Estimation of dry spells in three Brazilian regions — Analysis of extremes

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Abstract

The aim of this study was to model the occurrence of extreme dry spells in the Midwest, Southeast and Southern regions of Brazil and estimate the return period of the phenomenon indicating the time when the occurrence is more severe. The generalized extreme value distribution was the best fit for a series of maximum dry spell number and the parameters estimated by the maximum likelihood method. The data series adherence to the probability distribution was verified by the Kolmogorov–Smirnov test and the percentile–percentile charts. The positive trend of dry spells was verified by the Mann–Kendall test and non-stationarity rejected by Dickey– Fuller and augmented Dickey– Fuller tests. The irregular distribution of rainfall in the growing season for the Midwest region has increased the number of dry spells. The increase of rainy days in the Southeast and the South resulted in a decrease of dry spells in these regions. Regarding the return period of one year, dry spells occurred from 5 to 25 days in the Midwest region meaning a loss of productivity for Brazilian agriculture if it happened between the flowering and grain filling phases, making it, therefore the region with the largest agricultural risk. When the intensity of the dry spells was analyzed for different return periods, the Southern region was the most vulnerable.

Keywords:
Dry spells
Generalized extreme value distribution
Number of rainy days
Return period

1. Introduction

The rainfall in most of the Brazilian states is not uniformly distributed in all seasons. The rainy and dry periods alternate. The major crops are usually growing under rain-fed conditions which make them rely solely on natural rainfall. The irrigated crops are still in the minority (4% of total agricultural production), especially with regard to large planted areas. Thus, farming becomes exclusively seasonal, being practiced mainly in the rainy season known as “rain-fed crops” (Sousa and Frizzone, 1997). In the Midwest, Southeast and Southern regions, the summer period is characterized by the occurrence of rainfall which normally meets the hydration needs of developing major crops. However, the rainfall data does not provide precise information on the climate or on the existence of adequate conditions for the cultivation of certain plant under rain-fed conditions. The parameters of water storage in the soil and the gains should be analyzed along with the losses of humidity from the soil–plant–atmosphere system (Mota et al., 1992). A phenomenon known as dry spell, a sequence of dry days during the rainy season, is still a common occurrence. The occurrence of dry spells can be extremely harmful for agriculture, especially in periods in which the plants have need of water, that is, at critical periods such as flowering and fruiting which will have a serious effect on the final yield (Assad et al., 1993).

To reduce the economic losses in agriculture, the knowledge of the temporal and spatial distribution of precipitation and consequently periods of dry spell is important. A dry spell affects not only agriculture, but also other sectors such as fisheries, health, electricity, and so on. Electricity generation
in hydroelectric facilities may suffer interruptions in dry periods (Marengo, 2009). Information about the intensity of a drought could be used to determine which crop or variety should be used in a particular location. Therefore, the effects of a dry spell ultimately have a direct impact on the economy of a nation.

The occurrence of prolonged periods of drought is particularly common in the Midwest, but also occurs in the Southeast and Southern regions. According to Barbosa (1986) and Affolder et al. (1997), the occurrence of irregular dry spells from year to year makes the corn crop vulnerable to water stress at any stage of development with visible damage on its production. For maize, Espinoza et al. (1982) found reductions of up to 60% in crop yield when water deficits occurred between the stage of flowering and grain filling, and 40% when it occurred during floral initiation.

Sousa and Frizzone (1997) simulated production declines in corn growth of up to 65% for dry spells occurring at flowering stage in Piracicaba, Brazil. A major limitation to soybean production in the cerrado (Brazilian Savanna) is due to the dry spell, which significantly affects production. Espinoza (1982) found yields higher than 24–55% with irrigated soybean crops in relation to which water was the limiting factor. Magalhães and Millar (1978) found reductions of 20%, 38% and 52% in the production of beans undergoing dry spell of 14, 17 and 20 days occurring from the start of flowering, respectively. Guimarães et al. (1982) observed reductions of 49% in the cultivation of beans subjected to water stress. Stone et al. (1986), in studying the effects of dry spells in rice, concluded that the production of grain and dry matter yields were negatively affected by increases in periods of dry spells.

Numerous studies have been conducted to model the distribution of rainfall in several regions of the world. The result of such studies is useful in decisions regarding planning and management of water resources of the involved countries. Statistical distributions are used to model the long-term characteristics of precipitation parameters and knowledge of how the dry spell distribution plays an important role in this respect.

Several authors have used different statistical distributions to model the behavior of a dry spell. The Extreme Value distribution was used in the work of Assad et al. (1993), Henriques and Santos (1999), Lana et al. (2008), Vicente-Serrano and Beguería-Portugués (2003) and Lana et al. (2006); the Gamma distribution in Ribeiro et al. (2007) and Dan’azumi and Shamsudin (2011); the Geometric distribution in Mahamud et al. (2011) and Deni and Jemain (2009), Log-Normal distribution in Dan’azumi and Shamsudin (2011), the Pareto distribution in Lana et al. (2006) and Dan’azumi and Shamsudin (2011) and the Truncated Negative Binomial distribution in Deni et al. (2008) and Giuseppe et al. (2005). Arruda and Pinto (1980a, 1980b) developed simplified models for the distribution of rainfall and distribution of drought periods which were applied to agricultural production in Brazil.

The objective of this study was to model the occurrence of extreme dry spells in the Midwest, Southeast and Southern regions of Brazil and estimate the return period of the phenomenon, indicating the region and frequency where the occurrence is more severe.

2. Material and methods

The daily rainfall dataset was obtained from rainfall records of weather stations belonging to the National Water Agency ANA (2011) covering the three Brazilian macro regions for the period between 1940 and 2011. The data refer to the Midwest region with 1,228,562 observations from 559 rainfall stations, the Southeast region with 6,474,928 observations from 2941 rainfall stations and the Southern region with 2,917,075 observations from 1325 rainfall stations. Several studies published in Brazil, such as Farias et al. (2001), Pinto et al. (2001), among others, worked together to establish the best planting dates to coincide with the non-occurrence of dry spells during grain filling for soybean, maize and rice, respectively. The correct identification of these periods in terms of space-time, that is location and duration of periods of sporadic droughts defining the policy of climate risks agricultural zoning (Rossetti, 2001), has been widely adopted by the Ministry of Agriculture, Livestock and Supply of Brazil. The data refer to the maximum number of dry spell length per year for the months of October, November, December, January and February summer season for the three regions.

A computer program was developed, written in SAS (SAS, 2010) for calculating the number of dry spells, with at least 10 consecutive days without rainfall for each rainfall station. Every time a dry spell is recorded with rainfall greater than zero, verification is made to be sure the number of days without rain has exceeded ten. If this occurs, a dry spell is registered with the number of days without precipitation. The counter will then be cleared and will continue to account for the other records. When a new year begins, the method also resets the counter and the dry spell number. For the set of dry spells calculated for each rainfall station, the maximum number of dry spell length per year was used, totaling 71 observations (one for each year) for Midwest, Southeast and Southern regions. The graphs were constructed using the SGPLOT procedure (SAS, 2008).

In this work, four models, generalized extreme value distributions — GEV, Lognormal, Pareto and Gamma distributions (Johnson and Kotz, 1970) were fitted to the observed values x corresponding to the period of maximum annual dry spell length, with the following probability density functions and cumulative distribution functions below:

\[ f(x) = \begin{cases} \frac{1}{\sigma} \exp\left(-\left(1 + kz\right)^{-\frac{1}{k}}\right) & k \neq 0 \\ \frac{1}{\sigma} \exp\left(-z - \exp(-z)\right) & k = 0 \end{cases} \]

\[ P(X \leq x) = \begin{cases} 1 - \left[1 + k\left(\frac{x - \mu}{\sigma}\right)^{\frac{1}{k}}\right]^{-1} & k \neq 0 \\ 1 - \exp\left(-\frac{x}{\sigma}\right) & k = 0 \end{cases} \]
where \( k = \) shape parameter, \( \sigma = \) scale parameter \( \mu = \) location parameter and \( z = \frac{x - 0}{\sigma} \). The shape parameter \( k \) can be used to model a large number of distribution tails. The case where \( k < 0 \) corresponds to the Weibull distribution; for \( k > 0 \) corresponds to the Fréchet distribution; when \( k = 0 \) on the Gumbel distribution.

2 — Lognormal

• Domain

\[-\infty < x < +\infty\]

• Probability density function

\[
f(x) = \frac{\exp\left(-1/2\frac{(\ln(x-\mu))^2}{\sigma^2}\right)}{(x-\mu)/(\sigma\sqrt{2\pi})} \quad (3)
\]

• Cumulative distribution function

\[
F(x) = \Phi\left(\frac{\ln(x-\mu)}{\sigma}\right) \quad (4)
\]

where \( \sigma \) and \( \mu \) are continuous parameters (\( \sigma > 0 \)) and \( \gamma = \) location parameter and \( \Phi \) is the Laplace integral.

3 — Pareto distribution

• Domain

\[-\infty < x < +\infty\]

• Probability density function

\[
f(x) = \frac{\alpha \beta^\alpha}{x^{\alpha + 1}} \quad (5)
\]

• Cumulative distribution function

\[
F(x) = 1 - \left(\frac{\beta}{x}\right)^\alpha \quad (6)
\]

where \( \alpha = \) shape parameter (\( \alpha > 0 \)) and \( \beta = \) scale parameter (\( \beta > 0 \)).

4 — Gamma distribution

• Domain

\[-\infty < x < +\infty\]

• Probability density function

\[
f(x) = \frac{(x-\gamma)^{\alpha-1}}{\beta^\alpha \Gamma(\alpha)} \exp\left(-\frac{x-\gamma}{\beta}\right) \quad (7)
\]

• Cumulative distribution function

\[
F(x) = \frac{\Gamma(x-\gamma)/\Gamma(\alpha)}{\Gamma(\alpha)} \quad (8)
\]

where \( \alpha = \) shape parameter (\( \alpha > 0 \)), \( \beta = \) scale parameter (\( \beta > 0 \)) e and \( \gamma = \) location parameter.

The Kolmogorov–Smirnov adherence test (Wilks, 2006) was used to verify the degree of adjustment of the \( x \) series to the probability density function. The statistic \( D \) of Kolmogorov–Smirnov test is based on the largest vertical difference between the functions of cumulative theoretical and empirical distributions.

\[
D = \max_{1 \leq i \leq n} \left| F(x_i) - i - 1 \right| - \frac{i}{n} - F(x_i) \quad (9)
\]

where \( F(x) \) is the cumulative empirical frequency of the maximum annual dry spell length values and \( F(x) \) is the cumulative frequency given by Eq. (9).

The null and alternative hypotheses are set out below:

- \( H_0 \): the observed data follow a particular distribution;
- \( H_A \): the observed data do not follow a particular distribution.

The hypothesis is rejected on the fit of a particular distribution at a level of statistical significance \( \alpha \) if \( D \) is greater than the critical value obtained from theoretical tables.

To check the fit of the distribution with respect to the observed data, percentile–percentile (PP) graphs were presented factoring in the abscissa the empirical cumulative probability on the ordinate, the cumulative theoretical probability estimated through the density function. The graph is approximately linear if the theoretical distribution is the correct model.

According to Sansigolo (2008) and Blain and Moraes (2011), an important feature of the extreme value distribution is that it assumes that there are no systematic variations in the observed period. The nonparametric Run or Wald-Wolfowitz test (Wald and Wolfowitz, 1940; Thom, 1966), the Mann–Kendall test proposed by Mann (1945) and studied by Kendall (1975) and improved by Hirsch and Slack (1984) and the Pettitt test (Pettitt, 1979), are the most widely used to study the characteristics of the series of daily maximum rainfall.

Let’s examine the series \( x = \{x_1, x_2, \ldots, x_n\} \). The nonparametric Mann–Kendall (MK) test is defined as: 

\[
T = \sum_{i=1}^{n} \text{signal}(x_i) - \text{signal}(x_j) \quad \text{with} \quad \{i,j \in n \text{ and signal}(x_i - x_j) = \begin{cases} 1 & \text{for } (x_i - x_j) > 0; \ 0 & \text{for } (x_i - x_j) = 0; \ -1 & \text{for } (x_i - x_j) < 0. \end{cases} \]

Considering temporal independence between observations under the null hypothesis, there is no presence of trends, \( T \) is normally distributed with mean \( E(T) = 0 \) and variance \( \text{Var}(T) \)

\[
\text{MK} = \frac{T - 1}{\sqrt{\text{Var}(T)}} \quad \text{for } T > 0; 0 \text{ for } T = 0; -\frac{T + 1}{\sqrt{\text{Var}(T)}} \text{ for } T < 0 \quad (10)
\]

where \( \text{Var}(T) = \frac{n(n-1)(2n+5)}{18} \).

Coles (2004), Fawcett and Walshaw (2008), Gilleland and Katz (2005) and Marty and Blanchet (2011) state that for the types of data to which the extreme value theory is applied, the temporal independence is an unrealistic assumption. Extreme conditions persist over many consecutive observations. A detailed investigation requires a mathematical treatment with a high level of sophistication that can be found in Leadbetter et al. (1983). The generalization of a sequence of independent random variables is the stationary series. Stationarity is a more realistic assumption for most of the physical process and corresponds to a series where the variables may be mutually independent, but the stochastic properties are
Fig. 1. Maximum yearly dry spell in days for the Midwest, Southeast and Southern Brazilian regions.
homogeneous over time. That is, if a series \( x_1, x_2, \ldots, x_t \) is a stationary series then \( x_t \) has the same distribution of \( x_{100} \) and the joint distribution of \( (x_1, x_2) \) has the same distribution of \( (x_{100}, x_{101}) \) although \( x_t \) need not be independent of \( x_2 \) or \( x_{100} \). Wilks (2006) states that the data comprising a series of extreme values do not come from the same distribution. However empirically, this theoretical distribution is often appropriate even when not all assumptions are met.

To test the stationarity of the observed series, the unit root test was applied (Dickey and Fuller, 1979, 1981). We considered the stochastic model based on the difference of a first order autoregressive process, the difference of which generates the model described below:

\[
\nabla x_t = \phi x_{t-1} + \epsilon_t \tag{11}
\]

where \( x_0 \) = fixed initial value; \( \nabla x_t = (x_t - x_{t-1}) \rightarrow \) is the difference operator; \( \phi = \rho - 1 \rightarrow \) time series autoregressive coefficient; \( \epsilon_t \) = sequence of random variables independently and identically distributed.

The null hypothesis is that \( x_t \) is non-stationary, that is, there is an autoregressive unit root and \( \phi = 0 \), against the alternative hypothesis that \( x_t \) is an AR(1) process, in this case there is no unit root and consequently \( \phi < 0 \). To conduct this hypothesis test, an estimation process is used, the Ordinary Least Square model. In the presence of trend and intercept, the equation to be used is as follows:

\[
\nabla x_t = \alpha + \beta t + \phi x_{t-1} + \epsilon_t \tag{12}
\]

where \( \alpha \) is the intercept and the linear trend \( t \).

With the Dickey–Fuller test, part of the assumption is that error terms in the above equations are independently and identically distributed, that is, they do not exhibit autocorrelation. The Dickey–Fuller augmented test (Dickey and Fuller, 1979, 1981) incorporates lags in relation to the variable which is being analyzed so that the errors do not exhibit autocorrelation. The equation is:

\[
\nabla x_t = \alpha + \beta t + \phi x_{t-1} + \sum_{j=1}^{p-1} \rho_j \nabla x_{t-j} + \epsilon_t. \tag{13}
\]

The parameters of Eqs. (11), (12) or (13) and its significances can be estimated by the autoregressive procedure (SAS, 2010).

After calculating the distribution function associated with the maximum annual dry spell length for the three regions studied, their return period was estimated by:

\[
R(F(x)) = \frac{1}{\text{year} (1 - F(x))} \tag{14}
\]

where \( F(x) \) is the cumulative probability of occurrence of a given value of the maximum dry spell period for each region and 1/year denominator is the average sample frequency of the annual dry spell maximum period.

3. Results and discussion

Periods of maximum annual dry spells observed for the three Brazilian regions (Midwest, Southeast and Southern) for the months of October, November, December, January and February are representative of the rainy season (growing season) as shown in Fig. 1. Visually, some important features may be observed. There is a clear, increased trend in the annual maximum dry spell period of the Midwest region but a decreased dry spell period in the Southeast and Southern regions. The increasing trend associated with the migration for medium and early crop cycles increases the chances for productivity losses, particularly for soybean and corn.

The statistical confirmation of the trend obtained in Fig. 1 can be seen in Table 1 which shows the results of applying the nonparametric Mann–Kendall according to Eq. (10).

As the calculated p-value for the three regions is less than the significance level \( (\alpha = 0.05) \), the null hypothesis \((H_0): \) there is no trend in the series) should be rejected in favor of the alternative hypothesis \((H_1): \) There is a positive trend in the series). The risk of rejecting the null hypothesis when it is true for the Midwest, Southeast and South is, respectively, 0.21%, 4.97% and 1.51%.

The number of non-consecutive rainy days for each precipitation station was calculated and the maximum yearly rainy days for the growing season can be seen visually in Fig. 2. There is an increasing trend in the number of rainy days for these three Brazilian regions.

Table 2 shows the descriptive statistics for the maximum yearly rainy days for the three regions. The data series seen here presents similar mean values for the Midwest and Southern regions despite the dispersion around the mean being greater for the South. The average for the maximum yearly rainy days increases around 19% for the Southeast in relation to the other two regions. The dispersion around the mean can be considered low for all three regions.

The statistical confirmation of the trend obtained visually in Fig. 2 can be seen in Table 3 where the results of applying the nonparametric Mann–Kendall test according to Eq. (10) are presented.

As the p-value calculated for the Southeast and Southern regions is less than the significance level \( (\alpha = 0.05) \), the null hypothesis \((H_0): \) there is no trend in the series) is in favor of the alternative hypothesis \((H_1): \) There is a positive trend in the series). The risk of rejecting the null hypothesis when it is true for the Southeast and Southern regions is respectively 4.69% and 2.13%. For the Midwest region, the p-value is greater than calculated, so the null hypothesis \((H_0): \) there is no trend in the series) should not be rejected with a risk of 8.20%. Several authors have used nonparametric Mann–Kendall test to study trends in climatic variables, such as Subash et al. (2011a, 2011b), Casa and Nasello (2012), and Shahid et al. (2012).

As the amount of maximum yearly rainy days for the growing period is increasing significantly in the Southeast and Southern regions, the maximum number of dry spell length is decreasing. As there is no significant trend in the

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Mann–Kendall test for the maximum number of days of dry spell for the three regions (Midwest, Southeast and Southern).</th>
</tr>
</thead>
<tbody>
<tr>
<td>Region</td>
<td>Mann–Kendall</td>
</tr>
<tr>
<td>Midwest</td>
<td>0.252</td>
</tr>
<tr>
<td>Southeast</td>
<td>$-0.161$</td>
</tr>
<tr>
<td>Southern</td>
<td>$-0.118$</td>
</tr>
</tbody>
</table>
Fig. 2. Maximum yearly rainy days for the Midwest, Southeast and Southern Brazilian regions.
Table 3
Descriptive statistics for the maximum yearly rainy days for all three regions (Midwest, Southeast and Southern) at growing time.

<table>
<thead>
<tr>
<th>Region</th>
<th>Mean</th>
<th>Std deviation</th>
<th>Std error mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Midwest</td>
<td>104.98</td>
<td>10.26</td>
<td>1.22</td>
</tr>
<tr>
<td>Southeast</td>
<td>122.62</td>
<td>13.94</td>
<td>1.68</td>
</tr>
<tr>
<td>Southern</td>
<td>102.59</td>
<td>16.27</td>
<td>1.94</td>
</tr>
</tbody>
</table>

series of maximum yearly rainy days for the Midwest region, the increasing maximum number of dry spell length is associated with the uneven distribution of rainfall in the growing period for this region. Similar result was found in Assad et al. (1993), Barbosa (1986), Espinoza (1982), and Farias et al. (2001). These studies indicate the high degree of variation for the growing season in the Midwest region.

Table 4 presents the parameter estimates of the generalized extreme value distributions (Eq. (1)), Lognormal (Eq. (3)), Pareto (Eq. (5)) and Gamma (Eq. (7)) obtained by the maximum likelihood method, and the result of the Kolmogorov–Smirnov adherence test (Eq. (9)) to check the degree of adjustment of the x series to the probability density function.

Table 4 shows that the generalized extreme value distribution is the analytic function that best describes the frequency of occurrence of the annual values of maximum periods of dry spell length for the three regions with the lowest values of the statistic D for α = 5%. In the Midwest, as k > 0, the Fréchet distribution was the best fit. In the Southeast and Southern regions, as k < 0, the distribution that best represents the observed data was the Weibull.

Fig. 3 shows the percentile–percentile (PP) graphs used to check the fit of theoretical distributions in relation to the observed data. You can visually check the good fit of the annual maximum dry spell length data series in relation to the accumulated probability (theoretical and empirical) estimated by the density function. Even the extreme upper and lower distributions of the graph show approximately linear, indicating that the adjusted distribution is correct.

As Coles (2004) states, the stationarity assumption is more realistic for most physical processes and sufficient for the application of the extreme value theory. The non-stationarity was rejected by the Dickey–Fuller test and Dickey–Fuller augmented test (Dickey and Fuller, 1979, 1981) according to Eqs. (12) and (13) respectively, through the use of the autoregressive procedure of SAS software (SAS, 2010) using stationarity option = (ADF). Table 5 shows the results obtained for the Dickey–Fuller test.

For the three regions, setting a 5% level of significance, the probabilities obtained are lower indicating therefore that the series with the maximum dry spell length values are apparently stationary, that is, the classical statistical assumptions remain valid. As the unit root tests have low power, the inclusion or removal of parameters, such as the constant and the trend may change the results and thus a conclusion about stationarity of this variable cannot yet be considered definitive.

Table 6 shows the results for the three regions of the Dickey–Fuller augmented test with the average and trend included (ADF1) and (ADF2), respectively.

From Table 6, the inclusion of parameters for the three regions does not change at the 5% significance level. The null hypothesis rejects that the series is non-stationary, that is, there is an autoregressive unit root in favor of the alternative hypothesis that the series studied presents stationarity and in this case there is no unit root.

The previous analysis provides technical support for using the extreme value theory, employing the density distribution function defined in Eq. (1) to describe the frequencies of occurrence of dry spell data, such as Lugang et al. (1995), Henrique and Santos (1999), Lana et al. (2008), Vicente-Serrano and Beguería (2003) and Lena et al. (2006).

The return period expressed in years (Eq. (14)) for the three Brazilian regions is presented in Table 7 based on the maximum estimated annual period.

It can be seen in Table 7 that the Midwest region has a higher probability of dry spells than the other regions. For a 90-day dry spell, the return periods for the Midwest, Southeast and Southern regions at the agricultural growing season are respectively 28, 19 and 134 years. However, dry spells over as little as 14 days can cause reduced productivity of more than 20%, and in the case of the three regions for a return period of one year, it is possible to have an occurrence of dry spells between 5 and 25 days in the Midwest. This situation, happening during grain filling season, increases the productivity losses for the three Brazilian regions.

The dry spell length for the return period of one year is higher in the Southeast, Southern and Midwest, respectively. That is, the region most at risk of agricultural loss due to dry spells for a return period of one year is the Midwest region. If the dry spell length is from 40 to 50 days, the most vulnerable is the Southern region.
Fig. 3. Percentile–percentile graphs for the adjustment of the dry spell length extreme values observed within each year for the three regions under study.
observed for return periods of 4 to 5 years. To the Southeast, dry spells of 35–40 days were observed for a return period of one year. That is, using the series from 1940 through 1975 (Assad et al., 1993) and within the current series from 1940 through 2011, the intensification of the dry spell length doubles in the Midwest and increases ten times for Southeast. The same distributions were adjusted in both works.

### 4. Conclusions

The dry spell length increased in growing seasons for the Midwest region and decreased in the Southeast and Southern regions. Although the number of rainy days has increased in the growing season for the three regions, the distribution of rainfall in the Midwest is irregular at growing time. This result is similar to the results found by other authors for time series with fewer years, indicating that the irregularity in the distribution of rainfall for the Midwest region has intensified in recent years. The average number of rainy days in the growing season for the Southeast region is 19% higher than for the Midwest and South regions.

For all distributions studied, the generalized extreme value distribution was the best fit to the data series of dry spell length for the three regions.

It has been showed that 5–25 day dry spell lengths occur in return period of one year for the series analyzed from 1940 to 2011. Previous works clearly show that 5–25 day dry spell lengths were observed in return periods of 10 years. The dry spell length that has become more frequent in recent years may bring loss of productivity for the Brazilian agriculture, especially if it happens at the time of grain filling. The greatest risk of loss due to agricultural dry spells for the return period of one year is the Midwest region, and for the return period of two years, the Southern. The rapid change in dry spell length increases the vulnerability of agricultural production in all regions.

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### References


