Climate change scenarios and ENSO events: assessing soybean production and economic impacts in Brazil (2016-2023) via panel data and input-output analysis

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Resumo

Este estudo mensura os impactos econômicos resultantes do aumento de temperatura sobre a produção de soja no Brasil, considerando a ocorrência do fenômeno ENOS – *El Niño* e *La Niña*. Para isso, utiliza-se uma função de produção ampliada do tipo Cobb-Douglas e uma análise de Insumo-Produto (I-P). Inicialmente, estima-se, por meio de efeitos fixos, variações na produção da soja entre 2016 e 2023. Com base nessas estimativas, simula-se choques de oferta resultante do aumento de temperatura média durante a fase de crescimento da soja (0,5 ºC, 1,0 ºC e 1,5 ºC), usando um modelo de I-P para o Brasil. O aumento de 1 ºC na temperatura média durante a fase de crescimento da soja pode reduzir sua produção em 51.5% e 22.4% nos anos de *El Niño* e *La Niña*, respectivamente, o que levaria a uma redução de R$ 96.65 e 43.03 bilhões do Valor Bruto da Produção (VBP) do Brasil. Os resultados destacam a urgência de políticas para mitigar o aquecimento global e desenvolver estratégias adaptativas para reduzir as perdas na produção de soja e seus consequentes impactos na economia brasileira.

Abstract

This study quantifies the economic impacts of increasing temperature on Brazilian soybean production, focusing on the effects during the occurrence of the ENSO phenomena (*El Niño* and *La Niña*). We employed a modified Cobb-Douglas production function to estimate variations in soybean output through a fixed-effects panel regression. Based on these estimates, we simulated supply shocks resulting from temperature increases (0.5°C, 1.0°C, and 1.5°C) using an Input-Output analysis. The results suggest that a 1.0°C increase in average temperature during the growing season could reduce soybean production by 51.5% in *El Niño* years and by 22.4% in *La Niña* years. These production losses would reduce Brazil's Gross Value of Production (GVP) by R$ 96.65 billion and R$ 43.03 billion, respectively. The findings underscore the urgent need for policies to mitigate global warming and develop adaptive strategies to minimize losses in soybean production and their consequent impacts on the Brazilian economy.

Keywords: Climate change. ENSO. Soybean production. Input-Output analysis. Brazil.
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1 INTRODUCTION

Soybeans are one of the most economically relevant crops globally, playing a central role in agribusiness, biofuel production, and the food and chemical industries (Freitas, 2011). Soybeans are an important component of Brazil’s agricultural Gross Domestic Product (GDP) and trade balance. From 2010 to 2023, Brazil's production rose from 68.8 million tons to 152.1 million tons, alongside an expansion in cultivated area from 23.3 million to 44.4 million hectares. This growth reflects not only the expansion of the agricultural frontier but also technological advancements and productivity gains, with yields increasing from 2.9 to 3.4 tons per hectare (IBGE, 2025).

Soybean cultivation is highly sensitive to climatic conditions, as its growth depends on factors such as temperature, precipitation, and solar radiation (Farias *et al.*, 2007). The soybean productivity can be significantly impacted by variations associated with the El Niño-Southern Oscillation (ENSO) phenomenon, which includes *El Niño* and *La Niña* events. This phenomenon directly impacts Brazil, causing excessive rainfall during *El Niño* and droughts under *La Niña*, which unevenly affect different production regions (Cunha *et al.*, 2011).

According to the World Meteorological Organization (WMO), there is a 50% probability that the global average temperature will temporarily exceed 1.5°C above pre-industrial levels by 2026 (UN, 2022). In Brazil, climate projections for the end of the twenty-first century indicate rising temperatures and altered precipitation patterns (IPCC, 2015). Between 2006 and 2017, the country's average temperature increased by 0.35°C (CCKP, 2021). The Midwest region - particularly Mato Grosso, which accounted for 29.3% of Brazil's soybean production in 2023 - is expected to face significant impacts from climate change (Soares, 2011). Such changes could substantially compromise soybean production nationwide.

Recent studies have examined the relationship between climate change and agricultural productivity. Schlenker and Roberts (2009) demonstrated that crop productivity for corn, soybeans, and cotton increases to specific temperature thresholds (29°C, 30°C, and 32°C, respectively), beyond which yields decline sharply. These reductions are more severe in tropical and subtropical areas, where agriculture remains highly climate-dependent and faces additional challenges such as limited access to advanced technologies (Carvalho, 2022; Grigorieva *et al.*, 2023) and increasing pest incidence (Lal, 2021).

One of the pioneering studies conducted for Brazil was developed by Sanghi *et al.* (1997), who estimated the impacts of extreme temperatures on Brazilian agriculture using four cross-sectional models based on data from the 1970, 1975, 1980, and 1985 Agricultural Censuses. Their results demonstrated that a 2.5°C increase in the average temperature during the final month of each growing season would reduce Brazilian agriculture yields from 2.16% to 7.40%. The Midwest and parts of the North region would be the most vulnerable areas.

Sanghi and Mendelsohn (2008) subsequently expanded this analysis, projecting that a 2°C increase in average temperature combined with an 8% rise in average precipitation could lead to agricultural productivity losses of up to 20% in Brazil. Assunção and Chein (2016) furthered this research by examining climate change impacts on Brazilian agricultural productivity using IPCC temperature and precipitation projections. They found that a 6.57% increase in average temperature coupled with a 0.71% decrease in average precipitation would reduce national agricultural productivity by 18.2%. The study revealed particularly severe consequences for the Central-West region, where a 7.47% temperature increase combined with a 1.54% precipitation reduction would lead to a 28.3% decline in agricultural production value - the second highest regional impact after the North region's 35% projected loss.

Soybeans demonstrate vulnerability to climate change, with both global and regional studies confirming this. Research by Lee and McCann (2019), Mourtzinis *et al.* (2019) and Schauberger *et al.* (2017) has documented climate-induced yield variability across different soybean-producing regions worldwide, attributing these fluctuations primarily to changing temperature regimes and precipitation patterns. In the Brazilian context, Rio *et al.* (2016) identified yield reductions of up to 35% in southern growing areas, where rising temperatures and altered rainfall distribution patterns have adversely affected crop development.

According to Girardi *et al.* (2008), soybeans are projected to be the most affected crop by climate change in Brazil. In the worst-case scenario, production losses could reach 40% by 2070, resulting in economic losses of approximately R$7.6 billion. Similarly, Souza (2018) also identifies economic impacts on soybean production. Under the IPCC RCP 8.5 climate scenario for the 2020–2100 period, the study estimates losses of up to R$1.4 billion. These findings are particularly concerning given the central role of soybeans in the Brazilian economy.

Research on climate impacts on soybean production underscores the crop's global economic significance, particularly for Brazil as one of the world's foremost producers and exporters. As a climate-sensitive crop, soybean yields are substantially affected by extreme weather events, especially those related to the ENSO phenomenon. In Brazil, *El Niño* typically brings excessive rainfall while *La Niña* induces drought conditions, both affecting disproportionately different growing regions of the country. Current climate projections suggest these effects will intensify, particularly in key production areas like the Midwest, which accounts for most of the national production. In this context, this study addresses two critical questions: (1) How does climate change affect soybean production in Brazil? and (2) What are the consequent economic impacts for the country?

This study measures the economic impacts of increasing temperature on soybean production in Brazil, focusing on the effects during the occurrence of the ENSO phenomena. To do that, we estimate a modified production function to analyze how climatic variables affect soybean production between 2016 and 2023. Based on these estimates, we will then calculate the percentage variations in production under different temperature increase scenarios. Finally, these production variations will be incorporated into an input-output model for Brazil's soybean sector to quantify the resulting economic impacts of climate change.

The production function is estimated using fixed effects, which enhances the robustness of our estimates by controlling for unobserved heterogeneity across municipalities, as demonstrated by Cameron and Trivedi (2005) and Wooldridge (2010). The climatic variables are georeferenced at the municipal level, ensuring they accurately reflect local weather conditions. Furthermore, following CONAB's planting and harvesting calendar (CONAB, 2020), we organized these climatic variables according to soybean growth stages, thereby improving the precision of our estimates. For the economic impact analysis, we employed data from the 2015 Input-Output Matrix (IOM) (IBGE, 2015), which we diagonalized into a 127×127 product structure. This approach enables direct shocks to soybean production and facilitates a detailed assessment of economic impacts throughout the production chain.

This study distinguishes itself through three key methodological innovations: (1) the utilization of georeferenced data enabling spatially granular analysis of climatic conditions; (2) the incorporation of soybean-specific growth and harvest phases, enhancing estimation precision; and (3) the implementation of a fixed-effects panel model that controls for unobserved regional heterogeneity while providing more robust and detailed assessment of climate change impacts on soybean production.

This paper is structured as follows: Section 2 presents the methodological approach and describes the data used in the analysis. Section 3 discusses the main findings. Section 4 provides the concluding remarks, followed by the References.

2 METHODOLOGY AND DATA

This study assesses the economic impacts of climate change on soybean production in Brazil from 2016 to 2023, with a particular focus on the effects of the ENSO phenomena. Using an econometric panel data model and I-O analysis, we quantify the percentage changes in soybean production under different climate scenarios and their broader economic consequences. The dataset includes municipal-level information on soybean production, climate variables (such as *El Niño* and *La Niña* indicators), and data from Brazil's IOM.

This section is divided into three parts. The first describes the econometric model used in the study. The second presents the I-O methodology, emphasizing the hypothetical extraction technique. Finally, the third part describes the data used in this research.

2.1 Econometric modeling

The analysis of agricultural productivity is based on two main approaches: the Ricardian Approach and the Production Function. The Ricardian Approach, proposed by Mendelsohn *et al.* (1994), assesses the impact of climate on land value and yield, assuming that land value reflects the present value of future agricultural flows. However, in countries such as Brazil, land value can be influenced by factors beyond agriculture, such as economic instability, as highlighted by Assunção (2008). Additionally, Deschênes and Greenstone (2007) point out that this approach can be sensitive to methodological choices, such as the selection of controls and weighting variables. Because of these limitations, the study adopts the Production Function.

The Production Function is traditionally specified as a production function in which climatic variables are considered production inputs (Assunção and Chein, 2016). According to Chambers (1988), the more general relationship between production and inputs can be expressed as follows:

$$Y = f(X) \tag{1}$$

Where, Y represents the output originated by a combination of N input vectors X. Equation (1) is widely used in literature in its Cobb-Douglas functional form.

Research indicates that climatic variables such as temperature, precipitation, relative humidity, solar radiation, wind speed, and evaporation significantly impact agricultural productivity (Gornall *et al.*, 2010; Araújo, Uribe-Opazo and Johann, 2014; Shirley *et al.*, 2020). To incorporate these elements into productivity models, the general function presented in Equation (2) can be extended to include climatic variables, as expressed in the following formulation:

$$Y = T^{\alpha} L^{\beta} K^{\gamma} . f(Z) \tag{2}$$

Where T^{α}, L^{β} and $K^{\gamma}$are land, labor and capital, respectively; $f(Z)$ is a function that captures the effect of climatic factors on production.

Shirley *et al.* (2020) note that some models use additive or multiplicative terms for each climate variable, while others adopt more complex functional forms. In this sense, the authors emphasize that the function $f(Z)$ can be modeled in many ways, depending on data availability and study-specific requirements. Equation (2) in this study represents the soybean production function. In other words, soybean production depends on primary inputs (land, labor, and capital) combined with climatic variables and an exogenous technological factor.

In Brazil, capital and labor variables are unavailable annually, these data are census-based, that is, they are only available every ten years. Studies such as those by Tirfi (2022) and Li (2023) encountered a similar limitation due to incomplete time series of some classic production inputs. Given these data constraints, and following these two studies, the theoretical model of this research can be expressed as:

$$Y = T^{\alpha} . f(Z) \tag{3}$$

In other words, soybean production is a function of the planted land (T^{α}) and a set of climatic variables ($f(Z)$).

Based on the theoretical formulation presented in Equation (3), which adopts a modified Cobb-Douglas production function to incorporate climatic variables, the empirical model of this study can be expressed by the following functional equation:

$$ln(Y)_{it} = \beta_0 + \beta_1 ln(T)_{it} + \sum_{j=1}^{12} \beta_{2j} X_{it,j} + \sum_{k=13}^{18} \beta_{3k} ln\left(Z_{it,k}\right) + \alpha_i + \gamma_t + \epsilon_{it} \quad (4)$$

Here, $ln(Y)_{it}$ is the natural logarithm of the dependent variable, that is, the amount of soybean produced in the municipality i in the year t. $ln(T_{it})_{it}$ is the natural logarithm of the planted area in the municipality i in the year t. The vector $X_{it,j}$ includes a set of climatic variables, referring to the municipality i in the year t; the index j, which ranges from 1 to 12, represents the following variables: temperature, precipitation and humidity during the growing and the harvesting seasons, along with their quadratic terms. The vector $ln\left(Z_{it,k}\right)$ is the natural logarithm of the variable's radiation, evaporation, and wind speed in the periods of growth and harvest in the municipality i in the year t; the index k individually identifies each of these variables. In the model, the terms α_i and γ_t represent the year t and the municipality i, respectively. ϵ_{it} is the error term, and the coefficient β_0 is the model constant. Finally, β_1, β_{2j} and β_{3k} are the coefficients associated with the variations in each of the explanatory variables of the model.

The database constructed for this study is a panel dataset with observations from 2016 to 2023. It presents repeated observations for the same cross-sectional units over time (Wooldridge, 2010). However, the absence of observations for some municipalities in certain years characterizes this panel as unbalanced, as discussed by Gujarati and Porter (2011). Additionally, given that the number of units (2685 municipalities) is much greater than the number of periods (8 years), the panel dataset in this study is classified as short (Gujarati and Porter, 2011).

The use of a panel dataset improves the accuracy of estimates compared to a cross-sectional dataset, as the increase in the number of observations provides gains in degrees of freedom, which tends to improve the efficiency of estimates (Cameron and Trivedi, 2005). Moreover, the possibility of using multiple observations over time for each observed unit allows for the modeling temporal dynamics and controlling unobserved characteristics that are constant over time (Cameron and Trivedi, 2005; Gujarati and Porter, 2011), otherwise estimates may be biased if these observations are correlated with regressors (Cameron and Trivedi, 2005)

In addition, panel data improves the identification of causal relationships, allowing the analysis of the effect of independent variables on the dependent variable over time. Wooldridge (2010) points out that such data are especially useful for studying the effects of non-manipulable variables, such as economic policies or climate change, as is the case in this study. Finally, Cameron and Trivedi (2005) state that panel data allow for tests such as Hausman's to choose between random effects and fixed effects models, enabling a more informed and consistent approach.

In this study, the empirical model described in Equation (4) will be estimated using the Fixed Effects (FE) method. The within estimator of FE eliminates between-unit variation and focuses on within-unit differences each unit over time, expressing the value of the dependent variable and regressors as deviations from their respective mean values (Gujarati and Porter, 2011). This approach leverages the variation of data over time.

To ensure that the estimation method is the most appropriate, some tests will be conducted. First, the Breusch-Pagan test will be employed to determine whether the POLS model and the Random Effects (RE) model. According to Cameron and Trivedi (2005), the null hypothesis (H_0) of the test is that the errors are independently and identically distributed (i.i.d.), meaning that there are no random effects. As the authors explain, if the test rejects the null hypothesis, it is concluded that there is evidence for the existence of random effects, and the RE model would be the most appropriate.

In short panels, formal tests for the presence of individual-specific fixed effects are not possible due to the problem of incidental parameters. It is not feasible to test whether N parameters are equal to zero when there is only N×T and T is small. Instead, the Hausman Test is used to verify the H_0 of random effects against the alternative of fixed effects (Cameron and Trivedi, 2005). If the test rejects H_0, then the random (unobserved) effects are likely to correlate with one or more observed variables of the model, making the FE estimator preferable to the RE estimator (Gujarati and Porter, 2011). These tests play a crucial role in choosing the most appropriate model, enabling researchers to account for the specific characteristics of the data to be analyzed while ensuring more robust statistical inferences.

2.2 Input-Output (I-O) model

The seminal input-output model was developed by Leontief (1936) and is based on the concept of general interdependence among the various components of the economic system. This system includes all branches of production in an economy, as well as all the incomes of individuals, in aggregate terms. The IP model allows two distinct economic analyses to be made: one considering the closed structure of the model (with endogenous final demand and value added) and the other the open structure (with exogenous final demand and value added). This study adopts Leontief's open model, which implies that the components of the final demand are exogenous to the system.

According to Guilhoto (2011), this model preserves macroeconomic identities, that is, the equilibrium relationship between aggregate supply and demand, according to the following expression:

$$C + G + I + (E - M) = T + W \tag{5}$$

Here, C represents the aggregate consumption of households; G aggregate government expenditures; I the aggregate investment; (E – M) the aggregate balance between exports and imports; T the total net indirect taxes paid; and W the added value.

The basic structure of an IP model consists of a system of linear equations, each describing the distribution of an industry's output across the economy over time or space (Miller and Blair, 2009). Within this framework, the economy can be categorized into n industries, so that x_i represents the total output of the industry i, and y_i denotes the total final demand for the industry i. Equation (5), consequently, can be reformulated to explain how the industry i allocates its output through both sales to other sectors and final demand:

$$x_i = z_{i1} + \cdots + z_{ij} + \cdots + z_{in} + f_i = \sum_{j=1}^{n} z_{ij} + y_i \tag{6}$$

The terms z_{ij} represent the inter-industry sales made by the industry i (Intermediate sales) for all industries j (including intra-industry sales when $j = i$). Equation (6) describes the distribution of the production of industry i.

According to Miller and Blair (2009), there is an equation, such as Equation (6), that identifies the sales of production of each of the n industries as follows:

$$\begin{gathered} x_1 = z_{11} + \cdots + z_{1j} + \cdots + z_{1n} + y_1 \\ \vdots \\ x_i = z_{i1} + \cdots + z_{ij} + \cdots + z_{in} + y_i \\ \vdots \\ x_n = z_{n1} + \cdots + z_{nj} + \cdots + z_{nn} + y_n \end{gathered} \tag{7}$$

In matrix terms, Equation (7) is represented as follows:

$$\mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}, \mathbf{Z} = \begin{bmatrix} z_{11} & \cdots & z_{1n} \\ \vdots & \ddots & \vdots \\ z_{n1} & \cdots & z_{nn} \end{bmatrix} \text{ e } \mathbf{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \tag{8}$$

The allocation of sales in each industry i can then be summarized as:

$$\mathbf{x} = \mathbf{Z}_i + \mathbf{y} \tag{9}$$

Given the interdependence between sectors, producing a product requires the acquisition of inputs from one sector by another. The ratio between the purchased value of inputs from the industry i by producers of industry j, z_{ij}, and production value j is defined as the technical production coefficient, a_{ij}, according to Miller and Blair (2009), and it is given by:

$$a_{ij} = \frac{z_{ij}}{x_j} \tag{10}$$

In this way, Equation (9) can be rewritten as:

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \boldsymbol{y} \tag{11}$$

Where **A** is the matrix of the direct technical coefficients (a_{ij}) and $\mathbf{x}$ and $\boldsymbol{y}$ are the vectors of order $(n\ x\ 1)$. Given that **A** and $\boldsymbol{y}$ are exogenous components of the system, Equation (11) can be solved to obtain the total output that is necessary to satisfy the final demand, as shown below:

$$\mathbf{x} = \mathbf{B}\mathbf{y} \tag{12}$$

In which $\mathbf{B} = (\mathbf{I} - \mathbf{A})^{-1}$ it is the matrix of direct and indirect technical coefficients, also called Leontief's inverse matrix (Guilhoto, 2011).

Equation (12) represents the solution of Leontief's open model, in which interindustry relationships are evaluated within the internal context of a single region. Consequently, this model does not allow for the analysis of economic dynamics across multiple regions simultaneously. So, this model is well suited to the objective of this study, which is to assess how the impacts of climate change on soybean production affect the Brazilian economy.

This analysis will employ the hypothetical extraction method, which quantifies the change in total output of an economy if a given industry is partially or entirely removed (Miller and Blair, 2009). Essentially, this method compares the economy's output before and after the hypothetical removal of the industry, implemented by excluding the corresponding rows and/or columns from the technical-coefficients matrix **A** of technical coefficients (Dietzenbacher *et al.*, 1993). The magnitude of the resulting difference indicates the economic importance of the hypothetically extracted industry.

In this study, as in Fernandes *et al.* (2021), we employ a variant of the hypothetical extraction method. Instead of total extraction of the soybean product, a partial extraction will be conducted. This approach makes it possible to measure the magnitude of soybean production losses due to climate change and their effects on the Brazilian economy.

According to Miller and Blair (2009), $\bar{\mathbf{A}}_{(\mathrm{j})}$, $\bar{\mathbf{y}}_{(\mathrm{j})}$ and $\bar{\mathbf{x}}_{(\mathrm{j})}$ are defined as the matrix $(\mathrm{n}-1)$ x $(\mathrm{n}-1)$, the final demand vector and the product vector of the Brazilian economy are defined, and as the matrix, in this case, with partial extraction from the industry j, respectively. Therefore, we compute:

$$\bar{\mathbf{x}}_{(\mathrm{j})} = \left(\mathbf{I} - \bar{\mathbf{A}}_{(\mathrm{j})}\right)^{-1} \bar{\mathbf{y}}_{(\mathrm{j})} \tag{13}$$

Where $\left(\mathbf{I} - \bar{\mathbf{A}}_{(\mathrm{j})}\right)^{-1}$ is the Leontief inverse matrix of direct and indirect technical coefficients with the partial extraction of industry sector j – in this case, the soybean industry.

To capture the impact of soybean production losses on the Brazilian economy, the difference between Equation (12) and Equation (13) is calculated, that is, the production vector of the original input-output model is subtracted from the production vector of the model with the partial extraction of the soybean industry (j), as shown below:

$$T_j = \mathbf{i}'\mathbf{x} - \mathbf{i}'\bar{\mathbf{x}}_{(\mathrm{j})} \tag{14}$$

Where T_j it is an aggregate measure of the economic loss, representing the decrease in the value of gross output resulting from the partial extraction of industry j. Therefore, T_j is a measure of the importance or linkage of the industry j – in this case, the soybean sector – to the Brazilian economy (Miller and Blair, 2009).

2.3 Database and variables

The model proposed in this study is a modified production model that estimates soybean output, defined as the quantity of soybean produced, as a function of two types of variables: production inputs and climatic factors. The production input considered here is land, represented by the soybean planted area, and the climatic variables are the averages of temperature, precipitation, humidity, radiation, wind speed and evaporation during the soybean growing and harvesting seasons. The data are organized in panel format and cover the period from 2016 to 2023 for all soybean-producing municipalities in Brazil.

Soybean data – planted area and production – were obtained from the Municipal Agricultural Survey (PAM) of the Brazilian Institute of Geography and Statistics (*Instituto Brasileiro de Geografia e Estatística* – IBGE) (IBGE, 2025). Climate variables were collected using the ERA5-Land reanalysis dataset provided by the Copernicus Climate Data Store program (CCDS, 2025). These data were accessed via the CCDS Application Programming Interface (API) using the Python language in the Google Colab tool. The variables extracted include: average air temperature at 2 meters above the ground and average dew-point temperature of the dew point at 2 meters above the ground (both in Kelvin – K), representing air humidity; incident solar radiation accumulated at the surface (in joules per square meter – J/m^2); mean eastward (U10) and northward (V10) wind components average of the wind components in the east (U10) and west (V10) directions (both in meters per second – m/s); accumulated precipitation (in meters – m); and accumulated evaporation (m).

Some transformations were applied to the variables to enhance interpretability and align them with the most used units of measurement in the agricultural economics literature. Accordingly, temperature variables were converted from K to Celsius (°C), following the formula provided by CCDS (2025):

$$Temperature\ (Celsius) = Temperature\ (Kelvin) - 273{,}15 \tag{15}$$

Similarly, the wind direction components (U10 and V10) were combined to calculate wind speed, as recommended by ECMWF (2025):

$$v = \sqrt{(u^2 + v^2)} \tag{16}$$

Additionally, the variables for total precipitation and total evaporation, which were in meters (m), were converted into millimeters (mm):

$$Value\ em\ mm = Value\ in\ m * 1000 \tag{17}$$

After the individual treatment of these climatic variables, they were used to create other variables used in the model. For each year in the analyzed period (2016–2023), an average was calculated for both the growing and harvesting seasons of all climatic variables. Squared terms of the temperature, precipitation, and humidity variables were also created. The other variables were log-transformed, except for evaporation, for which the logarithm of its absolute value was used, since the logarithmic transformation applies only to positive values. These data were then merged with soybean production and planted area data. Table 1 presents the variables used in this study.

Table 1 – Variable descriptions and data sources

Variable	Description	Unit of Measure	Variable Type	Form	Source
Yield	Soybean production quantity	t	Dependent	Natural logarithm	PAM (IBGE, 2023)

Area	Soybean planted area	ha	Production input	Natural logarithm	PAM (IBGE, 2023)
Temperature	Average temperature during growth and harvest periods	°C	Climatic	Level	ERA5-Land (CCDS, 2025)
Precipitation	Average accumulated precipitation during growth and harvest periods	mm	Climatic	Level	ERA5-Land (CCDS, 2025)
Wind Speed	Average wind speed during growth and harvest periods	m/s	Climatic	Natural logarithm	ERA5-Land (CCDS, 2025)
Solar Radiation	Average accumulated incident solar radiation on surface during growth and harvest periods	J/m²	Climatic	Natural logarithm	ERA5-Land (CCDS, 2025)
Humidity	Average dew point temperature during growth and harvest periods	°C	Climatic	Level	ERA5-Land (CCDS, 2025)
Evaporation	Average accumulated evaporation during growth and harvest periods	mm	Climatic	Natural logarithm	ERA5-Land (CCDS, 2025)

Source: Own elaboration.

A categorical variable was also added to the dataset, indicating the occurrence of *El Niño*-Southern Oscillation (ENSO) weather events based on the criteria of the Climate Prediction Center (CPC) of the National Oceanic and Atmospheric Administration (NOAA). According to the CPC (2025), the occurrence of ENSO events is determined by the Oceanic Niño Index (ONI), defined as the quarterly moving average of the sea surface temperature anomaly in the Equatorial Pacific Ocean. When the anomaly shows values above 0.5°C for at least five consecutive periods of three months, ENSO is characterized as *El Niño*, when it is below -0.5°C *La Niña* occurs; otherwise, there is neutrality. Table 2 presents the classification of ENSO from 2016 to 2023, based on these criteria. In dark gray, the values of anomalies equal to or greater than 0.5 ºC are highlighted; in light gray, anomalies less than or equal to -0.5 ºC; and, in white, the values between these two intervals.

Table 2 – Quarterly Sea Surface Temperature (SST) Anomalies (2016-2023)

Year	**DJF**	**JFM**	**FMA**	**MAM**	**AMJ**	**MJJ**	**JJA**	**JAS**	**ASO**	**SON**	**OND**	**NDJ**	**ENSO**
2016	2.5	2.1	1.6	0.9	0.4	-0.1	-0.4	-0.5	-0.6	-0.7	-0.7	-0.6	*La Niña*
2017	-0.3	-0.2	0.1	0.2	0.3	0.3	0.1	-0.1	-0.4	-0.7	-0.8	-1.0	Neutro
2018	-0.9	-0.9	-0.7	-0.5	-0.2	0.0	0.1	0.2	0.5	0.8	0.9	0.8	Neutro
2019	0.7	0.7	0.7	0.7	0.5	0.5	0.3	0.1	0.2	0.3	0.5	0.5	*El Niño*
2020	0.5	0.5	0.4	0.2	-0.1	-0.3	-0.4	-0.6	-0.9	-1.2	-1.3	-1.2	*La Niña*
2021	-1.0	-0.9	-0.8	-0.7	-0.5	-0.4	-0.4	-0.5	-0.7	-0.8	-1.0	-1.0	*La Niña*
2022	-1.0	-0.9	-1.0	-1.1	-1.0	-0.9	-0.8	-0.9	-1.0	-1.0	-0.9	-0.8	*La Niña*
2023	-0.7	-0.4	-0.1	0.2	0.5	0.8	1.1	1.3	1.6	1.8	1.9	2.0	*El Niño*

Source: CPC (2023).

Note: The capital letters represent the initials of the months of the year. For example, in the second column, **DJF** represents the **D**ecember, **J**anuary, and **F**ebruary quarters.

The database used in the input-output analysis is the 2015 Input-Output Matrix (IOM) for Brazil, calculated by the IBGE. The IOM presents only monetary values of production, and its most disaggregated version comprises 127 products and 67 industries (IBGE, 2015).

The version used in this study is a product-product IOM. To obtain this, we diagonalized the product-sector IOM. First, a market share matrix was created by calculating the production shares of each product within each industry from the 'Supply of Goods and Services' table. Then, the transposed market-share matrix (127 × 67) was multiplied by the other tables (67 × 127), generating tables of dimension 127 × 127 with results consistent with the original data. Finally, an important assumption for this procedure is that demand allocation follows each activity's share in the production of the good (Betarelli Junior, 2013). Thus, the IOM used in this study has dimensions of 127 products × 127 products.

The version used in this study is a product-product IOM. First, a market share matrix was created by calculating the production shares of each product within each sector of the "Supply of Goods and Services" table. Then, the market-share transpose (127 x 67) was multiplied by the other tables (67 x 127), generating tables of dimension 127 x 127 and consistent results about the original data. Finally, an important hypothesis to this procedure is that the allocation of demand follows the participation of each activity in the production of the good (Betarelli Junior, 2013). Thus, the IOM used in this study has 127 products per 127.

3 RESULTS AND DISCUSSIONS

This section presents the results of this study. Section 3.1 presents the main descriptive statistics of the variables used. Section 3.2 presents and discusses the estimates of the econometric model adopted in this study. Finally, section 3.3 presents and discusses in more detail the effects of the variable growth temperature on soybean production in percentage terms based on the results of the estimates presented in section 3.2. Section 3.3 also presents the results of the economic impacts of these variations.

3.1 Descriptive statistics

Table 3 provides information on the mean, standard deviation, minimum, and maximum values for climate variables and soybean production from 2016 to 2023 (Total), with subgroups for 2019 and 2023 (*El Niño*) and for 2016 and 2020–2022 (*La Niña*). The average soybean production for the total period is 51,102.04 tons (t), with considerable variation, as indicated by the standard deviation (138,320.40 t). This variability is even more pronounced during *El Niño* events, when the average reaches 53,810.74 t, with a very high standard deviation (147,453.80 t). In contrast, average production during *La Niña* events is slightly lower (49,855.23 t), also accompanied by a high standard deviation (136,018.50 t). These statistics suggest that in the presence of climatic anomalies (*El Niño* and *La Niña*), soybean production tends to be more sensitive and variable.

The average planted area is 15,757.81 hectares (ha), with substantial variation, as evidenced by the standard deviation (40,121.16 ha). The average planted area during *El Niño* (16,233.41 ha) and *La Niña* (15,867.52 ha) events does not show significant differences. The fact that the planted area remains very similar across subgroups, while average production varies considerably, indicates that soybean production is sensitive to climatic anomalies.

Regarding the climatic variables, the average growth temperature was 23.78 °C for the total period. This average increased during *El Niño* years (24.77 °C) and decreased during *La Niña* years (23.44 °C). Average precipitation during the soybean growing season also varied: it averaged 4.16 mm in the total period, but dropped to 4.04 mm in *La Niña* years, decreasing even more in the *El Niño* period to 3.22 mm. These differences suggest that *El Niño* tends to be associated with warmer and drier conditions, whereas *La Niña* years are generally cooler and wetter. Other climatic variables—such as humidity, solar radiation, wind speed, and evaporation—also showed notable shifts between *El Niño* and *La Niña* years, reinforcing the distinct environmental patterns associated with each event.

Table 3 – Descriptive Statistics

Variable	Total (2016-2023)				*El Niño* (2019 and 2023)				*La Niña* (2016 and 2020-2022)			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Yield	51102.04	138320.40	2.00	2283300.00	53810.74	147453.80	2.00	2244375.00	49855.23	136018.50	2.00	2283300.00
Planted area	15757.81	40121.16	1.00	620000.00	16233.41	41495.32	1.00	605000.00	15867.52	40137.62	1.00	620000.00
Growth temperature	23.78	2.76	14.87	31.57	24.77	2.80	16.84	31.57	23.44	2.73	14.87	30.99
Growth precipitation	4.16	1.98	0.24	19.32	3.22	1.78	0.24	15.55	4.04	1.96	0.66	19.32
Harvest temperature	22.85	2.52	15.10	29.89	22.96	2.41	15.77	29.89	22.75	2.66	15.10	29.11
Harvest precipitation	4.14	1.89	0.10	12.37	3.43	1.98	0.10	10.39	4.33	1.75	0.11	12.37
Growth humidity	17.45	2.20	11.68	24.41	18.15	1.85	13.31	24.34	16.98	2.30	11.68	24.32
Harvest humidity	18.04	2.42	10.94	24.61	18.53	2.17	12.58	24.16	17.60	2.59	10.94	24.61
Growth radiation	18000.00	5727.80	5243.99	25700.00	14800.00	6712.80	5243.99	25500.00	18300.00	5672.45	6290.55	25700.00
Harvest radiation	16800.00	4242.56	5072.44	22700.00	12200.00	5666.77	5072.44	22700.00	18500.00	1697.56	8238.69	22100.00
Growth wind speed	0.97	0.39	0.08	4.00	0.93	0.40	0.11	4.00	0.99	0.40	0.08	3.56
Harvest wind speed	0.87	0.32	0.15	3.92	0.81	0.32	0.15	3.92	0.84	0.29	0.19	3.74
Growth evaporation	-2.99	1.12	-5.36	-0.31	-2.38	1.25	-5.36	-0.31	-2.98	1.05	-5.15	-0.72
Harvest evaporation	-3.11	0.85	-4.82	-0.38	-2.32	1.15	-4.68	-0.38	-3.33	0.47	-4.82	-0.71

Source: Own elaboration.

3.2 Production function estimates

This section presents the estimation results of Equation 4, a modified Cobb-Douglas production function that includes climatic variables and it is estimated using Fixed Effects (FE). This approach controls unobserved heterogeneity across municipalities and changes in the productive structure over time. The adequacy of the model was confirmed through statistical tests (Hausman and Breusch-Pagan).

Table 4 shows the estimates of the FE models, which analyze the factors affecting soybean production under different climatic conditions, such as *El Niño* and *La Niña*. The dependent variable is the quantity of soybeans produced, while the independent variables include climatic factors and the planted area. The analysis focuses primarily on the estimates related to temperature and precipitation during the growing and harvesting periods.

As explained in the methodology chapter, some explanatory variables are in logarithmic form, while others are in levels and squared terms. The planted area (in logarithms) significantly and positively affects soybean production under all conditions analyzed. The coefficient of 1.041 in the full model indicates that a 1% increase in the planted area leads to a 1.04% increase in soybean production. This effect remains consistent in *El Niño* and *La Niña* years, with coefficients of 1.02% and 1.03%, respectively. The behavior of the planted area aligns with the findings of Mendelsohn *et al.* (1994), which emphasize land as a crucial production input, even when new inputs are introduced.

The temperature during the soybean growth period shows a significant negative effect at the 1% level in all models. This effect is more pronounced in *El Niño* years, suggesting that higher temperatures during these periods are more detrimental to soybean production. Additionally, in *El Niño* years, harvest temperature negatively affects soybean production, whereas in *La Niña* years and the full model, it has a positive effect. Overall, the results of this study indicate that soybean production is sensitive to temperature increases. Schlenker and Roberts (2009) highlight the high sensitivity of tropical regions, such as Brazil. Farias *et al.* (2007) emphasize that the negative impacts of rising temperatures can be particularly harmful to soybean production during its growth phase.

Table 4 – Estimates of the modified production function for the Fixed Effects model

Variable	**Total**	***El Niño***	***La Niña***
Planted area (ln)	1.041	1.020	1.032
	(0.00493)	(0.00856)	(0.00911)
Growth temperature	-0.0993	-0.724	-0.253
	(0.0248)	(0.115)	(0.0434)
Growth temperature^2	0.00250	0.0130	0.00742
	(0.000496)	(0.00215)	(0.000915)
Growth precipitation	-0.0231	-0.0679	-0.00886
	(0.00647)	(0.0151)	(0.0130)
Growth precipitation^2	-0.000820	0.00130	-0.000658
	(0.000534)	(0.00107)	(0.000916)
Harvest temperature	0.275	-1.063	0.293
	(0.0625)	(0.127)	(0.0876)
Harvest temperature^2	-0.00941	0.0195	-0.0132
	(0.00137)	(0.00255)	(0.00188)
Harvest precipitation	-0.200	-0.0511	-0.281
	(0.0118)	(0.0177)	(0.0161)
Harvest precipitation^2	0.0145	0.00741	0.0189
	(0.000931)	(0.00130)	(0.00133)
Humidity of growth	0.417	-0.281	0.698
	(0.0260)	(0.0942)	(0.0465)

Humidity of growth^2	-0.0102	0.0112	-0.0183
	(0.000699)	(0.00255)	(0.00128)
Harvest humidity	0.393	0.782	0.0505
	(0.0343)	(0.0926)	(0.0519)
Harvest humidity^2	-0.0117	-0.0221	-0.00158
	(0.000870)	(0.00250)	(0.00143)
Growth radiation (ln)	-0.295	0.220	-0.686
	(0.0586)	(0.213)	(0.0877)
Growth wind speed (ln)	-0.0638	0.0640	-0.0553
	(0.00821)	(0.0206)	(0.0191)
Harvest radiation (ln)	-1.461	-0.256	-1.544
	(0.125)	(0.268)	(0.207)
Harvest wind speed (ln)	0.000375	0.129	-0.0904
	(0.0109)	(0.0348)	(0.0235)
Growth evaporation (ln)	-0.0568	-0.416	0.222
	(0.0382)	(0.0938)	(0.0629)
Harvest evaporation (ln)	1.329	1.359	1.115
	(0.0888)	(0.158)	(0.113)
Constant	21.45	19.51	32.50
	(2.418)	(4.808)	(4.105)
Observations	18,917	4,676	9,400
R^2	0.989	0.996	0.987
Adjusted R^2	0.988	0.992	0.983
Within R^2	0.988	0.992	0.983
F-statistic	2616	969.8	969
Prob > F	0	0	0
Year fixed effect	Yes	Yes	Yes
Municipality fixed effect	Yes	Yes	Yes

Source: Own elaboration.

Note: Robust standard errors in parentheses.

Table 4 shows that increased precipitation during the growth and harvest periods can negatively affect soybean production in all estimated models, except during the growth phase in *La Niña* years. Excessive rainfall may reduce the absorption of agricultural pesticides and shorten their protection period (Dinardo-Miranda *et al.*, 2004). Additionally, fertilization becomes less effective due to nutrient losses through leaching (Ceretta *et al.*, 2002), resulting in lower grain productivity.

Regarding humidity during soybean growth, its effect is negative only in *El Niño* years. Most of Brazil's soybean production is concentrated in the south-central region, where humidity levels tend to be higher during *El Niño* events. As a result, excessive humidity can favor the incidence of pests and diseases, as well as hinder the plant's transpiration and photosynthesis processes (Neumaier *et al.*, 2020).

Finally, Table 4 also presents estimates for other climatic variables, such as solar radiation, wind speed, evaporation, and temperature, during the growth and harvest periods. The effects of these variables on soybean production vary depending on the climatic phenomenon. For example, evaporation has a positive effect during the harvest period in all models, whereas during the growth period, its effect differs: negative in *El Niño* years and positive in *La Niña* years

Climatic variables significantly influence soybean production. As Farias *et al.* (2007) observes, soybean growth is directly affected by factors like temperature, particularly during the plant's growth period. Extreme temperatures can reduce productivity by either accelerating or delaying development. To evaluate these impacts, simulations will assess temperature increases of 0.5°C, 1°C, and 1.5°C during the soybean growth period. Based on the findings, the economic consequences of potential soybean production losses due to climate change will be quantified using the input-output technique.

3.3 Partial extraction results

This section presents the economic impacts caused by soybean production losses due to temperature increases during the plant's growth period. The decision to analyze this variable in greater detail is due to its importance in the soybean development stage, which is the one that most affects soybean production (Farias *et al.*, 2007). First, the percentage variations in soybean production resulting from increases in growth-period temperature are calculated based on the estimates in Table 3. These variations are then used as shocks in the input-output model.

It is projected that by 2026, the increase in the global average temperature will exceed 1.5°C. The likelihood of this has steadily increased since 2015, when it was close to zero. Between 2017 and 2021, the probability rose to 10%, and for the period up to 2026, it has jumped to nearly 50% (UN, 2022). Therefore, the temperature increased scenarios simulated in this study are 0.5°C, 1°C, and 1.5°C. The results are presented in Table 5.

The percentage variations in soybean production take into account the climatic phenomena of *El Niño*, *La Niña*, and the overall average (Total). In general, the negative effect is more pronounced in *El Niño* years, followed by *La Niña* years, with less severe impacts in the Total period. In the Total scenario, a 1°C increase in temperature during the soybean growth period leads to a 9.45% reduction in soybean production. This impact increases considerably during an *El Niño* event, resulting in a 51.52% drop in production, while under *La Niña* conditions, the reduction is less intense, with a loss of 22.35%.

Table 5 – Variation (%) in soybean yield under scenarios of increased soybean growth temperature

ENOS Event	Variation in growth temperature level (ºC)	Variation in soybean yield (%)
Total	+1	-9.45
El Niño	+1	-51.52
La Niña	+1	-22.35
Total	+0.5	-4.84
El Niño	+0.5	-30.37
La Niña	+0.5	-11.88
Total	+1.5	-13.84
El Niño	+1.5	-66.24
La Niña	+1.5	-31.58

Source: Own elaboration.

In the scenario with a 0.5°C increase, the reduction in soybean production is 4.84% in the Total period, 30.37% in *El Niño*, and 11.88% in *La Niña* years. Although the impact is smaller compared to the 1°C increase, it is still substantial, especially in *El Niño* years. This reinforces the idea that climate changes associated with this phenomenon have an even more damaging effect on soybean production.

Table 5 also shows that in the most dramatic scenario—a 1.5°C increase in the average temperature during the growth period—soybean production would decrease by 13.84% in the Total scenario and by 31.58% during *La Niña*. In *El Niño* years, losses would reach 66.24%. These results indicate that soybeans are highly vulnerable to temperature increases, particularly during *El Niño* and *La Niña* events.

The losses in soybean production presented in Table 5 are used as shocks in the partial extraction technique. This method involves the partial interruption — simultaneous or nonsimultaneous — of sales (supply) and purchase (demand) flows for soybeans. In this study, however, the shock was applied only to the supply side, representing a supply shock caused by the soybean production losses due to the increase in the growing temperature during *El Niño*, *La Niña,* and Total years.

As shown in Table 6, the greatest economic losses occur during *El Niño* years. With a 0.5°C increase, Brazil's GVP declines by R$ 57.1 billion. Under 1°C and 1.5°C increases, these losses rise to R$ 96.6 billion and R$ 124.1 billion, respectively. In relative terms, these reductions correspond to 0.56%, 0.95%, and 1.21% in Brazil's total GVP during *El Niño* years.

Regarding the products, Table 6 presents the ten most negatively impacted by the reduction in soybean production. Across all temperature increase scenarios (shown in Table 5), soybeans emerge as the most severely affected product - an expected outcome given the direct impact of temperature on crop yields. Soybean losses account for 58.4% of Brazil's total GVP losses in all scenarios. The fertilizers product follows with 6.2% losses, while wholesale and retail trade contribute approximately 5%. Other significantly affected products include agricultural pesticides and household disinfectants (4.1%), electricity, gas, and other utilities (2.7%), land freight transport (2.3%), and diesel-biodiesel (2.2%).

Table 6 – Partial extraction of soybean production value (GVP variation in million BRL) under scenarios of increasing soybean growth temperatures

Inputs	**0.5 ºC**			**1.0 ºC**			**1.5 ºC**				
	Total	***El Niño***	***La Niña***	**Total**	***El Niño***	***La Niña***	**Total**	***El Niño***	***La Niña***	**Gross variation (%)**	**Net variation (%)**
Soybean	-5328.02	-33340.4	-13063.2	-10394.15	-56459.84	-24553.77	-15211.44	-72511.69	-34663.06	58.42	
Fertilizers	-567.05	-3548.38	-1390.3	-1106.24	-6008.95	-2613.23	-1618.93	-7717.33	-3689.15	6.22	14.95
Wholesale and retail trade	-452.97	-2834.48	-1110.59	-883.67	-4800.00	-2087.47	-1293.22	-6164.67	-2946.92	4.97	11.94
Agricultural pesticides and household disinfectants	-375.99	-2352.79	-921.857	-733.50	-3984.30	-1732.73	-1073.45	-5117.06	-2446.13	4.12	9.91
Electricity, gas, and other utilities	-249.44	-1560.87	-611.572	-486.62	-2643.24	-1149.52	-712.14	-3394.73	-1622.80	2.73	6.58
Land freight transport	-211.06	-1320.69	-517.466	-411.74	-2236.51	-972.63	-602.56	-2872.36	-1373.09	2.31	5.57
Diesel - biodiesel	-200.31	-1253.47	-491.128	-390.78	-2122.67	-923.13	-571.89	-2726.16	-1303.20	2.20	5.28
Financial intermediation, insurance, and supplementary pension	-179.96	-1126.1	-441.222	-351.07	-1906.98	-829.32	-513.78	-2449.14	-1170.77	1.97	4.75
Other petroleum refining products	-160.49	-1004.25	-393.479	-313.08	-1700.63	-739.59	-458.19	-2184.13	-1044.09	1.76	4.23
Inorganic chemicals	-132.85	-831.326	-325.725	-259.17	-1407.80	-612.24	-379.29	-1808.04	-864.30	1.46	3.50
Organic chemicals	-124.37	-778.275	-304.939	-242.63	-1317.96	-573.17	-355.08	-1692.66	-809.15	1.36	3.28
Other sectors	-1137.79	-7119.77	-2789.63	-2219.65	-12056.87	-5243.40	-3248.37	-15484.71	-7402.22	12.48	30.00
Total	-9120.3	-57070.8	-22361.2	-17792.3	-96645.8	-42030.2	-26038.3	-124123	-59334.9	100	
Net total	-3792.28	-23730.4	-9297.91	-7398.15	-40185.9	-17476.4	-10826.9	-51611	-24671.8		100

Source: Own elaboration based on the 2015 input-output matrix (IBGE, 2015).

Note: Gross and net variations are independent of the shock size, remaining the same due to the proportionality of the coefficients in the input-output matrix and the linearity assumed in its equations.

4 FINAL REMARKS

This study provides a detailed analysis of the effects of climatic variables on soybean production in Brazil during *El Niño* and *La Niña* events. Econometric analyses, based on a modified Cobb-Douglas production function, enabled examination of the impacts of climatic variations, such as temperature in the growing period, on soybean production. Additionally, the research evaluated the economic consequences of these changes through input-output analysis.

Unlike most studies analyzing climate-productivity relationships, this research employs a panel data model that controls municipality and time fixed effects, leading to more consistent and less biased estimates. A key innovation involves incorporating precise climatic variable values during soybean growth and development periods for each Brazilian municipality. The climate data were extracted at the municipal level using centroid values, eliminating the need for data imputation. Furthermore, the model explicitly distinguishes between *El Niño* and *La Niña* events. The combined methodological approach - integrating high-resolution climate data with robust econometric modeling - provides more accurate estimates of the economic impacts of changing soybean growth temperatures.

Soybean production demonstrated significant variability, particularly in the occurrence of ENSO events. However, in the *El Niño* years, production volatility was markedly higher, reflecting the negative impacts of elevated temperatures and precipitation. Comparative analysis between *El Niño* and *La Niña* years pointed out that while the planted area effect on soybean production remained stable, productivity variations were predominantly determined by climatic conditions.

The results of the production function confirmed that both temperature and precipitation have significant effects on soybean production. An increase in temperature during the soybean growth period had a direct negative impact on productivity, particularly in *El Niño* years, as expected for tropical regions, as indicated by Schlenker and Roberts (2009). Excessive precipitation during the growth period was also associated with negative effects, although this impact was less pronounced in *La Niña* years.

During the harvest phase, temperature exhibited a positive effect on production in both *El Niño* and *La Niña* years, while precipitation demonstrated detrimental effects. Analysis of humidity, solar radiation, wind speed, and evaporation revealed that climatic impacts varied according to the specific conditions associated with each phenomenon. Overall, *El Niño* conditions proved more detrimental to soybean production, whereas La Niña events, despite their negative effects, showed less severe impacts.

Finally, the analysis of the economic impacts resulting from soybean production losses due to temperature increases revealed a significant decline in production, particularly during *El Niño* years. With a 1°C increase, the average total production loss was 9.45%, but this figure rose to 51.52% during *El Niño* years, corresponding to a GVP loss of R$ 96.6 billion. In the most pessimistic scenario, with a 1.5°C increase, production losses reached 66.24%, resulting in a GVP loss of R$ 124.1 billion, highlighting the strong vulnerability of soybean production to these climatic anomalies.

The analyses conducted in this study highlight the urgency of decision-making related to climate change adaptation, particularly during ENSO events, which cause greater damage to soybean production. It is essential to develop adaptation strategies that enhance the resilience of soybeans to adverse climatic conditions. At the same time, efforts to mitigate global warming must be intensified to reduce its impact on soybean production.

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