Worldwide Crop Supply Responses to El Niño Southern Oscillation

(Preliminary and Incomplete)

Nelson Villoria
(nvilloria@ksu.edu)
Department of Agricultural Economics, Kansas State University

Michael Delgado
(delgado2@purdue.edu)
Department of Agricultural Economics, Purdue University

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Nelson Villoria* and Michael Delgado†

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1 Introduction

Efforts to stabilize domestic food markets are pervasive in the developing world where both importing and exporting countries modify their trade policies to reduce the transmission of world price fluctuations into their domestic markets (Anderson, 2012). The simultaneous implementation of price insulation policies by many countries further exacerbates market volatility forcing governments to escalate interventions, thus eliminating the positive results of price stabilization sought by policy makers in the first place (Martin and Anderson, 2012).

The causes of food price fluctuations are complex; however, it is clear that events that simultaneously reduce food supply in several parts of the world, especially when grain stocks are low, can send prices spiraling upward (Anderson, 2012; Wright, 2011). El Niño Southern

*Corresponding author. Department of Agricultural Economics, Kansas State University, 222 Waters Hall, Manhattan, KS. Email: nvilloria@ksu.edu.

†Department of Agricultural Economics, Purdue University.

Oscillation (ENSO) is an event that can trigger such effects as it induces spatial correlation in the world climates making them teleconnected (Need to explain teleconnections).

However, although there is evidence that ENSO induces simultaneous negative and positive supply shocks in different parts of the world, the systemic effects of climate teleconnections in world food supply remains largely unexplored. So, a first objective of this paper is to to identify the extent to which ENSO induces synchrony in the global harvest of rice, maize, sorghum, and wheat with a particular focus on the geographic pattern of such correlation. ENSO is also predictable with moderately good reliability six to nine months in advance (e.g. Latif et al., 1998; Kirtman and Schopf, 1998; Ubilava and Helmers, 2013), in principle some of its effects can be attenuated with early warnings. In further stages of this work, we will use ENSOs global reach and predictability to investigate the effects of variable trade policies in mitigating the price fluctuation effects of extreme climate events affecting many regions of the world at the same time.

As reported in this preliminary version of the paper, we find that ENSO does indeed induce synchrony in the global production of cereals. Our preliminary results also indicate that ENSO is responsible for increasing food prices in some regions of the world. Our work in progress also indicates that obstructing markets when supply shocks are correlated further increase prices and diminishes the effectiveness of mitigation policies. Although ENSOs predictability can only partially explain otherwise unpredictable extreme weather events, these results offer a new perspective on the interactions between climate mitigation and trade policies, two of the main mechanisms available to policy makers to cope with the prospects of a more variable climate.

2 Literature Review

Grasping the global effects of ENSO on global agriculture is a daunting task due to the existence of a rich literature highly fragmented in terms of regional and focus crops. Two exceptions are Iizumi et al. (2013), who focus on crop impacts and Chen et al. (2002), who focus on global economic impacts. In this section we survey some of this literature. In order to keep the task manageable we concentrate on a subset of studies with an explicit economic focus on cereal agriculture; for a more comprehensive review, see Rosenzweig and Hillel (2008).

A number of studies examine the effect of ENSO on agriculture by comparing the deviations in crop yield/production during the "anomalous" years with those in the "normal" years, using simulation methods. Hansen et al. (1998) examine the ENSO impacts on multiple crops, including maize, in the Southeastern U.S. Their analysis suggested increase of maize yield during the La Niña episodes and decrease in yields during the El Niño Episodes. Legler et al. (1999) examine ENSO impacts on the U.S. maize, wheat, sorghum, and rice yields, among other crops. They find negative effects of La Niña on all crops but maize, and negative impact of El niño on all crops but winter wheat. The magnitude of the effects are more pronounced and heterogeneous at the regional level. Phillips et al. (1999) investigate the role of ENSO in maize yield variability in the U.S. corn belt using simulation methods. They report 5 percent yield decrease during the La Niña episodes based on observed data, and about 18 percent yield decrease based on simulation results. They conclude that the key source of low yields is water stress, along with the high temperatures, during the maize growing season. Chen and McCarl (2000) examine effects of ENSO phases on crop production in the major crop producing countries using stochastic model coupled with global trade model. They find negative aggregate effect of both El Niño and La Niña episodes on maize and sorghum production, while the effects on wheat varies across different wheat varieties, indicating spatio-temporal differences in ENSO impacts. Their findings highlight benefits of incorporating the magnitude of ENSO events in the analysis, as there appears to be economically valuable information in ENSO variable used as more than just a categorical variable. Chen et al. (2002) examine economic value of more refined ENSO information on the U.S. and global agriculture. Their analysis incorporates maize, wheat, and sorghum, among other field crops. They find economic benefits in more complete ENSO information on the U.S. and world agriculture. Amissah-Arthur et al. (2002) consider effects of ENSO on Kenya weather and maize yields. They use 20-years of data from 1979–1998 to find that the effects of El Niño are inconclusive. Even so, they find that all major positive deviations in maize yield from the trend-adjusted mean yields happened during the non-El Niño years. Martinez et al. (2008) investigate relationships between climate anomaly indices (including ENSO) and maize yields in the states of Alabama, Florida, and Georgia, U.S. They find negative correlation between ENSO and local weather and yields, meaning that cooler and wetter winter and spring conditions associated with El Niño result in reduced yields.

Another set of studies apply regression-based approach to directly estimate the ENSO impact on crop production. Naylor et al. (2001) examine relationship between ENSO and rice production in Indonesia. They find that much of the impacts of ENSO on rice production is through its effects on planting both in terms of timing and the area planted[1]. Falcon et al. (2004) examine ENSO effects on Indonesian rice production, area harvested, and yields. They find the significant effect of ENSO on rice production, which is true both on national level, and more disaggregated provincial levels. They also identify an evidence of ENSO impact on lower quality rice prices – a causal linkage that likely exists due to the ENSO effects on Indonesian rice production. Roberts et al. (2009) investigate the ENSO impact on precipitation and rice production in Luzon, Philippines. They find that both irrigated and rain-fed regions are affected by El Niño (1 degree positive deviation), resulting

[1] first differences of production

in 3.7 percent and 13.7 percent reduction in production, respectively. The impacts on total production are evident in the dry growing season, during which ENSO explains approximately 29 percent of variation in rice production, much of which is driven by area changes rather than yield changes. Deng et al. (2010) examine ENSO impacts on rice production in selected rice-producing regions in China. Contrary to the aforementioned studies, they find no evidence of the ENSO impact on rice yields. They conclude that the strongest ENSO–weather relationship occurs outside of the rice growing season, and also, much of China's rice is irrigated and, thus, is less sensitive to climate shocks.

Several studies further extend the analysis of ENSO – agriculture relationship by calculating the welfare effects of ENSO shocks. Adams et al. (1999) investigate economic consequences of extreme ENSO events on the U.S. agricultural sector using stochastic economic model of the U.S. agricultural sector. Their analysis incorporates maize, wheat, and sorghum, along with other five field crops. They estimate losses associated with both El Niño and La Niña to range between US$1.5 – US$1.7 billion and US$2.2 – US$6.5 billion, respectively. Podestá et al. (2002) examine economic benefits of ENSO forecasts on agricultural decision making in Argentina. They note that the usefulness of ENSO signals are mitigated by the fact that large variability of the precipitation is present in each of the ENSO phases. Selvaraju (2003) examines ENSO impact on cereal production in India. He finds strong negative correlation between ENSO anomalies and field crop production, with correlation coefficients being equal to -0.41, -0.36, and -0.21 for rice, wheat, and sorghum, respectively. He also finds that the production decrease during El Niño is larger in magnitude than production increase during La Niña. These translate to US$773 million losses during the El Niño episodes, and US$437 million gains during the La Niña episodes. Chen et al. (2008) analyze the impact of strong ENSO events on international rice market. They find that on average La Niña events result in poorer production levels (up to 10 percent reduction) compared to long-run mean, while the effect of El Niño events are less pronounced (up to 5 percent reduction). They also find little-to-no effect of ENSO on total amount of rice traded. However, they did find overwhelming evidence of region-specific impacts of ENSO shocks on trade. The total welfare impacts of El Niño and La Niña are estimated to be around US$0.7 and US$2.1 billion, respectively.

Finally, a number of studies investigate economic benefits of early ENSO warnings in the agricultural sector. Solow et al. (1998) analyze economic gains from improved ENSO prediction in the U.S. agricultural sector. Using simulation methods they find the expected value of ENSO prediction to range between US$240 – US$323 million, depending on the quality of ENSO forecasts. Phillips et al. (1998) examine the economic value of ENSO forecasts on maize yields and production management in Zimbabwe using simulation methods. They find that the usefulness of ENSO information varies across different regions of the country, depending on soil characteristics and other weather characteristics. Messina et al. (1999) investigate ENSO effects on crop production in the Pampas region of Argentina. They consider economic benefits land reallocation between several crops (including maize and wheat) conditional on ENSO forecasts. They find that optimal land allocation in response to ENSO phases increased net farm income by up to US$5 – US$15 per hectare. Jones et al. (2000) investigate the relationship between ENSO on crop yields, and calculate the economic value of ENSO forecasts in the Coastal Plain of the state of Georgia in the U.S., and Pampas region in Argentina. They report per hectare values of optimal maize management using ENSO forecasts to be US$3 – US$5 in Georgia, U.S., and US$11 – US$35 in the Pampas, Argentina. Adams et al. (2003) examine effects of information on approaching ENSO anomalies on Mexican agriculture. Their analysis incorporates maize, wheat, and sorghum, along with other field crops. An estimate of the average economic benefit of ENSO knowledge is measured in the order of US$10 million annually. Stige et al. (2006) address the effects of climate anomalies on field crop production in Africa. They find strong an negative impact of El Niño on maize and rice production in almost all considered regions, but positive, although less pronounced, impact on sorghum production, suggesting a possibility of adaptive rotation between maize and sorghum, if the ENSO-related information is available prior to the planting period.

3 Attribution of Changes in ENSO to Changes in Global Food Production

We now employ regression analysis to formally examine the hypothesis that ENSO teleconnections result in simultaneous crop productivity shocks across countries in the world. The parameter estimates of the ENSO-induced productivity changes also produce a set of globally consistent shocks that will be employed later to understand the interplay between adaptation to climate extremes and trade policy. Our method of choice is to pool the country-level time series of crop yields and SSTA measures and use panel data techniques to infer the effects of changes in the SSTA on changes in agricultural yields.

3.1 Regression Analysis

We treat each country-crop combination as the unit of observation. The regression models relate the natural log of detrended yields in country-crop pair i at time t, $log(y_{it})$, to the sea surface temperature anomaly (SSTA, described below) annualized over country i's growing season, $SSTA_{it}$. Additionally, we allow for asymmetries between the SSTA phases by allowing for different slopes in the warming and cold phases of ENSO. Time invariant factors that may condition the response of different countries to ENSO are controlled for by the use of detrended yields. Formally:

$$\begin{aligned}log(y_{it}) = \beta_0 + \beta_N D_N + \sum_{p=1}^{P} \beta_p SSTA_{it}^p + \sum_{p=1}^{P} \beta_{pN} SSTA_{it}^p D_N + \\ \sum_{k=1}^{K}\sum_{p=1}^{P} \beta_{pk} SSTA_{kt}^p I[1|k=i] + \sum_{k=1}^{K}\sum_{p=1}^{P} \beta_{pkN} SSTA_{kt}^p I[1|k=i] D_N + \epsilon_{it}. \quad (1)\end{aligned}$$

where β_0 is an overall intercept. The term D_N is an indicator variable that takes the value of 1 when $SSTA > 0$ (and zero otherwise); this implies that β_N is an additional intercept that captures the mean log of detrended yields during years in which $SSTA > 0$. The subindex p denotes the degree of the polynomial allowed for the SSTA variable so that β_1 is the coefficient for $SSTA$, β_2 for $SSTA^2$, and so forth. The coefficients β_{pN} are the slopes on the $SSTA$ polynomial terms when $SSTA > 0$. The last two terms of equation (1) allow for country-crop specific slopes for the i^{th} country: when $SSTA < 0$ the slope is is β_{pk} and when $SSTA > 0$ the slope is $\beta_{pk} + \beta_{pkN}$. Finally, ϵ_{it} is an error term assumed to be independent and homokedastic across time and cross-sectional units, centered around zero, and more importantly, uncorrelated with $SSTA_{it}$.

To fix ideas, for an equation with quadratic effects (p = 2), the equation for country s is:

$$\begin{aligned}log(y_{st}) = \beta_0 + \beta_N D_N + \beta_1 SSTA_{st} + \beta_2 SSTA_{st}^2 + \\ \beta_{1s} SSTA_{st} + \beta_{2s} SSTA_{st}^2 + \beta_{1sN} SSTA_{st} D_N + \beta_{2sN} SSTA_{st}^2 D_N + \epsilon_{st}. \quad (2)\end{aligned}$$

For practical purposes, we are interested in the conditional expectation of changes in yields given a value of the $SSTA$ in country i at time T. After differencing 2, and using the parameter estimates of 1 we obtain:

$$E[dlog(y_{st})|SSTA_{st} = SSTA_{sT}] = \\ SSTA_{st}\left[\widehat{\beta}_1 + \widehat{\beta}_N D_N + \widehat{\beta_{1s}} + \widehat{\beta}_{1sN} D_N + SSTA_{st}\left(\widehat{\beta}_2 + \widehat{\beta}_{2s} + \widehat{\beta}_{2sN} D_N\right)\right]. \quad (3)$$

which gives a unique supply shock for each country s under the state of nature prevailing at time T. Few cases of interest are *normal* times:

$$E[dlog(y_{st})|SSTA_{st} = 0] = 0; \quad (4)$$

A La Niña episode with $SSTA_sT = -1$:

$$E[dlog(y_{st})|SSTA_{st} = -1] = \left(\widehat{\beta}_2 - \widehat{\beta}_1\right) + \left(\widehat{\beta}_{2s} - \widehat{\beta_{1s}}\right), \quad (5)$$

where the first term on the right hand side (RHS) is common to all the crops and countries, and the second term is a country-crop specific slope; and an El Niño episode with $SSTA_sT = 1$:

$$E[dlog(y_{st})|SSTA_{st} = 1] = \left(\widehat{\beta}_N + \widehat{\beta}_1 + \widehat{\beta}_2\right) + \left(\widehat{\beta_{1s}} + \widehat{\beta}_{1sN} + \widehat{\beta}_{2s} + \widehat{\beta}_{2sN}\right). \quad (6)$$

where as before, the first RHS term is an intercept common to all countries and crops, and the second term is country-crop specific slope

In practice, the significance of $E[dlog(y_{st})|SSTA_{st}]$ is related to the significance of the β coefficients. Three possible options for determining whether $E[dlog(y_{st})|SSTA_{st}]$ is statistically significant are described next. First, we could to use a test for multiple restrictions whereby one could use a F-test strategy to determiner whether omitting the particular combination of parameters for a given country-crop and ENSO phase changes the overall explanatory power of the regression—this test of joint significance would indicate whether the marginal effects of the SSTA on yields is statistically different from zero at a given significance level. Another option is to calculate standard errors for expressions such as (5) and (6) using the delta method. Yet another option is to build confidence intervals based the distribution of $E[dlog(y_{st})|SSTA_{st}]$ obtained from random draws of the parameter estimates (and their covariances). Relative to F-tests and the delta method, the last option allows for exploring the uncertainty around having negative or positive supply shocks without being tied to a pre-specified significance level. This is particularly useful in the context of the modeling exercises of the paper (still in progress) where we can use the empirical distribution of $E[dlog(y_{st})|SSTA_{st}]$ to quantify the uncertainty in model outcomes.

3.2 Data Description

The dependent variable in the regressions discussed below are national yields of maize, wheat, sorghum and rice during the period 1961-2009 sourced from FAOSTAT. We discarded countries displaying constant yields for more than three consecutive years. In addition, to facilitate the aggregation of the productivity shocks to the GTAP regions used in the policy simulations, we kept only the countries included as disaggregated regions in the GTAP regional classification (CITE). The final sample represents 99% of maize world production (74 countries), 98% of wheat production (59 countries), and 95% of sorghum and rice production (45 and 61 countries, respectively).

Our exogenous variable is the Sea Surface Temperature (SST) from NOAA measured in the region Niño 3.4. These data are monthly and are a direct measure of ENSO. As mentioned above, a El Niño phenomenon is considered to occur if the average SSTA over a three period month is greater or equal than 0.5^0C for more than three consecutive, overlapping, periods. La Niña, on the other hand, is considered to be occurring when the SSTA is lower or equal than -0.5^0C from more than three consecutive, overlapping, periods. Because yields are measured annually and growing seasons differ across hemispheres, we calculated country-specific SSTA measures over the annual growing season. For this we used the global information on pixel-level planting and harvesting dates for the focus crops provided by Sacks et al. (2010) and constructed monthly weights whereby a low weight implies that in that given month, only few pixels are already growing a specific crop. A weight of one implies that a month is part of the growing season in the entire country. With these monthly weights, we constructed weighted averages.

4 Results

We estimated (1) using a second-degree polynomial. Of course, including country-crop and ENSO phase specific slopes by each polynomial term generates in excess of 1000 coefficients. However, the real interest is on expressions such as 5 and 6, which capture the effects of individual crops and countries. In order to get a better understanding of the model, in figure 1 we display the marginal effects of the SSTA (in the horizontal axes) on maize yields in the U.S., Argentina, India, and Zimbabwe. A glance at the figure reveals that the average yield during the cold and war phase of ENSO is quite different in Argentina, to a lesser degree in India and Zimbabwe, and practically the same in the U.S. Notice also how the ENSO phase-specif slopes can be quite different, as in the case of India. Such difference in slopes is verified in most countries.

A main interest of this paper is to determine whether the climate teleconnections result in teleconnected supply responses. In order to investigate this, we calculate the ration of 1000 random simulated effects from the parameter estimates (and their covariance, assuming a multivariate normal) that is negative. These shares are shown in figure 2, for year 1987 when there was a string Niõ, with the value of the SSTA ranging from 0.9 to 1.2, depending on the country. When all the effects are negative, the share is of course 1; conversely, if all the effects are positive, the ratio is 0. These ratios give a sense of the statistical significance of the effects of ENSO on the log of detrended yields in the sense that countries for which, say, 90% of the values are negative, would imply a 90% CI that does not include zero. Starting with maize, in the upper-left panel of figure 2, it can be seen that for most countries in Eastern and Southern Africa, the ratio of negative values on the total distribution of potential effects as estimated in (1) is negative (countries in red).

This can be take as strong evidence that ENSO has a statistically significant negative effects on the log of detrended maize yields in these countries. Similar effects are verified in the western northern tip of South America (Colombia nd Ecuador) few countries in Central America. Similarly, India, Nepal and Pakistan in South Asia also show negative effects. Taken together, these effects suggest that there are indeed teleconnected supply shocks, in the sense that yields are likely to be negatively affected in regions that are quite far from each other. Notice also that a number of countries the share of either negative of positive effects is close to 50% (countries in orange), which indicates quite imprecise confidence intervals, or said otherwise, insignificant effects of El Niõ on maize yields. Finally, some countries in lower South America (Argentina, Chile and Uruguay) tend to be dominated by positive effects, finding that coincides with ors in the literature.

In addition to maize, figure 2 also shows the ratio of effects for rice, sorghum, and wheat. An interesting pattern is that the effects of ENSO differ by crop, which is important because of the possibilities of substitution in both production and consumption. For instance, the effects of ENSO in Eastern Africa are much less negative than those in maize. Likewise, Brazil, shows a strong negative supply response, which contrasts with maize. India, is among the countries that have negative effects in both maize and yields.

5 Conclusions

The objective of this paper is to determine the patterns of cross-country teleconnections in the supply responses of maize, wheat, rice and sorghum associated with ENSO. Our results suggest that these patterns are discernible in the country-level data and that the diversity of supply responses across crops and countries has important consequences for how markets adjust to ENSO shocks. These consequences are part of our current work.

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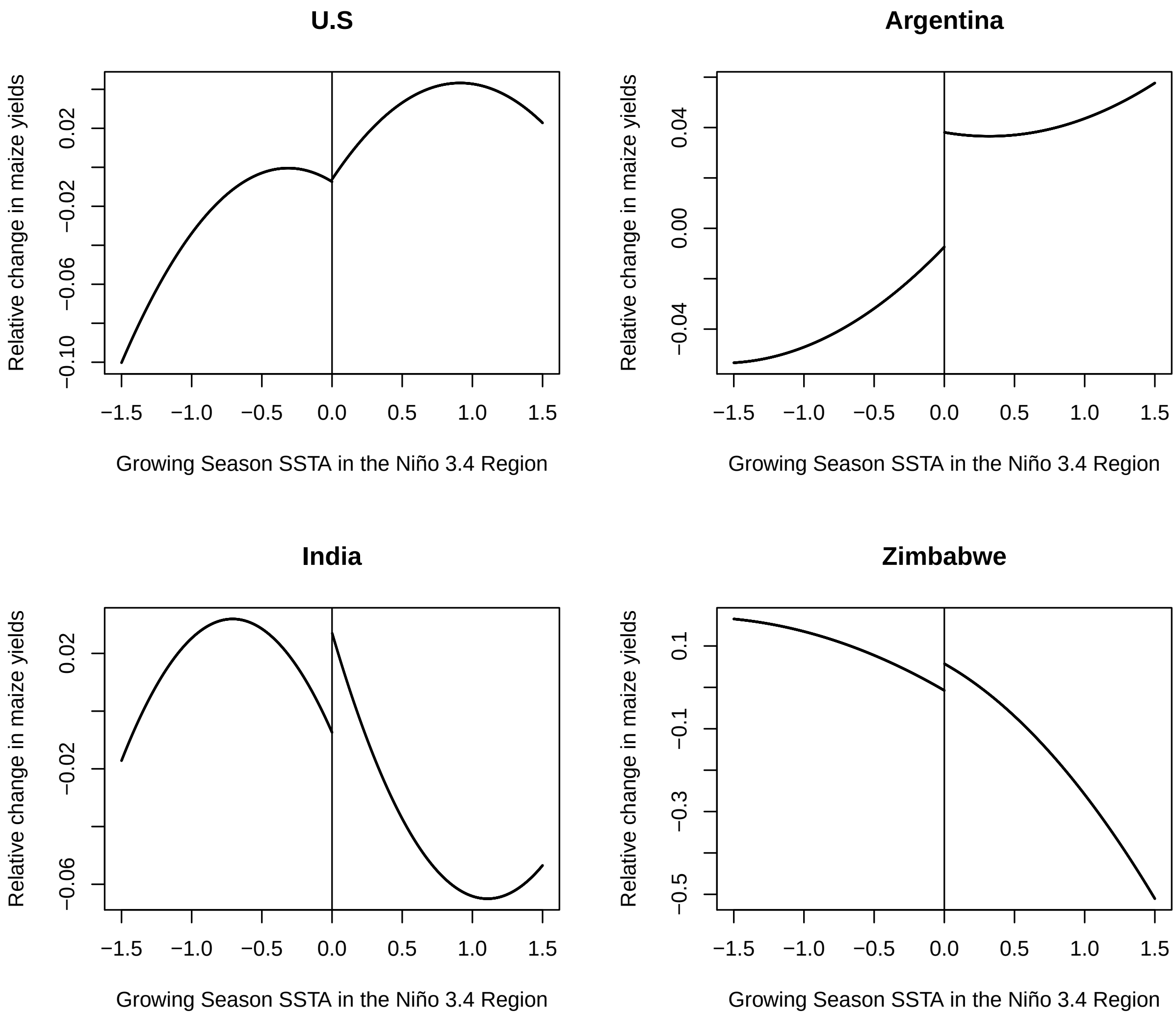

Figure 1: Estimated effects of sea surface temperature anomalies on maize yields in selected countries. The estimated model allows for asymmetric (different slopes and intercepts as well as non-linear effects of the cold and warn phases of ENSO.

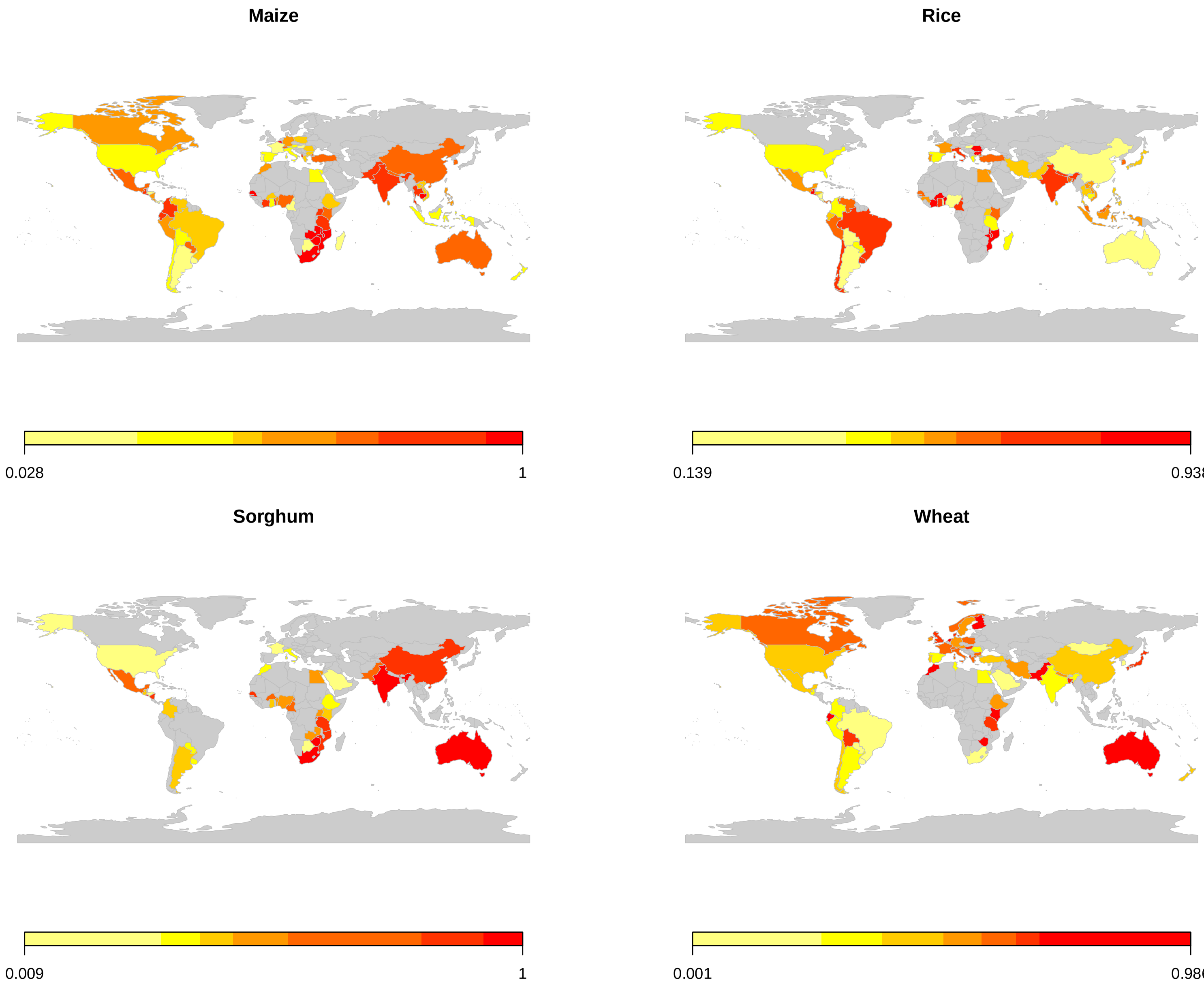

Figure 2: Teleconnections in Supply Responses. Model uncertainty about the effects of an El Niño episode (represented by the values of the SSTA in 1987). The model uncertainty is the share of randomly simulated effects drawn from a multivariate normal that are negative. A Ratio of 1 indicates that all the simulated effects are negative. A Ratio of 0 indicates that all the simulated effects are positive.