Indecis

Integrated approach for the development across Europe of user oriented climate indicators for GFCS high-priority sectors: Agriculture, disaster risk reduction, energy, health, water and tourism

Work Package 3

Deliverable 3.2a

Recommended Homogenisation Techniques based on Benchmarking Results

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This report arises from the Project INDECIS which is part of ERA4CS, an ERA-NET initiated by JPI Climate, and funded by FORMAS (SE), DLR (DE), BMWFW (AT), IFD (DK), MINECO (ES), ANR (FR), with co-funding by the European Union's Horizon 2020 research and innovation programme

The report for the Deliverable 3.2 (D3.2a) entitled: *Report on Recommended Homogenisation Techniques based on Benchmarking Results* is presented in this document, which has been conducted by the University Rovira i Virgili (URV) for the Work Package 3 (WP3 on Data Quality and Homogeneity) committed under the European ERA4CS Joint Call for Transnational Collaborative Research Project entitled *Integrated approach for the development across Europe of user oriented climate indicators for GFCS sectors: agriculture, disaster risk reduction, energy, health, water and tourism* (INDECIS: Grant agreement no.: 690462, <u>http://www.indecis.eu/</u>).

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1. Introduction

Many long surface instrumental time series are available to study climate change and variability worldwide. These datasets are the basis for assessing century scale trends, for the validation of climate models as well as the detection and attribution of climate change at regional scale. Nevertheless, the value of these datasets strongly depends on the homogeneity of time series. In fact, most of the long time series are affected by non-climatic factors that can introduce discontinuities in time series in terms of a shift or a gradual trends leading an artificial trends on data. Inhomogeneities can arise for a number of reasons such as station relocations, instrument/shelter changes, changes to surrounding environment and changes to observing/reporting practices (Trewin, 2010). Identifying the correct change point and magnitude for any inhomogeneity is difficult, even after detection, a series of decisions are required as to whether and how to adjust the data. This is especially problematic for large datasets where the whole process by necessity is automated (Willet et al., 2014). Thus, it is crucial to apply the appropriate correction method to get temporal and spatial comparability of any time series against itself or towards other time series before developing a climate analysis (Aguilar et al., 2003).

2. Homogenisation benchmarking projects

Benchmarking, in climate homogenization data context, is the assessment of homogenization algorithm performance against a set of realistic synthetic worlds of station data where the locations and size/shape of inhomogeneities are known *a priori* (Willet et al., 2014). Crucially, these inhomogeneities are not known to those performing the homogenization, only those performing the assessment. Assessment of both the ability of algorithms to find change points and accurately return the synthetic data to its clean form (prior to addition of inhomogeneity) has three main purposes: i) quantification of uncertainty remaining in the data due to inhomogeneity ii) inter-comparison of climate data products in terms of fitness for a specified purpose iii) providing a tool for further improvement in homogenization algorithms. The only way to measure the skill of a homogenisation algorithm for realistic conditions is to test it against a benchmark. The main benchmarking projects developed so far are described below.

2.1. HOME Project

The HOME project (<u>www.homogenisation.org</u>) is the most comprehensive benchmarking exercise to date and was developed in the framework of COST Action ES060 (HOME: 2006-



2011). The main objective of the Action was to achieve a general method for homogenizing climate and environmental datasets. The method was derived from the most adapted statistical procedures for detection and correction of varying parameters at different space and time scales. HOME used stochastic simulation to generate realistic networks of European temperature and precipitation records. Inhomogeneities were added to all stations and multiple homogenisation algorithms were tested showing that relative homogenisation methods performed best in the HOME benchmark. From the results of HOME-COST Action (Venema et al., 2012), a clear conclusions were obtained: i) Homogenization procedures improves climate data and does not cause artificial trends ii) Modern algorithms, which are designed to also work with an inhomogeneous reference, are clearly better than traditional ones and iii) Two new software packages containing some of the methods recommended by HOME are now available. The code has been produced by Olivier Mestre, École Nationale de la Météorologie, Météo France, Tolouse". **HOMER** (for monthly data) and **HOM/SPLIDHOM** (for daily data).

2.2. MULTITEST Project

The MULTITEST project (2015-2017) (http://www.climatol.eu/MULTITEST/) was a successful work to update and improve the results of a preliminary comparison exercise (Guijarro, 2011). The homogenization methods implemented in software packages were evolved since HOME project, and new inter-comparison performances were in need. MULTITEST project used synthetic datasets of monthly values of temperature and precipitation from 100 station locations to test several homogenization software packages over a variety of inhomogeneity problems. Test results were assessed through the comparison of the solutions provided by the tested packages with the true original homogeneous series by computing RMSE, errors of the trends, errors in the means and errors in standard deviations. Some homogenization methods performed better than others in a benchmarking exercise by computing statistical tests mentioned above.

2.3. ISTI Benchmark Dataset

The International Surface Temperature Initiative (ISTI) (<u>http://www.surfacetemperatures.org/</u>) developed the first comprehensive benchmarking system for homogenization of monthly land surface air temperature records on the global scale (Willet et al., 2014). Additional variables such



as maximum and minimum temperature as well as diurnal temperature range were also included at daily and sub-daily time-scales. The collection of all available surface air temperature records into an open access, traceable and version-controlled databank were crucial to maximize the value of the data through a robust international framework of benchmarking and assessment for product inter-comparison and uncertainty estimation. The focus were put on the uncertainties arose from the presence of inhomogeneities in monthly temperatures. In the benchmarking process, creation of global-synthetic temperature series close to the real-world database allowed to quantify the know inhomogeneities. Hence, algorithmic strengths and weakness were also assessed to quantify inhomogeneity uncertainties.

A relevant work related to benchmarking procedures is in need to be also mentioned here. The PhD Thesis defended by Rachel E. Killick (Killick, 2016) feeds into the larger ISTI project undertaking the creation of a synthetic and clean daily temperature series across four climatic diverse regions in United States. This was the first inter-comparison study to assess homogenization algorithm performance on daily temperature data. Inhomogeneity structures were added to the synthetic series to create constant shifts. Daily temperatures were modelled for the exploration of inhomogeneities impact on the homogenization algorithm performance. Eight homogenization techniques were applied to the corrupt data to assess the ability in change point detection and to return series closer to the clean data. This procedures enabled the possibility to quantify uncertainties in daily temperature data after homogenization.



3. Description of homogenisation techniques

Many algorithms exist with varying strengths, weakness and levels of skill. While these algorithms can improve the homogeneity of the data, some degree of uncertainty is extremely likely to remain depending on methodological choices (Venema et al., 2012).

The most commonly used method to detect and remove the effects of artificial changes is the relative homogenisation approach, which assumes that nearby stations are exposed to almost the same climate signal and that thus the differences between nearby stations can be used to detect inhomogeneities. In relative homogenisation testing, a candidate time series is compared to multiple surrounding stations either in a pairwise fashion or to a single composite reference time series computed for multiple nearby stations (Venema et al., 2012).

Most commonly used relative homogenisation methods are listed and described below.

3.1. HOMER

HOMER (Homogenisation Software in R) is a recently developed method for homogenising monthly and annual temperature and precipitation data. The last version called as HOMER 2.6 is available at; http://www.homogenisation.org/v 02 15/index.php?option=com_content&view=article&id=93:homer &catid=1:general&Itemid=1. It includes the best features of some other state-of-the-art methods such as PRODIGE (Caussinus and Mestre, 2004) and ACMANT (Domonkos, 2011). PRODIGE and ACMANT has the same theoretical base regarding the optimal segmentation with dynamic programming, an information theory based formula for determining the number of segments in time series and a network-wide unified correction model (ANOVA). The results of blind test experiments conducted during COST Action ES0601 (Venema et al., 2012) validates these approaches, since PRODIGE and ACMANT rank among the best methods for homogenising monthly and annual climate data. HOMER is an interactive semi-automatic method. In applying HOMER, users can choose a partly subjective pairwise comparison technique that is adapted from PRODIGE. Users can add subjective decisions based on metadata or research experiences (Mestre et al., 2013).

The structure of HOMER has built in a way that it intends to exploit optimally the positive characteristics of the contributing methods. The HOMER procedure is as follows: Detection is an iterative process. The initial detection phase usually reveals the most obvious changes which are corrected. Analysing the



result of this correction allows us to create an updated set of detected changes on a network. The joint detection is accompanied by the pairwise detection for allowing the use of metadata and for checking the results. The ACMANT detection follows the first cycle of detection and correction, since ACMANT detection needs pre-homogenized reference series. Note that correction is always performed on the initial data, simply by updating the set of the validated change-points before running ANOVA. The process ends, whenever pairwise, joint-detection, and ACMANT bivariate detection find no additional changes on corrected series.

3.2. ACMANT

ACMANT (Adapted Caussinus-Mestre algorithm for homogenizing networks of monthly temperature data: Domonkos, 2011) was developed from PRODIGE during the HOME period. ACMANT 3.1 is available at; <u>http://www.c3.urv.cat/softdata.php</u>. However, in contrast with PRODIGE and HOMER, ACMANT is fully automatic and it applies reference series built from composites for time series comparisons. Precipitation and temperature data can be performed at daily or monthly time scale (Domonkos, 2014 and 2015). ACMANT applies a pre-homogenization process in a way that the double use of the same spatial connection is excluded and it coordinates the operations on different time scales (from multiannual to monthly) in a unique way.

3.3. CLIMATOL

CLIMATOL is an R contributed package that integrates various routines to detect and correct inhomogeneities that remains in climate data (Guijarro, 2016). CLIMATOL 3.0 is available at; http://www.climatol.eu/. Daily data are used as input, which is submitted to a basic quality control before creating monthly series. CLIMATOL applies the Standard Normal Homogeneity Test (SNHT) (Alexandersson and Moberg, 1997) as the basis for data homogenisation at monthly time-scale. This method is based on the application of iterative process using a candidate time series together with a group of reference series. Then, all of them are used as candidate and reference time series during the process. Taking into account that the probability that all time series are affected by a shift at the same time is really poor, the comparison between candidate and reference time series should detect abrupt shifts and artificial trends in all stations. CLIMATOL includes multiple functions to make the process easier, such as functionalities to prepare input data, the ability to homogenize large datasets and data interpolation in a grid after homogenisation. Accompanying post-processing functions provide climatic summaries, OLS trends and grids of the homogenized series.



3.4. MASH

The MASH method (Multiple Analysis of Series for Homogenisation) (Szentimrey, 1998) was developed in the Hungarian Meteorological Service as a relative homogenisation method to detect and correct inhomogeneities by not assuming reference series are homogeneous. Possible break points can be detected and adjusted through mutual comparisons of series within the same climatic area. A multiple break points detection procedure were developed which assess significance and efficiency. Conventional statistics were applied to obtain estimated break points and can be adjusted by using them and interval estimates. MASH system is able to verify trough the evaluation of the actual and the final stage of the homogenisation procedure. The basic conception of the verification procedure is that confidence in the homogenized series can be increased by the joint comparative mathematical examination of the original and the homogenised series. MASHv3.03 (available at; https://www.met.hu/en/omsz/rendezvenyek/homogenization and interpolation/software/ is able to homogenize daily temperature and precipitation data where daily inhomogeneities can be derived from the monthly ones. Metadata can also be used automatically.

3.5. RHtests

The RHtestsV4 is an R software package written by Xiolan Wang and Yang Feng (Climate Research Division; Environment Canada) (Wang et al., 2010) created to homogenise daily and monthly temperature RHtestsV4 is available data. at: http://etccdi.pacificclimate.org/software.shtml. It can be used to detect, and adjust for, multiple change points that could exist in a data series that can have first order autoregressive errors. It is based on the penalized maximal t test and the penalized maximal F test, which are embedded in a recursive testing algorithm. The problem of uneven distribution of false alarm rate and detection power is also greatly alleviated by using empirical penalty functions. The time series being tested can have zero-trend or a linear trend throughout the whole period of record. A homogenous time series that is well correlated with the base series may be used as a reference series. The RHtestsV4 includes Quantile-Matching adjustments that are estimated with the use of a reference series. Additional functions such as mean-adjustments, choice of the segment to which the base series is to be adjusted (referred to as the base segment) and choices of the nominal level of confidence at which to conduct the test.



A software package called RHtests_dlyPrcp, which contains a set of functions for use in detection and adjustment of shifts in nonzero daily precipitation amounts, were also developed and is made available online at: (<u>http://cccma.seos.uvic.ca/ETCCDMI/software.shtml</u>). This includes a quantile matching algorithm for adjusting shifts in nonzero daily precipitation series, which is applicable to other nonnegative data such as wind speed and dewpoint depression.

3.6. AnClim and ProClimDB

The ProClimDB software (available at; <u>http://www.climahom.eu/software-solution/proclimdb</u>) was developed for processing climatological data (Stepanek, 2008) at daily and sub-daily scales at was aimed at complementing Anclim software (available at: http://www.climahom.eu/software-solution/anclim) which was developed for time series homogenization testing and analysis. Both softwares were created by Petr Stepanek (Global Change Research Institute, Czech Academy of Sciences). AnClim works under Windows and provides a user friendly platform from data treatment (QC and homogenization) to time series analysis ordered in a sequence (steps). Multiple functions are available for data management, transformation and analysis, such as; viewing the data, statistics computation, finding outliers, adjusting time series by applying absolute and relative homogenization techniques (SNHT, Vincent method,...), missing values infilling and time series analysis (trends, filtering,...). A lot of graphical components are feasible to show results in a clear way and better understanding.

3.7. Vincent's Method

Vincent et al., 2002 developed a method to homogenize daily temperatures (maximum and minimum) from annual and monthly adjustments. Inhomogeneities were first identified in annual mean, maximum and minimum temperature time series. Annual temperature anomalies are obtained at a candidate as well as at a number of surrounding stations. A first model is applied to determine if the candidate series is homogeneous. Significant autocorrelations at several consecutive low lags indicates a nonhomogeneous time series. A second model is applied to determine the position and magnitude of the shift. Monthly adjustments are obtained by applying an algorithm to the time series of the twelve individual months for the change point identified in the annual series. The monthly adjustments therefore correspond to the magnitude of the shift for



each month. Three approaches are considered for the adjustment of daily temperatures according to Vincent's method. The first one is simply apply the monthly adjustments directly to daily temperatures. However, this approach results in artificial discontinuities at the beginning/end of each month. Second approach is based on the procedure used to obtain monthly parameters. The second model is applied to each individual daily series for the change point identified in the annual series producing 365 daily adjustments. The main disadvantages of this approach are that the adjustments are subjected to substantial variability. The last approach is based on an interpolation procedure to provide an improved time-interpolation scheme that preserves monthly means and does not yield artificial shifts at the joining of calendar months. Finally, daily adjustments are derived from monthly adjustments obtained by linear interpolation between midmonth values.

3.8 HOM

The higher-order moments method (HOM) of homogenizing daily temperature (Della-Marta and Wanner 2006) is a technique which could be used when there are no overlapping measurements for the candidate station. This method is performed as a sequence of operations. First, homogeneous subperiods are defined for the candidate and as many reference stations as possible. Then, the highly correlated reference stations is found for the most recent inhomogeneity. The relationship between the paired candidate and reference series is modelled before the inhomogeneity and the temperature at the candidate station is predicted after the inhomogeneity by using observations from reference series. A paired difference series between the predicted and observed temperatures is created after the inhomogeneity. Then the probability distribution of the candidate station is found in the homogeneous subperiod 1 and the homogeneous subperiod 2. Each temperature difference is binned in the difference series according to its associated predicted temperature in a decile of the probability distribution of the candidate station in the homogeneous subperiod 1. A smoothly varying function between the binned decile differences is fitted to obtain an estimated adjustment for each percentile. Using the probability distribution of the candidate station in homogeneous subperiod 2, the percentile of each observation in homogeneous subperiod 2 is determined and adjusted by the amount calculated in previous step. Then, the homogeneous subperiod 2 is now homogenized with



respect to homogeneous subperiod 1. The HOM method reliably creates a daily composite record between two homogeneous subperiods of a candidate station that have different statistical moments of the mean, variance and skewness.

3.9. SPLIDHOM

The spline daily homogenization method (SPLIDHOM) relies on an indirect nonlinear regression method (Mestre et al., 2011). The goal is to provide realistic adjustments of individual temperature measurements of a candidate series, given the temperature of the series by itself, by means of an estimated transfer function. Like in HOM method (Della-Marta and Wanner 2006), close and well-correlated references series are needed and the definition of homogeneous subperiods are the same. Despite this, SPLIDHOM adjustments differ due to they are based on nonparametric regression whereas HOM involves fitting data to several candidate distributions. SPLIDHOM technique shows an improvement over HOM and Vincent's method for the correction of extreme quantiles if the correlation is lower than 0.9, Vincent's method is often superior and thus should be neglected. Therefore, the adjustment of extreme quantiles is only sensible if a highly correlated reference station exists. Correlation of the candidate station is the essential parameter that drives performance of both HOM and SPLIDHOM.

3.10. HOMAD

As previously mentioned, Della-Marta and Wanner 2006 developed a method for adjusting the mean and higher-order moments (HOM) of daily temperature series, which was used to homogenize daily western European and western Mediterranean temperature time series (Della-Marta et al. 2007). HOM has notable advantages compared to Vincent's method (Vincent et al. 2002), particularly when highly correlated reference temperature series are available. However, HOM depends on the choice of regression function parameters and it is affected by data autocorrelation. The correction of inhomogeneities affecting daily series is a delicate process. Therefore, it is essential to address potential sources of uncertainty in the adjustment estimations. On these grounds, improved version of HOM was proposed, the higher-order moments for auto-correlated data (HOMAD) (Toreti et al., 2010).

Since the complexity of a real inhomogeneity is not easily reproducible, the evaluation of correction methods can be performed in simple situations (e.g., Gaussian random term added to the series after a



certain point). HOMAD simulations outperforms HOM when applied to small samples, whereas the two methods provide similar results for larger ones. Further investigation is necessary to address other sources of uncertainty; however, results provide valuable information on HOMAD/HOM behavior and the relevance of autocorrelation and an objective selection of regression parameters. Three daily temperature series from the Mediterranean were used to compare the performance of HOMAD and HOM (Toreti et al., 2010). Differences between the adjustments suggested by the two methods were found in all three cases. These differences influence the outcome of analyses performed on the homogenized series.



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