Inhomogeneities detection in precipitation time series in Portugal using direct sequential simulation

Sara Ribeiro[a] , sribeiro@novaims.unl.pt

Júlio Caineta[a] , jcaineta@novaims.unl.pt

Ana Cristina Costa[a] , ccosta@novaims.unl.pt

Roberto Henriques[a] , roberto@novaims.unl.pt

Amílcar Soares[b] , asoares@tecnico.ulisboa.pt

[a] NOVA IMS, Universidade Nova de Lisboa

Address: Campus de Campolide, 1070-312, Lisboa, Portugal

[b] CERENA – Centro de Recursos Naturais e Ambiente, Instituto Superior Técnico

Address: Avenida Rovisco Pais, 1049-001, Lisboa, Portugal

Corresponding author: Sara Ribeiro

NOVA IMS, Universidade Nova de Lisboa

Address: Campus de Campolide, 1070-312, Lisboa, Portugal

Phone: +351 213 828 610

E-mail: sribeiro@novaims.unl.pt

This is the peer reviewed version of the following article:

Ribeiro, S., Caineta, J., Costa, A. C., Henriques, R., & Soares, A. (2016). Detection of inhomogeneities in precipitation time series in Portugal using direct sequential simulation. Atmospheric Research, 171, 147-158. https://doi.org/10.1016/j.atmosres.2015.11.014, *which has been published in final form at* https://doi.org/10.1016/j.atmosres.2015.11.014

Inhomogeneities detection in precipitation time series in Portugal using direct sequential simulation

Sara Ribeiro[a]
sribeiro@novaims.unl.pt

Júlio Caineta[a]
jcaineta@novaims.unl.pt

Ana Cristina Costa[a]
ccosta@novaims.unl.pt

Roberto Henriques[a]
roberto@novaims.unl.pt

Amílcar Soares[b]
asoares@tecnico.ulisboa.pt

[a] NOVA IMS, Universidade Nova de Lisboa
Address: Campus de Campolide, 1070-312, Lisboa, Portugal

[b] CERENA – Centro de Recursos Naturais e Ambiente, Instituto Superior Técnico
Address: Avenida Rovisco Pais, 1049-001, Lisboa, Portugal

Corresponding author: Sara Ribeiro
NOVA IMS, Universidade Nova de Lisboa
Address: Campus de Campolide, 1070-312, Lisboa, Portugal
Phone: +351 213 828 610
E-mail: sribeiro@novaims.unl.pt

Inhomogeneities detection in precipitation time series in Portugal using direct sequential simulation

Abstract

Climate data homogenisation is of major importance in climate change monitoring, validation of weather forecasting, general circulation and regional atmospheric models, modelling of erosion, drought monitoring, among other studies of hydrological and environmental impacts. The reason is that non-climate factors can cause time series discontinuities which may hide the true climatic signal and patterns, thus potentially bias the conclusions of those studies. In the last two decades, many methods have been developed to identify and remove these inhomogeneities. One of those is based on a geostatistical simulation technique (DSS – direct sequential simulation), where local probability density functions (pdf) are calculated at candidate monitoring stations using spatial and temporal neighbouring observations, which then are used for the detection of inhomogeneities. Such approach has been previously applied to detect inhomogeneities in four precipitation series (wet day count) from a network with 66 monitoring stations located in the southern region of Portugal (1980–2001). That study revealed promising results and the potential advantages of geostatistical techniques for inhomogeneities detection in climate time series. This work extends the case study presented before and investigates the application of the geostatistical stochastic approach to ten precipitation series that were previously classified as inhomogeneous by one of six absolute homogeneity tests (Mann–Kendall, Wald–Wolfowitz runs, Von Neumann ratio, Pettit, Buishand range test, and Standard normal homogeneity test (SNHT) for a single break). Moreover, a sensitivity analysis is performed to investigate the number of simulated realisations which should be used to infer the local pdfs with more accuracy. Accordingly, the number of simulations per iteration was increased from 50 to 500, which resulted in a more representative local pdf. As in the previous study, the results are compared with those from the SNHT, Pettitt and Buishand range tests, which were applied to composite (ratio) reference series. The geostatistical procedure also allowed to fill in missing values in the climate data series. Finally, based on several experiments aimed at providing a sensitivity analysis of the procedure, a set of default and recommended settings is provided, which will help other users to apply this method.

Keywords: Discontinuities; Homogenization; Homogeneity tests; Geostatistical simulation

1. Introduction

Several environmental and atmospheric studies depend on climate data, in which precipitation data assume a vital role. However, its measurement and recording is prone to systematic and random errors (Sevruk et al., 2009; Teegavarapu and Chandramouli, 2005). Systematic errors may occur due to the growth of trees or urbanisation around the location of the weather station or to precipitation gauge malfunctions, such as water loss during measurement, adhesion loss on the surface of the gauge and raindrop splash from the collector. Random errors include sporadic faults which happen during the process of collecting, recording and transmitting precipitation data records (Brunet and Jones, 2011). These non-natural errors are critical as they affect the continuity of precipitation data and ultimately influence the results of models that use precipitation as input. Indices calculated from daily precipitation data, such as the number of wet days per year (wet day count), are also influenced by the errors in the measurement. Spurious shifts often have the same magnitude as the climate signal, such as long-term variations, trends or cycles, and might lead to wrong considerations about the results of the studies (Caussinus and Mestre, 2004).

In order to obtain trustful results, climate data should be free from non-climatic irregularities. Hence, the detection and the correction of these errors are absolutely necessary before any reliable climate study is based on instrumental series (Auer et al., 2005; Brunetti et al., 2012; Domonkos, 2013; Tuomenvirta, 2001). Moreover, the World Meteorological Organization (WMO) emphasises the importance of homogenisation in one of the ten climate monitoring principles: "The quality and homogeneity of data should be regularly assessed as a part of routine operations." (World Meteorological Organization, 2010). Homogenisation includes the following steps (Štěpánek et al., 2006): detection, verification and possible correction of outliers, creation of reference series, homogeneity testing (through various homogeneity tests), determination of inhomogeneities in the light of test results and metadata, adjustment of inhomogeneities and filling in missing values. Various methods have been used in the homogenisation of climate data (Aguilar et al., 2003; Beaulieu et al., 2008; Domonkos et al., 2012; Peterson et al., 1998), and their efficiency is dependent on the climate variable, analysed time period, availability of data or other stations located in the same climatic region which may be used as reference series (Costa and Soares, 2009b). Homogenisation methods can be classified into different groups, depending on their characteristics (Aguilar et al., 2003): objective/subjective, direct/indirect and absolute/relative. Relative methods make use of data from neighbouring stations (called reference stations) for comparison with data series from the candidate station (the station to be homogenised). Absolute methods only consider the data from the candidate station in the detection of inhomogeneities.

Recently, the European initiative (COST Action ES0601) 'HOME' (Advances in homogenisation methods of climate series: an integrated approach), evaluated the performance of a set of statistical homogenisation methods, using a benchmark data set of temperature and precipitation. Due to their excellent performance, the algorithms ACMANT, Craddock, MASH, PRODIGE and USHCN are strongly recommended by Venema et al. (2012). These authors also refer the need to give priority to the homogenisation of precipitation, due to the less good results presented by the contributions for precipitation. Moreover, Domonkos et al. (2012) mention the need of further tests to better understand the performance of homogenisation methods. Due to the diversity of the characteristics of climatic time series, it is essential to perform more tests with different data set properties. These authors provide a thorough literature review on the methodological evolution of the homogenisation methods for temperature. Ribeiro et al. (2015) compare homogenisation methods based on literature reviews and discuss their advantages and disadvantages.

Craddock test (Craddock, 1979) accumulates the normalised differences between the test series and the homogeneous reference series in order to find inhomogeneities. This author applied the method to precipitation time series and concluded that best results were obtained by the use of station pairs with the minimum coefficient of variation of the ratio of the two series. This test is part of the homogenisation package THOMAS, from the Federal Office of Meteorology and Climatology in Switzerland (Begert et al., 2005; Michael Begert, 2015, personal communication).

MASH, Multiple Analysis of Series for Homogenisation (Szentimrey, 1999; 2007) is a homogenisation method originally developed for monthly series. This relative method does not assume reference series as homogeneous. It is a multiple breakpoint detection algorithm that increases its performance taking the problem of significance and efficiency in account. Metadata is used automatically, in particular the possible dates of breakpoints. The algorithm also includes a procedure for the evaluation of the homogenisation results. In the version of the MASH algorithm for daily data, the estimation of daily inhomogeneities is based on the monthly inhomogeneities calculated (Lakatos et al., 2008).

Caussinus and Mestre (2004) introduced a new methodology for the detection of inhomogeneities, which included pairwise comparison, step function fitting, the Caussinus and Lyazhri (1997) algorithm, and variance optimisation. This method, later named PRODIGE, is based on the idea that a series is homogeneous between two change points. Pairwise comparisons are then obtained between the candidate series and the other reference series, creating a series of differences. These series are tested against the Caussinus and Lyazrhi technique. If a common breakpoint is detected in all the difference series, it is attributed to the candidate station. The overall detection and correction are performed by moving neighbourhoods. The correction estimation is based on ANOVA.

ACMANT, Adapted Caussinus-Mestre Algorithm for Networks of Temperature Series (Domonkos, 2011; Domonkos et al., 2011), is a fully automated and relative homogenisation method, which uses the core of the detection and adjustment methods of the PRODIGE (step function fitting and ANOVA correction segments). It applies a bivariate-test for detecting change points that uses the annual mean and the summer-winter difference.

The USHCN homogenisation method is another automatic homogenisation method applied to the United States Historical Climatology Network (Menne and Williams, 2009). The detection part of this method is composed by an early version of SNHT, the cutting algorithm, a Bayesian-based decision about the form of the inhomogeneities (trend-like inhomogeneities can be detected), and a special purpose significance test. Pairwise comparisons are made in an automated way, and metadata can also be used automatically.

The present study provides a follow-up of a previous study (Costa and Soares, 2009b), where a new detection methodology based on direct sequential simulation (DSS) was tested with very auspicious results. However, due to technology and time limitations, a small number of simulations were performed at that time and the number of candidate series was limited to four. In this study, the number of simulations is increased, some sensitivity experiments are performed, and some conclusions are drawn regarding those analyses. For comparison purposes, the same data set was used, which is composed of 66 stations located in the south of Portugal. The analysed climate variable is the annual number of wet days (threshold of 1 mm), calculated from the measured daily value of precipitation, at each weather station, per year. Two sets of candidate stations are used in different stages of the study: the first set, composed of 4 stations, is used for the sensitivity analysis of the DSS parameters; the second set, comprising 10 stations, is used for the sensitivity analysis of the number of neighbour nodes used in the simulation of each node.

The results of the analysis of both sets of candidate stations are compared with the results achieved by Costa and Soares (2009b) through the Standard normality homogenisation test (SNHT, Alexandersson, 1986), the Buishand range test (Buishand, 1982) and the Pettitt test (Pettitt, 1979). These techniques are commonly used and generally accepted for the detection of inhomogeneities (e.g., Sahin and Cigizoglu (2010); Santos and Fragoso, 2013; Wijngaard et al., 2003). Pandžić and Likso (2010) indicate SNHT as one of the most popular methods. Wijngaard et al. (2003) make a brief description of the advantages and disadvantages of those three tests.

Section 2 details the network used in this study. Section 3 briefly describes the methodological framework, particularly the DSS process and the sensitivity analysis methodology. Results are presented in Section 4. Finally, some conclusions and future work are stated in Section 5.

2. Data and study background

The inhomogeneities detection methods were applied to precipitation data from 66 monitoring stations located in the south of Portugal (Figure 1). The annual number of wet days between 1980 and 2001 was used as the studied variable, which was calculated from the daily values of precipitation measured at each station, with a threshold of 1 mm defining a wet day. The annual wet day count was used because it is expected to be representative of important characteristics of variation at the daily scale (Wijngaard et al., 2003). This is one of the extreme climate indices defined by the joint CCl/CLIVAR/JCOMM Expert Team (ET) on Climate Change Detection and Indices (ETCCDI), which may contribute to gain a uniform perspective on observed changes in climate extremes (e.g., Klein Tank et al., 2009). The analysis of changes in climate extremes usually requires daily resolution data, but well-established statistical methods for homogeneity testing daily precipitation data are lacking. According to Wijngaard et al. (2003), this variable generally has a lower variability than the annual amounts, particularly in areas with a large contribution from convective precipitation. These authors also referred the easiness of inhomogeneities detection in this climate index, when compared with annual amounts.

The daily precipitation series were compiled from the European Climate Assessment (ECA) data set and the National System of Water Resources Information (Sistema Nacional de Informação de Recursos Hídricos (SNIRH), currently managed by the Portuguese Environment Agency) database. Data are available through free downloads from the ECA&D project website (http://eca.knmi.nl) and the SNIRH website (http://snirh.apambiente.pt, previously http://snirh.inag.pt), respectively (for more information please refer to Costa and Soares, 2009b).

A complete data set of 96 series was initially subjected to an absolute approach of six statistical tests (Costa and Soares, 2009a, 2009b): Mann-Kendall (Mann, 1945; Kendall, 1975), Wald-Wolfowitz runs test (Wald and Wolfowitz, 1943), Von Neumann ratio test (Von Neumann, 1941), SNHT (Alexandersson, 1986), Pettitt test (Pettitt, 1979), and Buishand range test (Buishand, 1982). Thirty stations whose data series were rejected by at least two of the referred absolute tests were discarded from the network. The remaining 66 stations, which are used in this study, are located in the river basins of Arade, Guadiana, Mira, Ribeiras do Algarve and Sado. A list of codes, names and role (candidate or reference) for the 66 monitoring stations used in the study is presented in the Appendix.

The analysis of precipitation time series is of particular importance in areas such as the south of Portugal due to its susceptibility to the desertification phenomenon (Costa and Soares, 2012; Pereira et al., 2006). Being located at the Mediterranean climate region, the south of Portugal is exposed to long periods of drought, causing land degradation through soil erosion, reduction of vegetation cover and water resources, increase of vulnerability to salinisation and exhaustion, and degradation of agricultural lands. Analysing the quality of precipitation time series contributes to the improvement of the input data that can be used in climate studies such as those related to desertification processes (Costa and Soares, 2009a).

Two sets of candidate stations were defined, containing 4 and 10 stations each (Figure 1). The first set, comprising the stations of Santiago do Escoural (SNIRH 22H.02), Aljezur (SNIRH 30E.01), Alferce (SNIRH 30G.01) and Beja (ECA 666), was used to undertake a sensitivity analysis regarding the number of simulations and other parameters of the DSS method. Those four candidate stations were chosen by Costa et al. (2008) to illustrate the proposed methodology. The four candidate stations have a long term time series with a common period of 20 years, from 1980 to 1999, with the exception of the Santiago do Escoural station in which the value for the year of 1998 is missing. Those four candidate stations are well spatially distributed in the study area, and they also are representative of the differences from elevation in the study area: 48 m (Aljezur), 243 m (Santiago do Escoural), 246 m (Beja) and 328 m (Alferce).

The second set was used for the sensitivity analysis of the number of neighbour nodes, and included the following stations: Azaruja (SNIRH 21K.01), Redondo (SNIRH 22L.01), Comporta (SNIRH 23E.01), Viana do Alentejo (SNIRH 24I.01), Odemira (SNIRH 28F.01), Aldeia de Palheiros (SNIRH 28H.01), Sabóia

(SNIRH 29G.01), Aljezur (30E.01), Picota (SNIRH 30K.02) and Beja (ECA 666). These ten candidate stations were selected since their data sets were rejected by one of the six above-mentioned absolute tests for homogeneity. Their time series have different lengths (Table 1). The time series from Azaruja and Redondo weather stations comprise three values only of the wet day count index (between 1980 and 1982). For these two stations, the major effect of the geostatistical analysis is expected to be the completion of the time series rather than the detection of inhomogeneities. It is also noteworthy that only two weather stations present wet day count values for the year of 2000: Comporta and Viana do Alentejo stations. Data completion, during this procedure, did not include assigning values for that year.

3. Methodological framework

3.1 Homogeneity tests

The two sets of candidate stations were analysed using the SNHT, the Buishand range test, and the Pettitt test. The null hypothesis for the three tests is that data are independent, identically distributed random quantities, and the alternative is that a step-wise shift in the mean (a break) is present. If such step cannot be determined in the time series data, the null hypothesis of homogeneity is not rejected.

The application of the SNHT begins with the creation of a ratio (or difference for temperature data) series between the candidate station values and some regional reference values. This composite series is then standardised. At a given moment v, averages are calculated for the previous and the following period of that composite series. If the difference between those averages meets a critical value, a step is inferred to exist at v, and the series is said to be inhomogeneous. Two of the most mentioned characteristics of this method are its capability to detect the time period where the breakpoint is likely (month or year) and the skill to easily identify an irregularity at the beginning or at the end of the time series (Ducré-Robitaille et al., 2003).

The application of the Buishand range test starts with the calculation of the sum from the differences between each value of the time series and the mean, at a given time period k. The time series will be considered homogeneous if the sum calculated for each k fluctuates around zero, since no systematic deviations will appear. If the time series is inhomogeneous around k, the sum of the differences will reach a maximum (for a negative shift) or a minimum (positive shift). Buishand (1982) provides critical values to evaluate the significance of the test.

Pettitt (1979) proposed a non-parametric test based on the ranks of the observations, which follows the calculation of test statistics proposed by Mann-Whitney. The test statistic will indicate the presence of a change point when its value is maximal or minimal at a given time period. Pettitt (1979) also provides the significance tables for this test.

The Pettitt test is distribution-free, thus it is applicable to variables with a measurement scale that it is, at least, ordinal. Therefore, applying it to testing variable series of the annual number of wet days is not problematic. However, the SNHT and the Buishand range test assume that data are independent, identically normally distributed random quantities. Costa and Soares (2009a) applied four normality tests (Shapiro-Wilk, Kolmogorov-Smirnov, Cramér-von Mises, and Anderson-Darling) to the testing variable series at 107 monitoring stations. This set of stations comprises the initial set of 96 stations considered in this study. Those authors concluded that the normal distribution fits well the testing variable data, thus the SNHT and the Buishand range test can be applied to the wet day count series. Furthermore, Wijngaard et al. (2003) also detected inhomogeneities in European daily precipitation series by testing series of the number of wet days (threshold 1 mm) using the SNHT for a single break, the Buishand range test, the Pettitt test, and the Von Neumann ratio test (Von Neumann, 1941).

3.2 Direct sequential simulation algorithm

In geostatistics, it is common to refer to simulation as a stochastic process, opposed to estimation which is regarded as a deterministic process. Besides correlating the values of different samples of a given variable, geostatistical interpolation adds their spatial structure to the equation. Interpolation usually leads to a smoothing effect of the distribution inferred by the observations and thus to a loss of variance. For example, it is well known that kriging is locally accurate in the minimum error variance sense, but does not provide representations of spatial variability given the smoothing effect of kriging (Yamamoto, 2005). To overcome this limitation, geostatistical stochastic simulation has become a widely accepted procedure to reproduce the spatial variability and uncertainty of highly variable phenomena in geosciences (e.g., Bourennane et al., 2007; Franco et al., 2006; Robertson et al., 2006).

While using the same sequential procedure, some versions of the sequential simulation require different transformations of variables and different approaches to estimate local distribution functions. Examples of those methods are the sequential Gaussian simulation and the sequential indicator simulation (Deutsch and Journel, 1998; Emery, 2004). Following the work of Journel (1994) and Caers (2000), Soares (2001) proposed the direct sequential simulation (DSS) method to reproduce the covariance and the histogram of the variable, a drawback initially found for sequential simulation algorithms without any variable transformation. DSS is also one of the geostatistical simulation methods that has been widely used in different contexts, such as air and water pollutants (e.g., Ribeiro et al., 2014), health (e.g., Oliveira et al., 2013), and climate (e.g., Costa and Soares, 2012; Durão et al., 2010).

Kriging methods used in the simulation process require a stationarity assumption, expressed in two parts. First, the mean of the process is assumed constant and invariant with spatial location (first order stationarity). Second, the variance of the difference between two values is assumed to depend only on the distance between the two points, and not on their location (second order stationarity). Stationarity assumptions on kriging are traditionally accounted for by using local search neighbourhoods so that the dependence on stationarity becomes local (Goovaerts, 1997).

3.3 Homogenisation with a geostatistical approach

As previously stated, this work extends the study by Costa and Soares (2009b), where a new method for the homogenisation of climate data was proposed, and the detection phase was illustrated with the data used in the current study. This method integrates the DSS in its algorithm, which serves the purpose of computing the local probability density functions (pdfs) at every candidate station's location, using the spatial and temporal observations of the surrounding reference stations, and excluding the observations of the candidate station itself. Those pdfs can later be used to identify the presence of irregularities at the candidate time series. An observation will be indicated as an inhomogeneity whenever the interval of a specified probability p (e.g. 0.95), centred in the estimated local pdf, does not contain the corresponding real value of the candidate station (Figure 2). Local pdfs are computed by the aggregation of the simulated maps. The method allow the correction of each irregularity (inhomogeneity or outlier) with the replacement of that value by one of the following options: mean, median, or other statistic calculated from the estimated pdf calculated at the candidate station's location for the inhomogeneous period(s). Similarly to Costa and Soares (2009b), irregular and missing values were replaced by the mean of the estimated pdf. Once a candidate station is tested, the corrected time series is included in the detection process of the next candidate station as a reference time series for the calculation of the local pdf. Hence, inhomogeneities detection in the second candidate station benefits from the corrections applied to the first candidate station, the third one will benefit from the previous two, and so on and so forth. These corrections are expected to be especially important for trend-type inhomogeneities.

The DSS algorithm guarantees that the spatial covariance and the global sample mean and variance of the original variable are reproduced, as well as the histogram (Soares, 2001). Hence, the statistical characteristics of the time series are accounted for, even though only individual annual values are examined for inhomogeneities detection purposes. The variance and the spatial correlation of the time series are considered in the semivariogram model used in the ordinary kriging applied during the simulation process. For long-term time series, it is advisable to split the series in smaller sections, in order to guarantee that the statistical properties are consistent within these sections, as recommended by Durão et al. (2010).

Some of the potential advantages of this method were mentioned in Costa and Soares (2009b): (i) avoids the iterative construction of composite reference series, increasing the contribution of records from closer stations, both in spatial and correlation terms, by accounting for the joint spatial and temporal dependence between observations; (ii) deals with the problem of missing values and varying availability of stations through time, by using different sets of neighbouring stations at different periods, and by including shorter and non-complete records; (iii) seems to be able to detect multiple breaks; (iv) is able to identify breakpoints near the start and end of the time series, while traditional approaches have less power in detecting them.

Two stochastic sequential simulation runs were undertaken for each of the candidate stations sets. Both stochastic simulations used the same semivariogram model from the previous study (Costa et al., 2008): a spherical semivariogram modelled from the complete set of 66 monitoring stations. The spatial dimension was modelled using an isotropic semivariogram model with a range of 72 km, and the temporal dimension was modelled with a range of 1.8 years. Simulations ran in three dimensions (x, y, z), considering time (years) as the *z* dimension.

For a given candidate station, within the first or second candidate data set, time series from the remaining 65 stations were used. Candidate stations are also used as reference stations in the simulations where they are not being tested, since they are also included in the calculation of the pdfs for the other candidate stations. It is also possible to choose the sequence in which the candidate stations are tested. In the case of the present study, the sequence of candidate stations to be tested was set to the descending order of variance. Assuming that large variance of a time series is an indicator of the presence of inhomogeneities, correcting and completing the data of candidate stations with high variance in the first place is expected to enhance the detection of irregularities in the following candidate stations.

3.4 Search parameters and sensitivity analysis

The DSS algorithm generates a set of equally probable realisations for each candidate station, using a set of reference time series, for every unit of time (e.g., every year). Each equally probable realisation is a regular grid of nodes with calculated values. It is possible to manage the set of parameters in the calculation of those realisations, in order to adjust the sequential simulation. Some of those parameters are related to the search of existing values (samples from reference stations and nodes previously calculated in the simulation maps). Search parameters that can be set are described as follows (Deutsch and Journel, 1998):

- Minimum number of data – the minimum number of data (samples or simulated nodes) used in the simulation of each node (minimum value of 1);
- Maximum number of samples – the maximum number of samples used in the simulation of each node (maximum of 64 samples);
- Number of nodes – the maximum number of nodes previously calculated to be considered for the simulation of each node;
- Search radius – maximum distance from the node to be estimated to the samples that may be considered for the calculation of each node; the search radius should cover the entire sampled area in the three directions (x, y, z);
- Search method – two different methods to select the data to be considered for the estimation of the grid nodes: “two part search” searches for samples and estimated grid nodes separately; “data nodes” searches for estimated grid nodes and samples concurrently.

To study the influence of the number of simulations in the detection of the irregularities, different experiments are executed based on the number of undertaken simulations (per candidate station): 50 and 500 simulations. Additionally, two search parameters are tested: search radius and search method. Hence, two sets of tests, comprising four tests each, are established. The first set aims to test the importance of the search radius and the number of simulations, with the “data nodes” search method. The second set tests the number of simulations and the importance of the search radius using the “two part search” method. The provided ranges for the search radius are named as follows: “wide” tests include the entire study area as search radius (220000, 200000, 20 for each of the main directions); and in the “narrow” tests the search radius consists in the variogram ranges (72000, 72000, 1). The minimum and maximum numbers of samples are kept constant in all the tests (1 and 16, respectively), as well as the maximum number of nodes (16). The maximum number of values included in the simulation of a new grid node is 16 for the first set of tests (search method as “data nodes”). In the second set of tests, with the “two part search” method, that maximum number increases to 32 (16 samples plus 16 nodes). In total, eight sensitivity experiments are undertaken (Table 2). All eight experiments are named with the following syntax: “DN”/”2PS” are the acronyms to identify the applied search method (DN – data nodes; 2PS – two part search), the values 50/500 describe the number of simulations computed, and the “narrow”/”wide” expressions identify the search radius used in the test (Table 2). It is important to note that if the minimum number of nodes is not found within the search radius, the radius will be ignored and the search will continue until the minimum number of nodes is reached.

The second set of ten candidate stations are later tested for the number of nodes included in the simulation of new grid nodes. The same search parameters as the “DN 500 wide” test are used, except for the number of nodes: 8, 16 and 32 nodes are tested (Table 2).

4. Results and discussion

4.1 Homogenisation of the first set: four candidate stations

The first set of four candidate stations is used to analyse the search parameters. Experiments named DN 50 wide, DN 50 narrow, DN 500 wide, DN 500 narrow, 2PS 50 wide, 2PS 50 narrow, 2PS 500 wide, and 2PS 500 narrow (Table 2) are performed aiming the detection of inhomogeneities for the candidate stations of Aljezur, Alferce, Santiago do Escoural and Beja. The results of these experiments are compared with SNHT, Pettitt and Buishand range tests, which were applied to a composite (ratio) reference series by Costa and Soares (2009b), named hereafter OTHER tests. The results are also compared with the geostatistical approach conducted by Costa and Soares (2009b).

The four candidate stations are considered inhomogeneous by all of the sensitivity tests (Tables 3 and 4). Comparing the number of performed simulations, the results show that a low number of simulations generally present a high number of detected inhomogeneities. This fact may be explained by the irregularity of the local pdf due to the low number of simulated values used in the pdf calculation (Figure 3).

Analysing the results between the “wide” and “narrow” experiments, the former presents a low number of detections when compared to the latter (Tables 3 and 4). In the case of the “wide” tests, the simulated local pdf of the candidate station is characterised by a higher variance due to the use of values that are more distant from the candidate stations, and therefore tend to be more different (Figure 4). Therefore, the percentile for inhomogeneities detection is also more distant from the mean of the distribution, i.e. the rejection interval is smaller and a lower number of detections is identified. The fact that the "narrow" version is detecting a sequence of years as inhomogeneous might be due to the capability to detect trends. However, a high number of identified irregularities may also correspond to the detection of false positives (i.e., correct values identified as inhomogeneous), which could not be verified because historical metadata was not available.

Comparing the "data nodes" and "two part search" experiments, it is only possible to identify a slight increase of detections when the tests are performed with 500 simulations, for the latter (Tables 3 and 4). However, the tests performed with "two part search" are quite longstanding when compared with the "data nodes" search method. For that reason, and since there are no significant advantages in the use of the "two part search" method it can be concluded that the "data nodes" search method should be the preferred search method.

Comparing the results per candidate station between the sensitivity experiments and the OTHER tests, some considerations must be stated. In the Santiago do Escoural station, the wet day count value for the year of 1989 is considered inhomogeneous by almost all of the sensitivity experiments and by the OTHER tests. The OTHER tests also detect the year of 1988 as irregular; however, the majority of the sensitivity experiments considered the year of 1987. Regarding Alferce, the year classified as a breakpoint by the sensitivity tests is 1983, while the OTHER tests detected the year of 1984. Those detections corresponding to one-year difference may be considered as the same breakpoint detection (Hannart and Naveau, 2009). For the Aljezur station, the year of 1988 is considered inhomogeneous by the eight sensitivity experiments, while the OTHER tests consider Aljezur as homogeneous. The year of 1996 is commonly detected by the sensitivity experiments in the Beja station, while the OTHER tests consider the station as homogeneous.

The organisation responsible for the monitoring network, SNIRH, has been contacted to provide some historical information (metadata) regarding the detected inhomogeneities. SNIRH communicated the absence of information regarding those irregular years.

4.2 Homogenisation of the second set: ten candidate stations

For the second set with ten candidate stations, three experiments with 500 simulations are carried out with different maximum numbers of nodes (8, 16 and 32). The remaining search parameters are: minimum number of data (1), search radius (220000, 200000, 1 for each search direction), and "data nodes" search method. These settings are assumed to be optimal, based on the results achieved in the previous set of tests: a higher number of simulations leads to a more representative pdf; a low minimum number of data contributes to the absence of non-simulated nodes; a wider search radius broadens the possible range of simulated values, while the spatial correlation is guaranteed by the variogram, which may be preferable when the relation between the pdfs of the candidate station and its neighbours is unknown; and, lastly, the "data nodes" search method is much faster than the "two-part search" method, albeit it provides similar results.

The detected inhomogeneous years for that second set are presented in Table 5. Azaruja, Redondo, Viana do Alentejo, Odemira and Aldeia de Palheiros stations are considered homogeneous by all the DN 500 wide and the OTHER tests. Comporta station is classified as inhomogeneous by the OTHER tests in 1986, but it is considered as a homogeneous time series by the sensitivity experiments. Alzejur and Beja stations are classified as homogeneous by the OTHER tests, whereas all the DN 500 wide tests consider them as inhomogeneous in the years of 1988 and 1996. Sabóia and Picota are considered inhomogeneous by all the tests. In the case of the Sabóia weather station, the inhomogeneous period comprises the years between 1981 and 1986: the DN 500 wide tests consider it irregular in the years of 1981, 1982, 1983 and 1986, while the OTHER tests classify it as inhomogeneous in 1984 and 1985. This fact may indicate the presence of a trend in the beginning of this time series. It may also be due to non-natural changes at that weather station (e.g., change of instrumentation, relocation of the time station, or change in the data collection procedure). In this case, metadata would be an essential auxiliary for the understanding of this inhomogeneous period detected (Trewin, 2013). Regarding the Picota weather station, the year of 1988 is commonly identified as inhomogeneous by all the tests. The DN 500 wide experiments also identified the years of 1993, 1995 and 1998.

Concerning the two stations included in both the first and second test sets, Aljezur and Beja, and in particular Aljezur, it is important to note that the detected inhomogeneities are different. For this station, two years are detected in the DN 500 wide experiment, when tested as part of the set containing four candidate stations (the years of 1988 and 1998). In the second set, the Aljezur station only has a breakpoint in 1988. This may be explained by the fact that the second test set uses references with different data, as some of them were tested and corrected when they previously assumed the role of candidates. These three tests, for the sensitivity of the maximum number of nodes included in the simulation, prove that increasing the number of nodes does not provide a substantial additional proficiency in the detection of inhomogeneities, as the detected irregularities are almost the same. Moreover, increasing the maximum number of nodes significantly extends the required processing time.

Figure 5 presents the wet day count values per year of corrected and original series for the second set of candidate series. The values of the wet day count for the year 2000 are not calculated. Although the original time series present high variability, the corrected series capture their temporal pattern appropriately in most cases.

5. Conclusion

Several sensitivity experiments were conducted in order to evaluate the performance of a method based on DSS for the detection of inhomogeneities in climate data series, continuing a previous study undertaken by Costa et al. (2008). In this sense, the geostatistical approach was used as a qualifying method for quality control, being compared with other detection methods. The inhomogeneities detected cannot be considered outliers, but breakpoints, because Costa and Soares (2009a) exhaustively scrutinised the same data set in order to remove the outliers present in the data.

A data set comprised of 66 monitoring weather stations located in the south of Portugal was compiled and the wet day count precipitation index was used as the climate variable. From the initial data set, two smaller sets, comprising four and ten candidate stations each, were selected in order to test some parameters used by the DSS algorithm. The evaluated parameters included the number of simulations and the search neighbourhood specification, thus determining the number of nodes to be included in each simulation of a grid node. It was concluded that this method succeeds in the detection of inhomogeneities for climate data series, since it provides similar results to other popular detection techniques (Costa and Soares, 2009b). Hence, the geostatistical approach has only been evaluated as an inhomogeneities detection technique, so it has not been sufficiently assessed to be considered a homogenisation procedure. Accordingly, the geostatistical approach should be further investigated.

It was also possible to conclude that a higher number of simulations leads to better detection results, since it produces a smoother local distribution function. However, increasing the number of nodes included in the simulations did not bring enough benefits to justify the increasing computing time. Another advantage of the geostatistical approach is the filling in of missing values in the climate data series. The estimation of missing data is one of the most important tasks required in many hydrological modelling studies (Teegavarapu and Chandramouli, 2005). Moreover, the inclusion of new values to replace missing data may similarly contribute to the improvement of the testing of the following candidate stations, since these new data values will also be considered in the process.

It should also be emphasised the importance of metadata to confirm inhomogeneities detection, regarding artificial discontinuities inserted to data series due to changes in the measurement procedure, as also referred in the third monitoring climate principle provided by the WMO: “The details and history of local conditions, instruments, operating procedures, data processing algorithms, and other factors pertinent to interpreting data (metadata) should be documented and treated with the same care as the data themselves.” (World Meteorological Organization, 2010).

Costa and Soares (2009b) considered the geostatistical approach as slow and laborious, since it required a considerable amount of user interaction in the creation of data files and parameters settings prior to its initialisation. For that reason, it was not practical to assess a large number of candidate stations. Nonetheless, that study revealed promising results and proved the potential advantages of geostatistical techniques for inhomogeneities detection in climate time series. The present study brought new developments to the geostatistical approach. The process was enhanced in terms of computational efficiency and ease of application, enabling the increase of the number of candidate stations and the number of simulations.

The performed analyses are very important for the construction of a new software package that uses the DSS in the homogenisation algorithm that should be further investigated. All the steps carried out in the procedure were completed with the assistance of computer scripts which will lead to the development of a new software package. This new package, called gsimcli, is a work in progress project aiming to make the inhomogeneities detection and homogenisation of climate data series easier and more straightforward, with less user interaction, by also including the management and automatic creation of input data files. The set of parameters that provided the best results in the sensitivity analysis (DN 500 wide test with 16 nodes) will be included in gsimcli as the default values.

Acknowledgements

The authors gratefully acknowledge the financial support of “Fundação para a Ciência e Tecnologia” (FCT), Portugal, through the research project PTDC/GEO-MET/4026/2012 (“GSIMCLI - Geostatistical simulation with local distributions for the homogenization and interpolation of climate data”).

The authors also thank three anonymous reviewers for their valuable suggestions, which helped them to improve the quality of this paper.

Appendix A: List of the 66 monitoring stations used in the study depicting the role of the station series (candidate in the set of 4 stations, candidate in set of 10 stations, or reference station)

ID	Name/Location	Role
SNIRH 21K.01	Azaruja	Candidate (set of 10)
SNIRH 22E.01	Águas de Moura	Reference station
SNIRH 22H.02	Santiago do Escoural	Candidate (set of 4)
SNIRH 22L.01	Redondo	Candidate (set of 10)
SNIRH 22M.01	Santiago Maior	Reference station
SNIRH 23E.01	Comporta	Candidate (set of 10)
SNIRH 23F.01	Montevil	Reference station
SNIRH 23G.01	Barragem de Pego do Altar	Reference station
SNIRH 23I.01	Alcáçovas	Reference station
SNIRH 23K.01	São Manços	Reference station
SNIRH 23L.01	Reguengos	Reference station
SNIRH 24I.01	Viana do Alentejo	Candidate (set of 10)
SNIRH 24J.02	Alvito	Reference station
SNIRH 24J.03	Cuba	Reference station
SNIRH 24K.01	Portel	Reference station
SNIRH 24K.02	Vidigueira	Reference station
SNIRH 24N.01	Amareleja (D.G.R.N.)	Reference station
SNIRH 25G.01	Azinheira Barros	Reference station
SNIRH 25P.01	Barrancos	Reference station
SNIRH 26I.01	Santa Vitória	Reference station
SNIRH 26I.02	Barragem do Roxo	Reference station
SNIRH 26J.04	Albernoa	Reference station
SNIRH 26K.01	Salvada	Reference station
SNIRH 26L.01	Serpa	Reference station
SNIRH 26L.02	Santa Iria	Reference station
SNIRH 26M.01	Herdade de Valada	Reference station
SNIRH 27G.01	Relíquias	Reference station
SNIRH 27H.01	Panóias	Reference station
SNIRH 27H.02	Barragem do Monte da Rocha	Reference station
SNIRH 27J.01	São Marcos da Ataboeira	Reference station
SNIRH 27J.02	Corte Pequena	Reference station
SNIRH 27J.03	Vale de Camelos	Reference station
SNIRH 27K.01	Algodôr	Reference station
SNIRH 27K.02	Corte da Velha	Reference station
SNIRH 28F.01	Odemira	Candidate (set of 10)
SNIRH 28H.01	Aldeia de Palheiros	Candidate (set of 10)
SNIRH 28I.01	Almodôvar	Reference station
SNIRH 28J.01	Alcaria Longa	Reference station
SNIRH 28J.03	Santa Barbara de Padrões	Reference station
SNIRH 28K.01	São João dos Caldeireiros	Reference station

SNIRH 28K.02	Álamo	Reference station
SNIRH 28L.01	Mértola	Reference station
SNIRH 29G.01	Sabóia	Candidate (set of 10)
SNIRH 29I.02	Santa Clara-a-Nova	Reference station
SNIRH 29J.05	Guedelhas	Reference station
SNIRH 29K.01	Martim Longo	Reference station
SNIRH 29K.03	Malfrades	Reference station
SNIRH 29L.03	Monte dos Fortes	Reference station
SNIRH 30E.01	Aljezur	Candidate (sets of 4 & 10)
SNIRH 30E.02	Marmelete	Reference station
SNIRH 30E.03	Barragem da Bravura	Reference station
SNIRH 30G.01	Alferce	Candidate (set of 4)
SNIRH 30H.03	São Bartolomeu de Messines	Reference station
SNIRH 30H.04	Santa Margarida	Reference station
SNIRH 30J.01	Barranco do Velho	Reference station
SNIRH 30K.01	Mercador	Reference station
SNIRH 30K.02	Picota	Candidate (set of 10)
SNIRH 30L.04	Alcaria (Castro Marim)	Reference station
SNIRH 31G.02	Porches	Reference station
SNIRH 31H.02	Algoz	Reference station
SNIRH 31J.01	São Brás de Alportel	Reference station
SNIRH 31J.04	Estoi	Reference station
SNIRH 31K.01	Santa Catarina (Tavira)	Reference station
SNIRH 31K.02	Quelfes	Reference station
ECA 666	Beja	Candidate (sets of 4 & 10)
ECA 675	Lisboa Geofísica	Reference station

References

Aguilar, E., Auer, I., Brunet, M., Peterson, T.C., Wieringa, J., 2003. *Guidelines on Climate Metadata and Homogenization*, Paul Llansó (Ed.), WMO/TD No. 1186, WCDMP No. 53, World Meteorological Organization, Geneva, Switzerland, 55 pp.

Alexandersson, H., 1986. A homogeneity test applied to precipitation data. *J. Climatol.*, 6, 661–675. doi: 10.1002/joc.3370060607

Auer, I., Bohm, R., Jurkovic, A., Orlik, A., Potzmann, R., Schoner, W., Ungersbock, M., Brunetti, M., Nanni, T., Maugeri, M., Briffa, K., Jones, P., Efthymiadis, D., Mestre, O., Moisselin, J.M., Begert, M., Brazdil, R., Bochnicek, O., Cegnar, T, Gajic-Capka, M., Zaninovic, K., Majstorovic, Z., Szalai, S., Szentimrey, T., Mercalli, L., 2005. A new instrumental precipitation dataset for the greater alpine region for the period 1800-2002. *Int. J. Climatol.*, 25(2), 139–166. doi:10.1002/joc.1135

Beaulieu, C., Seidou, O., Ouarda, T.B.M.J., Zhang, X., Boulet, G., Yagouti, A., 2008. Intercomparison of homogenization techniques for precipitation data. *Water Resour. Res.*, 44(2). doi: 10.1029/2006WR005615

Begert, M., Schlegel, T., Kirchhofer, W., 2005. Homogeneous temperature and precipitation series of Switzerland from 1864 to 2000. *Int. J. Climatol.*, 25(1), 65–80. doi: 10.1002/joc.1118

Bourennane, H., King, D., Couturier, A., Nicoullaud, B., Mary, B., Richard, G.., 2007. Uncertainty assessment of soil water content spatial patterns using geostatistical simulations: An empirical comparison of a simulation accounting for single attribute and a simulation accounting for secondary information. *Ecol. Model.* 205, 323–335. doi: 10.1016/j.ecolmodel.2007.02.034

Brunet, M., Jones, P., 2011. Data rescue initiatives: bringing historical climate data into the 21st century. *Clim. Res.*, 47(1), 29–40. doi: 10.3354/cr00960

Brunetti, M., Caloiero, T., Coscarelli, R., Gullà, G., Nanni, T., Simolo, C., 2012. Precipitation variability and change in the Calabria region (Italy) from a high resolution daily dataset. *Int. J. Climatol.*, 32(1), 57–73. doi: 10.1002/joc.2233

Buishand, T., 1982. Some methods for testing the homogeneity of rainfall records. *J. Hydrol.*, 58(1), 11–27. doi: 10.1016/0022-1694(82)90066-X

Caers, J., 2000. Adding local accuracy to Direct Sequential Simulation. *Math. Geol.*, 32(7), 815–850. doi: 10.1023/A:1007596423578

Caussinus, H., Lyazrhi, F., 1997. Choosing a Linear Model with a Random Number of Change-Points and Outliers. *Ann. Inst. Statist. Math*, Vol. 49, No. 4, 1997, 761–775. doi:10.1023/A:1003230713770

Caussinus, H., Mestre, O., 2004. Detection and correction of artificial shifts in climate series. *J. Roy. Stat. Soc. C-App.*, 53, 405–425. doi: 10.1111/j.1467-9876.2004.05155.x

Costa, A.C., Soares, A., 2009a. Trends in extreme precipitation indices derived from a daily rainfall database for the South of Portugal. *Int. J. Climatol.*, 9(13), 1956–1975. doi: 10.1002/joc.1834

Costa, A.C., Soares, A., 2009b. Homogenization of climate data: review and new perspectives using geostatistics. *Math.* Geosci., 41(3), 291–305. doi: 10.1007/s11004-008-9203-3

Costa, A.C., Soares, A., 2012. Local spatiotemporal dynamics of a simple aridity index in a region susceptible to desertification. *J. Arid. Environ.*, 87, 8–18. doi: 10.1016/j.jaridenv.2012.05.005

Costa, A.C., Negreiros, J., Soares, A., 2008. Identification of inhomogeneities in precipitation time series using stochastic simulation, in: Soares, A., Pereira, M. J. and Dimitrakopoulos, R. (Eds.), *geoENV VI – Geostatistics for Environmental Applications*, Springer, Netherlands, 275–282. doi: 10.1007/978-1-4020-6448-7_23

Craddock, J., 1979. Methods of comparing annual rainfall records for climatic purposes. *Weather*, 34(9), 332–346. doi: 10.1002/j.1477-8696.1979.tb03465.x

Deutsch, C.V., Journel, A.G., 1998. *GSLIB: Geostatistical Software Library*. Oxford University Press.

Domonkos, P., 2011. Adapted Caussinus-Mestre Algorithm for Networks of Temperature series (ACMANT). *Int. J. Geosci.*, *02*(03), 293–309. doi:10.4236/ijg.2011.23032

Domonkos, P., 2013. Measuring performances of homogenization methods. *Időjárás, Q. J. Hungarian Meteorol. Serv.*, 117(1), 91–112.

Domonkos, P., Poza, R., Efthymiadis, D., 2011. Newest developments of ACMANT. *Adv. Sci. Res.*, 6, 7–11. doi:10.5194/asr-6-7-2011

Domonkos, P., Venema, V., Auer, I., Mestre, O., Brunetti, M., 2012. The historical pathway towards more accurate homogenisation. *Adv. Sci. Res.*, 8, 45–52. doi:10.5194/asr-8-45-2012

Ducré-Robitaille, J.-F., Vincent, L A., Boulet, G., 2003. Comparison of techniques for detection of discontinuities in temperature series. *Int. J. Climatol.*, 23(9), 1087–1101. doi: 10.1002/joc.924

Durão, R.M., Pereira, M.J., Costa, A.C., Delgado, J., Del Barrio, G., Soares, A. 2010. Spatial–temporal dynamics of precipitation extremes in southern Portugal: a geostatistical assessment study. *Int. J. Climatol.*, 30(10), 1526–1537. doi: 10.1002/joc.1999

Emery, X., 2004. Properties and limitations of sequential indicator simulation. *Stoch. Env. Res. Risk A.*, 18(6), 414–424. doi: 10.1007/s00477-004-0213-5

Franco, C., Soares, A., Delgado, J., 2006. Geostatistical modelling of heavy metal contamination in the topsoil of Guadiamar river margins (S Spain) using a stochastic simulation technique. *Geoderma*, 136, 852–864. doi: 10.1016/j.geoderma.2006.06.012

Goovaerts, P., 1997. *Geostatistics for Natural Resources Evaluation*. Applied Geostatistics Series, Oxford University Press.

Hannart, A., Naveau, P., 2009. Bayesian multiple change points and segmentation: Application to homogenization of climatic series, *Water Resour. Res.*, 45, W10444. doi: 10.1029/2008WR007689.

Journel, A.G., 1994. Modeling uncertainty: some conceptual thoughts, in: Dimitrakopoulos, R. (Ed.), *Geostatistics for the Next Century*, Kluwer Academic Pub., Dordrecht, The Netherlands, pp. 30–43. doi: 10.1007/978-94-011-0824-9_5

Kendall, M., 1975. *Rank correlation methods*. Charles Griffin, London.

Klein Tank, A.M.G., Zwiers, F.W., Zhang, X., 2009. *Guidelines on Analysis of extremes in a changing climate in support of informed decisions for adaptation*. Climate data and monitoring, WCDMP No.72, WMO-TD No.1500, World Meteorological Organization, Geneva, Switzerland, 1–56.

Lakatos, M., Szentimrey, T., Bihari, Z., Szalai, S., 2008. Homogenization of daily data series for extreme climate indeces calculation. In M. Lakatos, T. Szentimrey, Z. Bihari and S. Szalai (Eds.), *Proceedings of the Sixth Seminar for Homogenization and Quality Control in Climatological Databases*, World Meteorological Organization, Budapest, Hungary, WCDMP No. 76, WMO-TD No. 1576, 100–109.

Mann, H., 1945. Non-parametric tests against trend. *Econometrica*, 13(3), 245–259. doi: 10.2307/1907187

Menne, M.J., Williams, C.N., 2009. Homogenization of temperature series via pairwise comparisons, *J. Climate*, 22, 1700–1717, doi:10.1175/2008JCLI2263.1

Oliveira, A.R., Branquinho, C., Pereira, M., Soares, A., 2013. Stochastic Simulation Model for the Spatial Characterization of Lung Cancer Mortality Risk and Study of Environmental Factors. *Math. Geosci.*, 45(4), 437–452. doi: 10.1007/s11004-013-9443-8

Pandžić, K., Likso, T. 2010. Homogeneity of average annual air temperature time series for Croatia. *Int. J. Climatol.*, 30, 1215–1225. doi: 10.1002/joc.1022.

Pereira, L.S., Louro, V., Rosário, L., Almeida, A., 2006. Desertification, territory and people, a holistic approach in the Portuguese context, in: Kepner, W.G., Rubio, J.L., Mouat, D.A., Pedrazzini, F. (Eds.), *Desertification in the Mediterranean Region: a Security Issue*. NATO Security Through Science Series, Vol. 3, 269–289. doi: 10.1007/1-4020-3760-0_11

Peterson, T.C., Easterling, D.R., Karl, T.R., Groisman, P., Nicholls, N., Plummer, N., Torok, S., Auer.I., Boehm, R., Gullett, Vincent, L., Heino, R., Tuomenvirta, H., Mestre, O., Szentimrey, T., Salinger, J., Forland, E., Hanssen-Bauer, I., Alexandersson, H., Jones, P., Parker, D., 1998. Homogeneity adjustments of *in situ* atmospheric climate data : a review. *Int. J. Climatol.*, 18, 1493–1517. doi: 10.1002/(SICI)1097-0088(19981115)18:13<1493::AID-JOC329>3.0.CO;2-T

Pettitt, A.N., 1979. A non-parametric approach to the change-point detection. *Appl. Stat.*, 28(2), 126–135. doi: 10.2307/2346729

Ribeiro, M.C., Pinho, P., Llop, E., Branquinho, C., Soares, A., Pereira, M.J., 2014. Associations between outdoor air quality and birth weight: a geostatistical sequential simulation approach in Coastal Alentejo, Portugal. *Stoch. Env. Res. Risk A.*, 28(3), 527–540. doi: 10.1007/s00477-013-0770-6

Ribeiro, S., Caineta, J., Costa, A.C., 2015. Review and discussion of homogenisation methods for climate data, *Phys. Chem. Earth.*, in press.

Robertson, R.K., Mueller, U.A., Bloom, L.M., 2006. Direct sequential simulation with histogram reproduction: A comparison of algorithms. *Comput. Geosci.*, 32(3), 382–395. doi: 10.1016/j.cageo.2005.07.002

Sahin, S., Cigizoglu, H.K., 2010. Homogeneity analysis of Turkish meteorological data set. *Hydrol. Process.*, 24(8), 981–992. doi:10.1002/hyp.7534

Santos, M., Fragoso, M., 2013. Precipitation variability in Northern Portugal: Data homogeneity assessment and trends in extreme precipitation indices. *Atmos. Res.*, 131, 34–45. doi: 10.1016/j.atmosres.2013.04.008

Sevruk, B., Ondrás, M., Chvíla, B., 2009. The WMO precipitation measurement intercomparisons. *Atmos. Res.*, 92(3), 376-380. doi: 10.1016/j.atmosres.2009.01.016

Soares, A., 2001. Direct sequential simulation and cosimulation. *Math. Geol.*, *33*(8), 911–926. doi: 10.1023/A:1012246006212

Štěpánek, P., Řezníčková, L., Brázdil, R., 2006. Homogenization of daily air pressure and temperature series for Brno (Czech Republic) in the period 1848–2005, in: M. Lakatos, T. Szentimrey, Z. Bihari and S. Szalai (Eds.), *Proceedings of the fifth seminar for homogenization and quality control in climatological databases*, World Meteorological Organization, Budapest, Hungary, WMO-TD No. 1493,106-121.

Szentimrey, T., 1999. Multiple Analysis of Series for Homogenization (MASH), *Proceedings of the Second Seminar for Homogenization of Surface Climatological Data*, Budapest, Hungary; WMO, WCDMP-No. 41, WMO-TD 1962, 27–46.

Szentimrey, T., 2007. Multiple Analysis of Series for Homogenization (MASH v3.02), Hungarian Meteorological Service, 68 pp.

Teegavarapu, R., Chandramouli, V., 2005. Improved weighting methods, deterministic and stochastic data-driven models for estimation of missing precipitation records. *J. Hydrol.*, *312*(1-4), 191–206. doi: 10.1016/j.jhydrol.2005.02.015

Trewin, B., 2013. A daily homogenized temperature data set for Australia. *Int. J. Climatol.*, *33*(6), 1510–1529. doi: 10.1002/joc.3530

Tuomenvirta, H., 2001. Homogeneity adjustments of temperature and precipitation series? Finnish and Nordic data. *Int. J. Climatol.*, *21*(4), 495–506. doi: 10.1002/joc.616

Venema, V., Mestre, O., Aguilar, E., Auer, I., Guijarro, J., Domonkos, P., Vertacnik, G., Szentimrey, T., Štěpánek, P., Zahradníček, P., Viarre, J., Muller-Westermeier, G., Lakatos, M., Williams, C., Menne, M., Lindau, R., Rasol, D., Rustemeier, E., Kolokythas, K., Marinova, T., Andresen, L., Acquaotta, F., Fratianni, S., Cheval, S., Klancar, M., Brunetti, M., Gruber, C., Prohom Duran, M., Likso, T., Esteban, P., Brandsma, T., 2012. Benchmarking homogenization algorithms for monthly data. *Clim. Past*, 8(1), 89–115.

Von Neumann, J., 1941. Distribution of the ratio of the mean square successive difference to the variance. *Ann. Math. Stat.*, 12(4), 367–395.

Wald, A., Wolfowitz, J., 1943. An exact test for randomness in the non-parametric case based on serial correlation. *Ann. Math. Stat.*, 14(4), 378–388

Wijngaard, J.B., Klein Tank, A.M.G., Können, G.P., 2003. Homogeneity of 20th century European daily temperature and precipitation series. *Int. J. Climatol.*, 23(6), 679–692. doi: 10.1002/joc.906

World Meteorological Organization, 2010. *Guide to Climatological Practices*, WMO No. 100, third edition, World Meteorological Organization, Geneva, Switzerland.

Yamamoto, J.K., 2005. Correcting the smoothing effect of ordinary kriging estimates. *Math. Geol.* 37(1), 69–94. doi: 10.1007/s11004-005-8748-7

Tables' captions

Table 1 - Length of annual time series for wet day count, per candidate station (dark grey - presence of value, light grey - missing value).

Table 2 - Search parameters used in the different sensitivity experiments.

Table 3 - Inhomogeneities detected for each of the sensitivity experiments (four candidate stations) using the "data nodes" search method.

Table 4 - Inhomogeneities detected for each of the sensitivity experiments (four candidate stations) using the "two part search" method.

Table 5 - Inhomogeneities detected for the second set of ten candidate stations.

Figures' captions

Figure 1 - Location of the 66 monitoring stations in the south of Portugal.

Figure 2 - DSS procedure schema and local pdf for a candidate station.

Figure 3 – Local pdfs of four candidate stations computed with 50 and 500 simulations (DN 50 wide and DN 500 wide sensitivity experiments).

Figure 4 – Local pdfs of four candidate stations computed with "narrow" and "wide" search methods (DN 500 wide and DN 500 narrow sensitivity experiments).

Figure 5 - Corrected versus original time series per candidate station.