# ESSAYS ON THE EFFECT OF CLIMATE CHANGE

# ON AGRICULTURE AND FORESTRY

A Dissertation

by

XAVIER ALFREDO VILLAVICENCIO CORDOVA

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

May 2010

Major Subject: Agricultural Economics

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# ABSTRACT

Essays on the Effect of Climate Change on Agriculture

and Forestry. (May 2010)

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In this dissertation, I study the effects of climate change on agricultural total factor productivity and crop yields and their variability. In addition, an examination was conducted on the value of select climate change adaptation strategies in forestry. Across the study, the climate change scenarios analyzed were based on the 2007 Intergovernmental Panel on Climate Change Assessment Report.

Climate change impacts on the returns to research investments were examined extending the work of Huffman and Evenson (2006), incorporating climatic effects. The conjecture is that the rate of return of agricultural research is falling due to altered resource allocations and unfavorable weather conditions, arising from the early onset of climate change. This work was done using a panel model of Agricultural Total Factor Productivity (TFP) for the forty-eight contiguous states over 1970–1999. Climatic variables such as temperature and amount and intensity of precipitation were added into the model. The main results are (1) climate change affects research productivity, varying

by region; (2) this effect is generally negative; (3) additional investments are needed to achieve pre-climate change TFP rates of growth; and (4) the predicted investment increases are on the order of 18%.

The second inquiry involved the impact of historical climatic conditions on the statistical distributions of crop yields through mean and variability. This was done statistically, using historical yields for several crops in the US, and climate variables, with annual observations from 1960 to 2007. The estimation shows that climate change is having an effect on the first two moments of the distribution, concluding that crop yield distributions are not stationary. The implication is that risk analysis must consider means and volatility measures that depend on future climatic conditions. The analysis shows that future mean yields will increase, but volatility will also be greater for the studied crops. These results have strong implication for future crop insurance decisions.

Finally, an examination was done on the value of select forestry adaptation strategies in the face of climate change. This work is motivated by the known fact that forestry sector is already heavily adapted to changing climatic conditions. Using the Forestry and Agriculture Sector Optimization Model for the United States (FASOM), I found that rotation age is the most effective adaptation strategy being worth about 60 billion dollars, while changes in species and management intensity are worth about 1.5 billion, and land use change between forestry to agriculture is worth about 200,000.

# DEDICATION

A Isabel y Jessica, mi fuente inagotable de alegría.

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Thanks to my friends, colleagues, and the department faculty and staff for making my aggie experience a memorable one. From all the universities I have studied before, and from all the available programs to take doctoral studies, the Ph.D. program in agricultural economics at Texas A&M University is the best choice I have taken in my life. When I am in College Station I really feel that I am at home, the best place on earth, the place where I was happier than ever the day my daughter Isabel was born. All the moments, places and people of this town will be in my heart forever.

Thanks to my parents for their moral and economic support. Thanks to all the great people who gave me a hand during the hard times, when I felt hopeless; I will never forget what you did for me. Finally, I want to thank specially to my wife Jessica, for all the effort, all the patience, and all the love. Thank you for being there, laughing and crying with me. Without your support, I would not have been able to make it.

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# 1. INTRODUCTION

Climate change is beginning to have observable effects on global and regional temperatures and precipitation in terms of both average levels and variability. In turn as a consequence it is having effects on agricultural inputs and outputs.

Observations and forecasts as developed in the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (2007) include a number of potential effects that would affect the agricultural activities. There is a high consensus over some significant facts, which include:

- Since 1750 Global atmospheric concentrations of GHG (greenhouse gases) carbon dioxide, methane and nitrous oxide have increased markedly as a result of human activities and now far exceed pre-industrial values as determined by measurements from ice core evidence over many thousands of years.
- The global increases in carbon dioxide concentration are due primarily to fossil fuel use and land use change, while much of the methane and nitrous oxide are due to agriculture.
- The understanding of anthropogenic warming and cooling influences on climate has improved in the last years, leading to very high confidence that the global average net effect of human activities since 1750 has been one of warming. Namely the IPCC states “Most of the observed increase in global average temperatures since the mid-20th century is very likely (>90%) due to the observed increase in anthropogenic greenhouse gas concentrations”.

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This dissertation follows the style of the *American Journal of Agricultural Economics*.

- At continental, regional and ocean basin scales, long-term changes in climate have been observed. These include changes in
    - arctic temperatures and ice thickness,
    - precipitation amounts and the quantity coming from intense events,
    - ocean salinity,
    - wind patterns
    - aspects of extreme weather including droughts, heavy precipitation, heat waves and the intensity of tropical cyclones.

Such effects are forecasted to become more severe into the future. Namely the projections of virtually all climate models predict that increasing emissions will cause the following effects

- More intense heat waves that are more frequent and longer lasting
- A global precipitation increase, but with general decreases in the subtropics
- Increases in precipitation intensity when it rains but with longer periods between rainfall events
- A tendency for drying of mid-continental areas during summer, meaning a greater risk of droughts in those regions
- A projected sea level rise by 2099 of 0.18 to 0.59 meters plus additional rise due to Greenland and Antarctica ice melting.
- An increase in hurricane peak wind intensities accompanied by an increase in the numbers of the most intense hurricanes
- An incidence of fewer mid-latitude storms with a poleward shift of storm tracks
- A change in the Atlantic Ocean Meridional Overturning Circulation (MOC) – with the Gulf Stream slowing down

These projections imply that past probability distributions are likely not directly usable as distributions of future variability and also increases the need for risk management.

This dissertation will examine, in three essays, the effects of climate change on several agricultural related issues in a US context, including crop yields, rates of yield improvement and adaptation possibilities. In Sections 2 and 3, this will be done using econometric investigations to examine the dependency between crop yield variability and factor productivity with climate attributes. These attributes will include both means and items describing the distribution of temperature and precipitation.

Adaptation possibilities will be examined in Section 4 given such changes using a partial equilibrium model for the U.S. forestry sector in which the new environmental conditions are taken into account. The projections of future effects on temperature and precipitation variability will be made based on scenarios from the IPCC reports.

The objectives of this work are summarized as follows:

- Develop several methods to address econometric estimations for climate change economics when dealing with non stationary variables.
- Identify the determinants of agricultural factor productivity and calculate the required amounts of additional public investments to overcome the effects of climate change.
- Determine whether climate change has altered the historical distribution of agricultural yields, affecting the crop mean yields and its volatility. Besides, present a methodology to simulate the effects of future climate on crop's yield distributions.

- Establish the welfare value of different adaptation strategies in the forestry sector. Also, improve the existing forestry and agricultural sectorial model, in order to have a better tool for policy evaluation when facing decisions of climate change adaptation with limited resources.

# 2. CLIMATE CHANGE INFLUENCES ON AGRICULTURAL RESEARCH PRODUCTIVITY[1]

## 2.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) and others indicate that the elevated carbon dioxide and associated climate change will influence agricultural productivity (IPCC, 2007). An associated but to our knowledge unstudied factor is effect of climate change and forcing agents on productivity growth. Economists have long evaluated the returns to agricultural research (Huffman and Evenson, 2006b; Pardey *et al*., 2007) and in this study we examine the effects of climate change on agricultural productivity growth.

Recently Pardey *et al*. (2007) argued that the rate of return as measured through a total factor productivity approach is falling. They speculate that this may be due to altered resource allocations and unfavorable weather conditions. One explanation for the unfavorable weather component may be the early onset of climate change and if this persists is both another manifestation of societal sensitivity to climate change and an area where adaptation investments may be needed as climate change proceeds (McCarl, 2007).

In this study we first econometrically investigate how temperature and various aspects of precipitation affect agricultural total factor productivity and then given those

[1] This section is an extended version of: McCarl, B.A., X. Villavicencio, and X. Wu. 2009. “The Effect of Climate Change over Agricultural Factor Productivity: Some Econometric Considerations”. Presented in the Agricultural and Applied Economics Association 2009 Annual Meeting at Milwaukee, WI. Document available online at `http://purl.umn.edu/49452.`

results project the consequences of selected IPCC climate change scenarios and the amount of added investment needed to compensate for the research productivity loss. In particular, we investigate the following hypotheses:

- Climatic conditions alter agricultural factor productivity returns of research investments.
- Projected climate change alters these returns.
- Higher levels of research investment will be needed under climate change in order to maintain the current rates of return of agricultural research (a measure of climate change adaptation costs).

## 2.2 Public Investment in Agricultural Research

Agricultural total factor productivity (TFP) can be defined as the ability or efficiency to produce agricultural outputs with a given amount of inputs such as labor, capital and materials (Huffman and Evenson, 2006b). It is usually measured as the ratio of product to one unit of equivalent input. Many studies have found that agricultural productivity is enhanced by public and/or private investments in agricultural research and development (Huffman and Just, 1994; Alston, Craig and Pardey, 1998; Huffman and Evenson, 2006b). Since climate is another factor of production and findings such as those in McCarl, Villavicencio and Wu (2007) show that climate conditions can alter (positively or negatively) productivity it is not a great leap to hypothesize that TFP will be altered by climate. Furthermore since recent evidence in the IPCC WGI report shows a changing climate during the recent past this may be consistent with the observations of Pardey *et al*. (2007).

A number of studies have examined how research and development investments affect agricultural productivity. Huffman and Just (1994) used state productivity data for 1948–1982 to show that federal formula funding has a larger impact on agricultural productivity than competitive grant funding, owing to the high transaction costs associated with external competitive grant programs.

Extending that work Alston, Craig and Pardey (1998) alter the assumptions regarding the way the stock of knowledge affects factor productivity over time. In particular, using US agriculture productivity data and a more flexible model, they found that impact of R&D on productivity was exerted over a much longer time period than assumed in previous studies. They estimated that the estimated annual marginal rate of return to public agricultural R&D in the United States was less than 10 percent, much smaller than the rates of return typically reported in previous studies.

Recently, Huffman and Evenson (2006a) investigated the impacts of public agricultural research capital, private agricultural research capital, and public agricultural extension capital on agricultural TFP using U.S. state level from 1970 through 1999. They found that both public agricultural research and agricultural extension have positive, significant impacts on state agricultural TFP. This study extends their work, exploring how climate conditions affect of the TFP contribution of agricultural research.

## 2.3 Data

In the estimation herein we use same data set as employed in Huffman and Evenson (2006a) augmented with state level climate data. The Huffman and Evenson data set consists of annual observations on research investments and productivity for the 48 contiguous United States spanning from 1970 to 1999, encompassing 1,440 observations[2]. These data therein include observations on

- State agricultural total factor productivity (TFP),
- Public agricultural research capital (RPUB), expressed in 1984 dollars,
- Share of the public budget coming from federal formula funds (SFF), and federal grants and contracts (GR),
- Stock of public extension capital (EXT),
- Public agricultural research spill-in stock[3] (RPUBSPILL),
- Private agricultural research capital (RPRI), and
- Regional dummies which group the states according to the Farm Production regions defined by the USDA Economic Research Service (ERS).

We also assembled state-level climate data motivated by the findings in IPCC 2007 and the climate variables used in similar studies. In particular the IPCC reports hotter conditions and altered amounts of precipitation so we drew data on temperature in degrees Fahrenheit plus precipitation in inches from the National Oceanic and Atmospheric Administration (NOAA) National Climatic Data Center website (as used in previous agricultural studies such as Adams *et al*., 1999b; Cline, 2007). In addition, we used data on climate variability, precipitation intensity and altered incidence of droughts

[2] The model for this study include the 48 continental US states to have comparable results with Huffman and Evenson's work. The methods used in this section are associated to a panel structure known as TSCS, a relatively "long" structure usually applied to countries of a region/the world, or states/provinces of a country (Baltagi, 2008; Beck and Katz, 1995). A procedure to evaluate the inclusion or not of some provinces or states is not usual in this framework.

[3] The impact on a given state of direct public agricultural research undertaken by other states in an area.

since these are highlighted in the IPCC materials. Summary statistics and definitions for all the variables are reported in Table 1.

### 2.4 The TFP Growth Model

Huffman and Evenson (2006a) - HE consider the following model for agricultural TFP

$$
\begin{aligned}
\ln TFP_{ilt} &= \beta_1 + \beta_2 \ln RPUB_{ilt} + \beta_3[\ln RPUB_{ilt}]SFF_{ilt} + \beta_4[\ln RPUB_{ilt}](SFF_{ilt})^2 \\
&\quad + \beta_5[\ln RPUB_{ilt}]GR_{ilt} + \beta_6[\ln RPUB_{ilt}](GR_{ilt})^2 + \beta_7 RPUBSPILL_{ilt} \\
&\quad + \beta_8 EXT_{ilt} + \beta_9 \ln RPRI_{ilt} + \beta_{10} trend + \delta_l D_l + u_{ilt}
\end{aligned} \tag{1}
$$

where the subscript $i$ and $t$ indicate state and year respectively, and the subscript $l$ represents the Farm production regions mentioned before.

Those regions are: *Northeast, Southeast, Central, North Plains, South Plains, Mountains*, and *Pacific*. The *Central* region is left out of the estimation, as a baseline for comparison with the other ones. Since agricultural research capitals are derived using thirty five years of data, SFF and GR were lagged twelve years, and placed at the mid-point of the total lag length. A linear trend was included in the model to account for the effect of exogenous or non observable technological progress.

This model is expressed in a double-logarithmic functional form such that the estimated coefficient $\beta_i$ represents the elasticity of TFP with respect to variables of interest (RPUBSPILL, EXT, RPRI). The funding shares (SFF and GR) are multiplied with the public agricultural research capital (RPUB) such that the elasticity of TFP with respect to RPUB depends on the funding composition:

$$\partial \ln(TFP) / \partial \ln(RPUB) = \beta_2 + \beta_3 SFF + \beta_4 (SFF)^2 + \beta_5 GR + \beta_6 (GR)^2 . \tag{2}$$

**Table 1. Variable Names, Definitions and Summary Statistics**

| Name | Symbol | Mean (SD) | Description |
|---|---|---|---|
| Total factor productivity | *TFP* | -0.205[a] (0.254) | Total factor productivity for the agricultural sector (Ball, Butault, and Nehring 2002) |
| Public agricultural capital | *RPUB* | 16.129[a] (0.879) | The public agricultural research capital for an originating state. The summation of past research capital investments in agricultural research within a state having an agricultural productivity focus (Huffman, McCunn, and Xu 2006) in 1984 dollars (Huffman and Evenson 2005, pp. 106–07). Capital stock obtained by summing past research expenditures with a two-through thirty-five-year lag and trapezoidal shaped timing weights |
| Budget share from federal formula funds | $SFF1_{t-12}$ | 0.230 (0.112) | The share of the SAES budget from Hatch, Regional Research, McIntire-Stennis, Evans-Allen, and Animal Health (USDA), i.e., formula funds, lagged twelve years |
| Budget share from state government appropriations | $SFF2_{t-12}$ | 0.521 (0.123) | The share of the SAES budget from state government appropriations (USDA), lagged twelve years |
| Budget share from federal formula and state appropriations | $SFF_{t-12}$ | 0.751 (0.132) | The share of the SAES budget from programmatic funding, $SFF1_{t-12} + SFF2_{t-12}$ |
| Budget share from federal grants and contracts | $GR_{t-12}$ | 0.096 (0.076) | The share of the SAES budget from the National Research Initiative, other CSRS funds, USDA contracts, grants and cooperative agreements, and non-USDA federal grants and contracts (USDA), lagged 12 years |
| Public agricultural research capital spillin | *RPUBSPILL* | 17.763[a] (0.567) | The public agricultural research spillin stock for a state, constructed from state agricultural subregion data (see Huffman and Evenson 1993, p. 195) |
| Public extension capital | *EXT* | 1.292[a] (0.976) | A state's stock of public extension, created by summing for a given state the public full-time equivalent staff Years in agriculture and natural resource extension, applying a weight of 0.50 to the current year and then 0.25, 0.125, 0.0625, and 0.031 for the following four years. The units are staff-years per 1,000 farms. |
| Private agricultural capital | *RPRI* | 6.076[a] (0.248) | A state's stock of private patents of agricultural technology. Each state's private agricultural research capital in the national total of agricultural patents awarded to U.S. and foreign inventors for each year (Johnson and Brown) obtained by weighting the number of private patents in crops (excluding fruits and vegetables and horticultural and greenhouse products) and crop services, fruits and vegetables, horticultural and greenhouse products, and livestock and livestock services by a state's sales share in crops (excludes fruits, vegetables, horticultural and greenhouse products), fruits and vegetables, horticultural and greenhouse products and livestock and livestock products, respectively. The annual patent totals are two-through eighteen-year lag using trapezoidal timing weights |

**Table 1 Continued**

| Name | Symbol | Mean (SD) | Description |
|---|---|---|---|
| Regional indicators | *Northeast* | | Dummy variable taking a 1 if state is CT, DE, ME, MD, MA, NH, NJ, NY, PA, RI, or VT |
| | *Southeast* | | Dummy variable taking a 1 if state is AL, FL, GA, KY, NC, SC, TN, VA, or WV |
| | *Central* | | Dummy variable taking a 1 if state is IN, IL, IA, MI, MO, MN, OH, or WI |
| | *North Plains* | | Dummy variable taking a 1 if state is KS, NE, ND, or SD |
| | *South Plains* | | Dummy variable taking a 1 if state is AR, LA, MS, OK, or TX |
| | *Mountains* | | Dummy variable taking a 1 if state is AZ, CO, ID, MT, NV, NM, UT, or WY |
| | *Pacific* | | Dummy variable taking a 1 if state is CA, OR, or WA |
| Precipitation | *Precipitation* | 3.498[a] (0.508) | Total yearly precipitation in inches |
| Temperature | *Temperature* | 3.942[a] (0.146) | Mean annual temperature in °F |
| Precipitation Intensity | *Intensity* | -1.782[a] (0.225) | Ratio of total amount of precipitation from the wettest month with respect to the yearly total. |
| Trend | *Trend* | | Annual time trend |

[a]Numbers reported in natural logarithms.

Similarly, the effect on TFP of a one percentage change in SFF (or GR) is not constant and it can include nonlinear impacts of funding composition:

(3) $$\partial \ln(TFP)/\partial \ln(SFF) = (\beta_3 + 2\beta_4 SFF)\ln RPUB$$

(4) $$\partial \ln(TFP)/\partial \ln(GR) = (\beta_5 + 2\beta_6 GR)\ln RPUB\,.$$

In addition we used a lagged effect structure regarding the manner in which R&D expenditures alter following Huffman, McCunn and Xu (2006). In particular, we assume that the R&D effect follows the following trapezoidal pattern:

- A initial gestation period of two years, during which the effects of research are negligible;
- A second impact period for the next seven years where returns are assumed to be positive and increasing;
- A mature, constant level which lasts six years;
- A constant decline of the impact which eventually reaches zero value after twenty years.

### *2.4.1 Incorporating Climate Effects*

To explore the impacts of climate conditions, we extend the HE model incorporating temperature, rainfall, and precipitation variables as follows:

(5) $$\begin{aligned}\ln TFP_{ilt} &= \beta_1 + \beta_2 \ln RPUB_{ilt} + \beta_3[\ln RPUB_{ilt}]SFF_{ilt} + \beta_4[\ln RPUB_{ilt}](SFF_{ilt})^2\\ &+ \beta_5[\ln RPUB_{ilt}]GR_{ilt} + \beta_6[\ln RPUB_{ilt}](GR_{ilt})^2 + \beta_7 RPUBSPILL_{ilt}\\ &+ \beta_8 EXT_{ilt} + \beta_9 \ln RPRI_{ilt} + \beta_{10} trend + \delta_l\ D_l + \gamma_l\,[\ln Temperature_{ilt}]D_l\\ &+ \beta_{11}\ln Precipitation_{ilt} + \beta_{12}\ln Intensity_{ilt} + u_{ilt}\end{aligned}$$

Where

- Temperature is a regional level measure in degrees Fahrenheit during the growing season and is interacted with a regional dummy variable to allow the model to reflect differentiated effects of temperature in each region because we hypothesize that a higher temperature can be harmful in some regions (the south), while it can be beneficial in others (the north).
- Precipitation is total precipitation measured over the entire year
- Precipitation Intensity is a measure of the intensity of precipitation. It is constructed as the ratio of total precipitation from the month with the highest relative to the amount of annual precipitation (this precipitation intensity measure ranges by construction from 1/12 –when rainfall is uniformly intense during the year– to 1 –when one month receives all of the yearly rain–).

The precipitation and intensity measures were included without regional interactions because we believe that those variables would be more uniformly applicable.[4]

## 2.5 Estimation Approach

The data we had are in the form of a panel with a large number of periods (*T*) and a medium to large number of individuals (*N*). McCarl, Villavicencio and Wu (2008) suggest that time behavior of agricultural output may not be stationary because of climate change. As a consequence, risk analysis and predictions based on historical yield means and variance could be misestimated if we rely on a stationarity assumption. Thus we need to use methods that deal with issues such as non-stationarity, spurious regressions and cointegration. We first test the hypotheses of panel stationarity and

[4] The regression results also suggest no interactions between regional dummies and Precipitation and Intensity.

cointegration. Based on the test results, we then adopt a panel error correction estimator to properly account for the presence of nonstationarity and cointegration issues.

### *2.5.1 Testing for Panel Stationarity and Cointegration*

In a stationary stochastic process the joint probability distribution does not change when shifted in time. As a result, parameters of the variable such as the mean and variance, if they exist, do not change over time (Hamilton, 1994). Granger and Newbold (1974) showed that deterministic and stochastic trends in time series –a feature usually found in non stationary variables– can induce spurious correlation between variables. That means that we can obtain "false" correlations between non stationary variables that are increasing for different reasons and in increments that are uncorrelated (Banerjee *et al*., 1993). A simple approach to correct this problem was to include into the estimated model a linear trend as an explanatory variable. However, spurious correlation can still be present after controlling for a linear time trend. Phillips (1986) stated that the *t*-statistic for the time trend is generally inflated when the other variables are not stationary, making us wrongly believe that a trend is significant.

In order to avoid spurious correlations, and obtain valid econometric estimations, it is necessary to test for stationarity of all the implied variables through a unit root test (Greene, 2003). Traditional unit root tests deal with testing one temporal series at a time. However, testing for unit roots in a panel structure is possible and will be done here.

We use three versions of the panel unit root test. The Levin, Lin and Chu (LLC, 2002) test examines the null hypothesis that each individual time series contains a unit root versus the alternative that each time series is stationary. This test provides a power improvement over an individual unit root test over each cross section. However, it assumes independence across cross sections, which does not necessarily hold; and that *all* cross sections have or do not have a unit root (common coefficient restriction), which is rather restrictive.

The Im, Pesaran and Shin (IPS, 2003) test relaxes LLC's common coefficient restriction, allowing heterogeneous coefficients for each cross section. Therein, the alternative hypothesis is that *some* cross sections have unit roots. Finally, we use a test proposed by Breitung (2000); that relies on the common coefficient restriction, but does not require a bias correction as LLC and IPS do, resulting in a test with greater power in the presence of individual trends. More details on the test specifications can be found in Appendix A.

If variables are found to be non stationary, any estimated model using them will result in a spurious regression. However, if residuals from a model involving non stationary variables are stationary, we say that those variables are cointegrated and there is a long run relationship between them. Therefore, we are interested in testing the existence of cointegration when the model variables are non stationary. If cointegration exists, an estimation method known as Error Correction Model, described below will be required.

In the conventional time series case, cointegration refers to the idea that for a set of variables that are individually non stationary, some linear combination (the model residuals for example) of these variables can be described as stationary. The vector of slope coefficients that gives this stationary combination is referred to as the cointegrating vector, which is generally not unique, and needs to be normalized in some way. The following set of tests do not address issues of normalization or questions regarding the particular number of cointegrating relationships, but instead they are interested in the simple null hypothesis of no cointegration versus cointegration.

One “natural” way to perform such a cointegration test is to take the residuals from a panel regression involving non stationary variables, and apply any of the aforementioned panel unit root tests. However, there are more sophisticated tests available which have more power, and deal with some particular structural issues that panels can exhibit.

Cointegration tests also depend on the assumptions we set on the model, as do panel unit root tests. To check for consistencies on our results, we employed three cointegration tests: Kao (1999) DF and ADF tests, Pedroni (1999) test, and Westerlund (2007) test. The main feature of Kao and Pedroni tests is that they based on testing non stationarity for the residuals from a model estimated using non stationary variables. Meanwhile the distinctive aspect of Westerlund’s test is that it considers a structural estimation, and test the significance of a key parameter of the model to check for cointegration of the variables. More technical details can be found in Appendix A.

### *2.5.2 Panel Error Correction Model*

In order to address non stationarity and cointegration problems, which are confirmed by our tests as reported in the next section, we will adopt the Panel Error Correction Model for estimation. An error correction model is a dynamic model in which the movement of the variables in any periods is related to the previous period's gap from long-run equilibrium. Following Greene (2003), suppose that a simplified model in which two non stationary variables $y_t$ and $z_t$ are cointegrated, with a cointegrating vector $[1,-\theta]$. Then all three variables $\Delta y_t$, $\Delta z_t$, and $(y_t - \theta z_t)$ are stationary. Therefore, the error correction model (ECM)

$$\Delta y_t = \gamma \Delta z_t + \lambda (y_{t-1} - \theta z_{t-1}) + \varepsilon_t \tag{6}$$

describes the variation in $y_t$ around its long-run trend in terms of the variation in $z_t$ around its long-run trend, and the error correction $(y_t - \theta z_t)$, which is the equilibrium error in the model of cointegration. This model is obviously stable because the implied variables are stationary. There is a tight connection between cointegration and error correction model (ECM) in the sense that ECM is consistent only if the implied variables are cointegrated. The same assumption that we make to produce cointegration implies (and is implied by) the existence of an ECM. This result is known as the Granger representation theorem (see Hamilton, 1994).

Taking the more general framework of a multivariate and heterogeneous panel model, the error correction equation can be expressed as:

$$\Delta y_{it} = \phi_i (y_{it-1} - \theta_i' X_{it}) + \sum_{j=1}^{p-1} \lambda_{ij}^* \Delta y_{it-j} + \sum_{j=0}^{q-1} \delta_{ij}' \Delta X_{it-j} + \mu_i + \varepsilon_{it} \tag{7}$$

where the parameter $\phi_i$ is the error-correcting speed of adjustment term. It is expected that $\phi_i < 0$, in which case there is evidence of cointegration. This means that the variables show a return to a long-run equilibrium. The vector $\theta_i'$ represents the long-run relationship between the variables, and the other estimated parameters $(\lambda_{ij}, \delta_{ij})$ characterize the short-run dynamics of the implied variables.

Pesaran, Shin and Smith (1999) proposed a Pooled Mean Group (PMG) estimator that combines both pooling and averaging: the estimator allows the intercept, short-run coefficients, and error variances to differ across the individuals but constrains the long-run coefficients to be equal across individuals. Since model (7) is nonlinear in the parameters, they developed a maximum likelihood method to estimate the parameters. The log likelihood function is

(8) $$l_T(\theta', \varphi', \sigma') = -\frac{T}{2}\sum_{i=1}^{N}\ln(2\pi\sigma_i^2) - \frac{1}{2}\sum_{i=1}^{N}\frac{1}{\sigma_i^2}\{\Delta y_i - \phi_i\, \xi_i(\theta)\}' H_i \{\Delta y_i - \phi_i\, \xi_i(\theta)\}$$

where $\xi_i(\theta) = y_{it-1} - X_i\theta_i$, $H_i = I_T - W_i(W_i' W_i)W_i$, $I_T$ is an identity matrix of order $T$, and $W_i = (\Delta y_{it-1}, \ldots, \Delta y_{it-p+1}, \Delta X_i, \Delta X_{it-1}, \ldots, \Delta X_{it-q+1})$. The estimators can be computed using the usual Newton-Raphson algorithm, which needs first and second derivatives of the likelihood function, or an iterative "back substitution" algorithm which requires only first derivative computations. More details are given in Pesaran, Shin and Smith (1999).

## 2.6 Results

The estimation method that Huffman and Evenson (2006a) used is the Prais-Winsten estimator defined in Beck and Katz (1995) and Greene (2003), which fits linear cross-sectional time-series models when the disturbances are not assumed to be independent and identically distributed (i.i.d.). In their estimations the errors are allowed to be heteroskedastic and contemporaneously correlated across panels. Additionally, that estimator may allow the disturbances to be autocorrelated within the panel. Their results are displayed in Table 2, and are labeled Model 1.

Our first alternative model ignored non stationarity issues, and used the Prais-Winsten estimation methodology but included climate variables. Comparing our results (Table 2, Model 2) with those from Huffman and Evenson (2006a), we find that

- The term for Public Capital multiplied by the shares of public budget coming from federal formula funds, and the squares of the shares from federal funds and grants: RPUB x SFF, RPUB x $SFF^2$, and RPUB x $GR^2$ are now not statistically significant.
- The elasticity of TFP to Public Research Capital (which is the percent return from public R&D investments) is reduced from 0.139 to 0.089.[5]
- The elasticity of TFP to Public Extension Capital is reduced from 0.110 to 0.077.
- The effect of Public Research Capital Spill-in from near states (RPUBSPILL) becomes insignificant.
- The elasticity effect of Private Agricultural Research Capital (RPRI) which was negative but not significant, now becomes significant and positive with a value of 0.044.
- Regarding the regional dummies individual effects, we find that with the Central region as benchmark, the Southeast and Pacific regions show a lower TFP level, while the Southern Plains exhibits a higher one. This is evidence of the existence of unobservable effects that affect the agricultural productivity at different degrees in each region.

With respect to climate we find the main climatic variable effects are related to precipitation. Total Yearly Precipitation has a positive effect on Agricultural TFP, with

[5] Calculated using equation (2), evaluated at the sample means for SFF and GR.

**Table 2. Panel Estimates Model of Agricultural Productivity**

| Dependent variable: ln (Ag. Total Factor Productivity) | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| | Coefficient | p_value | Coefficient | p_value | Coefficient | p_value |
| ln (Public Ag. Research Capital) | 0.1306 | 0.000 | 0.0919 | 0.000 | 0.1100 | 0.000 |
| ln (Public Ag. Research Capital) × $SFF_{t-12}$ | 0.0354 | 0.095 | 0.0235 | 0.259 | -0.0019 | 0.907 |
| ln (Public Ag. Research Capital) × $(SFF_{t-12})^2$ | -0.0277 | 0.055 | -0.0199 | 0.150 | -0.0078 | 0.490 |
| ln (Public Ag. Research Capital) × $GR_{t-12}$ | -0.0345 | 0.003 | -0.0302 | 0.007 | -0.0239 | 0.010 |
| ln (Public Ag. Research Capital) × $(GR_{t-12})^2$ | 0.0403 | 0.089 | 0.0303 | 0.191 | 0.0254 | 0.373 |
| ln (Public Extension Capital) | 0.1104 | 0.000 | 0.0770 | 0.000 | -0.0115 | 0.487 |
| ln (Public Ag. Research Capital Spilling) | 0.0348 | 0.036 | 0.0284 | 0.110 | 0.5959 | 0.000 |
| ln (Private Ag. Research Capital) | -0.0010 | 0.986 | 0.1075 | 0.044 | -0.1342 | 0.004 |
| D1 (Northeast = 1) | 0.0530 | 0.270 | -0.4321 | 0.587 | | |
| D2 (Southeast = 1) | 0.0045 | 0.900 | -5.9156 | 0.000 | | |
| D3 (Central = 1) | | | | | | |
| D4 (Northern Plains = 1) | 0.1937 | 0.000 | -0.4545 | 0.592 | | |
| D5 (Southern Plains = 1) | 0.0621 | 0.132 | 3.8236 | 0.012 | | |
| D6 (Mountains = 1) | 0.1147 | 0.022 | -0.4957 | 0.590 | | |
| D7 (Pacific = 1) | 0.0573 | 0.211 | -5.9601 | 0.000 | | |
| Trend | 0.0109 | 0.000 | 0.0125 | 0.000 | -0.0006 | 0.845 |
| ln (Temperature) × D1 | | | 0.1204 | 0.266 | -0.3196 | 0.005 |
| ln (Temperature) × D2 | | | 1.4404 | 0.000 | -0.2313 | 0.198 |
| ln (Temperature) × D3 | | | -0.0063 | 0.975 | -0.0606 | 0.611 |
| ln (Temperature) × D4 | | | 0.1664 | 0.499 | -0.0199 | 0.892 |
| ln (Temperature) × D5 | | | -0.9155 | 0.019 | -0.4020 | 0.162 |
| ln (Temperature) × D6 | | | 0.1661 | 0.171 | 0.1491 | 0.325 |
| ln (Temperature) × D7 | | | 1.5448 | 0.000 | -0.1189 | 0.728 |
| ln Total Precipitation | | | 0.0693 | 0.003 | 0.0868 | 0.000 |
| ln Precipitation Intensity | | | -0.0459 | 0.001 | -0.0530 | 0.000 |
| Intercept | -3.4178 | 0.000 | -3.5704 | 0.000 | | |

**Notes**: Model 1 - Eq. (1). Prais-Winsten regression, correlated panels corrected standard errors.
Model 2 - Eq. (5). Prais-Winsten regression, correlated panels corrected standard errors, with climatic variables.
Model 3 - Eqs. (5) and (7). Long run equation, Pooled Mean Group Regression for non stationary heterogeneous panels, with climatic variables.

an associated elasticity of 0.069. Precipitation Intensity has a negative impact, showing an elasticity with a magnitude of -0.046. These results are consistent with our initial hypotheses.

We also find statistical evidence that supports the idea of regionally differentiated effects of temperature on TFP. In particular, we find that for the Southeast and Pacific regions the statistical effect of higher temperature on factor productivity is positive, while it is negative for the Southern Plains. There is no conclusive evidence with respect to the other regions. Finally, we find evidence of a positive linear trend in the Agricultural TFP.

However our unit roots tests lead us to question those results. When the null hypothesis can not be rejected for a given variable, the tests indicate that the variable is non stationary (Table 3). For the model with individual effects only, we can summarize our results in the following way[6]:

- TFP is non stationary using all the available tests.
- RPUB is found to be non stationary using Breitung and IPS tests, while LLC test supports stationarity.
- RPUB x SFF is non stationary, using the LLC and Breitung tests at 95% of significance.
- RPUB x $SFF^2$ is non stationary using the LLC and Breitung tests.
- RPUB x GR and RPUB x $GR^2$ are found to be non stationary for LLC and IPS tests.

[6] The unit root test was also performed for the first differences of all the series, confirming that those variables which are I(1) in levels, become I(0) in first differences.

**Table 3. Panel Unit Root Test: Summary**

Sample: 1970 1999
Cross Sections: 48

| | Individual effects | | | Individual effects & linear trends | | |
|---|---|---|---|---|---|---|
| LTFP[a] | Statistic | P-value | Obs. | Statistic | P-value | Obs. |
| Null: Unit root (assumes common unit root process) | | | | | | |
| Levin, Lin & Chu t*[b] | 1.34 | 0.909 | 1329 | -11.87 | 0.000 | 1367 |
| Breitung t-stat | 2.70 | 0.997 | 1281 | -1.28 | 0.100 | 1319 |
| Null: Unit root (assumes individual unit root process) | | | | | | |
| Im, Pesaran and Shin W-stat | 7.52 | 1.000 | 1329 | -12.62 | 0.000 | 1367 |
| LRPUB | | | | | | |
| Levin, Lin & Chu t* | -8.34 | 0.000 | 1257 | 0.94 | 0.827 | 1265 |
| Breitung t-stat | 1.57 | 0.941 | 1209 | -8.01 | 0.000 | 1217 |
| Im, Pesaran and Shin W-stat | 0.10 | 0.542 | 1257 | -7.39 | 0.000 | 1265 |
| LRPUB × SF | | | | | | |
| Levin, Lin & Chu t* | -1.40 | 0.080 | 1353 | -3.94 | 0.000 | 1350 |
| Breitung t-stat | -1.06 | 0.145 | 1305 | -3.86 | 0.000 | 1302 |
| Im, Pesaran and Shin W-stat | -2.45 | 0.007 | 1353 | -5.43 | 0.000 | 1350 |
| LRPUB × SF2 | | | | | | |
| Levin, Lin & Chu t* | -1.45 | 0.073 | 1354 | -4.57 | 0.000 | 1356 |
| Breitung t-stat | -1.58 | 0.057 | 1306 | -3.73 | 0.000 | 1308 |
| Im, Pesaran and Shin W-stat | -2.85 | 0.002 | 1354 | -5.89 | 0.000 | 1356 |
| LRPUB × GR | | | | | | |
| Levin, Lin & Chu t* | -0.63 | 0.265 | 1371 | -2.38 | 0.009 | 1361 |
| Breitung t-stat | -2.25 | 0.012 | 1323 | 1.50 | 0.933 | 1313 |
| Im, Pesaran and Shin W-stat | -0.45 | 0.326 | 1371 | -2.38 | 0.009 | 1361 |
| LRPUB × GR2 | | | | | | |
| Levin, Lin & Chu t* | -1.13 | 0.130 | 1357 | -2.60 | 0.005 | 1352 |
| Breitung t-stat | -1.97 | 0.025 | 1309 | 0.41 | 0.658 | 1304 |
| Im, Pesaran and Shin W-stat | 0.78 | 0.783 | 1357 | -1.99 | 0.024 | 1352 |
| LEXT | | | | | | |
| Levin, Lin & Chu t* | -8.57 | 0.000 | 1369 | -7.52 | 0.000 | 1365 |
| Breitung t-stat | -2.17 | 0.015 | 1321 | -0.55 | 0.292 | 1317 |
| Im, Pesaran and Shin W-stat | -4.62 | 0.000 | 1369 | -8.37 | 0.000 | 1365 |
| LRPUBSPILL | | | | | | |
| Levin, Lin & Chu t* | -6.87 | 0.000 | 1288 | 11.88 | 1.000 | 1281 |
| Breitung t-stat | 3.96 | 1.000 | 1240 | -10.45 | 0.000 | 1233 |
| Im, Pesaran and Shin W-stat | 3.03 | 0.999 | 1288 | 0.26 | 0.601 | 1281 |

**Table 3 Continued**

| | Individual effects | | | Individual effects & linear trends | | |
|---|---|---|---|---|---|---|
| | Statistic | P-value | Obs. | Statistic | P-value | Obs. |
| LPRI | | | | | | |
| Levin, Lin & Chu t* | -27.50 | 0.000 | 1338 | -24.92 | 0.000 | 1344 |
| Breitung t-stat | -26.01 | 0.000 | 1290 | 0.45 | 0.675 | 1296 |
| Im, Pesaran and Shin W-stat | -26.05 | 0.000 | 1338 | -25.92 | 0.000 | 1344 |
| LTEMP | | | | | | |
| Levin, Lin & Chu t* | -24.45 | 0.000 | 1373 | -23.78 | 0.000 | 1356 |
| Breitung t-stat | -22.90 | 0.000 | 1325 | 2.65 | 0.996 | 1308 |
| Im, Pesaran and Shin W-stat | -21.21 | 0.000 | 1373 | -20.56 | 0.000 | 1356 |
| LPREC | | | | | | |
| Levin, Lin & Chu t* | -30.46 | 0.000 | 1372 | -26.37 | 0.000 | 1366 |
| Breitung t-stat | -18.68 | 0.000 | 1324 | -3.56 | 0.000 | 1318 |
| Im, Pesaran and Shin W-stat | -28.49 | 0.000 | 1372 | -24.58 | 0.000 | 1366 |
| LINTENS | | | | | | |
| Levin, Lin & Chu t* | -28.00 | 0.000 | 1385 | -24.51 | 0.000 | 1377 |
| Breitung t-stat | -19.79 | 0.000 | 1337 | -7.43 | 0.000 | 1329 |
| Im, Pesaran and Shin W-stat | -28.65 | 0.000 | 1385 | -26.71 | 0.000 | 1377 |

[a]Variable definitions are explained on Table 1. All the variables are expressed in natural logs.
[b]All the presented tests assume asymptotic normality.

- EXT is stationary using all three tests.
- RPUBSPILL is found to be non stationary using LLC and IPS tests.
- RPRI is found to be stationary using all three tests.
- The climatic variables Temperature, Precipitation and Intensity show a stationary pattern according to all tests that we considered[7].

The results above mentioned show us that some of the involved variables are in fact non stationary. One solution to this problem would be to take first differences to the non stationary variables and re-estimate the model. However, some information is lost in the differencing process. If the variables are cointegrated, we can still work with the non differenced variables and estimate an Error Correction Model (ECM), which is a richer specification that incorporates both the long-run relation and the short-run dynamics of the variables.

After verifying that some of the variables are non stationary, we proceeded to perform several tests of cointegration (Table 4). Our results are quite consistent regardless the method we used: The test statistics are significant, rejecting the null hypothesis of no cointegration. All the variants of the Pedroni test report that the variables are cointegrated, with the exception of two cases: the panel v-stat for a model with individual effects, and the group rho-stat for a model with individual constants and trends; Kao cointegration tests are fully consistent with those findings. Westerlund Error-correction-based test yields mixed results: one "group" statistic suggest

[7] This result for temperature contradicts in some way the results of IPCC supporting that climate change is actually happening. This is happening because the data span of 30 years and only covering the US, is too short compared to the global analysis made by IPCC. However, the use of cointegration and ECM is still valid because other variables of the model are non stationary.

**Table 4. Cointegration Test: Summary**

Sample: 1970 1999
Cross Sections: 48

| **Pedroni cointegration tests** | Constant | | Constant & Trend | |
|---|---|---|---|---|
| | Statistic | P-value | Statistic | P-value |
| panel v-stat | -0.82 | 0.205 | -3.76 | 0.000 |
| panel rho-stat | -4.60 | 0.000 | -2.45 | 0.007 |
| panel pp-stat | -20.10 | 0.000 | -23.80 | 0.000 |
| panel adf-stat | -9.88 | 0.000 | -9.69 | 0.000 |
| | | | | |
| group rho-stat | -2.22 | 0.013 | -0.03 | 0.489 |
| group pp-stat | -22.28 | 0.000 | -26.89 | 0.000 |
| group adf-stat | -8.24 | 0.000 | -9.12 | 0.000 |

**All reported values are distributed N(0,1) under null of unit root or no cointegration.
**Panel stats are unweighted by long run variances.

| **Kao cointegration tests** | Constant | | Constant & Trend | |
|---|---|---|---|---|
| | Statistic | P-value | Statistic | P-value |
| DFrho | -31.88 | 0.000 | -33.94 | 0.000 |
| DFt | -17.59 | 0.000 | -18.64 | 0.000 |

**Stats are distributed N(0,1) under null of no cointegration.

**Westerlund cointegration tests**

Lags: 1 - 2 — Average AIC selected lag length: 1.98
Leads: 0 - 1 — Average AIC selected lead length: .96

| | Constant | | | Constant & Trend | | |
|---|---|---|---|---|---|---|
| Statistic | Value | Z-value | P-value | Value | Z-value | P-value |
| Gt | -4.06 | -11.71 | 0.000 | -4.23 | -10.39 | 0.000 |
| Ga | -0.24 | 11.50 | 1.000 | -0.13 | 13.81 | 1.000 |
| Pt | -22.25 | -6.80 | 0.000 | -25.95 | -7.75 | 0.000 |
| Pa | -2.56 | 6.16 | 1.000 | -1.99 | 9.57 | 1.000 |

**Z-values are distributed N(0,1) under null of no cointegration.

**Pedroni tests:** v-stat, non-parametric variance ratio statistic; rho-stat, non-parametric, analogous to the Phillips and Perron rho-statistic; pp-stat, non-parametric, analogous to the Phillips and Perron t-statistic; adf-stat, parametric, analogous to the Augmented Dickey-Fuller t-statistic.
**Kao tests:** DFrho, Dickey-Fuller rho-statistic; DFt, Dickey-Fuller t-statistic.
**Westerlund tests:** Gt, group mean statistic, parametric version; Ga, group mean statistic, semi-parametric version; Pt, panel statistic, parametric version; Pa, panel statistic, semi-parametric version.

cointegration, and the other one does not, while one “panel” statistic implies cointegration, and the other one rejects it. Our conclusion is that the statistical evidence supporting cointegration is very strong.

With the cointegration and non stationary results at hand, we estimated the TFP model using an ECM framework. As explained before, we assume homogeneous coefficients for the long-run equation and heterogeneous coefficients for the short-run dynamic coefficients. Table 2, Model 3 only reports the long-run coefficients as they are compatible with the coefficients in the previous models. Notice that given the structure of the estimation method, the regional dummies cannot be identified in the ECM model.

Using the ECM framework, more variables become non-significant which suggests that using a model without correcting for non stationarity can lead us to assign spurious statistical effects to some variables. Using the same formulas aforementioned,

- The elasticity of Agricultural Total Factor Productivity (TFP) with respect to Public Agricultural research (RPUB) is now equal to 0.108, value that is in the midway between what we found with the previous two models and less than that found using the Huffman and Evenson model without considering cointegration and non stationary effects.
- Public Extension Capital (EXT) is now not significant.
- Capital spill-in effects become positive and significant, with an elasticity value of 0.596, several times higher than the values obtained before.
- The sign of the effect of Private Research Capital is now significantly negative, and its elasticity value is -0.134.

In terms of the climate variables:

- The long-run relationship between temperature and TFP is not significantly different from zero for most regions, with the exception of a negative effect for the Southeast.
- Precipitation and precipitation intensity are significant. Precipitation effect elasticity is 0.087, a value that is 25% greater than using Model 2. For precipitation intensity, we find that the associated elasticity is -0.053, which has the same sign as what found with Model 2, but with a 15% higher magnitude.

Also note that when using an ECM there is no a significant linear trend effect that suggests an exogenous Agricultural TFP growth[8].

## 2.7 Effects of Climate Change

Now let us examine what effects climate change has on agricultural TFP, the returns to R&D investments and the needed amount of additional research capital needed to maintain the current levels of productivity growth climate change.

To characterize climate change we use the predictions of Temperature, Precipitation, and Precipitation Intensity from the United Nations Intergovernmental Panel on Climate Change (IPCC) Data Distribution Centre website. Those predictions are based on scenarios from the IPCC Special Report on Emission Scenarios (SRES). That report identifies six scenario families for climate change that differentially characterize future human activity. From them, we used scenarios A1B, A2 and B1, which are described below.

[8] Table 19 in Appendix B reports different model specifications for the two estimation procedures above mentioned. That new specifications comprise the removal of funding, and grant shares; and the separation of Mountains and Pacific regions in north and south sub regions. The obtained results are very similar in sign and magnitude to what we obtained in Table 2.

- The A1B scenario depicts a relatively more integrated world, characterized by: rapid economic growth; global population that reaches 9 billion in 2050 and then gradually declines; quick spread of new and efficient technologies; a convergent world - income and way of life converge between regions; extensive social and cultural interactions worldwide; and balanced emphasis on all energy sources, fossil and non-fossil.
- The A2 scenario depicts a more divided world with the following characteristics: a world of independently operating, self-reliant nations; continuously increasing population; regionally oriented economic development; slower and more fragmented technological changes and improvements to per capita income.
- Finally B1 depicts a more integrated world, that is more ecologically friendly with rapid economic growth as in A1, but with rapid changes towards a service and information economy; population rising to 9 billion in 2050 and then declining as in A1; reductions in material intensity and the introduction of clean and resource efficient technologies; and an emphasis on global solutions to economic, social and environmental stability.

A number of research institutes performed climate simulations under these scenarios. For this article, we used the predictions of the Canadian Centre for Climate Modeling and Analysis (CCC) for the years 2020, 2050, and 2100. The CCC model predicts the world climate dividing the globe in a grid of 96 × 48 clusters with a size of 3.75° of longitude × 1.875° of latitude, allowing us to obtain different predictions across the U.S. States.

The coefficients estimated in Model 3 were used to make predictions for TFP assuming that the Public Agricultural Research Capital (RPUB), the public agricultural research spill-in stock (RPUBSPILL), and the private agricultural research capital (RPRI) will rise at their current growth rates.

First, we calculate the prediction of the TFP growth rate w*ith* and *without* climate change. The (baseline) state assumes climate remains at the average historical levels of the last 30 years. The state *with* climate change replaces the climate variables with the predictions of the CCC model under three climate change scenarios: A1B, A2, and B1. The results are reported on Table 5. We computed the TFP Annual Growth Rate for each State and then they were averaged by the Regions defined previously for climate scenarios for the years 2020, 2050 and 2100. Those values are reported in the first three columns of Table 5 only for the state *with* climate change.

The following columns report the percentage reduction that the *with* climate change scenario alters the TFP Annual Growth Rate from the *without* climate change case. For example under the Scenario A1B, the Northeast region TFP Growth Rate *with* climate change in 2020 is 1.89% greater *with* climate change in 2020 under Scenario A1B.

The main findings are that there are differential implication of climate change with some regions gaining in TFP Growth derived from climate change: by 2020 Pacific region will experience higher TFP Growth Rates under any of the Scenarios we have considered, with better outcomes under Scenarios A1B and A2 (around 13% and 10% higher). However those effects are reduced drastically in 2050 and 2100, giving negative but smaller effects under Scenarios A1B and B1 in 2050 and Scenario A2 in 2050 and 2100. The negative effect of climate change over the South Plains regions is worth

**Table 5. TFP Growth Rates and Alterations due to Climate Change**

| | TFP Growth Rates | | | Percent increase / reduction under climate change | | |
|---|---|---|---|---|---|---|
| **Scenario A1B** | 2020 | 2050 | 2100 | 2020 | 2050 | 2100 |
| Northeast | 1.12 | 1.05 | 0.97 | 1.89 | 2.35 | -3.32 |
| Southeast | 1.09 | 1.01 | 0.97 | 0.65 | -0.35 | -3.07 |
| Central | 0.99 | 1.03 | 0.97 | -1.75 | 3.78 | -1.41 |
| North Plains | 1.05 | 1.03 | 0.97 | 9.59 | 6.91 | -0.02 |
| South Plains | 0.85 | 0.93 | 0.89 | -22.32 | -8.94 | -11.20 |
| Mountains | 1.13 | 1.01 | 0.99 | 10.69 | 1.35 | 0.92 |
| Pacific | 1.14 | 0.98 | 0.98 | 13.70 | -0.67 | 0.04 |
| **National** | **1.06** | **1.01** | **0.96** | **1.37** | **0.93** | **-2.58** |
| | | | | | | |
| **Scenario A2** | 2020 | 2050 | 2100 | 2020 | 2050 | 2100 |
| Northeast | 1.17 | 0.99 | 0.96 | 6.88 | -3.74 | -3.81 |
| Southeast | 1.05 | 1.00 | 0.96 | -3.41 | -2.25 | -3.30 |
| Central | 0.98 | 0.99 | 0.95 | -3.36 | 0.71 | -2.95 |
| North Plains | 0.94 | 0.98 | 0.96 | -1.61 | 1.60 | -0.84 |
| South Plains | 0.69 | 0.87 | 0.88 | -37.32 | -15.42 | -12.16 |
| Mountains | 1.01 | 1.00 | 1.01 | -1.23 | 0.79 | 3.24 |
| Pacific | 1.10 | 0.97 | 0.96 | 10.00 | -1.42 | -2.20 |
| **National** | **1.02** | **0.98** | **0.96** | **-3.22** | **-2.59** | **-2.92** |
| | | | | | | |
| **Scenario B1** | 2020 | 2050 | 2100 | 2020 | 2050 | 2100 |
| Northeast | 1.09 | 0.98 | 0.98 | -0.53 | -3.90 | -2.19 |
| Southeast | 0.93 | 0.97 | 0.97 | -14.74 | -5.05 | -2.29 |
| Central | 1.00 | 0.95 | 1.00 | -1.07 | -3.41 | 1.89 |
| North Plains | 1.01 | 0.96 | 0.98 | 5.48 | -0.05 | 1.13 |
| South Plains | 0.72 | 0.89 | 0.93 | -33.78 | -13.48 | -7.30 |
| Mountains | 1.06 | 1.01 | 0.98 | 4.49 | 2.07 | 0.03 |
| Pacific | 1.03 | 0.98 | 0.99 | 3.42 | -1.06 | 0.64 |
| **National** | **0.99** | **0.97** | **0.98** | **-5.16** | **-3.54** | **-1.24** |

noting: there are consistently negative and large effects over TFP Growth Rate in 2020, going from 22% less in Scenario A1B to 37% less in Scenario A2. Those negative effects will be diminished in 2050 and 2100 but will remain in levels between 7% and 15% less *with* climate change.

For the Southeast the effects of climate change are generally negative with the only exception of Scenario A1B: in 2020 there is a 0.65% greater TFP Growth Rate, but turns to -0.35% and -3.07% in 2050 and 2100. For Scenario A2, the effects are around 2% to 3% less, while Scenario B1 reports a higher negative effect, around -14% in 2020 which fades to -5% and -2% in 2050 and 2100. The Central region reports the effects with smallest magnitudes ranging from a 3.78% greater to a 3.41% smaller TFP Growth Rates. Since there is no a clear pattern in the direction of the effect of climate change, the effects of climate change are not conclusive for this region.

The North Plains region seems to be favored by climate change according to Scenarios A1B for 2020, 2050 and B1 for 2020 with an increase in the rate of TFP growth between 5 and 9%. For this region the effects of climate change in 2100 are negative for Scenarios A1B and A2 and positive for Scenario B1. However, those effects are of reduced magnitude compared those for 2020 and 2050. Finally, according to Scenarios A1B and B1, the Mountains region will experience an important positive effect on agricultural TFP growth (10% and 4%) in 2020, which remains positive but smaller for the subsequent years, between 0% and 2% higher *with* climate change.

In summary, if we average all the effects at a National level, Scenario A1B suggest small benefits from climate change which are diminishing through time, becoming harmful by year 2100. On the other hand, Scenarios A2 and B1 suggest negative effects at a national level which are also declining through time.

Table 6 shows the equivalent effect of climate change on the returns to Public Agricultural Research Capital on Total Factor Productivity, defined as the percentage increase on TFP given by an increase of 1% on Agricultural Research Capital. The first three columns report the return *with* climate change, while the next three columns show the percentage change of public research returns comparing the situations *with* vs. *without* climate change.

Under Scenario A1B the Northeast reports an increase of 1.89% on the rate of return for year 2020, and 2.35% for year 2050, while it experience a decrease in the rate of return of 3.32% for year 2100. The situation with Scenario B1 is an increase of 6.88% for 2020, and a decrease in the rate of return for 2050 and 2100 of around 3.8%. The Rate of return is decreased under Scenario B1 for 2020, 2050 and 2100.

For year 2020 the highest increases in the rate of return is obtained in the North Plains (9.59%), Mountains (10.69%) and Pacific (13.70%) under Scenario A1B. For Scenario A2, the highest increases in the rate of return are reported in Northeast (6.88%) and Pacific (10%) regions. Under Scenario B1 and year 2020, the increase in the rate of return is not grater than 5.5% (North Plains). Regarding regions where the rate of return declines, we consistently find that for the South Plains it decreases between 22% (A1B) and 37% (B1). The Southeast also reports a decrease for Scenarios A2 (3.41%) and B1 (14.74%).

**Table 6. Effect of Climate Change on Public Agricultural Research Returns**

| | Return of Public Research Capital *with* Climate change | | | Percent increase / reduction under climate change | | |
|---|---|---|---|---|---|---|
| **Scenario A1B** | 2020 | 2050 | 2100 | 2020 | 2050 | 2100 |
| Northeast | 0.112 | 0.113 | 0.106 | 1.89 | 2.35 | -3.32 |
| Southeast | 0.111 | 0.110 | 0.107 | 0.65 | -0.35 | -3.07 |
| Central | 0.108 | 0.114 | 0.108 | -1.75 | 3.78 | -1.41 |
| North Plains | 0.121 | 0.118 | 0.110 | 9.59 | 6.91 | -0.02 |
| South Plains | 0.085 | 0.100 | 0.098 | -22.32 | -8.94 | -11.20 |
| Mountains | 0.122 | 0.112 | 0.111 | 10.69 | 1.35 | 0.92 |
| Pacific | 0.125 | 0.109 | 0.110 | 13.70 | -0.67 | 0.04 |
| **National** | **0.112** | **0.111** | **0.107** | **1.37** | **0.93** | **-2.58** |
| **Scenario A2** | 2020 | 2050 | 2100 | 2020 | 2050 | 2100 |
| Northeast | 0.118 | 0.106 | 0.106 | 6.88 | -3.74 | -3.81 |
| Southeast | 0.106 | 0.108 | 0.106 | -3.41 | -2.25 | -3.30 |
| Central | 0.106 | 0.111 | 0.107 | -3.36 | 0.71 | -2.95 |
| North Plains | 0.108 | 0.112 | 0.109 | -1.61 | 1.60 | -0.84 |
| South Plains | 0.069 | 0.093 | 0.097 | -37.32 | -15.42 | -12.16 |
| Mountains | 0.109 | 0.111 | 0.114 | -1.23 | 0.79 | 3.24 |
| Pacific | 0.121 | 0.108 | 0.108 | 10.00 | -1.42 | -2.20 |
| **National** | **0.106** | **0.107** | **0.107** | **-3.44** | **-2.69** | **-2.95** |
| **Scenario B1** | 2020 | 2050 | 2100 | 2020 | 2050 | 2100 |
| Northeast | 0.109 | 0.106 | 0.108 | -0.53 | -3.90 | -2.19 |
| Southeast | 0.094 | 0.104 | 0.108 | -14.74 | -5.05 | -2.29 |
| Central | 0.109 | 0.106 | 0.112 | -1.07 | -3.41 | 1.89 |
| North Plains | 0.116 | 0.110 | 0.111 | 5.48 | -0.05 | 1.13 |
| South Plains | 0.073 | 0.095 | 0.102 | -33.78 | -13.48 | -7.30 |
| Mountains | 0.115 | 0.112 | 0.110 | 4.49 | 2.07 | 0.03 |
| Pacific | 0.114 | 0.109 | 0.111 | 3.42 | -1.06 | 0.64 |
| **National** | **0.104** | **0.106** | **0.109** | **-5.73** | **-3.60** | **-1.27** |

For year 2050 we find the following noticeable results: the greatest increase in the rate of return occurs in the North Plains (6.91%) for Scenario A1B, however for the other Scenarios the “wining” regions do not get an increase greater than 2%. For those regions that reduce the rate of return, the South Plains is the one with the highest reductions: from 8.94% (A1B) to 15.42% (A2).

Regarding year 2100, the effects fade for the “wining” and “losing” regions. The regions that have an increase in the rate of return only report a small increase of around 2% for all Scenarios. Meanwhile the South Plains shows a reduction that ranges from 7.30% (B1) to 12.16% (A2).

Using the procedures and computations abovementioned, we were able to calculate the required investments in Public Agricultural Research Capital in order to cancel the effect of climate change on TFP growth and attain its current “pre-climate” rates of growth. Table 7 shows the percentage and the relative change that the current rate of growth of public research capital must increase/decrease such that the negative/positive effect of climate change on agricultural TFP is eliminated.

For that purpose we use the results from Table 5 as input, taking the reduction (or increase) in TFP growth rate given by climate change, and using the corresponding elasticity to calculate the needed amount of increase (or reduction) on RPUB growth rate that gives the negative of that amount of TFP growth reduction (or increase).

The regions that need the higher needed increases in public research are those where climate change has a larger negative implication for the TFP Growth Rates, for example the South Plains region, which is the most affected area, needs to increase its

**Table 7. Percentage Increases in Investment Rates in Public Agricultural Research Capital to Adapt to Climate Change**

| | Points of increase under climate change | | | Percent increase under climate change | | |
|---|---|---|---|---|---|---|
| **Scenario A1B** | 2020 | 2050 | 2100 | 2020 | 2050 | 2100 |
| Northeast | -0.22 | -0.27 | 0.37 | -11.29 | -13.55 | 18.73 |
| Southeast | -0.07 | 0.04 | 0.34 | -3.59 | 2.02 | 17.27 |
| Central | 0.19 | -0.42 | 0.16 | 9.65 | -21.09 | 7.82 |
| North Plains | -1.03 | -0.75 | 0.00 | -51.56 | -37.57 | 0.06 |
| South Plains | 2.82 | 1.04 | 1.26 | 141.81 | 52.34 | 63.29 |
| Mountains | -1.19 | -0.14 | -0.10 | -59.90 | -6.84 | -4.91 |
| Pacific | -1.46 | 0.10 | 0.01 | -73.53 | 5.18 | 0.33 |
| **National** | **-0.11** | **-0.09** | **0.29** | **-5.75** | **-4.74** | **14.63** |
| **Scenario A2** | 2020 | 2050 | 2100 | 2020 | 2050 | 2100 |
| Northeast | -0.84 | 0.43 | 0.43 | -42.42 | 21.69 | 21.52 |
| Southeast | 0.41 | 0.26 | 0.37 | 20.83 | 12.98 | 18.59 |
| Central | 0.38 | -0.08 | 0.33 | 18.89 | -3.89 | 16.35 |
| North Plains | 0.17 | -0.17 | 0.09 | 8.78 | -8.75 | 4.57 |
| South Plains | 4.62 | 1.78 | 1.36 | 231.99 | 89.44 | 68.59 |
| Mountains | 0.16 | -0.08 | -0.36 | 8.06 | -3.97 | -17.86 |
| Pacific | -1.00 | 0.19 | 0.25 | -50.28 | 9.46 | 12.60 |
| **National** | **0.41** | **0.30** | **0.33** | **20.43** | **15.27** | **16.48** |
| **Scenario B1** | 2020 | 2050 | 2100 | 2020 | 2050 | 2100 |
| Northeast | 0.07 | 0.45 | 0.25 | 3.72 | 22.62 | 12.38 |
| Southeast | 1.79 | 0.58 | 0.26 | 89.94 | 29.11 | 12.82 |
| Central | 0.11 | 0.38 | -0.21 | 5.72 | 19.06 | -10.47 |
| North Plains | -0.58 | 0.01 | -0.12 | -29.06 | 0.30 | -6.17 |
| South Plains | 4.27 | 1.55 | 0.82 | 214.75 | 77.85 | 41.36 |
| Mountains | -0.45 | -0.23 | 0.00 | -22.82 | -11.67 | -0.08 |
| Pacific | -0.25 | 0.14 | -0.06 | -12.40 | 6.80 | -3.19 |
| **National** | **0.68** | **0.41** | **0.14** | **34.04** | **20.43** | **7.08** |

public research capital by 2.8 to 4 percentage points, which represent an increase of 140 (Scenario A1B) to 231% (Scenario A2) of the current rate of growth of public research (around 2% by year). The Southeast is the other region that consistently reports the need of an increase in public research growth rate to overcome climate change effect on TFP, finding the greatest effects on Scenario B1, and the smallest effects on Scenario A1B.

If we summarize the results at a national scale, Scenario A1B suggest an increase in public research capital only for year 2100, while Scenarios A2 and B1 indicate that we need to increase the current growth rates during all the periods of study, ranging from 20% to 16% for Scenario A2, and from 34 to 7% for scenario B1.

## 2.8 Conclusions

We examine the impact of climate change on returns to research investments extending the work of Huffman and Evenson (2006). We estimated a panel model of agricultural productivity fitted to annual data for forty-eight contiguous states over 1970–1999. In this article we performed the following activities:

We evaluate and account for problems due to non stationarity of some of the variables. We found statistical evidence that supports the use of an Error Correction Model for estimation.

We include in the estimation climatic variables temperature, amount and intensity of precipitation, which result to be significant.

Based on our estimations, we conduct extensive simulations to demonstrate the impact of projected climate on agricultural TFP growth, and rates of return of public research.

We find that the biggest effects are due to precipitation, where increases in it raises returns to research investments, but increases in intensity with more precipitation happening in shorter time periods diminishes returns to research investments. On the other hand we find that temperature has a differentiated regional effect with negative implications in the southwest.

Finally, we forecast the growth rates of agricultural research investments required in order to compensate the impact of climate change. Regionally we find that rates of return vary with positive effects in Northeast and Pacific, and negatives in South Plains and Southeast. If one wishes to adapt investments to achieve pre-climate TFP rates of growth, we find that around 18% increase is needed in the public research growth rate at a national level, with this again being regionally variable and the largest incidence needed in the South Plains and reductions occurring in the Mountains and Pacific regions.

# 3. CLIMATE CHANGE AND FUTURE ANALYSIS: IS STATIONARITY DYING?[9]

## 3.1 Introduction

Economists often do risk analysis in support of management decisions. Commonly, such analyses are based on probability distributions arising from historical data. Also commonly the distributions developed are based on at least a partial assumption of stationarity. For example it is common in water-based risk analysis that one assumes the distribution is entirely stationary and uses concepts like the 100 year drought. More generally in many risk analysis settings analysts typically use history to develop a distribution assuming that the mean is changing with time (proxying for technological progress along with monetary inflation) but that the variance is stationary.

Climate change may alter the property of stationarity of the distribution (as asserted in a water setting by Milly *et al*. 2008). In particular, evidence exists that climate change will shift the mean (Mendelsohn et al 1994 among others) and variance (Chen *et al*. 2004) of crop yields, challenging the stationarity assumption. If this is true, risk analysis would need to use evolving distributions with non stationary means and variances along with possibly shifting higher order moments[10]. In this document, we consider this prospect extending the existing literature in several fronts. First, we review

[9] This section is an extended version of: McCarl, B.A., Villavicencio, X., and Wu, X. 2008. "Climate Change and Future Analysis: Is Stationarity Dying?" *American Journal of Agricultural Economics* 90(5): 1241–1247.

[10] However, Bessler (1982) argues that this fact also occurs without climate change, because technological change will induce non stationarity in the distributions too.

the climate change and stationarity concept and draw out the implications of prior findings for stationarity. Second we conduct a US agricultural yield based study investigating the implications of climate change on stationarity in a framework that allows both the mean and variance of crop yields to be affected not only by average climate conditions, but also climate variability. Third, we numerically investigate stationarity consequences of projected climate change simulating the impact of projected changes based on the IPCC climate change scenarios based on the parameters developed in our estimated models. Finally, we presents concluding comments.

## 3.2 Background on Climate Change and Yields

The influence of climate change on agricultural crop yields has been widely studied, as reviewed in documents such as the Intergovernmental Panel on Climate Change assessments (2007, 2001) or the U.S. National Assessment (Reilly *et al*. 2002). Many studies indicate that climate change alters mean yields (e.g., Adams *et al*. 1990; Reilly *et al*. 2002; Deschenes and Greenstone 2007) and/or land values (Mendelsohn, Nordhaus and Shaw, 1994). Chen, McCarl and Schimmelpfennig (2004) also indicate that in addition to climate change affecting mean yields, it will contribute to a change in crop yield variability, while Mearns, Rosenzweig and Goldberg (1992) provide crop simulation results to the same point. In particular, Chen, McCarl and Schimmelpfennig (2004) show that across the country that climate variation leads to statistically detectable alterations in yield variability. Specifically, they investigate the mean and variance of crop yields for corn, cotton, sorghum, soybeans and wheat by modeling them as functions of climate conditions, agricultural land usage and other inputs, time trends and regional dummies using spatial analogue techniques.

A novelty of the Chen, McCarl and Schimmelpfennig (2004) study is that they employ an estimation method that allows statistical determination of the influence on climate on yield variability based on the concept of a stochastic production function, in particular the Just-Pope production function (Just and Pope 1978), wherein the variance of crop yield is allowed to be a flexible function of exogenous explanatory variables. Hence, both crop yield mean and variability are modeled in a unified framework.

Conventional predictions of climate change impacts based on historical data often assume the series of the climate variables, such as temperature and precipitation, are stationary in the sense that their distribution is stable over an extended period that spans the observation period and the prediction period. A linear or quadratic time trend is often used to remove the likely secular evolution of the variable of interest. However, as suggested by Milly *et al*. (2008), not only did the average climate conditions change over time, there were substantial evolutions of their entire distribution as well. Consequently, the higher moments, such as the variance, skewness and kurtosis of the distributions of climate variables, also changed considerably over time. Thus, predications based on historical data, or mere adjustment for some change in the trend of average climate conditions, might not be reliably as they fail to take into account the evolution of the underlying distribution.

### 3.3 Model Specification

The Chen, McCarl and Schimmelpfennig (2004) study employs an estimation method based on the Just-Pope production function (1978) that allows statistical determination of the influence of climate on the stationarity of the crop yield mean and variance, and we will use that here but develop a richer specification. In particular we explicitly control for weather variability shifts. For temperature we use both its mean and variance during the growing season as exogenous variables. In addition we include average precipitation along with a precipitation intensity index and the Palmer Drought Severity Index (PDSI). Also, we incorporate interaction between regions and weather conditions. We pool data from 1960 through 2007. We separate time invariant state-specific effects of the constructed panel.

Estimation is based on the Just and Pope (1978) specification of a stochastic production function, which explicitly models the mean and variance - heteroskedaciticy effects of independent variables on the probability distribution of output. The production function has the following form:

(9) $$y = f(X, \beta) + h(X, \alpha)\varepsilon,$$

where: $y$ is crop yield; $f(\cdot)$ is an average production function; $X$ is a set of independent variables; and $\alpha$ and $\beta$ are unknown parameters to be estimated. In addition, $h(\cdot)$ is a functional form that accounts for explicit variable-dependent heteroskedasticity, allowing yield variability as a function of observed covariates. Under the assumption that the error term $\varepsilon$ is distributed with mean zero and unitary variance, $h^2(\cdot)$ is the yield variance.

Just and Pope (1978, 1979) described both a Maximum Likelihood Estimator (MLE) (1978) and a three-step, Feasible Generalized Least squares (FGLS) (1979) procedure for estimating the function. In turn, Just and Pope production functions have been traditionally estimated by the FGLS method. Saha *et al*. (1997) showed that the MLE is more efficient for small samples in Monte Carlo experiments; however, this method relies heavily on the correct specification of the likelihood function. For that reason, we decided to estimate the model using FGLS, following this procedure:

1. Estimate the model by Ordinary Least Squares (OLS). Get the residuals.
2. Regress the logarithm of squared residuals against $X$ as independent variables.
3. Get the predicted values of those residuals, which are calculated as the antilogarithm of the predictions from step 2. They are consistent estimators of the variances.
4. Estimate the original model by Weighted Least Squares (WLS) using the squared root of the variance predictions as weights.

## 3.4 Data Set

Our estimation was done over US crop yields by state for the crops corn, cotton, sorghum, soybeans, and winter wheat using annual observations from 1960 to 2007 drawn from USDA-NASS website. Associated climate data were drawn from NOAA as discussed below. Yearly and state level data were used because of the availability of data on crop yields. The intertemporal and cross sectional variations of the constructed panel enable us to separate time invariant state-specific effects, time trends and the contribution of climate change to agricultural productivity.

Not all crops are grown in all states and the data for some crops are not always available information for given years at some states. When missing observations were present in a given state, we used the available data instead of deleting that state from the estimation, resulting in unbalanced panels in some cases.

State-level climate data were obtained from the NOAA website. We used information on mean and standard deviation of temperature corresponding to the growing season: November to March for winter wheat, April to November for all other crops. For rainfall data, we used total yearly precipitation, to take into account the direct effect on the crop as well as inter-seasonal water accumulation into the soil. We also constructed a measure of the intensity of yearly precipitation, defined as the ratio of total precipitation from the month with the highest amount of precipitation to the yearly total. This measure can range by construction from 1/12 (uniformly intense during the year) to 1 (one month gets all yearly rain).

In addition, we included a yearly drought measure given by the Palmer Drought Severity Index (PDSI), which indicates the severity of a wet or dry spell. This index is based on the principles of a balance between moisture supply and demand. The index generally ranges from -6 to +6; with negative values denoting dry spells and positive values indicating wet spells.

A linear and a quadratic trend were included in the model to incorporate the effect of technological progress with the possibility of decreasing marginal returns.

## 3.5 Estimation Results

In this section we discuss in detail our estimation methods and results. We first test the hypothesis of panel unit roots, under which the classical inferences are generally invalid. This hypothesis is rejected. We then proceed to estimate the proposed model using the Fixed Effects model estimator for the stochastic production function.

### *3.5.1 Panel Unit Roots*

The Just-Pope structure is estimated exploiting the time series cross sectional panel data structure present in the data set. This procedure allows us to measure the effect of the explanatory variables as well as state-specific effects that could affect the mean and variability of the crop yields. This kind of estimation relies on the assumption of stationarity, or integration of order zero $I(0)$ of the involved series. Granger and Newbold (1974) showed that deterministic and stochastic trends in the series can induce spurious correlation between variables; as a result we can obtain correlations between variables that are increasing for different reasons. The inclusion of time trends to control for this issue may not solve the problem when spurious correlation is present (Phillips, 1986).

For these reasons it is necessary to test for non stationarity (unit root) for each variable of the model prior to estimating the model explained above. If a series is found to be non stationary, it must be differenced before being included in the model. Traditional unit root tests are used to deal with testing one temporal series at a time; however, relatively new tests are available to test for unit roots of all cross-sections using the panel structure as a whole.

The objective is to test whether a given series is non-stationary for all the individual units (states in our case). We assume that the series follows a general panel data model structure (for i states, and t periods):

(10) $$y_{it} = (1-\phi_i)\mu_i + \phi_i y_{i,t-1} + \varepsilon_{it}, \quad i = 1,\ldots,N; \quad t = 1,\ldots T,$$

where $y_{it}$ represents the variable to be tested, $\mu_i$ is a state-specific constant, $\phi_i$ is a state-specific parameter, and $\varepsilon_{it}$ is an error term.

This equation can be expressed as:

(11) $$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \varepsilon_{it}.$$

We want to test if $\phi_i = 1$ for all $i$. The null hypothesis of unit root becomes:

(12) $$H_0 : \beta_i = 0 \text{ for all } i.$$

We performed two kinds of panel unit root tests. Im, Pesaran and Shin (IPS, 2003) proposed one in which the alternative hypothesis is that the series is stationary for some cross-sections (individuals) and not stationary for other cros-sections: $H_1 : \beta_i < 0, i = 1,\ldots,N_1, \quad \beta_i = 0, i = N_1+1,\ldots,N$. In addition, Levin Lin and Chu (LLC, 2002) proposed a test in which the alternative hypothesis is that the series is stationary for all the individuals, say $H_1 : \beta_i < 0, i = 1,\ldots,N$. Both tests allow the inclusion of lags of $\Delta y_{it}$ into equation (11), which makes the test robust for serially correlated errors. Also, Im, Pesaran and Shin (2003) test has a 'demeaned' version which is robust when the disturbances are correlated across groups. In that case equation (11) becomes $\Delta\tilde{y}_{it} = \tilde{\alpha}_i + \beta_i \tilde{y}_{i,t-1} + \tilde{\varepsilon}_{it}$, where the tilde above the variables means that the cross sectional mean was subtracted from each variable.

In Table 8 we show the results for the three versions of the panel unit root test abovementioned, for each one of the variables used in the econometric model. Since these tests require the panel structure to be balanced, we deleted all states with missing observations. The way to construct those tests is explained with detail in the cited articles. All the tests explained above are distributed standard normal under the null hypothesis. Those are lower tail tests, thus the null hypothesis is rejected at 95% of confidence if the value of the test is less than -1.645. In the next section, the estimated models are not balanced panels in order to include the highest possible number of available observations.

The results show that using the different test specifications, we consistently reject the null hypothesis that the series of the econometric model are I(1) for all the cross-sections of the panel because with very few exceptions, all the t-statistics are less than the critical value of -1.645. There is not any single series that result to be non-stationary under the 3 tests simultaneously. In addition, the LLC test tells us that not only are the series stationary for a set of states as IPS shows, but also they are for the full set of states included in the sample. Thus, the panel unit root tests do not suggest differencing the data before the estimation.

### *3.5.2 Panel Data Estimation*

We use the Fixed Effects estimation procedure for our panel data for two reasons. The primary reason is that the Fixed Effects model allows us to estimate a unit-specific effect for each state in the model. In addition, the Fixed Effects model does not require the restrictive assumption that the state-specific effect is independent of the included

**Table 8. Panel Unit Root Tests**

| *Equation* | **Corn** | **Cotton** | **Sorghum** | **Soybeans** | **Wheat** |
|---|---|---|---|---|---|
| *(N, T)* | (40,48) | (16,34) | (18,48) | (29,48) | (36,47) |
| | | | Yields | | |
| *IPS* | -16.47 | -5.38 | -10.14 | -17.44 | -11.68 |
| *IPSd* | -13.79 | -6.81 | -10.53 | -17.08 | -12.34 |
| *LLC* | -13.11 | -11.06 | -15.91 | -19.80 | -14.13 |
| | | | Planted Acreage | | |
| *IPS* | -0.65 | -1.43 | -4.11 | 2.83 | -3.89 |
| *IPSd* | -4.21 | -2.48 | -4.57 | 2.14 | -4.46 |
| *LLC* | -2.85 | -2.41 | -6.59 | -0.73 | -6.57 |
| | | | Precipitation | | |
| *IPS* | -20.32 | -10.23 | -13.21 | -19.18 | -18.01 |
| *IPSd* | -21.90 | -11.73 | -14.62 | -20.76 | -20.16 |
| *LLC* | -22.10 | -13.33 | -19.68 | -24.06 | -21.14 |
| | | | Temperature | | |
| *IPS* | -22.06 | -12.47 | -13.90 | -20.15 | -18.53 |
| *IPSd* | -21.07 | -8.91 | -13.49 | -17.53 | -21.25 |
| *LLC* | -23.19 | -13.39 | -18.36 | -21.95 | -24.34 |
| | | | Std. Dev. Temperature | | |
| *IPS* | -24.84 | -12.95 | -15.06 | -20.84 | -17.58 |
| *IPSd* | -25.35 | -9.56 | -14.24 | -19.62 | -19.72 |
| *LLC* | -27.31 | -12.55 | -21.13 | -23.97 | -19.98 |
| | | | PDSI | | |
| *IPS* | -17.12 | -9.88 | -11.72 | -15.94 | -15.58 |
| *IPSd* | -16.81 | -8.82 | -12.35 | -15.51 | -15.55 |
| *LLC* | -18.50 | -9.66 | -13.05 | -17.30 | -17.27 |
| | | | Intensity | | |
| *IPS* | -23.51 | -9.91 | -13.96 | -19.29 | -21.59 |
| *IPSd* | -22.58 | -10.74 | -14.32 | -18.81 | -20.36 |
| *LLC* | -24.78 | -17.42 | -22.53 | -26.22 | -24.02 |

Im, Pesaran and Shin $\bar{\psi}$ (IPS, 2003); and Levin, Lin and Chu $t^*$ (LLC, 2002) Panel Unit Root Tests with 1 lag to account for serial correlation. IPSd is the demeaned version of IPS that accounts for correlation across groups. Both, $\bar{\psi}$ and $t^*$ are adjusted t-statistics distributed standard normal under the null hypothesis of non stationarity.

covariates as the Random Effects model does. State dummies are included in our regression to capture state-specific effects that are invariant over time. This procedure was applied in all the stages explained in previous sections: in the first stage OLS estimation, variance estimation, and second stage WLS estimation. This estimation procedure allows us to identify individual state effects over the mean yields as well as their variability, which is not possible using the FE method known as within estimator.

In addition to the variables we described in the data section, we included the interaction between temperature and region, reasoning that the effect of higher temperatures is not uniform across regions. Similar interaction terms between precipitation and regional dummies were also included in alternative specifications. Since there appears to be little variation in the effects of precipitation across regions, we decided not to include them in the reported results. Our results, however, are not sensitive to this alternative specification.

The final estimates of the parameters of the proposed stochastic production function are presented in Table 9, where the models are estimated by the Feasible Generalized Least Squares method and the standard errors have been adjusted appropriately to account for the first-stage variation. The functional form for the average yield equation is linear for both the independent and the dependent variables; meanwhile the variance equation is linear for the independent variables but the dependent variable appears logarithmically to assure positive predicted variances. To save space, the coefficients for the individual state dummies are not reported herein.

**Table 9. Yield Mean Regression – Second-staged WLS with Predicted Standard Deviations as Weights [a]**

| | Corn | | Cotton | | Sorghum | | Soybeans | | Winter Wheat | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Coef.** | **z-test** | **Coef.** | **z-test** | **Coef.** | **z-test** | **Coef.** | **z-test** | **Coef.** | **z-test** |
| *Acreage* | 0.002 | 6.48 | -0.024 | -4.10 | 0.003 | 10.31 | 0.001 | 11.05 | 0.000 | 2.35 |
| *Precipitation* | 0.000 | 0.01 | 1.605 | 3.06 | -0.027 | -0.84 | 0.018 | 1.36 | -0.200 | -11.15 |
| *Temperature* | -0.412 | -1.47 | 0.784 | 0.12 | -0.160 | -0.36 | 0.585 | 6.22 | 0.085 | 1.26 |
| *SD Temperature* | -3.478 | -22.49 | -37.988 | -15.18 | -2.334 | -16.05 | -1.002 | -17.76 | -0.198 | -4.57 |
| *Temp X D2* [b] | -4.572 | -8.18 | | | | | -1.021 | -5.89 | 0.427 | 3.98 |
| *Temp X D3* | -4.567 | -11.72 | -19.598 | -2.64 | -2.086 | -4.23 | -1.631 | -11.81 | -0.676 | -7.24 |
| *Temp X D4* | 0.206 | 0.49 | 32.523 | 2.21 | -0.129 | -0.23 | -0.333 | -2.32 | -0.845 | -5.29 |
| *Temp X D5* | -2.423 | -4.41 | -8.256 | -1.11 | -0.590 | -1.18 | -1.270 | -9.24 | -1.076 | -9.47 |
| *Temp X D6* | 3.688 | 8.42 | -5.153 | -0.62 | -1.677 | -2.82 | | | 0.300 | 2.64 |
| *Temp X D7* | 7.992 | 11.53 | 30.497 | 2.31 | 0.636 | 0.98 | | | 0.516 | 2.33 |
| *PDSI* | 0.898 | 7.48 | -7.974 | -4.16 | 0.558 | 4.81 | 0.496 | 10.22 | 0.266 | 4.50 |
| *Intensity* | -41.638 | -8.37 | -273.033 | -4.14 | -9.579 | -2.24 | -17.427 | -9.00 | -8.408 | -3.28 |
| *Trend* | 1.881 | 39.82 | 11.559 | 7.22 | 0.850 | 21.12 | 0.139 | 8.09 | 0.426 | 18.09 |
| *Trend^2* | 0.000 | -0.41 | 0.002 | 0.08 | -0.005 | -5.92 | 0.003 | 8.80 | 0.003 | 6.51 |
| *Constant* | 402.381 | 19.20 | 1858.600 | 7.83 | 204.715 | 12.84 | 101.612 | 13.19 | 63.546 | 17.82 |
| *Number of obs* | 1920 | | 579 | | 940 | | 1392 | | 1732 | |
| *Model chi2 (df)* | 49376.59 (53) | | 13188.84 (30) | | 15674.12 (32) | | 14474.4 (40) | | 21225.22 (50) | |
| *Prob > chi2* | 0.000 | | 0.000 | | 0.000 | | 0.000 | | 0.000 | |

[a] $f(X, \beta)$ in Eq. (9). Dependent variable: yearly average crop yield by state. Independent variables: crop acreage, yearly amount of precipitation, yearly mean temperature, yearly standard deviation of temperature, PDSI (Palmer Drought Severity Index), and precipitation intensity.
[b]Regional Interacted Dummies. D1 –Central- (IN, IL, IA, MI, MO, MN, OH, WI); D2 –Northeast- (CT, DE, ME, MD, MA, NH, NJ, NY, PA, RI, VT); D3 –Southeast- (AL, FL, GA, KY, NC, SC, TN, VA, WV); D4 -North Plains- (KS, NE, ND, SD); D5 -South Plains- (AR, LA, MS, OK, or TX); D6 – Mountains- (AZ, CO, ID, MT, NV, NM, UT, WY); D7 –Pacific- (CA, OR, WA).

The average yield estimations show that climate affects average yields for cotton and winter wheat through a significant coefficient on precipitation, being positive for cotton and negative for winter wheat. This suggests that holding acreage and all other involved variables constant, a higher amount of total annual precipitation increases cotton yields, decreases winter wheat yields, and does not affect the other crops. Precipitation effects are also covered through the PDSI and intensity variables. The coefficient for PDSI is positive and significant for all crops except for average cotton. Since a higher PDSI implies better humidity conditions, the positive significance of the coefficient implies that mean yields respond favorably to lessened drought incidence. The parameter for precipitation intensity is significant and negative for all the crops. This suggests that a shift toward greater intensity –in terms of periods with high amounts of rain while the rest of the year is relatively dry– is harmful for the crops. This result, combined with what we get from precipitation alone, suggests that precipitation intensity and droughts are of greater concern than the annual amount of precipitation alone.

For the independent variables related to temperature, a higher variability in temperature implies a decrease in the yields for all crops, which is consistent with the idea of the negative effect of more extreme events –higher maximums and lower minimums– on agriculture. The variable “Temperature” should be understood as the effect of temperature for the base region (Central), while the coefficients for all of the interaction terms reflect the differences between the temperature effects over a given region with respect to the Central region. Positive (negative) signs indicate a beneficial (harmful) effect of higher temperatures on crop yields. Notice that because some crops are not grown in some regions, some of the regional dummy interaction terms do not appear in the cotton, sorghum, and soybeans equations. It is suggested that temperature has no significant effect over Central regions (positive for soybeans), with negative relative effects for the Southeast and Northeast regions (for NE the relative effect is positive for winter wheat). We get mixed results for the North Plains and negative relative effects for the South Plains (though the relationship is not significant for cotton and sorghum). Finally, the linear trend is positive and significant for all crops, while the quadratic term is negative for sorghum but positive for soybeans and wheat. This indicates the not unexpected results that temperature increases in the hotter areas (the South) are mainly detrimental while increases in the colder (northern) areas are mainly beneficial with the Central areas largely unchanged.

We report the regression results of variance of the residuals from the first stage in Table 10. Regarding the variance equation, the interpretation of a positive coefficient implies that an increase in the associated variable leads to a higher yield variance. Notice that for cotton, the joint significance test implies a null effect of all the variables of that model, so cotton yields are found to have a stationary variance. Precipitation affects negatively the log variance of corn, sorghum, and soybeans. Higher temperature decreases log variance for soybeans in Central region, while it increases the relative volatility of corn and soybeans in the Northeast. For South Plains, higher temperatures increase log variance of soybeans yields. Finally, higher precipitation intensity seems to increase the log variance of sorghum yields.

**Table 10. Log Yield Variance Regressions [a]**

| | Corn | | Cotton | | Sorghum | | Soybeans | | Winter Wheat | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Coef.** | **t-test** | **Coef.** | **t-test** | **Coef.** | **t-test** | **Coef.** | **t-test** | **Coef.** | **t-test** |
| *Acreage* | 0.000 | -3.51 | 0.000 | -0.26 | 0.000 | 1.17 | 0.000 | -0.36 | 0.000 | -2.19 |
| *Precipitation* | -0.021 | -1.63 | 0.009 | 0.38 | -0.041 | -2.36 | -0.032 | -2.15 | 0.006 | 0.45 |
| *Temperature* | -0.080 | -0.87 | 0.203 | 0.63 | -0.254 | -1.33 | -0.270 | -2.79 | -0.063 | -1.32 |
| *SD Temperature* | 0.141 | 2.78 | -0.012 | -0.12 | 0.026 | 0.34 | -0.010 | -0.17 | -0.021 | -0.65 |
| *Temp X D2* [b] | 0.474 | 2.86 | | | | | 0.500 | 2.69 | 0.033 | 0.41 |
| *Temp X D3* | 0.244 | 1.81 | 0.129 | 0.37 | 0.146 | 0.65 | 0.108 | 0.75 | 0.050 | 0.71 |
| *Temp X D4* | -0.100 | -0.68 | -0.124 | -0.25 | 0.324 | 1.36 | -0.039 | -0.26 | 0.023 | 0.23 |
| *Temp X D5* | 0.233 | 1.52 | -0.040 | -0.11 | 0.367 | 1.60 | 0.368 | 2.33 | 0.101 | 1.15 |
| *Temp X D6* | 0.062 | 0.44 | -0.338 | -0.84 | 0.425 | 1.69 | | | 0.031 | 0.39 |
| *Temp X D7* | -0.179 | -0.88 | -0.910 | -1.69 | 0.309 | 0.74 | | | 0.014 | 0.12 |
| *PDSI* | 0.007 | 0.18 | -0.020 | -0.23 | 0.072 | 1.23 | -0.024 | -0.45 | -0.047 | -1.11 |
| *Intensity* | 1.735 | 1.11 | 1.394 | 0.49 | 4.409 | 1.93 | 1.001 | 0.48 | 1.324 | 0.78 |
| *Trend* | -0.028 | -1.87 | 0.017 | 0.24 | -0.041 | -1.85 | -0.018 | -0.92 | 0.004 | 0.25 |
| *Trend^2* | 0.001 | 1.85 | 0.000 | 0.07 | 0.001 | 2.61 | 0.001 | 2.18 | 0.000 | 0.93 |
| *Constant* | -7.617 | -1.02 | -16.496 | -1.48 | 10.890 | 1.16 | 14.628 | 1.77 | 1.947 | 0.69 |
| *Number of obs* | 1920 | | 579 | | 940 | | 1392 | | 1732 | |
| *F (df1,df2)* | 5.08 (53,1866) | | 1.22 (30,548) | | 3.62 (32,907) | | 2.42 (40,1351) | | 3.50 (50,1681) | |
| *Prob > F* | 0.000 | | 0.196 | | 0.000 | | 0.000 | | 0.000 | |

[a] $h(X, \alpha)$ in Eq. (9). Dependent variable: logarithm of squared residuals from first stage OLS. Independent variables: crop acreage, yearly amount of precipitation, yearly mean temperature, yearly standard deviation of temperature, PDSI (Palmer Drought Severity Index), and precipitation intensity.

[b] Regional Interacted Dummies. D1 –Central- (IN, IL, IA, MI, MO, MN, OH, WI); D2 –Northeast- (CT, DE, ME, MD, MA, NH, NJ, NY, PA, RI, VT); D3 –Southeast- (AL, FL, GA, KY, NC, SC, TN, VA, WV); D4 -North Plains- (KS, NE, ND, SD); D5 -South Plains- (AR, LA, MS, OK, or TX); D6 – Mountains- (AZ, CO, ID, MT, NV, NM, UT, WY); D7 –Pacific- (CA, OR, WA).

### 3.6 Simulation of Climate Change Impacts

In this section we use simulation methods to evaluate the likely impacts of future climate changes. Parameters estimated from the above models are used in this simulation. We first investigate the potential impact of change in average intra-annual temperature and precipitation on future crop yield average and variability using projected climate changes from the Hadley and Canadian General Circulation Models (GCM) as used in the U.S. Global Climate Research Program's (USGCRP) National Assessment. In particular, we fix the level of temperature, precipitation intensity and PDSI at the current level to set a benchmark.

We next examine the combined effects of future average climate conditions and its variability on agricultural productivity. To the best of our knowledge, existing climate studies do not project the magnitude of future climate variability but they do suggest it will increase. The simulations include the changes in average and variability of future climate conditions as inputs. For temperature variability, we used two kind of predictions: the constructed future temperature variability using GCM predictions as inputs; or assuming that future temperature variability will increase by 10% and 20% with respect to the current levels.

The results for mean yields in year 2030 are summarized in Table 11 for all crops and regions. We observe that those results are similar regardless of the GCM used (Canadian or Hadley). The type of assumption about future climate variability does not affect the results in a large amount, except for he case of sorghum. If we follow the predictions of the GCMs for future temperature variability and the Canadian Model, we find that future climate will affect mean yields positively for corn (between 10% higher in the South Plains and 32% in the Northeast), cotton (between -4% in South Plains and 57% in North Plains), soybeans (from 10% in South Plains to 24 in Central), and winter wheat (from 19% in Pacific to 46% in South plains). The effect for sorghum is less optimistic, with changes in yields between -18% in the South Plains and 10% in North Plains. The results for Hadley Model are very similar. If we compare the results assuming 10% grater temperature variability versus 20% greater variability, the results suggest that a greater future temperature variability will imply a slight smaller increase in mean crop yields.

The predictions for standard deviation of yields in year 2030 are reported in Table 12, using the same parameters of previous table. The results for the Canadian Model suggest that future climate will increase yield variability for all crops except cotton. Using the Hadley Model, almost all crops and regions report increases in variability. The magnitudes of the increases range from 56% in Central to 173% in South Plains higher variability for corn, from 131% in Central to 503% in Pacific for sorghum, 77% in Central to 373% in Northeast for soybeans, and from 68 in Central to 169% in Northeast higher standard deviation for winter wheat.

The results with a 10% and 20% higher temperature variability are similar to what we found using the GCM temperature predictions. Greater difference can be found for corn in South plains, Mountains and Pacific regions using the Canadian Model. The results from the last two tables show us that the GCM predictions of future temperature

**Table 11. Percentage Change in Mean Yields Under Climate Change, Year 2030**

| | CANADIAN | | | | | HADLEY | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Corn | Cotton | Sorghum | Soybeans | W. wheat | Corn | Cotton | Sorghum | Soybeans | W. wheat |
| *Projected SD of Temperature as GCM predicts* | | | | | | | | | | |
| Central | 21 | 26 | 2 | 24 | 31 | 21 | 28 | 1 | 26 | 27 |
| Northeast | 32 | | | 18 | 23 | 29 | | | 28 | 25 |
| Southeast | 31 | 21 | -4 | 21 | 28 | 36 | 34 | 2 | 33 | 19 |
| N. Plains | 29 | 57 | 10 | 23 | 38 | 26 | 50 | 6 | 21 | 34 |
| S. Plains | 10 | -4 | -18 | 10 | 46 | 12 | 8 | -15 | 26 | 41 |
| Mountain | 18 | 10 | -4 | | 41 | 12 | 4 | -17 | | 45 |
| Pacific | 15 | 7 | -5 | | 19 | 14 | 4 | -7 | | 19 |
| *Projected SD of Temperature increased by 10%* | | | | | | | | | | |
| Central | 22 | 28 | 3 | 25 | 29 | 22 | 30 | 3 | 27 | 26 |
| Northeast | 32 | | | 18 | 23 | 30 | | | 28 | 26 |
| Southeast | 40 | 34 | 9 | 31 | 28 | 39 | 39 | 7 | 36 | 20 |
| N. Plains | 24 | 43 | 4 | 18 | 36 | 24 | 45 | 4 | 20 | 33 |
| S. Plains | 26 | 33 | 6 | 28 | 45 | 24 | 38 | 4 | 40 | 40 |
| Mountain | 23 | 17 | 8 | | 40 | 22 | 17 | 7 | | 42 |
| Pacific | 23 | 18 | 5 | | 19 | 24 | 18 | 6 | | 19 |
| *Projected SD of Temperature increased by 20%* | | | | | | | | | | |
| Central | 20 | 23 | 0 | 23 | 29 | 19 | 24 | -1 | 25 | 26 |
| Northeast | 29 | | | 15 | 22 | 27 | | | 25 | 25 |
| Southeast | 36 | 29 | 4 | 27 | 28 | 36 | 34 | 2 | 32 | 20 |
| N. Plains | 21 | 33 | 0 | 15 | 35 | 21 | 35 | 0 | 17 | 32 |
| S. Plains | 24 | 29 | 3 | 26 | 45 | 22 | 33 | 1 | 38 | 39 |
| Mountain | 20 | 13 | 2 | | 40 | 19 | 14 | 1 | | 42 |
| Pacific | 22 | 16 | 3 | | 18 | 23 | 16 | 4 | | 19 |

**Table 12. Percentage Change in Standard Deviation of Yields Under Climate Change, Year 2030**

| | CANADIAN | | | | | HADLEY | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Corn | Cotton | Sorghum | Soybeans | W. wheat | Corn | Cotton | Sorghum | Soybeans | W. wheat |
| *Projected SD of Temperature as GCM predicts* | | | | | | | | | | |
| Central | 56 | 65 | 131 | 77 | 68 | 37 | 95 | 67 | 32 | 74 |
| Northeast | 87 | | | 373 | 169 | 56 | | | 121 | 90 |
| Southeast | 99 | -9 | 302 | 234 | 123 | 34 | 19 | 108 | 93 | 120 |
| N. Plains | 61 | -1 | 326 | 257 | 86 | 58 | 12 | 233 | 178 | 87 |
| S. Plains | 173 | 30 | 253 | 140 | 125 | 56 | 202 | -2 | -31 | 81 |
| Mountain | 113 | 7 | 317 | | 115 | 108 | 70 | 139 | | 68 |
| Pacific | 150 | -33 | 503 | | 162 | 223 | -57 | 982 | | 182 |
| *Projected SD of Temperature increased by 10%* | | | | | | | | | | |
| Central | 44 | 66 | 127 | 78 | 58 | 32 | 95 | 66 | 32 | 70 |
| Northeast | 79 | | | 374 | 165 | 53 | | | 121 | 94 |
| Southeast | 60 | -8 | 287 | 240 | 125 | 25 | 20 | 106 | 93 | 129 |
| N. Plains | 76 | -1 | 333 | 255 | 77 | 65 | 12 | 235 | 177 | 80 |
| S. Plains | 62 | 36 | 221 | 149 | 121 | 6 | 212 | -9 | -29 | 77 |
| Mountain | 74 | 9 | 301 | | 112 | 51 | 75 | 125 | | 58 |
| Pacific | 80 | -31 | 468 | | 161 | 124 | -56 | 911 | | 176 |
| *Projected SD of Temperature increased by 20%* | | | | | | | | | | |
| Central | 64 | 65 | 133 | 77 | 56 | 44 | 94 | 69 | 31 | 68 |
| Northeast | 102 | | | 370 | 163 | 66 | | | 120 | 92 |
| Southeast | 77 | -9 | 294 | 237 | 124 | 34 | 19 | 109 | 93 | 127 |
| N. Plains | 103 | -3 | 345 | 251 | 75 | 82 | 11 | 241 | 176 | 78 |
| S. Plains | 78 | 35 | 226 | 147 | 119 | 13 | 211 | -8 | -30 | 75 |
| Mountain | 97 | 8 | 311 | | 110 | 64 | 74 | 128 | | 57 |
| Pacific | 97 | -31 | 477 | | 160 | 138 | -56 | 922 | | 174 |

variability is somewhere between 10 and 20% higher than the current situation. Therefore, the assumptions of future variability seem to be appropriate.

Finally, we show the effect of future climate on the participation probabilities for crop insurance in year 2030. This table is constructed using the results obtained in Coble *et al.* (1996). That study uses a probit analysis to study the determinants of crop insurance participation. Among the explanatory variables, there are expected market return and variance of market returns, which are function of expected average and variability of crop yields. Even though that study is made using Kansas wheat product data, we use that results to approximate the effect of the future yield distribution on the probability of acquiring crop insurance.

The results are shown in Table 13. We are using both future mean and variability of yields as inputs and get the percentage increase in the probability of crop insurance participation. In Coble *et al.* (1996), the effect of higher mean yields is a reduction in the participation probability, while a higher yield variability leads to a increase in the participation probability. Our results suggest that the effect of a higher yield variability outweighs the effect of a higher yield mean for all crops except cotton. Using the Hadley Model, the increase in the participation probability is smaller for corn, sorghum and soybeans than using the Canadian Model. Assuming future climate variability as GCMs predict, corn participation probability increases from a 31% in Central to 160% in South Plains, from 108% in Central to 892% in Pacific for sorghum, from 48% in Central to 534% in Northeast for soybeans, and from 38% in Central to 152% in Northeast for winter wheat.

**Table 13. Percentage Change in Crop Insurance Participation Probabilities Under Climate Change, Year 2030**

| | CANADIAN | | | | | HADLEY | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Corn | Cotton | Sorghum | Soybeans | W. wheat | Corn | Cotton | Sorghum | Soybeans | W. wheat |
| *Projected SD of Temperature as GCM predicts* | | | | | | | | | | |
| Central | 31 | 38 | 108 | 48 | 38 | 17 | 64 | 45 | 12 | 45 |
| Northeast | 55 | | | 534 | 152 | 29 | | | 91 | 60 |
| Southeast | 67 | -10 | 384 | 252 | 94 | 11 | 3 | 84 | 61 | 92 |
| N. Plains | 33 | -14 | 430 | 291 | 53 | 31 | -5 | 252 | 165 | 55 |
| S. Plains | 160 | 19 | 293 | 117 | 92 | 33 | 203 | 3 | -19 | 47 |
| Mountain | 84 | 1 | 413 | | 82 | 81 | 47 | 122 | | 35 |
| Pacific | 129 | -15 | 892 | | 144 | 235 | -21 | 2928 | | 170 |
| *Projected SD of Temperature increased by 10%* | | | | | | | | | | |
| Central | 22 | 38 | 104 | 49 | 31 | 13 | 64 | 44 | 12 | 41 |
| Northeast | 48 | | | 538 | 147 | 27 | | | 91 | 63 |
| Southeast | 30 | -12 | 349 | 258 | 96 | 5 | 2 | 80 | 61 | 102 |
| N. Plains | 47 | -11 | 447 | 287 | 45 | 38 | -4 | 257 | 164 | 49 |
| S. Plains | 35 | 14 | 232 | 124 | 87 | -3 | 212 | -5 | -22 | 44 |
| Mountain | 45 | 1 | 378 | | 79 | 27 | 48 | 101 | | 28 |
| Pacific | 51 | -17 | 785 | | 142 | 95 | -24 | 2550 | | 162 |
| *Projected SD of Temperature increased by 20%* | | | | | | | | | | |
| Central | 38 | 38 | 111 | 48 | 30 | 22 | 64 | 47 | 12 | 40 |
| Northeast | 71 | | | 529 | 144 | 38 | | | 90 | 62 |
| Southeast | 46 | -11 | 365 | 255 | 94 | 12 | 3 | 84 | 61 | 100 |
| N. Plains | 74 | -9 | 473 | 282 | 44 | 53 | -2 | 268 | 162 | 47 |
| S. Plains | 49 | 14 | 242 | 123 | 85 | 2 | 210 | -4 | -22 | 43 |
| Mountain | 67 | 1 | 399 | | 77 | 38 | 48 | 106 | | 27 |
| Pacific | 68 | -17 | 813 | | 140 | 112 | -24 | 2609 | | 160 |

### 3.7 Conclusions

In this study we investigate the impact of historical climate changes on the stationarity of the crop yield distribution, considering temperature, precipitation, variance of intra-annual temperature, a constructed index of rainfall intensity, and the Palmer Drought Severity Index (PDSI). The regression results show that stationarity does not hold as we find that both the mean and the variance of crop yields evolved over time as function of key climatic variables. In turn the average climate conditions and their variability appear to contribute in a statistically significant way to not only average crop yields but to their variability as well. In particular we find that the mean of the crop yields are affected by the average temperature and precipitation. In addition, we also note that higher variances in climate conditions tend to lower average crop yield and inflate yield variability, although the magnitude of this effect varies across crops. The variability of precipitation, as measured by a rainfall intensity index and PDSI, is shown to have significant impact on crop yields as well.

These results suggest that stationarity of yields is in fact a questionable assumption and that risk analysts should consider this when developing probabilistic models where climate plays an important direct or indirect role. It appears likely that climate change will increase the variability of crop yield distributions, and this means that historical distributions are going to need dynamic updating particularly since the pace of climate change is increasing as indicated by the recent IPCC reports. Stationarity is certainly dying and risk increasing, creating a demand for improved analysis under climate-related risk.

# 4. FORESTRY AND CLIMATE CHANGE: CALCULATING THE ECONOMIC COST OF NO ADAPTATION

## 4.1 Introduction

Forests cover almost 4 billion ha or 30% of global land; 3.4 billion $m^3$ of wood were removed in 2004 from this area, 60% as industrial roundwood. Intensively managed forest plantations comprised only 4% of the forest area in 2005, but their area is rapidly increasing (2.5million ha annually). In 2007, these forests supplied about 39% of global roundwood; [11] this share is expected to increase to 44% by 2020.

Forestry will be affected by climate change. The IPCC Third Assessment Report predicts increased global timber production. Simulations with yield models show that climate change can increase global timber production through location changes of forests and higher growth rates, especially when positive effects of elevated $CO_2$ concentrations are taken into consideration.

In the IPCC Fourth Assessment Report, further evidence is presented including:

- Although models suggest that global timber productivity will likely increase with climate change, regional production will exhibit large variability. Mendelsohn (2003), analyzing production in California, projected that, at first (2020s), climate change will increase harvests by stimulating growth in the standing forest. In the long run, up to 2100, he argues that these productivity gains will be offset by reductions in productive area for softwoods growth. Climate change will also substantially impact other services, such as seeds, nuts, hunting, resins,

[11] Information taken from http://faostat.fao.org.

plants used in pharmaceutical and botanical medicine, and in the cosmetics industry; these impacts will also be highly diverse and regionalized.

- $CO_2$ enrichment effects may be overestimated in models; models need improvement. New studies suggest that direct $CO_2$ effects on tree growth may be revised to lower values than previously assumed in forest growth models.
- In spite of improvements in forest modeling, model limitations persist. Most of the major forestry models don't include key ecological processes. Development of Dynamic Global Vegetation Models (DGVMs), which are spatially explicit and dynamic, will allow better predictions of climate-induced vegetative changes by simulating the composition of deciduous and evergreen trees, forest biomass, production, and water and nutrient cycling, as well as fire effects. DGVMs are also able to provide Global Circulation Models (GCMs) with feedbacks from changing vegetation.

There are still inconsistencies, however, between the models used by ecologists to estimate the effects of climate change on forest production and composition and those used to predict forest yield. Future development of the models that integrate both the Net Private Productivity (NPP) and forestry yield approaches (Nabuurs *et al*., 2002; Peng *et al*., 2002) will significantly improve the predictions.

One approach for dealing with climate change is to adapt production operations so that firms can produce successfully under climate change (McCarl, 2007). The objective of this section is to calculate the associated values of known adaptation strategies in the forestry sector to gain insight into the relative value of various strategies. In particular we will disallow various strategies to see what their relative value is under data for altered growth under the climate scenarios reported in 2001 by the National Assessment Synthesis Team, of the US Global Change Research Program.

Adaptation is a fundamental and ongoing forestry sector activity. Production is highly dependent upon climate and other environmental forces. Such forces vary substantially over space. This environmental evolution dependence leads to large variations in place to place production conditions and mandates adaptation. For example, forests are at much greater risk of fire in some places than others with adjustments possible through management and prevention practices.

Forest species choice and management regularly adapt to long run forces such as climate differences, pest presence, invasive species, and changes in government policies among numerous other forces. Managers can also adapt to short run forces such as pest and disease outbreaks, El Niño Southern oscillation events, drought cycles, and extreme event cycles among numerous other forces.

It is clear that the forestry sector is already heavily adapted to climate conditions. Production occurs across the nation with highly productive systems occurring in areas with temperature and rainfall conditions much different than those projected under climate change. The climatic conditions between forestry US regions are much more different than the 1.4-1.6 degrees Celsius that is projected to be the consequence by 2030 under the climate scenarios reported by IPCC. As a consequence, we can infer that forestry sector can adapt globally to climate change.

Some of the basic forms of climate change adaptation in forestry sector that the persons who manage land, trees and facilities can take are

- **Tree species/varieties** -- one can choose in the face of climate change to adapt by altering the mix of trees species employed for example growing trees which are more heat tolerant. More generally this involves replacing some proportion of the tree species populating the land with alternative species that perform more suitably in the face of the altered climatic regime. Typically this involves adopting practices from areas that have historically exhibited warmer climates. Adaptation can also involve adoption of alternative varieties of the same trees that are more suitable in the face of the altered climate due to for example lower water needs, increased resistance to pests and diseases etc.

- **Tree management** -- one can change the management of the items being grown. Trees and can be managed with increased inputs, altered rotation ages, thinning to mitigate fire risk, replanting, or altered pest management among other possibilities. Producers may also use seasonal climate forecasting to reduce production risk.
- **Moisture management** -- climate change can decrease water availability, decrease soil moisture holding capacity and/or increased flooding/water logging. Adaptation may occur in the form of altering time of planting/harvesting to better match water availability, or changing species to more drought tolerant trees.
- **Pest and disease management** – Climate change is likely to exacerbate pest and disease problems. Adaptation can occur through wider use of integrated pest and pathogen management, development and use of varieties and species resistant to pests and diseases, outbreak monitoring programs, prescribed burning and adjusting harvesting schedules.
- **Management of natural areas** – Some forestry production relies principally on passively managed, natural ecosystems which may require more active management

under climate change to migrate in new better adapted species or deal with climate change enhanced pest, disease or fire risks.

- **Fire management** – Forests are vulnerable to fire and climate change induced increases in fire risk. Such risks may stimulate adaptive actions like salvaging dead timber, landscape planning to minimize fire damage, and adjusting fire management systems.
- **Land use or enterprise choice change** -- climate change may alter the suitability of land or a region to such an extent that certain enterprises are no longer sustainable and that it may be desirable to adapt by changing the land use from trees to grazing land. In this case one would use the associated land, capital and labor resources in other productive enterprises outside of the forestry sector.

The objective of this work is to calculate the value to the forestry sectors of particular adaptation strategies. In particular, I will compute the effects on aggregate welfare of the presence of a set of adaptation strategies. One of the reasons to calculate welfare implications with and without climate change adaptation is to see the relative value of particular approaches and identify approaches that might be promoted in outreach efforts.

The kind of adaptation activities that will be restricted are: kind of species, rotation age, management intensity, and land transfers. These activities will be explained with more detail in subsequent sections.

### 4.2 Methodology

In order to achieve the objectives of this study, I will adapt a mathematical programming model that includes the agricultural and forest sectors in a dynamic framework. The Forest and Agricultural Sector Optimization Model—Green House Gas version (FASOMGHG) is an intertemporal, price-endogenous, spatial equilibrium model depicting land transfers between the agricultural and forest sectors in the United States. The model simulates the allocation of land over time to competing activities in both the forest and agricultural sectors and the resultant consequences for the commodity markets supplied by these lands, and for net greenhouse gas emissions (GHG, not calculated in this study though). The model was developed to evaluate the welfare and market impacts of public policies that cause land transfers between the sectors and alterations of activities within the sectors. The equilibrium occurs where prices and production maximize the present value of aggregated producers' and consumers' surpluses in both sectors.

The model solution portrays simultaneous market equilibrium over an extended time, typically 70 to 100 years on a five-year time step basis. The results from FASOMGHG yield a dynamic simulation of prices, production, management, consumption, GHG effects, and other environmental and economic indicators within these two sectors, under the scenario depicted in the model data.

FASOMGHG's key endogenous variables can include (if needed):

- commodity and factor prices,
- production, consumption, export and import quantities,

- land use allocations between sectors,
- management strategy adoption,
- resource use,
- economic welfare measures,
  - -- producer and consumer surplus,
  - -- transfer payments,
  - -- net welfare effects,
- environmental impact indicators,
  - -- GHG emission/absorption of carbon dioxide (CO2), methane (CH4), and nitrous oxide (N2O)
  - -- surface, subsurface, and groundwater pollution for nitrogen, phosphorous, and soil erosion.

To date, FASOMGHG and its predecessor model FASOM have been used to examine the effects of GHG mitigation policy, climate change impacts, public timber harvest policy, federal farm program policy, biofuel prospects, and pulpwood production by agriculture. It can also aid in the appraisal of a wider range of forest and agricultural sector policies as shown in Alig *et al.* (1998), Adams *et al*. (1999a), McCarl *et al*. (2000), among others.

### 4.3 The Forest and Agricultural Sector Model (FASOM) Overview

FASOM solves a multi-period, multi-market optimization problem by maximizing the present value of aggregated consumers' and producers' surpluses in the agricultural and forest sectors subject to resource constraints. The solutions reveal the prices and quantities of agricultural and forest markets in each period under the assumption that producers and consumers have perfect knowledge of market responses at the beginning of the modeling period. The basic structure of FASOM follows the formulation in McCarl and Spreen (1980) in which the life of the activities, such as forest, is determined endogenously and production activities adjust over time. The model includes 48 primary agricultural, 45 secondary agricultural commodities, and 8 forest products produced in 11 geographical regions. The agricultural sector activities are based on the agricultural sector model described in Chang, McCarl, and Adams (1989).

### *4.3.1 Basic Structure of the Model*

This partial equilibrium model depicts commodity demand for multiple products without explicit supply for those products, but rather with a production process and factor supply for inputs. The model has exogenous factor supply and product demand curves, but implicit factor demand and product supply. Such a model can be expressed as follows.

$$
\begin{array}{llllll}
\text{Max} & \sum_h \int_0^{Z_h} P_{dh}(Z_h)\, dZ_h - \sum_i \int_0^{X_i} P_{si}(X_i)\, dX_i & & & & \\
\text{s.t.} & Z_h \qquad - \sum_\beta \sum_k C_{h\beta k} Q_{\beta k} & \leq & 0 & & \forall\, h \\
 & - X_i + \sum_\beta \sum_k a_{i\beta k} Q_{\beta k} & \leq & 0 & & \forall\, i \\
 & \sum_k b_{j\beta k} Q_{\beta k} & \leq & Y_{j\beta} & & \forall\, j, \beta \\
 & Z_h, \quad X_i, \quad Q_{\beta k} & \geq & 0 & & \forall\, i, h, k, \beta
\end{array}
$$

This problem assumes that a number of different types of firms (β) are being modeled. Each firm has a finite set of production processes (k) which depict particular ways of combining fixed factors (j) with purchased factors (i) to produce commodities (h). The symbols in the formulation are: $P_{dh}(Z_h)$ is the inverse demand function for the

$h^{th}$ commodity; $Z_h$ is the quantity of commodity h that is consumed; $P_{si}(X_i)$ is the inverse supply curve for the $i^{th}$ purchased input; $X_i$ is the quantity of the $i^{th}$ factor supplied; $Q_{\beta k}$ is the level of production process k undertaken by firm β; $C_{h\beta k}$ is the yield of output h from production process k; $b_{j\beta k}$ is the quantity of the $j^{th}$ owned fixed factor used in producing $Q_{\beta k}$; $a_{i\beta k}$ is the amount of the $i^{th}$ purchased factor used in producing $Q_{\beta k}$ and $Y_{j\beta}$ is the endowment of the $j^{th}$ owned factor available to firm β.

The first line of this very simplified formulation is the objective function: maximize the area under the all the input supply curves minus the area under all the commodity demand curves (aggregate producers and consumers' welfare). The first constraint (which is actually a set of similar constraints for each h) shows how we link the inputs with the productive processes. The second constraint links the production process with the final produced commodities. The last constraint relates the production processes with the required resources to perform those activities (land, labor, etc.).

### *4.3.2 Forestry Model Elements*

In this section I describe key forest sector characteristics and the ways that the FASOMGHG model structure accommodates them. Forest stands grow at differential rates due to differences in management, site quality, ownership, climate, tree age and tree species. The FASOMGHG forest stand and inventory representation reflects these characteristics on current timberland and potentially afforested land in the contiguous 48 states under private ownership (Alig *et al.* 1998). Pubic lands are treated exogenously. Private timberland is characterized by:

- Geographic region (nine regions as defined below),
- Type of land owner (private lands only- two owners)
- Land use suitability for transfer to or from agriculture (5 groups),
- Forest types (ten) as defined below,
- Site productivity potential for wood volume growth (three levels) as defined below,
- Management intensity (23 timber management regimes applied to the area) as defined below, and
- Five-year age cohorts up to 100+ years of age.

#### 4.3.2.1 Regions

FASOMGHG covers forest and agricultural activity across the conterminous US, broken into 11 market regions meshed with 63 subregions for agricultural sector coverage. The 11 larger regions are a consolidation of regional definitions that would otherwise differ if the forest and agricultural sectors were treated separately. They are shown on Table 14. The 11-region breakdown reflects the existence of regions for which there is agricultural activity but no forestry, and vice versa.

Forest production occurs in 9 of the 11 regions used in FASOMGHG with the major timber producing regions being (a) the Pacific Northwest west of the Cascade Mountain Range (PNWW); (b) the South Central (SC) and (c) the South East (SE). National Forest timber and Canadian production are also represented but with exogenous harvest levels.

**Table 14. FASOMGHG 11 Region Definitions**

| Key | Region | States/Subregions |
|---|---|---|
| CB | Corn Belt | All regions in Illinois, Indiana, Iowa, Missouri, Ohio |
| NP | Northern Plains | Kansas, Nebraska, North Dakota, South Dakota |
| LS | Lake States | Michigan, Minnesota, Wisconsin |
| NE | Northeast | Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont, West Virginia |
| PNWE | Pacific Northwest-east side | Oregon and Washington, east of the Cascade mountain range |
| PNWW | Pacific Northwest-west side | Oregon and Washington, west of the Cascade mountain range |
| PSW | Pacific Southwest | All regions in California |
| RM | Rocky Mountains | Arizona, Colorado, Idaho, Montana, Eastern Oregon, Nevada, New Mexico, Utah, Eastern Washington, Wyoming |
| SC | South Central | Alabama, Arkansas, Kentucky, Louisiana, Mississippi, Eastern Oklahoma, Tennessee, Eastern Texas (TxEast) |
| SE | Southeast | Virginia, North Carolina, South Carolina, Georgia, Florida |
| SW | Southwest | Western and Central Oklahoma, All of Texas but the Eastern<br>Part -- Texas High Plains, Texas Rolling Plains, Texas Central Blacklands, Texas Edwards Plateau, Texas Coastal Bend,<br>Texas South, TexasTrans Pecos |

#### 4.3.2.2 Land Ownership

The only forested stands explicitly represented are those owned by private parties. Two ownership classes are defined

- Forest industry (FI) --private lands owned by companies or individuals operating wood manufacturing plants.
- Non industrial private forest --private lands owned by individuals or companies who do not operate wood manufacturing plants.

#### 4.3.2.3 Land Use Suitability

Five land suitability classes are used in tracking timberland:

**FORONLY** -- Timberland acres that are not suitable for conversion to agricultural uses;

**FORCROP** -- Acres that begin in timberland but could be converted to crop land uses

**FORPAST** -- Acres that begin in timberland but could be converted to pasture uses

**CROPFOR** -- Acres that begin in crop land uses but are converted to timberland. All afforested crop land is in this category and after conversion into forest can be returned to agricultural crop land later in the model time frame.

**PASTFOR** -- Acres that begin in pasture land uses but are converted to timberland. All afforested pasture land is in this category and after conversion into forest can be returned to agricultural pasture later in the model time frame.

The classification name identifies the type of allowed land use changes. The second part identifies the type of use for which the land is potentially suited for conversion (crop, pasture, or forest only) and by the prior use (first part of name). For example, **FORCROP** is land that was in forest cover and is suitable for conversion to crop land.

#### 4.3.2.4 Forest Type

Ten forest types are defined. These are listed in Table 15. The definitions used in all regions but the SC, SE, and PNWW are limited to HARD and SOFT. In the SC and SE regions the definitions BOT_HARD, UP_HARD, NAT_PINE, OAK_PINE, and PLNT_PINE are used. The three definitions DOUG_FIR, OTH_SWDS, and HARDWOODS are used in the PNWW region.

#### 4.3.2.5 Site Productivity

Three site productivity types are defined. These are based on a classification of forestland in terms of potential annual cubic-foot volume growth per acre at culmination of mean annual increment in fully-stocked natural stands (Smith *et al.* 2001). Specific productivity ranges can vary by region and an example for the South is given in Table 16 below.

**Table 15. Forest Types**

| Forest Type | Description |
|---|---|
| SOFT | Broad softwood forest type |
| HARD | Broad hardwood forest type |
| BOT_HARD | Bottomland hardwood forest type in the South |
| UP_HARD | Upland hardwood forest type in the South |
| NAT_PINE | Natural pine forest type in the South |
| OAK_PINE | Oak-pine forest type in the South |
| PLNT_PINE | Planted pine forest type in the South |
| DOUG_FIR | Douglas-fir forest type in the PNWW region |
| OTH_SWDS | Representative softwood forest type, excluding Doug-fir |
| HARDWOODS | Composite hardwood forest type for the PNWW region |

**Table 16. Timberland Site Classes for the South**

| Site Class | Cubic feet per acre per year |
|---|---|
| LO | 20-49 cubic feet |
| MED | 50-84 cubic feet |
| HI | 85+ cubic feet |

#### 4.3.2.6 Management Intensity Classes

The model allows several different levels of timber management intensity for newly regenerated timber stands. These management intensity classes (MICs) were largely derived from the MICs developed for modeling by the Aggregate TimberLand Analysis

System (ATLAS) (Mills and Kincaid, 1992) in the 2000 RPA Timber Assessment (Haynes, 2003; Mills and Zhou, 2003). The number and type of MICs vary by region, forest type, and site class. The largest numbers are in the SC, SE and PNWW where the bulk of the nation's timber harvest originates. In other regions, two relatively low intensity levels of timber management are used that approximate the regional forms of timber management: passive (PASSIVE) -- depicting no management intervention of any type between timber harvests of naturally-regenerated aggregates; and low (LO) -- custodial timber management of naturally-regenerated aggregates (Adams *et al.*, 1996).

The management options in the South and PNWW regions involve a combination of harvest method -- (clearcut or partial cutting) and silvicultural practices including thinning. The management alternatives are listed in Table 17.

#### 4.3.2.7 Cohorts

For an even-aged stand, a FASOMGHG stand is characterized by a range of ages for the trees therein. Even-aged stands are those where 70% or more of the tree stocking falls within a 30-year grouping. Five-year cohorts are used to classify even-aged stands, to provide indications about how long different stands have occupied the land. In the South the first year of occupancy is commonly trees that are older as trees are transplanted in at older ages. The cohorts for land occupancy are 0-4, 5-9, 10-14, 14-19 and so on in five-year intervals up to 95-99 and 100+. No differentiation is done between age groups beyond 100 years.

**Table 17. Forest Management Intensity Codes (MICs) Used**

| MIC Code | Description |
|---|---|
| AFFOR | Afforestation of bottomland hardwood (SE and SC) |
| AFFOR_CB | Afforestation of hardwood and softwood forest types (CB) |
| LO | Natural regeneration (or afforestation) with low management |
| NAT_REGEN | Natural regeneration with low management (PNWW) |
| NAT_REGEN_PART_CUT_HI | Partial cutting with high level of management (PNWW) |
| NAT_REGEN_PART_CUT_LO | Partial cutting with medium level of management (PNWW) |
| NAT_REGEN_PART_CUT_MED | Partial cutting with low level of management (PNWW) |
| NAT_REGEN_THIN | Natural regeneration with a commercial thin (PNWW) |
| PART_CUT_HI | Partial cutting with medium level of management (SE and SC) |
| PART_CUT_HI+ | Partial cutting with high level of management (SE and SC) |
| PART_CUT_LO | Partial cutting with low level of management (SE and SC) |
| PASSIVE | Passive management (minimal amount of management) |
| PLANT | Plant with no intermediate treatments (PNWW) |
| PLANT_THIN | Plant with medium level of management (PNWW) |
| PLANT+ | Plant with high level of management (PNWW) |
| PLNT_HI | Planted pine with high level of management (SE and SC) |
| PLNT_HI_THIN | Planted pine with commercial thin and high level of management (SE and SC) |
| PLNT_LO_THIN | Planted pine with commercial thin and no intermediate treatments (SE and SC) |
| PLNT_MED | Planted pine with medium level of management (SE and SC) |
| PLNT_MED_THIN | Planted pine with commercial thin and medium level of management (SE and SC) |
| RESERVED | Reserved from harvest |
| SHORT_ROTSWDS | Short rotation softwoods with high level of management (SE and SC) |
| TRAD_PLNT_PINE | Planted pine with no intermediate treatments (SE and SC) |

## 4.4 Imposing Climate Change Scenarios

The analysis will be done under two Global Climate Change forecasts. These scenarios are drawn from the Forest Section of the US Global Climate Change Research Program National Assessment that was done in 2001, and are specifically discussed in Irland *et al*. (2001).

The range of scenarios considered alternate assumptions about 1) climate (the Hadley and the Canadian scenarios), 2) forest productivity (the TEMM and CENTURY biogeochemistry models), and 3) timber and agricultural product demand (determined by population growth and economic growth).

The specific details for each scenario used in this work are:

- Canadian Model with adaptation (cc_wt_adpt_avgg): assumes future climatic conditions as Canadian Global Circulation Model (GCM) predicts. The scenario allows adaptation in forestry using TEMM vegetive simulator, as well as adaptation for crops and agricultural related issues such as pests, water and livestock. Crop exports are assumed to follow an average of GCMs (GISS, UKMO, and Darwin), and climatic effects are assumed to happen in year 2030.
- Hadley Model with adaptation (hc_wt_adpt_avgg): the same as the previous model, but using the Hadley GCM explained in previous sections of this work. In general, the results obtained are very similar regardless the GCM we used.

## 4.5 How the Adaptation Model Works

The model restricts whether particular adaptation options are available to the forestry sector through 4 types of constraints:

### *4.5.1 Forest Type Adaptation Constraint (No Species Adaptation)*

The first restriction disallows the changing of species type thus eliminating the possibility of switching to more adapted types of trees. Suppose that a stand located in a particular region, of a particular owner, productivity site and period is cut. The agent's replanting decisions could differ in many ways with respect to the previous stand's characteristics: we could replant trees using a different management intensity procedure, or we could replant trees that will be cut at a different age, or we can transfer land from/to agricultural uses. However, we are imposing a constraint that prevents the agent from changing the type of forest that is replanted. The constraints in the program look like the following:

```
CONS_SUCCESSORGROUP(reg,pvtlogowner,site,period,successorgroup) $ (sum((class),
        isnew3(reg,class,pvtlogowner,successorgroup,site))
        and yesfor gt 0 and yesxav2)..

* acres from existing stands
  sum(isexist(period,cohort,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy)
            $examine(policy),
          FORPRDEXIST(period,cohort,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy))

* acres from reforested and afforested stands
 + sum((oldperiod,when)$( date(oldperiod)+elapsed(when) eq date(period)),
     sum(isnew(when,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy)
            $( examine(policy) and whendone(oldperiod,when)),
          ( FORPRDNEW(oldperiod,when,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy)
           +FORPRDNEWAFFOREST(oldperiod,when,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy)
              $(yesag and ardclasses("afforest",class)))))

=l=

* acres to reforest
  sum(when$whendone(period,when),
    sum(isnew(when,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy)$examine(policy),
          FORPRDNEW(period,when,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy))).
```

This constraint says that in a given period and site, and for a given variety of trees, the total amount of acres of new planting must be greater than or equal to the amount of acres that were just harvested in that site. All the other adaptation strategies are allowed (rotation age, or management intensity).

The sets over which this constraint (and the next ones) is defined are

***reg*** -- log producing region
***pvtlogowner*** -- type of private owner
***site*** -- site productivity class
***period*** – period is which stand is cut
***succesorgroup*** -- forest type
***mgtintensity*** -- management intensity class
***cohort (when)***-- tree age cohort

***class*** -- land suitability for agriculture or forestry

Notice from the constraint that the cut lands can come from existing stands and from previously replanted or afforested stands. The constraint also sums the land across all the dimensions that are allowed to be altered (rotation age, management intensity and land transfers).

### *4.5.2 Management Intensity Constraint (No MIC Adaptation)*

The second restriction disallows the changing of Management Intensity Class (MIC) type thus eliminating the possibility of switching to more management. Using a similar structure, this constraint allows replanting trees altering the age of the future stands, the species, and the type of land used. The restriction that the constraint imposes is on the acres reforested by  kind of management intensity, which is set to be fixed from one rotation to the next one. In summary, the constraint states that the amount of acres planted by MIC in a given period and site is greater than or equal to the amount of harvested acres by MIC, with the possibility to alter all the other dimensions (forest type and age).

. The constraint in the program is:

```
*** NO MIC ADAPTATION ***

CONS_MGTINTENSITY(reg,pvtlogowner,site,period,MgtIntensity) $ (sum((class,successorgroup),
        isnew3(reg,class,pvtlogowner,successorgroup,site))
        and yesfor gt 0 and yesxav1)..

* acres from existing stands
  sum(isexist(period,cohort,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy)$examine(policy),
          FORPRDEXIST(period,cohort,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy))

* acres from reforested and afforested stands
 + sum((oldperiod,when)$( date(oldperiod)+elapsed(when) eq date(period)),
     sum(isnew(when,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy)$(
            examine(policy) and whendone(oldperiod,when)),
```

```
        ( FORPRDNEW(oldperiod,when,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy)
         +FORPRDNEWAFFOREST(oldperiod,when,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy)
              $(yesag and ardclasses("afforest",class)))))

=l=

* acres to reforest
  sum(when$whendone(period,when),
    sum(isnew(when,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy)$examine(policy),
        FORPRDNEW(period,when,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy))).
```

### *4.5.3 Cohorts Constraint (No Rotation Age Adaptation)*

In this case, the constraint prevents the agent from changing the age of the forest stands. In other words, if a stand is cut at the age of 40 years, the next rotation will be when the new planted trees are 40 years old. This constraint implies that for a given site and period, the amount of acres by harvest age of new planting is greater than or equal to the acres by harvest age of old harvest. As before, we are allowed to change everything else: management intensity, species, and land use. The constraint is:

```
*** NO ROTATION AGE ADADTATION ***

CONS_ROTATIONAGE(reg,pvtlogowner,site,period,when) $ (sum((class,successorgroup),
      isnew3(reg,class,pvtlogowner,successorgroup,site))
      and yesfor gt 0 and yesxav3)..

* acres from existing stands
  sum(isexist(period,cohort,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy)$(
           examine(policy) and (date(period)-today+TREEAGE(COHORT) eq HARVAGE(WHEN)+ 2.5)) ,
        FORPRDEXIST(period,cohort,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy))


* acres from reforested and afforested stands
 + sum((oldperiod)$( date(oldperiod)+elapsed(when) eq date(period)),
     sum(isnew(when,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy)$(
          examine(policy) and whendone(oldperiod,when)),
        ( FORPRDNEW(oldperiod,when,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy)
         +FORPRDNEWAFFOREST(oldperiod,when,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy)
              $(yesag and ardclasses("afforest",class)))))

=l=

* acres to reforest

    sum(isnew(when,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy)$ (examine(policy) and
whendone(period,when)),
        FORPRDNEW(period,when,reg,class,pvtlogowner,successorgroup,site,MgtIntensity,policy)).
```

### *4.5.4 Land Use Constraint (No Land Transfer Adaptation)*

This kind of constraint restricts the agent from changing the use of forest land. It states that the amount of land used for forestry must continue to be used in forestry with no outmigration. Constraint states that the amount of acres of new planting is greater than or equal to the acres of old harvested, by period and site. As before, we are allowed to alter all the other dimensions that the agent can change. The constraint looks in this way:

```
*** NO LAND TRASFER TO AG ALLOWED ***

CONS_LANDTRANSFER(reg,pvtlogowner,site,period) $ (sum((class,successorgroup),
        isnew3(reg,class,pvtlogowner,successorgroup,site))
        and yesfor gt 0 and yesxav4)..

* flow of forest land to ag
  sum((class,successorgroup),FORSIDE_LAND_TOAG(reg,class,pvtlogowner,successorgroup,site,period)
        $whentran(reg,class,pvtlogowner,site,"toag")
        $(landcon gt 0 and yesag and yesfor ))

=e=

0.
```

## 4.6 Results

The study was done under the two GCM models to examine the value of the adaptation strategies. The results are depicted in Table 18 in terms of total reduction in welfare from a base situation in which there is no adaptation constraints. The welfare units are measured as the net present value of consumer and producer surpluses in 2004 US dollars.

The total economic costs of not allowing the abovementioned adaptation strategies are:

- For no MIC adaptation on forests: around 1.26 billion dollars for Canadian and Hadley models.

- Also, when species adaptation is not possible, the cost for the society is around 1.26 billion dollars.
- In case that rotation age adaptation is not possible, we have a total cost of 60.3 billion dollars, being this adaptation strategy the most expensive for the society when it is not allowed.
- Also, the smallest cost for the society occurs when land transfer is not permitted, with a total cost of around 185,000 dollars.

**Table 18. Summary Welfare Report NPV in 2004$**

| | Canadian Model with adaptation (cc_wt_adpt_avggcm) | Hadley Model with adaptation (hc_wt_adpt_avggcm) |
|---|---|---|
| Management Intensity | 1,263,186,512 | 1,263,187,051 |
| Species | 1,263,797,814 | 1,263,798,354 |
| Rotation Age | 60,296,941,863 | 60,296,942,401 |
| Land Transfer | 184,657 | 185,196 |

Notice from the results that the magnitudes are very similar regardless the climate scenarios used in the model.[12]

## 4.7 Conclusions

This section estimates the value of various forest adaptation strategies. For this purpose, I imposed a set of constraints to a price-endogenous mathematical programming model of the Forestry and Agriculture Sector for the United States (FASOM) that disallow particular types of adaptation to see what they were worth. The main feature of this model is the ability to calculate disaggregated gains and losses for different economic sectors into the country as well as overseas.

[12] Table 20 in Appendix C shows the details of percentage increase in production, prices, imports and exports of forestry products using each set of constraints.

The kinds of constraints imposed in this model are of four types: 1) no management intensity adaptation, 2) no species adaptation, 3) no rotation age adaptation, and 4) no land transfers adaptation.

In global terms, the model calculates losses for the society when we do not allow the before mentioned adaptation strategies. The biggest society losses occur when rotation age adaptation is not allowed, with a cost of around 60 billion dollars. Then, we have constrained MIC and species adaptation strategies, with a cost of around 1.26 billions. Finally, the restricted strategy with the slightest effect for society is land transfer, with a cost of around 180,000 dollars.

Since adaptation is automated in the model, and agents are not necessarily able to perform full adaptation to climate change, a recommendation from these results is that policy makers should sponsor, through tutoring and resource allocation, those strategies which represent a greater gain for the society, the ones that are more costly when not allowed.

# 5. CONCLUSIONS, LIMITATIONS AND FURTHER RESEARCH NEEDS

This dissertation examined the effects of climate change on agricultural and forestry issues. Specifically, using econometric models of panel data, and a spatial equilibrium model for the U.S. forestry sector, I examined

- The effects of climate and projected climate change on crop yields examining their mean and variance.
- The effects of climate and projected climate change on returns to research investments in technical progress in agriculture
- The value of forest adaptation strategies in the face of climate change.

More specifically in Section 2, I examined the impact of climate change on returns to research investments extending the work of Huffman and Evenson (2006), using a pooled cross-section time-series model of agricultural productivity for the forty-eight contiguous states over 1970–1999. Climatic variables temperature, amount and intensity of precipitation result to be significant in the econometric model.

Based on projected climate simulations, I found that climate change alters the rate of return to research. The biggest effects are due to precipitation, which increases returns to research investments. Besides higher rainfall intensity, where more precipitation happens in shorter time periods, decreases returns to research investments. On the other hand, I found that temperature has a differentiated regional effect with negative implications in the southwest.

I also forecasted the growth rates of agricultural research investments required in order to compensate for the impact of climate change. If one wishes to increase investments to adapt to climate change restoring pre climate change TFP rates of growth, around an 18% increase is needed at the national level. This varies by region, with the largest increase needed in the Southern Plains and reductions calculated as appropriate in the Mountain and Pacific regions.

Section 3 reported on an investigation of the impact of climate on the stationarity of the crop yield distribution, considering temperature, precipitation, variance of intra-annual temperature, a constructed index of rainfall intensity, and the Palmer Drought Severity Index (PDSI). I found that the mean of the crop yields are affected by the average temperature and precipitation. In addition, I also note that higher variances in climate conditions tend to lower average crop yield and inflate yield variability, although the magnitude of this effect varies across crops. The variability of precipitation, as measured by a rainfall intensity index and the Palmer Drought Index has a significant impact on crop yields as well.

Finally, I examined the welfare value of alternative adaptation measures for forestry in adaptation to future climate change. For this purpose, I imposed a set of adaptation constraints on a price-endogenous mathematical programming model, the Forestry and Agriculture Sector Optimization Model for the United States (FASOM). The main feature of this model is the ability to simulate the forest and agricultural sectors, and yield estimates of the gains and losses for different economic sectors into the country as well as overseas. The nature of the constraints is related to not allowing certain adaptation practices related to forestry activities, such as management intensity, type of species, age of rotation, and land transfers to agriculture and urban development.

Adaptation strategies constraints in the model states that the amount of acres of new planting for a given MIC (type of forest or rotation age) must be greater than or equal to the amount acres of old harvest. This means that for a given period and site, the agent is not allowed to change the way he has been working with the forest stands.

In global terms, the model calculates losses for the society when we do not allow the before mentioned adaptation strategies. The biggest society losses occur when rotation age is not allowed, with a cost of around 60 billion dollars. Then, we have constrained MIC and species adaptation strategies, with a cost of around 1.26 billion. Finally, the restricted strategy with the slightest effect for society is land transfer, with a cost of around 180,000 dollars.

## 5.1 Limitations

This work embodies a number of limitations which can be summarized as follows:

- Section 2 works with an aggregate index of agricultural factor productivity. This could be problematic in the sense that different crops could respond in different ways to public research capital investments, and the aggregation could obscure such results.
- Also, there is a need to decompose the regional effects into more disaggregate, more homogeneous regions to avoid the lack of significance in the estimations due to an excessive aggregation.

- Another limitation in the econometric part of this work is given by the endogeneity of the regressors. Particularly, public research investment is a variable that can be endogenous to the level of total factor productivity. This problem can cause the estimators to be biased.

- A major problem in the econometric estimations is that in Section 2, the unit root test showed that temperature is a stationary variable. This occurs because of the short span of the data with respect to IPCC's works. According to IPCC, temperature is a variable that has been increasing globally, which is precisely the argument of climate change, using data that covers a time span of more than 100 years. With a data set from 1970 to 1999, only for the continental US, it is not possible for the econometric tests to identify the sustained increase in temperature that IPCC has found.

- In Section 3, the main limitations involve the method of estimation for the econometric model. Greene (2003) argues that Generalized Least Squares –GLS– method (2 stage least squares being a particular case) yields more efficient results than Ordinary Least Squares if the real structure of the underlying heteroscedasticity is known and modelled properly. However if unknown heteroscedasticity is incorrectly modelled, GLS estimation will likely yield more problems than the ones intended to be corrected. Since the structure of the variance equation is imposed as given, in case it is not modelled correctly the estimations could be biased.

- Another issue is the lack of more disaggregated data, which could provide more information for the estimations. It would be more preferable to have access to county-level observations than to state-level observations.

- A problem with the econometric estimations is the inability of the model to incorporate $CO_2$ concentration (one of the major drivers of climate change) effects on climate change. This is because it is not possible to separate the effect of technological change from the levels of $CO_2$ concentration. This happens because both variables are increasing through time. As a consequence, we can not identify what part of Agricultural TFP increase is caused by innovation, and what part is due to more $CO_2$, which is proven to make crops to grow faster.

- In Section 4, the main limitation is the lack of a method to provide confidence intervals on the calculations for the welfare effects of the various adaptation strategies. Specifically, optimization models are deterministic as apposed to econometric models; therefore the obtained results are only point estimations.
- Finally, one limitation is the fact that the results of mathematical programming models are highly dependent on the parameters of the model. These parameters are sometimes taken as given from other works; sometimes those parameters are calibrated or estimated using econometric methods, sometimes they are just assumed. Some problems could arise if those parameters are not constant through time, making the results somewhat sensitive to the choice of parameters.

## 5.2 Suggestions for Further Research

This work opens many possibilities for future research. In general, all the models could be refined with the availability of more data: with more time series observations or with more disaggregate observations –county level–. Each one of those cases gives new opportunities to use state-of-the-art panel data methods, which differ depending on the relative “length” or “width” of the panel structure.

Another opportunity derived from this work is to study the effects on agricultural yields and volatilities of extreme events. Since those events do not occur frequently, an alternative methodology should be developed in order to take into account events that happen with low regularity, but with very strong effects.

One more possibility of future work is to develop a method to compute agricultural factor productivities by crop. If this could be done, it would give a lot of information about the effects of public research investment and would help to set priorities on crops for future investment driven by climate change.

A suggestion for future research is the development of new tests and procedures, as an alternative to unit root tests, to account for climate change in variables such as temperature and precipitation. One suggestion is to develop a test of structural break in panels for the level/variance of the climatic variables. The idea is that those variables have had a “stable” mean or variance, which has changed at some moment of time. Another possibility is to include Bayesian methods to the unit root tests, incorporating somehow historical information from a longer time span, and establishing evolving parameters that follow a prior distribution.

At last, one of the FASOM most important properties is its flexibility and capacity to be expanded incorporating more variables and equations. A natural extension of this work is to expand the model to include more species, markets and sectors. Also, we can expand the model to include new adaptation strategies, and to compute carbon sequestration under different forest adaptation scenarios.

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# APPENDIX A

# PANEL UNIT ROOT AND COINTEGRATION TESTS

## A.1 Panel Unit Root Tests

### *A.1.1 Levin, Lin and Chu (LLC) Test*

Levin, Lin and Chu (2002) suggest a panel unit root test that examines the null hypothesis that each individual time series contains a unit root versus the alternative that each time series is stationary. The structure to be tested has a form similar to an Augmented Dickey-Fuller (ADF) test but is applied in a panel framework:

$$\Delta y_{it} = \rho_i y_{i,t-1} + \sum_{L=1}^{p_i} \theta_{iL} \Delta y_{i,t-L} + \alpha_{mi} d_{mt} + \varepsilon_{it}, \qquad m = 1, 2, 3 \tag{13}$$

where

$y$ are the variables to be tested[13] for unit roots,

$\Delta$ is the lag operator,

$p_i$ is the lag order, which is allowed to vary across cross sections and is determined in the test procedure, these terms are included to take into account heterogeneous serial correlation across cross sectional units;

$d_{mt}$ can take three values depending on the model specification: $d_{1t}$ ={empty set}, $d_{2t}$ ={1} including an individual constant and $d_{3t}$ ={1, $t$} including an individual constant and an individual linear trend;

$\varepsilon$ is an error term, and

[13] Normal panel model notation is used here where $i$ = 1,…,$N$ denotes cross section (state) and $t$ = 1,…,$T$ denotes time period (year).

$\rho_i$, $\theta_{iL}$, $\alpha_{mi}$ are parameters to be estimated.

The null hypothesis is $H_0 : \rho_i = \rho = 0$ for all $i$ while the alternative is $H_1 : \rho_i = \rho < 0$ for all *i*. Levin, Lin and Chu (2002) show that their estimator $t_\rho^*$, which is a modified version of the *t* test for $\rho = 0$, is asymptotically distributed as $N(0,1)$.

This test provides a power improvement over individual unit root test over each cross section. However, it assumes independence across cross sections, which does not necessarily hold; and that *all* cross sections have or do not have a unit root, which is very restrictive.

### *A.1.2 Im, Pesaran and Shin (IPS) Test*

As stated above, the LLC test is restrictive in that it requires $\rho$ being homogeneous across individuals. Im, Pesaran and Shin (2003) permit a heterogeneous coefficient on $y_{i,t-1}$, proposing an alternative testing procedure that averages the individual unit root test statistics. The estimated model is also the one given in equation (13). However, the null hypothesis is that each series in the panel has a unit root, $H_0 : \rho_i = \rho = 0$ and the alternative hypothesis states that some individual series have unit roots while some are stationary, which can be expressed as $H_1 : \rho_i < 0$ for $i$ = 1, 2,…, $N_1$ and $\rho_i = 0$ for $i = N_1 + 1, \ldots, N$.

The IPS $\bar{t}$ statistic is defined as the average of all the *N* individual ADF statistics:

(14) $$\bar{t} = \frac{1}{N} \sum_{i=1}^{N} t_{\rho_i}$$

where $t_{\rho_i}$ is the individual ADF *t*-statistic that tests $H_0 : \rho_i = 0$.

Im, Pesaran and Shin (2003) show that when the lag order is non zero for some cross sections, and after a proper standardization of $\bar{t}$, the resulting estimator, $t_{IPS}$ is distributed as $N(0,1)$.[14] Using Monte Carlo experiments, they found that the small sample properties of IPS test outperform those from LLC test and that both LLC and IPS tests present important size distortions when either *N* is small or *N* is relatively large with respect to *T*.

### *A.1.3 Breitung Test*

Breitung (2000) finds that LLC and IPS tests suffer a remarkable loss of power if individual trends are included because a bias adjustment is needed. He suggests a test statistic that does not require bias correction, that he shows possesses greater power. The test involves performing the following pooled regression

$$e_{it}^* = \rho v_{i,t-1}^* + \varepsilon_{it}^* \tag{15}$$

and then testing using the *t*-statistic for $H_0 : \rho = 0$. The terms $e_{it}^*$ and $v_{i,t-1}^*$ are corrected error terms defined in Breitung (2000), and the test is asymptotically distributed as $N(0,1)$.

[14] For details on the construction and the asymptotic properties of the test, see Im, Pesaran and Shin (2003).

## A.2 Panel Cointegration Tests

### *A.2.1 Kao Tests*

This is a residual-based Dickey-Fuller (DF) kind of test. It is based on testing whether the residuals of the panel estimation are stationary or not. Kao (1999) proposed DF and ADF tests of unit root for the residuals $e_{it}$ as a test for the null of no cointegration. The DF test is applied to the fixed effect residuals using this specification:

(16) $$\hat{e}_{it} = \rho \hat{e}_{i,t-1} + v_{it}\,.$$

We use two versions of the test which assume strong exogeneity of the regressors, those are:

(17) $$DF_\rho = \frac{\sqrt{N}T(\hat{\rho}-1) + 3\sqrt{N}}{\sqrt{10.2}}$$

and

(18) $$DF_t = \sqrt{1.25}\,t_\rho + \sqrt{1.875N}$$

where $\hat{\rho}$ and $t_\rho$ are the estimated parameter of equation (16) and its *t*-statistic, respectively. The asymptotic distribution of the tests converges to a standard normal distribution $N(0,1)$ by sequential limit theory.

### *A.2.2 Pedroni Tests*

Pedroni (1999) proposed several tests and critical values for the null hypothesis of panel cointegration, which allow a considerable degree of heterogeneity and endogenous regressors. Indeed, an important feature of these tests is that they allow not only the dynamics and fixed effects to differ across members of the panel, but also that they allow the cointegrating vector to differ across members under the alternative hypothesis. These tests are applied over the regression residuals from the hypothesized cointegrating regression. In the most general case, this may take the form:

(19) $$y_{it} = \alpha_i + \delta_i t + \beta_{1i} x_{1it} + \ldots + \beta_{Mi} x_{Mit} + e_{it}$$

where $M$ refers to the number of regression variables. Notice that this structure allows heterogeneity for the panel individuals at different levels: individual effects ($\alpha_i$), individual linear trends ($\delta_i$), and regressor coefficients ($\beta_{mi}$).

Pedroni (1997) derives the asymptotic distributions and explores the small sample performances of seven different statistics. Of these seven statistics, four are based on pooling along what is commonly referred to as the within-dimension, and three are based on pooling along what is commonly referred to as the between-dimension. For the within-dimension statistics the test for the null of no cointegration is implemented as a residual-based test of the null hypothesis $H_0 : \gamma_i = 1$ for all *i*, versus the alternative hypothesis $H_1 : \gamma_i = \gamma < 1$ for all *i*, so that it presumes a common value for $\gamma_i$ (the autoregressive coefficient of the estimated residuals). By contrast, for the between-dimension statistics the null of no cointegration is implemented as a residual-based test of the null hypothesis $H_0 : \gamma_i = 1$ for all *i*, versus $H_1 : \gamma_i < 1$ for all *i*, so that it does not presume a common value for $\gamma_i$ under the alternative hypothesis, allowing an additional source of potential heterogeneity across individual members of the panel.

### *A.2.3 Westerlund Tests*

Westerlund (2007) proposes four panel tests of the null hypothesis of no cointegration that are based on structural rather than residual dynamics. These structural kind of test does not impose any common factor restriction,[15] which is a main reason associated to loss of power for residual-based cointegration tests. However, Westerlund tests are more restrictive than Pedroni's residual-based tests in the sense that the former do not allow endogenous regressors in the model.

The tests are based on the estimation of the following error correction equation:

$$\Delta y_{it} = \delta_i' d_t + \alpha_i (y_{it-1} - \beta_i' x_{it-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{it-j} + \sum_{j=0}^{p_i} \gamma_{ij} \Delta x_{it-j} + e_{it} \tag{20}$$

where

$y$ is the dependent variable,

$x$ is a vector of independent variables,

$d_t = (1,t)'$ is the set of deterministic components, and

$\Delta$ is the first difference operator.

Notice from equation (20) that if $y$ and $x$ are I(1) variables, their first differences are I(0); so for that equation to be stable, we need $y_{it-1} - \beta_i' x_{it-1}$ to be stationary, or equivalently $y_{it}$ and $x_{it}$ must be cointegrated. From the estimated

[15] Kremers, Ericsson and Dolado (1992) define common factor restriction to the fact that residual-based tests require the long-run cointegrating vector for the variables in their levels being equal to the short-run adjustment process for the variables in their differences.

parameters, $\alpha_i$ is known as the error correction parameter, and $\beta_i$ is the long-run equilibrium relationship between $y_{it}$ and $x_{it}$.

Westerlund (2007) states that if $\alpha_i < 0$, then there is error correction, which implies that $y_{it}$ and $x_{it}$ are cointegrated, whereas if $\alpha_i = 0$, there is no error correction and no cointegration. From the four statistics proposed by Westerlund, for two of them, referred as "panel" statistics ($P_\tau$ and $P_\alpha$), the null and alternative hypotheses are formulated as $H_0 : \alpha_i = 0$ for all *i*, versus $H_1^p : \alpha_i = \alpha < 0$ for all *i*, which indicates that a rejection should be taken as evidence of cointegration for the panel as a whole. For the second pair, defined as "group" statistics ($G_\tau$ and $G_\alpha$) the null hypothesis remains the same, while $H_1^g : \alpha_i < 0$ for at least some *i*, suggesting that a rejection should be taken as evidence of cointegration for at least one of the cross-sectional units. See details on test construction and asymptotic distributions of $P_\tau$, $P_\alpha$, $G_\tau$, and $G_\alpha$ in Westerlund (2007).

# APPENDIX B

## ALTERNATIVE AG-TFP MODEL SPECIFICATIONS

### Table 19. Alternative Agricultural TFP Model Specifications

| Dependent Variable: | Model 2 | | Model 3 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|---|---|
| ln (Ag. Total Factor Productivity) | Coefficient | p_value | Coefficient | p_value | Coefficient | p_value | Coefficient | p_value |
| ln (Public Ag. Research Capital) | 0.0900 | 0.000 | 0.0941 | 0.002 | 0.0841 | 0.000 | 0.0929 | 0.002 |
| ln (Public Extension Capital) | 0.0718 | 0.000 | -0.0235 | 0.168 | 0.0660 | 0.001 | -0.0243 | 0.154 |
| ln (Public Ag. Research Capital Spilling) | 0.0337 | 0.047 | 0.4937 | 0.000 | 0.0470 | 0.006 | 0.4953 | 0.000 |
| ln (Private Ag. Research Capital) | 0.1095 | 0.040 | -0.1358 | 0.004 | 0.1258 | 0.019 | -0.1347 | 0.004 |
| D1 (Northeast) | -0.2992 | 0.697 | | | -0.4064 | 0.597 | | |
| D2 (Southeast) | -6.0873 | 0.000 | | | -6.2579 | 0.000 | | |
| D4 (Northern Plains) | -0.3178 | 0.706 | | | -0.4181 | 0.619 | | |
| D5 (Southern Plains) | 3.7331 | 0.013 | | | 3.6181 | 0.016 | | |
| D6 (Mountains) | -0.3416 | 0.698 | | | | | | |
| D7 (Pacific) | -5.8040 | 0.000 | | | | | | |
| D6_1 (Mountains North) | | | | | -1.2427 | 0.361 | | |
| D6_2 (Mountains South) | | | | | 0.0506 | 0.955 | | |
| D7_1 (Pacific North) | | | | | 0.7708 | 0.652 | | |
| D7_2 (Pacific South) | | | | | -1.5932 | 0.626 | | |
| Trend | 0.0127 | 0.000 | 0.0029 | 0.348 | 0.0126 | 0.000 | 0.0029 | 0.345 |
| ln (Temperature) × D1 | 0.1165 | 0.290 | -0.2497 | 0.027 | 0.1374 | 0.219 | -0.2498 | 0.027 |
| ln (Temperature) × D2 | 1.5126 | 0.000 | -0.0536 | 0.807 | 1.5458 | 0.000 | -0.0543 | 0.805 |
| ln (Temperature) × D3 | 0.0203 | 0.917 | -0.0200 | 0.877 | 0.0099 | 0.959 | -0.0192 | 0.881 |
| ln (Temperature) × D4 | 0.1654 | 0.483 | -0.0320 | 0.843 | 0.1851 | 0.433 | -0.0312 | 0.847 |
| ln (Temperature) × D5 | -0.8618 | 0.023 | -0.4812 | 0.065 | -0.8418 | 0.027 | -0.4811 | 0.065 |
| ln (Temperature) × D6 | 0.1557 | 0.194 | -0.1129 | 0.497 | | | | |
| ln (Temperature) × D7 | 1.5330 | 0.000 | 0.0161 | 0.966 | | | | |
| ln (Temperature) × D6_1 | | | | | 0.3879 | 0.184 | 0.0288 | 0.904 |
| ln (Temperature) × D6_2 | | | | | 0.0486 | 0.692 | -0.2587 | 0.272 |
| ln (Temperature) × D7_1 | | | | | -0.1804 | 0.642 | -0.1891 | 0.628 |
| ln (Temperature) × D7_2 | | | | | 0.5225 | 0.495 | 1.1413 | 0.283 |
| ln Total Precipitation | 0.0706 | 0.003 | 0.0349 | 0.020 | 0.0755 | 0.001 | 0.0352 | 0.019 |
| ln Precipitation Intensity | -0.0468 | 0.001 | -0.0246 | 0.080 | -0.0452 | 0.001 | -0.0255 | 0.070 |
| Intercept | -3.7073 | 0.000 | | | -3.9227 | 0.000 | | |

**Notes**: Model 2 - Eq. (5). Prais-Winsten regression, correlated panels corrected standard errors, with climatic variables.
Model 3 - Eqs. (5) and (7). Long run equation, Pooled Mean Group Regression for non stationary heterogeneous panels, with climatic variables.

# APPENDIX C

# FORESTRY ACTIVITY SUMMARY

**Table 20. Forestry Activity Summary**

| | | Scenario | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | cc_wt_adpt_avgg | | | | hc_wt_adpt_avgg | | | |
| | | **Intensity** | **Species** | **Age** | **Land** | **Intensity** | **Species** | **Age** | **Land** |
| Forest Land | Remaining Exist | 0.38 | 0.43 | 1.52 | 0.08 | 0.37 | 0.43 | 1.51 | 0.08 |
| Forest Land | New on hand | 96.33 | 91.27 | -14.76 | 16.11 | 96.93 | 91.27 | -14.76 | 16.11 |
| Forest Land | Age of New on hand | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Management | Harvested Exist Acres | -25.26 | -28.66 | -100 | -5.31 | -24.68 | -28.49 | -100 | -5.08 |
| Forest Management | Afforested Acres | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Management | Reforested Acres | 652.73 | 618.46 | -100 | 109.13 | 656.8 | 618.46 | -100 | 109.13 |
| Forest Management | Deforested Acres to Dev | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Management | Deforested Acres to Ag | -100 | -100 | -100 | -100 | -100 | -100 | -100 | -100 |
| Forest Rotation Age | softwood | 17.5 | 25.08 | -100 | -0.49 | 17.39 | 25.2 | -100 | -0.39 |
| Forest Rotation Age | hardwood | 0.93 | 0.87 | -100 | -0.08 | 0.41 | 0.84 | -100 | -0.11 |
| Forest Acres Exist Harvest - OP | SOFT | -71.21 | -81.94 | -100 | -13.46 | -71.23 | -81.81 | -100 | -12.85 |
| Forest Acres Exist Harvest - OP | HARD | -45.79 | -46.95 | -100 | -23.15 | -45.65 | -47.08 | -100 | -23.34 |
| Forest Acres Exist Harvest - FI | SOFT | 379.31 | 418.73 | -100 | 36.37 | 379.31 | 418.73 | -100 | 36.37 |
| Forest Acres Exist Harvest - FI | HARD | 264.32 | 283.72 | -100 | 125.43 | 269.21 | 283.72 | -100 | 125.43 |
| Forest Acres New Planting - OP | existing | 63.6 | 53.68 | 0 | 0 | 63.62 | 53.68 | 0 | 0 |
| Forest Acres New Planting - FI | existing | 285.36 | 308.42 | -100 | 109.13 | 289.35 | 308.42 | -100 | 109.13 |
| Forest Acres New Planting - All | existing | 96.33 | 91.27 | -14.76 | 16.11 | 96.93 | 91.27 | -14.76 | 16.11 |
| Forest Total Harvest by MIC | Average | -1.71 | 1.5 | -100 | 1.34 | -1.83 | 1.46 | -100 | 1.29 |
| Forest Total Harvest by MIC | PLNT_MED | -100 | 18.69 | -100 | 0 | -100 | 18.69 | -100 | 0 |
| Forest Total Harvest by MIC | LO | -20.92 | -28.16 | -100 | -6.62 | -20.17 | -27.95 | -100 | -6.34 |
| Forest Total Harvest by MIC | PART_CUT_HI | -30.36 | -23.89 | -100 | -1.85 | -30.36 | -23.89 | -100 | -1.85 |
| Forest Total Harvest by MIC | NAT_REGEN | -90.46 | -62.21 | -100 | 0 | -90.46 | -62.21 | -100 | 0 |
| Forest Inventory Existing | softwood | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Inventory Existing | hardwood | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Table 20 Continued**

| | | Scenario | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | cc_wt_adpt_avgg | | | | hc_wt_adpt_avgg | | | |
| | | Intensity | Species | Age | Land | Intensity | Species | Age | Land |
| Forest Inventory Total | softwood | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Inventory Total | hardwood | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Inventory | OP | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Product Prices | SLUM | 7.59 | 14.67 | 115.3 | 3.1 | 7.02 | 14.06 | 114.16 | 2.54 |
| Forest Product Prices | SPLY | 4.42 | 9.5 | 72.99 | 1.82 | 3.52 | 8.56 | 71.51 | 0.94 |
| Forest Product Prices | OSB | 0 | 0 | 184.64 | 0 | 0 | 0 | 184.64 | 0 |
| Forest Product Prices | HLUM | 4.85 | 2.65 | 98.91 | 0.78 | 4.85 | 2.65 | 98.91 | 0.75 |
| Forest Product Prices | NEWSPRINT | 2.23 | 5.24 | 5.86 | 0.19 | 2.25 | 5.25 | 5.87 | 0.2 |
| Forest Product Prices | UNCFREESHEET | 3.17 | 3.57 | 48.58 | 0.81 | 3.18 | 3.58 | 48.6 | 0.83 |
| Forest Product Prices | UNCGROUNDWOOD | 0 | 0 | 43.8 | 0 | 0 | 0 | 43.8 | 0 |
| Forest Product Prices | CGROUNDWOOD | 0 | 1.01 | 39.84 | 0 | 0 | 0.99 | 39.84 | 0 |
| Forest Product Prices | TISSUE | 0 | 0 | 8.12 | 0 | 0 | 0 | 8.12 | 0 |
| Forest Product Prices | KRAFTPKG | -0.01 | -0.01 | 1.71 | 0.08 | -0.01 | -0.01 | 1.72 | 0.08 |
| Forest Product Prices | LINERBOARD | 2.45 | 3.49 | 9.23 | 0 | 2.45 | 3.49 | 9.23 | 0 |
| Forest Product Prices | CORRUGMED | -0.2 | -0.2 | 2.08 | 1.39 | -0.13 | -0.13 | 2.15 | 1.45 |
| Forest Product Prices | SBLBOARD | -0.12 | -0.12 | 27.86 | 0.87 | -0.08 | -0.08 | 27.92 | 0.9 |
| Forest Product Prices | RECBOARD | 0.02 | 0.04 | 0.41 | 0 | 0.02 | 0.04 | 0.41 | 0 |
| Forest Product Prices | CONSTPAPER | -0.09 | -0.09 | 1.71 | 1.12 | -0.02 | -0.02 | 1.78 | 1.18 |
| Forest Product Prices | DISPULP | 0.34 | 3.17 | 7.62 | 0.72 | 0.39 | 3.21 | 7.66 | 0.75 |
| Forest Product Harvest | PVT_SWSLOG_WOODS | -6.36 | -10.63 | -58.66 | -2.56 | -6.08 | -10.36 | -58.54 | -2.27 |
| Forest Product Harvest | PVT_HWSLOG_WOODS | 1.04 | 0.98 | -70.75 | -0.58 | 0.9 | 0.84 | -70.79 | -0.72 |
| Forest Product Harvest | PVT_SWPLOG_WOODS | -19.28 | -25.25 | -62.16 | -4.38 | -19.04 | -25.03 | -62.04 | -4.1 |
| Forest Product Harvest | PVT_HWPLOG_WOODS | -2.51 | 0.18 | -58.56 | -1.14 | -1.39 | 0.14 | -58.58 | -1.18 |
| Forest Product Harvest | PVT_SWFLOG_WOODS | -15.53 | -20.38 | -54.83 | -2.54 | -15.49 | -20.35 | -54.81 | -2.51 |
| Forest Product Harvest | PVT_HWFLOG_WOODS | -20.76 | -23.98 | -65.39 | -2.54 | -20.04 | -24.05 | -65.42 | -2.63 |
| Forest Product Harvest | softwood | -19.47 | -27.06 | -100 | -5.13 | -19.11 | -26.75 | -100 | -4.72 |
| Forest Product Harvest | hardwood | -5.78 | -4.35 | -100 | -2.36 | -5.2 | -4.47 | -100 | -2.49 |
| Forest Product Harvest | Clear Cut | -12.19 | -14.98 | -100 | -3.66 | -11.69 | -14.87 | -100 | -3.53 |

**Table 20 Continued**

| | | Scenario | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | cc_wt_adpt_avgg | | | | hc_wt_adpt_avgg | | | |
| | | **Intensity** | **Species** | **Age** | **Land** | **Intensity** | **Species** | **Age** | **Land** |
| Forest Product Harvest | Thin + Partial Cut | 3.86 | 4.09 | 16.98 | 1.49 | 3.86 | 4.09 | 16.98 | 1.49 |
| Forest Product Harvest | All Harvest | -7.12 | -8.96 | -63.05 | -2.03 | -6.78 | -8.87 | -63.02 | -1.94 |
| Forest Imports - canada | HWPULP | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | SWPULP | 0 | 0 | 574.81 | 0 | 0 | 0 | 574.81 | 0 |
| Forest Imports - canada | OLDNEWSPAPERS | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | OLDCORRUGATED | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | WASTEPAPER | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | PULPSUBSTITUTE | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | HIGDEINKING | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | NEWSPRINT | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | UNCFREESHEET | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | CFREESHEET | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | UNCGROUNDWOOD | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | CGROUNDWOOD | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | TISSUE | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | SPECIALTYPKG | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | KRAFTPKG | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | LINERBOARD | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | CORRUGMED | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | SBLBOARD | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | RECBOARD | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | CONSTPAPER | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | DISPULP | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | SWKMPULP | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | HWKMPULP | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | RECMPULP | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - canada | CTMPMPULP | 0 | 3.61 | 3.61 | 0 | 0 | 3.61 | 3.61 | 0 |
| Forest Imports - not canada | SLUM | 10.21 | 22.81 | 119.3 | 5.26 | 8.26 | 20.69 | 115.52 | 3.45 |

**Table 20 Continued**

| | | Scenario | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | cc_wt_adpt_avgg | | | | hc_wt_adpt_avgg | | | |
| | | Intensity | Species | Age | Land | Intensity | Species | Age | Land |
| Forest Imports - not canada | SPLY | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | HLUM | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | HWPULP | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | SWPULP | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | NEWSPRINT | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | UNCFREESHEET | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | CFREESHEET | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | UNCGROUNDWOOD | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | CGROUNDWOOD | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | TISSUE | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | SPECIALTYPKG | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | KRAFTPKG | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | LINERBOARD | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | CORRUGMED | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | SBLBOARD | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | RECBOARD | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | CONSTPAPER | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | DISPULP | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | SWKMPULP | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | HWKMPULP | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | RECMPULP | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Imports - not canada | CTMPMPULP | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Manufacturing | PVT_SWSLOG_MILL | -6.36 | -10.63 | -58.66 | -2.56 | -6.08 | -10.36 | -58.54 | -2.27 |
| Forest Manufacturing | PVT_HWSLOG_MILL | -2.99 | -3.07 | -64.2 | -0.73 | -3.15 | -3.23 | -64.26 | -0.89 |
| Forest Manufacturing | PVT_SWPLOG_MILL | -19.38 | -25.36 | -63.01 | -4.47 | -19.13 | -25.14 | -62.9 | -4.19 |
| Forest Manufacturing | PVT_HWPLOG_MILL | -3 | -0.61 | -77.32 | -1.49 | -1.9 | -0.64 | -77.33 | -1.52 |
| Forest Manufacturing | PVT_SWFLOG_MILL | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Manufacturing | PVT_HWFLOG_MILL | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Table 20 Continued**

| | | Scenario | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | cc_wt_adpt_avgg | | | | hc_wt_adpt_avgg | | | |
| | | Intensity | Species | Age | Land | Intensity | Species | Age | Land |
| Forest Manufacturing | PUB_SWSLOG_MILL | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Manufacturing | PUB_HWSLOG_MILL | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Manufacturing | PUB_SWPLOG_MILL | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Manufacturing | PUB_HWPLOG_MILL | -14.36 | 0 | 0 | -3.99 | -12.73 | 0 | 4.15 | 0 |
| Forest Manufacturing | IMP_SWSLOG_MILL | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Manufacturing | IMP_HWSLOG_MILL | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Manufacturing | EXP_SWSLOG | 0 | 0 | -3.72 | 0 | 0 | 0 | -3.72 | 0 |
| Forest Manufacturing | EXP_HWSLOG | 0 | 0 | -75.95 | 0 | 0 | 0 | -75.95 | 0 |
| Forest Manufacturing | SW_FUELLOG | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Manufacturing | HW_FUELLOG | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Manufacturing | SLUM | -5.61 | -10.1 | -61.47 | -2.76 | -5.3 | -9.8 | -61.34 | -2.44 |
| Forest Manufacturing | SPLY | -2.87 | -4.88 | -41.6 | -0.96 | -2.87 | -4.88 | -41.6 | -0.96 |
| Forest Manufacturing | OSB | 0 | -0.14 | -16.7 | 0 | 0 | -0.14 | -16.7 | 0 |
| Forest Manufacturing | HLUM | -0.9 | -0.9 | -65.66 | -0.9 | -1.14 | -1.14 | -65.74 | -1.14 |
| Forest Manufacturing | HPLY | 0 | 0 | -50.54 | 0 | 0 | 0 | -50.54 | 0 |
| Forest Manufacturing | SWPANEL | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Manufacturing | HWPANEL | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Manufacturing | SWMISC | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Manufacturing | HWMISC | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Manufacturing | HWPULP | -25.39 | -17.8 | -40.48 | 0.58 | -25.47 | -17.91 | -40.44 | 0.65 |
| Forest Manufacturing | SWPULP | -3.51 | -4.53 | -14.45 | -2.16 | -3.41 | -4.44 | -14.37 | -2.07 |
| Forest Manufacturing | NEWSPRINT | -2.15 | -2.15 | -2.44 | 0 | -2.15 | -2.15 | -2.44 | 0 |
| Forest Manufacturing | UNCFREESHEET | -1.02 | -1.08 | -18.29 | 0 | -1.02 | -1.08 | -18.29 | 0 |
| Forest Manufacturing | CFREESHEET | 0 | 0 | -1.76 | 0 | 0 | 0 | -1.76 | 0 |
| Forest Manufacturing | UNCGROUNDWOOD | 0 | 0 | -42.99 | 0 | 0 | 0 | -42.99 | 0 |
| Forest Manufacturing | CGROUNDWOOD | 0 | -1.01 | -16.72 | 0 | 0 | -1.01 | -16.72 | 0 |
| Forest Manufacturing | TISSUE | 0 | 0 | -2.58 | 0 | 0 | 0 | -2.58 | 0 |
| Forest Manufacturing | SPECIALTYPKG | 0 | -0.7 | -18.99 | 0 | 0 | -0.7 | -18.99 | 0 |

**Table 20 Continued**

| | | Scenario | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | cc_wt_adpt_avgg | | | | hc_wt_adpt_avgg | | | |
| | | **Intensity** | **Species** | **Age** | **Land** | **Intensity** | **Species** | **Age** | **Land** |
| Forest Manufacturing | KRAFTPKG | 0 | 0 | -2.19 | 0 | 0 | 0 | -2.19 | 0 |
| Forest Manufacturing | LINERBOARD | -0.56 | -1.06 | -2.22 | 0 | -0.55 | -1.06 | -2.22 | 0 |
| Forest Manufacturing | CORRUGMED | 0 | 0 | -1.03 | -1.03 | 0 | 0 | -1.03 | -1.03 |
| Forest Manufacturing | SBLBOARD | 0 | 0 | -6.35 | -0.83 | 0 | 0 | -6.35 | -0.83 |
| Forest Manufacturing | RECBOARD | 0 | 0 | -1.04 | 0 | 0 | 0 | -1.04 | 0 |
| Forest Manufacturing | CONSTPAPER | 0 | 0 | -0.42 | 0 | 0 | 0 | -0.42 | 0 |
| Forest Manufacturing | DISPULP | -0.11 | -0.87 | -1.63 | -0.11 | -0.11 | -0.87 | -1.63 | -0.11 |
| Forest Manufacturing | SWKMPULP | 3.5 | 3.5 | 6.77 | 0.12 | 3.5 | 3.5 | 6.77 | 0.12 |
| Forest Manufacturing | HWKMPULP | 2.71 | 2.71 | -4.23 | -1.41 | 2.71 | 2.71 | -4.23 | -1.41 |
| Forest Manufacturing | RECMPULP | 29.77 | 29.77 | 26.7 | 26.7 | 29.77 | 29.77 | 26.7 | 26.7 |
| Forest Manufacturing | CTMPMPULP | 0 | -100 | -100 | 0 | 0 | -100 | -100 | 0 |
| Forest Consumption | SLUM | -2.04 | -3.93 | -28.41 | -1.02 | -2.04 | -3.93 | -28.41 | -1.02 |
| Forest Consumption | SPLY | -3.13 | -5.32 | -45.31 | -1.04 | -3.13 | -5.32 | -45.31 | -1.04 |
| Forest Consumption | OSB | 0 | -0.08 | -9.32 | 0 | 0 | -0.08 | -9.32 | 0 |
| Forest Consumption | HLUM | -1.08 | -1.08 | -71.8 | -1.08 | -1.37 | -1.37 | -71.88 | -1.37 |
| Forest Consumption | NEWSPRINT | -0.99 | -0.99 | -1.01 | 0 | -0.99 | -0.99 | -1.01 | 0 |
| Forest Consumption | UNCFREESHEET | -0.96 | -1.02 | -16.81 | 0 | -0.96 | -1.02 | -16.81 | 0 |
| Forest Consumption | CFREESHEET | 0 | 0 | -1.57 | 0 | 0 | 0 | -1.57 | 0 |
| Forest Consumption | UNCGROUNDWOOD | 0 | 0 | -17.85 | 0 | 0 | 0 | -17.85 | 0 |
| Forest Consumption | CGROUNDWOOD | 0 | -0.78 | -12.44 | 0 | 0 | -0.78 | -12.44 | 0 |
| Forest Consumption | TISSUE | 0 | 0 | -2.28 | 0 | 0 | 0 | -2.28 | 0 |
| Forest Consumption | SPECIALTYPKG | 0 | -0.73 | -20.01 | 0 | 0 | -0.73 | -20.01 | 0 |
| Forest Consumption | KRAFTPKG | 0 | 0 | -1.89 | 0 | 0 | 0 | -1.89 | 0 |
| Forest Consumption | LINERBOARD | -0.59 | -1 | -2 | 0 | -0.58 | -1 | -2 | 0 |
| Forest Consumption | CORRUGMED | 0 | 0 | -0.97 | -0.97 | 0 | 0 | -0.97 | -0.97 |
| Forest Consumption | SBLBOARD | 0 | 0 | -7.4 | -0.96 | 0 | 0 | -7.4 | -0.96 |
| Forest Consumption | RECBOARD | 0 | 0 | -0.94 | 0 | 0 | 0 | -0.94 | 0 |
| Forest Consumption | CONSTPAPER | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Table 20 Continued**

| | | Scenario | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | cc_wt_adpt_avgg | | | | hc_wt_adpt_avgg | | | |
| | | **Intensity** | **Species** | **Age** | **Land** | **Intensity** | **Species** | **Age** | **Land** |
| Forest Consumption | DISPULP | 0 | -0.95 | -1.92 | 0 | 0 | -0.95 | -1.92 | 0 |
| Forest Exports | EXP_SWSLOG | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Exports | EXP_HWSLOG | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Exports | SLUM | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Exports | SPLY | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Forest Exports | HLUM | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

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