Weather and Climate Extremes 5-6 (2014) 7–15

Contents lists available at ScienceDirect

Weather and Climate Extremes

journal homepage: www.elsevier.com/locate/wace

Annual maximum daily rainfall trends in the Midwest, southeast and southern Brazil in the last 71 years

José Ruy Porto de Carvalho [a,*], Eduardo Delgado Assad [a], Aryeverton Fortes de Oliveira [a], Hilton Silveira Pinto [b]

[a] Embrapa Informática Agropecuária, CP: 6041, CEP: 13083-886 Campinas, SP, Brazil
[b] CEPAGRI—Universidade Estadual de Campinas, CEP: 13083-970 Campinas, SP, Brazil

ARTICLE INFO

Article history:
Received 5 December 2013
Received in revised form
6 October 2014
Accepted 9 October 2014
Available online 23 October 2014

Keywords:
Climate trends
Generalized extreme values distribution
Trend test
Goodness-of-fit test
Return period

ABSTRACT

The aim of this study was to model, based on the overall distribution of extreme values, the probability of occurrence of a particular level of annual maximum daily rainfall in three Brazilian regions (Midwest, Southeast and South) and study their behavior over the past 71 years. The parameters of the general distribution of extreme values were estimated by the maximum likelihood method. The Mann–Kendall test showed that there is a positive trend in the annual maximum daily rainfall data series. The non-stationarity was rejected by the augmented Dickey–Fuller test supporting the use of the density function of extreme value distribution to describe the values of the occurrence of annual maximum daily rainfall. The Kolmogorov–Smirnov/Lilliefors goodness-of-fit test showed the good fit of the studied variable to the probability distribution function. The Midwest region has a return period of more frequent annual maximum daily rainfall below 300 mm in comparison with other regions. There is a clear change in the behavior of this extreme event in the Southern region. According to the literature, in past decades annual maximum daily rainfall of 248 mm has been estimated for a return period of 100 years for the state of Santa Catarina-South region, while the results found with the current series, annual maximum daily rainfall of 250 mm was estimated for a return period of 10 years. Extreme annual maximum daily rainfalls for return periods smaller were also found in other regions.

Contents

1. Introduction

The annual maximum daily rainfall is defined as an extreme instance, with critical duration for a river basin, state or region, with immediate consequences to agriculture, soil conservation, roads, dams and drainage (Beijo and Avelar, 2010; Willems et al., 2012). In many statistical applications the interest is directed towards the estimation of the central features such as mean value of a variable based on random samples from the population under study and draws on ideas that have such key moments which are approximately normal distribution, with theorems of analysis based on the central limit theory.

However, as in many applied areas, the climatological characterization of the annual maximum daily rainfall requires a suitable choice of methodology. These events are not in a central position in the probability distribution. The interest is to identify the occurrence of extreme events, that is, maximum values.

The information about the probability of extreme values occurrence is fundamental to the society to prepare for extremes like heavy precipitations events. The characterization of rainfall

* Corresponding author. Tel.: +55 19 3211.5871.
E-mail address: jose.ruy@embrapa.br (J.R. Porto de Carvalho).

http://dx.doi.org/10.1016/j.wace.2014.10.001
2212-0947/

and its intensity is important for the conservation of soil and water (Moreti et al., 2003; Chaves and Piau, 2008). As a direct consequence of the increasing trends of daily maximum rainfall, there is an increase of soil loss, increased carrying out of sediments, and increased loss of fertility resulting in decreased agricultural production (Romkens et al., 2001; Zhang and Liu, 2005). Extreme value theory is a branch of the probability that studies the stochastic behavior of the extremes of a set of random variables (Mendes, 2004; Heaton et al., 2011).

The extreme value theory has emerged as one of the most important disciplines of applied science in the last 50 years. It has been used in various fields of science, such as: climate change (Blain and Moraes, 2011; Caires et al., 2006; Brown and Caesar Ferro, 2008; Guttorp and Xu, 2011; Rusticucci, 2012; Szolgay et al., 2009), oceanic modeling (Dawson, 2000; Bernier et al., 2007; Menedez et al., 2008), thermodynamics of earthquakes (Lavenda and Cipollone, 2000), finance (Mendes, 2004), biomedics (Roberts, 2000), and maximum wind speed (Bautista, 2002; VanDen Brink et al., 2004; Hundecha et al., 2008).

The aim of this study was to model, based on the overall distribution of extreme values, the probability of occurrence of a particular level of annual maximum daily rainfall in three Brazilian regions (Midwest, Southeast and South) and study their behavior over the past 71 years. In each of these three regions there is a well-defined rainy season which restricts the harvest calendar and influences seasonal production, income generation, agriculture-based jobs and affects all businesses in supply chains.

2. Material and methods

The annual maximum 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. For the Midwest region 41 rainfall stations were used, for the Southeast 407 rainfall stations, and for the South 145 rainfall stations. All the observations refer to the annual maximum daily rainfall (MDR) expressed in millimeters per day (mm/day) which represents the total depth of rainwater (mm), during 24 h, for the months of October, November, December, January, February and March, corresponding to the summer rainy season of the three regions. During this period, it has been observed that 95% of dry land planting occurs in November/December (Assad et al., 2001). Extreme precipitation is usually defined as the annual maximum daily rainfall within each year, so one would have as many extreme values as the total number of years, known as the block-maxima method (Feng et al., 2007).

The long climatic series can be affected by isolated and non-climatic factors that do not truly represent the climatic behavior. These non-climatic factors can be changes in the location of the station, changes in the instrument, and changes in the way the data are processed, among others (Heino, 1994). Therefore, several statistical methods are employed to analyze the behavior of the time series, such as analyzing the homogeneity of the data series and detecting periods of possible breaks in the data set. Since this is the first step in the analysis of a climatic series, enabling a further investigation which has the goal of detecting if the non-homogeneity is related to climate or other factors. Homogenization of time series is widely recognized as one of the steps that must be taken in the construction of reliable long term data sets from weather observations (Tuomenvirta, 2002).

For a series of climatic data to be regarded as homogeneous, variations of weather and climate fluctuations must be regular through the time. This would require that the observation should be measured at the same location within an unchanged environment using the same instrument calibrated in accordance with the same method. In fact, these conditions are rarely met in long series, and this "absolute homogeneity" is always questionable. Instead, climatologists are content with series that are "relatively homogeneous", where the differences or ratio between series of climatic station and reference series created from the set of neighboring stations, are statistically independent and similarly distributed.

Few missing values have been found in the climatological series used in this work in which case the average of observations in the series was used to replace the missing values. To test the relative homogeneity, the parametric Standard Normal Homogeneity Test—SNHT (Alexandersson, 1986) was used. It uses the neighboring stations as a reference to identify non-homogeneity in the time series of the station being tested (test station). The non-homogeneity occurs when linear or abrupt differences occur between the reference series and the series being tested. In Brazil, the climate change policy is always made by biomes. In this study, the Midwest region is representative of the cerrado, the Southeast has the Cerrado and Atlantic Forest biomes and southern Atlantic Forest biomes and pampas. The test of homogeneity of the series is carried out to verify the representativeness of stations for each biome.

The basic assumption behind SNHT is the ratio, Q, between precipitation test station and reference station remains relatively constant over time. This requires a sufficient correlation between the test station and reference stations. A lack of homogeneity happens to a systematic change of this ratio, Q, which is defined as (Tuomenvirta, 2002)

$$Q_i = \frac{Y_i}{\left[\sum_{j=1}^{k} V_j X_{ji} \, (\overline{Y}/\overline{X}_j)\right] / \sum_{j=1}^{k} V_j} \tag{1}$$

where Y is the test series, Q_i is the value of the ratio at a specific year i, X_j is the reference series at station j and V_j is the weighting factor for the reference station j. Most often V_j is the square of the correlation coefficient between the series of a test station and the series of reference.

The normalized series of the ratio $Z_i\left(Q_i - \overline{Q}\right)/\sigma_Q$ is used by SNHT where $\overline{Q}$ and σ_Q are the sample mean and standard deviation of the ratio Q_i. Relative homogeneity is achieved when the null hypothesis is not rejected at a significance level set, that is, $H_0 = Z_i \in N(0,1) i \{1, \ldots, n\}$. All values in the normalized series of ratios are normally distributed with zero mean and one standard deviation.

The reference series were built with neighboring stations using weighted average ratios (Alexandersson, 1986; Sahin and Cigizoglu, 2010). The use of several neighboring series to construct the reference series reduces the effects of spatial variation and the non-homogeneity in the reference series. To construct the reference series and all homogeneity tests, the software AnClim (Stepánek, 2008) was used. It allows the calculation of basic statistics performs tests of homogeneity using different methods and creates plots with the series used and their results.

The extreme value theory has been used for the development of methods describing the behavior of outliers, that is, the points furthest from the mean. The generalized distribution of extreme value—GEV shows great descriptive and predictive abilities to capture skewness and kurtosis common to the MDR data, without any a priori constraint. It is robust for estimating quantiles of the distribution and allows making predictions about the level of return (Mannshardt-Shamseldin et al., 2010; Zalina et al., 2002; Markose and Alentorn, 2005). Extreme value theory provides the statistical framework to make inferences about the probability of very rare or extreme events. Jenkinson (1955) proposed that three kinds of distributions of extreme values (Gumbel, Fréchet and Weibull) may be represented in a single parametric form, called generalized distribution of extreme values with the density distribution below (Beijo and Avelar, 2010)

$$f(\mathrm{MDR}) = \left(\frac{1}{\sigma}\right)\exp\left\{-[1+\xi Z]^{-(1/\xi)}\right\}(1+\xi Z)^{(-1-1/\xi)} \tag{2}$$

expressed by the cumulative distribution function:

$$F(\mathrm{MDR}) = \exp\left\{-[1+\xi Z]^{-(1/\xi)}\right\} \tag{3}$$

where $\xi \neq 0$ and $Z = (\mathrm{MDR}-\mu)/(\sigma)$. The$\mu$, σ and ξ are the parameters of position, scale and form, respectively. The shape parameter ξ can be used to model a large number of distribution tails. In the cases where $\xi < 0$ corresponds to the Weibull distribution, the $\xi > 0$ corresponds to the distribution of Fréchet, when $\xi = 0$ have the Gumbel distribution. A similar study restricted to the Brazilian "cerrado" was made by Assad et al. (1992).

The parameters of Eq. (2) were estimated by the maximum likelihood method for the three regions. The Kolmogorov–Smirnov goodness of fit test (Wilks, 2006) was used to verify the degree of adjustment of the x series to the probability density function. The statistic D of the Kolmogorov–Smirnov test is based on the maximum vertical difference between the theoretical and empirical cumulative distributions functions.

$$D = \frac{\max}{1 \le i \le n}\left(F'(x_i) - \frac{i-1}{n},\ \frac{i}{n} - F(x_i)\right) \tag{4}$$

where $F'(x)$ is the empirical cumulative frequency of the values of the annual maximum daily rainfall period and $F(x)$ is the cumulative frequency given by Eq. (3).

The null and alternative hypotheses are defined as follows:

H_0. the observed data follow a specified distribution;

H_A. the observed data do not follow a specified distribution.

The hypothesis regarding the distributional form is rejected at the chosen significance level α if the test statistic D, is greater than the critical value obtained from a theoretical table.

According to Sansigolo (2008), Blain and Moraes (2011), an important feature of GEV distribution is its assumption that there is no systematic variation in the observed period. Non-parametric tests of Run or Wald–Wolfowits (Wald and Wolfowitz, 1940; Thom, 1966), and Mann–Kendall proposed by Mann (1945) are frequently used to study the characteristics of the MDR series.

Consider a general series defined as $Y = \{y_1, y_2, \dots, y_n\}$. The nonparametric Mann–Kendall (MK) test is defined as $T = \sum_{j<i}$ $\mathrm{sign}(y_i - y_j)$, with $i, j \in n$ where sign $(y_i - y_j)$={1 for $y_i - y_j > 0$; 0 for $y_i - y_j$=0 and -1 for $y_i - y_j < 0$}. Whereas temporal independence lies between observations, under the null hypothesis, there is no presence of trends, and T is approximately normally distributed when the sample size is large with mean $E(T) = 0$ and variance $Var(T)$:$(n(n-1)(2n+5))/18$.

$$\mathrm{MK} = \frac{T-1}{\sqrt{Var(T)}} \text{ for } T > 0; \quad 0 \text{ for } T = 0; \quad \frac{T+1}{\sqrt{Var(T)}} \text{ for } T < 0 \tag{5}$$

Coles (2004) stated that for the data types to which the theory of extreme values is applied, temporal independence is an unrealistic assumption. The 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 a stationary series. Stationarity is a more realistic assumption for most of the physical process and corresponds to a series in which the variables may not be mutually independent, but the stochastic properties are homogeneous over time. That is, if a series $y_1, y_2, \dots, y_n$ is a stationary series then y_1 has the same distribution as y_{100} and the joint distribution of (y_1, y_2) has the same distribution as (y_{100}, y_{101}), although y_1 need not be independent of y_2 or of y_{100}. Wilks (2006) states that the data composing a series of extreme values may not be from the same distribution. However, empirically this theoretical distribution is often appropriate, even when not all requirements are met.

To test stationarity, the unit root test was applied (Dickey and Fuller, 1979, 1981) using the stochastic model based on the difference of a first-order autoregressive process, the difference generates the model described below:

$$\nabla y_t = \varphi y_{t-1} + \varepsilon_t \tag{6}$$

where y_0 is the fixed initial value; $\nabla y_t = (y_t - y_{t-1})$ is the difference operator; $\varphi = \rho - 1$ is the autoregressive coefficient of the time series; ε_t is the sequence of random variables independently and identically distributed.

The null hypothesis is that y_t is not stationary, that is, there is a unit root autoregressive and $\varphi = 0$, against the alternative hypothesis that y_t is an auto regressive model of order 1 [AR (1)], in this case there is no unit root and consequently $\varphi < 0$. In order to perform this, the hypothesis test used in the estimation process used the ordinary least square model.

With the presence of trend and the intercept, the equation to be used is as follows:

$$\nabla y_t = \alpha + \beta t + \varphi y_{t-1} + \varepsilon_t \tag{7}$$

where α is the intercept and t the linear trend.

The Dickey–Fuller test assumption is that the error terms in the above equations are identically and independently distributed, or that it has no autocorrelation. The augmented Dickey–Fuller test (Dickey and Fuller, 1979, 1981) incorporates lags in relation to the variable that is being analyzed so that the residuals do not exhibit autocorrelation. Its equation is

$$\nabla y_t = \alpha + \beta t + \varphi y_{t-1} + \textstyle\sum_{j=1}^{p-1} \rho_{j+1} \nabla y_{t-j} + \varepsilon_t \tag{8}$$

The parameters of Eqs. (6), (7) or (8) and their significance can be estimated by the autoregressive procedure (SAS Institute Inc, 2010). This procedure estimates and forecasts linear regression models for time series data when the errors are auto correlated or heteroscedastic (The presence of heteroscedasticity refers to the circumstance in which the variability of a variable is unequal across the range of values of a second variable that predicts it.)

After calculating the distribution function associated with the annual maximum daily rainfall for the three regions studied, the return period was estimated by

$$R(F(\mathrm{MDR})) = \frac{1}{(1/\mathrm{year})(1 - F(\mathrm{MDR}))} \tag{9}$$

where F(MDR) is the cumulative probability of occurrence of a given value of the annual maximum daily rainfall for each region and 1/year is the average sampling frequency of the annual maximum daily rainfall.

3. Results and discussion

For each region, one reference series with 71 annual maximum daily rainfalls and the 10-year average was constructed as shown in Fig. 1. As can be seen in Fig. 1, there is a break in the 1970s with an increasing trend for the decennial averages in the Southeast and South regions. For the Midwest region decennial averages keeps constant during the study period. Splitting the series into two periods based on the year 1970, the total maximum precipitation average increases in 6.10% for the Southeast and 13.40% for the South regions. In the Midwest region there is a decrease of 1.56%.

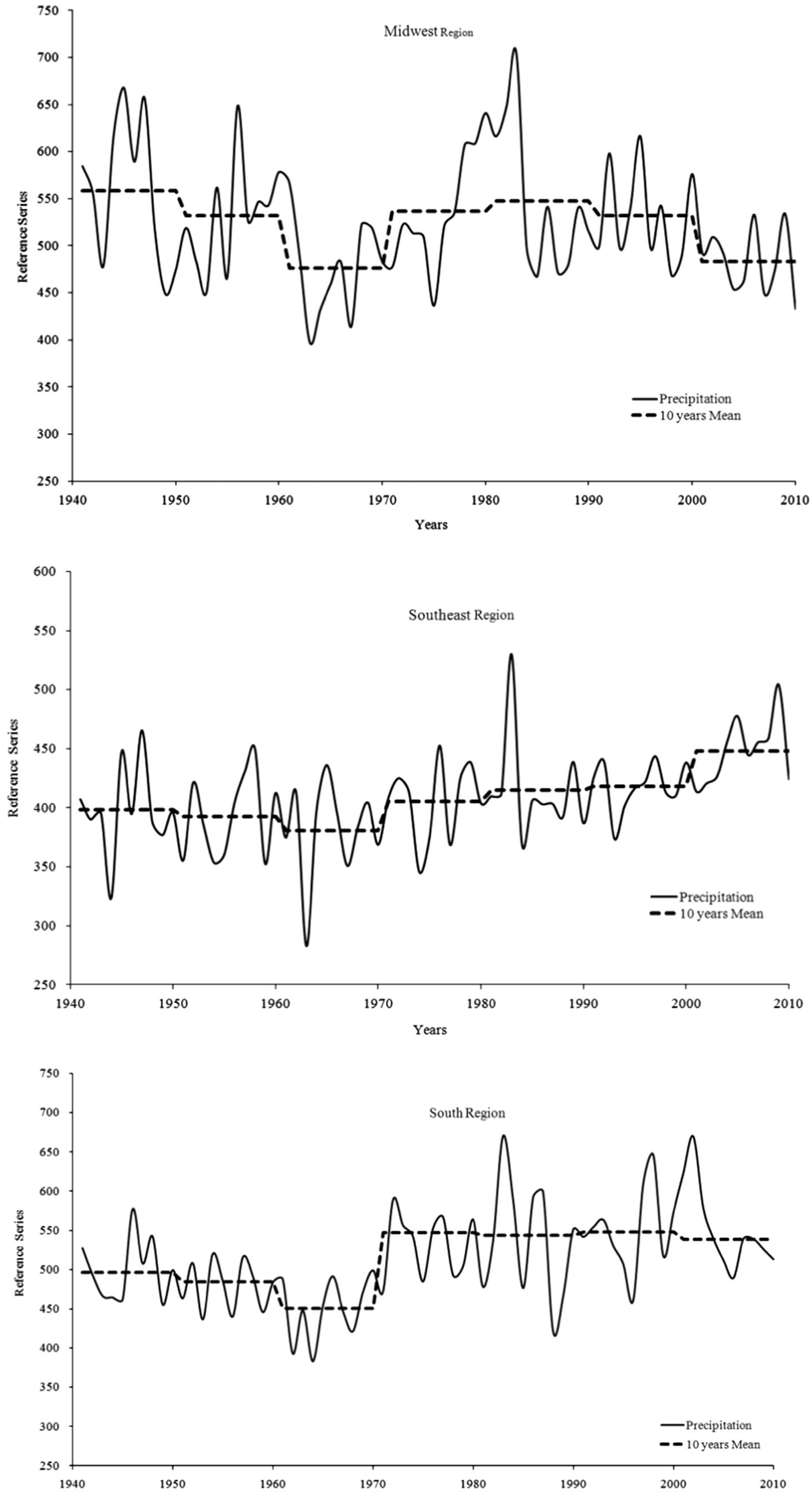

Fig. 1. Decennial means and reference series for Midwest , Southeast and South regions.

This non-homogeneity point in the reference series for the Southeast and South regions can be explained by the abrupt change in the behavior of the El Niño—Southern Oscillation which occurred in the 1970s. This new scheme called climate change-1970s has persisted to the present day (NCDC, 2012). These results were corroborated to South America by the work of Carvalho et al. (2010) where they

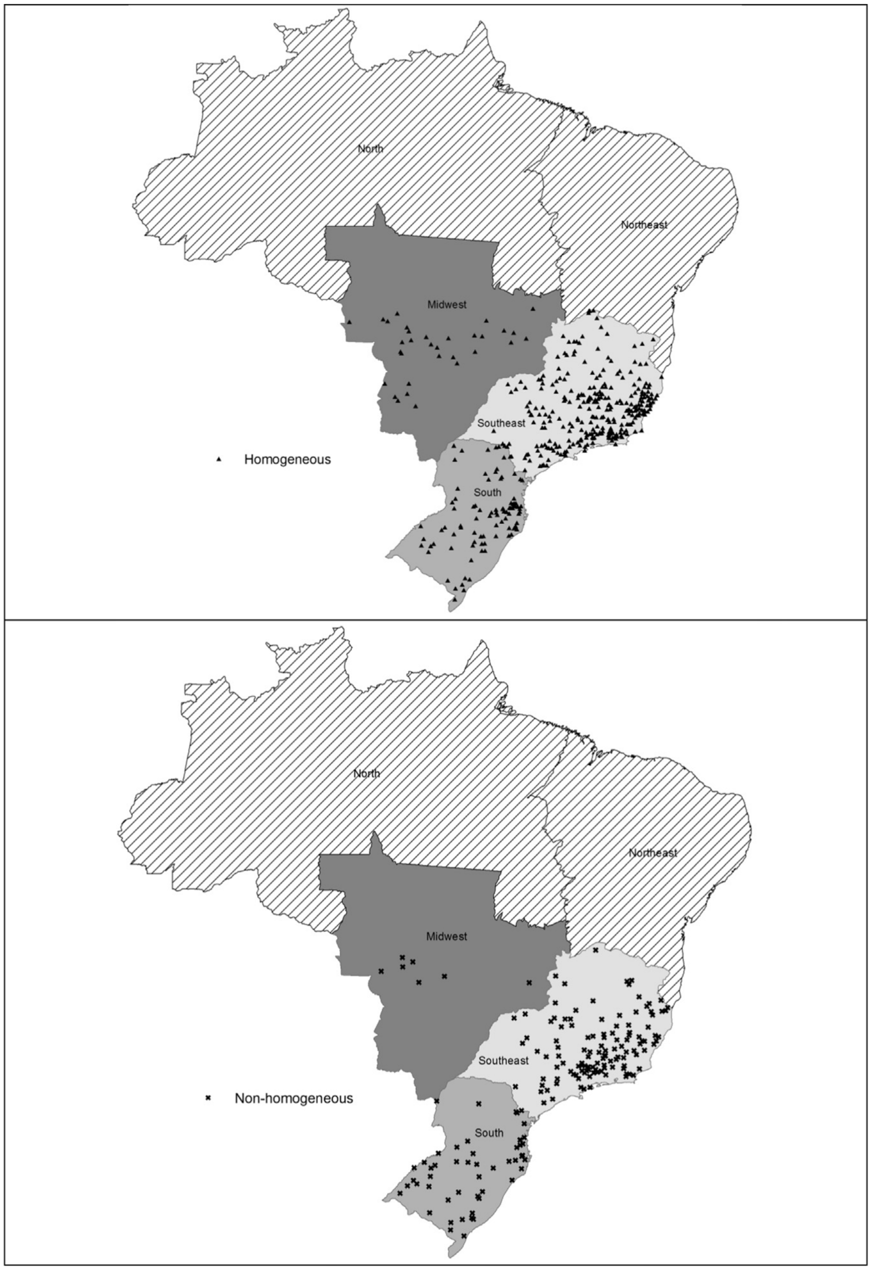

Fig. 2. Spatial distributions of the homogeneous and non-homogeneous weather stations for Midwest, Southeast and South regions.

introduced an extended large scale index to understand decadal changes in the South American Monsoon System which is characterized by intense convective activity and precipitation during austral summer. They concluded that the South American Monsoon System duration presented a statistical change point in the early 1970s. The impacts of climate transition of the 1970s are also verified by Marengo (2004) for the Amazon basin located in northern region of Brazil. Although there is no evidence of pronounced effect on rainfall in the Midwest region due to El Niño, in the South region there is a substantial increase in average temperature and precipitation. To the Southeast, there is a moderate increase in average temperatures although there is not a characteristic pattern of changes in rainfall (CPTEC, 2012).

From the total of 41 meteorological stations studied in the Midwest region, 81% have relative homogeneity when compared with the reference series using SNHT test (Eq. (1)) at a significance level of 1%. For the Southeast region from 407 stations, 69% are homogeneous and in the South, from 145 stations, 61% are homogeneous. Fig. 2 shows, respectively, the spatial location of the homogeneous and non-homogeneous stations for the three regions studied. The result shows that the homogeneity and the non-homogeneity of these stations scatter randomly.

For the Southeast 31% of the weather stations showed relative non-homogeneity, 39% in the South region and 19% in the Midwest region. The non-homogeneity occurs when there is an abrupt differences between the reference series and the series being tested and cannot be considered as natural effect. This phenomenon may occur due to several causes, some of which are related to changes in instrumentation and observation practices, the relocation of the weather station and others which relate to modification of the environmental conditions of the site. All these stations should be considered suspect and should not be used at this work.

The observed MDR data for the three Brazilian regions (Midwest, Southeast and South) for the months of October, November,

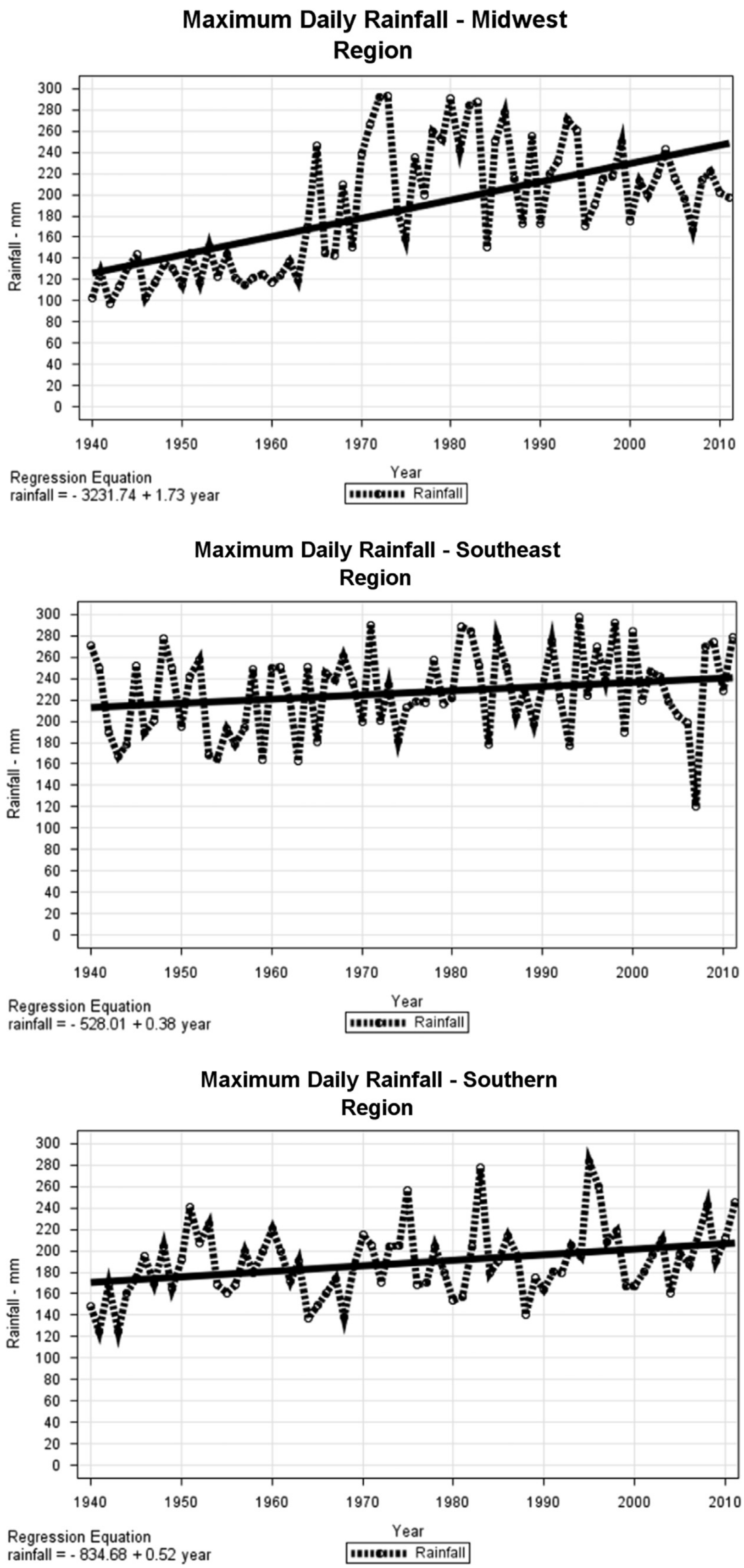

Fig. 3. Maximum daily rainfall for the Midwest, Southeast and Southern.

December, January, February and March, which represents the rainy season, is shown in Fig. 3 and was constructed using the procedure SGPLOT (SAS Institute Inc, 2008).

There is a clear upward trend in annual maximum daily rainfall for the three regions; this tendency is more accentuated in the Midwest and Southern regions. Lombardi Neto and Moldenhauer

(1992), Mello et al. (2007), Colodro et al. (2002) already pointed out the tendency of increase of the annual maximum daily rainfall and its relation to the erosivity. That is, the greater the intensity of rainfall, the greater the increase in soil loss. A similar result was found by Bertol (2000) in Campos Novos city, Santa Catarina state, Southern region. Using geostatistics and time series analysis, Vieira and Lombardi Neto (1995) evaluated the spatial variability of the rainfall erosivity potential in São Paulo state—Southeast region. This potential is directly related to the maximum daily rainfall.

The trends found in Fig. 3 are consistent with the work done by Aguilar et al. (2009) with signs reversed; Alexander et al. (2006) analyzed the global climatic extremes for rainfall and temperature in South Africa, Costa and Soares (2009) with studies in Portugal, Michaelides et al. (2009) with studies in Cyprus, and Marengo et al. (2011) with studies in the Amazon basin. 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), Shahid et al. (2012).

The statistical confirmation of the trend shown in Fig. 3 can be observed in Table 1 where the results of applying the nonparametric Mann–Kendall test according to Eq. (5) are presented.

From Table 1 we see that the p-value is smaller than the significance level of 5% indicating that there is no trend in the series for the three regions.

The non-stationarity was rejected by the augmented Dickey–Fuller test (Dickey and Fuller, 1979, 1981) according to Eq. (8), through the use of an autoregressive procedure of SAS software (SAS Institute Inc, 2010) using the option = stationarity (ADF). Table 2 shows the results obtained for the augmented Dickey–Fuller test.

For the three regions, setting a 5% level of significance, the probabilities obtained are smaller, so the series with the values of maximum daily precipitation are apparently stationary, that is, the assumptions of classical statistics are valid (constant variance or homoscedasticity, uncorrelated errors or conditional independence, normality). As the unit root tests have low discriminating power, the inclusion or removal of parameters such as the constant and trend, might change the results, so a conclusion about stationarity of this variable cannot yet be considered definitive.

Table 3 shows the results for the three regions of the augmented Dickey–Fuller test with the average and trend included (ADF1) and (ADF2), respectively.

As can be seen in Table 3 at 5% level, the inclusion of average and trend parameters in the augmented Dickey–Fuller test maintains the stationarity of the series.

The previous analysis provides technical support for using the extreme value theory, employing the density distribution function defined in (2) to describe the frequency of occurrence of the annual maximum daily rainfall values for the three regions under study. These results are consistent with the adjustment of the generalized extreme value distribution to the precipitation variable, made by Blain and Moraes (2011), Beijo and Avelar (2010), Sansigolo (2008), Feng et al. (2007), Miroslava (1992), Mannshardt-Shamseldin et al. (2010), Coles and Tawn (1996), Koutsoyiannis (2004), Shukla et al. (2010), Nadarajah and Choi (2007).

Table 4 shows the estimated position parameters (μ), scale (σ) and shape (ξ) from Eq. (2) set to the three series of annual maximum daily rainfall for the three regions under study. For the Midwest and Southeast region the distribution that best fit was the Weibull distribution ($\xi < 0$) and for the Southern region, the Fréchet distribution ($\xi > 0$).

Table 5 shows the series degree of adjustment of the number of annual maximum daily rainfall to the probability density of the generalized extreme value distribution using Kolmogorov–Smirnov/Lilliefors test (Eq. (4)). As the D_{max} statistic showed, the three regional values are lower than the critical value at the 5% (1.36) significance level, and the null hypothesis stating that the data follow the specified distribution is accepted.

The return period expressed in years (Eq. (9)) for the three Brazilian regions is presented in Table 6, estimated with the maximum daily probability for each year.

Table 6 presents the Southern region with a higher regime of annual maximum daily rainfall above 300 mm if compared with other regions. For a rainfall of 300 mm, the return periods for the Midwest, Southeast and South are respectively 332, 44 and 34 years. The southeastern region, however, presents more frequent return periods of rainfall below 300 mm if compared with other regions. Back (2001) estimated that Santa Catarina state in South region would have annual maximum daily rainfall of 248 mm for a return period of 100 years using a data series through 2000. In recalculating the analysis to periods in this work from 1940 to 2011, annual maximum daily rainfall of 250 mm was estimated for a return period of 10 years for the southern region, and evidenced a clear change in the behavior of this extreme event.

Table 1
Mann–Kendall test for the three regions (Midwest, Southeast and Southern).

Region	MK	p-Value
Midwest	0.497	< 0.0001
Southeast	0.468	< 0.0001
Southern	0.261	0.0014

Table 2
Augmented Dickey–Fuller test (ADF) for the three regions (Midwest, Southeast and Southern).

Region	ADF	p-Value
Midwest	−4.854	0.00
Southeast	−6.359	< .0001
Southern	−4.304	0.005

Table 3
Augmented Dickey–Fuller test (ADF) for the three regions (Midwest, Southeast and Southern) with average (ADF1) and trend (ADF2) included.

Region	ADF1	p-Value	ADF2	p-Value
Midwest	−3.912	0.017	−3.373	0.015
Southeast	−4.678	0.002	−3.713	0.028
Southern	−4.028	0.012	−3.582	0.039

Table 4
Estimation of the position (μ), scale (σ) and shape (ξ) parameters of the extreme values probability density function.

Region	μ	σ	ξ
Midwest	150.12	39.473	−0.158
Southeast	214.16	40.884	−0.348
Southern	174.06	29.502	0.106

Table 5
Kolmogorov–Smirnov/Lilliefors goodness of fit test (D_{max}).

Region	D_{max}	p-Value
Midwest	0.043	0.157
Southeast	0.066	0.157
Southern	0.073	0.158

Table 6
Return period (years) for the three Brazilian regions based on annual maximum daily rainfall value (MDR) in mm.

Return periods (years)			
MDR (mm)	Midwest	Southeast	Southern
<= 140	1	1	1
150	2	1	1
160	2	1	1
170	2	1	1
180	3	1	2
190	4	1	2
200	5	1	3
210	6	1	4
220	8	2	5
230	12	2	6
240	17	3	8
250	26	3	10
260	40	5	13
270	63	7	17
280	105	11	21
290	181	20	27
300	332	44	34
310	647	130	43
320	1,366	776	54
330	3,189	> 10,000	67
340	8,497	> 10,000	83
350	> 10,000	> 10,000	102
360	> 10,000	> 10,000	125
370	> 10,000	> 10,000	153
380	> 10,000	> 10,000	186
390	> 10,000	> 10,000	225
400	> 10,000	> 10,000	272

The results presented by Assad (1994) indicated for a 260 mm of annual maximum daily rainfall a return period of 100 years until 1990 for the Midwest region. When these results are compared with the series of annual maximum daily rainfall from 1940 to 2011, the return period is 40 years. The change in the behavior of the extreme values for annual maximum daily rainfall in this region seems to be evident.

4. Conclusions

The annual maximum daily precipitation has an increasing trend for the three regions studied, particularly for the Midwest and South regions. For the Midwest and Southeast region the distribution that best fit the annual maximum daily precipitation was the Weibull distribution ($\xi < 0$) and for the Southern region, the Fréchet distribution ($\xi > 0$).

The IPCC (2012) models indicate greater frequency of extreme phenomena in the world. By analyzing the rainfall data for the period 1940–2011, it is observed that the daily maximum annual rainfall exceeding 140 mm occurs at return periods of 1–2 years for the three regions of Brazil. Assad et al. (1992) using rainfall series from 1960 to 1985 indicate that rainfall of 140 mm in the Midwest region occurs at return periods of 10 years.

The Southern and Southeastern regions may be more likely to face dangerous extreme precipitation events. The vulnerability to these events must be considered both for risk analysis of production in agriculture and for adaptation actions in urban areas vulnerable to extreme events and natural disasters. The increase in the return period indicates that losses may reach successive agricultural production being potentially negative to economic projections. The costs of adapting to such events must be measured carefully considering the higher or lower return rate of extreme events as an important factor in the evaluation.

The studies of extreme events require longer and consistent historical series, therefore it must be pointed out as an important area of research and technical work in Brazil. In the specific cases of the Midwest, Southeast and Southern regions, the statistical tests suggested changes in the behavior of extreme maximum daily rainfall, being evidenced in the reduction in the return period of annual maximum daily rainfall greater than 100 mm in all regions. These results are in agreement with the analysis made by the IPCC (2012) for other regions of the globe.

For future work we will study the behavior of the return period in two different time periods, from 1940 to 1970 and 1970 to 2011, to check for change in return period due to changes of meteorological trend of the 1970s.

References

Aguilar, E., Barry, A.A., Brunet, M., Ekang, L., Fernandes, A., Massoukina, M., Mbah, J., Mhanda, A., Nascimento, D.J., do, Peterson, T.C., Thamba Umba, M., Tomou, M., Zhang, X., 2009. Changes in temperature and precipitation extremes in western central Africa, Guinea Conakry, and Zimbabwe, 1955–2006. J. Geophys. Res. 114, D02115. http://dx.doi.org/10.1029/2008JD011010.

Alexander, L.V., Zhang, X., Peterson, T.C., Caesa, J., Gleason, B., Klein Tank, A.M.G., Haylock, M., Collins, D., Trewin, B., Rahimzadeh, F., Tagipour, A., Rupa Kumar, K., Revadekar, J., Griffiths, G., Vincent, L., Stephenson, D.B., Burn, J., Aguilar, E., Brunet, M., Taylor, M., New, M., Zhai, P., Rusticucci, M., Vazquez-Aguirre, J.L., 2006. Global observed changes in daily climate extremes of temperature and precipitation. J. Geophys. Res. 2006, 111. http://dx.doi.org/10.1029/2005JD006290.

Alexandersson, H., 1986. A homogeneity test applied to precipitation data. J. Clim. 6, 661–675.

ANA, 2011. Agência Nacional de Águas—Sistema Nacional de Informações sobre Recursos Hídricos. Accessed in December 2011. ⟨http://www.ana.gov.br/portalsnirh/Esta%C3%A7%C3%B5esdaANA/tabid/359/Default.aspx⟩.

Assad E.D., 1994. Chuvas no cerrado: analise e espacialização. EMBRAPA-CPAC, SPI, Brasília, 423 pp.

Assad, E.D., Evangelista, B., Silva, F.A.M., Cunha, S.A.R., Alves, E.R., Lopes, T.S.S., Pinto, H.S., Zullo Junior, J., 2001. Zoneamento agroclimático para a cultura do café (*Coffea arabica* L.) no Estado de Goiás e sudoeste do Estado da Bahia. Rev. Bras. Agrometeorol. 9, 510–518.

Assad, E.D., Masutomo, R., Lopes Assad, M.L., 1992. Estimativas das predipitações máximas prováveis com duração de 24 horas e de 30 minutos. Caso dos cerrados brasileiro. Pesq. Agropec. Bras 27, 677–686.

Back, A.J., 2001. Seleção de distribuição de probabilidade para chuvas diárias extremas do estado de Santa Catarina. Rev. Bras. Meteorol. 16, 211–222.

Bautista E.A., 2002. A distribuição generalizada de valores extremos no estudo da velocidade máxima do vento em Piracicaba. SP. Dissertation. ESALQ/USP.

Beijo, L.A., Avelar, F.G., 2010. Distribuição generalizada de valores extremos no estudo de dados climáticos: Uma breve revisão. Revista Estatística UFOP 1, 10–16.

Bernier, N.B., Thompson, J.O., Ritchie, H., 2007. Mapping the return periods of extreme sea levels: allowing for short sea level records, seasonality, and climate change. Global Planet. Change **57**, 139–150.

Bertol, I., 2000. Avaliação da erosividade da chuva na localidade de Campos Novos (SC) no período de 1998–1990. Pesq. Agropec. Bras 29, 1453–1458.

Blain, G.C., Moraes, S.O., 2011. Caracterização estatística de oito séries de precipitação pluvial máxima diária da secretaria de agricultura e abastecimento do estado de São Paulo. Rev. Bras. Meteorol. 26, 225–234.

Brown, S.J., Caesar Ferro, C.A.T., 2008. Global changes in extreme daily temperature since 1950. J. Geophys. Res., 113.

Caires, S., Swail, V.R., Wang, X.L., 2006. Projection and analysis of extreme wave climate. J. Clim. 19, 5581–5605.

Carvalho, L.M.V., Jones, C., Silva, A.E., Liebmann, B., Silva Dias, P.L., 2010. The South American Monsoon System and the 1970s climate transition. Int. J. Climatol. 31, 1248–1256.

Casa, A.C. de la, Nasello, O.B., 2012. Low frequency oscillation of rainfall in Córdoba, Argentina, and its relation with solar cycles and cosmic rays. Atmos. Res. 113, 140–146.

Chaves, H.M.L., Piau, L.P., 2008. Efeito da variabilidade da precipitação pluvial e do uso e manejo do solo sobre o escoamento superficial e o aporte de sedimento de uma bacia hidrográfica do Distrito Federal. R. Bras. Ci. Solo 32, 333–343.

Coles, S.G., Tawn, J.A., 1996. Modeling extremes of the areal rainfall process. J. R. Stat. Soc. Ser. B: Methodological 58, 329–347.

Coles, S., 2004. An Introduction to Statistical Modeling of Extreme Values, first ed. Springer, London.

Colodro, G., Carvalho, M.P., Roque, C.G., Prado, R.M., 2002. Erosividade da chuva: distribuição e correlação com a precipitação pluviométrica de Teodoro Sampaio (SP) Revista Brasileira de Ciência do Solo 26, 809–818.

Costa, A.C., Soares, A., 2009. Trends in extreme precipitation indices derived from a daily rainfall database for the South of Portugal. Int. J. Climatol. 29, 1956–1975.

CPTEC, 2012. Centro de previsão de tempo e estudos climáticos. El Niño e La Niña. Accessed in December 2012.⟨http://enos.cptec.inpe.br⟩.

Dawson, T.H., 2000. Maximum wave crests in heavy seas. J. Offshore Mech. Arct. Eng.-Trans. AMSE 122, 222–224.

Dickey, D.A., Fuller, W.A., 1981. Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica 49, 1057–1072.

Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with unit root. J. Am. Stat. Assoc. 74, 427–431.

Feng, S., Nadarajah, S., Hu, Q., 2007. Modeling annual extreme precipitation in China using generalized extreme value distribution. J. Meteorol. Soc. Jpn. 85, 599–613.

Guttorp, P., Xu, J., 2011. Climate change, trends in extreme, and model assessment for a long temperature time series from Sweden. Environmetrics 22, 456–463.

Heaton, M.J., Katzfuss, M., Ramachandar, S., Pedings, K., Gilleland, E., Mannshardt-Shamseldin, E., Smith, R.L., 2011. Spatio-temporal models for large-scale indicators of extreme weather. Environmetrics 22, 294–303.

Heino, R., 1994. Climate in Finland During the Period of Meteorological Observations. Finnish Meteorological Institute Contributions, vol. 12. Finnish Meteorological Institute p. 209.

Hundecha, Y., ST-Hilaire, A., TBMJ, Ouarda, Adlouni, S., Ganchon, P., 2008. A nonstationary extreme value analysis for the assessment of changes in extreme annual wind speed over the Gulf of St. Lawrence, Canada. J. Appl. Meteorol. Climatol. 47, 2745–2759.

IPCC, 2012. Managing the risks of extreme events and disasters to advance climate change adaptation. In: Field, C.B., Barros, V., Stocker, T.F., Qin, D., Dokken, D.J., Ebi, K.L., Mastrandrea, M.D., Mach, K.J., Plattner, G.K., Allen, S.K., Tignor, M., Midgley, P.M. (Eds.), A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, and New York, NY, USA, p. 582.

Jenkinson, A.F., 1955. The frequency distribution of the annual maximum (or minimum) values of meteorological elements. Q. J. R. Meteorol. Soc. 81, 158–171.

Koutsoyiannis, D., 2004. Statistics of extremes and estimation of extreme rainfall: I. Theoretical investigation. Hydrol. Sci. J. 49, 575–590.

Lavenda, B.H., Cipollone, E., 2000. Extreme value statistics and thermodynamics of earthquakes: aftershock sequences. Ann. Geofis. 43, 967–982.

Leadbetter, M.R., Lindgrren, G., Rootzén, H., 1983. Extremes and Related Properties of Random Sequences and Series. Springer Verlag, New York, NY.

Lombardi Neto, F., Moldenhauer, W.C., 1992. Erosividade da chuva: sua distribuição e relação com as perdas de solo em Campinas. Bragrantia 51, 189–196.

Mann, H.B., 1945. Nonparametric tests against trend. Econometrica 13, 245–259.

Mannshardt-Shamseldin, E.C., Smith, R.L., Sain, S.R., Mearns, L.O., Cooley, D., 2010. Downscaling extremes: a comparison of extreme value distributions in point-source and gridded precipitation data. Ann. Appl. Stat 4, 484–502.

Marengo, J.A., 2004. Interdecadal variability and trends of rainfall across the Amazon basin. Theor. Appl. Climatol. **78**, 79–96.

Marengo, J.A., Tomasella, J., Soares, W., Alves, L., Nobre, C., 2011. Extreme climatic events in the Amazon basin. Theor. Appl. Climatol. , http://dx.doi.org/10.1007/s00704-00011-00465-00701.

Markose, S., Alentorn, A., 2005. The Generalized Extreme Value (GEV) Distribution, Implied Tail Index and Option Pricing. Department of Economics, Centre for Computational Finance and Economics Agents (CCFEA). University of Essex p. 37.

Mello, C.R. de, Sá, MAC de, Curi, N., Mello, J.M. de, Viola, M.R., Silva, A.M. da, 2007. Erosividade mensal e anual da chuva no Estado de Minas Gerais. Pesq. Agropec. Bras. 42, 537–545.

Mendes, B.V.M., 2004. Introdução à análise de eventos extremos, first ed. E-papers Serviços Editoriais, Rio de Janeiro.

Menedez, M., Menedez, F.J., Losada, I.J., Graham, N.E., 2008. Variability of extreme wave heights in the northeast Pacific Ocean. Geophys. Res. Lett. 35 (27 November).

Michaelides, S.C., Tymvios, F.S., Michaelidou, T., 2009. Spatial and temporal characteristics of the annual rainfall frequency distribution in Cyprus. Atmos. Res. 94, 606–615.

Miroslava, U., 1992. The extreme value distribution of rainfall data at Belgrade, Yugoslavia. Atmósfera 5, 47–56.

Moreti, D., Carvalho, M.P., Mannigel, A.R., Medeiros, L.R., 2003. Importantes características de chuva para a conservação do solo e da água no município de São Manuel (SP). Rev. Bras. Ciênc. Solo 27, 713–725.

Nadarajah, S., Choi, D., 2007. Maximum daily rainfall in South Korea. J. Earth Syst. Sci. 116, 311–320.

NCDC, 2012. National Climatic Data Center – Global Warming – Frequently Asked Questions. 〈http://www.ncdc.noaa.gov/cmb-faq/globalwarming.html〉 (accessed in December 2012).

Roberts, S.J., 2000. Extreme value statistics for novelty detection in biomedical data processing. IEE Proc.: Sci. Meas. Technol. 147, 363–367.

Romkens, M.J.M., Helming, K., Prasad, S.N., 2001. Soil erosion under different rainfall intensities, surface roughness and soil water regimes. Catena 46, 103–123.

Rusticucci, M., 2012. Observed and simulated variability of extreme temperature events over South America. Atmos. Res. 106, 1–17.

Sahin, S., Cigizoglu, H.K., 2010. Homogeneity analysis of Turkish meteorological data set. Hydrol. Processes 24, 981–992.

Sansigolo, C.A., 2008. Distribuições de extremos de precipitação diária, temperatura máxima e mínima e velocidade do vento em Piracicaba, SP (1917–2006). Rev. Bras. Meteorol. 23, 341–346.

SAS Institute Inc, 2008. SAS/GRAPH 9.2: Statistical Graphics Procedures Guide. 〈http://support.sas.com/documentation/onlinedoc/ graph/index.html〉 (accessed in April 2012).

SAS Institute Inc, 2010. SAS/ETS® 9.22 User's Guide. Cary, NC: SAS Institute Inc.

Shahid, S., Harun, S.B., Katimon, A., 2012. Changes in diurnal temperature range in Bangladesh during the time period 1961–2008. Atmos. Res. 118, 260–270.

Shukla, R., Trivedi, M., Kumar, M., 2010. On the proficient use of GEV distribution: a case study of subtropical monsoon region in India. Anale. Seria Informatica. VIII, 81–92.

Stepánek P.M., 2008. AnClim—Software for Time Series Analysis. Dept. of Geography, Fac. of Natural Sciences, MU, Brno. 1.47 MB.

Subash, N., Singha, S.S., Priya, N., 2011a. Extreme rainfall indices and its impact on rice productivity—a case study over sub-humid climatic environment. Atmos. Res. 98, 1373–1387.

Subash, N., Singha, S.S., Priya, N., 2011b. Variability of rainfall and effective onset and length of the monsoon season over a sub-humid climatic environment. Atmos. Res. 99, 479–487.

Szolgay, J., Parajka, J., Kohnová, S., Hlavčová, K., 2009. Comparison of mapping approaches of design annual maximum daily precipitation. Atmos. Res. 92, 289–307.

Thom, H.C.S., 1966. Some Methods of Climatological Analysis. Geneve: World Meteorological Organization, 53 (WMO, 199, TP, 103, Technical note, 81).

Tuomenvirta, H., 2002. Homogeneity testing and adjustment of climatic time series in Finland. Geophysica 38 (1–2), 15–41.

VanDen Brink, H.W., Konen, G.P., Opsteegh, J.D., 2004. Statistics of extreme synoptic-scale wind speeds in ensemble simulations of current and future climate. J. Clim. 17, 4564–4574.

Vieira, S.R., Lombardi Neto, F., 1995. Variabilidade espacial do potencial de erosão das chuvas do estado de São Paulo. Bragantia 54, 405–412.

Wald, A., Wolfowitz, J., 1940. On a test whether two samples are from the same population. Ann. Math. Stat 11, 147–162.

Wilks, D.S., 2006. Theoretical probability distributions. In: Statistical Methods in the Atmospheric Sciences, first ed. Academic Press, San Diego.

Willems, P., Arnbjerg-Nielsen, K., Olsson, J., Nguyen, V.T.V., 2012. Climate change impact assessment on urban rainfall extremes and urban drainage: methods and shortcomings. Atmos. Res. 103, 106–118.

Zalina, M.D., Desa, M.N.M., Nguyen, V.T.V., Kassim, A.H.M., 2002. Selecting a probability distribution for extreme rainfall series in Malaysia. Water Sci. Technol. 45, 63–68.

Zhang, X.C., Liu, W.Z., 2005. Simulating potential response of hydrology, soil erosion, and crop productivity to climate change in Changwu tableland region on the Loess Plateau of China. Agric. For. Meteorol. 131 (3–4), 127–142.