Assessing the value of climate information in agriculture, forestry and livestock using a Stochastic Production Frontier Approach

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Introduction

- The value of climate forecasts can be defined and evaluated in different ways.
- Most studies have focused on the potential effect of climate information on the **financial performance** (revenues, profit, etc.) of a farm.
- However, the use of **economic performance** measures, such as productivity, input substitution, inefficiency, etc., have received much less attention.

Introduction

- Farm **productivity** and **efficiency** are important from a **practical** as well as from a **policy** point of view.
- **Farmers** could use this information to improve their performance.
- **Policymakers** could use this knowledge to identify and target public interventions to improve farm productivity and farm income.

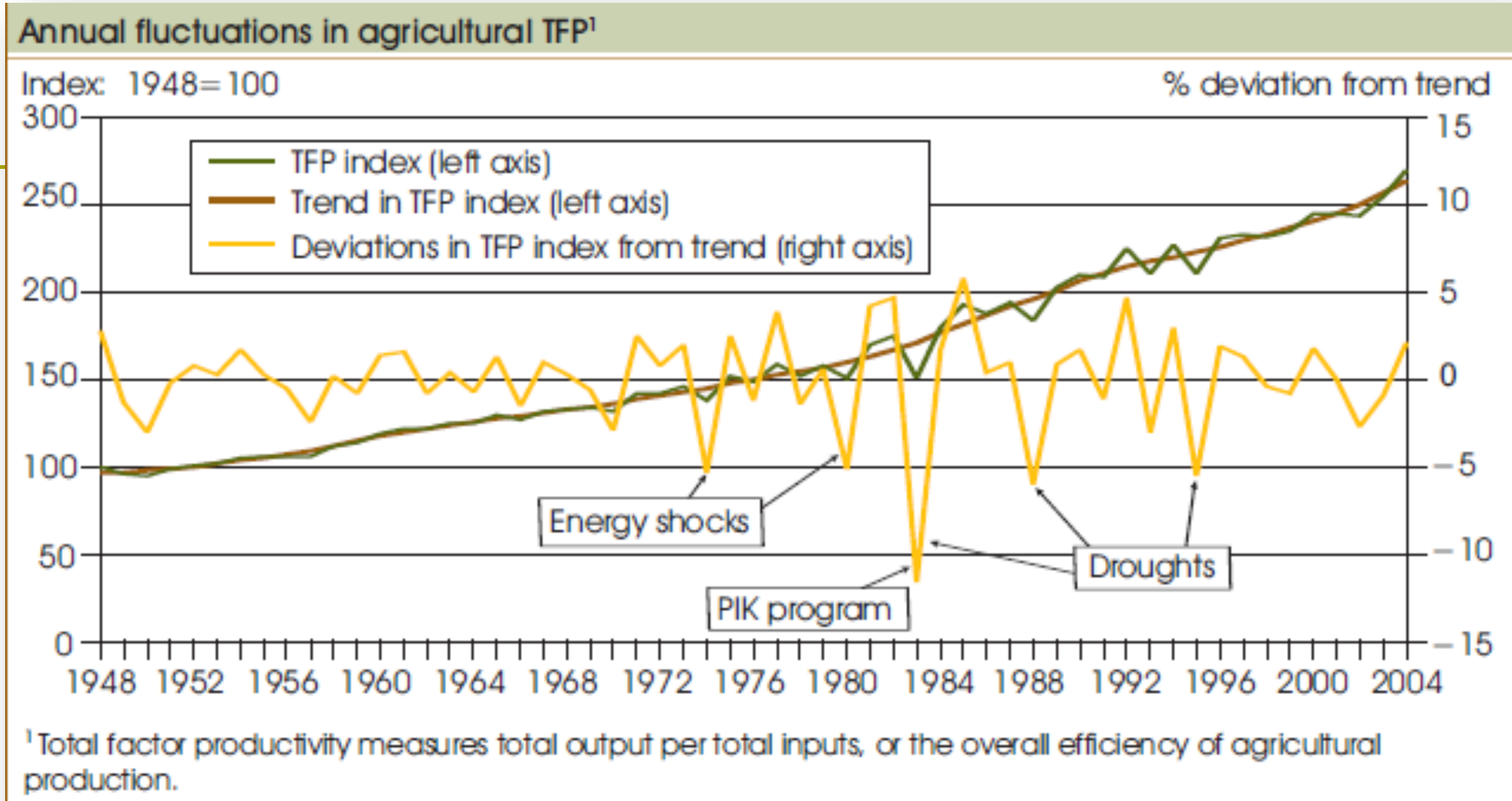
Introduction

- A review of the agricultural **productivity** and **efficiency** literature reports few studies include climate in their models (Bravo-Ureta et al., 2007)
- Researchers have omitted climate from their empirical models by arguing that such variability is beyond the control of the producers; therefore, it should be treated as a random variable.
- However, climate variability is not a pure random variable (Demir and Mahmud, 2002).

Introduction

- Historical differences in climatic conditions are known with a reasonable degree of certainty.
- Advances in climate forecasting and the ability to predict climate fluctuations provide opportunities to improve farm management.
- Thus, omission of climate variables may lead to an inadequate representation of the production model.

Historical Evidence



Main drops in productivity

1) Global energy crises of 1974 and 1979,
2) **Serious droughts** in 1983, 1988 and 1995, and
3) Agricultural policy intervention (in 1983 the Federal Government encouraged farmers -using the Payment-In-Kind, or PIK program- to reduce crop production to lower accumulated government-held commodity surpluses).

Objectives

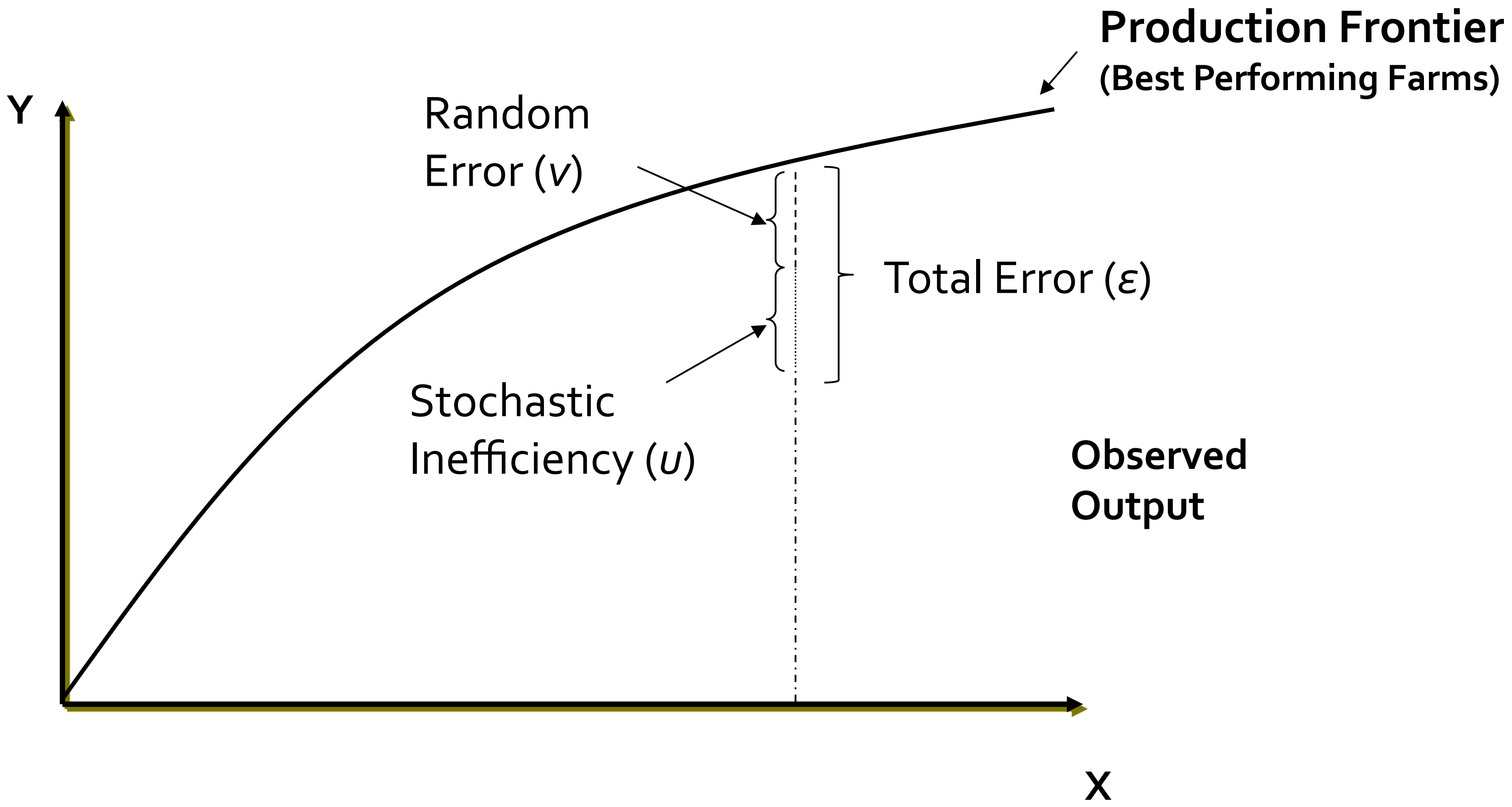
The overall purpose of this study are:

- To evaluate the effect of climate biased in the estimation of **Agricultural Productivity** and **Efficiency** using aggregate data and the Southeast US as a case of study.
- To measure the effect (elasticity) of climatic variability on the Southeast US **Agricultural Productivity** and its three sector **(Crop, Forestry and Livestock)**
- To measure the **value of climate information** on the **efficiency** of US agriculture.

Methodology

- We implement the **Stochastic Production Frontier (SPF)** analysis, which is based on an econometric (parametric) specification of a production frontier.
- **Frontier function** provides the shape of the technology for the best performing decision making units.
- The frontier approach allows us to evaluate the effective gap between **current farm productivity** and the **potential productivity** level given the existing technology in a particular region.
- SPF is designed to incorporate stochastic disturbances into the model.

Stochastic Production Frontier: A Graphical Representation



Empirical model

To estimate the production frontier we use two alternative methods.
•**First** we estimate an aggregate model (**SPF**) which uses the total agricultural value-added for each State as the output.

•**Second** we re-estimate the model using a multi-output approach (IDF = Input Distance Function) in which total agricultural output is disaggregated in its three components: agriculture, forestry and livestock.
These models can be represented as follows:

$$LnY_i = \beta_0 + \sum_{j=1}^{m} \beta_j LnX_{ji} + 0.5 \sum_{j=1}^{m} \sum_{k=1}^{m} \beta_{jk} LnX_{ji} \ln X_{ki} + v_i - u_i$$

SPF

$$-\ln x_{1i} = \alpha_0^I + \sum_{m}^{M} \alpha_m^I \ln y_{mi} + 0.5 \sum_{m_l}^{M} \sum_{m_k}^{M} \beta_m^I \ln y_{m_l i} \ln y_{m_k i} + \sum_{n}^{N-1} \beta_n^I \ln\left(\frac{x_{ni}}{x_1 i}\right) +$$

$$0.5 \sum_{n_l}^{N-1} \sum_{n_k}^{N-1} \beta_n^I \ln\left(\frac{x_{n_l i}}{x_{1i}}\right) \ln\left(\frac{x_{n_k i}}{x_{1i}}\right) + \sum_{n}^{N-1} \sum_{m}^{M} \delta_{nm}^I \ln\frac{x_{ni}}{x_{1i}} \ln y_{mi} + D_s + v_i^I - u_i^I;$$

IDF

Empirical model

In these two model the error term is composed of two terms, *v* (stochastic shocks) and *u* which captures the technical inefficiency (TI) relative to the stochastic frontier.

Technical efficiency can be then estimated as:

$$\mathrm{TE}_i = \exp\left(-\mathrm{E}\left[u_i \middle| \varepsilon_i\right]\right).$$

Empirical model

To evaluate the effect of climate information on TE, we regress the TI scores against selected climatic indexes

$$u_i = \alpha_0 + \sum_{n=1}^{m} \alpha_n I_{ni} + e_i$$

where u_i is the inefficiency effect, I_{ni} is a vector of climate information variables, the α_s are unknown parameters and e_i is random noise.

Variables

Outputs:

y1 = Aggregate agricultural value-added (US$) → **SPF**

y2 = Crop value-added (US$)

y3 = Forestry value-added (US$) → **IDF**

y4 = Livestock value-added (US$)

Inputs:

x1 = Cultivated land (Mz)

x2 = Labor (US$)

x3 = Capital (worker days)

x4 = Set of climate variables:

- ENSO phase
- Predicted seasonal rainfall
- Predicted seasonal TEMP

D = Regional dummies (5 States)

Inefficiency:

Vector of alternative climate information variables including:

- **ENSO phase**
- Predicted seasonal rainfall
- Predicted seasonal TEMP

Data

- **Production** and **Input Use** data were collected from USDA-ERS.
- **Climate** data come from South East Regional Climate Center
- We construct a state-by-year panel, covering 5 contiguous states in the SE US over 50 years from 1960-2010 inclusive.
- Ball et al (2001) was follow to account for differences in quality and value of inputs and outputs.

Results - Outline

- Linkage Between Production and Climate Conditions (Correlation analysis)
- Climate Biased (SPF)
- Climate Elasticity by Sector (IDF)
- Value of Climate Information (Inefficiency Model)

Linkage Between Land Productivity and Seasonal Precipitation

Correlations Analysis (1960-2010)

State	Annual	Spring	Summer	Fall	Winter
Region	0.130	0.082	0.493	-0.146	-0.232
AL	0.033	0.054	0.108	-0.061	-0.029
FL	0.135	-0.065	0.110	0.153	0.088
GA	0.052	-0.058	0.226	-0.005	-0.024
NC	0.057	0.004	0.197	-0.056	-0.056
SC	0.029	0.040	0.224	-0.118	-0.166

- **+** correlation between **Annual** and **Summer PP** and Productivity
- Spring has a positive correlation but in **FL** and **GA** (FL and GA are big in vegetable production which is affected by wet winters)
- **Fall** and **Winter PP** have a **(–)** correlation but in **FL**

Linkage Between Land Productivity and Seasonal temperature

Correlations Analysis (1960-2010)

State	Annual	Spring	Summer	Fall	Winter
Region	0.179	0.048	0.030	0.165	0.211
AL	0.433	0.017	0.178	0.130	0.449
FL	0.542	0.125	0.399	0.267	0.443
GA	0.314	-0.033	0.028	0.106	0.413
NC	0.011	-0.175	-0.108	0.053	0.125
SC	0.027	-0.157	-0.123	0.166	0.190

- Big **sub-regional variability**, Northern states behave differently than Southern States
- **+** correlation between **Annual**, **Fall** and **Winter** and **Productivity**
- **Spring** and **Summer** display **mixed results**

Climate biases - SPF

- We estimated 4 alternative models:
  - **Model 1** does not include any climatic variables.
  - **Model 2** includes climatic variables only in the inefficiency function with neutral effects.
  - **Model 3** is a non-neutral specification with climatic variables in the inefficiency function.
  - **Model 4** is a non-neutral specification with climatic variables in the production frontier and the inefficiency function (**Full specification**).

Climate biases - SPF

- Three separate null hypotheses were tested using the likelihood ratio test (LRT):
  - The null hypothesis that all production coefficients associated with the climatic variables are zero is strongly rejected.
  - The null hypothesis that all efficiency coefficients associated with the climatic variables are zero is strongly rejected.
  - Based on a LRT Model 4 (full representation) is the best representation for the data .

Climate biases - Elasticities

- It tells how much the level of production changes when we change one of the parameter in the SPF

Table 1. Elasticities of mean output and returns to scale with and without environmental variables inputs

Variables	Without Environmental Variables	With Environmental Variables
Land	0.20	0.68
Labor	0.54	0.35
Capital	0.72	0.12
Return to Scale	*1.46*	*1.15*

- The introduction of climate variable significantly affects the elasticity of inputs.
- RTS decreases by including climate

Climate biases - Ranking by level of productivity

USDA/ERS Official Ranking

State	Rank in 2004
California	1
Florida	2
Iowa	3
Illinois	4
Delaware	5
Idaho	6
Indiana	7
Rhode Island	8
Georgia	9
Massachusetts	10
Arizona	11
Arkansas	12
North Carolina	13
Connecticut	14
Oregon	15
New Jersey	16
Maryland	17
Minnesota	18
Ohio	19
Alabama	20
Nebraska	21
Maine	22
Washington	23
New York	24
Mississippi	25
South Carolina	26

Without Including Climate variability

State	Ranking
Florida	1
Georgia	2
N. Carolina	3
Alabama	4
S. Carolina	5

This model present same results than in the official raking

Including Climate Variability

State	Ranking
Florida	1
Georgia	2
N. Carolina	3
S. Carolina	4
Alabama	5

Rankings are different which may affect <u>national</u> *<u>agricultural policies</u>*

Climate Elasticity by Sector - IDF

	Region	AL	FL	GA	NC	SC
			WHOLE SECTOR			
El Niño	0.11	0.07	0.08	**0.08**	0.11	0.09
La Niña	-0.08	**-0.05**	**-0.06**	**-0.04**	-0.09	-0.08
			CROPS			
El Niño	0.15	**0.10**	**0.08**	**0.09**	**0.15**	**0.14**
La Niña	**-0.09**	**-0.09**	**-0.07**	**-0.08**	**-0.12**	**-0.11**
			FORESTRY			
El Niño	0.06	0.05	0.04	**0.06**	**0.08**	**0.07**
La Niña	-0.04	-0.04	-0.03	**-0.04**	**-0.05**	**-0.05**
			LIVESTOCK			
El Niño	0.09	**0.07**	**0.08**	**0.08**	0.07	0.06
La Niña	**-0.06**	**-0.06**	**-0.07**	**-0.06**	-0.03	-0.04

Value in **BOLD** are statistically significant, $p<0.1$

Climate Elasticity by Sector - IDF

- Summary
  - Regional Climate variability (5 states together) shows <u>NO</u> significant impact on production. However, State level climate variability <u>DOES</u>. This difference could be explain by the <u>within region variability</u>.
  - The impact of ENSO on the aggregate model display mixed results.
  - Crops have the highest elasticities followed by livestock and forestry.
  - The Northern region in the SE-US (SC & NC) displays the higher impact of climate variability of crop production.
  - Climate variability has the highest impact on livestock production in the southern regions (heat shock, pasture production, etc.)

Value of climate information

- We estimated 5 alternative models
  - **Model 1**: Knowing that the cropping season is either **El Niño** or **La Niña**
  - **Model 2**: Knowing that the cropping season is not normal (**Neutral**)
  - **Model 3**: Knowing the predicted annual **rainfall** and **average MAX TEMP**
  - **Model 4**: Knowing the predicted seasonal **rainfall** and **MAX TEMP**
  - **Model 5**: Knowing that the cropping season is not normal (neutral) and the predicted seasonal **rainfall** and **MAX TEMP**

Value of climate information

	El Niño	La Niña	Enso	Annual Rainfall	Summer Rainfall	Spring Rainfall	Average Max T°	Summer Max T°	Spring Max T°
Model 1	+	-							
Model 2			+						
Model 3				+***			+		
Model 4					+***	+***		+*	+
Model 5			+	+***			+		

***, p>0.01; **, p>0.05, *, p>0.1

Conclusions

- Productivity and efficiency studies on agriculture using regional data tend to ignore environmental effects, assuming that such variables are random.
- But it is found that agricultural production is under the influence of variations of climatic variables that are location-specific.
- If these environmental variables are ignored, it may cause improper specification of the TIE in models of agricultural production.
- Results shows that climatic variables affect directly and indirectly through interactions, mean output elasticities, economies to scale and technical efficiencies.

Conclusions

- When the climatic conditions are taken into account, States at locations with relatively unfavorable environmental conditions, are able to gain in terms of TE.
- Significant changes are observed in the size and spread of TE scores when climatic variables are incorporated in the production and inefficiency functions.
- The effect of **Climate Information** on agricultural efficiency present mixed results.
  - Non-significant results were found when **ENSO** was used as the climate indexes.
  - However information on **seasonal rainfall** and **Max Temp** display a positive and significant effect on reducing the inefficiency in this sector.

Work in Progress

- Re estimate the models using a new dataset (1960 to 2010)
- Re estimate the TE model using alternative methodology
  - Alvarez (2007) regional model
- Estimate the elasticity of climate information on TE.
  - Wang (2002) model
- Conduct a sensitivity analysis of the impact of seasonal rainfall and max temp forecasts on TE.

Deliverables

- Regional economic values for climate prediction.
- Transferable process for assessing value ($) of weather and climate predictions to sectors.
- Method for estimating future value based on improved predictions.
- Presentation at professional conferences, publication of research, and final report.

Presentations

- Preliminary results have been presented in the following professional conferences:
  - 35th NOAA’s annual Climate Diagnostics and Prediction Workshop (CDPW) Raleigh, NC, Oct 4-7, **2010**.
  - Southern Agricultural Economics Association annual Meeting, Corpus Christi, TX, February 5-8, **2011**.
  - 9th NOAA's annual Climate Prediction Application Science (CPAS) Workshop, Des Moines, IA, March 1-4, **2011.**
  - 2nd Climate Information for Managing Risks Symposium, Orlando, FL, May 24-27, **2011**.
  - 36th NOAA’s annual Climate Diagnostics and Prediction Workshop (CDPW) Fort Worth, TX, Oct 3-6, **2011**.

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