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# Rainfed Crops Forecasting in the Semi-arid Region under Scenarios of Rainfall Instability in Ceará, Brazil

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**Abstract:** This paper aimed to analyze the projections of rainfed crops (rice, beans, cassava and corn) in the semi-arid region under scenarios of rainfall instability in Ceará, in the period from 1945 to 2020. The data were collected from the Meteorology and Water Resources Foundation of Ceará (FUNCEME) and the Brazilian Institute of Geography and Statistics (IBGE), through the IBGE System of Automatic Recovery (SIDRA), which provides data on Municipal Agricultural Production (PAM-2020). The rainfall periods were organized in three categories: drought, normal and rainy periods. This was done using the historical average and standard deviation of rainfall from 1945 to 2020. The projections of production variables were made through the Autoregressive Integrated Moving Average (ARIMA) methodology. The results show that the rainfall distribution in Ceará State between 1945 and 2020 was quite unstable. The coefficient of variation (CV) of the rainfall periods ranges between 33% in normal period and 54% in the drought period. Based on the results, it is observed that the general hypothesis of the article was confirmed, showing that rains have an impact on rainfed agricultural production in Ceará in the variables: harvested area, productivity and prices of rice, beans, corn and cassava crops. The results also showed that the cassava crop presents favorable results in relation to the interference of rainfall, suggesting that the crop is better adapted to the climatic adversities of the region.

**Key words:** Rainfed crops, semi-arid, forecast, environmental risks, drought.

## 1. Introduction

The aggressive condition of the semi-arid climate is described as rainfall concentrated in the first three to four months of a year, high temperatures and predominantly relatively low humidity. It makes agricultural practices difficult, especially when performed without the use of appropriate technologies adapted to these difficulties. Another characteristic of this climatic is its instability in rainfall precipitation both spatially and temporally [1-5]. In the most common cases of water scarcity, the use of technologies that neutralize or at least mitigate the impacts of rainfall irregularities is quite rare. These facts make agricultural practices under this climatic regime difficulty in its conduction and subject to economic, social and environmental risks [6-11].

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The semi-arid is internationally defined by the relationship between rainfall and potential evapotranspiration that is named aridity index (AI). AI in semi-arid regions varies between 0.20 and 0.50 [12-14]. In general, agricultural activities on dry lands that exclusively depend on rainfall prevail in the Brazilian semi-arid region. Soil and water managements in these areas are the main constraints in maintaining sustainable production and productivity of crops [15-17]. Ceará farmers do not use irrigation and genetically modified seeds adapted to the hostile conditions of the semi-arid environment, which makes the agricultural practices difficulty and less profitable in this state. The rainfed crops grown on the semi-arid northeastern region mainly are rice, beans, cassava and corn. They provide food, job opportunity and monetary income for family farmers in these semi-arid areas [5, 7-11, 17-19].

Notwithstanding the technical definition for climatic regimes, the political selection of Brazilian municipalities that are officially part of the semi-arid region is defined by the AI and two other characteristics. The municipality will be officially recognized by the Federal Government to receive differential assistance if it meets at least one of them. And, based on these that are not immutable over the years, the Deliberative Council of Sudene (CONDEL/SUDENE), from time to time (generally four years), revised these definition criteria and the political composition of the Brazilian semi-arid region [20].

In view of these criteria, the new official definition of the Brazilian Semiarid reaches all nine states of the Northeast and municipalities of the states of Minas Gerais and Espírito Santo situated in Southeast region of Brazil. According to the last definition of the semi-arid that occurred in December 2021, the semi-arid region now has 1,427 municipalities. Of the 184 municipalities in the state of Ceará, 171 are currently recognized by the Federal Government as being inserted in this climatic regime [20]. The Brazilian position of Ceará State can be seen in the black part of Fig. 1.

Given the contextualization of the problem, this search tries to get answer to the following question: can forecasts of production defining variables (harvested area, land productivity and price) of rice, beans, cassava and corn in the semi-arid region of Ceará State, capture the exogenous effect of rainfall instability? With this perspective, we raise the central hypothesis of this research, which supposes that the rainfall distribution between 1945 and 2020 tends to interfere with the possibility of predicting the harvested areas, productivity and prices of food crops in rainfed system in the semi-arid region of Ceará State.

Given the considerations, this study aims to: (i) assess the descriptive statistics of the variables involved in the production of rice, beans, cassava and corn in Ceará State between 1945 and 2020; (ii) estimate how the producers of Ceará State prepared


**Fig. 1 Ceará State position in Brazil.**
Source: Based on Brazilian Institute of Geography and Statistics (IBGE).

their projections about the harvested area, productivity and average price of selected crops in the period between 1945 and 2020; and (iii) measure the impact of rainfall on the forecast models estimated for the production of agricultural crops under analysis.

## 2. Methodology

The information related to rainfall was collected from the Meteorological and Hydrological Resources Foundation of Ceará State (FUNCEME). The information regarding harvested areas, productivity and prices of the crops was collected from the Brazilian Institute of Geography and Statistics (IBGE), which provides data on Municipal Agricultural Production [21]. The period of analysis corresponds to the interval between 1945 and 2020. There were selected food crops: rice, beans, cassava and corn, because they are mostly cultivated by farmers in Ceará as shown in the data made available by the Agricultural Census of 2017 [22]. Prices were corrected to 2020 values using the General Price Index as an indexer (IGP-DI), and converted in USD using the average exchange rate of 2020. The variables selected for this study are classified into two types: endogenous and exogenous, as described in Table 1.

In this research, it is attributed that the producers of rainfed crops establish the planning framework of agricultural activities and crop forecasts by gathering information obtained by their own experiences and experiences of their ancestors, including mistakes and successes.

### *2.1 Measurement of Instabilities*

The stability/unstability of the selected variables was measured by the coefficient of variation (CV). In practice, the CV measures the degree of homogeneity or heterogeneity of the distribution values of a random variable around its mean. Since rainfall is such a random variable, one can assume that the CV affects instability at different levels, depending on its magnitude. The greater the magnitude of the CV, the more unstable or more heterogeneous will be the distribution of observed values of a random variable around its mean. Thus, the CV can also be used as a risk measurement and has the additional advantage to compare the variables measured in different measurement units [23-26].

It is worth noting that in order to use the CV as a measure of homogeneity or heterogeneity of a distribution, it is necessary to establish the parameters of its critical values. In this conception, Gomes's [24] limits for the classification of the calculated CVs are set as described in Table 2.

**Table 1 Description of selected variables to be studied.**

| Variables | Description | Sources |
|---|---|---|
| Endgenous | $A_t$ = harvested area (ha)<br>$R_t$ = yield (kg/ha) | PAM-2020 (IBGE, 2020) |
| Exogenous | $P_t$ = average price of crops (rice, beans, cassava and corn), in USD/kg, deflated for the year 2020<br>$C_t$ = annual average of rainfall (mm) | PAM-2020 (IBGE, 2020);<br>FUNCEME (2022) |

Sources: Prepared by the authors (2022).
PAM: Municipal Agricultural Production.

**Table 2 Classification of CV levels according to their ranges.**

| Classification of CV | Ranges of CV |
|---|---|
| Low | CV < 10% |
| Medium | 10% ≤ CV < 20% |
| High | 20% ≤ CV < 30% |
| Very high | CV ≥ 30% |

Source: Gomes [24].

### *2.2 Models Used to Make the Projections of the Decision Variables in the Production of Rainfed Crops in Ceará State*

It is noteworthy that a time series is a group of observations ordered in time, and that exhibits serial dependence [27]. In time series analysis, some concepts are relevant to the understanding required for the preparation of forecasting models. In this conception, it is worth emphasizing that a random or stochastic process is configured as a collection of random variables ordered in time [28]. For the authors, in general, a stochastic process will be called stationary if its mean and variance are constant over time and the covariance between the variables does not depend on time.

Thus, considering the time series represented by the random variable $Y_t$, its expected value $E(Y_t)$ will be different from the observed value due to the occurrence of random factors ($\xi_t$) along its path. This information can be summarized by Eq. (1).

$$Y_t = E(Y_t) + \xi_t \tag{1}$$

The necessary conditions for performing the forecasts proposed in this research require some criteria to be observed. These conditions are: the random variable series ($Y_t$) must be stationary and the random error term ($\xi_t$), which takes on positive and negative values, must have zero expected values. In addition, it is required that the random term has constant variance and is not autoregressive over time [27-29].

This study aims to assess the impact of annual rainfall on the predictive ability of the variables: harvested areas, yields and prices of the rainfed crops. The hypothesis to be tested is that these impacts will occur on the noises generated in the forecast model, moving them away or bringing the observed value closer to the projected value. Thus, it is assumed that the random term $\xi_t$ can be represented according to what is shown in Eq. (2):

$$\xi_t = f(C_t) \tag{2}$$

Substituting this value of $\xi_t$ into Eq. (1) yields the result that will be tested in this research:

$$Y_t = E(Y_t) + f(C_t) \tag{3}$$

The values of $E(Y_t)$ are estimated in this research using the Autoregressive Integrated Moving Average (ARIMA) process developed by Box and Jenkins [29]. Following is a brief explanation of the ARIMA method as it applies to this study.

### *2.3 ARIMA Model*

This model aims to capture the behavior of a random variable that has values distributed in the form of time series. This model is suitable for time series that are stationary, or variables whose means, variances, and autocovariances are constant over time [27, 28].

Admitting that the time series $Y_t$ can be represented by Eq. (4):

$$Y_t = \mu + \psi(B)u_t \tag{4}$$

where the definition of the linear filter ($\psi$) is represented as follows:

$$\psi(B) = \theta(B)/\phi(B) \tag{5}$$

Eq. (5) can be evidenced from the definition of the polynomials described below:

$$\theta(B) = 1 - \theta_1 B_1 - \theta_2 B_2 - .... - \theta_q B_q$$

and

$$\phi(B) = 1 - \phi_1 B_1 - \phi_2 B_2 - ... - \phi_p B_p$$

For this condition, Box *et al.* [30] state that: (1) $\phi(B)$ will be called an autoregressive operator. It is considered stationary. The roots of $\phi(B) = 0$ are outside the unit circle; (2) $\psi(B)$ will be called a generalized autoregressive operator, i.e., a non-stationary operator with "$d$" roots of $\varphi(B) = 0$ equal to unity, i.e., "$d$" unit roots; and (3) $\theta(B)$ will be called the moving average operator. It is assumed to be invertible and that the roots of $\theta(B) = 0$ are outside the unit circle.

Given the previous demonstrations, $A_t = Y_t - \mu$, so it will be possible to obtain its transformation, as shown in Eq. (6):

$$\phi(B)\tilde{Y}_t = \theta(B)u_t \tag{6}$$

For the definition of Eq. (6), the random term "$u_t$"

must present the following characteristics to be considered “white noise” [31]:

$E(u_t) = 0$;

$E(u_t^2) = \sigma_u^2 < \infty$; and

$E(u_t, u_{t+k}) = 0$, when $k = \pm 1, \pm 2, \ldots$

Based on this set of information, Eq. (6) can be rewritten, as the Box-Jenkins model [29], and is known as the $p$-order autoregressive and $q$-order moving average or ARMA($p$, $q$). This result is shown in Eq. (7):

$$\tilde{Y}_t = \theta(B)\phi^{-1}(B)u_t \tag{7}$$

Fig. 2 describes some models that use time series as a starting point, showing some differences between them.

It is worth emphasizing that, when adopting the Box-Jenkins methodology, one must have a stationary time series. When the series is not stationary, its stationarity must be provided by performing differentiations on the time series. In general, with up to three differentiations it is possible to transform into stationary series that was shown to be no stationary. This is because the objective of this method is to determine and estimate a statistical model that can be interpreted as having been generated by the sample data. When used to estimate forecasts, it should be assumed that its characteristics are constant over the period, especially over future periods [27, 28].

The steps to predict the values of a time series via the Box-Jenkins model follow the following steps: (i) examine the series for stationarity. This step can be examined by measuring the sample correlation function (ACF) and sample partial correlation function (PACF) and or by performing a unit root analysis. The correlograms associated with ACF and PACF are good visual diagnostic strategies; (ii) In case the time series is not stationary it will be necessary to perform the differentiation one or more times until stationarity is reached [28, 29, 32].

To better fit the models, the present research used some criteria to achieve the proposed objectives. One of them is that the smaller the number of parameters, the better the model adjustment is. Besides this, other parameters were used: unit root test; Augmented Dickey-Fuller (ADF); coefficient of determination ($R^2$); percentage of the absolute average error (MAPE); Ljung-Box $Q$ statistic (test if residues are white noise) and Pearson’s correlation coefficient between the observed series and the series projected by the estimated models. This coefficient must be high (close to one) and statistically different from zero [27, 29, 30, 32].

### *2.4 Analysis of the Relationship between the Forecast Models for Rainfed Crops and Rainfall in the State of Ceará*

The research under analysis admits that, in the forecast scenario of harvested area, yields and prices of selected crops (rice, beans, cassava and corn), the shocks $\xi_t$, could be affected by exogenous variable: rainfall ($C_t$). Thus, the noise $\xi_t$ associated with the

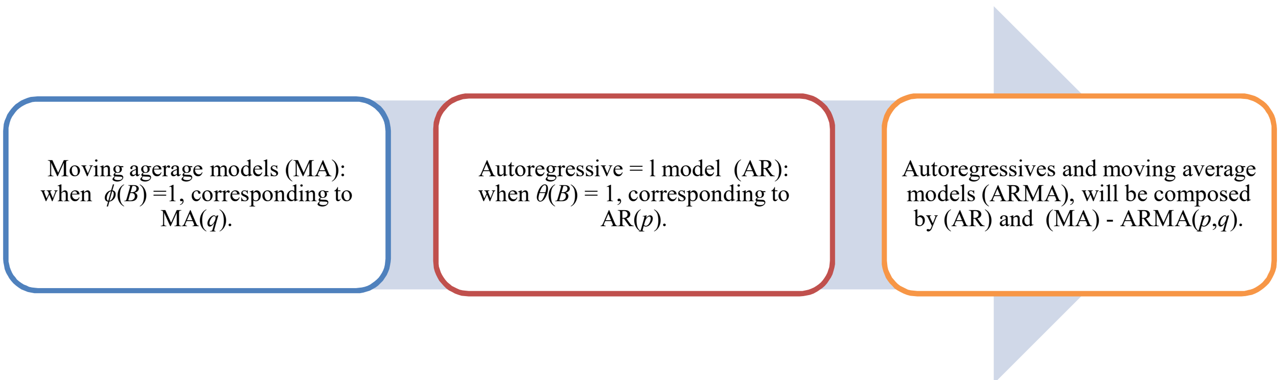


**Fig. 2 Time series modeling.**
Source: Prepared by the authors based on Gujarati and Porter [28].

projections of harvested areas, yields and prices of these crops between 1945 and 2020, can be shown in Eq. (2), which is explained as estimated in this study (Eq. (8)):

$$\xi_t = \lambda_0 + \lambda_1 C_t + \upsilon_t \qquad (8)$$

In Eq. (8) the coefficient $\lambda_0$ represents the linear parameter; $\lambda_1$ is the angular coefficient which, being statistically different from zero, gauges the sensitivity of the error term of the forecast model ($\xi_t$) to the oscillations of the annual rainfall ($C_t$). The random term $\upsilon_t$, by hypothesis, is also endogenously "white noise" in Eq. (8). This hypothesis being true the coefficients $\lambda_0$ and $\lambda_1$ can be estimated by the ordinary least squares (MQO method) [27].

## 3. Results and Discussion

Initially, the descriptive statistics associated with the annual rainfall occurring in Ceará between 1945 and 2020 were estimated, as well as those referring to the harvested areas, yields, and prices of rice, beans, cassava, and corn. These results are shown in Table 3.

From the evidence shown in Table 3, one can infer the very high instability observed in the annual precipitation in Ceará between 1945 and 2020, captured by the CV of the order of 33.6%, classified as "very high" in the scale designed by Gomes [24]. It is also observed that this rainfall instability was transmitted in synergy to all variables studied, all classified as "very high" according to that reference, with CVs ranging from 32.2% for the annual productivity of cassava to 54.5% for the average price of beans (Table 3).

### *3.1 Results Found in the Estimation of ARIMA Models to Perform the Forecasts*

The results found in the estimations of the parameters of the forecast models are shown in Table 4. The results presented in Table 2 suggest that only the cassava harvested area series was originally stationary. The other series were not stationary and needed to be process of stationarization procedures that, in all cases, required only one difference ($d$ = 1). Overall, the estimated models are parsimonious with respect to the number of estimated parameters.

It is observed that all estimates show statistically non-significant Ljung Box statistics, at least with 10% error. This ensures that the noise generated in all estimates is random. In all the estimated models it was observed that the linear parameters were not statistically different from zero. From the evidences shown in Table 4, it also appears that the percentages of the mean absolute errors (MAPE) also presented

**Table 3 Descriptive statistics associated with the research variables.**

| Variables | Minimum | Maximum | Average | CV (%) |
|---|---|---|---|---|
| Annual rainfall (mm) | 286.90 | 1,773.40 | 777.76 | 33.56 |
| Harvested area with rice (ha) | 5,250.00 | 79,993.00 | 40,532.01 | 45.34 |
| Yield per hectare of rice (kg/ha) | 409.68 | 3,130.82 | 1,939.54 | 33.87 |
| Average price of rice (US$/kg) | 0.17 | 1.14 | 0.52 | 43.94 |
| Harvested area with bean (ha) | 74,775.00 | 765,654.00 | 381,713.85 | 42.14 |
| Yield per hectare of bean (kg/ha) | 116.85 | 608.22 | 340.80 | 40.44 |
| Average price of bean (US$/kg) | 0.41 | 2.91 | 0.93 | 54.43 |
| Harvested area with cassava (ha) | 32,283.00 | 176,000.00 | 89,810.80 | 39.75 |
| Yield per hectare of cassava (kg/ha) | 3,356.92 | 16,905.08 | 10,178.85 | 32.25 |
| Average price of cassava (US$/kg) | 0.00 | 0.23 | 0.08 | 51.15 |
| Harvested area with corn (ha) | 78,460.00 | 726,777.00 | 433,491.71 | 39.21 |
| Yield per hectare corn (kg/ha) | 120.00 | 1,254.14 | 646.66 | 42.3 |
| Average price of corn (US$/kg) | 0.10 | 0.67 | 0.32 | 41.53 |

Source: Prepared by the authors based on data from IBGE [21] and FUNCEME [33].
Prices were deflated having 2020 as base year.

**Table 4 Models fitted to the forecasts of harvested areas, yield and prices of rice, beans, cassava and corn in Ceará State between 1945 and 2020.**

| | Variables | Area | Yield | Price |
|---|---|---|---|---|
| Rice | Estimated models | ARIMA (0,1,1) | ARIMA (0,1,1) | ARIMA (2,1,2) |
| | Constant | 0.000 | 0.000 | 0.000 |
| | AR Lag1<br>Lag2 | 0.000 | 0.000 | 0.598 *<br>-0.622* |
| | MA Lag1<br>Lag2 | 0.455* | 0.643* | 0.997*<br>-0.578* |
| | $R^2$ | 0.638 | 0.579 | 0.771 |
| | Ljung Box | 14.857 $^{NS}$ | 10.765$^{NS}$ | 20.049$^{NS}$ |
| | MAPE | 27.059 | 24.334 | 15.476 |
| | *R* Pearson | 0.803* | 0.764* | 0.880* |
| | Variables | Area | Yield | Price |
| Bean | Estimated models | ARIMA (0,1,1) | ARIMA (0,1,1) | ARIMA (2,1,2) |
| | AR Lag1<br>Lag2 | 0.000 | -0.261** | 0.670*<br>-0.433* |
| | MA Lag1<br>Lag2 | 0.725 | 0.678* | 1.295<br>-0.679 |
| | $R^2$ | 0.481 | 0.342 | 0.424 |
| | Ljung-Box | 8.149$^{NS}$ | 16.278$^{NS}$ | 13.836$^{NS}$ |
| | MAPE | 32.943 | 35.309 | 32.304 |
| | *R* Pearson | 0.701* | 0.597* | 0.671* |
| | Variables | Area | Yield | Price |
| Cassava | Estimated models | ARIMA (0,1,1) | ARIMA (0,1,1) | ARIMA (2,1,2) |
| | Constant | 88232.191* | 0.000 | 0.000 |
| | AR Lag1<br>Lag2 | 0.847* | 0.000 | 0.347** |
| | MA Lag1<br>Lag2 | 0.000 | 0.439* | 0.741 |
| | $R^2$ | 0.728 | 0.700 | 0.433 |
| | Ljung Box | 17.298$^{NS}$ | 8.323$^{NS}$ | 24.103$^{NS}$ |
| | MAPE | 16.040 | 15.785 | 101.726 |
| | *R* Pearson | 0.853* | 0.842* | 0.601* |
| | Variables | Area | Yield | Price |
| Corn | Estimated models | ARIMA (0,1,1) | ARIMA (2,1,0) | ARIMA (0,1,1) |
| | Constant | 0.000 | 0.000 | 0.000 |
| | AR Lag1<br>Lag2 | 0.000 | -0.789*<br>-0.438* | 0.000 |
| | MA Lag1<br>Lag2 | 0.661* | 0.000 | 0.517* |
| | $R^2$ | 0.475 | 0.074 | 0.620 |
| | Ljung Box | 10.817$^{NS}$ | 22.067$^{NS}$ | 0.662$^{NS}$ |
| | MAPE | 33.342 | 48.769 | 17.040 |
| | *R* Pearson | 0.698* | 0.388* | 0.792* |

Sources: Estimated values from IBGE data [21].

*Significant at 1%; **Significant at 10%; NS = not significant at least 15% error.

relatively low magnitudes, suggesting good fit with the smallest estimated value for the rice price series (15.476). However, it was observed that in the best adjustment for the cassava price forecast, the estimated MAPE was 101.726 and quite high. This suggests caution in using these estimates to forecast cassava prices, although they were the best estimates found in the survey. The research also estimated the correlation coefficients between the observed values in the series and the predicted ones. All these correlations were statistically different from zero with an error of at least 1%.

### *3.2 Relation between the Residues Generated in the Models and Rainfall*

Table 5 shows the results found in the estimation of the relationship between rainfall and the estimated residuals in each of the models created for the forecasts of the studied variables. In general it is found that, as was the assumptions of the research, the rainfall significantly affects the residuals that make the predicted values differ from the observed values not only by casualty as supposed in this study.

It is also observed that only in the cases of forecasts for prices of rice, cassava and for the model related to the area harvested with cassava, the regression coefficients estimated to gauge the impact of rainfall on the residues of these variables were not statistically different from zero.

The fact that the results generated in the rice price forecast model were not affected by rainfall instability may be due to the fact that the state is a large importer of this product and; for this reason, the prices received by the state's producers are associated with those of the imported product (Table 5).

The fact that the residuals generated in the model for predicting harvested areas and cassava prices have not been sensitive to rainfall variations, as well as the fact that the residuals associated with the adjusted model to predict productivity have been significant only at the level of 9.1% error may be a reflection of the fact that farmers always seek to cultivate cassava in their areas, regardless of the history of rainfall, which reinforces the relevance of this activity as an important source of food security, in the feeding of domestic animals and income enhancement (Table 5).

This information corroborates with that found by Lemos *et al.* [34], who when using the shift share method, concluded that cassava production did not exhibit sensitivity to the occurrence of rainfall in Ceará. It is worth noting that Lemos *et al.* [34] reached a similar result by concluding that cassava crop had exhibited less variability given the climatic instability of rainfall in Ceará during the investigated period in that search between 1987 and 2016. However, this can be also explained by the capacity of cassava to tolerate adverse situations, such as: water deficit, soil conditions and the characteristic environment of the investigated region.

**Table 5 Results of the relationship between the residuals of the models adjusted for forecast and the annual rainfall observed between 1945 and 2020 in Ceará.**

| Crops | Variables (noise) | Constant | | Regressor | | $R^2$ Adjusted |
|---|---|---|---|---|---|---|
| | | Coef. | Sig. | Coef. | Sig. | |
| Rice | Harvested area | -12,205.024 | 0.002 | 15.669 | 0.001 | 0.123 |
| | Yield | -482.001 | 0.001 | 0.672 | 0.000 | 0.156 |
| | Average price | 0.022 | 0.917 | -7.577E-005 | 0.768 | 0.001 |
| Bean | Harvested area | -140,620.973 | 0.001 | 183.044 | 0.000 | 0.155 |
| | Yield | -96.334 | 0.018 | 0.119 | 0.017 | 0.063 |
| | Average price | 2.056 | 0.004 | -0.003 | 0.002 | 0.124 |
| Cassava | Harvested area | -3,282.076 | 0.630 | 4.105 | 0.621 | 0.030 |
| | Yield | -1,052.990 | 0.110 | 1.367 | 0,.091 | 0.039 |
| | Average price | 0.025 | 0.692 | -3.264E-005 | 0.669 | 0.030 |
| Corn | Harvested area | -177,134.947 | 0.000 | 232.864 | 0.000 | 0.239 |
| | Yield | -330.204 | 0.000 | 0.457 | 0.000 | 0.184 |
| | Average price | 0.469 | 0.003 | -0.001 | 0003 | 0.114 |

Source: Prepared by the authors based on data from IBGE [21] and FUNCEME [33].

The corn crop is very sensitive to rainfall instability since it cannot withstand annual oscillations of average rainfall such as the periodic occurrences of droughts in Ceará. This information is confirmed in Table 5, when estimating the impact of rainfall considering the residuals of the variables related to production, which proved to be significant.

In this perspective, when performing crop yield forecasting in the Brazilian semiarid region using meteorological observations and seasonal climate forecasts, effective drought management in the Northeast region of Brazil requires specific preparedness plans. It is observed that droughts have severe impacts on small-scale rainfed agricultural production. In this context, existing drought monitoring programs in the region do not quantify its potential impacts.

## 4. Conclusions

The objective of the present work was to design models for forecasting of rainfed crops in the semi-arid region under rainfall instability scenarios in Ceará State. Based on the proposed study, we can confirm the general hypothesis that rainfall has an important impact on agricultural production of food crops in Ceará State, especially on the variables: (i) harvested area (beans and corn); (ii) average yield (rice, beans, cassava and corn); and (iii) price (beans and corn), thus influencing the income generation of their producers in the state.

Based on the evidence found and demonstrated in the research that the projections made for harvested areas, yields, prices of rice, beans, cassava and corn are affected by the rainfall instability observed in Ceará State from 1945 to 2020. In this way, the motivating question of this research was answered from the evidences found and shown.

The distribution of rainfall in Ceará, between 1945 and 2020, is shown to be quite unstable, by the scale defined by Gomes [24]. The CV of rainfall distribution showed “very high” values, reinforcing the result of rainfall instability in Ceará during the analyzed period. This reflected in the instability of all studied variables used to evaluate the production of rice, bean, cassava and corn in Ceará: the harvested area, yield and price of rice, beans, cassava and corn in that period.

The evidences captured in the studies showed that, in general, the annual rainfall influenced the noises achieved in the adjusted forecasting models, excluding those used to forecast prices of rice and cassava and harvested areas of cassava. In the particular case of cassava, it was possible to conclude that due to the characteristics of its production, where this crop adapts well to climatic adversities, the interference of rainfall does not significantly influence the decisions and expectations of producers since this crop has a certain resistance to drought when compared to other crops investigated.

Overall, the main conclusion of this study is that the rainfall instability observed in the State of Ceará between 1945 and 2020 played an important role in the behavior of the projections of the variables that define the production of rice, beans and corn. In view of this, the projections made promote the dissemination of information about the impacts that rainfall instability can cause in the productions of these crops. Having access to the information, such as that demonstrated in this research, can help producers to design better planning and decision-making strategies, trying to circumvent the impacts caused by rainfall instability that is real and part of the daily lives of these farmers. In view of this, the discussion about the results found in this research configures itself as a contribution to the literature related to rainfed production and rainfall instability since this discussion is also relevant to the impact of climate instability in semi-arid regions. It is suggested for future research other agricultural crops be included as well as impact variables for other states and/or regions, respecting the availability of data and regional peculiarities.

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