not likely persist across state boundaries, we also include errors clustered by the Economic Research Service's Farm Resource Regions, which aggregate large portions of several states, and find that the results are consistent across both approaches.

The temperature and precipitation estimates are consistent with those of Schlenker and Roberts (2009). Extending their results, we find the inclusion of El Niño and La Niña dummy variables to be warranted. Looking at the left panel of Figure S1 in the Supplementary Material, the majority of the ENSO dummy variable effects are statistically significant at a Bonferroni-adjusted five percent significance level, which implies that there are additional vectors beyond temperature and precipitation by which yields are affected.[3] The right panel of Figure S1 provides 95 percent confidence intervals for the state specific trend parameters and illustrates the importance of controlling for technological change.

The impact of El Niño (La Niña) on mean corn yields is measured as the percentage change in the mean of the El Niño (La Niña) regime relative to the mean of the Neutral regime. We use the estimated coefficients in Table S1 to predict these impacts for each county i according to

$$impact_i^r = 100\frac{e^{\hat{\alpha}_i+\hat{\beta}\bar{\mathbf{x}}_i^r} - e^{\hat{\alpha}_i+\hat{\beta}\bar{\mathbf{x}}_i^{neutral}}}{e^{\hat{\alpha}_i+\hat{\beta}\bar{\mathbf{x}}_i^{neutral}}}, r \in \{nino, nina\}, \tag{1}$$

where the $\bar{\mathbf{x}}_i^r$ are county-specific predictors under each regime. For the El Niño regime, we fix the temperature and precipitation variables at their sample average for the El Niño years, and the El Niño and La Niña dummy variables are set to one and zero respectively. We do the same for the La Niña regime using the La Niña years, but fix the El Niño and La Niña variables to zero and one respectively. For the Neutral regime, we use the Neutral years to construct sample averages and fix both dummy variables to zero. Since temperature, precipitation, and the ENSO dummy variables are the only variables varying across regimes, the impact reduces to

$$impact_i^r = 100\left[e^{\hat{\beta}_{\mathbf{w}}\left(\bar{\mathbf{x}}_{wi}^r - \bar{\mathbf{x}}_{wi}^{neutral}\right)}e^{\hat{\beta}_{ir}} - 1\right], r \in \{nino, nina\}, \tag{2}$$

where the subscript w denotes vectors including only the weather (temperature and precipitation) variables and parameters, and β_{ir} are the respective county specific ENSO dummy variable parameters.

Figure 1 and Supplementary Figure S8 report county-level impacts estimated using equation (2). The acreage-weighted aggregate impacts across counties for El Niño and La Niña are -1.6 and -2.4 percent, respectively. These numbers alone suggest that ENSO impacts are relatively small, however they mask a considerable amount of spatial heterogeneity as evidenced by the maps provided in Figure 1. Overall, our findings suggest that there are both positive and negative ENSO impacts, which suggests that imposing too much structure on the modeling process (e.g. imposing common El Niño and/or La Niña parameters) could severely hamper identification.

The county-level impacts range from -24 to 33 percent for El Niño, with the geographic center of losses occurring in the Illinois/Iowa/Missouri tri-state area. A reduction of mean yield is found throughout the corn belt region as a result of El Niño, with impacts turning positive as one migrates both to the East and West. This pattern holds for La Niña as well, however the geographical center of losses shifts to Iowa/Nebraska border. The range of impacts is similar to El Niño at -25 to 36 percent, however the geographic shifting of impacts relative to El Niño is non-negligible as hypothesis tests reject the null of equal El Niño and La Niña impacts for 978 of the 989 counties at a five percent significance level. Thus, we find that even though the range of impacts is similar across El Niño and La Niña, there exists a statistically significant shift in the spatial pattern that distinguishes one from the other.

Comparison of our findings to previous studies is not straightforward as some studies measure ENSO events using anomaly data prior to the growing season (as we do here) while others use

[3]While these tests provide evidence that the included dummy variable effects are non-zero, it is possible that subsets of the estimates are statistically indistinguishable from one another. This could arise if the regional signatures of ENSO have spatial scales broader then a few counties. Determining the appropriate clusters of homogeneous signatures would require a thorough statistical analysis, as such it is left for future research to consider.

data during the growing season. The multiplicity of approaches is driven by uncertainty regarding how quickly teleconnections reach the U.S. Putting this issue aside, we find the same pattern of results as Legler et al (1999); specifically, a negative yield response under both events across most of the corn belt coupled with a positive (negative) effect for La Niña (El Niño) in the southern U.S. Phillips et al (1999) also find evidence of a yield reduction under La Niña in the corn belt, while Martinez et al (2008) found the same opposite-sign effects in the southern U.S. As in Adams et al (1999), we find that the spatially-aggregated effect is negative for both events.

To address whether temperature and precipitation alone are sufficient to summarize ENSO's effect on yields, we drop the ENSO dummy variables from equation (S1), re-estimate the parameters using the same data, and then construct alternative impacts as in equation (2) with $\hat{\beta}_{ir}$ set to zero. A spatial map of these alternative impacts is provided in Supplementary Figure S9, and a comparison to Figure 1 reveals that the rather large yield increases to the West of the corn belt under El Niño are now negative, and many of the impacts along Lake Michigan and the Atlantic Coast have been dampened considerably under La Niña. These differences are summarized by the kernel density plots of the impacts under both identification approaches reported in Supplementary Figure S10. In general, the mean yield impacts are much broader when including the dummy variables, and it is clear that omitting the ENSO dummy variables truncates the larger El Niño and La Niña impacts and completely misses the large positive El Niño impacts.

This findings suggests that temperature and precipitation alone are not sufficient to summarize the effect of the global climate on corn yields. This is similar to the finding in Hsiang et al (2011), and implies that the impacts from the restricted model in Figure S9 are biased. This finding does not suggest that temperature and precipitation are unimportant determinants of ENSO effects, as results presented in the Mean Impact Decomposition section of the Supplementary Material suggest that temperature and precipitation are important (but not sufficient) components for measuring ENSO impacts.

4.2 El Niño and La Niña Risk Effects

Following the procedure outlined in Section 2.2 of the Supplementary Material, we estimate three yield distributions for each county according to each of the three ENSO regimes, denoted $f_i^r(y)$. To evaluate whether ENSO effects can be characterized by a variance-preserving shift of the distributional mean, we measure the impact of El Niño (La Niña) on the variance of yields as the percentage change in the variance of the El Niño (La Niña) distribution relative to the Neutral distribution. We find evidence of both positive and negative impacts clustered by different geographic regions for both El Niño and La Niña, thus suggesting that these ENSO regimes do not result in a variance-preserving shift of the mean. More details regarding these impacts are provided in Section 7 of the Supplementary Material.

Mean and variance effects provide some guidance regarding distributional shape changes, however one cannot infer changes in downside risk from these effects alone. We define a lower tail event in county i, denoted Ω_i, as any outcome below some fraction α of the mean of the Neutral Regime, i.e. $\Omega_i = \left\{y_i : y_i \leq \alpha m_i^{neutral}\right\}$. Further, we define $y_i^* = \alpha m_i^{neutral}$ to be the threshold for this event and denote by $F_i^r(y)$ the cumulative distribution function. Producers exposure to downside risk is then calculated as $F_i^r(y_i^*)$, and we measure ENSO impacts on a percentage change basis using $100 \times \left[F_i^r(y_i^*) - F_i^{neutral}(y_i^*)\right] / F_i^{neutral}(y_i^*)$, $r \in \{nino, nina\}$. We first discuss risk impacts for $\alpha = 0.75$, in which case bad outcomes are ones that are below 75 percent of the mean, and then discuss findings for alternative values of α.

Figure 2 reports these estimates at the county-level. The acreage-weighted aggregate impacts across counties for El Niño and La Niña are 5.2 percent and 7.4 percent, respectively, however there is considerable spatial heterogeneity. Regions with large concentrations of positive (red) impacts are particularly vulnerable to ENSO events in that increases to downside risk are highly spatially correlated. This spatial dependence has important implications for regional supply patterns, as ENSO-driven shocks could simultaneously trigger large-scale crop losses across large production regions. This finding is consistent with state-dependent risk, in which spatial correlations of yields strengthens during extreme weather events (Goodwin, 2001). The positive aggregate impacts suggests this is likely to remain a concern even after the off-setting negative (green) impacts are taken into account. We find that the same pattern of results holds for alternative values of α, and that the percentage change in downside risk intensifies as one moves further out into the tail. Spatial maps are provided in Section 7 of the Supplementary Material.

Comparing these impacts to Figure 1 suggests a strong inverse relationship between mean and risk impacts. Indeed, a pooled regression of the risk impacts on the mean impacts produces a negative coefficient and an R^2 of 0.6904. Interestingly, including higher order powers of the mean impacts in this regression only marginally increases the R^2 (we went up to a 5^{th} order polynomial), suggesting that mean impacts are a leading, but not perfect, indicator of downside risk impacts.

5 Conclusions

Previous approaches linking ENSO to agricultural production primarily focus on the mean of the yield distribution. This approach is likely short sighted as our findings show significant changes in risk exposure. We present an empirical framework that is tractable, utilizes publicly available yield data, and is capable of detecting changes in the shape of the yield distribution. This approach has several advantages over simulation-based exercises, and we demonstrate how ENSO's effect can be modeled through multiple causal vectors in a regression based framework.

Our findings have implications for corn producers as they complement previous studies focusing on the value of improved ENSO forecasts for agricultural decision makers (e.g. Legler et al, 1999; Chen et al, 2002). As with these studies, the value of our findings will depend on identification and adoption of alternative farm management and cropping practices. Given the current high level of corn prices, it is not likely that growers will dramatically alter corn acreage. However, the results here can be combined with findings from cotton and soybeans studies to analyze whether ENSO forecasts can enhance economic returns for conventional corn-soybean rotations as well as the recently popularized corn-cotton rotations in the Southern U.S.

We find evidence of strong spatial dependence among downside risk impacts, which suggests that crop insurance products could be especially vulnerable to the "formula that felled Wall St" criticism that has been (at least) partially linked to the global financial crisis (Jones, 2009). Future research might consider measuring the economic significance of mis-priced products using the repeated game of Harri et al (2011). Our measure of ENSO events is based on public information available *before* the deadline for crop insurance enrollments, but *after* the Risk Management Agency's legal deadline for setting rates. Thus, private crop insurance companies posses a natural information asymmetry that could be exploited via the Standard Reinsurance Agreement, which allows them to cede "mis-priced" policies back to the government. The extent to which economic rents can be accrued is an open question, and the current size of the Federal Crop Insurance Program (over \$100 billion in total liabilities as of 2012) suggests it is an important one.

The nexus of climate change and agricultural production research continues to focus on the mean of the yield distribution, and assumes that the key predictive variables are temperature and precipitation. These approaches omit the impacts of ENSO events under future climate scenarios, even though there is some evidence suggesting that ENSO events and climate change are correlated. Our findings suggest that temperature and precipitation alone are not sufficient to summarize the effect of the global climate on agriculture, and that there exist other elusive variables (which ENSO serves as a proxy for) that are strong determinants of climate-driven changes in agricultural production. Thus, our findings have broad implications for researchers and policy-makers within the climate change community.

There exists a burgeoning scientific literature linking climatic phenomenons to civil unrest in developing countries (Hsiang et al, 2011). The exact mechanism linking ENSO to social unrest has not been credibly identified, however high commodity prices have been linked to social unrest (Bellemare, 2011).[4] We find evidence that ENSO events can generate large increases in downside risk exposure. Given that this increased risk occurs over a wide range of production regions, realized crop losses could occur simultaneously across large geographic areas. This is exactly the type of outcome that could trigger large price spikes and consequently civil unrest. Thus, our findings provide a candidate for the missing piece in the causal chain linking ENSO events to civil unrest.

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[4] It should be noted that there is unresolved debate regarding the causal linkage between food prices and civil unrest (e.g. Bazzi and Blattman, 2011).

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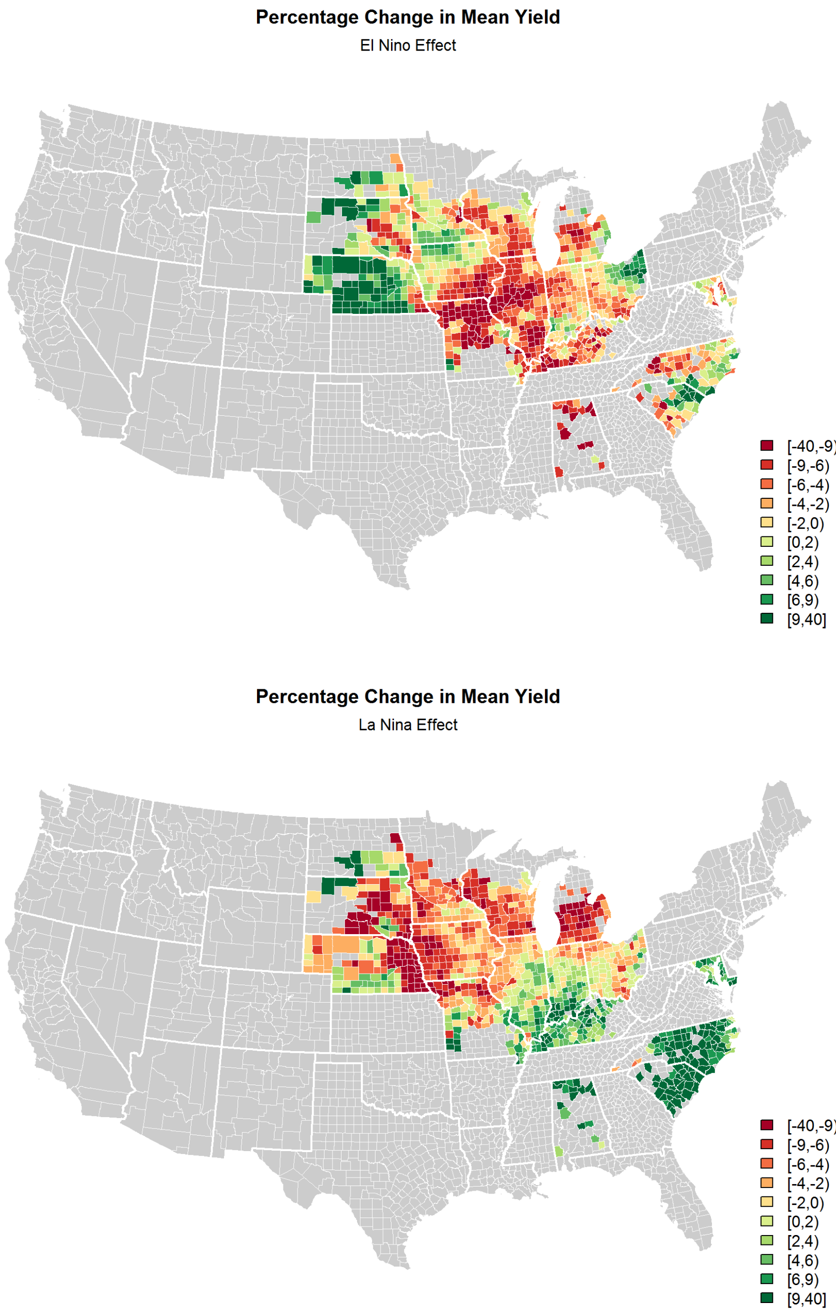

Figure 1: Spatial Representation of the ENSO Impacts on Mean Yields. Thresholds are chosen so that each band around zero contains roughly 20 percent of observations.

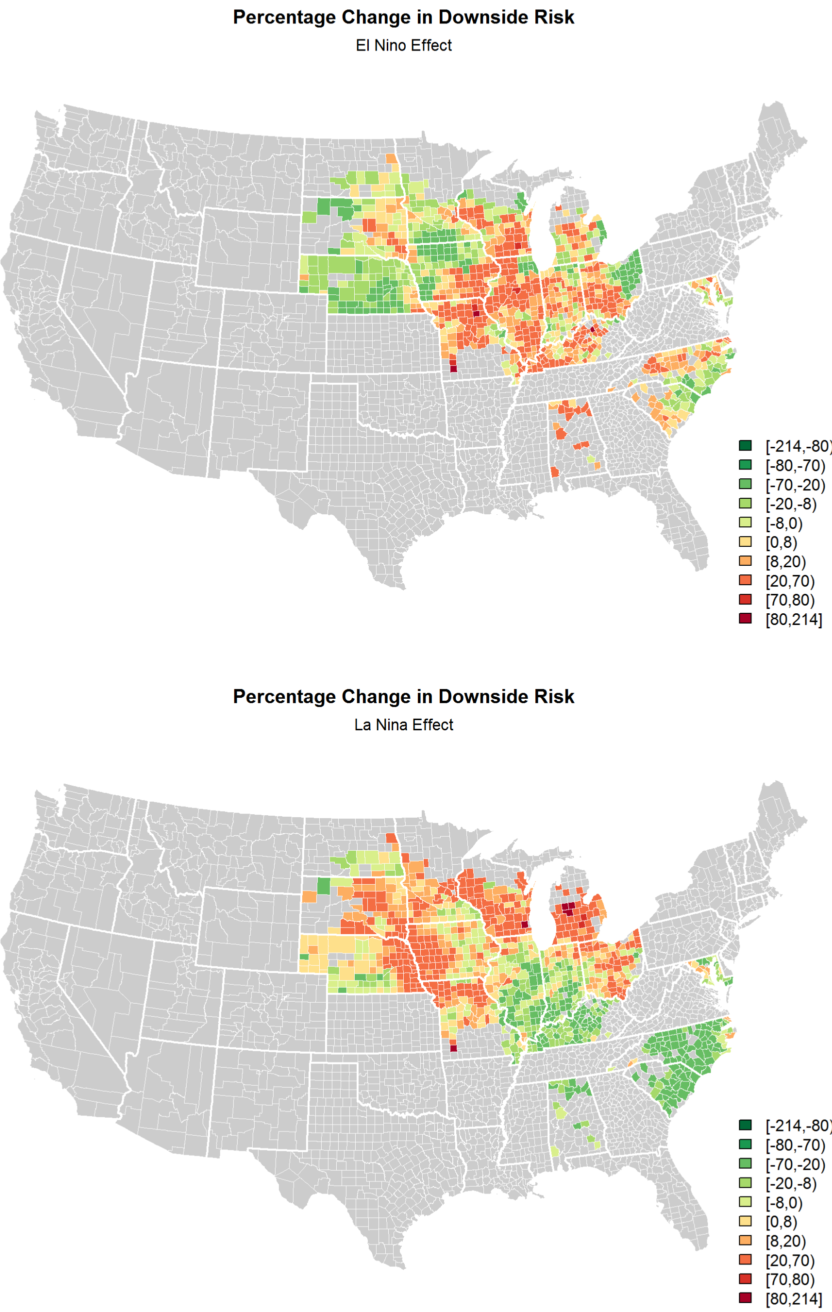

Figure 2: Spatial Representation of the ENSO Impacts on Downside Risk, $\alpha = 0.75$. Thresholds are chosen so that each band around zero contains roughly 20 percent of observations.