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Climate Change in Brazil: Dealing with Uncertainty in Agricultural Productivity Models and the Implications for Economy-wide Impacts

Bruno Souza², Eduardo Haddad³

ABSTRACT

This paper estimates the economic impacts of climate change over the Brazilian regions until the end of the century. We estimate the direct impact of the projected chances in climate on the yield of the country's main agricultural crops. We also estimate the indirect impact of such changes over the Brazilian economy.

Our results point to a broad spatial heterogeneity of impacts across the country. Using the most and least optimistic scenarios created by IPCC (RCP 2.6 and 8.5), our predictions indicate that the average annual losses due to climate change range from 0.4% to 1.8% of the Brazilian GDP until the end of the century.

Keywords: Climate Change, Agricultural Productivity, Spatial Economics, Brazil.

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2 NEREUS – The University of Sao Paulo Regional and Urban Economics Lab and University of Warwick.

3 NEREUS – The University of Sao Paulo Regional and Urban Economics Lab.
1 INTRODUCTION

The intensity and spatial variability of climate change and its potential effect to agricultural productivity are central concerns in the recent policy debate. Agriculture is one of the economic sectors most affected by climate change. Permanent changes in the global climate system can seriously affect the crop productivity around the world, and these effects on agriculture can influence other sectors in the economy. Hence, the study of the impacts of climate change on agricultural productivity is fundamental from a public policy perspective. The different pattern of such impacts on space must also be considered. Some regions might observe an increase in productivity for some crops and a decrease for other crops. The general equilibrium effect of such changes is not easy to anticipate.

Brazil, a country with continental dimensions, is a good example in which spatial variability can play an important role to access the economic effects of climate change on agricultural output. The economic and political importance of the country, as well as its preponderant position in the world’s agricultural system, make the analysis of climate change and agricultural productivity essential. In this paper, we estimate the effects of climate change on the yield of the main Brazilian crops. We call these as direct impacts. We also estimate the effects of crop yield losses over the other sectors and regions of Brazil. We call these as indirect impacts.

Regarding the direct effects of climate change on crop yield, the literature points to a broad heterogeneity of results. Kucharick and Serbin (2008) show that a 1°C increase in the US’ temperature during the summer months has the potential to reduce the productivity of soybean and maize in 16% and 13%, respectively. Other studies also find significant spatial variability in the results. McCarl (2008) estimates that the agricultural productivity can vary from -21% to 8.7% depending on the culture and region studied. Burke and Emerick (2016) estimates median losses of 15% on maize’s productivity in the US by mid-century.

Lobbel et al. (2011) predict that the net impact of climate change on crop yield between 1980-2008 is very variant: they estimate that China and Brazil lost between 5% and 10% of its maize productivity between 1980 and 2008 due to changes in climate. The same estimate for US is not statistically significant. A similar analysis for soybean indicates no statistically significant impact for Brazil and China, but a small reduction in productivity for US. Assunção and Chein (2016) estimate agricultural productivity losses of 18% between 2030-2049 in Brazil. They also find heterogenous impacts across regions, with impacts ranging from -40% to +15% among Brazilian cities.

The indirect impacts of climate over the other sectors of the economy are less explored in the literature. However, the importance of such impacts cannot be ignored. Agriculture is one of the sectors that most interact with the other sectors in the economy. The influence of climate on agricultural productivity can, therefore, affect other sectors, regions, and production factors across time.

Tanure et al. (2020) employ a CGE model to analyze the impacts of climate change over the economy of the Brazilian Legal Amazon Region. They estimate losses equivalent to 1.18% of Legal Amazon’s GDP between 2030 and 2049. The authors argue that these losses are mainly driven by the loss of production and employment in the agricultural
sector of the region. They also highlight that these impacts are not homogenous across space and will affect the regions that are more dependent on agriculture.

Ferreira Filho and Moraes (2015) perform a similar analysis with a CGE model calibrated for the Brazilian economy in 2005. They use two different climate change scenarios and estimate accumulate losses in the Brazilian agricultural sector from the order of US$ 2.6 by 2020 and US$ 10.4 by 2070. They also predict a high variability among the regions of the country: Piaui, one of the poorest States of Brazil, will observe GDP losses of 16.4% by 2070 and Sao Paulo, the richest State in the country, will have a modest increase of 0.5% of its GDP due to climate change by 2070.

This paper enters in this discussion by integrating three different models to assess the direct and indirect economic impacts of climate change over the different regions of Brazil until the end of the century. We first propose an econometric approach to calculate the impact of climate on crop yield and estimate this model using historical data. Then, we combine this model with the climate projections based on the scenarios provided by the Intergovernmental Panel on Climate Change (IPCC) to estimate the direct impacts of the projected changes on climate over agricultural productivity. Finally, we use the direct impacts to generate productivity shocks to be introduced into a CGE model calibrated for the Brazilian economy. This model allows us to estimate the indirect impacts of climate change across the Brazilian regions. We also explicitly deal with the uncertainties of the results by using the variations arising from the climate projections coupled with the econometric estimates to analyze the sensitivity of our results.

The results point to a broad regional heterogeneity of impacts across the country. Using the most and least optimistic scenarios created by the IPCC (RCP 2.6 and 8.5, respectively), our predictions indicate that the average annual losses due to climate change range from 0.4% to 1.8% of the Brazilian GDP until the end of the century. In a regional perspective, Sao Paulo – the richest, most populous, and most integrated State in Brazil – is the biggest loser in both scenarios. In terms of direct impacts, the regions more dependent on agriculture (Mato Grosso, Mato Grosso do Sul, and Minas Gerais) are the most vulnerable. In terms of indirect impacts, the most regionally integrated States are more affected (Paraná, Rio de Janeiro e Rio Grande do Sul). For the whole country, our results show that for each dollar lost in the national agriculture due to climate change, an additional amount of US$ 3.41 is lost due to indirect impacts in RCP 2.6, and US$ 2.50 in RCP 8.5. This does not mean, however, that the indirect impacts under RCP 8.5 are smaller: in fact, they are 320% higher in comparison to the optimistic scenario.

We believe that this paper has three main contributions to the literature: (a) it integrates a physical and a CGE models to estimate the total economic impacts of climate the over the Brazilian regions due to changes in agricultural productivity; (b) the calibration of our CGE model uses a new interregional input-output structure based on the Interregional Input-Output Adjustment System (IIOS), proposed by Haddad et al. (2016). Nevertheless, we use the most recent available data on climate change projections based on IPCC’s 5th Assessment Report (AR5); (c) it deals explicitly with the uncertainties of the results. We check the robustness of our findings with respect to perturbations in the climate change effects over the agricultural sector of the Brazilian regions. Moreover, our study is the first in the literature to integrate these methods to study the climate change impacts in the Brazilian economy.

\[4\] We summarize other literature findings in table A1 in the online appendix.
Beyond this introduction, the paper is divided into four other sections. The next section presents the methodology employed, emphasizing the integration of our physical model with the CGE model calibrated for Brazil. Section 3 describes the data and gives a brief description of the climate projections assumed to estimate our results. The fourth section introduces the results, presenting the direct, indirect, and total impacts of climate change on the Brazilian economy, and proposing a methodology to deal with the uncertainty of the results in an explicit way. The fifth section concludes the paper.
2 METHODOLOGY

The methodology employed here is based on CGE models. We use a model calibrated for Brazil in 2011 and map the direct and indirect economic impacts that climate change may have on Brazilian regions due to changes in the productivity of the country’s main agricultural crops. To do this, it is necessary to generate a productivity shock in the theoretical structure of this model. The magnitude of this shock is calculated from a set of econometric estimates that relate climate to agricultural productivity. We use these econometric estimates combined with the climate projections provided by IPCC to forecast productivity shocks in the agriculture of Brazilian regions until the end of the century. The productivity shocks in agriculture are what we call direct impacts of climate change in Brazilian agriculture. To calculate the indirect impacts of climate change in the Brazilian economy, we introduce these productivity shocks in the structure of our CGE model and run some simulations using a long run closure.

This section details the procedure employed to run such simulations and is divided into three parts: the description of the econometric model, the premises that guided the construction of the climate projections, and the description of the CGE model. Appendix B presents a scheme of the methodology for the reader.

2.1 ECONOMETRIC MODEL

The main channel of influence of climate on the agricultural sector is its potential to affect productivity. Understanding the relationship between agricultural yield and potential variations in rainfall and temperature is the first methodological step in our analysis. This will enable us to examine how projected changes in climate variables can affect the average productivity of the most diverse agricultural crops in Brazil. We start with a theoretical specification relating the productivity of a crop $h$ with the observed climate, prices, and technology available in each period $t$. Equation (1) denotes this specification for a given region $i$:

$$y_{it}^h = f(T_{it}, P_{it}, Q_i, A_{it}, \varepsilon_{it})$$ (1)

where $y_{it}^h$ is the log of crop yield of $h$ in city $i$ in year $t$, $T_{it} = \{T_{i,1}, T_{i,2}, \ldots, T_{i,M}\}$ is the history of temperatures in the same city and year between months 1 and $M$, $P_{it} = \{P_{i,1}, P_{i,2}, \ldots, P_{i,M}\}$ is the history of precipitation, $Q_i$ is the quality of the soil in that city (assumed to be constant), $A_{it}$ is the level of technology, and $\varepsilon_{it}$ represents other inputs affecting crop yield.

In short, we follow Huang and Khanna (2010) to estimate the following equation:

$$y_{it}^h = \alpha_i + \gamma_{st} + \sum_c \theta_c f_c(W_{cit}) + X_{it}' \beta + \varepsilon_{it}$$ (2)

In the equation above, we regress the productivity of crop $h$ as a function of control variables specific to each city $X_{it}'$ and a vector of climatic variables $W_{cit} = \{T_{it}, P_{it}\}$. The vector of climatic variables is constructed as the percentage deviations of temperature and accumulated rainfall in all months of the year in Brazilian cities with respect to their

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5 Our measure of productivity is calculated as the average yield of crop $h$ calculated as the total yield of this crop divided by its planted area in city $i$ in year $t$.

6 The control variables used are described in table Al in the Appendix.
respective historical averages\textsuperscript{7}, as proposed by Deschenes and Greenstone (2007). Nevertheless, quadratic terms are included to capture the non-linearity of these effects\textsuperscript{8}.

The parameter of interest is \( \theta_c \), which measures the impact that a given climate variable has on the productivity of the crop \( h \). Since our productivity measure is the average value of the crop yield in a city, this is likely to be affected by soil quality, cropping practices, and local prices. These, in turn, tend to be correlated with the local climate. For this reason, we also control our model for a fixed effect of city \( \alpha_i \), and a fixed effect of State per year \( \gamma_{st} \).

To estimate equation (2), we construct a city-level panel based on data provided by the Agricultural Survey of Brazilian Municipalities (henceforth, \textit{ASBM}). The estimated equation is used to predict the level of productivity of crop \( h \) given the projections of climate change provided by IPCC’s AR5. Equation (2) is estimated using a within-group estimator for each of the 6 cultures we are working with\textsuperscript{9}. With the estimates obtained, each coefficient in \( \theta_c \) is multiplied by its respective climate anomaly projection (best described in the next section). Such calculation will generate, ceteris paribus, a projection of productivity change of the commodity \( h \) in each city analyzed from 2020 to 2100\textsuperscript{11}. This forecast will be fundamental to construct the agricultural productivity shocks used in our CGE model.

\textbf{2.2 RAINFALL AND TEMPERATURE PROJECTIONS}

Several research institutes around the world develop and estimate different climate models to design and replicate the global climate system. Each model uses different scenarios to make its projections and each scenario is based on different assumptions about the trajectories of emissions, deforestation, sea currents, and the mitigating actions of humanity. Such assumptions lead to different results and forecasts. These are based on physical principles and are now able to reproduce many important aspects of the observed

\textsuperscript{7} These historical averages are calculated by averaging the monthly temperature and precipitation available in all Brazilian meteorological stations between 1994 and 2015. These observations are interpolated to create average monthly observations for each city in the country. The deviations of temperature are calculated by the percentage difference between the average temperature observed in a month and the historical average temperature in the same month. The precipitation deviations are calculated as the percentage difference between the accumulated precipitation in each month and the historical average of accumulated precipitation in the same month. We decided to estimate the model using deviations from the long-run averages for two reasons: (a) because estimating the model in levels would not exactly give the effect of climate on agricultural productivity, but the average effect of weather in a given year. The model using deviations from the long-run trend imply that a year with a deviation equal to zero is a typical year for the agriculture of a region. A year with a large weather deviation can be considered an atypical year and, therefore, a proxy to climate change. We also consider the issue of adaptation to climate change in our predictions. This is better described in the next section; and (b) because the climate projections scenarios, that are used to perform our forecasts, are given as long-run deviations.

\textsuperscript{8} We performed several robustness checks to test also cubic and quartic terms, as well as interactions and different time periods. None of these changes resulted in meaningful differences for the results.

\textsuperscript{9} Inserting this State-year trends allow the model to have a different productivity trend for each Brazilian State and, therefore, help us to estimate the effect of climate deviations on productivity while keeping the State-specific technological progress fixed. In the next section, we describe how we introduce technological progress in our predictions, to account for the adaptation to climate change.

\textsuperscript{10} More details about these crops are provided in Section 3. Since we are dealing with 6 crops and each equation has 48 climate coefficients, we do not present the results for the econometric model here. These can be obtained \textit{here}. This analysis and all the replication files used in this paper can be accessed \textit{here}.

\textsuperscript{11} We also calculate confidence intervals for our projections, more details are provided in the online appendix.
climate (IPCC, 2013). Considering this, the scientific community argues that there is great precision when it comes to its ability to quantify future climate projections.

In this way, the IPCC generates the so-called Representative Concentration Pathways (RCPs), which are used to create future emission projections. These are used as inputs to carry out simulations of the climate models and help to create the climate projections for the future. These RCPs are divided into 4 scenarios: a rigorous mitigation scenario (RCP 2.6), two intermediate scenarios (RCP 4.5 and RCP 6.0) and a scenario with high GHG emissions (RCP 8.5). In this paper, we use the most heterogeneous scenarios (RCPs 2.6 and 8.5). More details on the model used in this paper are provided in section 3.

2.3 CGE MODEL

The climate change projections combined with the econometric estimates allow us to generate the predicted productivity shocks and use the framework provided by the CGE models in order to capture their impact on the economic system. This class of models has attracted considerable attention in recent years not only in academic circles but also in policy-making debates.

One of the main contributions of this methodology is enabling one to define the parts of an economic system (sectors, regions, families, governments, etc.) as components of an interdependent system. The framework also makes it possible to analyze the policy effects and shocks of a sector in a region on the other sectors and regions of the country. The demarcation used in this study divides the Brazilian economy into 27 regions that produce, consume, and trade goods produced by 68 sectors. Among these goods, we analyzed the effect of climate change on the productivity of six of the country's main agricultural crops: sugarcane, soybean, maize, beans, coffee, and orange.

Each region has a consumer and a representative investor, as well as a government. All regions can trade among themselves, in addition to being able to import and export their production to an external sector (under a certain exchange rate). The scope of this class of models allows us to capture the effect of the change in agricultural productivity on a series of economic variables. Most notably: production, prices, welfare, employment, wages, household and government consumption, imports and exports volume, among others. The effect on these variables can be analyzed both from a national or a regional point of view. It is possible to observe, for example, the effect of a change in the productivity of sugarcane cultivation in one State on the level of wages in another State. In this paper, we will focus our analysis mostly on the effects of agricultural productivity shocks on regional and national GDP.

In terms of production, each industry can produce a good using a composite good specification that allows each product to be manufactured using a fixed combination of primary factors and intermediate goods. The factors used in our model are capital, labor, and land which, in turn, are combined by means of a CES function to form the compound of primary goods. The intermediate inputs, which may be of domestic and foreign origin, are also combined by means of a CES function to form the compound of intermediate inputs. Finally, intermediate inputs and primary factors are combined through a Leontief function to generate firm output.

We use the B-MARIA model, which structure is proposed by Haddad (1999)\textsuperscript{12}. The construction of the database required for its calibration was done through a top-down

\textsuperscript{12} There are many CGE models that use different assumptions in their structure. Good examples dealing with similar issues are in Ferreira Filho and Moraes (2015) and Tanure (2020). Despite the use of similar
disaggregation approach, which uses the structure of the nation input-output system to anchor the estimate of the interregional input-output data. Such database enables us to have a snapshot of the Brazilian economy as an integrated interregional system at a given point in time. Our model was calibrated and parametrized for the year 2011, following the methodology proposed by Haddad, Gonçalves Junior, and Nascimento (2017). The data used the construction of this database comes mainly from the Brazilian Institute of Geography and Statistics (IBGE), the national accounts system, and the National Logistics and Transport Plan (provided by the Brazilian Ministry of Transportation for 2011). To the best of our knowledge, this is the first paper in the literature to use this new data set applied to the study of climate change. Given the economic interdependence captured by the functional structure of the model, it is possible to disaggregate the direct economic impacts (caused by productivity losses in the agriculture of Brazilian states) and indirect ones caused by these changes in the productivity of the Brazilian agricultural sector.

A decrease in agricultural productivity in each region of Brazil will have the initial effect of raising the price of agricultural goods and, consequently, reduce the regional income of households, firms, and investors. Families will be less likely to consume because of price increases, agricultural firms will become less competitive as productivity declines and investors will see a reduction of potential returns. This will reduce the general demand for goods produced in that region, forcing the firms of that locality to reduce their production. Such firms will reduce their demand for intermediate goods and productive factors, causing a general downward pressure on the price level of the region.

Moreover, the fall in agricultural productivity ends up, ceteris paribus, increasing the relative productivity of agriculture in other regions. This makes the agricultural production of the affected region to migrate to other parts of the country, generating an increase in the activity level of the other regions and increasing the availability of factors of production within the affected locality. The excess supply of factors in this region will tend to cause a decrease in their remuneration, and a consequent drop in their price level. The net effect on the price level is unknown and can only be measured after the necessary simulations have been carried. Once this has been done, it will be possible to quantify the effect that the projected climatic changes in the coming years can have on agricultural productivity and, with these changes in productivity, to analyze its potential effect on the economy of the different regions of Brazil.

To conduct our simulations, we use the long-run closure, which assumes that the level of real wages, regional GDP and capital investment are endogenous while the level of employment and technology are exogenous. The productivity shocks described below are implemented in the model structure through the parameter $a_{prim}$, which refers to the technological increase of the primary factors. In other words, the introduction of

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methodological approach, there are differences in the analytical, functional, and numerical structures of these models (for interested readers, please refer to the specific papers). For instance, in this version of the B-MARIA model we did not include the explicit modelling of land use changes, as in Faria and Haddad (2017). Ferreira Filho and Moraes (2015) and Tanure (2020) do include land use in their approaches. The implicit assumption in our exercise is that aggregated land use patterns within States remain unchanged throughout the simulation adjustments. Thus, we fail to capture adaptation through this mechanism. In a sense, our results may be placed in the upper bound of the potential impacts.

13 Figure B1 in the online appendix presents a systematic view of these causal relationships.
productivity shocks into the functional structure of the model assumes that the primary factors of the agricultural sector will lose efficiency throughout the years\textsuperscript{14}.

3 DATA

In this section we perform a description of the data used to generate our predictions. To implement the strategy described above, we collected data on agricultural production, historic observations of temperature and precipitation, and the most recent climate projections based on the 5\textsuperscript{th} Assessment Report published by the IPCC (AR5). In addition, a description of the productive structure captured through the regional input-output system used in our CGE model will be performed.

Data on production, yield, planted, and cropped areas are provided by ASBM. This information is available for all Brazilian cities and was collected with annual observations between 1994 and 2015. Six of the main agricultural crops of Brazil were selected: soybean, sugarcane, maize, coffee, beans, and orange.

The criterion used to choose these crops sought to cover several dimensions of the Brazilian agricultural production: most representative crops in terms of area planted (soybeans and sugar cane); most representative crops in terms of the agricultural GDP of the cities of most regions (corn and beans), and crops in which Brazil has a dominant position in terms of world production (coffee and orange). In addition, we also tried to merge the analysis of annual crops (soybeans, sugarcane, maize, and beans) and perennial crops (coffee and orange). Table 1 shows how representative these crops are in terms of area planted from 2010 to 2015, which, when added up, accounted for more than 81\% of the country’s planted area in the period.

<table>
<thead>
<tr>
<th>Crop</th>
<th>2010</th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
<th>2014</th>
<th>2015</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soybeans</td>
<td>35.70</td>
<td>35.26</td>
<td>36.26</td>
<td>38.58</td>
<td>39.76</td>
<td>41.93</td>
<td>37.92</td>
</tr>
<tr>
<td>Beans</td>
<td>5.59</td>
<td>5.73</td>
<td>4.60</td>
<td>4.20</td>
<td>4.46</td>
<td>4.07</td>
<td>4.78</td>
</tr>
<tr>
<td>Coffee</td>
<td>3.31</td>
<td>3.15</td>
<td>3.07</td>
<td>2.89</td>
<td>2.63</td>
<td>2.59</td>
<td>2.94</td>
</tr>
<tr>
<td>Orange</td>
<td>1.30</td>
<td>1.20</td>
<td>1.10</td>
<td>0.99</td>
<td>0.90</td>
<td>0.89</td>
<td>1.07</td>
</tr>
<tr>
<td>TOTAL</td>
<td>79.75</td>
<td>79.42</td>
<td>80.90</td>
<td>82.47</td>
<td>82.25</td>
<td>83.36</td>
<td>81.36</td>
</tr>
</tbody>
</table>

The climate data was taken from the website of the National Institute of Meteorology (INMET) which provides historical climate data from its 265 stations across Brazil. Monthly observations of cumulative precipitation and average compensated temperature\textsuperscript{15} were collected between January 1994 and December 2015. The data is spatially interpolated\textsuperscript{16} to create the city average precipitation and temperature measures.

\textsuperscript{14} Furthermore, to address the issue of adaptation to climate change, we introduce a culture-specific trend for each shock in productivity across time. These trends are constructed by extrapolating the average annual productivity increase of each crop between 1974 and 2016. For a more detailed discussion about time trends and adaptation, see Keane and Neal (2020).

\textsuperscript{15} According to INMET, the mean compensated temperature of a meteorological station calculates the weighted average of the maximum (weight 1), minimum (weight 1), noon (weight 1) and midnight temperature (weight 2) within a 24-hour period.

\textsuperscript{16} The State of Rondonia is the only one with no meteorological station, so we decide to exclude this State from the econometric estimates. The spatial interpolation of climatic data was performed using Matlab\textsuperscript{®}.
throughout the months included in the period. This interpolation aims to create an annual panel with climate information for the Brazilian cities over the years.

The average behavior across the months during these 21 years will represent the climate pattern of Brazilian regions and the monthly deviations from this pattern will be used to estimate the relationship between crop productivity and weather variability. One should not confuse this relationship to what we are aiming to estimate, which is the effects of a permanent change in the climate pattern across the years. The key assumption here is that the sensibility of agricultural productivity to weather variation (estimated using an econometric model) is good enough to mimic the effect of a permanent change in the climate pattern of Brazilian regions (estimated using the CGE model under a long-run closure).

In this paper, the monthly temperature and precipitation projections were collected from January 2020 to December 2100 using the data provided by the National Center for Atmospheric Research (NCAR). This is the most recent outputs of the latest model developed by NCAR (CCSM-4) and are on a global scale. These projections are based on the IPCC’s AR5. In addition, the RCP 2.6 and RCP 8.5 scenarios were used to perform our analysis. This data is related to the average of the 9 ensemble members of CCSM-4.

Figures C1 to C4 in the online appendix show the trajectories of the climate anomalies of temperature and rainfall in Brazil. RCP 2.6 has discrete anomaly trajectories. It is possible to highlight the tendency of a decrease in rainfall in the Brazilian mid-north (around 10%), and a discrete increase in the southern part of the country (about 5%). In terms of temperature, the projections in this scenario point to a median increase of 4% (about 0.9°C) in Brazil until the end of the century, and the South of the country is the most affected region.

Under RCP 8.5 the trajectories are much more intense and volatile over space and time. In the years between 2020-2040, the average decrease in precipitation in Brazil is of the order of 5%. At the end of the century this decrease is three times greater. Nevertheless, the scenario predicts a worsening of the drought process in the northeastern semi-arid region of the country, with a decrease in its average rainfall of up to 35%. This is in line with the literature, with the phenomena called “desertification of the Brazilian semi-arid”. The Southern Brazil will face more intense rainfall regimes, reaching an average rainfall increase of around 15% by the end of the century. In terms of temperature, the projections indicate that, at the beginning of the period, projected average heating for Brazil is around 5% (1°C), while at the end of the century this increase is about 17% (or 3.8°C), reaching 25% in the cities of the South region.

A matrix of inverse distances was constructed using the geographic coordinates of each INMET station and the centroid of each Brazilian city to perform this interpolation. This matrix was used to construct a weighted spatial mean of average temperature and accumulated precipitation for all months between January 1994 and December 2015.

Climatic anomalies are described in the literature as the percentage difference between the value that a given climatic variable assumes under a given scenario and a historical average of that same variable. In the current paper, all temperature and precipitation anomalies are calculated based on the averages of the period between 1960-2000.
4 RESULTS

This section has two parts and presents the estimates for direct and indirect impacts of climate change on the Brazilian economy until the end of the century. In addition, it uses a methodology described in the literature to explicitly model the uncertainty of the results.

4.1 DIRECT AND INDIRECT IMPACTS

In this section we describe the main results of our paper. We start the discussion by the direct impacts of the projected changes in climate over agricultural productivity. Figures D1 to D6 in the online appendix present the trajectories of productivity variation for each of the crops studied between 2020 and 2100 in the two scenarios analyzed.\(^{18}\)

The analysis of impacts on crops reflects, to a large extent, the behavior of the climate scenarios considered and described above: they present similar trajectories until the middle of the century but depart from 2050 onwards with a significant aggravation under scenario RCP 8.5, and an almost constant path in RCP 2.6. Under RCP 2.6 the adjusted rates of change in annual productivity are statistically equal to zero for all crops. However, under RCP 8.5, the deterioration of productive losses is evident in all crops studied. Bean, maize, and soybean show smaller annual losses, culminating in an annual productivity loss of approximately 16%, 22% and 30% by the end of the century, respectively. Sugarcane, orange, and coffee, in turn, show more pronounced loss trajectories: approximately 33%, 34% and 50%, respectively.

These impacts are in line with some findings in the literature. Lobell and Asner (2003) predict that a 1°C in temperature in the US has the potential to decrease the average yield of maize and soybean by around 17%. Kucharik and Serbin (2008) study the same crops and find variations in the same range. Burke and Emerick (2016) estimate median losses of maize productivity of around 15% by mid-century.\(^{19}\)

To calculate the direct impacts of climate change on the Brazilian agriculture, the losses were converted to the USD rate of 2020 (considering constant prices) for each crop.\(^{20}\) Then, for each year between 2020 and 2100, the individual losses of each crop were aggregated to calculate the total impact of climate change in the agricultural sector of each Brazilian State. Finally, these impacts were brought to their present value to assess the direct impact of climate change in Brazil until the end of the century. These results are described in the second and fifth columns of table C1 in the appendix (representing RCPs 2.6 and 8.5, respectively).

The estimated direct impacts totaled US$123 billion in RCP 2.6 and almost US$705 billion in RCP 8.5. This is equivalent to 7% and 42% of the projected Brazilian GDP in 2020, respectively. From a regional point of view, the pattern of impacts among the Brazilian regions remains similar in both scenarios, differing only in magnitude: direct

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\(^{18}\) These rates were adjusted to account for a specific technical advance in each crop. To that end, we assume that each culture has an annual rate of specific technical progress accumulated over time. This rate is estimated using the average growth of the crop yield in Brazil in the past 40 years.

\(^{19}\) For more results, see table A1 in the online appendix.

\(^{20}\) To translate our impacts over time and following the best practices in the literature (HALSNAES et al., 2007 and IPCC, 2013), all values were discounted by an annual rate of 1.37% per year (MARGULIS et al. 2011).
impacts are, on average, 5.7 times higher under the pessimist scenario than under the optimistic scenario. The regions that are the most affected in terms of magnitude under RCP 2.6 are São Paulo (accounting for 20.8% of total impacts), Minas Gerais (16.4%) and Paraná (13.7%). Under RCP 8.5 the pattern is similar, with São Paulo accounting for 27.8% of total impacts, Paraná for 14.1%, and Minas Gerais for 13.4%.  

To evaluate the total effects of these losses, we used the framework provided by the CGE model described in section 2.3. To that end, it is necessary to introduce a productivity shock into the functional structure of the model. This is performed within the agricultural sector of each region in the country. Thus, to construct these productivity shocks, the impact trajectories described above were taken into consideration. The difference between the current level of productivity of each crop and its projected productivity level in 2100 is calculated to generate the productivity shock. Therefore, the percentage difference in crop’s $h$ productivity, at city $i$, between the present and the end of the century will be given by:

$$\Delta prod^h_i = \frac{prod^h_{i,2100} - prod^h_{i,2020}}{prod^h_{i,2020}}$$

Where $prod^h_{i,2020}$ represents the productivity level of culture $h$, in city $i$ in 2020 and $prod^h_{i,2100}$ is the level of productivity projected by the end of the century. However, since the B-MARIA model is built at the state level of disaggregation, it is necessary to aggregate the city-level data appropriately. Thus, for each State $S$:

$$\Delta prod^h_S = \sum_{i \in S} w^h_i \ast \Delta prod^h_i$$

Where $w^h_i$ represents the relative importance of city $i$ in the total amount of crop $h$ produced by State $S$. Finally, given that the sectoral breakdown of the model considers only a large sector of agriculture (without crop breakdown), it is necessary to consider the weight of each crop within the total produced by the agriculture of each State:

$$shock_S = \sum_{h \in H} p^h_S \ast \Delta prod^h_S$$

Where $shock_S$ is the productivity shock in the agricultural sector of State $S$ and $H = \{\text{Sugarcane, Soybean, Maize, Bean, Coffee, Orange}\}$.

However, to introduce these shocks into the B-MARIA simulation structure, it is necessary to distribute them in a homogeneous way over time. This transformation is necessary so that they can be simulated under the long-term closure of the model. To do this, it is necessary to assume that the accumulated impacts throughout the century are homogeneously distributed in the between 2020 and 2100. In other words, to construct the productivity shocks we subdivide the 80 years analyzed into 16 quinquennia using the following formula:

\[\text{This similarity between scenarios is expected since we are assuming no change in the agricultural spatial pattern over time.}\]

\[\text{All estimates consider current productivity levels as the average productivity of each Brazilian city between 2011 and 2015. Given that the projected climatic projections begin in 2020, the average between 2011-2015 was considered as the initial level of productivity in 2020.}\]
\[ effective\_shocks_s = (1 + final\_shocks_s)^{\frac{1}{16}} - 1 \]

Table 2 presents the effective shocks on each State that will be introduced in the structure of B-MARIA to evaluate the total impacts of climate change on the Brazilian economy. The analysis is clear: on average, the impacts under RCP 8.5 are much more intense than in RCP 2.6, both from a physical and economic points of view.

Table 2 – Final Shocks on Brazilian States.

<table>
<thead>
<tr>
<th>State</th>
<th>RCP 2.6</th>
<th>RCP 8.5</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>AC</td>
<td>-0.006%</td>
<td>-0.103%</td>
<td>-0.098%</td>
</tr>
<tr>
<td>AL</td>
<td>-5.029%</td>
<td>-4.504%</td>
<td>0.525%</td>
</tr>
<tr>
<td>AM</td>
<td>-0.392%</td>
<td>-0.632%</td>
<td>-0.240%</td>
</tr>
<tr>
<td>AP</td>
<td>0.228%</td>
<td>-0.589%</td>
<td>-0.817%</td>
</tr>
<tr>
<td>BA</td>
<td>-0.493%</td>
<td>-2.344%</td>
<td>-1.851%</td>
</tr>
<tr>
<td>CE</td>
<td>-2.151%</td>
<td>-2.954%</td>
<td>-0.804%</td>
</tr>
<tr>
<td>DF</td>
<td>-0.629%</td>
<td>-4.996%</td>
<td>-4.367%</td>
</tr>
<tr>
<td>ES</td>
<td>-0.425%</td>
<td>-0.398%</td>
<td>0.026%</td>
</tr>
<tr>
<td>GO</td>
<td>1.164%</td>
<td>-7.761%</td>
<td>-8.925%</td>
</tr>
<tr>
<td>MA</td>
<td>-0.029%</td>
<td>-5.082%</td>
<td>-5.053%</td>
</tr>
<tr>
<td>MG</td>
<td>-3.190%</td>
<td>-6.700%</td>
<td>-3.510%</td>
</tr>
<tr>
<td>MS</td>
<td>-1.264%</td>
<td>-11.606%</td>
<td>-10.342%</td>
</tr>
<tr>
<td>MT</td>
<td>0.257%</td>
<td>-8.650%</td>
<td>-8.907%</td>
</tr>
<tr>
<td>PA</td>
<td>-0.137%</td>
<td>-1.310%</td>
<td>-1.174%</td>
</tr>
<tr>
<td>PB</td>
<td>-2.044%</td>
<td>-2.124%</td>
<td>-0.080%</td>
</tr>
<tr>
<td>PE</td>
<td>-2.403%</td>
<td>-2.233%</td>
<td>0.170%</td>
</tr>
<tr>
<td>PI</td>
<td>-0.138%</td>
<td>-7.787%</td>
<td>-7.649%</td>
</tr>
<tr>
<td>PR</td>
<td>-0.023%</td>
<td>-8.878%</td>
<td>-8.855%</td>
</tr>
<tr>
<td>RJ</td>
<td>-0.445%</td>
<td>-1.085%</td>
<td>-0.640%</td>
</tr>
<tr>
<td>RN</td>
<td>-1.096%</td>
<td>-1.149%</td>
<td>-0.052%</td>
</tr>
<tr>
<td>RO</td>
<td>-2.020%</td>
<td>-4.797%</td>
<td>-2.777%</td>
</tr>
<tr>
<td>RR</td>
<td>-0.427%</td>
<td>-0.687%</td>
<td>-0.260%</td>
</tr>
<tr>
<td>RS</td>
<td>0.409%</td>
<td>-4.283%</td>
<td>-4.691%</td>
</tr>
<tr>
<td>SC</td>
<td>0.003%</td>
<td>-3.533%</td>
<td>-3.536%</td>
</tr>
<tr>
<td>SE</td>
<td>-3.649%</td>
<td>-4.847%</td>
<td>-1.198%</td>
</tr>
<tr>
<td>SP</td>
<td>-4.530%</td>
<td>-6.546%</td>
<td>-2.017%</td>
</tr>
<tr>
<td>TO</td>
<td>-0.859%</td>
<td>-7.023%</td>
<td>-6.164%</td>
</tr>
</tbody>
</table>

RCP 2.6 stands out for the more stable behavior of the agricultural productivity variations among the states. Alagoas, Sao Paulo, and Sergipe are the states that are most affected in this context, presenting average decreases of 5.02%, 4.53% and 3.65%, respectively. Some states, however, present growth potential in their mean agricultural productivity under this scenario, with Goias (with an average increase of 1.16%), Rio Grande do Sul (0.41%) and Mato Grosso (0.22%) as the winners.

Under RCP 8.5 the results are more drastic: no region has an average productivity gain, and the magnitude of the losses is much larger in comparison to RCP 2.6. In this context, the states of the Midwest region emerge as the most affected, with agricultural productivity losses of 11.6% in Mato Grosso do Sul, 8.5% in Mato Grosso, and 7.76% in Goias. Acre (losses of 0.1%), Espirito Santo (-0.4%) and Amapá (-0.59%) were on the other end of these effects.
The difference in magnitude of the shocks between scenarios indicates that only Alagoas, Pernambuco and Espírito Santo present more intense productive losses under RCP 2.6 in comparison to RCP 8.5. All other States have more intense losses under the pessimistic scenario, particularly the Midwest region, with average differences of approximately 9.4% between the scenarios.

Table 3 shows the results of the simulations on some economic aggregates at the national level. In terms of real household consumption and aggregate investment, the cumulative five-year variation is -0.12% and -0.16% under RCP 2.6. Under RCP 8.5, these variations are -0.53% and -0.77, respectively. In both aggregates, the impact under the second scenario is approximately 4.5 times greater than under the RCP 2.6. The nominal wage level of the workers accumulates falls of -0.22% and -0.99% under RCP 2.6 and 8.5, respectively.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>RCP 2.6</th>
<th>RCP 8.5</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real Household Consumption</td>
<td>-0.121</td>
<td>-0.536</td>
<td>-0.415</td>
</tr>
<tr>
<td>National Investment</td>
<td>-0.164</td>
<td>-0.770</td>
<td>-0.606</td>
</tr>
<tr>
<td>Nominal Wage to Workers</td>
<td>-0.220</td>
<td>-0.996</td>
<td>-0.776</td>
</tr>
<tr>
<td>National Employment Level</td>
<td>-0.001</td>
<td>-0.011</td>
<td>-0.011</td>
</tr>
<tr>
<td>Relative Equivalent Variation</td>
<td>-0.435</td>
<td>-1.829</td>
<td>-1.394</td>
</tr>
<tr>
<td>Exports</td>
<td>-0.025</td>
<td>-0.270</td>
<td>-0.245</td>
</tr>
<tr>
<td>Imports</td>
<td>-0.167</td>
<td>-0.800</td>
<td>-0.632</td>
</tr>
<tr>
<td>Terms of Trade</td>
<td>0.012</td>
<td>0.135</td>
<td>0.123</td>
</tr>
</tbody>
</table>

Welfare, measured by the equivalent income variation, fell by 0.43% and 1.82%, respectively. Among all the analyzed aggregates, this is the one that presents the greatest divergence between scenarios. In real terms, the production losses are from the order of 0.055% every five years under RCP 2.6 and 0.26% under RCP 8.5. Finally, the fall in imports is about 6.7 times larger than the fall in exports under RCP 2.6 and 3 times larger under RCP 8.5.

To understand the total impact on the Brazilian regions, we analyze the effect over GDP. Table C1 in the appendix presents these results. The 4th and 7th columns of this table present these total impacts, indicating a considerable difference with respect to the analysis of the direct effects over the states. Under RCP 2.6, the total negative impacts on the Brazilian economy due to climate change amount to US$543.6 billion, while under RCP 8.5 these impacts amount to losses of almost US$2.5 trillion.

Thus, the relationship between the direct and indirect economic impacts on the national level changes considerably from one scenario to another: in RCP 2.6, the results indicate that for each dollar lost in the national agricultural production due to climate change until the end of century, an additional amount of US$ 3.41 is lost due to indirect impacts; under RCP 8.5 this ratio is about 27% lower. For each US$ 1.00 lost on agricultural production, there is an additional loss of US$ 2.50. This does not mean that the indirect impacts under

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23 Mas-Colell, Whinston, and Green (1995) define the equivalent income variation as a measure of economic welfare given by the income variation necessary before a shock so that a representative consumer reaches the same level of utility after the shock. Thus, a negative equivalent variation indicates that the individual is losing welfare since he will become relatively poorer before the introduction of the shock to possess an equivalent utility level after the shock.
RCP 8.5 are smaller: in fact, they are 320% higher in comparison to the optimistic scenario.

However, all the mentioned impacts carry a series of uncertainties inherent to the methodology. The next section uses a method proposed by Haddad and Garber (2012) to explicitly deal with the degree of uncertainty related to the productivity shocks estimated above.

4.2 THE SNOWBALL EFFECT OF UNCERTAINTY

Stern (2006) argues that the climate change analysis deals with several levels of uncertainty. No one can really determine when and where a certain impact will occur. In other words, a series of uncertainties emerge, hindering the precise quantification of the economic impacts of climate change. In this paper, the econometric model estimated integrates two sources of uncertainty in the construction of its database. The first one concerns the reliability of agricultural data. The second is related to the uncertainty regarding information provided by the INMET meteorological stations and the potential measurement errors during its construction and interpolation. The confluence of these two factors is still added to the uncertainty regarding the econometric model itself, which produces estimates that not necessarily are accurate.

In addition, the climate projections generated by the IPCC scenarios themselves have their own degree of uncertainty. Stern (2006) argues that such models reflect a cascade of uncertainties inherent to the scenarios considered: political uncertainties, emissions, global mitigation actions, population growth, technological progress, among others. Next come the uncertainties related to the direct impact projections described in Section 4.1. These involve uncertainties regarding the intertemporal discount used to evaluate them, not to mention the hypotheses of constant prices and the pattern of the productive structure of the Brazilian agricultural sector over the century.

Regarding the construction of the productivity shocks for the CGE model, the uncertainties are related to both the projected productivity trajectories in the scenarios and the rates of specific technical progress of each crop. Finally, the analysis of the total economic impacts of climate change, beyond accumulating all the uncertainties mentioned above, involves a series of hypotheses about the regional and sectoral productive structure of the Brazilian economy, as well as the assumptions coming from the analytical and functional structure of B-MARIA.

The confluence of all these uncertainties generates a snowball effect documented in the literature (STERN, 2006). To deal with this effect, we use a methodology that treats this process explicitly, based on the framework proposed by Garber and Haddad (2012). To implement this method, we explore the potential connections in our physical model with the functional structure of the CGE model. For the case in question, the idea is to conduct simulations that reproduce the behavior of a certain set of endogenous variables inside B-MARIA. Thus, it is enough to replicate the desired information within the set of exogenous variables of the model and simulate their shocks to achieve the best combination of effects for their endogenous variables.

In other words, we will consider the long-run closure described in the previous section, using the results described in section 4.124 and set them as a target to the in the CGE model. To achieve this, the idea is to calibrate the exogenous productivity shocks in the

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24 Here, the endogenous variable that will be used as a target is the real GDP of the States.
B-MARIA structure in such a way to endogenously generate the targeted results. The CGE model used here is included in the class of models known as Johansen models, which obtains its solutions by solving a system of linearized equations. Thus, consider a given set of equations coming from the structure of B-MARIA:

\[ F(V) = 0 \quad (3) \]

Where \( V \) represents an equilibrium vector of dimension \( n \) (number of variables) and \( F \) is a function vector of order \( m \) (number of equations), which is assumed to be differentiable. To find a solution, it is necessary to assume that \( n > m \), whereas \( n - m \) variables should be considered exogenous. In addition, we must assume that the model has a known solution, that is, \( \exists V = V^* \) such that \( F(V^*) = 0 \).

Thus, Johansen’s approach is to use a linearized version of (3), which can be represented as:

\[ A(V)v = 0 \quad (4) \]

Where \( A(V) \) is a matrix of order \( mxn \) containing the partial derivatives of \( F(V) \) and \( v \) represents the percentage changes in the vector \( V \). The next step to obtain such percentage changes is to evaluate \( A(.) \) in an initial equilibrium vector \( V^I \) and then solve (4). To do this, it is necessary to partition \( A(.) \) and the vector \( v \) into two parts, separating the endogenous and exogenous variables from the closure of the model. Call \( \alpha \) the index for the endogenous variables and \( \beta \) the index for the exogenous variables. This way, we have:

\[ A(V^I)v = A_\alpha(V^I)v_\alpha + A_\beta(V^I)v_\beta = 0 \]

Rearranging:

\[ v_\alpha = -A(V^I)^{-1}A_\beta(V^I)v_\beta \]

Define \(-A(V^I)^{-1}A_\beta(V^I) = B(V^I)\). Then:

\[ v_\alpha = B(V^I)v_\beta \quad (5) \]

Where \( v_\alpha \) is an \( mx1 \) vector containing the expected percentage changes in the endogenous variables calculated from the exogenous shocks inside the vector \( v_\beta \). Now consider (5) represented as follows:

\[
\begin{bmatrix}
v_{\alpha 1} \\
\vdots \\
v_{\alpha m}
\end{bmatrix} =
\begin{bmatrix}
B_{11} & \ldots & B_{1(n-m)} \\
\vdots & \ddots & \vdots \\
B_{m1} & \ldots & B_{m(n-m)}
\end{bmatrix}
\begin{bmatrix}
v_{\beta 1} \\
\vdots \\
v_{\beta m}
\end{bmatrix}
\]

Which can be rearranged as:

\[
\begin{bmatrix}
v_{\alpha 1} \\
\vdots \\
v_{\alpha m}
\end{bmatrix} =
\begin{bmatrix}
B_{11} \\
\vdots \\
B_{m1}
\end{bmatrix}v_{\beta 1} +
\begin{bmatrix}
B_{12} \\
\vdots \\
B_{m2}
\end{bmatrix}v_{\beta 2} + \cdots +
\begin{bmatrix}
B_{1(n-m)} \\
\vdots \\
B_{m(n-m)}
\end{bmatrix}v_{\beta (m-n)} \quad (5')
\]

Equation (5') allows one to directly see two important properties that will be used. The first is that, when considering a shock in a certain exogenous variable \( q \) \( (v_{\beta q}) \), the effect on the vector of endogenous variables \( v_\alpha \) should be proportional to the vector that multiplies this variable in (5'). In addition, when assessing the effect of a

\[ 25 \text{ For more details, see Dixon and Parmenter (1996).} \]
multidimensional shock (as in the case analyzed here, where we will assess shocks in the 27 States of the federation), the total impact on \( \nu_\alpha \) can be computed as the sum of the effects of the shocks on the separate endogenous variables.

Suppose, then, that a subset of dimension \( k \) of elements of \( \nu_\alpha \) is selected as a target. We construct the vector \( t_{(k \times 1)} \) which contains all these targets. Assume that a subset of order \( j \) of the vector \( \nu_\beta \) contains exogenous variables considered relevant to influence the variables in \( t_{(k \times 1)} \). Now, (5) is simply rewritten by clearing all the elements of \( \nu_\alpha \) which are not contained in \( t_{(k \times 1)} \) and all the elements of \( \nu_\beta \) which are not in the subset of dimension \( j \) above. Call \( \nu_\alpha \) the vector of endogenous variables considered for the analysis and \( \nu_\beta \) the vector of exogenous variables considered important to determine them. Using the same notation as (5):

\[
\nu_\alpha = \tilde{B} \nu_\beta
\]

or:

\[
\begin{bmatrix}
\nu_{\alpha 1} \\
\vdots \\
\nu_{\alpha k}
\end{bmatrix} = \begin{bmatrix}
\tilde{B}_{11} \\
\vdots \\
\tilde{B}_{kj}
\end{bmatrix} \nu_{\beta 1} + \begin{bmatrix}
\tilde{B}_{12} \\
\vdots \\
\tilde{B}_{kj}
\end{bmatrix} \nu_{\beta 2} + \cdots + \begin{bmatrix}
\tilde{B}_{1j} \\
\vdots \\
\tilde{B}_{kj}
\end{bmatrix} \nu_{\beta j}
\]

Notice that \( \nu_\alpha \) is not the choice of values for the exogenous variables contained in \( \nu_\beta \). Thus, given the values of a target \( t \), the best choice for \( \nu_\beta \) will be the one that solves:

\[
\nu_\beta^* = \text{argmin} \left\{ \frac{(\nu_\alpha - t)^2}{t^2} \right\}
\]

Put differently, the best choice for the exogenous shocks \( \nu_\beta \) is the one that minimizes the quadratic percentage distance between the values of the endogenous variables and the selected target. Finally, the solution of the equation (7), \( \nu_\beta^* \), will generate a corresponding vector of endogenous variables, \( \nu_\alpha^* \).

To apply this methodology in the context of this paper, it is necessary to establish one or more transmission channels in the functional structure of the CGE model to capture the impact of interest due to agricultural productivity shocks. We will set as a target the results of the regional GDP from the simulations described in section 4.1. In other words, the target vector will contain the variations in the real GDP of the States constructed from the estimates obtained with the shocks described in table 2 for each of the scenarios studied.

The shocks inside \( \nu_\beta \) are the 27 productivity shocks in the agricultural sector of the Brazilian states. Therefore, equation (6) will represent a vector of 27 rows (one for each State) as the multiplication of square matrix of order 27 (the cross elasticities of the GDP of state \( r \) with respect to the productivity shock of State \( s \)) and a vector of 27 rows (the productivity shocks in the agricultural sector of each State).

To implement the method, we need first to estimate the matrix \( B \). To achieve this, we simulate the impact of a joint agricultural productivity shock on the 27 States and capture their corresponding cross-elasticities when it comes to the regional GDP each of these States. Thus, given the intrinsic uncertainty in the magnitude of the agricultural productivity shocks of the States, the method can be applied to integrate the results in the
previous section with the structure of the B-MARIA model and explicitly treat the uncertainty in the construction of productivity shocks.

In this way, we target the impacts on GDP derived from the results of the simulations described in the previous section. For this paper, 10,000 productivity shock simulations were performed to evaluate the one that minimizes (7). Each simulation was constructed from a random draw for the productivity shock using a multidimensional Gaussian distribution. The mean of this distribution is equal to the shocks described in table 2 and variance is calculated from the econometric estimates combined with the climate projections described above.

Figure D1 in the appendix shows the distributions of these simulations for each Brazilian State. It allows us to compare both the magnitude and the difference of the agricultural productivity shocks between scenarios. Comparing the average of the shock distributions makes it possible to verify that these have smaller means under RCP 8.5, according to what is expected in this scenario. When comparing the dispersion of these distributions, however, it is possible to observe a greater heterogeneity among regions. Roughly, Northeastern states have lower shock variability under RCP 8.5, while other regions have greater dispersion under this scenario.

Figure D2 shows the effects on the real GDP ($\bar{v}_a$) corresponding to each simulation of productivity shock. Such distribution of effects must be understood as the potential response that States' production may have to uncertain agricultural productivity shocks. Here, the analysis becomes more complex, with cases in which the distribution of impacts on the GDP has a worse average under RCP 8.5 and vice-versa. However, the behavior on the dispersion of these shocks has the same pattern as those described in the previous image. The analysis allows us to observe the consistency of the results with those described in table 2.

Figures E1-E5 in the appendix show the relation of the simulated impacts on the GDP of the five great Brazilian regions ($\bar{v}_a$) in relation to the simulated impacts for the national GDP. The gray line represents the set of points in which this simulated variation is the same in the regions and in the country. The analysis of these images allows us to infer that the effect of climate change on the regional GDP, beyond being quite heterogeneous within each region, varies substantially depending on the scenario analyzed.

There are three possible dimensions to be analyzed using these images: the relationship between regional and national GDP in an isolated way, the same relation between the climatic scenarios studied, and the dispersion of these summarized impacts. Under RCP 2.6, the association between regional impacts and national impacts demonstrates a homogeneous relationship between the regions: Northeast and Southeast have modest five-year average losses (but higher than the national average) in the order of 0.15%, while the North, South and Midwest show average production gains of 0.025%, 0.03% and 0.10%, respectively (better than the national average). Under RCP 8.5, however, the effect is more complex: the Northern region has production gains, but this is not very significant in view of its small importance in the formation of the national GDP.

The Northeast region, in turn, although performing better than the national average (it is above the 45º line), presents average losses of 0.2%. The results for the Southeast region show that the relationship of its impacts with respect to Brazil is reversed depending on the scenarios: although under RCP 2.6 the region is in better shape than the national average, under RCP 8.5 the Southeast is worse off, with average simulated impacts in the order of 0.45%. The South also shows a similar pattern, but with slightly larger dispersion.
Finally, the Midwest is the one with the greatest dispersion of results in both scenarios. In addition, it is the one that shows more expressive losses in terms of GDP under RCP 8.5 (around 0.6%, on average), very much due to its high dependence on the agricultural sector on its production.

In summary, the analysis of these images highlights two important points: the relative loss of the Northeast and Southeast regions compared to the rest of the country under RCP 2.6 and the relative gain of the North and Northeast regions under RCP 8.5. Two possible conjectures to explain this outcome are related to the intensity of climate change under different scenarios and the structure of economic integration between regions: the indirect climate impacts under RCP 8.5 (much more intense than the optimistic scenario) are amplified due to the economic integration of the center-south of Brazil, making the losing regions precisely the most economically integrated.

If, instead of using equation (7) to generate the estimates for \( \hat{\nu}_\alpha^* \), we use \( \hat{\nu}_\beta^* \) as productivity shocks to run a simulation of B-MARIA, we obtain the results presented in Table E1 in the online appendix, referring to the variation of the state GDP (\( \tilde{\nu}_\alpha^{B-MARIA} \)). The analysis shows the maintenance of the impact of regional GDP in each scenario (denoted by color classification: cold for increasing GDP, hot for decreasing), as well as the aptitude of our methodology to replicate the simulated results using the B-MARIA model.
5 CONCLUSION

The United Nations Framework Convention on Climate Change is the largest international cooperation treaty aimed at mitigating the harmful effects that human activity can have on the environment. This treaty, developed during the United Nations Conference on Environment and Development in 1992, defines climate change as changes in climate attributed to human activities that - whether directly or indirectly - alter the composition of the global atmosphere beyond natural climate variation (in comparable periods). Its objective is to stabilize the emission of greenhouse gases (GHG) in the atmosphere at levels that prevent their interference in the global climate system.

Brazil, the venue of the conference, was the first country to sign the treaty, ratifying it in early 1994. In this sense, the country recognized its influence on the phenomenon of climate change by voluntarily committing itself to, complying with and respecting the terms set in the agreement. Another 140 nations are signatories to this conference, signaling to the world that efforts to mitigate the human impact on the climate are the subject of great concern across the globe. While the treaty did not set any specific targets for the level of GHG emissions, it set the precedent for the elaboration of protocols (such as the Kyoto Protocol and The Paris Agreement) that would create mandatory emission limits over time.

In 2008, Brazil presented the National Plan on Climate Change, whose main objective was to encourage the development and improvement of emission mitigation actions within its national territory. One of the pillars of this plan was the generation of research and development on the measurement of impacts, vulnerability, and adaptation of Brazil in relation to climate changes projected in the country. More recently, the country has regressed considerably in its environmental policies. Brazil’s current president, Jair Bolsonaro, has constantly denied human influence on the phenomenon of climate change, and a series of environmental deregulations are taking place in the country.

The economic impacts of these changes in climate are, however, not clear. This paper estimated the direct and indirect impacts of climate change over the Brazilian economy. More specifically, we estimated the potential direct effects of the projected changes in climate may have over the Brazilian agricultural sector. We also estimated the indirect impacts of such shocks in agriculture among the regions of the country.

Our estimates point to a broad regional heterogeneity of these impacts across the country. Using the most and least optimistic scenarios created by the IPCC (RCP 2.6 and 8.5, respectively), our predictions indicate that total economic losses by the end of the century vary from annual losses of 0.4% of national GDP under RCP 2.6, and 1.8% under RCP 8.5. Furthermore, while explicitly dealing with the uncertainties inherent in the methodology used, we conclude that the Northeast and Southeast regions will be consistently more negatively affected under RCP 2.6, while under RCP 8.5 the South, Southeast, and Midwest regions will be the most affected.
REFERENCES


10. **Haddad, E. A., Garber, G.;** “Target Fitting and Robustness Analysis in CGE Models”, in discussion texts of NEREUS.


### APPENDIX

#### Appendix A – Control Variables

Table A1 – Control Variables used in Equation (2)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rainfall Anomaly</td>
<td>INMET</td>
</tr>
<tr>
<td>Rainfall Anomaly ²</td>
<td></td>
</tr>
<tr>
<td>Temperature Anomaly</td>
<td></td>
</tr>
<tr>
<td>Temperature Anomaly ²</td>
<td></td>
</tr>
<tr>
<td>Yield (in ton.) of crop X</td>
<td>ASBM (IBGE)</td>
</tr>
<tr>
<td>Production (in R$ 2000) of culture X</td>
<td></td>
</tr>
<tr>
<td>Proportion of culture X in total produced by the city</td>
<td></td>
</tr>
<tr>
<td>Area intended for planting crop X</td>
<td></td>
</tr>
<tr>
<td>Proportion of area intended for planting Culture X in relation to the entire planted area of the city</td>
<td></td>
</tr>
<tr>
<td>Area intended for crop X</td>
<td></td>
</tr>
<tr>
<td>Proportion of area used for harvesting crop X in relation to the entire harvested area of the city</td>
<td></td>
</tr>
</tbody>
</table>

Note: "X" represents each of the 6 crops analyzed, while each of the 6 estimated models used the yield information, planted area, harvested area, and yield value of all crops as control variables.
Appendix B - Methodology

Figure B1 – Methodology’s Flowchart.
Appendix C - Direct, Indirect and Total Impacts.

Table C1 - Direct, Indirect and Total Impacts over the Brazilian States (in US$ billions).

<table>
<thead>
<tr>
<th>State</th>
<th>RCP 2.6</th>
<th>RCP 8.5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Direct Impact</td>
<td>Indirect Impact</td>
</tr>
<tr>
<td>AC</td>
<td>$ -0.10</td>
<td>$ 0.96</td>
</tr>
<tr>
<td>AL</td>
<td>$ -1.99</td>
<td>$ -34.40</td>
</tr>
<tr>
<td>AM</td>
<td>$ -0.11</td>
<td>$ 1.52</td>
</tr>
<tr>
<td>AP</td>
<td>$ -0.00</td>
<td>$ -0.15</td>
</tr>
<tr>
<td>BA</td>
<td>$ -6.61</td>
<td>$ 16.82</td>
</tr>
<tr>
<td>CE</td>
<td>$ -0.47</td>
<td>$ -30.76</td>
</tr>
<tr>
<td>DF</td>
<td>$ -0.40</td>
<td>$ -6.00</td>
</tr>
<tr>
<td>ES</td>
<td>$ -2.42</td>
<td>$ 10.13</td>
</tr>
<tr>
<td>GO</td>
<td>$ -10.39</td>
<td>$ 50.90</td>
</tr>
<tr>
<td>MG</td>
<td>$ -20.24</td>
<td>$ -118.67</td>
</tr>
<tr>
<td>MS</td>
<td>$ -7.62</td>
<td>$ 1.80</td>
</tr>
<tr>
<td>MT</td>
<td>$ -12.76</td>
<td>$ 56.69</td>
</tr>
<tr>
<td>PA</td>
<td>$ -0.80</td>
<td>$ 31.27</td>
</tr>
<tr>
<td>PB</td>
<td>$ -0.66</td>
<td>$ -9.40</td>
</tr>
<tr>
<td>PE</td>
<td>$ -1.45</td>
<td>$ -35.91</td>
</tr>
<tr>
<td>PI</td>
<td>$ -1.05</td>
<td>$ 4.04</td>
</tr>
<tr>
<td>PR</td>
<td>$ -16.90</td>
<td>$ 22.58</td>
</tr>
<tr>
<td>RJ</td>
<td>$ -0.15</td>
<td>$ -46.24</td>
</tr>
<tr>
<td>RN</td>
<td>$ -0.30</td>
<td>$ -6.10</td>
</tr>
<tr>
<td>RO</td>
<td>$ -0.63</td>
<td>$ -5.07</td>
</tr>
<tr>
<td>RR</td>
<td>$ -0.02</td>
<td>$ -0.08</td>
</tr>
<tr>
<td>RS</td>
<td>$ -5.74</td>
<td>$ 48.86</td>
</tr>
<tr>
<td>SC</td>
<td>$ -2.88</td>
<td>$ -5.29</td>
</tr>
<tr>
<td>SE</td>
<td>$ -0.59</td>
<td>$ -12.14</td>
</tr>
<tr>
<td>SP</td>
<td>$ -25.66</td>
<td>$ -365.50</td>
</tr>
<tr>
<td>TO</td>
<td>$ -1.24</td>
<td>$ -0.70</td>
</tr>
</tbody>
</table>

TOTAL: $ -123.22 | $ -420.37 | $ -543.59 | $ -704.88 | $ -1,764.49 | $ -2,469.37
Appendix D – Simulations

Figure D1 - Distribution of Simulated Productivity Shocks.
Figure D2 - Distribution of Simulated Impacts on State GDP.
Appendix E - Uncertainties

Simulated Impact on Regional and Brazilian GDP - $\nu_\alpha (\ln \%)$

Figure E1 - Simulated Impact on the National and Regional GDP - North.

Figure E2 - Simulated Impact on the National and Regional GDP - Northeast.
Figure E3 - Simulated Impact on the National and Regional GDP - South.

Figure E4 - Simulated Impact on the National and Regional GDP - Southeast.
Simulated Impact on Regional and Brazilian GDP - $\nu(\ln \%)$

Figure E5 - Simulated Impact on the National and Regional GDP - Midwest.