# ACMANT: HOMOGENISING TEMPERATURE SERIES WITH CONFIDENCE AND ACCURACY

Peter DOMONKOS
*Centro de Cambio Climático, Univ. Rovira i Virgili, Campus Terres de l'Ebre, Tortosa*
**peter.domonkos@urv.cat**

**ABSTRACT**

Changes in location, instrumentation or observing hours, and lot of other factors may cause artificial biases in observed climatic data. These undesired biases are often referred as inhomogeneities of time series, and homogenisation is applied for their elimination. For spatially dense networks of temperature observations the use of objective statistical methods is recommended. After a successful homogenisation the observable climatic characteristics (trend, variability, distribution function, etc.) are substantially closer to the reality than in the raw inhomogeneous series. ACMANT is a newly developed, fully automatic method for homogenising networks of monthly temperature series. Its excellent performance has been proved with a series of objective experiments, among others with the tests of the benchmark of the European project HOME. ACMANT is particularly good in the minimisation of root mean squared error, because it harmonises the work on different time scale in a unique way.

**Key words:** homogenisation, data quality control, observed climatic data, surface temperature, efficiency.

**RESUMEN**

Los cambios en la ubicación, la instrumentación o las horas de observación, y muchos otros factores pueden causar sesgos artificiales en las series temporales. Estos sesgos no deseados se refiere a menudo como non-homogeneidades de las series, y se aplica homogeneización para su eliminación. Para las redes espaciales densas de las observaciones de temperatura la utilización de métodos estadísticos objetivos se recomienda. Después de una homogeneización con éxito, las características observables (tendencia del clima, la variabilidad, la función de distribución, etc.) están mucho más cerca de la realidad que en la serie de datos originales. ACMANT es el resultado de nuevo desarrollo metodológico para homogeneizar las redes de las series mensuales de la temperatura. El funcionamiento de ACMANT es totalmente automático. Su excelente rendimiento ha sido probado con experimentos objetivos, entre otros, con las pruebas del proyecto europeo HOME. ACMANT es particularmente bueno en la minimización de error cuadrático medio, debido a la armonización del trabajo en las escalas temporales diferentes de una manera única.

**Palabras claves:** homogeneización, control de calidad de datos, datos climáticos observados, temperatura, rendimiento.

## 1. INTRODUCTION

One important source of our knowledge about climate is the analysis of observed climatic data. The examination of statistical characteristics of observed data makes it possible to assess the general climatic characteristics of specified geographical regions, as climatic means, extreme values, trends and many other features. For the examination of spatial and temporal variability data of standardised observation techniques is needed. At present large number of long series of observed climatic data are available for climatic analyses, since the usefulness of observations was recognised very early in the development of climatology. The lengths of surface temperature, precipitation and air pressure time series are often longer than 100 years and sometimes even longer than 200 years.

Although it has been devoted a great effort to maintain the uniformity of technical conditions of observations since the very beginning, it often could not be managed for many reasons (economical and political reasons, changes of the preferred measurement method, changes in human resources, etc.). Technical changes that may influence the temporal and spatial comparativeness (with usual word: homogeneity) of observed data are often documented and archived together with the observations to foster the most accurate evaluation of long- term climatic variability and climate trends. These documents are named metadata.

The thorough inspection of observed data shows that in spite of the efforts to maintain uniformity, most observed time series contain inhomogeneities (IHs) i.e. biases that are caused by the alteration of technical conditions and not by the climate. Before climate variability examinations IHs should be eliminated, but the information of metadata is often missing or incomplete, and even when it is available with fair completeness, the quantification of this information is problematic. An example: if documents show that a station was relocated from site A to site B at time $j$, it is a clear indication that the data after $j$ are not homogeneous with the data before $j$. But this piece of metadata does not indicate the degree of the bias in the observed values due to the relocation. The most typical form of IHs is the sudden shift relative to the true climate, as it occurs in the previous example at time $j$. These shifts are often referred as change-points. Change-points in the mean values are examined much more frequently than the shifts in other statistical properties, since the importance is the highest and the detection is relatively the easiest for the changes in the means. Note that an IH may also develop in gradual way, e.g. due to growing urbanisation. In this case the local change cannot be characterised by one change-point, but it can be fairly approached by a series of change-points and this approach is frequent in homogenisation methods.

When large number of time series are available for the same climatic region, the observed data contain the common climatic signal in each series of the network. It is often the case with surface temperature and precipitation total time series, particularly in Europe and North America. For such networks homogenisation of observed climatic data can be performed with statistical tools. Differences (for temperature) or ratios (for precipitation) of time series must be constructed and in the time evolution of such series (hereafter: relative time series) the variation of local effects appears, since the common climatic signal has been dropped. Note that although the urban climate is a true climate for the people who live in town, the local urban effects are detected as IHs in relative homogenisation procedures, and macroclimatic signals only that are common for an entire climatic region are preserved.

Large number of methods have been developed for the statistical homogenisation of observed time series (Aguilar et al. 2003, Reeves et al. 2007, Domonkos et al. 2012, etc.). Their use is recommended for the homogenisation of relative time series of dense observing networks (so-called relative homogenisation) and not for the direct homogenisation of the series under inspection (so-called absolute homogenisation), because otherwise the true climatic variability cannot be distinguished from the technical born IHs. Once the IHs have been detected in relative time series, the "culprit" time series are adjusted to eliminate the non-climatic biases from the observations. There are various techniques to find the culprit series and it is usually not difficult when the signal to noise ratio is large. Exceptions from the rule of relative homogenisation may occur when the IHs are large enough to identify them even with absolute homogenisation and when metadata supports the homogenisation.

A relative homogenisation method has at least three segments: (i) Time series comparisons for performing relative homogenisation; (ii) Identification of timings of IHs; and (iii) Assessment of the adjustment factors for the accomplishment of the homogenisation.

Recently an European project "Advances in homogenisation methods of climate series: an integrated approach" (HOME) has been devoted to develop and test the homogenisation methods applied in climatology. During HOME a new method (ACMANT) was developed for homogenising monthly temperatures and the tests of various methods with the surrogated temperatures section of HOME benchmark (hereafter: Benchmark) showed the highest efficiency for ACMANT. In this paper the causes of the success of ACMANT are analysed, some efficiency results are shown for ACMANT and some other widely used homogenisation methods, and some pieces of advice are provided about the practical use of homogenisation methods.

## 2. DEVELOPMENT OF ACMANT

The full description of ACMANT has already been published (Domonkos, 2011a). Instead of repeating the full description here, we concentrate on the factors that explain the good performance of the method. The ACMANT was developed from the earlier method PRODIGE whose creators were Caussinus and Mestre (2004). This fact is included also in the name of ACMANT (Applied Caussinus Mestre Algorithm for homogenising Networks of Temperature series). Therefore PRODIGE is characterised here first then the main novelties added during the development of ACMANT are presented.

### 2.1. PRODIGE

In most homogenisation methods one change-point is detected only in one particular step, and the steps of the detection procedure are organised sequentially (e.g. in t-test, Staudt et al., 2007), or more frequently, hierarchically (e.g. in SNHT [Standard Normal Homogeneity Test] by Alexandersson, 1986; Bayes-test by Perrault et al. 2000; RHTest by Wang et al. 2007, among many others). However, there exist detection methods for direct detection of multiple structures of change-points, these are MASH (Multiple Analysis of Series for Homogenization, Szentimrey, 1999), PRODIGE (Caussinus and Mestre, 2004) and ACMANT (Domonkos, 2011a). The direct detection methods have small but significant surplus efficiency relative to hierarchic methods when the cutting algorithm (Easterling and Peterson, 1995) is applied to organize the steps of the detection. (In the cutting algorithm a time series is split into two parts at the timing of the change-point detected last then the two parts of the series are examined for further change-points. The cutting can be repeated any times until the part-series are long enough for further examination.) The surplus efficiency of direct methods is even larger relative to sequential methods (Domonkos, 2011b). As we see, PRODIGE is one of the very few methods with direct detection of multiple structures of change-points.

In PRODIGE step functions are fitted to the relative time series. In the model function each step is a change-point and the values are constant between any two steps. In this model the only one form of IHs is the sudden shift of the means, other type IHs of means are approached with series of change-points, while IHs of the higher moments of the statistical distribution are not considered. We mention that there exist methods which detect two kinds of IHs, namely trend-like IHs and change-points of means (late version of SNHT by Alexandersson and Moberg, 1997; MLR [Multiple Linear Regression] by Vincent, 1998; USHCN [United States Historical Climatology Network homogenisation] by Menne and Williams, 2009), but tests show that the latter methods are not more effective than the methods detecting change-points only (Domonkos, 2011b). Its likely explanation is that the detection methods of two kinds of IHs often detect trend instead of two adjacent change-points and vice versa due to the masking effect of background noise. (The origin of the background noise in relative time series is the natural variability of differences between station values.) The search of the optimal step function for a given number of change-points is based on the minimisation of the sum of squared error.

Let a relative time series of length $n$ be denoted by $\mathbf{T}$ ($\mathbf{T} = t_1, t_2, \ldots t_n$). It contains $K$ change-points and thus $K + 1$ segments. The timings of change-points are $j_1, j_2, \ldots j_K$. All the possible combinations of timings are examined, and the minimum is selected with Eq.1 .

$$\min_{[j_1, j_2, \ldots j_K]} \sum_{k=0}^{K} \sum_{i=j_k+1}^{j_{k+1}} (t_i - \overline{\mathbf{T_k}})^2 \tag{1}$$

In eq. 1, $\mathbf{T_k}$ stands for the $k$-th section of series $\mathbf{T}$ and the upper stroke denotes arithmetic average. Note that although the number of possible change-point combinations is very large, it was revealed rather early how one can construct an economic computer program for accomplishing this task (Hawkins, 1972). It is referred as dynamic programming algorithm, and with its application the time consumption of this examination is insignificant even for large $n$ and $k$ (in true homogenisation tasks the most frequent time resolution is annual, and $n$ is seldom larger than 200). The search of the best fitting step function is repeated for each possible $K$ then the optimal segmentation with the most appropriate $K$ is retained. With rising $K$ better fitting can be achieved, but the increase of change-points is penalised in the evaluation (Eq. 2).

$$\ln\left\{1 - \frac{\sum_{k=0}^{K} (j_{k+1} - j_k) \cdot (\overline{\mathbf{T_k}} - \overline{\mathbf{T}})^2}{\sum_{i=1}^{n} (t_i - \overline{\mathbf{T}})^2}\right\} + \frac{2K}{n-1} \ln(n) \tag{2}$$

Eq. (2) is the Caussinus – Lyazrhi criterion (Caussinus and Lyazrhi, 1997). For the finally selected step function this score is minimal. The development of this score has theoretical basis and tests prove that it functions well in practice.

In PRODIGE the correction-terms are calculated by an equation system in which the observed values are considered to be the compositions of the climate effect and the station effect. The climate effect changes in time freely, but it is common for each time series. The station effects change both spatially and temporally, but they are constant between two adjacent change-points of a given time series. The name of the procedure is ANOVA. The main advantage of ANOVA is that it takes into account the common effects of IHs in different time series. If the macroclimate is the same for all the series (it is approximately true in a given climatic area) and all the timings of change-points are accurately detected (this point is more critical), ANOVA serves the optimal estimation of the correction-terms (Caussinus and Mestre, 2004).

### 2.2. ACMANT

ACMANT has been developed from PRODIGE and the favourable characteristics described in Sect. 2.1 are preserved. PRODIGE has been modified with three main additional characteristics.

• ACMANT applies a bivariate detection which means that change-points of two time series are searched jointly. The two time series are the series of annual means and the series of summer-winter differences. This development is based on the fact that technical changes in surface temperature observations often cause different biases according to the seasons of the year. More specifically, the degree of bias often depends on the intensity of irradiation, thus it is larger in summer than in winter and the seasonal cycle is quasi-harmonic (Drougue et al., 2005; Domonkos and Štěpánek, 2009; Brunet et al., 2011, etc.). In the bivariate detection the search of optimal step function is performed with Eqs. 3 and 4.

$$\min_{[j_1, j_2, \ldots j_K]} \left\{ \sum_{k=0}^{K} \sum_{i=j_k+1}^{j_{k+1}} (t_i - \overline{\mathbf{T_k}})^2 + c_0 (td_i - \overline{\mathbf{TD_k}})^2 \right\} \tag{3}$$

$$\ln\left\{ 1 - \frac{\sum_{k=0}^{K} (j_{k+1} - j_k) \cdot \left[ (\overline{\mathbf{T_k}} - \overline{\mathbf{T}})^2 + c_0 (\overline{\mathbf{TD_k}} - \overline{\mathbf{TD}})^2 \right]}{\sum_{i=1}^{n} (t_i - \overline{\mathbf{T}})^2 + c_0 (td_i - \overline{\mathbf{TD}})^2} \right\} + \frac{2K}{n-1} \ln(n) \tag{4}$$

In Eqs. 3 and 4 **TD** stands for the series of summer-winter differences, while $c_0$ is an empirical constant ($c_0 = 0.5$). The values of **TD** are derived from the monthly temperature values ($t_{j,m}$, $m$ denotes the serial number of month in year $j$, see Eq. 5).

$$td_j = \frac{t_{j,5} + t_{j,6} + t_{j,7} + 0.5t_{j,8} - t_{j,11} - t_{j,12} - t_{j,1} - 0.5t_{j,2}}{3.5} \tag{5}$$

The application of bivariate detection is generally favourable when two variables often have change-points with the same timings (see another example in Guijarro, 2011). Bivariate detection could be implanted into many other detection methods, not only into the fitting of optimal step function. In the development of ACMANT, PRODIGE was chosen to be the parent method due to its known good performance.

• In ACMANT the work on different time scales is organised in a unique way. As the signal to noise ratio is the highest for annual series and long-term biases can be detected with the highest reliability, IHs are searched in the annual scale first and the minimum length of a segment is 3 years at this phase. In the second phase, the timings of change-points detected in the first phase are re-examined on the monthly scale, applying a 4-year symmetric window around the timing of the first detection. In the third phase, short-term large biases are searched on the monthly scale, after the biases caused by long-term IHs are eliminated with ANOVA. After this phase the list of change-points is supplied with the change-points of short-term biases then the application of ANOVA on the raw data is repeated.

• ACMANT is a fully automatic method. It is capable of treating time series of different lengths, missing data and outliers. For converting PRODIGE to an automatic procedure, several technical changes have been introduced. The detailed description can be read in Domonkos (2011a). The software of ACMANT, its manual and scientific description are freely downloadable from the Internet (www.homogenisation.org or www.c3.urv.cat/members/pdomonkos.html).

## 3. EFFICIENCY RESULTS

The efficiency of ACMANT in comparison with the efficiencies of the other best methods participated in HOME is examined using Benchmark (Fig. 1). The root mean squared error of

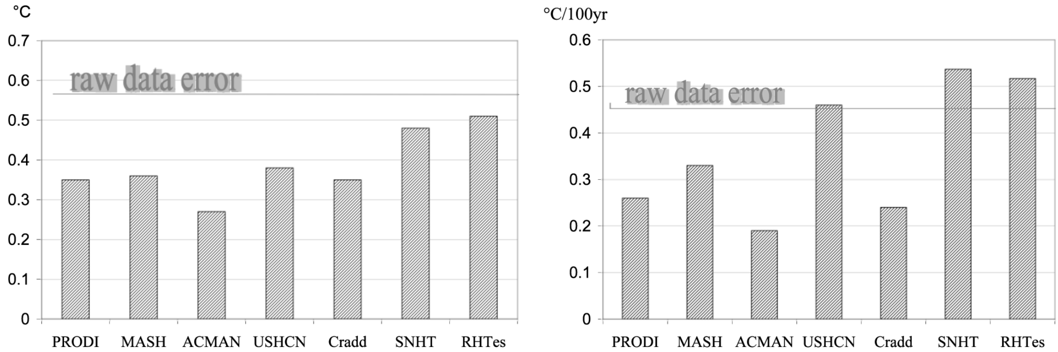


FIG. 1: *Residual errors of homogenised time series in the tests with HOME Benchmark. Left: Root mean squared error (RMSE) of monthly values. Right: RMSE of network-mean linear trends for the entire lengths of time series. The names of some homogenisation methods are shortened to their first five letters. Cradd = Craddock-test (Craddock, 1979).*

monthly data and that of the network-mean linear trends are shown. In Fig. 1 small values indicate small residual errors. Most results indicate positive efficiency in homogenising Benchmark, and the relatively poor performances in the right panel of Fig. 1 are due to the high rate of missing data in the early part of the Benchmark period (Venema et al. 2012).

It can be seen that the relatively popular SNHT and RHTest have significantly poorer performance than the five best methods, while the performance of ACMANT is clearly the best among all the methods examined. However, in the development of ACMANT Benchmark had already been used, thus a slight over-fitting effect appears in Fig. 1. Further tests with moving parameters (Domonkos, 2012) proved that ACMANT is really the best in homogenising Benchmark, although with less advantage than which is shown in Fig. 1.

## 4. DISCUSSION

### 4.1. Are there other good homogenisation methods than ACMANT and PRODIGE?

HOME found five methods to be better than the other tested methods in homogenising monthly temperatures, i.e. PRODIGE, ACMANT, MASH, USHCN and the subjective homogenisation with Craddock-test (Venema et al. 2012). Although method-dependent differences in the observed performances can be found even for the highlighted five methods (hereafter HIGH5), all of the

HIGH5 are recommended by HOME, first, because the performance for each of them shows large positive difference relative to the other, not highlighted methods, and second, because further tests with other test datasets than Benchmark might show other rank orders than the experiments with Benchmark. Note that although USHCN seems significantly poorer than the other methods of HIGH5 in Fig. 1, USHCN has been selected as one of the best methods because it produced the lowest false alarm rate (Venema et al., 2012) and this characteristic also has great importance. Taking into account that large number of known homogenisation methods were not tested by HOME, one may think that among them other very efficient methods can be found than HIGH5. However, as we know the theoretical structures of the homogenisation methods applied in climatology, we assess that there is no other method is recommendable than HIGH5, except one, HOMER. HOMER was constructed at the late phase of HOME. Its development was based on the test results with Benchmark, and followed a similar way than the development of ACMANT short time before. The parent method of HOMER is PRODIGE and the bivariate detection and the precision on monthly scale are adopted from ACMANT. However, HOMER is not an automatic method and it differs in large number of details from ACMANT. HOMER has not been tested yet, but it could be considered an additional method of HIGH5, relying on its known properties.

### 4.2. How can be applied the experiences with PRODIGE and ACMANT to the homogenisation of other climatic elements?

The statistical properties of climatic variables often strongly differ and these differences often claim the application of different homogenisation methods. ACMANT has been constructed only for homogenising monthly temperatures. Even it is not optimal for homogenising temperatures observed in the tropical belt or monsoon regions, because there the assumption of harmonic seasonal cycle is false. Note that tests have proved that the latter problem is minor, as ACMANT still performs well when the biases have no seasonal cycle at all (not shown). Beyond surface temperature, precipitation total is the climatic variable which has dense observing networks and the observed data are often subdued to relative homogenisation. According to our present knowledge, MASH, PRODIGE, HOMER and the Craddock-test can be recommended for the homogenisation of precipitation datasets.

### 4.3. Exceptions

From the analyses presented in the previous sections it could seem that any homogenisation task should be treated by HIGH5 or at least with a method that is derived from one of HIGH5. However, we know some important examples when relative time series cannot be constructed, but the changes in the distribution function clearly indicate IHs (Dai et al. 2011, Petrovic, 2004, etc.). Another kind of exception is the application of parallel measurements. The most accurate homogenisation possible is based on the dual observation of the same climatic element in the same observing site but with different technical conditions. When such data is available, the correction terms can be directly calculated from them (e.g. Brunet et al. 2011).

## 5. CONCLUDING REMARKS

We have a general concept of relative homogenisation and the linked statistical tools (HIGH5) with demonstrated skills. The application of HIGH5 is recommended when the conditions are given for accomplishing relative homogenisation. After checking the existence of the necessary conditions, the homogenisation is relatively easy, particularly with the use of automatic methods such as for instance ACMANT.

The methodological development of homogenisation methods still goes on, even for monthly temperature and precipitation. ACMANT and HOMER are also under further developments.

Daily data homogenisation is not discussed here, due to the limited extent of the paper.

The diversity of homogenisation tasks does not justify the use of homogenisation methods of relatively poor performance when the conditions for using high quality relative time series are given. Unfortunately, there are large number of methods (old ones and newer ones) which have seemingly appealing mathematical structure, but they have not been tailored well to the task of homogenising real datasets. Therefore author again strongly recommends the use of HIGH5 when there is no contraindication against that.

Tests with Benchmark showed the highest efficiency for ACMANT in homogenising monthly temperatures. To decide if ACMANT is really the best method or "only" one of the best methods, further tests would be necessary, as the achieved efficiencies depend also on the properties of the test dataset. When Benchmark was created it was intended to approach the properties of real observed datasets, but one test dataset as like Benchmark cannot represent all kinds of the real datasets, even not for a given climatic variable.

***Acknowledgements***

The research was supported by the European project EURO4M FP7-SPACE-2009-1/242093 and by the Spanish project "Tourism, Politics and Environment" ECO 2010-18158.

## REFERENCES

Aguilar, E.; Auer, I.; Brunet, M.; Peterson, T.C. and Wieringa, J. (2003). *WMO Guidelines on climatemetadata and homogenization*. World Meteorological Organization, Geneva, WCDMP-No. 53, WMO-TD No 1186.

Alexandersson, H. (1986). "A homogeneity test applied to precipitation data". *J. Climatol*., 6, pp. 661–675.

Alexandersson, H. and Moberg, A. (1997). "Homogenization of Swedish temperature data. Part I: Homogeneity test for linear trends". *Int. J. Climatol*., 17, pp. 25-34.

Brunet, M.; Asin, J.; Sigró, J.; Bañon, M.; García, F.; Aguilar, E.; Palenzuela, J.E.; Peterson, T.C. and Jones, P. (2011). "The minimization of the screen bias from ancient Western Mediterranean air temperature records: an exploratory statistical analysis". *Int. J. Climatol*., 31, pp. 1879-1895.

Caussinus, H. and Lyazrhi, F. (1997). "Choosing a linear model with a random number of change-points and outliers". *Ann. Inst. Statist. Math*., 49, pp. 761–775.

Caussinus, H. and Mestre, O. (2004). "Detection and correction of artificial shifts in climate series". *J. Roy. Stat. Soc., Series* C53, pp. 405–425.

Craddock, J.M. (1979). "Methods of comparing annual rainfall records for climatic purposes". *Weather*, 34, pp. 332-346.

Dai, A.; Wang, J.; Thorne, P.W.; Parker, D.E.; Haimberger, L. and Wang, X.L. (2011). "A new approach to homogenize daily radiosonde humidity data". *J. Climate*, 24, pp. 965-991.

Domonkos, P. (2011a). "Adapted Caussinus-Mestre Algorithm for Networks of Temperature series (ACMANT)". *International Journal of Geosciences*, 2, pp. 293-309.

Domonkos, P. (2011b). "Efficiency evaluation for detecting inhomogeneities by objective homogenisation methods". *Theor. Appl. Climatol*., 105, pp. 455-467.

Domonkos, P. (2012). "ACMANT: Why is it efficient?" Seventh Seminar for homogenization and Quality Control in Climatological Databases, 2011, Budapest, www.c3.urv.cat/publicacions/publicacions2012.html.

Domonkos, P. and Štěpánek, P. (2009). "Statistical characteristics of detectable inhomogeneities in observed meteorological time series". *Studia Geoph. et Geod*., 53, pp. 239–260.

Domonkos, P.; Venema, V.; Auer, I.; Mestre, O. and Brunetti, M. (2012). "The historical pathway towards more accurate homogenisation". *Adv. Sci. Res*., 8, pp. 45-52,

Drogue, G.; Mestre, O.; Hoffmann, L.; Iffly, J-F. and Pfister, L. (2005). "Recent warming in a

Small region with semi-oceanic climate, 1949-1998: what is the ground truth?" *Theor. Appl. Climatol.* 81, pp. 1-10.

Easterling, D.R. and Peterson, T.C. (1995). "A new method for detecting undocumented discontinuities in climatological time series". *Int. J. Climatol*., 15, pp. 369-377.

Guijarro, J.A. (2011). "Joint homogenization of sunshine duration and global solar radiation Spanish series". 10th European Conference on Applied Meteorology, 12-16 Sept, Berlin, Germany, EMS2011-679.

Hawkins, D.M. (1972). "On the choice of segments in piecewise approximation". *J. Inst. Math. Appl.*, 9, pp. 250–256.

Menne, M.J. and Williams Jr., C.N. (2009). "Homogenization of temperature series via pairwise comparisons". *J. Climate*, 22, pp. 1700–1717.

Perreault, L.; Bernier, J.; Bobée, B. and Parent, E. (2000). "Bayesian change-point analysis in hydrometeorological time series. Part 1. The normal model revisited". *J. Hydrology*, 35, pp. 221-241.

Petrovic, P. (2004). "Detecting of inhomogeneities in time series using real precision method". In: *Fourth Seminar for Homogenization and Quality Control in Climatological Databases* (Eds. Szalai, S. and Szentimrey, T.), WCDMP-56, WMO-TD, 1236, WMO, Geneva, pp. 79-88.

Reeves, J.; Chen, J.; Wang, X.L.; Lund, R. and Lu, X. (2007). "A review and comparison of change-point detection techniques for climate data". *J. Appl. Meteor. Climatol*., 46, pp. 900-915.

Staudt, M.; Esteban-Parra, M.J. and Castro-Díez, Y. (2007). "Homogenization of long-term monthly Spanish temperature data". *Int. J. Climatol*., 27, pp. 1809-1823.

Szentimrey, T. (1999). "Multiple Analysis of Series for Homogenization (MASH)". In: *Second Seminar for Homogenization of Surface Climatological Data* (Eds. Szalai, S.; Szentimrey, T. and Szinell, Cs.), WCDMP 41, WMO-TD 962, WMO, Geneva, pp. 27-46.

Venema, V.; Mestre, O.; Aguilar, E.; Auer, I.; Guijarro, J.A.; Domonkos, P.; Vertacnik, G.; Szentimrey, T.; Stepanek, P.; Zahradnicek, P.; Viarre, J.; Müller-Westermeier, G.; Lakatos, M.; Williams, C.N.; 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.; Duran, M.P.; Likso, T.; Esteban, P. and Brandsma, T. (2012). "Benchmarking monthly homogenization algorithms". *Clim. Past*, 8, pp. 89-115.

Vincent, L.A. (1998). "A technique for the identification of inhomogeneities in Canadian temperature series". *J. Climate*, 11, pp. 1094-1104.

Wang, X.L.; Wen, Q.H. and Wu, Y. (2007). "Penalized maximal t test for detecting undocumented mean change in climate data series". *J. Appl. Meteor. Climatol*., 46, pp. 916-931.