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**Assessing the Value of Climate Information and Forecasts for the Agricultural Sector in the Southeastern United States: Multi-Output Stochastic Frontier Approach**

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**Abstract**

A multi-output/input stochastic distance frontier model is used to analyze the effect of interannual climatic variability on agricultural production and to assess the impact of climate forecasts on the economic performance of this sector in the Southeastern United States. The results show that the omission of climatic conditions when estimating regional agricultural production models could lead to biased technical efficiency estimates. This climate bias may significantly affect the effectiveness of rural development policies based on regional economic performance comparisons. We also found that seasonal rainfall and temperature forecasts have a positive effect on economic performance of agriculture. However, the effectiveness of climate forecasts on improving TE is sensitive to the type of climate index used. Policy implications stemming from the results are also presented.

Keywords: US Agriculture; climate bias; value of information; production frontier.

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## 1. Introduction

In the past decades, federal agencies have financed numerous climate research programs aiming to improve the accuracy of forecasting techniques and to enhance the dissemination of usable information (National Oceanic and Atmospheric Administration 2012). While resources have been invested, the issue of how to measure the economic value of climate information and forecasts is still discussed in the literature (Msangi et al. 2006).

The economic value of climate information and forecasts can be defined and evaluated in different ways. In agriculture, most published studies on this subject have focused on evaluating the potential effect of climate information on the financial performance (i.e., revenues, profit, etc.) of a farm (e.g., Liu et al. 2009; Cabrera et al. 2009; Letson et al. 2005; among others). However, the use of economic performance measures, such as productivity, input substitution, and technical efficiency (TE), has received much less attention in the literature.[2]

Studying the sources of productivity and efficiency in agriculture is an important matter as it allows farmers and policy makers to identify and target private and public resources in the most appropriate manner to improve agricultural production, inputs used and agricultural incomes (Solís et al. 2007). However, in an extensive review of the agricultural productivity and efficiency literature, Bravo-Ureta et al. (2007) report few published articles that include climate-related variables in the empirical models. In general, authors have argued that weather and climate are beyond the control of the farmers and should be treated as stochastic shocks (Demir and Mahmud 2002). But some authors have questioned this approach, claiming that the omission of environmental variables could bias the results of empirical agricultural production models (Haim et al. 2007).

In recent years, some studies have offered evidence of the impact of climate variability on the US agricultural sector. For instance, Lazo et al. (2011) show that, in the US, agriculture is one of the most sensitive economic sectors to fluctuations in climatic conditions. Specifically, the authors argue that agricultural output could vary by up to 12% (or $127 billion) a year due to weather variability. Fuglie et al. (2007) depict that, during the past 60 years, the lowest levels of agricultural productivity in the US are highly correlated with severe drought. Furthermore,

[2] A review of the literature on the economic value of climate forecasts can be found in Katz and Murphy (2005).

climate forecasts have the potential to influence the efficiency of this sector. Previous research suggest that when historical climatic information is available and fluctuations in seasonal climate are known in advance, farmers can tailor their production strategies to account for climate variability (Breuer et al. 2007; Cabrera et al. 2007; Haim et al. 2007; Letson et al. 2005; among others).

The goals of this study are as follows: 1) to identify whether there is a bias in the estimation of agricultural productivity and TE due to the omission climate related variables; 2) to measure the effect of climatic variability on agriculture and its subsectors (i.e., crops, forestry and livestock); and 3) to assess the impact of climate forecasts on the economic performance of this sector. To do so, we explore the case of the agricultural sector in the Southeast (SE) US.[3] This geographical region is influenced seasonally by El Niño Southern Oscillation (ENSO) phenomena, making it ideal for studying the interaction of climate variability and agricultural productivity.[4] To assess the value of climate information and forecasts on efficiency and productivity we implement a stochastic distance production frontier (SDPF) approach. Although different methodological strategies have been developed to study productivity and efficiency, SDPF offers advantages over other available methodologies to study the agricultural sector (Kumbhakar and Lovell 2003).

The rest of this article is organized as follows. The next section gives an overview of the methodology followed by a description of the empirical model and data used. Then, we discuss the empirical results and present some concluding remarks.

## 2. Methodology

Variations in climatic conditions and accessibility to climate information impact agricultural productivity from two different angles. First, climate variability may affect the shape of the production technology by directly influencing the production structure. Haim et al. (2008)

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[3] In this study we consider the following states: Alabama (AL), Florida (FL), Georgia (GA), North Carolina (NC) and South Carolina (SC). These states were selected because they display climate variability patterns in temperature and precipitation associated with ENSO events.

[4] Researchers have shown that ENSO is a strong driver of seasonal climate variability that impacts crop yields in this geographical area (e.g., Hansen 2002; Jones et al. 2000).

and Demir and Mahmud (2002) argue that changes in rainfall and temperature patterns may lead to productivity gains or losses by modifying returns to input use (i.e., water, fertilizers, pesticides, etc.). Second, climate forecasts can have a direct effect on production efficiency. Information about seasonal environmental conditions can affect the distance that separates observed from potential (frontier) outputs. In this study, we also take into consideration that the agricultural sector in the SE US is composed by three distinctive subsectors; i.e., crops, forestry and livestock. Thus, climate variability and forecasts may affect these subsectors in different ways due to their intrinsic characteristics.

Under these circumstances, the SDPF method is appropriate to study productivity and TE for the following reasons: 1) it allows for multiple outputs (agricultural subsectors in our case) and inputs, which is essential for the study of impact of climate variability on production; and 2) it can incorporate directly variables affecting inefficiency, which is useful in evaluating the effect of climate information. In addition, SDPFs have major strengths over other multi-output techniques commonly applied in agriculture, such as the deterministic data envelopment analysis (DEA) method, including: dealing with stochastic noise; accommodating traditional hypothesis testing; and allowing for single step estimation of the inefficiency effects (Kumbhakar and Lovell 2000).

The SDPF can be formulated with an input and/or an output orientation. The input orientation gives the proportional reduction in all inputs that would bring a farm to the frontier isoquant, while the output model reflects the proportional increase in outputs attainable by moving to the production possibilities frontier holding input quantities constant (Kumbhakar *et al.* 2007). In this paper, we choose the input orientation because it relies on a cost minimization framework, a maintained behavioral hypothesis for the agricultural sector. Given that producers use a vector of $N$ inputs ($x = (x_1, ..., x_N) \in R_+^N$) to produce $M$ outputs ($y = (y_1, ..., y_M) \in R_+^M$), the input-oriented distance function is defined as:

$$D^I(x, y) = \max\{\lambda : (x/\lambda) \in L_x(y)\} \qquad [1]$$

where $D^I$ is the input distance function, $L_x(y)$ is the set containing all input vectors $x$ that can generate the output vector $y$, and $\lambda$ is the efficiency score (Coelli and Perelman 1999).

From an empirical point of view, to estimate a distance function (or frontier) it is necessary to specify a functional form that adequately captures the relationship between inputs and outputs. Coelli and Perelman (1999) indicate that a second-degree approximation to a true input distance function can be represented, respectively, by the following *translog* equations with symmetry and homogeneity imposed:

$$\ln\left(\frac{D_{it}^{I}}{x_{1it}}\right)=\alpha_0+\sum_{m}^{M}\alpha_m \ln y_{mit}+0.5\sum_{m_j}^{M}\sum_{m_g}^{M}\beta_m \ln y_{m_jit}\ln y_{m_git}+\sum_{n}^{N-1}\beta_n \ln\left(\frac{x_{ni}}{x_{1it}}\right)+$$
$$0.5\sum_{n_j}^{N-1}\sum_{n_g}^{N-1}\beta_n \ln\left(\frac{x_{n_jit}}{x_{1it}}\right)\ln\left(\frac{x_{n_git}}{x_{1it}}\right)+\sum_{n}^{N-1}\sum_{m}^{M}\delta_{nm}\ln\frac{x_{nit}}{x_{1it}}\ln y_{mit}+\sum_{e}^{E}\phi_e c_{et}+\sum_{s}^{S}\omega_s d_s \qquad [2]$$

where $i$ and $t$ are a subindex for State and year, respectively, $c_e$ are climate variables and $d_s$ represents all *dummy* variables included in the model.

Following the same rationale of the stochastic production frontier method proposed by Aigner *et al.* (1977), we can formulate an Input Stochastic Distance Frontier (ISDF) in which the distance from each observation to the ISDF represents the sum of inefficiency and a traditional error term (i.e., $D^I = \varepsilon = v - u$). The *translog* normalized ISDF can then be expressed as:

$$-\ln x_{1it}=\alpha_0+\sum_{m}^{M}\alpha_m \ln y_{mit}+0.5\sum_{m_j}^{M}\sum_{m_g}^{M}\beta_m \ln y_{m_jit}\ln y_{m_git}+\sum_{n}^{N-1}\beta_n \ln\left(\frac{x_{nit}}{x_{1it}}\right)+$$
$$0.5\sum_{n_j}^{N-1}\sum_{n_g}^{N-1}\beta_n \ln\left(\frac{x_{n_jit}}{x_{1it}}\right)\ln\left(\frac{x_{n_git}}{x_{1it}}\right)+\sum_{n}^{N-1}\sum_{m}^{M}\delta_{nm}\ln\frac{x_{nit}}{x_{1it}}\ln y_{mit}+\sum_{e}^{E}\phi_e c_{et}+\sum_{s}^{S}\omega_s d_s+v_{it}-u_{it} \qquad [3]$$

where $u_i$ and $v_i$ are the elements of the composed error term, $\varepsilon_{i,}$ defined by Aigner et al. (1977). Specifically, $v_i$ is a random variable reflecting noise and other stochastic shocks, and $u_i$ captures the TE relative to the stochastic frontier. The maximum-likelihood (ML) estimation of Equation [3] will produce consistent parameter estimates for the ISDF.

Following, Shao and Lin (2001) we analyze the value of information (climate forecasts in our case) by measuring its impact on efficiency. Within ISDF framework, the predictor of TE can be obtained as the expectation of the term $u_i$ conditional on the composed error term $\varepsilon_i$ (Jondrow et al. 1982). Therefore, TE can be measured as:

$$\text{TE} = \exp(-u_i) \quad [4]$$

Battese and Coelli (1995) developed a single-step ML model to evaluate the extent to which TE or, more precisely, technical inefficiency (TI) is a function of farm (firm) characteristics among other variables. By using this approach, the parameters of the ISDF as well as those of the TI factors are estimated jointly. This step is accomplished by incorporating the following expression into the model:

$$\mu_i = \rho_0 + \sum_n \rho_n F_{ni} + e_i \quad [5]$$

where $\mu_i$ is the conditional mean of $u_i$ defined as normal random variables truncated at zero, $F_{ni}$ is a vector of exogenous variables (including alternative indexes for climate forecasts), $\rho_o$ and $\rho_n$ are unknown parameters, and $e$ are unobservable random variables, assumed to be independently distributed. A detailed derivation of this inefficiency model can be found in Battese and Coelli (1995).

## 3. Data and Variables

The production data used in this study comprise 250 observations on US agriculture inputs and outputs, covering the five states in the SE US over 50 years from 1960 to 2009, inclusive. The data were obtained from the Economic Research Service at the US Department of Agriculture. The dataset was created following the framework described in Ball et al. (1999) to account for differences in quality and value of inputs and outputs. In this study, agricultural production is divided into three alternative subsectors: ***Crop*** (C); ***Livestock*** (A); and ***Forestry*** (F). Our data contain output levels for each of these subsectors defined as the value of gross production leaving the farm. In addition, the empirical model includes the following specific inputs: ***Purchased Inputs*** (P), given by the total expenditures in fertilizers, agricultural chemicals, animal feed, etc.; ***Capital*** (K), defined as depreciation of equipment, buildings and land; and, ***Labor*** (L), measured as total compensation to employees and farm operators. All the variables are measured in 2009 thousand of US dollars to control for inflation. To account for the effect of climate conditions on production two additional inputs are include in the IDPF model (eq. [3]), statewide ***Precipitation*** (R) (measured in millimeters) and ***Temperature*** (T) averages (measured in Celsius). The climatic data are specific for each state and year. This information was provided by the Southeast Regional Climate Center. Table 1 presents descriptive statistics by State for all the output and input variables included in the analysis.

Following, Shao and Lin (2001), we measure the value of information (climate forecast in our case) by assessing its impact on TE. TE measures the difference between the maximum (ideal) and actual production levels, and information is crucial to minimize this discrepancy. As described in Section 2, the ISPF used here makes it possible to evaluate factors related with TE. Specifically different combinations of ENSO phases and seasonal precipitation and temperature are included in the inefficiency model (eq. [5]). Since our production data are aggregated by years, we selected the Japan Meteorological Agency (JMA) ENSO index as our climate signal. Meza et al. (2008) indicate that this climate index is well known by farmers in the SE US. Several authors have also found a systematic correlation between climate variability due to ENSO and crop yields in SE US (e.g., Hansen 2002; Mavromatis et al. 2002; Jones et al. 2000; among others). The ENSO is a climatic phenomenon characterized by changes in the sea surface temperature of the Equatorial Pacific Ocean that influences the regional climate. Rainfall is especially sensitive to ENSO phases (i.e., El Niño, La Niña and Neutral) in SE US with an above average rainfall during an El Niño year, and with a below average rainfall during a La Niña year. Temperature is also affected by ENSO. Lower (higher) temperatures, especially before planting season, are observed during El Niño (La Niña) (Jagtap et al. 2002). It is important to indicate that in this model we are assuming a perfect phase forecast. Thus the results presented in this study should be interpreted as upper bound estimates of the true economic effect of climate forecasts. The seasonal climate information was obtained from the Florida Climate Center.

Figure 1 presents the evolution of productivity (total output per total input) by sector for the studied period. This figure shows evidence of the impact of climate variability on agriculture. Specifically, a negative relationship can be observed for years following multiple La Niña events and for those years with severe drought. It is important to notice that these impacts are greater for crop and livestock than for forestry. The following section presents a more thorough analysis of this issue using the ISDF model presented above.

## 4. Results and Discussion

This section is divided into 3 subsections. First, we analyze the effect of omitting climate variables in the estimation of a production frontier. Then, we assess the linkage between productivity and climate variability. Lastly, we discuss the value of climate information in agriculture.

### *4.1. Model performance and evaluating the effect of omitting climate in the estimation of a production frontier*

Table 2 presents the ML estimates for ISDF model with and without climatic variables. In this study we selected a TL functional form since preliminary analyses based on generalized likelihood ratio tests rejected the Cobb-Douglas in favor of the more flexible specification. In general, the estimated parameters follow comparable patterns in both ISDF models; however, their magnitudes diverge. A log-likelihood ratio test confirms that the estimated parameters differ between the two models. In addition, the null hypothesis that all production coefficients associated with the climatic variables are zero is strongly rejected. In fact, most of the variables associated with climatic conditions (especially precipitation) present statistically significant coefficients. These results offer evidence that the model including climatic variables presents the most adequate representation of the data.

Following common practice, all variables are normalized by their geometric mean (GM); thus, the first-order coefficients can be interpreted as distance elasticities evaluated at the sample means. All the elasticities possess the expected signs at the GM. Thus, both estimated ISDF satisfy the property of monotonicity (i.e., non-decreasing in outputs and decreasing in inputs). The parameters for $\lambda$, the ratio of the standard error of $u$ to that of $v$, are statistically significant at the 1% level with an estimated values of 1.034 and 1.084 for the model with and without climatic variables, respectively. These results indicate that inefficiency is highly significant among the studied sample. In addition, the null hypothesis that $\lambda = 0$ is rejected, suggesting that it is appropriate to use a stochastic frontier model. To capture the time trend effect on production, which could result from adoptions of new technologies, the variable $t$ was included in both models. Coefficients for $t$ are significant and positive in both models, indicating an improvement in production over time.

Although the two alternative models satisfy necessary conditions of a theoretical ISDF, the estimates for input elasticities and return to scale (RTS) differ between them. Input elasticity measures the proportional increase in output attributed to a 1% increase in a particular input; while RTS measures the proportional increase in output for a 1% increase in all inputs[5]. Table 2 shows that the introduction of climate variables significantly affects the elasticity of inputs[6]. The estimated parameters reveal that for the model with climate variables, the most important production input is capital, followed by purchased inputs and labor. Conversely, for the model without climatic variables the most important production input is purchased inputs. RTS is also affected by incorporating climatic conditions in the model. Specifically, RTS decreases from 0.91 to 0.84 when climate is taken into account.

Using the estimates for ISDF presented in Table 2 we computed the average level of productivity of each of the five states in the SE US with and without including climate variables. In this case productivity was measured as the expected frontier output at the mean level of input use in the sample. Without climate variables the most productive state was FL, followed by GA, NC, AL and SC. It is important to notice that this ranking agrees with the official ranking published by USDA/ERS.[7] However, when climate conditions are included in the model, SC moved up to the fourth place, while AL became the least productive State in the SE US. [8]

TE means for each model are presented at the end of Table 2 and the Kernel distributions of TE are presented in Figure 2. The comparison of these descriptive statistics shows that the inclusion of climatic variables also affects the level of TE. Specifically, the mean TE score are 0.81 and 0.76 for the models with and with climate variable, respectively. A t-test confirms that this two mean TE levels are statistically different at a 5% significance level. This results show

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[5] In an ISDF the RTS correspond to the inverse of the sum of output elasticities (Coelli and Perelman 1999).

[6] The input elasticities for Purchased Inputs (the variable used to normalize the ISDF) were estimated by homogeneity conditions. The elasticities for Purchased Inputs are 0.270 and 0.486 for the models with and without climate variables, respectively.

[7] The official raking can be found at http://www.ers.usda.gov/data/agproductivity/

[8] This change in the ranking positions could be explained by the following reasons: 1) NC has proportionally more land under irrigation than AL, and farmers with irrigation may be better able to respond to climatic fluctuations; and, 2) controlling for climate variations may have a larger impact on SC than on AL, since the former has a greater exposure to the coast, making it more sensitive to variations associated to ENSO. However this is an area that deserves further research.

that controlling for climate conditions improves the average and reduces the spread of TE scores in the sample. It is worth noting that the levels of efficiency obtained here are comparable to those presented by Bravo-Ureta et al. (2007) in their meta-regression analysis of TE in agriculture.

The results presented above suggest that when climatic conditions are included in the analysis, states with relatively unfavorable climatic conditions are able to gain in terms of economic performance (i.e., productivity and TE). For instance SC, a state with harder and longer winters, improved its performance with respect to AL, a state with relative better climate, after controlling for the regional climatic conditions. This trend is compatible with Demir and Mahmud (2002). These authors also found that the omission of agro-climatic variables affects the estimation of a production model; and consequently, produce biased estimates of regional economic performance.

### *4.2. Linkage between productivity and climate variability*

As indicated above the ISDF model including climatic variables offers the best representation of the data. In addition, this model gives us the opportunity to measure directly the impact of climate variability (precipitation and temperature in our case) on aggregate regional production as well as in its three subsectors, i.e., crops, livestock and forestry. Thus, in this section we used the estimated parameters for this model to estimate a series of indexes for climate elasticities (CEs). CE reflects the proportional gain or loss in output due to variations in annual climatic conditions. To measure the CEs at different geographic and sectoral levels we use the following approach: 1) since the ISDF was estimated at the GM mean of the sample, the overall impact of precipitation and temperature on the regional agricultural sector can be measured as the first-order coefficients for these two variables; 2) regional CEs are measured as the mixed partial derivative of the ISDF with respect to output and climatic variables; 3) to compute state specific CEs, we use the interaction terms controlling for the effect of climate on each state and subsector. The coefficients for these interaction terms give us the CEs for each subsector in each of the five states in the SE US.

Table 3 summarizes the estimated CEs. In general, variations in annual precipitation have larger impacts on production than temperature. These results could be explained by the fact that most raw crops and pastures in the SE US are grown under rainfed technology making them extremely sensitive to variations in precipitation (Cabrera et al. 2009). A similar outcome is presented in Haim et al. (2006). All estimated CEs present absolute values less than one, that is, a 1% change in precipitation or temperature would lead to a less than 1% change in output. Inelastic responses to climate fluctuations are also reported by Lazo et al. (2011).

At a sectoral level, the subsector of crops is the most sensitive to climate variability followed by Livestock and Forestry. On average, 1% increase in precipitation increases crop production by 0.32%. At the state level, AL presents the highest elasticity for precipitation followed by NC and SC; whereas, FL and GA are the least sensitive to fluctuation in rainfall. With respect to temperature, only the states of NC and SC show CEs with statistically significant effects for crops. These results suggest that for the northern states in the SE US, warmer years are associated with higher level of production.

For Livestock, precipitation displays positive and statistically significant CE for all the states. This outcome is in line to those presented by Alvarez et al. (2008). These authors found that years with higher levels of precipitation allow for longer grazing period improving output levels among pasture-based production systems. Conversely, temperature shows negative and statistically significant CEs in AL, FL and GA. St-Pierre et al. (2003) explain the heat-stress could significantly affect livestock production especially in areas with hot summers, like those in the southern states of the SE US.

Lastly, Forestry presets a low but positive CE for precipitation and they are statistically significant in NC and SC. On the other hand, temperature displays consistently negative and statistically significant CEs. Westerling et al. (2006) shows that warmer year present higher probabilities for wildfire and consequently lead to loss of production in this sector.

### *4.3. The impact of climate forecasts on the economic performance of the SE US agriculture*

In this paper we follow Wang's (2002) framework to estimate the marginal effects (ME) of climate forecasts on TE. MEs measure the percentage change in expected TE due to the effect of climate forecasts. Five alternative specifications of the inefficiency model (eq. [5]) are implemented here to study the impact of different combinations of climatic indexes. The estimated models are: Model I: Knowing that the cropping season is either El Niño or La Niña; Model II: Knowing that the growing season is normal (Neutral); Model III: Knowing the predicted annual rainfall and average maximum temperature; and Model IV: Knowing the predicted seasonal rainfall and maximum temperature. The MEs for each of these models are presented in Table 4.

Climate forecasts display mixed effects on agricultural TE. For instance, no statistically significant results were found when ENSO (neutral years) or its phases (El Niño and La Niña) were used as the climate indexes (Models I and II). These results agree with Meza et al. (2008) and Chen and McClark (2000). These authors found that the use of discrete type of forecasts, like ENSO-based forecasts, offers modest value to farmers as increases in income or production. Chen and McClark (2000) argue that this type of forecast ignore important intrinsic climatic characteristics like the strength and duration of the event.

Rainfall presents positive MEs in both models III and IV, and they are statistically significant for annual, spring and summer rainfall. That is, information on annual and growing season rainfall have a positive and statistically significant impact on the TE of the SE US agricultural sector. Following Wang (2000) these MEs translate to an increase in total output of 6.6, 7.3 and 8.2% for the annual, summer and spring rainfall, respectively. In monetary terms, this increase in TE equals to an average of $2.8 billion for the whole SE US during the studied period (50 years). As indicated, this value should be interpreted as upper bound estimates of the true economic effect of climate forecasts.

With respect to temperature, this variable also presents positive MEs and they are statistically significant for seasonal forecasts during spring and fall (Model IV). A possible explanation for these results could be that forecasts during fall and spring offer row crop farmers the necessary information to plan the implementation of multiple cropping during the year. Livestock producers could also benefit from this seasonal forecast by helping them in the assessment of the availability of pastures for their animals. The increase on TE from seasonal temperature forecasts could be translated as $170 million for the studied period.

## 5. Summary and Conclusion

This paper analyzed the effect of omitting climate variables in the estimation of agricultural production and assessed the value of climate forecasts on technical efficiency (TE). To do so, we implemented an input-oriented stochastic distance frontier model (ISDF) and used the agricultural sector in the Southeast United States as the case of study. We also disaggregated the agricultural sector into its three components (i.e., crops, forestry and livestock) to account for sectoral impact of climate variability on production and TE.

We found that the estimation of an ISDF is indeed influenced by variations in climatic conditions and that the impacts of climatic variability are location and subsector specific. The results showed significant changes in the magnitude and spread of TE scores, output and input elasticities, and returns to scale, when climatic conditions are included in ISDF. The ranking of states based on productivity and TE is also affected by climate. Specifically, after controlling for climatic conditions, states with relatively unfavorable climatic conditions are able to gain in terms of economic performance.

Information on seasonal rainfall and temperature forecasts showed a positive effect on improving the economic performance of agriculture. However, ENSO-based forecasts offered no significant economic value to this regional sector. Previous research suggests that the use of discrete-type of forecasts missed important intrinsic climatic features such as the duration and strength of the event (Che and McCarl 2000). In addition, ENSO displays a greater effect in coastal areas, so the impact of the ENSO signal could be diluted in a regional study, like this one, where most of the cultivated land is located inlands. It is worth noticing, that some local-level studies conducted in FL and GA have found value for ENSO-based forecasts (e.g., Cabrera et al. 2009; Hansen 2002; Jones et al. 2000). Conversely, a quantitative-type of forecast, such as seasonal rainfall and temperature seem to offer a greater value to agricultural production. This type of information is easier for farmers and producers to understand, and appeared to better contribute to the production decision making-process.

The results presented in this sudty have some policy and managerial implications. First, the ISDF analysis presented here depicts the best combination of inputs which achieve the maximum level of outputs. Thus, if climatic variations significantly affect productivity and TE, but they are not taken into account, recommendations seeking improvements in TE may not be the most adequate ones. In addition, regional comparisons based on the productivity or TE may also be inadequate if climatic variability is ignored. This may diminish the effectiveness of rural development programs established to improve regional agricultural performance or competitiveness.

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Table 1. Descriptive statistics. All values in 2009 thousands of US dollars.

| Variables | ALABAMA | | FLORIDA | | GEORGIA | | NORTH CAROLINA | | SOUTH CAROLINA | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | S.D. | Mean | S.D. | Mean | S.D. | Mean | S.D. | Mean | S.D. |
| *Output* | | | | | | | | | | |
| Agriculture | 1,146,310 | 401,840 | 5,387,197 | 901,660 | 2,363,725 | 505,307 | 3,810,237 | 938,757 | 1,143,445 | 400,124 |
| Forestry | 525,079 | 189,431 | 334,326 | 108,944 | 601,002 | 228,677 | 1,059,255 | 463,597 | 229,678 | 57,113 |
| Livestock | 2,524,460 | 331,820 | 1,635,639 | 355,618 | 3,224,505 | 403,140 | 3,430,060 | 808,096 | 797,698 | 107,957 |
| *Inputs* | | | | | | | | | | |
| Capital | 429,672 | 116,280 | 432,492 | 154,853 | 527,376 | 136,085 | 759,646 | 263,422 | 274,501 | 89,263 |
| Labor | 466,658 | 112,139 | 1,281,094 | 239,627 | 824,989 | 248,916 | 1,402,595 | 289,789 | 376,667 | 131,753 |
| Material | 2,213,998 | 298,178 | 2,886,599 | 451,025 | 3,221,728 | 472,240 | 3,605,742 | 667,901 | 1,035,206 | 163,601 |

Table 2. Maximum likelihood estimates of the translog ISDF with and without climate variables. SE US agriculture from 1960 to 2009

| Variables^ | With Climate Variables | Without Climate Variables | Variables | With Climate Variables | Without Climate Variables |
|---|---|---|---|---|---|
| C | -0.490*** | -0.591*** | F*R | 0.081 | -- |
| A | -0.361** | -0.340** | F*T | -0.043* | -- |
| F | -0.252** | -0.263** | AL*R*C | 0.341*** | -- |
| $C^2$ | -0.074*** | -0.065*** | FL*R*C | 0.284*** | -- |
| $A^2$ | -0.062*** | -0.081*** | GA*R*C | 0.292** | -- |
| $F^2$ | -0.053*** | -0.032*** | NC*R*C | 0.311* | -- |
| K | 0.505*** | 0.333*** | SC*R*C | 0.314* | -- |
| L | 0.225*** | 0.181** | AL*R*A | 0.111** | -- |
| R | 0.251** | -- | FL*R*A | 0.083* | -- |
| T | -0.084 | -- | GA*R*A | 0.084* | -- |
| $K^2$ | 0.091* | 0.011* | NC*R*A | 0.07* | -- |
| $L^2$ | 0.001 | 0.001 | SC*R*A | 0.006** | -- |
| $R^2$ | 0.005** | -- | AL*R*F | 0.022 | -- |
| $T^2$ | 0.001 | -- | FL*R*F | 0.009 | -- |
| C*A | -0.042* | -0.037* | GA*R*F | 0.012* | -- |
| C*F | -0.089* | -0.079* | NC*R*F | 0.028* | -- |
| A*F | -0.009* | -0.011 | SC*R*F | 0.031** | -- |
| K*L | 0.021* | 0.073** | AL*T*C | -0.087 | -- |
| K*R | 0.008* | -- | FL*T*C | -0.073 | -- |
| K*T | 0.006 | -- | GA*T*C | -0.082 | -- |
| L*R | 0.005* | -- | NC*T*C | 0.121* | -- |
| L*T | 0.007 | -- | SC*T*C | 0.111* | -- |
| R*T | 0.001 | 0.001 | AL*T*A | -0.062* | -- |
| C*P | 0.034** | 0.062** | FL*T*A | -0.071* | -- |
| C*K | 0.065 | 0.033 | GA*T*A | -0.059* | -- |
| C*L | 0.077** | 0.067** | NC*T*A | -0.033 | -- |
| C*R | 0.024** | -- | SC*T*A | -0.041 | -- |
| C*T | 0.083 | -- | AL*T*F | -0.038* | -- |
| A*P | 0.011** | 0.023** | FL*T*F | -0.031* | -- |
| A*K | 0.002* | 0.008* | GA*T*F | -0.042* | -- |
| A*L | 0.043* | 0.037* | NC*T*F | -0.048* | -- |
| A*R | 0.111* | -- | SC*T*F | 0.051** | -- |
| A*T | -0.062* | -- | TREND | 0.016*** | 0.021*** |
| F*K | 0.026* | 0.056* | CONSTANT | -3.119*** | -4.238*** |
| F*L | 0.001 | 0.001 | | | |
| $\lambda = \sigma_{u/}\ \sigma_v$ | 1.034*** | 1.084*** | | | |
| Log. Likelihood | -121,368 | -103,649 | | | |
| Mean TE | 0.81 | 0.76 | | | |

*$P < 0.10$; **$P < 0.05$; ***$P < 0.01$

^ C: Crop, A: Livestock, F: Forestry, P: Purchased Inputs, K: Capital, L: Labor, R: Precipitation, T: Temperature, AL: Alabama, FL: Florida, GA: Georgia, NC: North Carolina and SC: South Carolina.

Table 3. Climate elasticities by sector

| | Region | AL | FL | GA | NC | SC |
|---|---|---|---|---|---|---|
| | | | | WHOLE SECTOR | | |
| **Precipitation** | 0.25** | -- | -- | -- | -- | -- |
| **Temperature** | -0.08 | -- | -- | -- | -- | -- |
| | | | | CROPS | | |
| **Precipitation** | 0.32** | 0.34*** | 0.28** | 0.29** | 0.31** | 0.31** |
| **Temperature** | 0.08 | -0.09 | -0.07 | -0.08 | 0.12** | 0.11* |
| | | | | LIVESTOCK | | |
| **Precipitation** | 0.11** | 0.11** | 0.08* | 0.08* | 0.07* | 0.06* |
| **Temperature** | -0.06 | -0.06 | -0.07 | -0.06 | -0.03 | -0.04 |
| | | | | FORESTRY | | |
| **Precipitation** | 0.08 | 0.02 | 0.01 | 0.01* | 0.03* | 0.03** |
| **Temperature** | -0.04* | -0.04* | -0.03* | -0.04* | -0.05* | -0.05* |

*$P < 0.10$; **$P < 0.05$; ***$P < 0.01$

Table 4. Marginal effects of climate forecasts on TE

| Variables | Model I | Model II | Model III | Model IV |
|---|---|---|---|---|
| ENSO | -- | 0.008 | -- | -- |
| El Niño | 0.013 | -- | -- | -- |
| La Niña | 0.011 | -- | -- | -- |
| Annual Rainfall | -- | -- | 0.066* | -- |
| Summer Rainfall | -- | -- | -- | 0.072* |
| Spring Rainfall | -- | -- | -- | 0.083** |
| Fall Rainfall | -- | -- | -- | 0.012 |
| Winter Rainfall | -- | -- | -- | 0.001 |
| Average Max. Temp. | -- | -- | 0.045 | -- |
| Summer Max Temp. | -- | -- | -- | 0.008 |
| Spring Max Temp. | -- | -- | -- | 0.006* |
| Fall Max Temp | | | | 0.005* |
| Winter Max Temp | | | | 0.003 |

*$P < 0.10$; **$P < 0.05$; ***$P < 0.01$

Figure 1. Effect of climate variability on land productivity by subsector

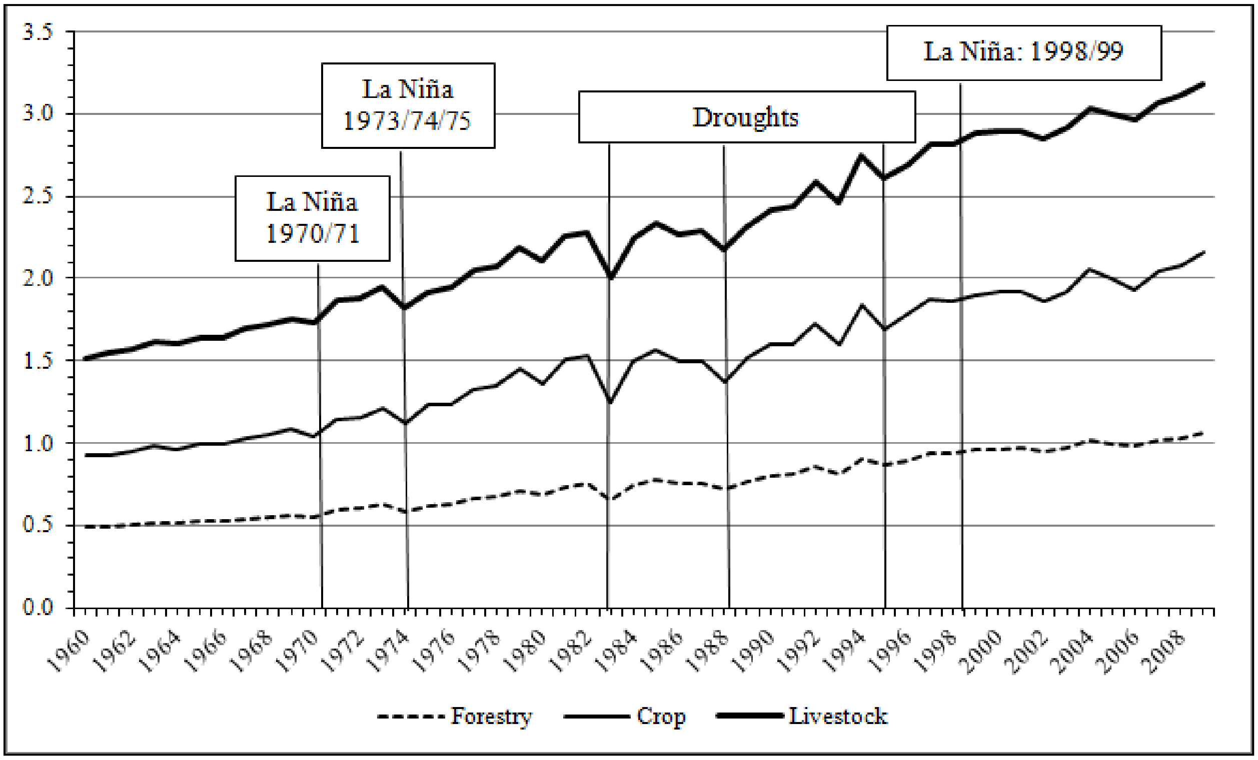

Figure 2. Kernel distributions of TE estimate with and without climate variables.