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Edited by M. Lakatos, T. Szentimrey, Z. Bihari and S. Szalai

PREFACE

The Hungarian Meteorological Service and the World Meteorological Organisation have organized Seminar for homogenisation and quality control in climatological databases for the 6th time. COST Action ES0601, Advances in Homogenisation Methods of Climate Series: an Integrated Approach (HOME) was the main sponsor and co-organizer this time. This Action makes regular and planned development of the homogenisation methods possible. The seminar was an open meeting giving a good occasion for information exchange between the participants of the HOME project and other researchers of homogenisation community.

The 31 Seminar's presentations followed the structure of the COST Action. The 1st Working Group (WG1) deals with the inventory of homogenisation methods, and the preparation of a benchmark dataset for the other working groups, WG2 has a task of break point detection, WG3 the correction of time series and WG4 the work with the daily data. The last working group, WG5 deals with the recommendation of the best available homogenisation method.

The organisational circumstances, topics and the high scientific level of presentations show a clear positive shift in the administrative and scientific development of homogenisation procedures. First, the data management issue appeared on the European level, officially. It is clear, that the development of data availability and common or at least comparable management methods are not a national tasks, but have to be solved on the international level with participation of national data holders and international donor organisation(s). Wide range of countries presented their homogenisation efforts during the seminar. Unfortunately, not all countries are able to develop, or even to adopt homogenisation methods by their own resources. Therefore, further support is required, especially for the countries without homogenized database.
Secondly, many different meteorological parameters were objects of homogenisation procedures at the presentations. It is very positive, but the scientific basis needs further development and enlargement. All measured meteorological parameters should be involved in the homogenisation on a climatologically and mathematically well established basis.

Many daily based homogenisation methods were presented, which is very beneficial and have been among the recommendations since the very long time. Furthermore, the COST Action pays attention to the wider availability of homogenisation methods.

We can detect many positive scientific and administrative features at the homogenisation procedures. The accent should be made on transboundary developments now. Large international projects, like Climate Data Regional Climate Centre, South-European Drought Management Centre, Climate of the Carpathian Region, etc. apply homogenisation methods, but they need further, practically applicable homogenisation procedure developments. Our task is keeping these existing tendencies alive in the future, and in that case we can be optimistic.

Sándor Szalai

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METHODOLOGICAL QUESTIONS OF SERIES COMPARISON

Tamás Szentimrey
Hungarian Meteorological Service, H-1525, P.O. Box 38, Budapest, Hungary,
szentimrey.t@met.hu

1. INTRODUCTION

The aim of the homogenization procedures is to detect the inhomogeneities and to correct the series. In practice there are absolute and relative methods applied for this purpose. However the application of absolute methods is very problematic and hazardous since the separation of climate change signal and the inhomogeneity signal is essentially impossible. Relative methods can be applied if there are more station series given, which can be compared mutually. The methodology of comparison is related to the following questions: reference series creation, difference series constitution, multiple comparisons of series etc. These topics are very important for detection as well as for correction, because the efficient comparison of series can increase both the significance and the power. The development of efficient comparison methods can be based on the examination of the spatial covariance structure of data series. Consequently the statistical spatiotemporal modelling is also a key question of data series homogenization. The adequate comparison, break point detection and correction procedures are depending on the statistical model.

2. GENERAL FORM OF ADDITIVE MODEL

In case of relative methods a general form of additive model for more monthly series belonging to the same month in a small climate region can be written as follows,

$$X_j(t) = \mu(t) + E_j + IH_j(t) + \varepsilon_j(t) \qquad \left(j = 1,2,\ldots,N\,;\; t = 1,2,\ldots,n \right), \qquad (1)$$

where $\mu(t)$ is the common and unknown climate change signal (temporal trend), E_j are the spatial expected values (spatial trend), $IH_j(t)$ are the inhomogeneity signals and $\varepsilon_j(t)$ are normal white noise series. The signal $\mu(t)$ is a fixed parameter without any assumption about the shape. The type of inhomogeneity $IH(t)$ is in general a 'step-like function' with unknown break points T and shifts $IH(T) - IH(T+1) \neq 0$, and $IH(n) = 0$ is assumed in general. Consequently the expected values are,

$$\mathrm{E}\left(X_j(t)\right) = \mu(t) + E_j + IH_j(t) \qquad \left(j = 1,2,\ldots,N\,;\; t = 1,2,\ldots,n \right).$$

The inhomogeneity can be written as linear function of the shifts, $IH_j(t) = \mathbf{T}_j^{\mathrm{T}}(t)\mathbf{v}_j$, so from model (1) the following form can be obtained,

$$X_j(t) = \mu(t) + E_j + \mathbf{T}_j^{\mathrm{T}}(t)\mathbf{v}_j + \varepsilon_j(t) \qquad \left(j = 1,2,\ldots,N\,;\; t = 1,2,\ldots,n \right), \qquad (2)$$

where $\mathbf{T}_j(t)$ is the vector of one break point functions, and $\mathbf{v}_j$ is the vector of shifts at the break points.

The above additive (linear) model (2) may be written also in vector form,

$$\mathbf{X}(t) = \mu(t)\mathbf{1} + \mathbf{E} + \mathbf{T}(t)\mathbf{v} + \boldsymbol{\varepsilon}(t) \qquad (t = 1,...,n) \qquad (3)$$

where $\mathbf{X}^{\mathrm{T}}(t) = [X_1(t),....., X_N(t)]$, $\mathbf{E}^{\mathrm{T}} = [E_1,....., E_N]$, $\mathbf{T}(t) = [\mathbf{e}_1\mathbf{T}_1^{\mathrm{T}}(t),..., \mathbf{e}_N\mathbf{T}_N^{\mathrm{T}}(t)]$, $\mathbf{v} = [\mathbf{v}_1^{\mathrm{T}},.., \mathbf{v}_N^{\mathrm{T}}]^{\mathrm{T}}$, vector $\mathbf{1}$ is identically one, and the normal distributed vector variables $\boldsymbol{\varepsilon}(t) = [\varepsilon_1(t),.., \varepsilon_N(t)]^{\mathrm{T}} \in N(\mathbf{0}, \mathbf{C})$ $(t = 1,...,n)$ are totally independent in time. The spatial covariance matrix $\mathbf{C}$ may be an arbitrary covariance matrix which describes the spatial structure of the series and it can have a key role in the methodology of comparison.

3. COMPARISON OF SERIES FOR DETECTION AND CORRECTION

According to the model (1), (2), (3) the expected values of examined series are,

$$\mathrm{E}(X_j(t)) = \mu(t) + E_j + IH_j(t) \qquad (j = 1,2,\ldots,N;\ t = 1,2,\ldots,n), \qquad (4)$$

that are covered with normal white noise series,

$$\boldsymbol{\varepsilon}(t) = [\varepsilon_1(t),....., \varepsilon_N(t)]^{\mathrm{T}} \in N(\mathbf{0}, \mathbf{C}) \qquad (t = 1,...,n),$$

where the vector variables $\boldsymbol{\varepsilon}(t)$ $(t = 1,...,n)$ are totally independent in time, and matrix $\mathbf{C}$ is the spatial covariance matrix between the stations. This station covariance matrix $\mathbf{C}$ may have a key role in methodology of comparison of series.

The aim of the homogenization procedure is to detect the inhomogeneities and to correct the series. During the procedure the series can be compared mutually and the role of series – that may be candidate or reference ones – is changing in the course of procedure. The reference series are not assumed to be homogeneous at the correct examinations! The significance and the power of the procedures can be defined according to the probabilities of type of errors. Type one error means the detection of false or superfluous inhomogeneity while type two error means neglecting some real inhomogeneity.

The problem of comparison of series is related to the following questions: reference series creation, difference series constitution, multiple comparisons of series etc. These topics are very important for detection as well as for correction, because the efficient comparison of series can increase both the significance and the power. The development of efficient comparison methods can be based on the examination of the spatial covariance structure of data series. The maximum likelihood methods also take into account the mentioned spatial covariance structure (section 4.2).

3.1 Difference series constitution

At the examinations the main problem arises from the fact that the shape of the common climate change signal is unknown. Therefore so-called difference series are examined in order to filter out the climate change signal $\mu(t)$.

Let us use the following notations, $X_j(t)$, $j \in \mathrm{N} = \{1,2,\ldots,N\}$ is the chosen candidate series and the other series $X_i(t)$, $i \in \mathrm{N}_{-j} = \mathrm{N} \setminus \{j\}$ are the references.

The simple difference series by pairs are, $Z_j(t) = X_j(t) - X_i(t)$ $(i \in \mathrm{N}_{-j})$.

However the difference series constitution can be formulated in more general way as well, namely

$$Z_j(t) = X_j(t) - \sum_{i \in \mathrm{J}} \lambda_{ji} X_i(t) = IH_j(t) - \sum_{i \in \mathrm{J}} \lambda_{ji} IH_i(t) + \varepsilon_{Z_j}(t) \qquad (\mathrm{J} \subseteq \mathrm{N}_{-j}) \qquad (5)$$

with condition of $\sum_{i \in \mathrm{J}} \lambda_{ji} = 1$ for the weighting factors. As a result of the last condition, the unknown climate change signal $\mu(t)$ has been filtered out. Consequently the inhomogeneities of candidate series $X_j(t)$ can be detected and corrected by the examination of the difference series defined according to formula (5). Nevertheless the quality of the examination depends on the weighting factors. Furthermore the weighted sum of reference series $\sum_{i \in \mathrm{J}} \lambda_{ji} X_i(t)$ $(\mathrm{J} \subseteq \mathrm{N}_{-j})$ can be considered as created reference series for candidate series $X_j(t)$.

3.2 Simple weighting methods in practice

In practice several simple weighting methods are used, i.e. simple arithmetic mean, or the calculation of weighting factors are based on the distances (inverse distance method) else on the correlations. For example at the SNHT method (*Alexandersson*, 1986) the following weighting is used for creation of reference series $\sum_{i \in \mathrm{J}} \lambda_{ji} X_i(t)$ $(\mathrm{J} \subseteq \mathrm{N}_{-j})$ belonging to the candidate series $X_j(t)$ $(j \in \mathrm{N})$,

$$\lambda_{ji} = r_{ji}^2 \Big/ \sum_{i \in \mathrm{J}} r_{ji}^2 \qquad (i \in \mathrm{J} \subseteq \mathrm{N}_{-j}), \quad r_{ji} = \mathrm{corr}(X_j(t), X_i(t)). \qquad (6)$$

This latter weighting seems to be a correct mathematical formulation however it is without any theoretical basis. Moreover a generally used unrealistic assumption at the SNHT method is that the created reference series $\sum_{i \in \mathrm{J}} \lambda_{ji} X_i(t)$ is homogeneous. It is a false assumption because there is no reason to assume that $\sum_{i \in \mathrm{J}} \lambda_{ji} IH_i(t) = 0$, where $IH_i(t)$ $(i \in \mathrm{J} \subseteq \mathrm{N}_{-j})$ are the inhomogeneities of reference series $X_i(t)$ $(i \in \mathrm{J} \subseteq \mathrm{N}_{-j})$.

3.3 Optimal weighting and optimal difference series constitution

If we want to obtain difference series with good mathematical properties first let us examine their structure according to the formula (5),

$$Z_j(t) = X_j(t) - \sum_{i \in \mathrm{J}} \lambda_{ji} X_i(t) = IH_j(t) - \sum_{i \in \mathrm{J}} \lambda_{ji} IH_i(t) + \varepsilon_{Z_j}(t) \qquad (\mathrm{J} \subseteq \mathrm{N}_{-j}) \qquad (7)$$

where $X_j(t)$ $(j \in \mathrm{N})$ is the candidate series and the condition for the weighting factors is $\sum_{i \in \mathrm{J}} \lambda_{ji} = 1$. In respect of the detection and correction of the candidate inhomogeneity $IH_j(t)$ there are some disturbing terms namely the mixed inhomogeneity of reference series $\sum_{i \in \mathrm{J}} \lambda_{ji} IH_i(t)$ and the noise term $\varepsilon_{Z_j}(t)$ which covers the signals. In order to increase the power of homogenization we have to intend to increase the signal to noise ratio of difference series that is equivalent with the minimization of the variance of noise term $\mathrm{var}(\varepsilon_{Z_j}) = \mathrm{var}(Z_j)$.

The exact solution of this minimum problem is that the optimal weighting factors λ_{ji}

$\left(i \in \mathrm{J} \subseteq \mathrm{N}_{-j}\right)$ written in vector form are,

$$\boldsymbol{\lambda}_{j,\mathrm{J}} = \mathbf{C}_{\mathrm{J,J}}^{-1}\left(\mathbf{c}_{j,\mathrm{J}} + \frac{\left(1 - \mathbf{1}^{\mathrm{T}}\mathbf{C}_{\mathrm{J,J}}^{-1}\mathbf{c}_{j,\mathrm{J}}\right)}{\mathbf{1}^{\mathrm{T}}\mathbf{C}_{\mathrm{J,J}}^{-1}\mathbf{1}}\mathbf{1}\right) \tag{8}$$

where $\mathbf{c}_{j,\mathrm{J}}$ is the candidate-reference covariance vector and $\mathbf{C}_{\mathrm{J,J}}$ is the reference-reference covariance matrix (*Cressie*, 1991; *Szentimrey*, 1999, 2007b). It can be seen that the covariance matrix $\mathbf{C}$ uniquely determines the optimum weighting factors that minimize the variance, and the optimal difference series created in this manner can be applied efficiently for the detection and correction procedures. Changing the combinations of the reference series $X_i(t)$ $\left(i \in \mathrm{J} \subseteq \mathrm{N}_{-j}\right)$ altogether $2^{N-1} - 1$ optimally weighted difference series can be constituted for a chosen candidate series $X_j(t)$.

Remark 1

We call the attention to the connection with the spatial interpolation techniques built in GIS. The optimal weighting factors $\boldsymbol{\lambda}_{j,\mathrm{J}}$ are just the ordinary kriging weighting factors when the candidate (predictand) $X_j(t)$ is interpolated with reference series (predictors) $X_i(t)\left(i \in \mathrm{J} \subseteq \mathrm{N}_{-j}\right)$. Consequently, the optimal difference series are theoretically identical with the interpolation error series of ordinary kriging. Practically at the homogenization the necessary covariance matrix $\mathbf{C}$ can be estimated on the basis of data series while the ordinary kriging methods built in GIS cannot efficiently use the data series for modelling the necessary statistical parameters (*Szentimrey*, 2007b).

Remark 2

The missing data completion or filling the gaps is also an interpolation problem at the homogenization. In accordance with the optimal difference series formula the following interpolation is suggested for missing value completion,

$$\hat{X}_j(t) = E_j + \sum_{i \in \mathrm{J}} \lambda_{ji}\left(X_i(t) - E_i\right) \tag{9}$$

where $\hat{X}_j(t)$ is the interpolated candidate series value and the values $X_i(t)$ $\left(i \in \mathrm{J} \subseteq \mathrm{N}_{-j}\right)$ are the reference ones, the weighting factors λ_{ji} $\left(i \in \mathrm{J} \subseteq \mathrm{N}_{-j}\right)$ are calculated according to (8), furthermore E_j, E_i $\left(i \in \mathrm{J} \subseteq \mathrm{N}_{-j}\right)$ are the spatial expected values by model (1). These optimal interpolation parameters minimize the RMSE, and this procedure is built in the MASH method for missing data completion (*Szentimrey*, 1999).

Remark 3

We mention if we substitute the generalized-least-squares estimation of unknown climate change signal $\mu(t)$ into the formula of linear regression between predictand $X_j(t)$ and predictors $X_i(t)\left(i \in \mathrm{J} \subseteq \mathrm{N}_{-j}\right)$ then also the above introduced optimal difference series is obtained with minimal variance (*Szentimrey*, 2007b).

4. APPLICATION OF OPTIMAL DIFFERENCE SERIES FOR DETECTION AND CORRECTION

As a consequence of the mixed inhomogeneities of difference series (7) we have to examine more optimal difference series in order to estimate and separate the appropriate

inhomogeneities for the candidate series. Various strategies and procedures can be implemented for this purpose.

4.1 Iteration procedures

A typical iteration procedure is the MASH algorithm (*Szentimrey*, 1999, 2007a). At this procedure a so-called optimal difference series system is examined during one iteration steps. The system elements are optimal difference series and created without common reference series what makes possible to detect and separate the inhomogeneities for the chosen candidate series. The outline of one iteration step is as follows.

1. To choose the candidate series.
2. Series comparison: constitution of optimal difference series system.
3. Multiple break points detection for difference series based on hypothesis tests: point estimations, confidence intervals.
4. Estimation of shifts of difference series: point estimations, confidence intervals.
5. Analysis of results: separation of break points and shifts for candidate series.
6. Correction of candidate series based on the above results.

During the procedure the iteration steps 1-6 are repeated and each series can be examined many times! As it can be seen the optimal difference series have a key role at this procedure. As regards the correction part we emphasize that almost all the methods use point estimation for the correction factors at the detected break points. The MASH procedure is an exception because the correction factors are estimated also on the basis of confidence intervals.

4.2 Maximum Likelihood procedures

Another possibility is to apply the maximum likelihood principle. Nevertheless in this case also certain optimal difference series are examined implicitly. But first let us see the structure of maximum likelihood estimation.
We use again the model (2), (3) that is,

$$\mathbf{X}(t) = \mu(t)\mathbf{1} + \mathbf{E} + \mathbf{T}(t)\mathbf{v} + \boldsymbol{\varepsilon}(t) \qquad (t = 1,\dots,n) \tag{10}$$

where the vector variables $\boldsymbol{\varepsilon}(t) \in N(\mathbf{0},\mathbf{C})\ (t = 1,\dots,n)$ are totally independent in time. We assume spatial covariance matrix $\mathbf{C}$ is known and inverse $\mathbf{C}^{-1}$ exists.
Then the basic minimum tasks to obtain the maximum likelihood estimations for various parameters in case of normal distribution are as follows.

i, Maximum likelihood estimation for $\mu(t), \mathbf{E}, \mathbf{v}$, if $\mathbf{T}(t)$ (breaks) are given:

$$\min_{\mu(t),\mathbf{E},\mathbf{v}} \left(\sum_{t=1}^{n} \left(\mathbf{X}(t) - \left(\mu(t)\mathbf{1} + \mathbf{E} + \mathbf{T}(t)\mathbf{v}\right)\right)^{\mathrm{T}} \mathbf{C}^{-1} \left(\mathbf{X}(t) - \left(\mu(t)\mathbf{1} + \mathbf{E} + \mathbf{T}(t)\mathbf{v}\right)\right) \right)$$

ii, Maximum likelihood estimation for $\mu(t), \mathbf{E}, \mathbf{T}(t), \mathbf{v}$, if the total number of break points K is given:

$$\min_{\mu(t),\mathbf{E},\mathbf{T}(t),\mathbf{v}} \left(\sum_{t=1}^{n} \left(\mathbf{X}(t) - \left(\mu(t)\mathbf{1} + \mathbf{E} + \mathbf{T}(t)\mathbf{v}\right)\right)^{\mathrm{T}} \mathbf{C}^{-1} \left(\mathbf{X}(t) - \left(\mu(t)\mathbf{1} + \mathbf{E} + \mathbf{T}(t)\mathbf{v}\right)\right) \right)$$

iii, Bayesian approach (model selection), penalized likelihood methods,

if the total number of break points K is also estimated:

$$\min_{K}\left[\min_{\substack{\mu(t),\mathbf{E},\\ \mathbf{T}(t),\mathbf{v}}}\left(\sum_{t=1}^{n}\left(\mathbf{X}(t)-\left(\mu(t)\mathbf{1}+\mathbf{E}+\mathbf{T}(t)\mathbf{v}\right)\right)^{\mathrm{T}}\mathbf{C}^{-1}\left(\mathbf{X}(t)-\left(\mu(t)\mathbf{1}+\mathbf{E}+\mathbf{T}(t)\mathbf{v}\right)\right)\right)+pen_K\right]$$

where the penalty terms $pen_K = pen_K(p_{IH})$ depend on p_{IH} and p_{IH} is some 'a priori' probability of break at each time $(t=1,..,n-1)$ and each station. Some examples for 'a priori' probabilities applied in practice: $p_{IH}=\dfrac{e^{-1}}{1+e^{-1}}$ (Akaike),

$p_{IH}=\dfrac{\sqrt{n^{-1}}}{1+\sqrt{n^{-1}}}$ (Schwarz), $p_{IH}=\dfrac{n^{-\frac{n}{n-1}}}{1+n^{-\frac{n}{n-1}}}$ (Caussinus-Lyazrhi).

According to the minimum task i, this correction model can be applied if the break points $\mathbf{T}(t)$ $(t=1,..,n)$ are known and we want to give maximum likelihood estimations for the shifts $\mathbf{v}$. This estimation is the so-called generalized-least-squares estimation of the shifts. If we use the identity matrix $\mathbf{I}$ instead of $\mathbf{C}$ then we obtain the least-squares estimation which was implemented by *Caussinus and Mestre*, 2004.

Returning to the relation of maximum likelihood estimation and the optimal difference series, let us consider the following special optimal difference series,

$$Z_j(t)=X_j(t)-\sum_{i\in N_{-j}}\lambda_{ji}X_i(t) \qquad (j=1,\dots,N),$$

where the weighting factors are optimal according to formula (8).

Hereinafter let us denote the above optimal series in vector form:

$$\mathbf{Z}(t)=[Z_1(t),\dots,Z_N(t)]^{\mathrm{T}}=(\mathbf{I}-\mathbf{\Lambda})\mathbf{X}(t) \qquad (t=1,\dots,n).$$

Theorem (without proof)

In case of arbitrary inhomogeneity terms $\mathbf{T}(t)(t=1,\dots,n)$, $\mathbf{v}$:

$$\min_{\mu(t),\mathbf{E}}\left(\sum_{t=1}^{n}\left(\mathbf{X}(t)-\left(\mu(t)\mathbf{1}+\mathbf{E}+\mathbf{T}(t)\mathbf{v}\right)\right)^{\mathrm{T}}\mathbf{C}^{-1}\left(\mathbf{X}(t)-\left(\mu(t)\mathbf{1}+\mathbf{E}+\mathbf{T}(t)\mathbf{v}\right)\right)\right)=$$

$$=\sum_{t=1}^{n}\left(\mathbf{Z}_c(t)-(\mathbf{I}-\mathbf{\Lambda})\mathbf{T}_c(t)\mathbf{v}\right)^{\mathrm{T}}\mathbf{C}_{\mathbf{Z}}^{-1}\left(\mathbf{Z}_c(t)-(\mathbf{I}-\mathbf{\Lambda})\mathbf{T}_c(t)\mathbf{v}\right) \qquad (11)$$

where $\mathbf{Z}_c(t)=\mathbf{Z}(t)-\overline{\mathbf{Z}}$ and $\mathbf{T}_c(t)=\mathbf{T}(t)-\overline{\mathbf{T}}$ are centered values,

and $\mathbf{C}_{\mathbf{Z}}^{-1}$ is a generalized inverse of $\mathbf{C}_{\mathbf{Z}}$ that is the covariance matrix of $\mathbf{Z}(t)$.

The concept of generalized inverse means, that $\mathbf{C}_{\mathbf{Z}}\mathbf{C}_{\mathbf{Z}}^{-1}\mathbf{C}_{\mathbf{Z}}=\mathbf{C}_{\mathbf{Z}}$, in spite of the fact that $\mathbf{C}_{\mathbf{Z}}$ is a singular matrix since the optimal difference series $Z_j(t)$ $(j=1,\dots,N)$ are linearly dependent. Essentially the formula (11) can be obtained by the substitution of the generalized-least-squares estimations of $\mu(t)$, $\mathbf{E}$.

As a consequence of this theorem the minimum tasks i, ii, iii, can be rewritten also with the optimal difference series $\mathbf{Z}(t)$.

i, Maximum likelihood estimation for $\mathbf{v}$, if $\mathbf{T}(t)$ (breaks) are given:

$$\min_{\mathbf{v}}\left(\sum_{t=1}^{n}\left(\mathbf{Z}_c(t)-(\mathbf{I}-\mathbf{\Lambda})\mathbf{T}_c(t)\mathbf{v}\right)^{\mathrm{T}}\mathbf{C}_{\mathbf{Z}}^{-1}\left(\mathbf{Z}_c(t)-(\mathbf{I}-\mathbf{\Lambda})\mathbf{T}_c(t)\mathbf{v}\right)\right)$$

ii, Maximum likelihood estimation for $\mathbf{T}(t), \mathbf{v}$, if the total number of break points K is given:

$$\min_{\mathbf{T}(t),\mathbf{v}}\left(\sum_{t=1}^{n}\left(\mathbf{Z}_c(t)-(\mathbf{I}-\mathbf{\Lambda})\mathbf{T}_c(t)\mathbf{v}\right)^{\mathrm{T}}\mathbf{C}_{\mathbf{Z}}^{-1}\left(\mathbf{Z}_c(t)-(\mathbf{I}-\mathbf{\Lambda})\mathbf{T}_c(t)\mathbf{v}\right)\right)$$

iii, Bayesian approach (model selection), penalized likelihood methods,

if the total number of break points K is also estimated:

$$\min_{K}\left[\min_{\mathbf{T}(t),\mathbf{v}}\left(\sum_{t=1}^{n}\left(\mathbf{Z}_c(t)-(\mathbf{I}-\mathbf{\Lambda})\mathbf{T}_c(t)\mathbf{v}\right)^{\mathrm{T}}\mathbf{C}_{\mathbf{Z}}^{-1}\left(\mathbf{Z}_c(t)-(\mathbf{I}-\mathbf{\Lambda})\mathbf{T}_c(t)\mathbf{v}\right)\right)+pen_K\right]$$

CONCLUSION

The solutions of the minimum tasks for $\mathbf{v}$ (i, ii, iii,) and $\mathbf{T}(t)$ (ii, iii,) are functions of the optimal difference series $\mathbf{Z}(t)\,(t=1,...,n)$. That means the maximum likelihood methods also perform series comparison and examine implicitly optimal difference series!

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EXPERIENCES WITH QUALITY CONTROL AND HOMOGENIZATION OF DAILY SERIES OF VARIOUS METEOROLOGICAL ELEMENTS IN THE CZECH REPUBLIC 1961-2007

P. Štěpánek and P. Zahradníček
Czech Hydrometeorological Institute, Regional Office Brno, Czech Republic,
Phone: +420-541 421 033,
petr.stepanek@chmi.cz

Abstract

Quality control and homogenization has to be undertaken prior to any data analysis in order to eliminate any erroneous values and inhomogeneities in time series. In this work we describe and then apply our own approach to data quality control, combining several methods: (i) by applying limits derived from interquartile ranges (ii) by analyzing difference series between candidate and neighbouring stations and (iii) by comparing the series values tested with "expected" values – technical series created by means of statistical methods for spatial data (e.g. IDW, kriging).

Because of the presence of noise in series, statistical homogeneity tests render results with some degree of uncertainty. In this work, the use of various statistical tests and reference series made it possible to increase considerably the number of homogeneity test results for each series and thus to assess homogeneity more reliably. Inhomogeneities were corrected on a daily scale.

These methodological approaches are demonstrated by use of the daily data of various meteorological elements measured in the area of the Czech Republic. Series were processed by means of developed ProClimDB and AnClim software (www.climahom.eu).

INTRODUCTION

In recent years considerable attention has been devoted to the analysis of daily data. Prior to analysis, the need to homogenize data and check their quality arises (Brandsma, 2000, Vincent et al. 2002, Wijngaard et al. 2003, Petrovic 2004, Della-Marta 2006 and others). Several kinds of problem have to be taken into consideration in the course of data processing,. These involve selection of a proper method for homogenization with regard to the data used, i.e. fulfilling all the conditions necessary to applying selected tests of relative homogeneity (e.g. normal distribution), creation of reference series (defining selection criteria), adjustment of inhomogeneities revealed, completion of missing values, and others. To date, no widely accepted homogenization approach has appeared that could be generalized and applied to a wider range of meteorological elements and different climatic regions. However, such approaches are needed. The creation of a general method of homogenization is also the main goal of the ongoing COST project ES0601, planned to culminate in 2011.

Because of presence of noise in series, statistical homogeneity tests render results with some degree of uncertainty. In this work, the use of various statistical tests and types of reference series made it possible to increase considerably the number of homogeneity tests results for each series tested and thus to assess homogeneity more reliably.

Considering quality control, the lack of a generally accepted methodology is even more profound than in the case of homogenization. Without treating outliers, homogenization and analysis may render misleading results. We therefore devoted consierable time to the

methodology of detecting outliers, something that could moreover be automated to process large datasets of daily (subdaily) values.

In terms of this work, processing included the following steps: detection, verification and possible correction of outliers, creation of reference series, homogeneity testing (various homogeneity tests), determination of inhomogeneities in the light of test results and metadata, adjustment of inhomogeneities and filling in missing values (Fig. 1).

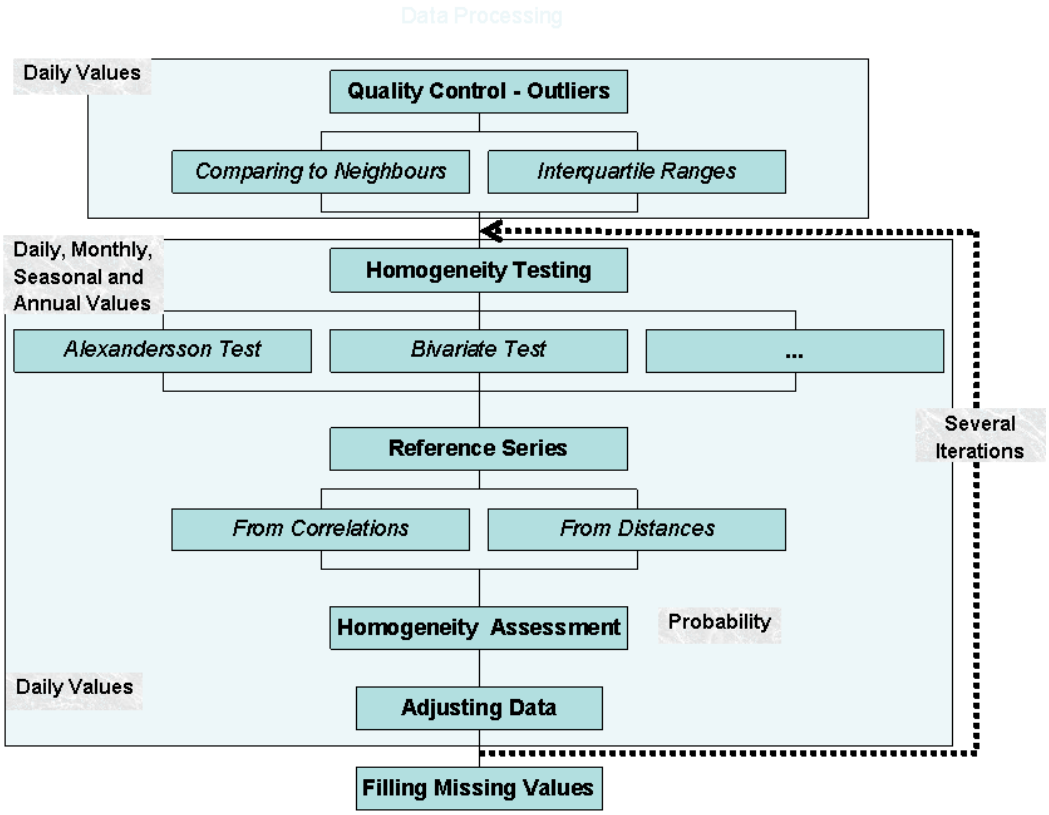


Figure. 1. Scheme of quality control and homogenization process

DESCRIPTION OF THE DATASET EMPLOYED

Quality control and homogenization was performed on the daily values for all the basic meteorological elements in the area of the Czech Republic. This paper concentrates especially upon air temperature, precipitation, water vapour pressure and wind speed. The study covers the period 1961-2007; measurements before 1961 will be subject to processing in the near future.

Mean minimum distance between climatological stations (measuring air temperature, water vapour pressure, wind speed, sunshine duration, etc.) was 13.3 km (some 270 stations in the area of the Czech Republic are available) while for precipitation stations the mean minimum distance was 6.5 km (787 stations). Fig. 2 shows the spatial distribution of the climatological and precipitation stations involved.

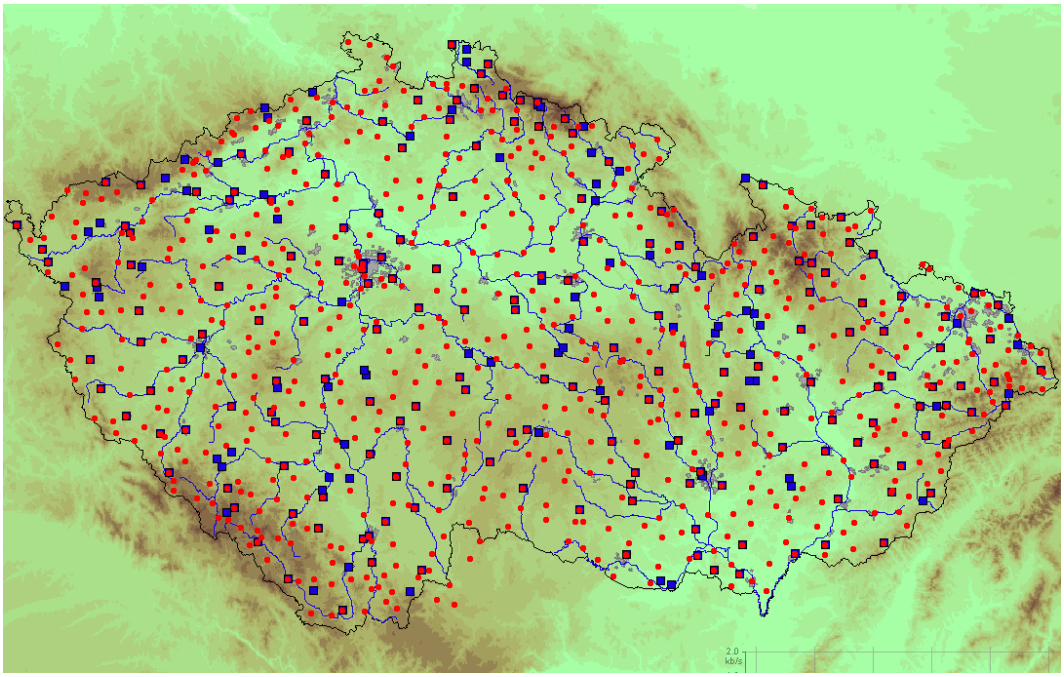


Figure. 2. Spatial distribution of climatological (blue squares) and precipitation (red circles) stations

The altitude of the stations ranges from 150 to 1490 m.a.s.l. Ten stations are at an altitude of more than 1000 m, while median altitude stands at 410 m.a.s.l for climatological stations and 415 m.a.s.l for precipitation stations.

QUALITY CONTROL

Prior any homogenization and data analysis, data quality control has to be undertaken to check outlier values and to eliminate erroneous values in time series.

In this work, data quality control was carried out by combining several methods: (i) by analyzing difference series between candidate and neighbouring stations (ii) by applying limits derived from interquartile ranges (this can be applied either to individual series, i.e. absolutely or, better, to difference series between candidate and reference series, i.e. relatively) and (iii) by comparing the series values tested with "expected" values – technical series created by means of statistical methods for spatial data (e.g. IDW, kriging).

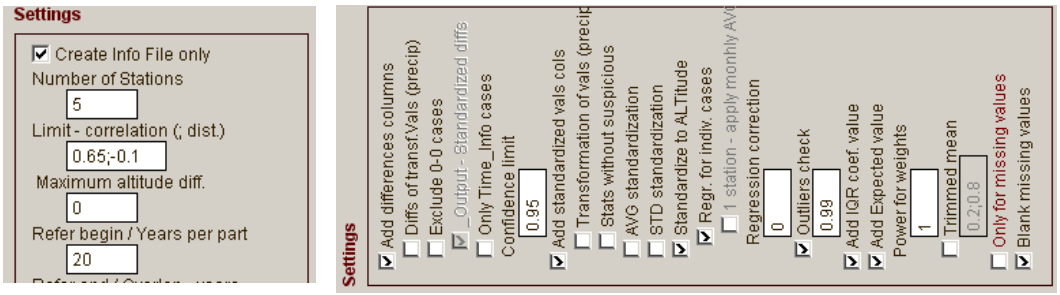
Neighbouring stations (method i) or reference series (method ii) may be selected either by means of correlations or distances (in the case of temperature the results are different, while for precipitation the selection coincides). Correlation coefficients can be applied either to normal series or to series of first differences (see e.g. Peterson, 1998). The latter is preferable at this stage of processing, since homogenization has not been carried out. In our case, for comparison with neighbour stations, up to eight of the nearest stations were selected, with a distance limit of 300 km and altitude difference restricted to 500 m. Only series within the same observation hours were selected.

Various characteristics were considered for the evaluation of outliers. For example, a count of statistically significant different neighbours (confidence limit 0.95) was evaluated by means of difference series (neighbour minus candidate station, or "equitable" ratios for precipitation: see below for description). Further, the values of neighbours were standardized with respect to base (candidate) station altitude and a new (theoretical) value for the candidate station was calculated – as a weighted average from the standardized values of the neighbours. Further, the coefficients of interquartile ranges (q75–q25) above q75 (or below

q25) were evaluated (calculated from the standardized neighbour values), and applied to candidate station value; this was done in order to assess similarity of neighbour values used with regard to the test value: the more values of neighbours are similar, the higher the value of the coefficient becomes.

The final decision on removing outliers was based on a combination of factors: the percentage of the count of significantly different neighbours (for automation of quality control, 75% was applied); the probability of median of all neighbours-base differences or ratios (for automation CDF>0.95, normal distribution, was taken); difference between base station value and median calculated from standardized neighbours values, expressed as probability (for automation CDF>0.95 applied again); coefficient of interquartile range – base station value compared to standardized neighbours values (considering coefficient of IQR of more than 3 for automation); difference between expected value and median calculated from original values of neighbours divided by standard deviation of base station (CDF<0.9 with respect to automation), and finally, after automatic selection applying the limits mentioned, by visual (subjective) comparison of the standardized values of neighbours with the candidate station values. Fig. 3 shows an example of the parameter settings for calculation in ProClimDB software and final output for decision-making about outliers.

Further details on the quality control process may be found in the documentation for ProClimDB software (Štěpánek, 2008).



	Station_Element				Suspected v	Expected value		Neighbouring stations							
REGION	ID	YEAR	MONTH	DAY	ST_BASE	EXPECT_VAL	REMARK	ST_1	ST_2	ST_3	ST_4	ST_5	ST_6		CDF_B_OMI
T_21:00	B1BRBY01_T_21:00				350.0		Altitude	254.0	315.0	450.0	415.0	387.0	211.0		
T_21:00	B1LUHA01_T_21:00						st_1, di	18.3							
T_21:00	B1VIZO01_T_21:00						st_2, di		18.7						
T_21:00	O3HUSL01_T_21:00						st_3, di			23.7					
T_21:00	O3HALE01_T_21:00						st_4, di				26.3				
T_21:00	O3VSET01_T_21:00						st_5, di					26.8			
T_21:00	B1ZLIN01_T_21:00						st_6, di						29.3		
T_21:00	B1BRBY01_T_21:00	1970	6	26	21.9	16.1		16.5	16.2	15.0		16.2	18.1		0.950
T_21:00	B1BRBY01_T_21:00				350.0		Altitude	254.0	315.0	450.0	387.0	211.0	385.0		
T_21:00	B1LUHA01_T_21:00						st_1, di	18.3							
T_21:00	B1VIZO01_T_21:00						st_2, di		18.7						
T_21:00	O3HUSL01_T_21:00						st_3, di			23.7					
T_21:00	O3VSET01_T_21:00						st_4, di				26.8				
T_21:00	B1ZLIN01_T_21:00						st_5, di					29.3			
T_21:00	B1STRN01_T_21:00						st_6, di						31.8		
T_21:00	B1BRBY01_T_21:00	1988	8	20	27.7	20.5		19.2	21.4	19.6	21.3	19.8	21.1		0.980

Figure 3. Setting the ProClimDB software for outlier values evaluation. Top (two-way processing: selection of neighbours and calculation of characteristics for evaluation of outliers). Bottom: example of output with auxiliary characteristics for quality control evaluation.

HOMOGENIZATION

Although daily values were the subject of processing in this work, detection of inhomogeneities was performed using monthly means (or sums in the case of precipitation). Inhomogeneities are easier to detect in monthly series because they involve less noise than daily values. Moreover, daily values for some meteorological elements (e.g. air temperature) are dependent, so application of common statistical tests is difficult. Transformation of daily

precipitation sums to normal distribution is not easy either, even where possible, and there are certain drawbacks to such processing, for example fewer values available for analysis when omitting zero values).

The relative homogeneity tests applied were: Standard Normal Homogeneity Test [SNHT] (Alexandersson, 1986, 1995); the Maronna and Yohai bivariate test (Potter, 1981); and the Easterling and Peterson test (Easterling, Peterson, 1995). Reference series calculations were based on distances from the five nearest stations, with a distance limit of 300 km and an altitude difference limit of 500 m. The power for weights (inverse distance) for temperature and water vapour pressure was taken as 1, for wind speed as 2 and for precipitation as 3. Neighbouring station values were standardized to average and standard deviation of candidate station. An example of parameter settings for the calculation of reference series by means of ProClimDB software is shown in Fig. 4. Detection of inhomogeneities was performed for series to a maximum duration of 40 years, while the overlap for two consecutive periods was 10 years (requirements of SNHT tests for one shift). The tests were applied on monthly as well as seasonal and annual averages (sums).

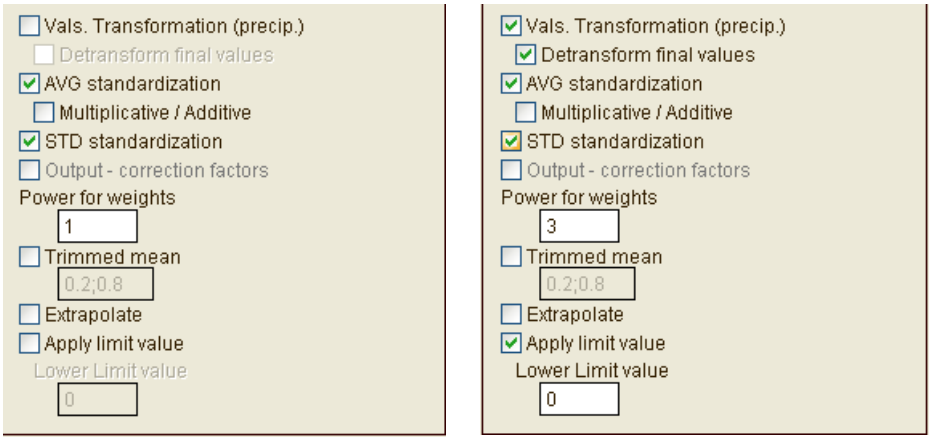


Figure 4. Settings for calculation of reference series in ProClimDB software, air temperature (left) and precipitation (right)

The main criterion for determining a year of inhomogeneity was the probability of detection of a given year, i.e. the ratio between the count of detections for a given year from all test results for a given station (using type of reference series, range of tests applied, monthly, seasonal and annual series) and the count of all theoretically possible detections. Further details of reference series creation and testing may be found in Štěpánek et al. (2007).

After evaluation of detected breaks and comparison with metadata, a final decision on correction of inhomogeneities was made. Data were corrected on a daily scale. Adjustment of such inhomogeneities was addressed by means of a reference series calculated from the weighted average over the five nearest stations (weights as inverse distance and with a power of 0.5 for temperature, water vapour pressure and with a power of 1 for precipitation and wind speed), applying standardization of neighbour station series to average and standard deviation of candidate station. Reference series for inhomogeneity corrections were calculated on a daily scale, five years before and after a break.

We created our own correction method, an adaptation of a method for the correction of regional climate model outputs by Déqué (2007), itself based on assumptions similar to those implicit in methods described by Trewin and Trevitt (1996) and Della-Marta (2006), which apply variable correction according to individual percentiles (or deciles). Our process is based on comparison of percentiles (empirical distribution) of differences (or ratios) between

candidate and reference series before and after a break. Percentiles are estimated from candidate series and values for differences of candidate and references series are taken from the same time (date). Each month is processed individually, but also taking into account the values of adjacent months before and after it to ensure smoother passage from one month to another. Candidate – reference differences for individual percentiles are then differenced before and after a break and smoothed by low-pass filter to obtain a final adjustment based on a given percentile (see Fig. 5 for illustration). Values (before a break) are then adjusted in such a way that we find a value for the candidate series before a break (interpolating between two percentile values if needed) and the corresponding correction factor, which is then applied to the value to be adjusted. Special treatment is needed for outlier values at the ends of distributions.

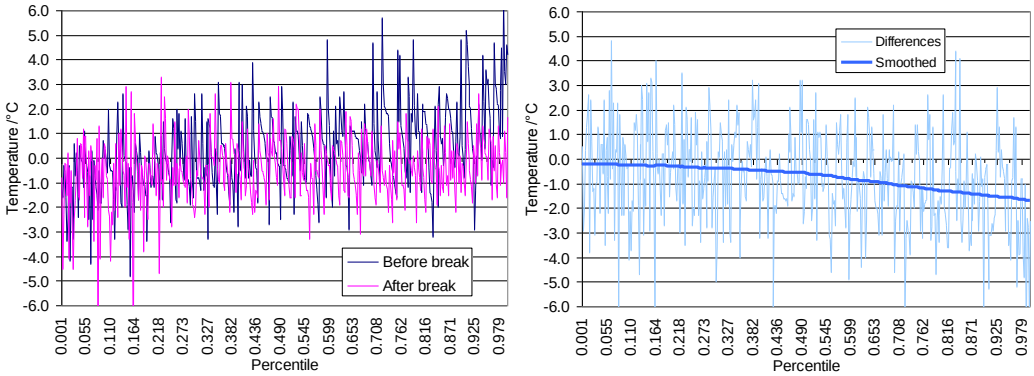


Figure 5. Deriving corrections for individual percentiles from differences between candidate and reference series before and after a break

Various characteristics were analyzed before applying the adjustments: the increment of correlation coefficients between candidate and reference series after adjustments; any change of standard deviation in differences before and after the change; presence of linear trends, etc. In the event of any doubt, the adjustments were not applied.

The above-mentioned steps (homogeneity testing, evaluation and correction of inhomogeneities detected) were performed in several iterations. At each iteration, more precise results were obtained. Missing values were filled in only after homogenization and adjustment of inhomogeneities in the series. The reason for this was that the new values were estimated from data not influenced by possible shifts in the series. Moreover, when missing data are filled in before homogenization, they may influence inhomogeneity detection in a negative way.

QUALITY CONTROL RESULTS

Various meteorological elements were subject to thorough quality control according to the methodology described in section 3. An optimal set of parameters was found for each meteorological element (by cross-validation). For temperature this was, for example, standardization to altitude (for each day individually), power of weight (reciprocal value of distance) of 1, trimmed mean (applying 0.2 and 0.8 percentiles), no regression correction and outliers check (CDF=0.99). For precipitation, water vapour pressure and wind speed, trimmed mean was not applied; power of weights was taken as 3 for precipitation, 2 for wind and 1 for water vapour pressure. Moreover, for precipitation, transformation of values was applied to obtain a comparable value not dependent upon the mode of division (i.e. X/Y or Y/X have the same distance from 1).

It is important to analyze only measured values in a quality control check; in derivatives of them such as daily averages, errors are already masked to some extent. This fact is well illustrated in Figs. 6 and 7. For air temperature, more outliers were detected in the morning and evening measurements (probably associated with steeper gradients). The same is true of relative humidity and wind speed. On the other hand, water vapour pressure shows more outliers for the 14:00 observation hour compared to morning or evening measurements. In all these cases, the number of outliers detected in daily mean values is the lowest and in monthly averages it would be even worse, i.e. only the largest outliers would then be detected.

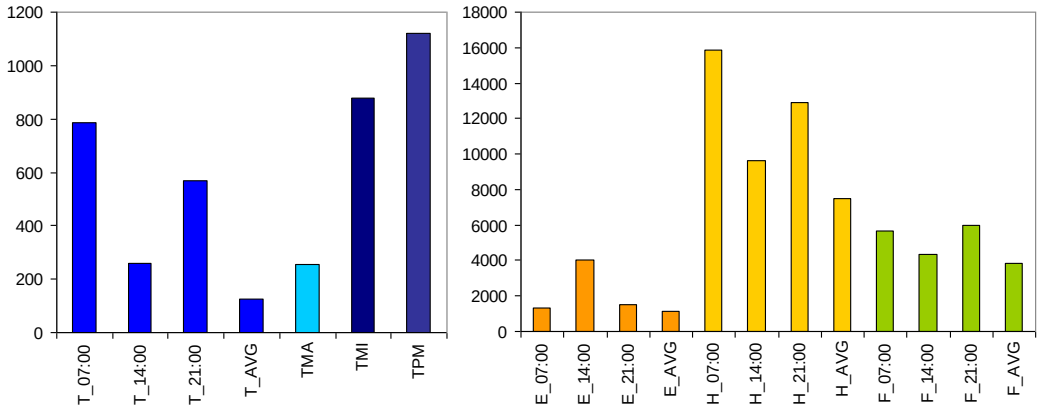


Figure 6. Number of outliers for air temperature (T) at observation hours 07:00, 14:00, 21:00, AVG – daily average; daily maximum temperature (TMA), daily minimum temperature (TMI), daily ground minimum temperature (TPM); water vapour pressure (E), relative humidity (H), wind speed (F). For period 1961-2007, from 3,431,000 station-days.

The number of detected outliers differs considerably between the various meteorological elements, e.g. for relative humidity the number is ten times higher than that for air temperature. The number of outliers for sunshine duration (not shown on the plot) is similar to that for minimum temperature (1022). For precipitation, this is almost 8000, for new snow about half of this and for snow depth about a third (however, there are about four times more precipitation stations than climatological stations).

The number of outliers has clear annual cycle. For most of the elements, a higher number of outliers was detected in summer months than in winter months (see Figure 7). For air temperature and minimum temperature, the maximum occurs in July, for water vapour pressure in August, for wind speed in August. For precipitation there are two maxima per year, in the summer months and then in January and December, while during spring and autumn a lower number of outliers was detected. In contrast, sunshine duration shows a higher number of outliers in January and December, new snow in December (zero in summer of course) and snow depth in November and April.

Air temperature, as has already been shown (Fig. 6), exhibits more errors in daily minimum (or ground minimum) temperature compared to maximum temperature, but the ratios change considerably in the course of the year. While in summer months the number of detected outliers for minimum or ground minimum temperatures is much higher (e.g. ten times so in July), in the winter months the number is the same; the number of maximum temperature outliers does not change very much in the course of the year.

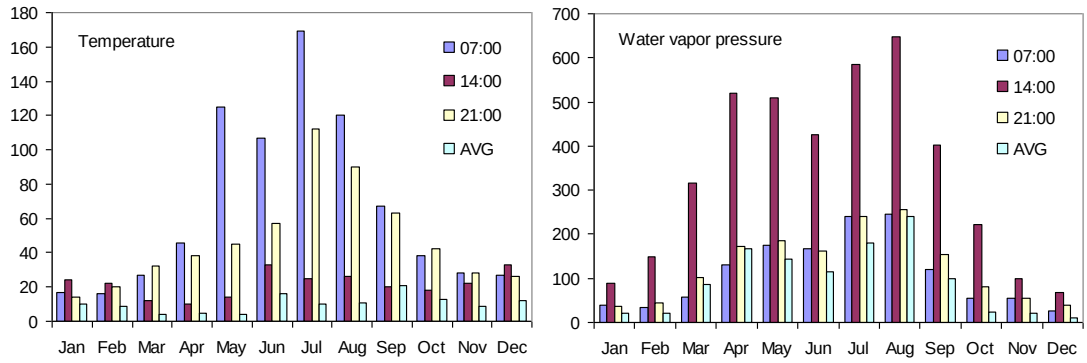


Figure 7. Number of outliers for air temperature at observation hours, AVG – daily mean temperature (left) and water vapour pressure at observation hours, AVG – daily average (right). For period 1961-2007, from 3,431,000 station-days

The number of detected outliers also changes with time (see Fig. 8). For air temperature, the higher number of outliers since the late 1990s coincides well with transition to automatic measurements. The same holds true for minimum temperatures. Water vapour pressure shows higher numbers since the early 1990s. On the other hand, no trend was found for maximum temperature and relative humidity. For precipitation and wind speed, the highest number occurs in the late 1960s, with outliers diminishing from then onwards.

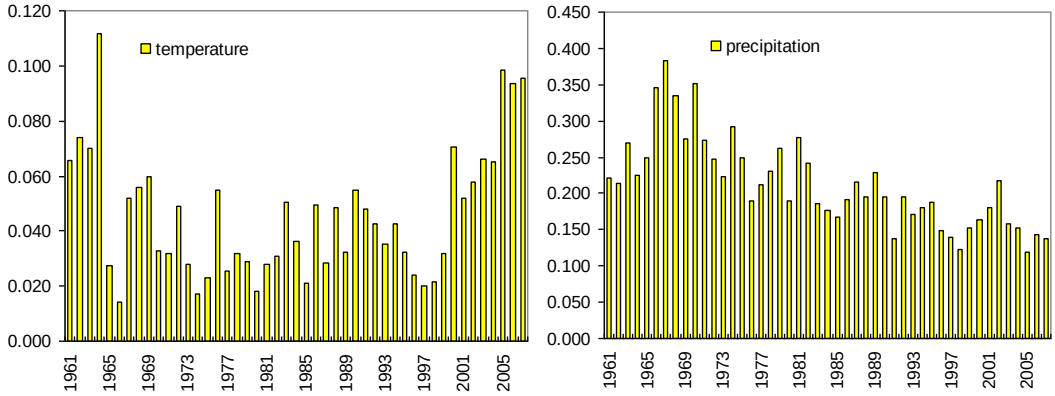


Figure 8. Number of outliers per one station for air temperature (all observation hours and daily average) (left) and precipitation (right). Period 1961-2007

Once quality control has been applied on a daily scale (observation hours), the series of various meteorological elements are finally ready for homogenization.

HOMOGENIZATION RESULTS

Daily averages, rather than individual observation hours, were worked upon for data homogenization (methodology as described in section 4). Observation (direct) measurements should be better for homogenization, for the same reason as given for quality control, i.e. possible inhomogeneities are better manifested and thus detectable and correctable in measured values then in some their derivatives. However, the object, at this stage, was largely to tune the methodology to daily data homogenization. A return to working with observation measurements is planned for the near future.

Detection of inhomogeneities was performed for monthly averages. The main reasons for this were less noise in the series and fewer (or no) problems with the statistical properties of series such as dependence of values (present e.g. in daily air temperature series). Fig. 9. shows

the correlation coefficients between candidate and reference series and monthly values for various meteorological elements. While for air temperature (daily mean, maximum and minimum) and precipitation the correlations are very high (median above 0.95 or 0.90 respectively), for relative humidity they remain high enough (median values drop to 0.5 in winter months), but for wind speed the medians of correlation drop in the summer months to the limit of statistically significant values (0.05). Correlations for precipitation are very high because the precipitation station network is much denser than the climatological one (mean minimum distance is 6.5 km). Correlation coefficients show a clear annual cycle.

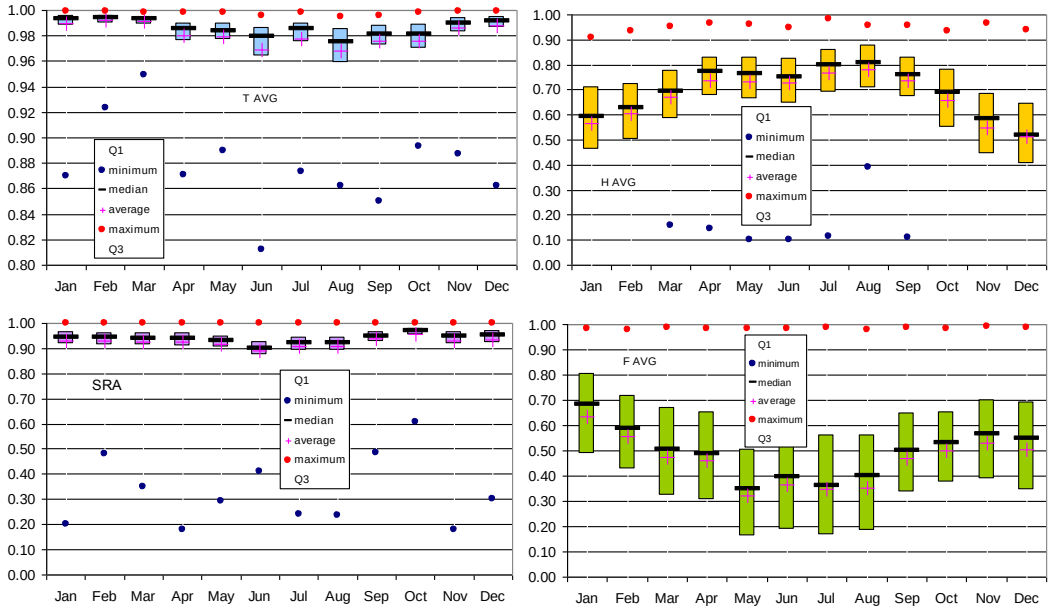


Figure 9. Correlation coefficients between candidate and reference series (monthly values) for air temperature (T_AVG), precipitation (SRA), relative humidity (H_AVG) and wind speed (F_AVG). For 200 climatological stations and 750 precipitation stations (at least 20 years of measurement).

Homogeneity tests applied for inhomogeneities detection were SNHT, Bivariate test and the Easterling and Peterson test. Fig. 10 shows the number of statistically significant inhomogeneities detected (0.05) by Alexandersson's SNHT and the Bivariate test together. Again, a clear annual cycle emerges. For air temperature and wind speed more breaks occur in the summer months while this occurs for precipitation in the winter months (mainly due to problems associated with measurement of solid precipitation). For water vapour pressure, the annual cycle is not so clearly manifested.

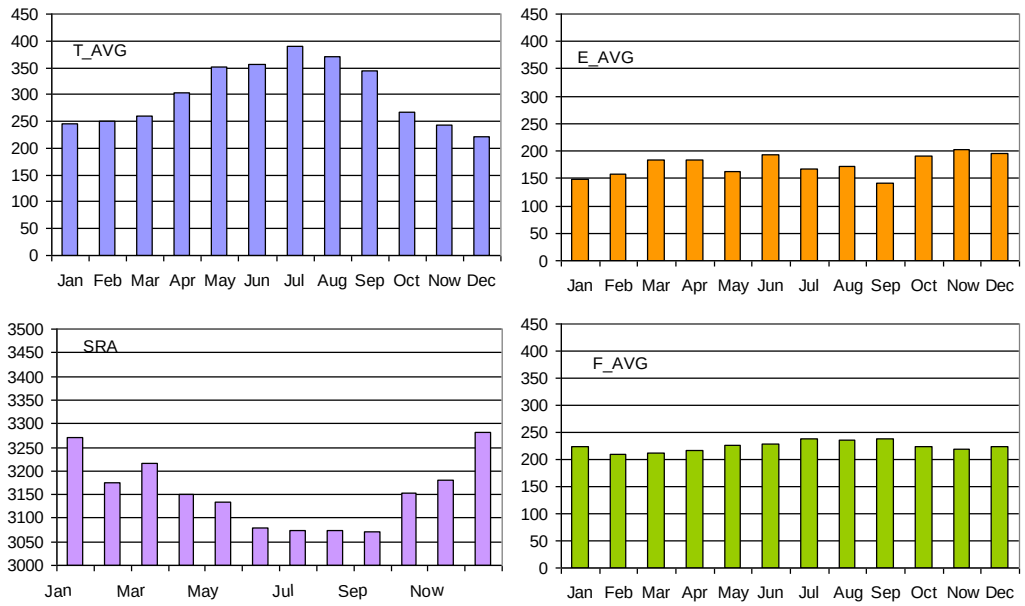


Figure 10. Number of statistically significant inhomogeneities (0.05) for air temperature (T_AVG), precipitation (SRA), water vapour pressure (E_AVG) and wind speed (F_AVG), detected for monthly values. For 200 climatological stations and 750 precipitation stations.

Breaks correction was decided upon after thorough comparison of the results of inhomogeneity detection with metadata. The number of corrected inhomogeneities differs for individual meteorological elements (see Fig. 11). For example, more breaks were corrected for maximum temperature than for minimum temperature. Water vapour pressure and wind speed were corrected about twice as frequently as temperature. In contrast, precipitation was corrected less frequently taking into account the fact that there are 4.5 times more precipitation stations than climatological stations.

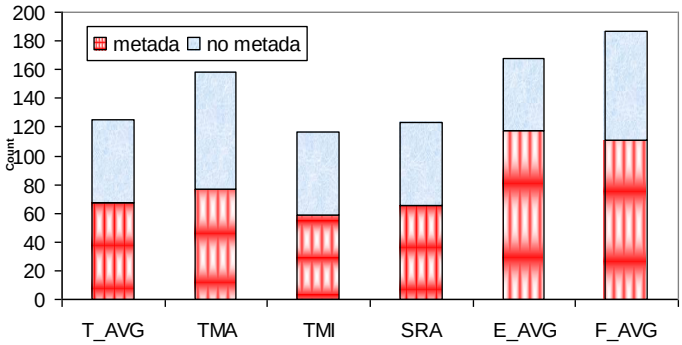


Figure 11. Number of inhomogeneities explained by metadata for air temperature (T_AVG), maximum temperature (TMA), minimum temperature (TMI), precipitation (SRA), water vapour pressure (E_AVG) and wind speed (F_AVG). For 200 climatological stations and 750 precipitation stations.

The number of corrected inhomogeneities varies with time (for example see Fig. 12). For air temperature (daily mean and maximum temperature) and water vapour pressure, an increase appears after the late 1990s when automation started to be introduced into the station network (associated with change of instruments, shelter, "observer"). For wind speed and minimum temperature there is no clear trend in the number of inhomogeneities over time (but the percentage of inhomogeneities explained by metadata increases considerably after the 1990s – before in fewer than then half of cases, after in more than half). The highest number of corrected inhomogeneities for precipitation is found in the 70s.

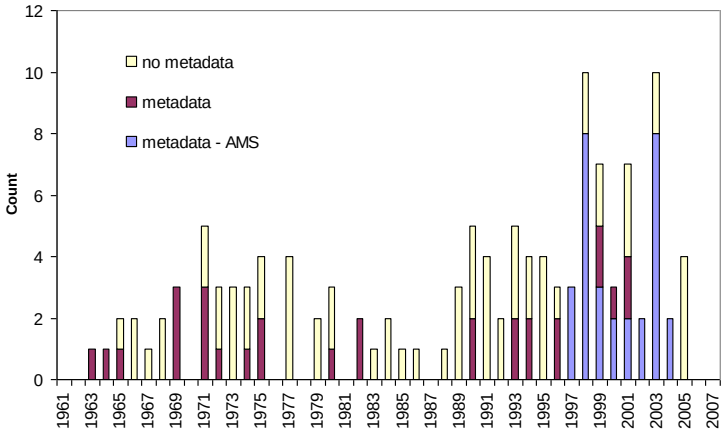


Figure 12. Number of corrected inhomogeneities for air temperature for individual years, divided into the number of unexplained breaks (no metadata), explained by metadata (metadata) and associated with automation (metadadata – AMS). For 200 climatological stations

An annual cycle is also clearly manifested in the correction of inhomogeneities (data corrected on a daily scale as described in section 4). Considering the absolute values of corrections, the degrees of adjustment were higher during the summer months for air temperature and water vapour pressure, while for wind speed slightly lower adjustments were made in the summer months compared with those of winter. For precipitation, major corrections (ratios) were applied in winter months. After correction, correlation coefficients increased mainly in the summer months (air temperature, water vapour pressure and also wind speed).

Future work will lead to the application of observation hour measurements for homogenization, not just daily averages. On preliminary comparison, the results achieved (homogenized daily data) should differ only negligibly from the results obtained by application of observation hours, so a start can be made on using the currently acquired series for various data analyses requiring homogeneous daily data, e.g. studies of extremes.

CONCLUSIONS

The current work presents a methodology for outlier detection and series homogenization for various meteorological elements in the area of the Czech Republic in the period 1961-2007.

A method for outlier detection that could be automated to the greatest extent was a priority, since millions of values had to be processed for each meteorological element. Such a method was finally found and successfully applied. It utilizes a combination of several methods for outlier detection. No one method alone was found adequate; only a combination leads to satisfying results – the discovery of real outliers and suppression of fault alarms. Parameters (the settings appropriate to the methods) had to be found individually for each meteorological element.

In the outlier detection itself, errors must be sought in straight, measured data rather than merely daily averages or even monthly averages (sums), since outliers are masked to a greater or lesser extent in the latter. Errors in measurement tend to occur more frequently in certain parts of the year, generally in the summer months.

A clear annual cycle also emerged in several of the characteristics of the inhomogeneities detected. For example, air temperature inhomogeneities occur mainly in the summer months and the same holds for the amount of corrections applied, while in the case of precipitation

more inhomogeneities were detected in the winter months (associated with solid precipitation measurements); the corrections applied were also higher in the winter months. Automation of measurements had very strong influence on the homogeneity of station time series (and even the occurrence of outliers) in terms of most of the meteorological elements (with the exception of minimum temperature, precipitation and wind speed). Fortunately, automation was introduced successively into the station network so it was possible to detect it and make corrections without major problems.

The data processing for this work was carried out by means of ProClimDB software for processing whole datasets (finding outliers, combining series, creating reference series, preparing data for homogeneity testing, etc.) and AnClim software for homogeneity testing (http://www.climahom.eu). Further development of the software, e.g. connection with R software, is ongoing.

Further steps in quality control and homogenization will lead to analysis of individual observation hours and also historical data.

Acknowledgements

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QUANTIFYING EFFICIENCY OF HOMOGENISATION METHODS

Peter Domonkos
H-1155 Budapest, Vasvári P. u. 5, Hungary
dopeter@t-online.hu

INTRODUCTION

Nowadays a large number of statistical methods are applied for homogenising climatic time series. A challenging task is to evaluate the differences between the efficiencies of various homogenisation methods, since beyond the homogenisation method examined efficiency depends also on the statistical properties of time series and the efficiency measure applied. Objective homogenisation methods can be evaluated quantitatively only, and the study deals with detection parts (OMID) only, i.e. the skills in detecting and correcting inhomogeneities (IHs) in given relative time series are considered, but the way of the creation of relative time series, and the impacts of possible iterative elements in the full process of dataset homogenisation are not. This presentation focuses on the usability of different kind efficiency measures. Results comprise the efficiencies for 15 OMIDs for several test datasets of various statistical properties of IHs included in time series.

EFFICIENCY MEASURES

Before efficiency measures are discussed it is worth to look through the general expectations from "good" homogenisation methods, as it is more than identifying IHs of time series. When an OMID is applied on time series, the general aims and expectations are as follows: i) obtaining the real climatic trends, ii) obtaining the real picture of climate fluctuations, iii) identifying correctly all the IHs of large magnitudes, iv) identifying as many IHs of moderate magnitudes as it is possible.

Usually the identification of change-point type IHs are tested only, and the most frequently applied measure is the hit rate (or power), since it has both theoretical and practical importance. Nevertheless, minimising the rate of false detections has also high importance, therefore some combinations of hit rate and false detection rate are also applied (Mestre et al., 2008). Beyond the presentation of hit rates Ducré-Robitaille et al. (2003) show the SSE values (sum of squared errors) for adjusted series to obtain information about the under- or over-detection of IHs in time series.

Matthew and Menne (2005) use several measures. Let the sum of right detections, that of false detections, and total number of change-points in the dataset be denoted by S_R, S_F and S, respectively, and the sample size is N. (Supposing k time series of n-year length, $N = k \cdot n$.) The hit rate (H), false detection rate (F), false alarm rate (FAR), bias of detection frequency (B), and the improvement in skill compared to random forecasts (HSS) can be built from S_R, S_F, S and N.

$$H = \frac{S_R}{S}; \qquad F = \frac{S_F}{N - S}; \qquad FAR = \frac{S_F}{S_R + S_F};$$

$$B = \frac{S_R + S_F}{S}; \qquad HSS = \frac{2[S_R(N - S - S_F) - S_F(S - S_R)]}{S(N - S_R - S_F) + (N - S)(S_R + S_F)}$$

The diversity of efficiency measures can be reasoned by the fact that efficiency depends on the purpose of the homogenisation, as well as on the statistical characteristics of time series. In addition, even such simple concepts as "right detection" and "false detection" are not absolutely objective, because their definitions need subjective decisions about the tolerance in lapse of timings (j) and magnitudes (m). We apply arbitrary, but reasonable choices for the estimation of efficiencies. In this study the H, FAR, and three further measures are applied. Two of the latter three (E_A and E_B, see below) are for evaluating detection skill, while the third one (E_T) is dedicated to control the impact of OMIDs on the reliability of linear trend estimations.

$$E_A = \frac{S_R - S_F}{S} \qquad E_B = \frac{S_R - S_F + k}{S + k}$$

The conception of E_A is that the importance of finding real IHs and avoiding false detections is practically the same. However, in case of low number of factual IHs, E_A can easily be negative, even if only a few false detections occurred. In contrast, this inconvenience cannot happen with E_B. In case of a pure white noise the target value of (1 - E_B) equals with the probability of first type error in hypothesis testing for the existence of homogeneous or inhomogenous character of time series. In case of large number of large IHs in time series E_B shows similar values to E_A. With moderate intensity of IHs E_B is always substantially higher than E_A, but just because of the systematic character of (E_B - E_A), the rank order among OMIDs is not affected by the choice between E_A and E_B.

For controlling the reliability of trend estimations, the difference between the mean bias of trend estimations for homogenised time series (f), and that for time series without homogenisation (f_0) is calculated:

$$E_T = \frac{f_0 - f}{f_0}$$

E_T shows the improvement in preciseness of trend estimations owing to homogenisation. In this study the trend estimations for the whole (100-year long) time series, and those for the last 50 year sections are evaluated.

Definitions for calculating detection skill:

- In the detection process IH magnitudes are expressed in the proportion of the estimated standard deviation of noise (s_e*) in the examined time series.

$$s_e{*} = \sqrt{1 - \mathrm{R}^2} \cdot s_T \quad \text{if } \mathrm{R} > 0$$
$$s_e{*} = s_T \quad \text{if } \mathrm{R} \le 0 \quad ,$$

where R denotes 1-year lag autocorrelation, and s_T means the empirical standard deviation of the time series. The application of the unit s_e* is reasoned by the fact that during the detection process the factual standard deviation of noise process (s_e) is known only for simulated time series, while for time series from observations this characteristic is unknown. In contrast, s_e* can easily be calculated for any time series. s_e* is usually higher than s_e, but never higher than s_T. Thus s_e* is a better estimation of s_e, than s_T would be.

- In calculating E_A or E_B factual IHs only with $m > m_o$ magnitudes are considered, and m_o is 2 or 3 in this study.
- Right detection: A shift with $m \geq 1.5$ for $m_o = 2$ ($m \geq 2$ for $m_o = 3$) is detected with maximum $j = 1$ time lapse.

- False detection: A shift with $m \geq 1.5$ for $m_o = 2$ ($m \geq 2$ for $m_o = 3$) is detected at year j, but there is no shift of the same direction than the detected one with $m > 0$ within the (j-2,j+2) period.

Considering that individual efficiency measures may reflect only some special features of OMIDs instead of their efficiency in a broader sense, some combinations of different kind measures, especially the combination of detection skill and skill in trend estimations might be beneficial. Domonkos (2006a) introduced such an efficiency measure ("general efficiency"), but we admit that such a measure is rather complicated and its structure is based on subjective decisions. In this presentation the general efficiency is not used.

HOMOGENISATION METHODS EXAMINED

Fifteen OMIDs are examined in the presentation, all of them are the same as those were used in Domonkos (2006a). In this paper basic parameterisations are used only, thus Caussinus - Mestre method and MASH are represented here only with one-one version. Details about method parameterisation, handling of outliers and the way of detecting multiple IHs can be found in Domonkos (2006a, 2006b). The fifteen OMIDs are listed here in alphabetical order.

a) Bayesian test (Ducré-Robitaille et al., 2003) with penalised maximum likelihood method for calculating number of change-points (Caussinus and Lyazrhi, 1997; Mestre, 2004) [Bay]
b) Bayesian test (Ducré-Robitaille et al., 2003) with serial correlation analysis (Sneyers, 1999) [Ba1]
c) Buishand-test [Bu1] (maximum of the absolute values of accumulated anomalies, Buishand, 1982)
d) Buishand-test [Bu2] (difference between maximum and minimum values of accumulated anomalies, Buishand, 1982)
e) Caussinus - Mestre method [C-M] (Caussinus and Mestre, 2004)
f) Easterling-Peterson test [E-P] (Easterling and Peterson, 1995)
g) Mann-Kendall test [M-K] (Aesawy and Hasanean, 1998)
h) Multiple Analysis of Series for Homogenisation [MAS] (Szentimrey, 1999)
i) Multiple Linear Regression [MLR] (Vincent, 1998)
j) Pettitt-test [Pet] (Pettitt, 1979)
k) Standard Normal Homogeneity Test for shifts only [SNH] (Alexandersson, 1986)
l) Standard Normal Homogeneity Test for shifts and trends [SNT] (Alexandersson and Moberg, 1997)
m) t-test [tt1] (Ducré-Robitaille et al., 2003)
n) t-test [tt2] (Kyselý and Domonkos, 2006)
o) Wilcoxon Rank Sum test [WRS] (Karl and Williams, 1987)

DATASETS FOR EFFICIENCY TESTING

Efficiency of OMIDs strongly depends on the statistical properties of IHs in datasets examined. Therefore the creation of proper datasets has crucial importance in the test procedure. In Domonkos (2006a) a dataset was developed in which the statistical properties of IHs highly resemble that of observed temperature time series in Hungary. More precisely, the resemblance is valid for relative time series with at least 0.4 autocorrelation, and the relative time series are derived from the observed data field by Peterson and Easterling (1994). This presentation uses again that dataset, but together with four other datasets, since one aim of the study is to compare the performances of efficiency measures in different tasks. Each dataset

comprises 10,000 one hundred year long relative time series. The time series are built from a standard white noise and artificially inserted IHs. In the creation of test datasets IH magnitudes are expressed with their proportion to s_e. Because of the difference in the applied unit magnitudes here are denoted with *m'*.

The IH properties in the five datasets are as follows.

a) "1 IH only": One IH is included in each time series. Its type is change-point, the timing (*j*) is 40 or 60, and *m'* = 3.

b) "1+4 IHs": Five change-points are included, one with *j* = 40 and *m'* = 3, while the others are with random timing and a fixed magnitude, *m'* = 1.5. Minimum distance between adjacent IHs and from the endpoints of the series is 4 years.

c) "EXP, m'< 6": The mean frequency occurrence is one IH per decade, but IH-frequencies in individual time series may deviate from the average. All the IHs are change-points, their signs (positive or negative), timings and magnitudes are random. Magnitudes (*m'*) are between 0 and 6, they are exponentially distributed for *m'* > 1, and equally distributed for *m'* < 1. In the below formula *q* is a random variable with equal distribution between 0 and 1.

$$m' = e^{2.8\cdot(q-0.36)} \qquad \text{if } q \geq 0.36$$

$$m' = \frac{1}{0.36}\cdot q \qquad \text{if } q < 0.36$$

d) "EXP, m'< 2": It is similar to "EXP, m'< 6", some parameters differ only. The mean frequency occurrence is one IH per decade again. All the IHs are change-points, their signs (positive or negative), timings and magnitudes are random. Magnitudes (*m'*) are between 0 and 2, they are exponentially distributed for *m'* > 1, and equally distributed for *m'* < 1. Since all the IH magnitudes are smaller than 2, their appearance is similar to common noise. For this dataset E_A cannot be applied, as the denominator of the formula would be zero.

$$m' = e^{1.69\cdot(q-0.59)} \qquad \text{if } q \geq 0.59$$

$$m' = \frac{1}{0.59}\cdot q \qquad \text{if } q < 0.59$$

e) "HU standard": A complex structure of randomly distributed IHs of different types (change-points, platform-like IH-pairs, trends) and magnitudes. The title "HU standard" refers to the high resemblance of the statistical properties of IHs between this dataset on one hand, and relative time series with at least 0.4 first order autocorrelation, derived from an observed Hungarian temperature dataset, on the other hand. (High autocorrelation in relative time series is an indicator of substantial pollution by IHs, see e.g. Sneyers, 1999.)

The mean frequency of IHs is about 3 per decade, but most of them have short duration and small magnitude. The decline of frequency with growing magnitudes is considerably faster for *m* < 2.9 magnitudes, than in case of EXP, m'< 6. As a result of this difference in the magnitude distribution, there are much less IHs of 1.5 < *m* < 4 in HU standard, than in EXP, m'< 6, in spite of the fact, that the frequency of all IHs is higher in HU standard. See more details about the properties of this dataset in Domonkos (2006a).

RESULTS

Fig. 1 presents the detection skills for the OMIDs examined. It comprises eight parts (fig. 1a…1h) differing in the test dataset or m_o parameter applied. Usually formula E_A (for dataset

EXP, m'< 2 the E_B) was used. Results show that i) Detection skill is almost always positive (number of correct identification is usually larger, than that of false detection for each OMID examined); ii) Differences according to test dataset characteristics are often larger, than according to different OMIDs; iii) If results for each specific dataset - OMID pair are compared, detection skill is always higher with large IHs (m_o = 3), than for moderate and high IHs together (m_o = 2), with one exception only (dataset EXP, m'< 2 with M-K); iv) Rank order of skills are hardly affected by the arbitrary choice of m_o; v) For dataset "1 IH only" detection skills are higher, than for other datasets (except for tt1), despite the fact that m_o = 2 is applied with "1 IH only", since the size of the IH magnitude does not allow the application of the higher threshold.

Comparing the results for individual OMIDs, it can be find that C-M, E-P and MAS usually perform better, than the other methods, particularly with datasets HU standard and EXP, m'< 6. In contrast, C-M and MAS are the poorest when there is no IH of substantial size in the time series (dataset EXP, m'< 2).

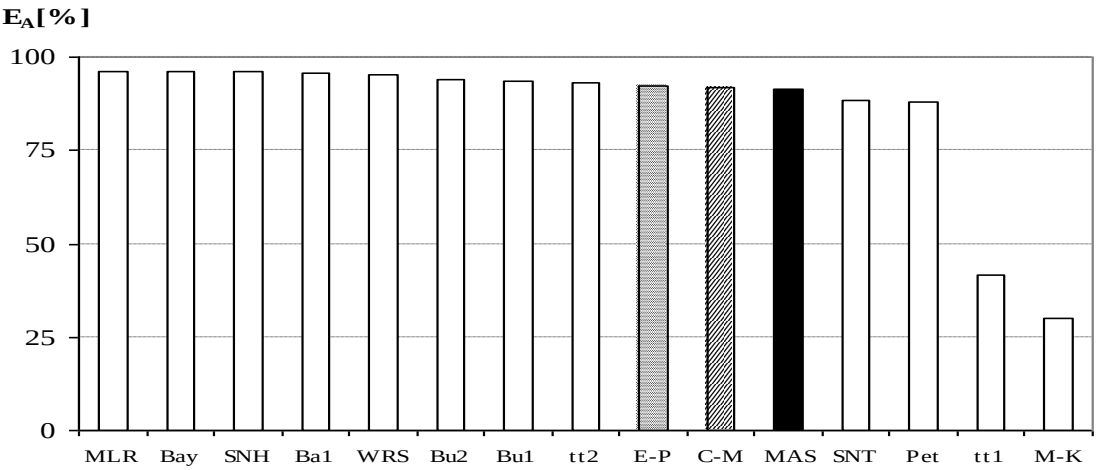

Figure 1. Detection skills for individual OMIDs. Striped: C-M, filled: MAS, dotted: E-P. a) dataset "1 IH only", m_o = 2.

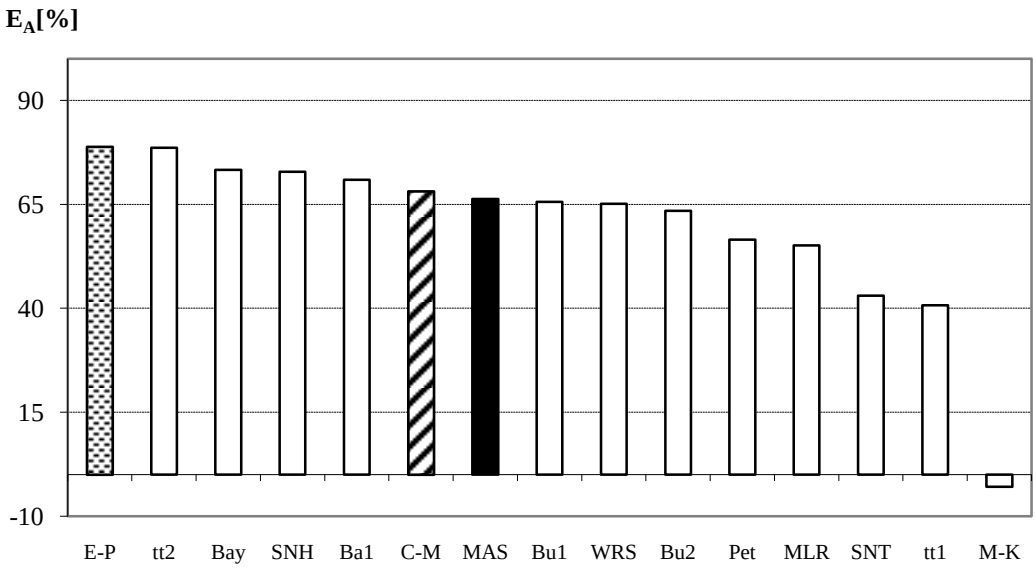

Figure 1b. Dataset "1+4 IH", m_o = 2

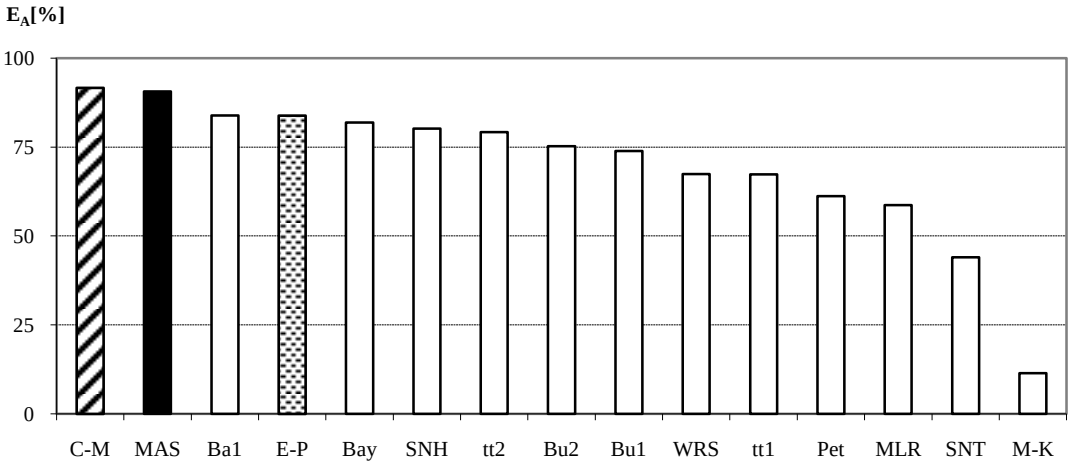

Figure 1c. Dataset "EXP, m'< 6", $m_o = 2$

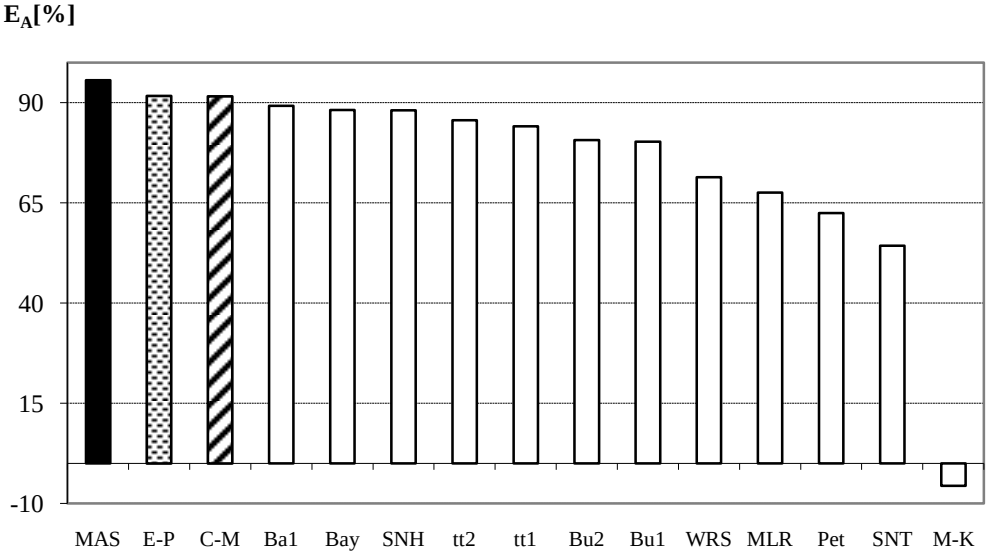

Figure 1d. Dataset "EXP, m'< 6", $m_o = 3$

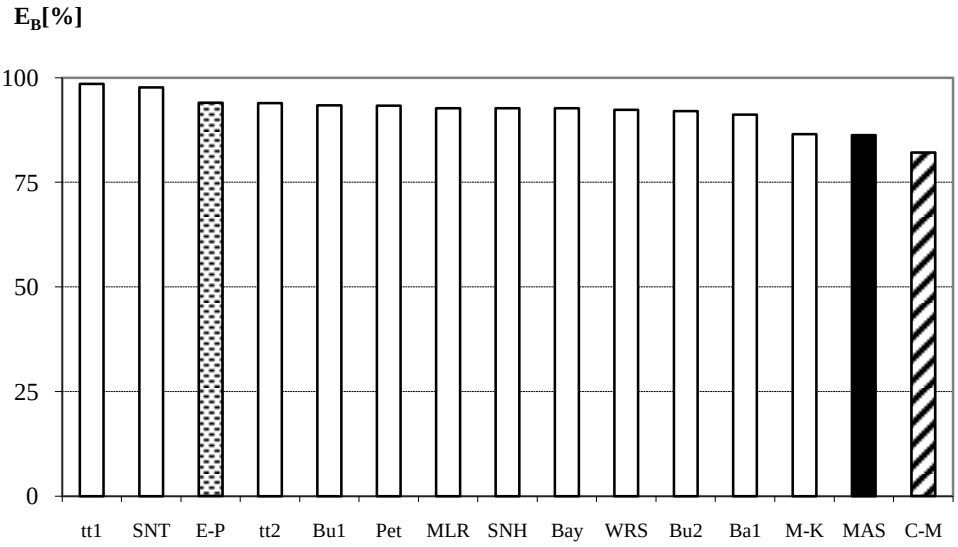

Figure 1e. Dataset "EXP, m'< 2", $m_o = 2$

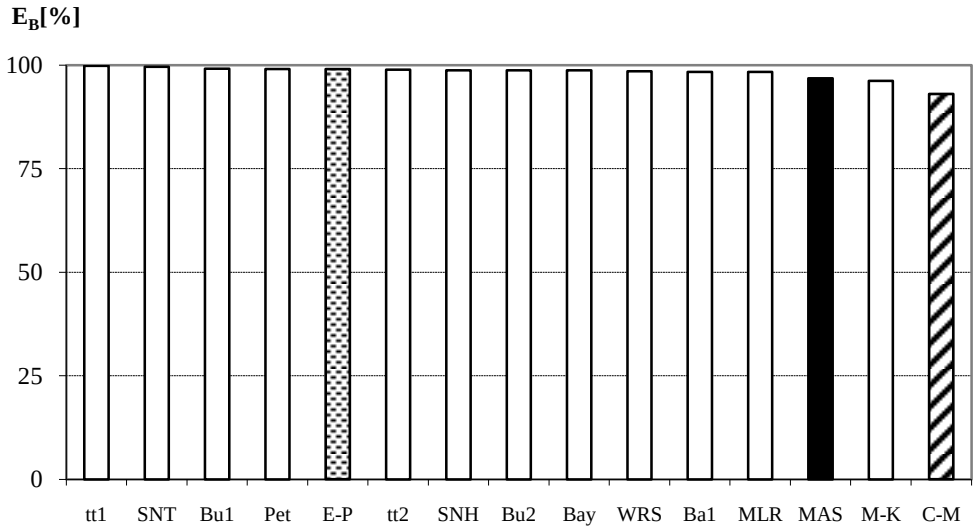

Figure 1f. Dataset "EXP, m'< 2", $m_o = 3$

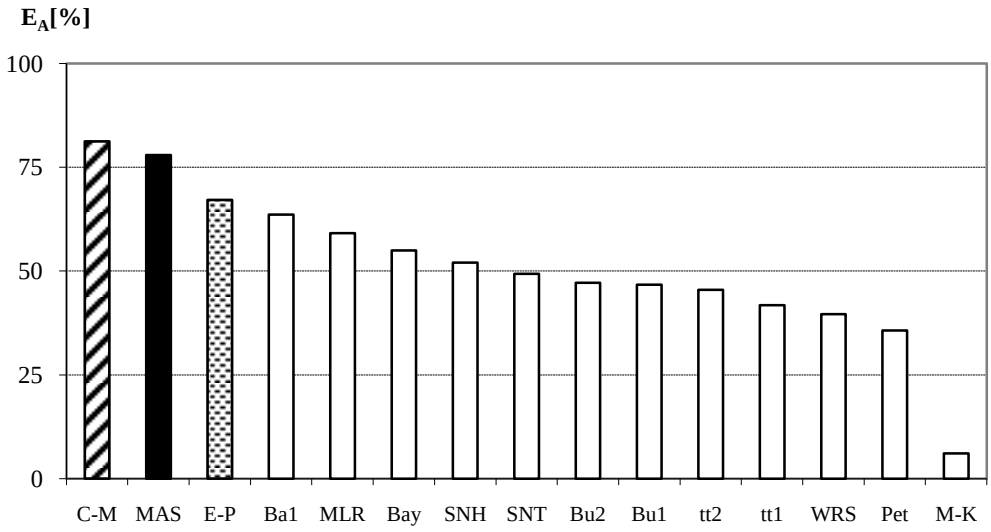

Figure 1g. Dataset "HU standard", $m_o = 2$

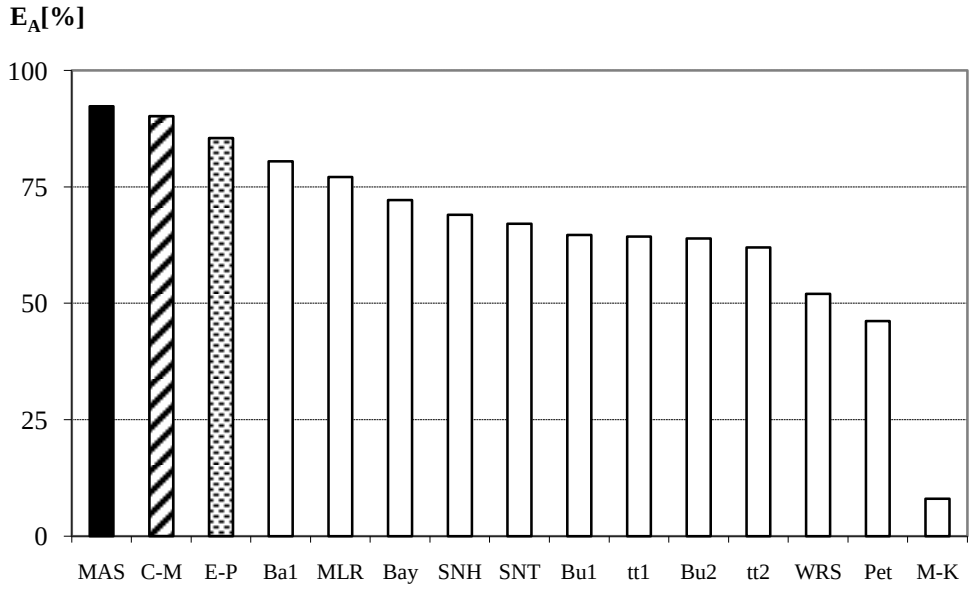

Figure 1h. Dataset "HU standard", $m_o = 3$

It seems that E-P method has the most stable high performance in detection skill. MAS, C-M, Bay, SNH and MLR have also favourably high detection skill, while non-parametric methods, as well as t-tests and SNT have poorer results. Surprisingly low detection skill belongs to M-K in each experiment.

Fig. 2 presents hit rates and false alarm rates for six selected OMIDs (MLR, C-M, E-P, MAS, SNH, tt1). While fig 2a shows differences according to datasets and the choice of m_o, fig 2b shows the differences among specific OMIDs. Best results appear near the upper left corner of the figures, while moving down or right, skills are decreasing. It can be seen again that highest detection skills belong to the dataset "1 IH only". In fig. 2a filled black symbols are used for the results of experiments with m_o = 3, to demonstrate that for large IHs the detection skills are higher, than for medium and large IHs together.

It seems that within the results of a given test dataset higher H values tend to be paired with higher FAR, although there are several exceptions. C-M has the highest H, but FAR is also higher for this method, than the average FAR for the other OMIDs. MAS always has lower H and lower FAR, than C-M does, but the differences between the results of these OMIDs are not very large, and they both can be characterised with high H and moderate FAR. E-P, SNH and MLR also have high power, but H < 75% occurs with them in some experiments. tt1 produces the lowest FAR, but together with poor H values.

Fig. 3 presents the E_T values for individual OMIDs. The values are always positive again (with one exception: tt1 with HU standard), which fact proves that linear trend estimations are more precise if time series are homogenized before the

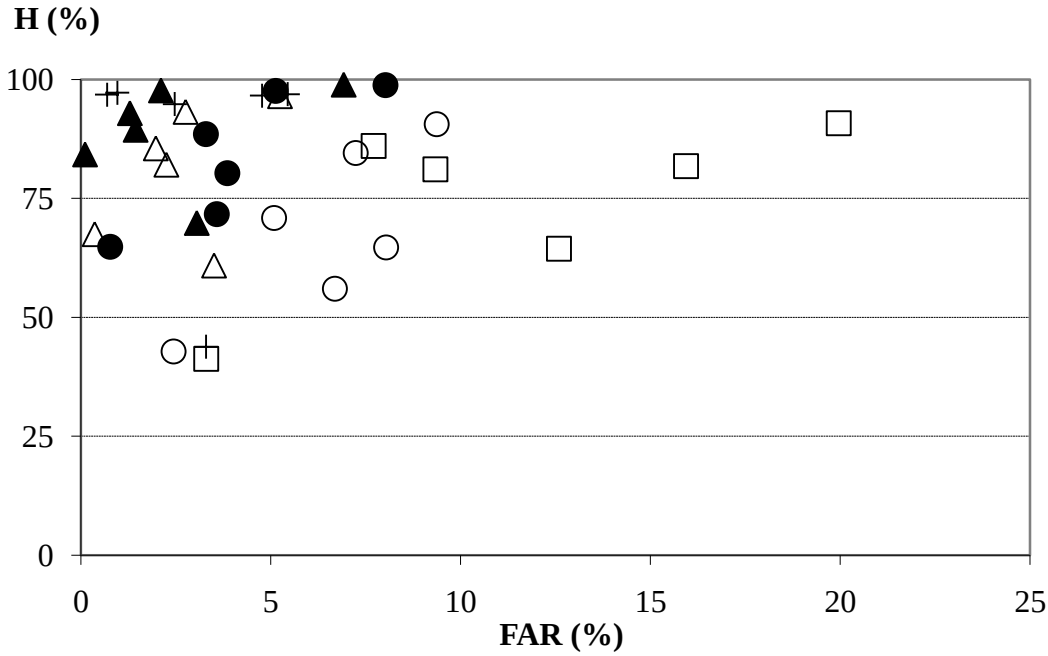

Figure 2. H-FAR value-pairs. a) "1 IH only", m_o = 2: + , "1+4 IHs", m_o = 2: ΐ, "EXP, m'< 6", m_o = 2: Δ , "EXP, m'< 6", m_o = 3: ▲ , "HU standard", m_o = 2: o , "HU standard", m_o = 3: • .

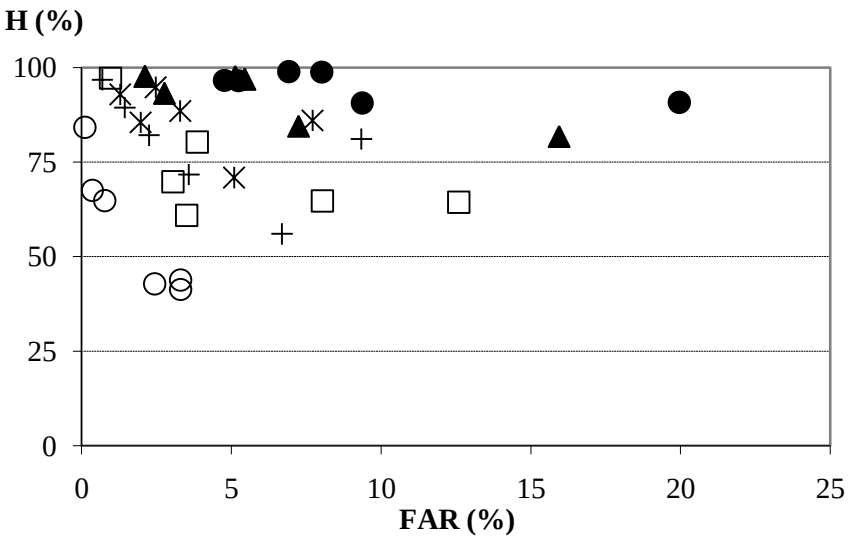

Figure 2b. C-M: ●, E-P: *, MAS: ▲, MLR: ∫, SNH: +, tt1: o

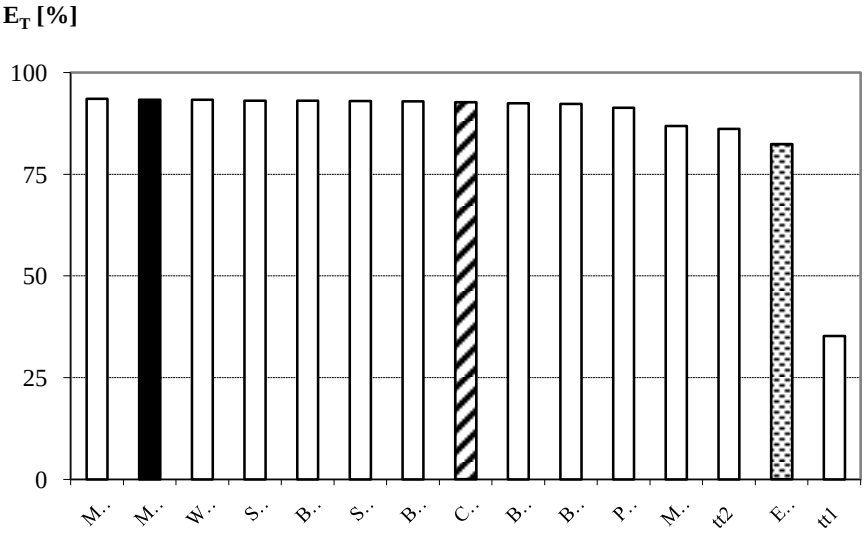

Figure 3. Skill in linear trend estimations for individual OMIDs. Striped: C-M, filled: MAS, dotted: E-P. a) Dataset "1 IH only".

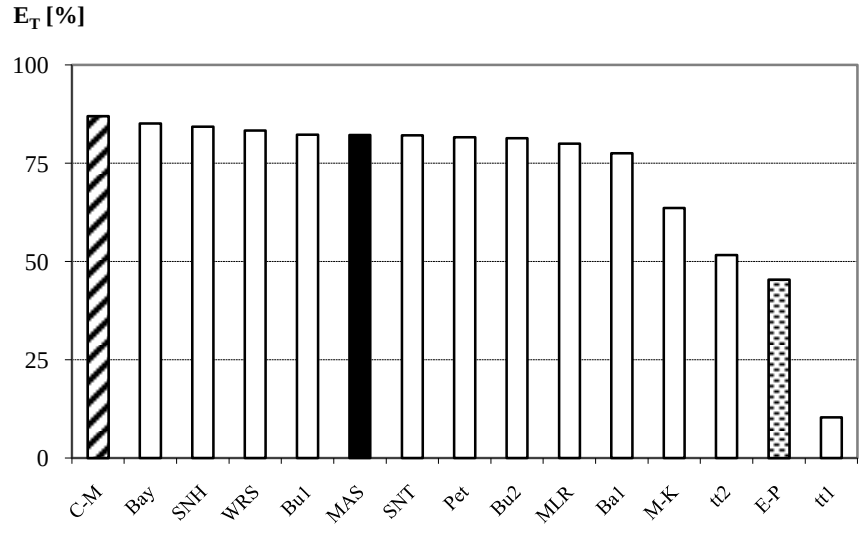

Figure 3b. Dataset "1+4 IHs"

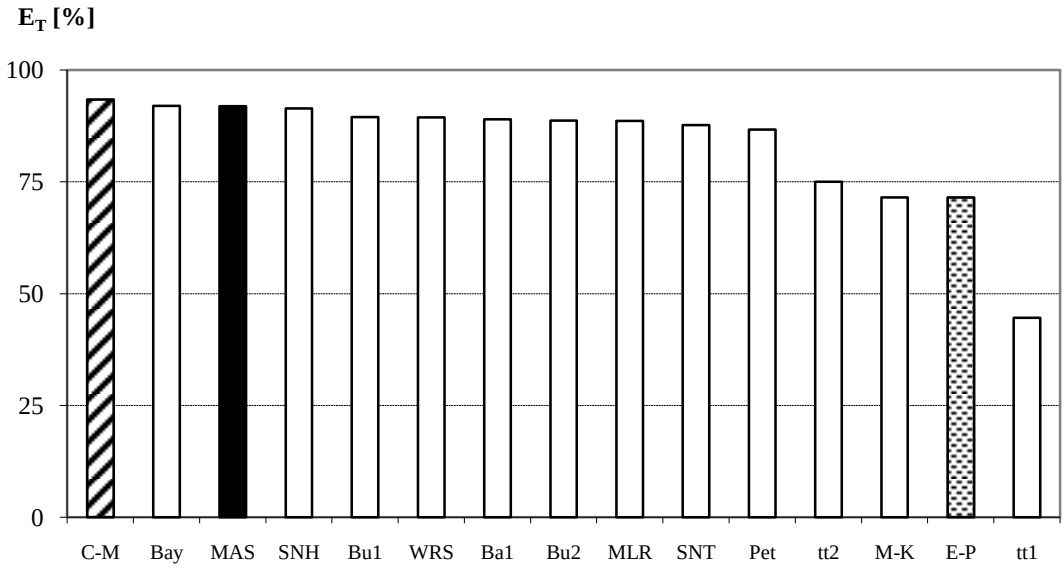

Figure 3c. Dataset "EXP, m'< 6"

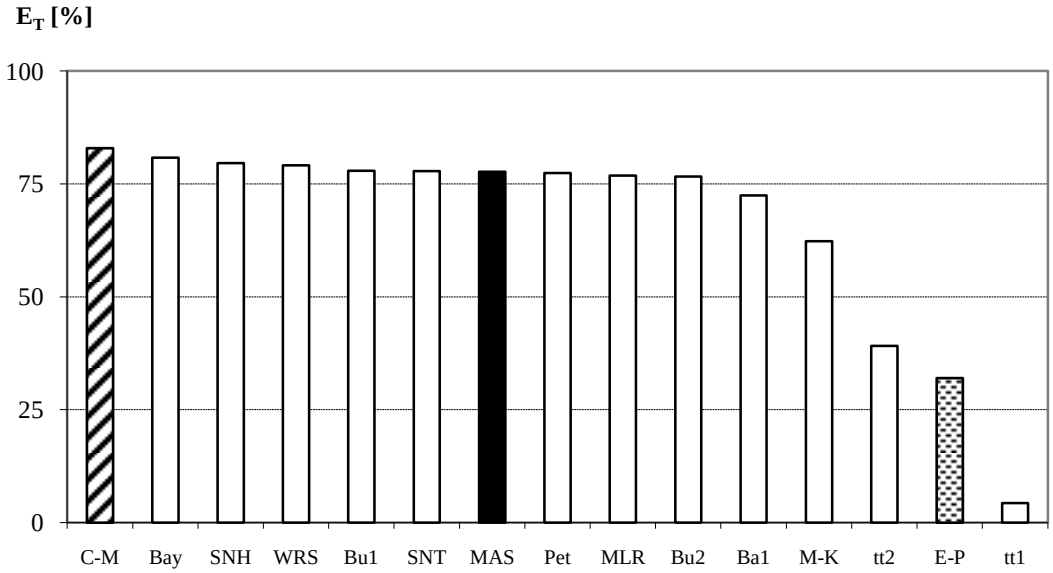

Figure 3d. Dataset "EXP, m'< 2"

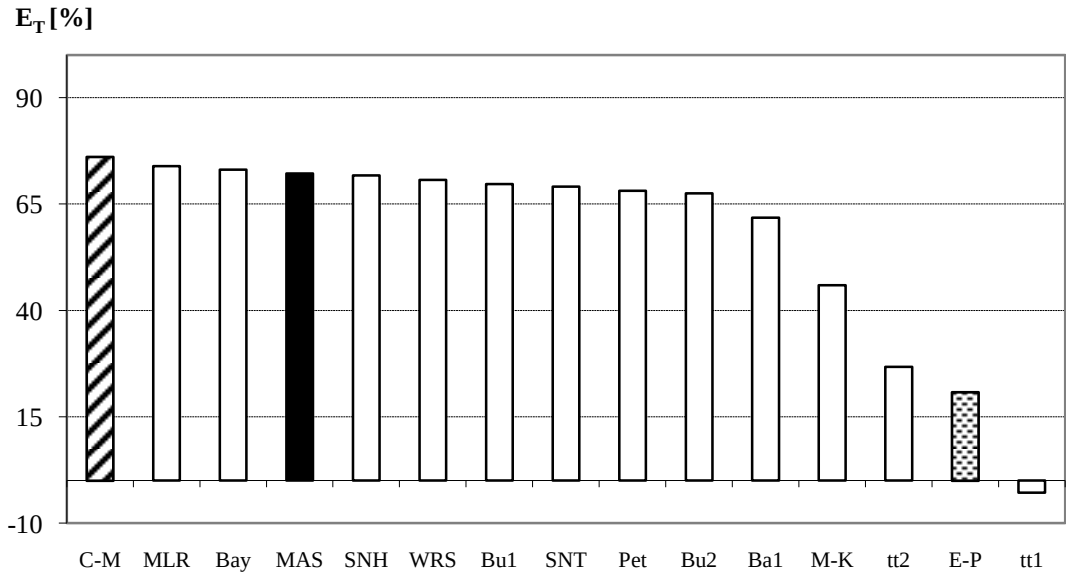

Figure 3e. Dataset "HU standard"

calculation of trends. The five parts of the figure (fig. 3a…3e) are for the five test datasets applied. Results for different datasets have several common
Characteristics, particularly if the very special case of "1 IH only" is excluded from the comparisons. Results show that 10-11 OMIDs produce rather similar E_T values, while the last 4 ones always have much poorer results. The poorest trend detection skills always belong to the tt1, E-P, tt2 and M-K. The rank order has similarities also among the best OMIDs. C-M is always the best according to E_T values, the rank of Bay is always 2 or 3, that of SNH is 3-5, while that of MAS,
Bu1 and WRS is always between 3 and 7. E_T values of MLR are usually slightly lower, than that of several other OMIDs, but in case of HU standard MLR has the second highest skill. This special feature of the results for MLR may be in connection with the fact that HU standard is the only test dataset used in this study which contains linear change type IHs beyond change-points.

DISCUSSION

Efficiencies of fifteen OMIDs were estimated using different efficiency measures and five different test datasets. The picture is mixed, since the efficiencies strongly depend on the efficiency measures and test datasets applied. However, several common features were found among the different kind results. The dependence of the rank order of OMID efficiencies is strong on the efficiency measure, but moderate only on the test dataset characteristics (with some exceptions, whose occurrences are rather unlikely in real climatic datasets). The rank order of skills in trend estimations turned out to be surprisingly independent from test datasets used. On the other hand, the performances and ranks for a specified OMID are often markedly different according to different efficiency characteristics, i.e. a specific OMID may perform very different skills in hit rate, false alarm rate and reliability of trend estimation, the most striking examples were mentioned in the previous section. The following principles may help to obtain a general evaluation of OMID efficiencies:

- Various characteristics (hit rate, false alarm rate, etc.) must be evaluated together,
- If the role of one factor (e.g. false alarm rate) is overemphasized, it may result in misleading consequences. In fact an uncovered IH has very similar impact on the reliability of climate variability investigations, to the one that can be caused by a false IH of the same magnitude.
- Since homogenisation procedures often contain iterations, the impacts of iterations on the growing or abatement of detection errors should also be considered, but it is beyond the scope of the present study. We note that the performance of detection skill (both the hit rate and the false alarm rate) likely has higher practical importance, than that of the E_T values has, since detection errors may influence harmfully the forthcoming results of iterations. On the other hand, low E_T values are also indications of certain type detection errors, therefore such a large negative difference that was experienced with E-P relative to the performance of most OMIDs, is an indication of limited appropriateness, in spite of high E_A and E_B values.
- Unified evaluation for the results of various test dataset and parameterization applications is advantageous.

Our results show that C-M and MAS usually perform better, than the other OMIDs, and it is particularly valid for dataset "HU standard" which is close to a real, observed dataset. This finding is not a surprise, since these two methods were developed to detect multiple IHs without hierarchic algorithm, while some hierarchic way of detection process cannot be avoided using the other OMIDs. The drawback of hierarchic detection was analysed e.g. by Menne and Williams (2005), so our results confirm only the superiority of direct methods for detecting multiple IHs. The results also confirm the theory that non-parametric OMIDs are

less powerful in comparison with other OMIDs, although there are some exceptions for this rule.

It was found that MAS and C-M have clearly higher detection skills in datasets those mimic observed climatic time series with considerable pollution by IHs (i.e. with at least 0.4 serial correlation in relative time series), and C-M is always the best method according to E_T values. However, the superiority of these OMIDs is not uniform; other "common" OMIDs sometimes perform better. We name this phenomenon inverse rank order. The main cases of inverse order are as follows: i) Only one IH exists in the time series (all the evaluated skills), 2) Detection skill is relatively poor when there are several IHs in the time series, but non of them has large magnitude (in our experiments, when m' is smaller than 2 for each IH), 3) C-M (and in some experiments MAS) has slightly higher FAR, than most of the examined OMIDs have, 4) Trend detection skill is often slightly poorer with MAS, than with Bay and SNH.

It must be stressed that in spite of the occurrences of inverse rank order, MAS and C-M are highly recommended for practical use, particularly, because they very often provide the highest skill, and even in cases of inverse rank orders their efficiencies are not low. On the other hand, it can be stated that Bay, SNH and MLR are also rather good OMIDs. What is more, in some specific tasks those have methodological connection with homogeneity investigations the application of some OMIDs with not very high efficiencies can be the most advantageous. For instance, in detecting climatic jumps, E-P seems to be an outstandingly good OMID, because of its uniformly high detection skill in various test datasets.

To reduce the chance of false detection with C-M and MAS, we mention two opportunities: i) Although both C-M and MAS have inner test to decide about homogeneous or inhomogeneous character of time series, they tend to detect more false IHs than several other OMIDs, when there are very few or small IHs only in the time series examined. Therefore time series with multiple IHs of considerable magnitudes should be preselected before the application of C-M or MAS. There is also a problematic point, that during the iterations, if OMIDs are applied repeatedly on the same time series, the chance of false detection may increase. ii) Another possibility is to introduce optimised parameterisations, as it was shown in Domonkos (2006a).

Finally we note that further experiments are needed with the use of various test datasets and efficiency measures, to obtain a more complete picture about OMID efficiencies.

CONCLUSIONS

- Results of efficiency calculations strongly depend on the efficiency measures applied. Therefore a profound evaluation of the efficiencies for individual OMIDs needs the combined use of several efficiency measures.
- Efficiencies of individual OMIDs are almost always positive what proves that homogenised time series are more usable for climate variability investigations, than raw time series.
- The results of this study confirm that parametric OMIDs usually perform better, than non-parametric OMIDs, and the highest skills are usually experienced with OMIDs capable of detecting multiple IHs in a direct (non-hierarchic) way. Two direct OMIDs exist: C-M and MAS. Their practical use is highly recommended.
- The usefulness of individual OMIDs depends on the statistical properties of time series. Further examinations of OMID efficiencies are needed relying on experiments with more various test datasets and parameterizations of efficiency measures, in order to obtain more exact information about the practical usefulness of OMIDs.

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UNDERSTANDING INTER-SITE TEMPERATURE DIFFERENCES AT THE KNMI TERRAIN IN DE BILT (THE NETHERLANDS)

Theo Brandsma
Royal Netherlands Meteorological Institute (KNMI), PO Box 201,
3730 AE De Bilt, the Netherlands, Tel: +31 302206911, Fax: +31 302210407,
theo.brandsma@knmi.nl

Abstract

From May 2003 through June 2005 a field experiment was carried out at the KNMI terrain in De Bilt. At five sites, including the operational site, temperature and wind speed were measured at a height of 1.5 m every minute, using identical instruments. The temperature differences between the sites have been studied in connection with the wind speed differences and operationally measured weather variables. During the experiment (in October 2004) a renovation of the nature area just west of the operational temperature screen took place. The renovation introduced an inhomogeneity in the temperature time series at the operational site. The inter-site temperature differences are largest in summer and smallest in winter. Except for the most enclosed site, these temperature differences have opposite signs for daily maximum and minimum temperatures. As could be expected, the magnitudes of the differences strongly depend on the weather conditions. The understanding of these dependencies is an important condition for improving the homogenization of daily temperature series.

INTRODUCTION

Temperature measurements are often an object of debate. Questions arise whether the measurements are representative for the area that the stations are supposed to represent, or whether the temperature time series are homogeneous enough to allow studies of climate trends and climate variability. Meteorologists mostly emphasize the first question while climatologists are generally more concerned about the second question.

In this context, thermometer exposure and siting are important. WMO (1996) states: “In order to achieve representative results when comparing thermometer readings at different places and at different times, a standardized exposure of the screen and, hence, of the thermometer itself is also indispensable. For general meteorological work, the observed temperature should be representative of the free air conditions surrounding the stations over as large an area as possible, at a height of between 1.25 and 2 m above ground level. The height above the ground level is specified because large vertical temperature gradients may exist in the lowest layers of the atmosphere. The best site for the measurements is, therefore, over level ground, freely exposed to sunshine and wind and not shielded by, or close to, trees, buildings and other obstructions.” From this statement it is obvious that sheltering, and changes in sheltering due to e.g. growth of trees or relocation are undesirable for air temperature measurements.

The present study aims at quantifying the possible effects of sheltering on temperature measurements. These effects have been studied at the local scale of the KNMI-terrain in De Bilt in a two-year experiment by comparing five different sites. Other causes that may affect temperature series, e.g., urbanization and reclamation of land, are not taken into account. The effect of urbanization on the temperature series of the De Bilt is discussed in Brandsma *et al*. (2003).

This paper summarizes some of the results of the experiment in De Bilt. An extensive description of the instrumental setup and calibration can be found in Brandsma (2004) that presents the results of the first year of the measurements.

BACKGROUND AND METHODOLOGY

Background

The particular exposure problems in De Bilt are illustrated in Figure 1. The figure shows the location of the operational thermometer screen De Bilt 260 (DB260) at the instruments field of KNMI. The first problem originates from the lines of trees that run from south of DB260 to north-northeast. The present height of the trees varies from about 20 to 30 meter. Because the

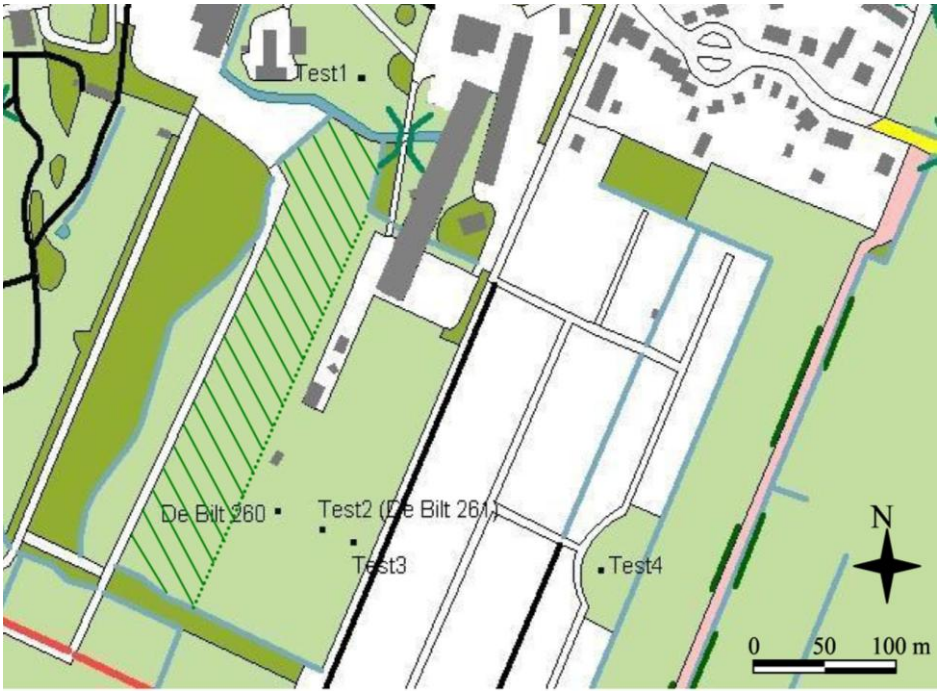

Figure 1: Location of the operational site (DB260) and the 4 parallel sites (Test1-Test4) at the KNMI terrain in De Bilt. Light green is grass cover and dark green trees. The white area that runs from mid bottom to top right consists mainly of vegetable gardens. The KNMI buildings are in gray (left from the vegetable gardens). The green hatched area represents a nature area.

thermometer screen at DB260 is amply within the range of 8-12 times the obstacle height, local effects may affect the temperature measurements. The predominant southwesterly flow further attributes to this problem. In addition, in 2–3 years before the start of the experiment, the area west of DB260 (the green hatched area) had been transformed into nature. During the period May 2003–September 2004 the bushes in the nature area had heights up to 2 to 3 m at a distance of only 12 m from DB260, thus creating an extra shelter effect. In October 2004 the nature area has been renovated completely (see Figure 2), introducing an inhomogeneity in the measurements during the experiment.

Figure 2: Aerial photo of the measurement field after the renovation of the nature area west of DB260 in October 2004. The arrows point to two new bodies of water.

The second problem deals with long-term homogeneity. At 27 August 1951 the operational thermometer screen was moved from location Test1 to the current DB260 location. It is known that this relocation, combined with a change in screen type and a minor relocation on 16 September 1950 caused a jump downwards in the maximum temperatures, especially in the summer. The change in screen type was accompanied by parallel measurements. We digitized and analyzed these data and found that the screen transition partly explains the downward dump in summer maximum temperature. Unfortunately, no parallel measurements were performed for the relocation, making it difficult to correct for the jump, especially for the daily series. Moreover, since the relocation in 1951 the height of the line of trees increased considerably. The height of the line of trees varied at that time between 5 and 25 m, indicating a gradual growth of the trees between that time and present.

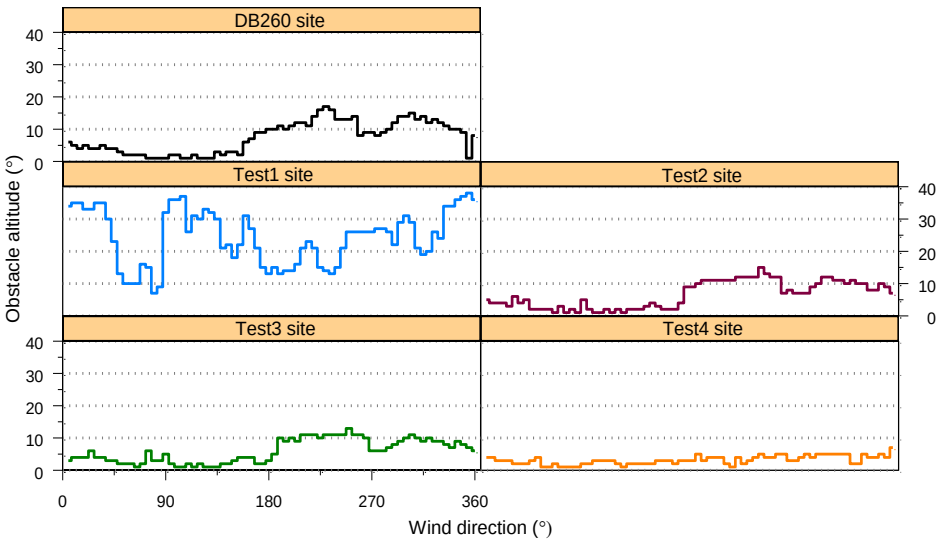

Figure 3: Obstacle altitude as a function of wind direction at the operational site DB260 and the 4 parallel locations

Figure 1 shows the position of the current operational site DB260 and the four selected experimental parallel locations indicated by TestN (N = 1,…,4). Test1 is located at the historical operational site; Test2 (the current back-up site) is situated 30 m from DB260 at 118°, and Test3 at 50 m from DB260 at 118°. Test4 is situated about 220 m east of DB260 near the operational wind mast, which measures wind direction and speed at 20 m height.

Besides the large barrier of trees that runs from south of DB260 to north-northeast, there is also a shallow barrier between the vegetable gardens and the KNMI terrain (see Figure 1). The distance of Test3 to the barrier equals 23 m (perpendicular to the barrier). The barrier consists of a 2 m high permeable fence. Behind the fence, there are garden houses with a height of 2–3 m scattered over the vegetable gardens.

Figure 3 shows the obstacle altitude for each site. The figure clearly shows that Test1 is the most enclosed location and Test4 the most open location. This is also reflected in the annual cycle of the percentage of shade hours (not shown). During winter, Test1 is in the shade for almost the whole day, while for Test4 this only happens for a small fraction (< 13%) of the day.

Instrumental setup

All 5 locations are equipped with identical instruments and sensors. Figure 4 shows the instruments at DB260. Air temperature is measured at 1.5 m above ground level in naturally

Figure 4: Instruments at the operational site DB260. To the left the KNMI multi-plate radiation shield for measuring temperature and to the right the cup anemometer. Both instruments operate at 1.5 m above ground level. The 4 parallel locations are equipped with the same instruments.

ventilated KNMI multi-plate radiation shields. The standard measurement uncertainty of the sensors is 0.1°C but this is reduce to about 0.03°C by correcting the data with the calibration curves.

Wind speed is measured at each site with cup anemometers on top of a pole (see Figure 4) at the same height as the air temperature measurements (1.5 m). The anemometers are situated at a distance of 4 m northeast of the thermometerscreens. The standard uncertainty of the sensors is 0.5 m/s. As for temperature, a higher accuracy was obtained by correcting the measurements with the calibration data.

Besides the experimental temperature and wind speed measurements also the following operational 10-minute measurements at the KNMI terrain are stored and used: wind direction, actual total cloud cover and total cloud cover in the last 30 minutes (both with ceilometer), air pressure reduced to mean sea level, precipitation duration, mean precipitation intensity, direct radiation, diffuse radiation, global radiation, grass minimum temperature at 10 cm, and horizontal visibility.

Methodology

The differences between the 5 locations are studied by comparing the air temperature differences ΔT(SiteX – Test4), where SiteX stands for the Test1, Test2, Test3 and DB260 sites. Test4 is used as the reference site. This site is likely not affected by the renovation of the nature area and is also a candidate future operational location. In this paper we focus on the monthly mean temperature differences between the 5 locations from May 2003 – June 2005 and on the diurnal temperature cycle differences. Special attention is given to the impact of the renovation of the nature area.

RESULTS

Maximum temperature. Figure 5 shows the monthly means of the daily maximum temperature differences ΔT. The temperature differences are largest in the summer half year and may amount to 0.4-0.5°C for Test1 and DB260 (summer 2003). Before the renovation of the nature area in October 2004, ΔT for DB260 and Test 1 are comparable, while after the renovation DB260 is close to Test2 and Test3. Keep in mind that that the temperature at Test1 and the reference Test4 are probably not affected by the renovation.

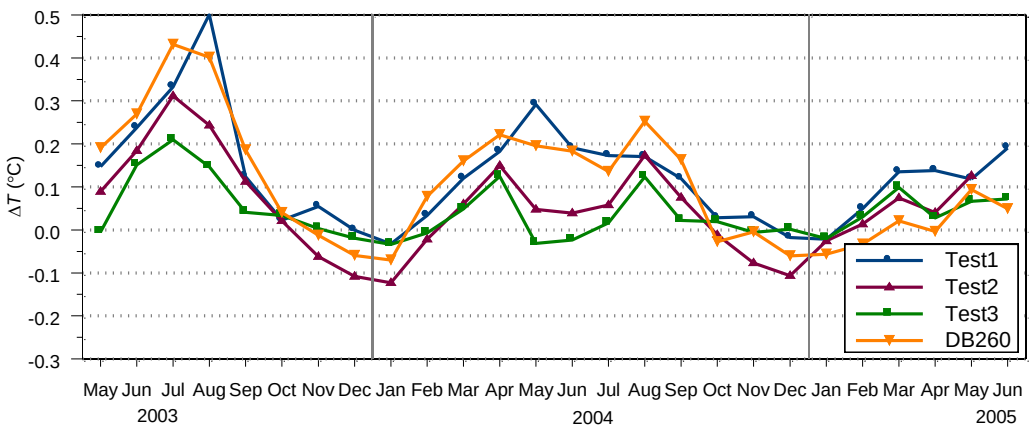

Figure 5: Monthly means of the daily maximum temperature differences ΔT between SiteX and Test4 for the period May 2003–June 2005

Minimum temperature. Figure 6 shows the monthly means of the daily minimum temperature differences ΔT. Compared to Figure 5 it is noteworthy that the sign of ΔT changed, except for Test1. Test1 is warmer than Test4, both in the maximum and minimum temperature, where the relative warmth is largest for the minimum temperature. After de renovation, ΔT for DB260, Test2 and Test3 are all close to zero. This suggests that the renovation influenced all of these three sites.

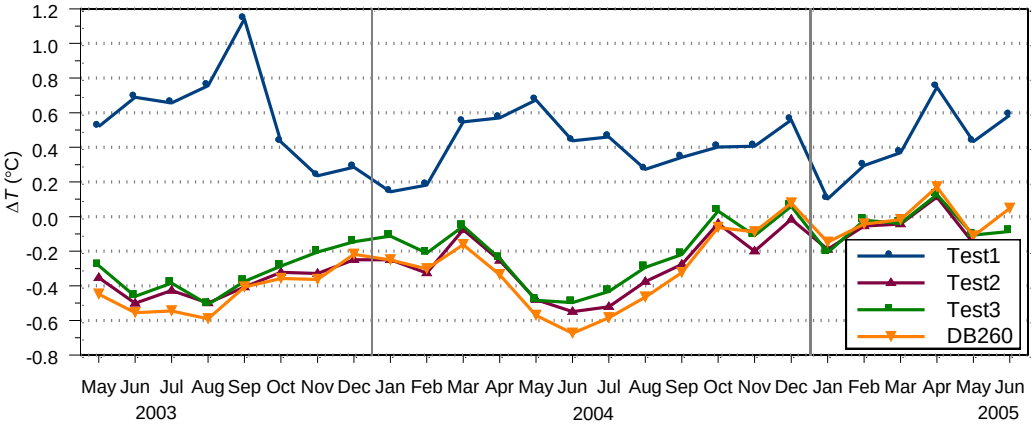

Figure 6: Same as Figure 5 but now for daily minimum temperature

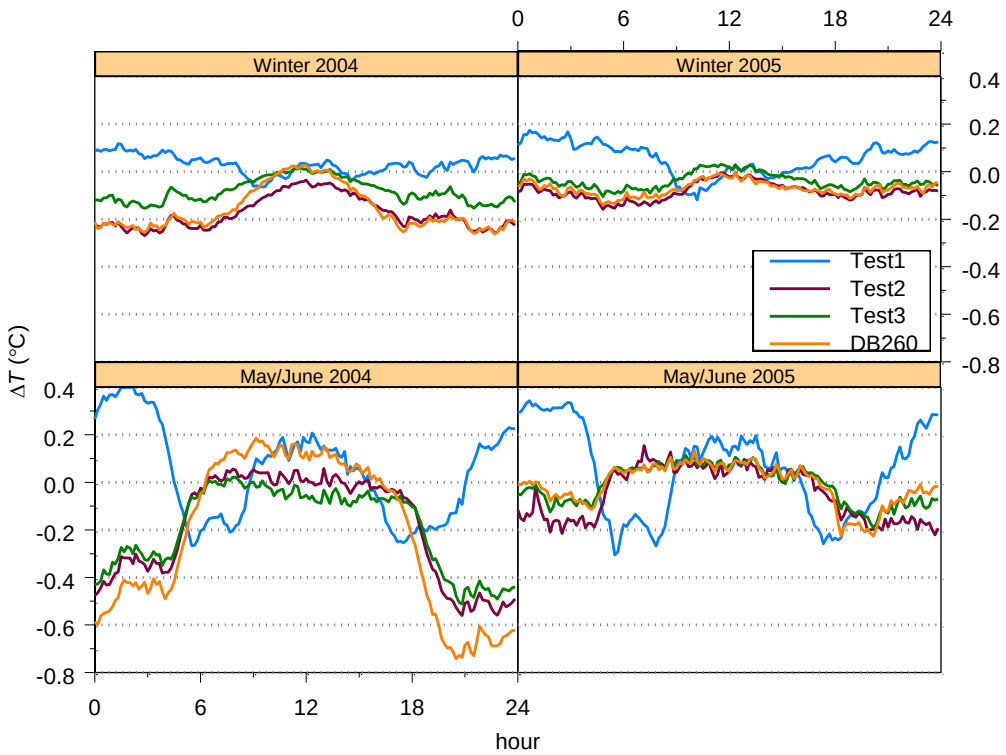

Figure 7: Mean diurnal temperature cycle differences between SiteX and Test4 for (a) winter 2004 (DJF), (b) winter 2005 (after the renovation), (c) May-June 2004, and May-June 2005 (after the renovation)

Diurnal temperature cycle differences. Figure 7 presents the mean diurnal temperature cycle differences between siteX and Test4. Note the behavior of Test1, especially in the summer, during sunrise and sunset. Because the site is in the shade during sunrise and sunset, temperatures at these times are lower than that of the other sites. Note also the decrease in the diurnal cycle differences with respect to Test4 for DB260, Test2 and Test3 after the renovation (especially for the May/June period). After the renovation, the diurnal cycle differences for DB260, Test2 and Test3 are almost identical, especially during daytime.

Diurnal temperature cycle differences as a function of windspeed and cloudiness. Figure 8 presents the mean diurnal temperature cycle differences between siteX and Test4 in summer for 4 combinations of windspeed *W* and cloudiness *N* (cloud cover fraction). The figure clearly shows that the inter-site temperature differences strongly depend on the prevailing

weather conditions. Low windspeed and clear-sky condition results in large inter-site temperature differences while large windspeed and cloudy conditions result minimize the differences.

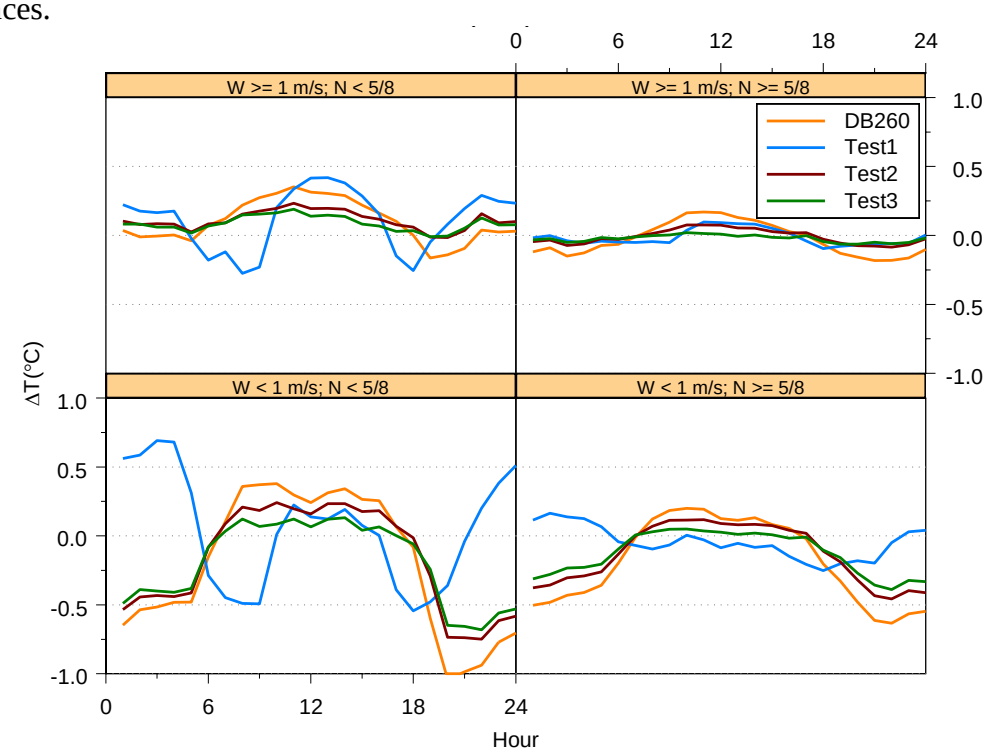

Figure 8: Mean diurnal temperature cycle differences between SiteX and Test4 for the summers (JJA) of 2003 and 2004 (before the renovation) for four combinations of windspeed *W* and cloud cover *N* (fraction of cloud cover) as indicted on top of each panel

DISCUSSION AND CONCLUSIONS

In this study we quantified the possible effects of sheltering on temperature measurements at the KNMI-terrain in De Bilt. It appeared that, especially in summer, these effects may have the same order of magnitude as the long-term temperature trend (about 1.0°C/100yr in De Bilt). However, for most sites the inter-site temperature differences for maximum and minimum temperature have opposite signs. The net effect on the daily mean temperatures (not shown) is, therefore, small. In practice, the largest inhomogeneities in mean temperature series may be anticipated in case of relocations from very enclosed sites (like Test1) to more open sites (the other sites). The renovation of the nature area, close to the operational site DB260, had a significant effect on the temperature.

The results indicate that the magnitude of the inter-site temperature differences strongly depends on windspeed and cloud cover. In case of homogenization of daily temperature series, it is important to take this into account. A complication may be that for windpeed the largest effects on inter-site temperature differences occur in the range 0.0-1.0 m/s at screen level. In practice (a) windspeed is mostly not measured at screen level but at heights of 10-20 m (during stable nights, windspeeds at these heights are uncoupled from those at screen height), and (b) the measurement error for small windspeeds is large. The first problem may be solved by installing additional anemometers at screen height at locations important for climate monitoring. The second problem may largely be met by the introduction of sonic anemometers.

Improvement of our understanding of inter-site temperature differences may enable the modeling them. In case of De Bilt there are certain aspects that are likely important and should be studied further. First, the non-uniformity of the KNMI-terrain may affect downstream sites by daytime advection. Especially the vegetable gardens seem to have energy balances different from those of the surrounding grassland. This results in different Bowen ratios (sensible heat flux/latent heat flux). Second, local stability differences are most important during nighttime stable conditions (small wind speeds, clear sky) when inversions develop, causing low temperatures near the ground. Differences in wind speed between the locations may then cause different strengths of the inversion, resulting in higher temperatures at the location with the larger wind speed. Third, screen ventilation differences are especially important during the day when radiation errors increase with decreasing wind speed. Fourth, small sky-view factors restrict radiation. This is mainly important at the Test1 location. Fifth, local differences in soil type and groundwater levels between the locations may affect the energy balance and may cause differences in observed temperatures. It is known that at the Test4 site groundwater levels are shallower than at the other sites. Especially in dry summers this may result in local differences in the Bowen ratio. Finally, instrumental errors may play a role, though these are minimized here by the calibration procedures.

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DETECTED INHOMOGENEITIES IN WIND DIRECTION AND SPEED DATA FROM IRELAND

Predrag Petrović[1] and Mary Curley[2]
[1]Republic Hydrometeorological Institute of Serbia, Kneza Višeslava 66, Belgrade, Serbia, tel. +381/11/3050-803, predrag.petrovic@hidmet.sr.gov.yu,
[2]Met Éireann, Glasnevin Hill, Glasnevin, Dublin, tel. +3531/8065530, mary.curley@met.ie

INHOMOGENEITIES OF WIND DATA

Detection of inhomogeneities in wind direction and speed data is a specific problem. First, instead of a single element, a pair of elements must be examined simultaneoulsy. None of the existing detection methods deal with more than one element at a time. Second, averaged values in series seem to contain insufficient information about examined weather element. Since some changes might occur only in certain ranges of values, consideration of distributions as an alternative solution gives some previously unavailable information about changes in series.

Another difficulty with wind direction and speed data is the proper approach to various calculations. Wind series are coupled into a pair of completely different elements with different type and range of values, which are azimuth and speed. While wind speed could be treated as any scalar, wind direction data are limited to a fixed range of 360 degrees. Thus, wind data are defined in polar coordinates, which cannot be processed in homogenisation without some conversion of values or adaptation of existing methods. Neither splitting wind data to a pair of north and east component seems to be a satisfactory solution (Petrović, 2008). Therefore, a new method had to be used as an alternative solution.

The ReDistribution Method (Petrović, 2004) deals with distributions of values instead of mean or extreme values. Hence, some additional information about changes in series are revealed. The ReDistribution Method is based on calculation of changes in frequencies of values by subranges between two distributions, generated from subsets with fixed moving window length. The intercomparison between two consecutive distributions detect significancy of changes and hence inhomogeneities.

One of the advantages of the method is its ability to process data with small gaps, infrequent error occurence (i.e. typing errors) or outliers. Since such data appear in a very small number (once in hundreds of thousands of records or even less), their influence on data distribution values is practically insignificant. Average values might be greatly influenced by outliers, which appear to be a disadvantage, because of the rigorous needs for accurate data. Thus, even suspicious or incomplete data might be used with a very small risk of uncertainties.

AVAILABLE DATASET

Figure 1. Locations of stations in Ireland with available wind data

Station	latitude (N)	longitude (W)	altitude (m)	start date
Birr	53.1	7.9	73	01.10.1954
Casement Aerodrome	53.3	6.4	94	01.01.1964
Claremorris	53.7	9.0	71	01.01.1950
Clones	54.2	7.2	89	01.01.1951
Cork Airport	51.8	8.5	154	01.01.1962
Dublin Airport	53.4	6.2	71	01.11.1941
Kilkenny	52.7	7.3	66	01.06.1957
Malin Head	55.4	7.3	22	01.05.1955
Mullingar	53.5	7.4	104	01.01.1950
Roche's Point	51.8	8.2	43	01.12.1955
Rosslare	52.3	6.3	26	01.12.1956
Shannon Airport	52.7	8.9	6	01.09.1945
Valentia Observatory	51.9	10.2	11	01.10.1939

Table 1. List of stations in Ireland with available wind data

A good example of using this method is given by examination of wind direction and speed datasets from Ireland. These datasets are hourly wind direction and speed values from 13 stations located countrywide (Figure 1), covering different periods beginning between 1939 and 1954 up to end of 2007 (Table 1).
A large number of metadata was also available and used for verification of this analysis.

THE PROCEDURE FOR DETECTION OF INHOMOGENEITIES

Initial settings

The ReDistribution Method requires initial settings that depend upon some summary information. To establish a number of categories for counts, it is necessary to review a range of values and overall value resolution Wind direction data have a 10-degree resolution, or 37 possible values (36 values for direction plus one for calms). Wind speed range is from 0 to 63 knots with resolution of 1 knot. Since values over 50 knots are very rare, this value can be considered for the top of the range.

The best results from the method are obtained with 10-20 categories throughout the whole range. More categories would produce higher noise levels, while a lesser number of categories weakens the precision features of the method. Thus, there are 19 categories set for wind direction (18 for direction by 20 degrees plus one for calms) and 18 categories for wind speed (16 subranges by 3 knots, one for speed over 51 knots and one for calms).

Another initial setting of the ReDistribution Method is the moving data window length. To avoid seasonal changes, it is best to use a whole number of years. To avoid taking into account a year that might feature some extreme situations (i.e. extreme values, prevailing wind direction more present than usual), a minimum of two years is the least acceptable choice for a start. However, the method has to be re-run at least once more, but with longer data window length. This returns lower noise level and more precise peaks of ReDistribution Index (RDI) values in temporal scale for detection of break points. The greater the number of different runs, the more reliable the information returned from the method. Still, too long window will diminish break points that appear in time shorter than the window length.

In the case of Irish data, 2-year moving window runs produced quite high noise level. Additional runs were of 4-year and 6-year windows, which reduced noise to an acceptable level and confirmed detected break points.

Although the ReDistribution Method is capable of dealing with sub-daily values, it is time consuming and it is recommended to calculate daily distributions first. Calculations using daily distribution values save a lot of time wasted in hourly values without any significant loss of power of the method that still indicate break points in daily resolution. This procedure requires recalculations of counted values into relative values (percentages) in order to get valid results.

Selection of RDI peak values as break points

The ReDistribution Method may calculate the RDI values for more than one series at a time. In this case, the RDI values are derived from two series, wind direction and speed. It is an important feature of the method, because detected break points might be more or less certain, and also explained by some presumed cause, depending on their (non)simultaneous occurence. If the peaks are more or less at the same point in time, the detected break point is more certain and even more accurate in temporal scale. Non-simultaneous RDI peaks more rely on the magnitude and signal/noise ratio.

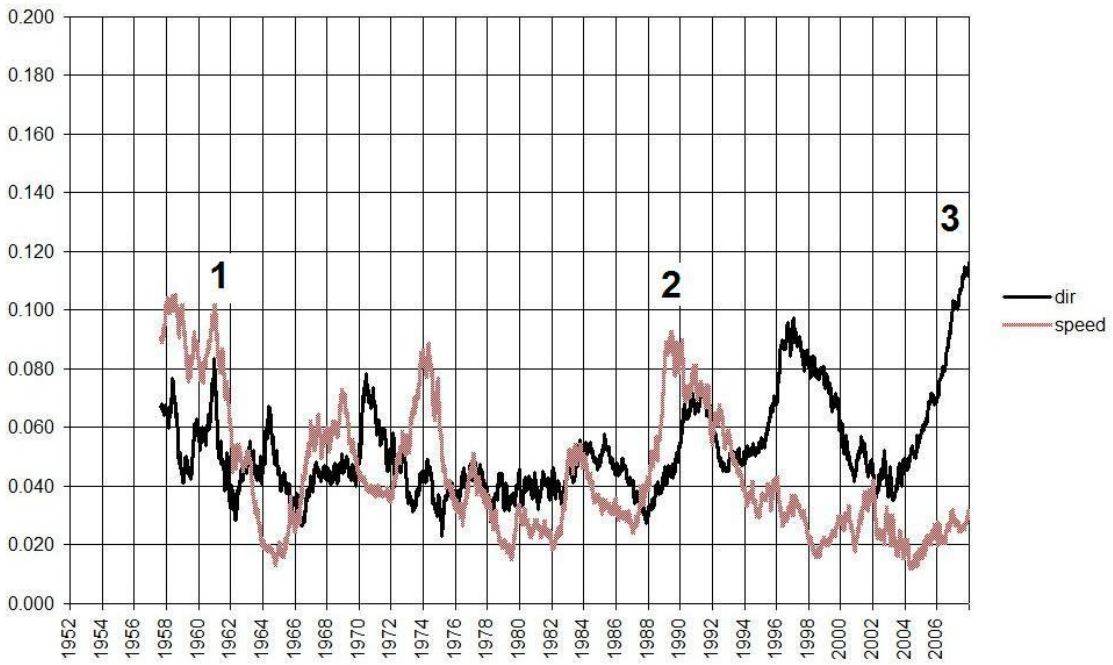

Figure 2. Examples of RDI peaks; simultaneous peaks of both series over noise level (1), peak of series below 0.100 but over noise level (2) and peak of wind direction series only (3) (Shannon Airport, 6-year moving window)

Magnitudes of RDI peaks indicate the possibility and accuracy of detected break points. If the RDI value is over 0.125, the break is quite certain (Figure 3, point 2). Smaller peaks of RDI, but still over 0.100 might indicate a possible break (Figure 2, point 2). Even smaller RDI peak values might be a break point, but only if the peaks from two series are simultaneous and significantly higher than the noise level (Figure 2 and 1).

Differences in time between detected break points and their causes are in a great accordance with RDI peak magnitudes. High RDI values return the break point information with very high precision (up to daily resolution, even the very day of change). When dealing with small

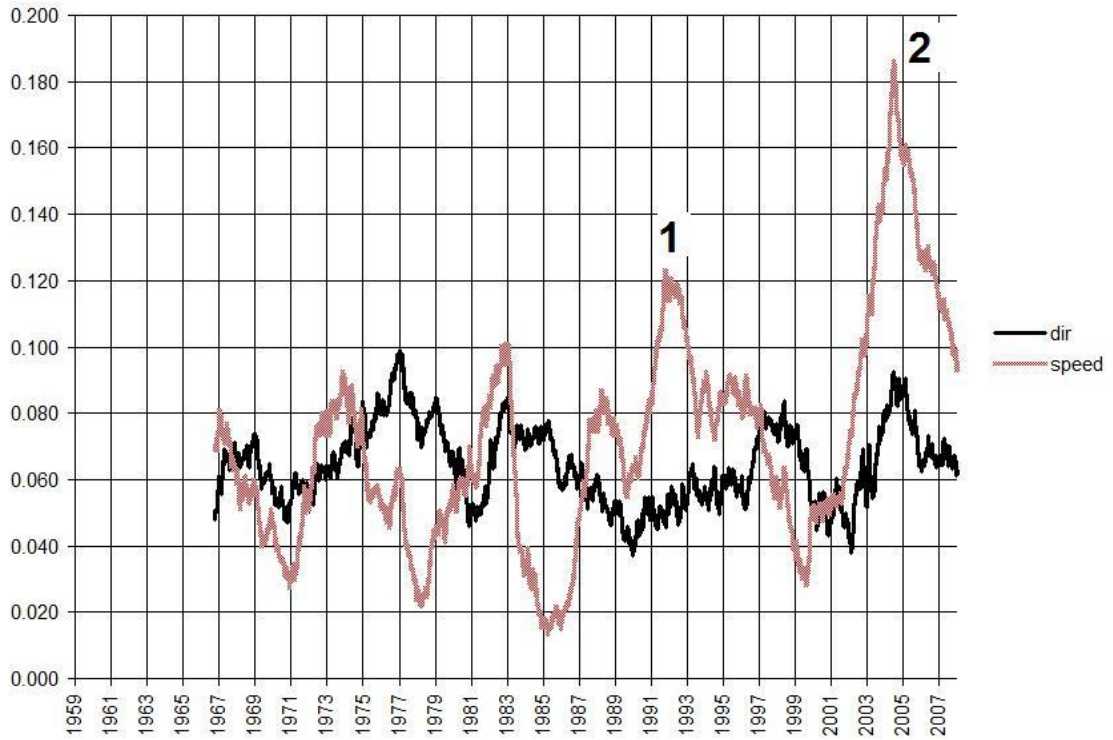

Figure 3. Examples of RDI peaks; possible break with RDI > 0.100 and break of wind speed only (1) and ceratin break with RDI > 0.125 (2) (Birr, 6-year moving window)

RDI peaks, differences in time between the detected break and its cause might be quite large (even a couple of years). Such low magnitudes might even question the significance of the detected break and thus consider series as homogenuous at that point.
Finally, detected break points have to be considered according to its type and verified by metadata or any other source of information, which might include simultaneous breaks from different weather elements or results from any other reliable homogeneity test. Further examination of detected break points should be considered as a part of a homogenisation (correction of values) procedure.

TYPES OF BREAK POINTS ACCORDING TO POSSIBLE CAUSES

Main types of inhomogeneities

There are three main types of inhomogeneities:
Both direction and speed affected at the same time (Figure 3, point 2; Figure 2, point 1). This type of inhomogeneity is generally caused by one or more following reasons: change of instrument type, relocation of a measurement site, abrupt change of station surroundings, even change of observer.
Wind direction only (no break point with wind speed) (Figure 1, point 3). Causes for this type of inhomogeneity include: change of instrument orientation or functionality (usually wind vane orientation, change of friction or inertia), misorientation of instrument (false orientation, i.e. according to magnetic instead of geographical north) and change of precision (number of wind rose directions). This is a quite rare type of inhomogeneity because there are very few situations in which only wind direction is affected by the change.
Wind speed only (no break point with wind direction) (Figure 3, point 1). Breaks only in wind speed series are generally caused by change of instrument calibration, functionality (usually friction in mechanism associated with wind cups), change of threshold for initialization of an instrument, change of precision (including measurement units). Other causes for changes in wind speed only are mentioned with the first main type of inhomogeneity.

TYPES OF INHOMOGENEITIES IN WIND DIRECTION SERIES

Present experience gained with the ReDistribution Method has given several types of inhomogeneities in wind direction series. Examples of these types are given from processing wind data from Ireland.
Shifting distribution of directions (Figure 4) is a type of change where distributions from one sector of directions (up to half a circle) move to another, different or even opposite sector. It is generally caused by a change in station surroundings or relocation of instrument. The example of Valentia wind direction break in 1950 corresponds to metadata information of building a balloon filling hut south of the measurement site in 1947. This event reduced frequencies of southern winds and slightly increased northern wind frequencies. The

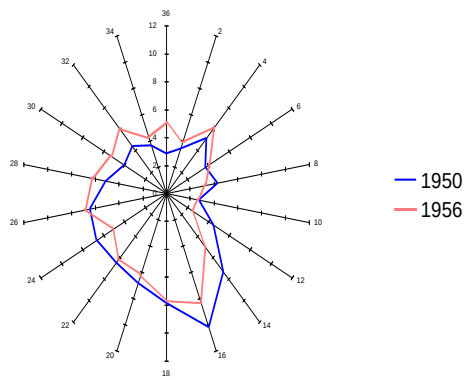

Figure 4. Shifting distribution of directions (Valentia, 1950)

redistribution of wind direction frequencies is associated mainly with low wind speeds, indicating change of local winds, while high wind speeds were still had the same distribution by directions. Since the magnitude of change is quite low (RDI is 0.100), and no other breaks were detected close to this one, the change of surroundings appears to have taken effect on wind direction data a few years later.

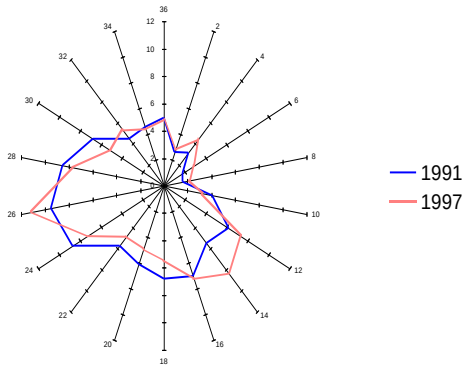

Figure 5. Narrowing of wind rose (Shannon, 1991)

Widening / narrowing of wind rose (Figure 5) is a type of change where frequencies of prevailing wind directions become lower / higher, making wind rose appear widened / narrowed. This is another type of change caused by changes in instrument environ-ment, but also an instrument replacement, which is featured with the given example of Shannon in 1991. A new instrument was placed on a different mast, some distance away from the previous location, hence the change of location took effect on data.

Spreading / contracting of wind rose (Figure 6) is a type of change where all frequencies become evenly higher / lower. The most probable cause is an instrument being replaced by one with lower / higher initialization threshold. Such changes frequently occur when mechanical anemometers are replaced by a new generation of wind instruments during automation of a station. This type of change usually has a small magnitude and it might be quite uncertain in time. An example of introducing an AWS in Kilkenny during 1998 shows such type of change.

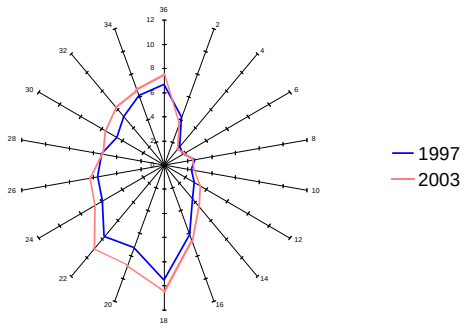

Figure 6. Spreading of wind rose (Kilkenny, 1997)

Moving of prevailing wind (Figure 7) is a type of change where prevailing wind is being redirected by an angle, while other directions remain generally the same. This is due to change in measurement site environment, emerging or removing an obstacle near the instrument. Also, the reason could also be an instrument replacement, like in a given example of Clones in 1997.

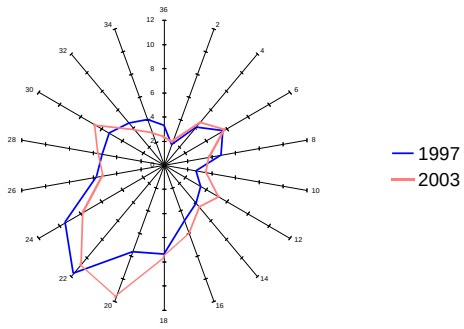

Figure 7. Moving of prevailing wind (Clones, 1997)

Other types of inhomogeneities associated with wind direction were not found in the wind datasets from Ireland. These include:

Rotation of a wind rose (Petrović, 2004) is a type of change where all frequencies seem to be shifted by an angle. The cause for this type is usually a misorientation of an instrument which is corrected at certain point in time.

"Starry" wind rose (Petrović, 2004) is a type of change where some directions are just missing or not sufficiently present in the distribution of direcions. This is equal to low precision measurements (or measurement unit) problem, where new instrument introduces more wind

direction classes than old measurements (i.e. changing a number of wind directions from 8 to 16 or more).

Irregular redistribution (Petrović, 2004) is any other type of change that is neither described here, nor easy to detect any pattern of change. The causes for this heavy distortion of a wind rose include change of surroundings, relocation of a measurement site or errorneous mixed-up dataset.

TYPES OF INHOMOGENEITIES IN WIND SPEED SERIES

The ReDistribution Method has detected break points in wind speed series that could be sorted by several types.

Shift up (Figure 8) is one of the most frequent type of changes, moving maximum distribution frequencies to higher values of wind speed. Lower values are less frequent, while higher values of wind speed are more present in the dataset. The cause for this type of break is generally an instrument replaced by one with different calibration. The given example of Malin Head, 1962, shows how wind speed distribution affected by instrument malfunction. Older instrument readings returned a continuous variation between zero and the true wind speed values, occasionally stopping the instrument working properly.

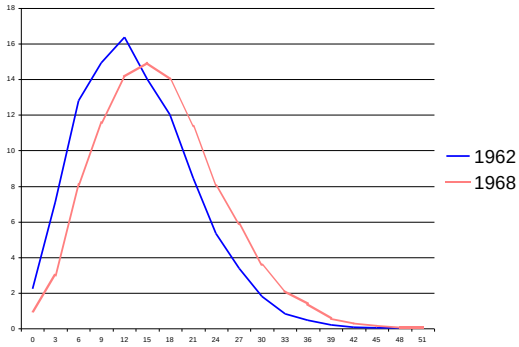

Figure 8. Shift up of wind speed distribution (Malin Head, 1962)

Shift down (Figure 9) is as frequent a type of change as the previously described shift up type. Here, maximum distribution frequencies are moved to lower wind speed. Higher values are less frequent, while values lower than the most frequent wind speed are more featured in the dataset. The cause for this type of break is the same as the cause for shift up type. An example from Claremorris at the beginning of 1968, gives a good example of the effect of instrument overhaul in May 1967 which caused changes in the of wind speed distributions.

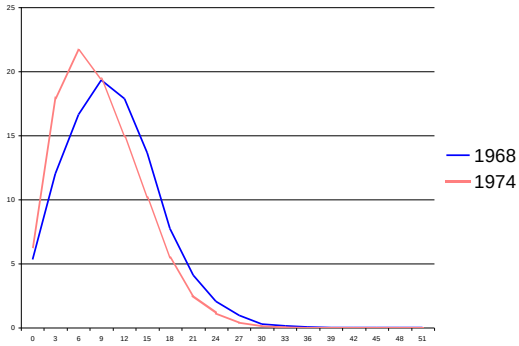

Figure 9. Shift down of wind speed distributions (Claremorris, 1968)

Calms up (Figure 10) is a type of change that increases the number of calms, while other wind speed frequencies are practically unchanged. The cause for this type of change is the increase of threshold for instrument initialization, which is generally due to enhanced friction. However, the reason could not be instrument sheltering by obstacles, because such change would distort the air flow at the instrument position. The break point in Claremorris, 1958, suggested such a problem with the anemometer. There are reports in the metadata that the instrument was insensitive to winds below 4 knots and due to this the instrument was overhaul in

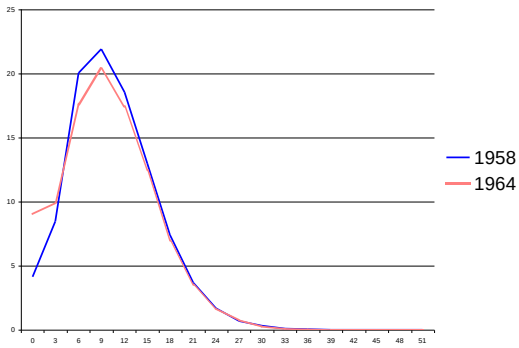

Figure 10. Calms up (Claremorris, 1958)

1967. During the overhaul bad corrosion was discovered which explains the fact that the instrument had become less sensitive. Sometimes this type of break might come up with shift down type, having the same cause of change.
Calms down / calms out (Figure 11) is a type of change that reduces number of calms to near zero values. This is due to introduction of an instrument with much lower initialization threshold. This is often featured in introduction of AWS, like in a given example of Claremorris, 1995.

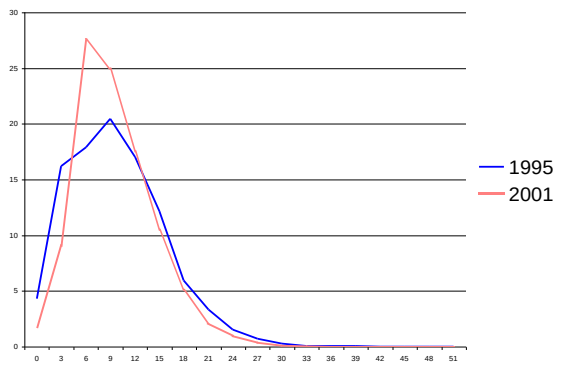

Figure 11. Calms down / calms out (Claremorris, 1995)

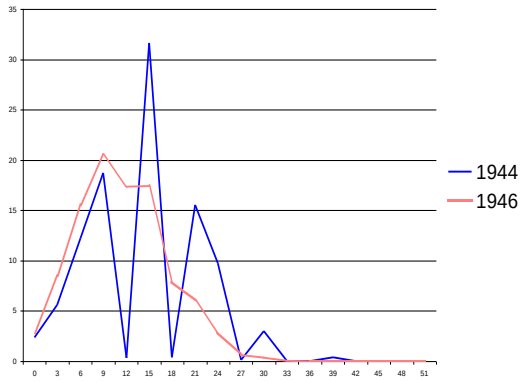

Figure 12. Change of measurement unit (estimates to measurements, Dublin Airport, 1944)

Measurement unit (Figure 12) is a type of change featured as "gaps" in some categories of wind speed. This is due to conversion of measurement unit, like in a given example of Dublin Airport, 1944, where knots were introduced after Beaufort scale estimates.

Irregular redistribution (Petrović, 2004) is any other type of change that is neither described here, nor easy to detect any pattern of change. The causes for such breaks include change of surroundings, relocation of a measurement site, instrument malfunction or erroneous mixed-up dataset. Such changes were not found in the data sets from Ireland.

HOMOGENISATION POSSIBILITIES

The ReDistribution Method is primarily a break point detection tool. Since it is based on comparison between consecutive distributions of values instead of mean values, present homogenisation tools and methods are of a little use. This method has to develop a new approach to homogenisation in order to establish proper corrections for distributions of values.
Present homogenisation methods usually return a certain value as a correction factor for the inhomogenuous data subset. Additive correction factor could be positive or negative, but negative correction returns some values to undefined (negative) range. Hence, present methods are not applicable to elements that are defined for no negative values, such as wind speed. This factor can also be multiplicative, which avoids such error, but disturbs

distributions. Wind speed data are often inhomogenuous by subranges of values (i.e. low and initialization threshold values), thus such correction would produce more erroneous data at subranges that were not previously affected by inhomogeneity.
On the other hand, wind direction as azimuth value is an element with strictly defined range of values from 0 to 360 degrees, with ability to switch from one limit of range to another by definition (when crossing north direction). So far, there are no homogenisation tools that could correct such values. Secondly, wind direction and speed are quite independent one from another, while inhomogeneities frequently affect both series at the same time, especially when a change on surroundings or instrumentation occurs.
As mentioned, some inhomogeneities of wind speed affect only a subrange of values. Homogenisation tool must use a method for correction of distributions. In general, overall distributions are easy to homogenise by applying a correction related to distribution of values. The real problem is to go to the source values and apply an established correction. That correction must be a set of correction values applicable by categories of values, bearing in mind that sum of all occurences must be preserved.
Any possible homogenisation must incorporate mathematical tools that would consider distribution (i.e. probability density function) instead of adding / multiplying all homogenising values. An investigation of such correction function is in the plans for future work on development of the ReDistribution Method.

RESULTS

NUMBER OF DETECTED BREAKS

Investigation of wind direction and speed data sets from Ireland by using the ReDistribution Method was quite successful. Nearly half of all detected break points were confirmed by metadata (Table 2). Metadata for anemometers is currently being digitized in Met Éireann. Hence more metadata may be available in the future (e.g. calibration details). Thus it may be possible to confirm more of the breaks in the future.

type of break	number of detected breaks	confirmed by metadata
wind direction	27	12
wind speed	47	20
wind direction and speed	19	9
wind direction only	8	3
wind speed only	28	11
total	55	23

Table 2. Overall number of detected and confirmed break points in wind data sets from Ireland

ACCURACY OF BREAK POINT DETECTION

The accuracy of break point detection improves with higher RDI peak values. The highest RDI peak value is 0.186 (Birr, 1998), strongly indicating redistribution of wind speed value coming from the instrument replacement (introduction of AWS). This break is also detected with very short difference between the indicated break point and true change. In this case, the precision of break detection was only four days (detected 20th June 1998, true change 24th June 1998). However, the shortest difference was only two days (Claremorris: detected 10th September 1995, true change 12th September 1995).
On the contrary, low RDI values of under 0.100 are generally suspicious breaks and these might be taken for real breaks only after metadata confirmation. The lowest RDI break recognised as a break point is 0.087 (Dublin Airport, 1994). In such cases, the differences between detected and confirmed break extend to 6 months and more.

Some RDI temporal changes return double or multiple peaks of almost the same magnitude in a period of time shorter that the data window length. It is not necessary to pick up the highest value as the break point, but the closest one to the true break, if metadata are available. Such cases indicate problems with observational data that occur for a certain period in time (i.e. period between instrument malfunction and its service, multiple breaks in time shorter than the power of the method may detect).

METADATA

Metadata information was available for much of the wind data from Ireland. However there were some periods without metadata records and also some of the data had not yet been digitized. It was presumed that there were no important changes during this time, but there is a possibility that some of the metadata is incomplete Metadata were quite valuable when they contained the exact date and information about the changes on the measurement site. Such metadata are of major importance when the method has to be tested and verified.
There were also some cases when metadata did not match completely the returned results. Also, some of the metadata has not yet been examined/digitised (e.g. calibration lists). It is necessary to examine this data in order to get the most complete information possible. In this work such cases were left as not confirmed breaks.

UNCERTAINTIES

Low RDI peaks often return many uncertain break points. Bearing in mind given causes, the next question is the importance of these breaks. Although some of the low RDI peaks are the true breaks, it is difficult to decide whether such break point might be neglected and treat series as homogenuous at that point.
Gradual changes (trends) are not certainly detected by the ReDistribution Method. It is also difficult to detect slow redistributions of wind direction and / or speed which might be due to gradual changes (i.e. tree growth, increase of friction in instruments). For the time being, such changes were suspected in periods with increased RDI noise level. Further development of the method will show whether this assumption is correct.

COMPARISON WITH KNOWN METHODS (SNHT)

Since there were no methods for detection of inhomogeneities in wind direction data, comparison of the ReDistribution Method is made only with wind speed data. The comparison method for detection was chosen to be Standard Normal Homogeneity Test (SNHT). The hourly data were recalculated to the monthly and annual resolution before they were processed. Data gaps were not filled in order not to bias any result returned from the SNHT and thus make a correct comparison of the two detection methods.
The comparison of the results returned that from 47 detected break points using ReDistribution Method, 20 were also detected by SNHT. On the other hand, SNHT has not detected any new break point that was undetected by the ReDistribution Method. Although SNHT has also detected some minor breaks, some major breaks with high RDI values (up to 0.162, Mullingar, June 1996) were not detected by the comparison method. This might be the case with periods with increased RDI values (as it was in the mentioned case). However the SNHT depends on homogeneous reference series with high correlation between the reference and candidate series and it is not very suitable for use with Irish wind data.

Differences in time between detected break points from both methods were not significant in annual resolution. SNHT has no ability to detect breaks in any finer than monthly resolution.
Since the ReDistribution Method has returned better results than SNHT, it is highly recommended for further use.

PLANS FOR THE FUTURE

Present experience with the ReDistribution Method has established a basis in break point detection with respect to the causes of inhomogeneities. However, these basis have to be extended with more experience with the method (more data coupled with metadata).
The construction of surrogate wind data sets might show the true power of the detection method. However, most inhomogeneities are coming from measurement problems, while climatic signal (if any detected or suspected) is highly suppressed by the method, making difficult to detect gradual changes. Therefore, surrogate wind data sets must include a "given" climatic singnal, "cleaned" from instrumentation problems in order to examine possibilities for climatic signal detection.
Since the ReDistribution Method is capable of operating with more than one series at a time, introduction of wind gusts as the third element is also planned. Naturally, wind gusts must be strictly defined (10-minute, hourly or daily maximum wind speed) for the whole dataset, but this is not necessary for the method in general. Amongst other features, wind gusts depend on roughness by directions of the surrounding terrain, which will make calculations a bit more difficult. As the first step, it is planned to introduce wind gusts with an approximation of evenly distributed roughness from all directions.
The ReDistribution Method might also have a variation that would substitute intercomparisons between subsequent distributions with distributions from two different measurement sites. That variation would make the ReDistribution Method capable to work as a parallel, relative method.
Also, the ReDistribution Method is applicable to some other weather elements. Sometimes, these elements might not have any climatological sense (i.e. visibility ranges), while any inhomogeneity detected with such series might discover a valuable metadata information (i.e. change of observer). Such break points might help in full investigation of inhomogeneities of other elements that occur at approximately the same time.
Finally, the possibilities for making a correction method based on distributions is being considered. The initial work would be based on a redistribution matrix calculated from the changes in distributions and establishing a correction function applicable to the whole dataset. Such method would make the ReDistribution more complete.

CONCLUSIONS

The ReDistribution Method is the inhomogeneity detection method with a wide set of possibilities. It is also able to detect inhomogeneities with very high precision in certain cases. Amongst other features, the method also considers the causes of inhomogeneities as crucial information.
Whilst present experience of the ReDistribution Method returns, in general very good results, further experience of the method will lead to even better results in determining the causes of inhomogeneities. A wider use of the method is the best way for obtaining more experience with data from other climate regions (i.e. climate regions with periodic winds) or data that have special and presently uninvestigated causes for inhomogeneities.

Accuracy of the ReDistribution Method might be better determined after more processed data is compared and verified with metadata. Some basic principles are already given, while quantitative relations might be established with more detected and verified break points.
Correction method based on distributions has to be developed and tested with the detection method. Corrections that would be detected have to be compared to corrections delivered from other, classical homogenisation methods.
Finally, metadata must be as complete as possible, even with additions delivered from the ReDistribution Method findings, if necessary (Petrović, 2007).

Acknowledgements
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A METHOD FOR DAILY TEMPERATURE DATA INTERPOLATION AND QUALITY CONTROL BASED ON THE SELECTED PAST EVENTS

Gregor Vertačnik
Environmental Agency of the Republic of Slovenia, Ljubljana, Slovenia,
tel: +386 1 4784 581, fax: +386 1 4784 054, gregor.vertacnik@gov.si

Abstract

A method for daily interpolation of temperature at classical climate stations, based on the selected past events, is discussed. The method was developed due to unsuitable results obtained by simple interpolation methods in some cases. The basis of the method is the selection of reference data set from the reference period. The reference data set consists of temperature data from the target and reference stations in days that are similar to the target day. The similarity is calculated as weighted Euclidean distance, considering spatial correlation and spatiotemporal evolution. The reference data set is used in the interpolation procedure with the final result being a combination of estimations based on each of the reference stations. Preliminary tests have shown more or less significant reduction of the standard error compared to the case when all the data from the reference period is used for the interpolation. However, we have found it is impossible to infer on local phenomena in some cases, resulting in a still considerable error. Incorporation of other types of meteorological data and data from the target station should thus further improve the results.

INTRODUCTION

Simple methods for daily temperature data quality control and completion at a meteorological station are usually based on measurements at nearby stations and the corresponding climate normals. Station climatology used for the data interpolation is the same regardless of the weather situation (e.g. sunny, rainy, windy). However, in complex terrain, like in Slovenia, air temperature frequently varies significantly on a short distance, depending on the weather type. An example of such a case is presented in Fig. 1, where strong precipitation gradient led to strong temperature gradient. Among the most frequent cases, when the horizontal temperature gradient is particularly strong is, when föhn wind is blowing (e.g. bora from the northeast or Karavanke föhn from the north to northwest). Föhn causes pronounced temperature difference between the windward and the leeward side of the mountain barrier. Diurnal temperature range can also be very different on a particular day from region to region. As the spatial density of the network of temperature stations is not sufficient for straightforward interpolation in some cases, taking the weather situation into account can improve the interpolation result noticeably. In this manner we can infer for example on strong temperature inversion from the temperature data at nearby stations although the microclimate at the target station is not comparable to any of the nearby stations.

For this reason we have developed a more sophisticated method which is based on the selection of measurements according to the weather situation.

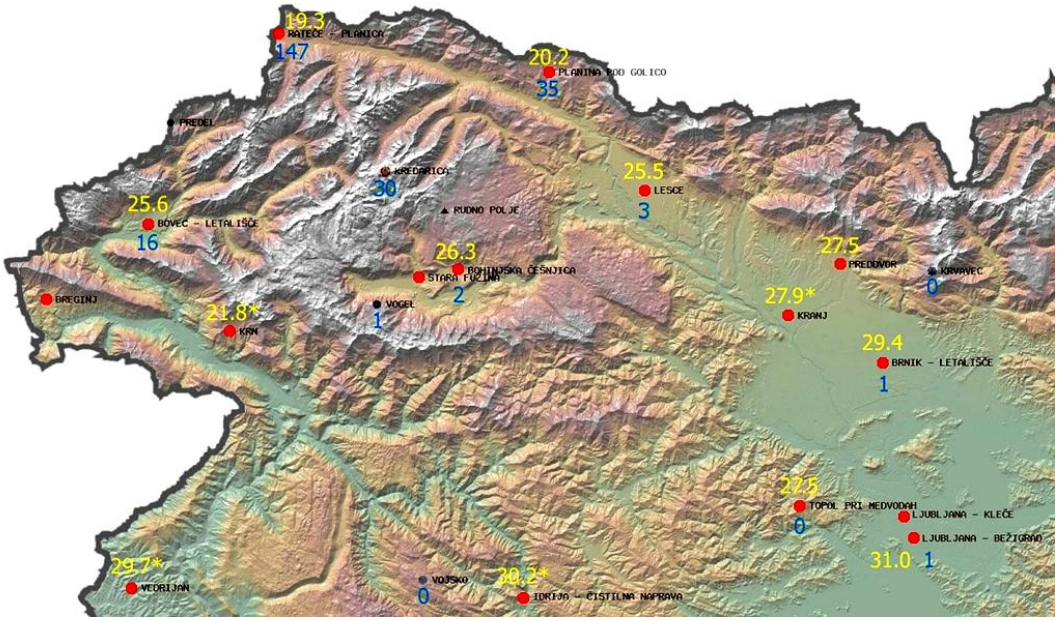


Figure 1. An example of strong horizontal gradient of daily maximum temperature (yellow) due to daily precipitation gradient (blue) on August 29, 2003 (Val Canale flood). Stations below 1000 m MSL are marked by a red circle, values with asterisk are the highest hourly values that day. (background from http://www.geopedia.si/)

METHOD DESCRIPTION

The method is aimed to give a good estimate of temperature value at a target station on a target day. It is a two-step method consisting of the selection of similar days according to the weather situation and the interpolation part.

Meteorological variables considered in the method can be classified into three types, with regard to their function. A group of variables, called reference variables, are used for the selection of the most similar days to the given one. Interpolation is performed using the data of one explanatory variable from the reference stations. The explanatory variable is normally the same as the interpolated variable, except in cases when no measurements of the interpolated variable exist at the reference stations (e.g. only few stations measured daily temperature extremes in the early 20th century in Slovenia).

First part of the method is the selection of similar days. The most similar days from the reference period are extracted and combined into the group of similar days, which can be of arbitrary size. The similarity is determined on the basis of measurements of reference variables at reference stations. This measurements can be temperature readings at different times and/or extreme values (e.g. at 7:00, 14:00, minimum temperature 21:00–21:00 local time (LT) etc.), thus both temperature ranges and spatial pattern could be taken into account.

The second step represents the interpolation procedure, where an estimation of the interpolated variable at the target station on the target day is calculated using:

- explanatory variable data from the reference stations in the group of similar days and on the target day
- interpolated variable data from the target station only from the group of similar days

As explanatory and interpolated variables can be different, it is possible, for example, to estimate the maximum temperature at the target station considering the values at 14:00 LT at the reference stations.

Group of similar days

The group of similar days is constructed by using weighted Euclidean distance between all the considered temperature measurements at reference stations on the target and a candidate day. Weighting is done through Pearson correlation coefficients between the series of the reference variables at the reference stations and the interpolated variable at the target station. Although more appropriate weights can be found, we decided to use correlation-based weights as the iterative process searching the optimal weights could be very time-consuming. Days with the smallest Euclidean distance are selected into a group of similar days.

A special issue is a construction of a measure for the degree of similarity, since at least two kinds of similarity can be specified in our case, regarding:

1) Absolute values (similar air mass)
2) Spatiotemporal pattern (similar weather phenomena)

An example showing the difference between the types is presented in Fig. 2.

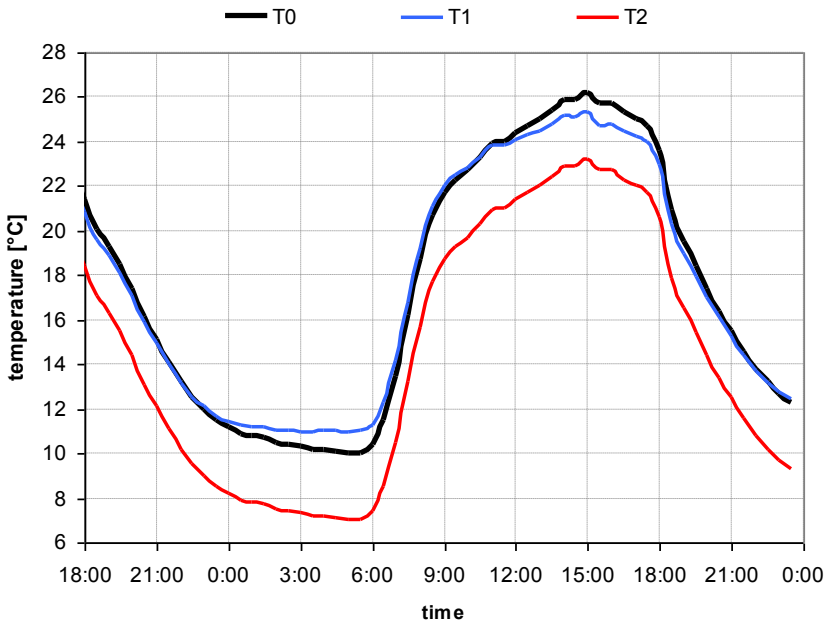


Figure 2. Measured temperature time series (T0) on Rudno polje (Pokljuka) 18–19 July, 2007, and arbitrary similar series (T1 - similar absolute values, T2 - similar temporal pattern)

Since the computation of the optimal weights would be very time-consuming, we decided to use simple basic weighs, which are used in further computation:

$$\omega_{v,s} = \frac{\rho_{v,s}}{1-\rho_{v,s}} \qquad (1)$$

where $\rho_{v,s}$ denotes Pearson correlation coefficient between the series of variable v at reference station s and the series of the interpolated variable at the target station. Eq. (1)

satisfies two fundamental conditions: the weight is 0 when the correlation coefficient is 0 and infinity when the correlation coefficient equals 1. Besides, reference stations with very high (~0.9) correlation coefficient have many times higher weight than those with weak or moderate correlation coefficient (~0.5).

To consider the second type of aforementioned similarity (spatiotemporal similarity), we need to calculate average temperature deviation of the candidate day from the target day:

$$\tau_{dev,d} = \frac{\sum_{v,s}\left[\omega_{v,s}{}^{p_1}\left(\frac{T_{v,s,d} - T_{v,s,D}}{\sigma_{v,s}}\right)\right]}{\sum_{v,s}\omega_{v,s}{}^{p_1}} \tag{2}$$

where $\sigma_{v,s}$ represents standard deviation of the temperature series in the reference period, d indicates a candidate and D the target day. Since all the considered temperature variables do not have the same variance (e.g. daily minimum temperature in Ljubljana is less variable than daily maximum temperature), normalised (by $\sigma_{v,s}$) variables are used. Weighting is done by using the power p_1 of the basic weights.

When the average deviation is obtained, we can calculate the normalised weighted Euclidean distance between a candidate and the target day:

$$E_d = \frac{\sum_{v,s}\left\{\omega_{v,s}{}^{p_2}\left[k_{dev}\left(\frac{T_{v,s,d} - T_{v,s,D}}{\sigma_{v,s}} - \tau_{dev,d}\right)^2 + \left(1 - k_{dev}\right)\left(\frac{T_{v,s,d} - T_{v,s,D}}{\sigma_{v,s}}\right)^2\right]\right\}}{\sum_{v,s}\omega_{v,s}{}^{p_2}} \tag{3}$$

where k_{dev} determines the influence of each type of the aforementioned similarities. Weights are, as in Eq. (2), powers of the basic weights.

Interpolation

Two basic ideas were used for the interpolation part of the method. First of all, a link between (target station S, interpolated variable i) and (reference station s, explanatory variable e) is established using the data from the group of similar days. In this way we calculate the average difference, $\delta_{D,s}$, for each combination target station–reference station:

$$\delta_{D,s} = \frac{1}{n_{D,s}} \sum_{d \in sim.days} \left(T_{i,d,S} - T_{e,d,s}\right) \tag{4}$$

where $n_{D,s}$ counts the number of considered similar days for reference station s and the target day D. It is worth a remark that $n_{D,s}$ may differ from station to station, as some data ($T_{e,d,s}$) in the group of similar days could be missing.

The differences serves as an input for the final equation, which gives us the interpolated value:

$$T_{i,D,S} = \frac{\sum_s n_{D,s} \omega_{e,s}{}^{p_3} \left(T_{e,D,s} + \delta_{D,s} \right)}{\sum_s n_{D,s} \omega_{e,s}{}^{p_3}} \qquad (5)$$

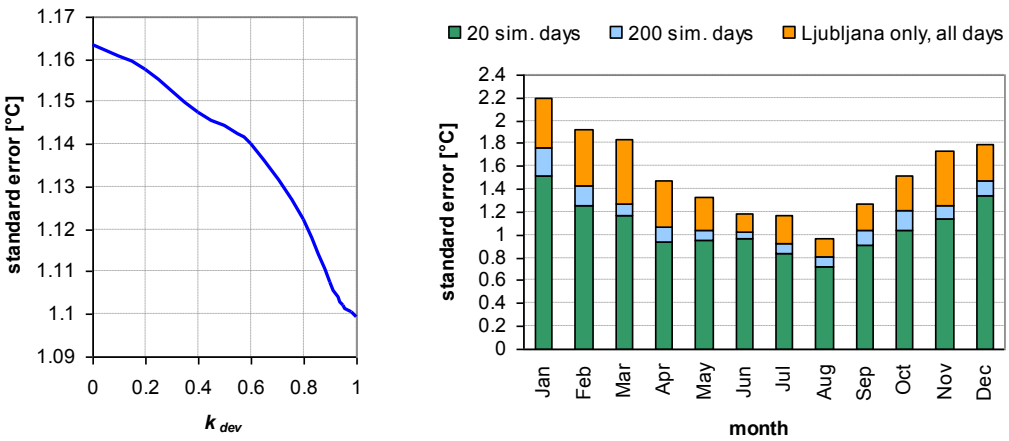
The sum of the temperature at a reference station and the difference $\delta_{D,s}$ represents a single estimation for the interpolated value. All the estimations are weighted by the correlation term ($\omega_{e,s}{}^{p_3}$) and the number of considered days from the group of similar days ($n_{D,s}$) to obtain the interpolated value. The latter term is added to balance the influence of reference stations on the interpolation result in cases with a lot of missing data. By the reduction of available measurements which are used to determine the difference in Eq. (4) the uncertainty of the calculated difference increases, therefore it is better to minimize the influence of stations with sparse data.

Near-optimal values of parameters p_1, p_2, p_3, k_{dev} and the number of similar days were found by an ensemble run with each member having different combination of the parameter values. The combination with the minimum standard error of the interpolated series was determined as the best choice. The procedure was carried out for each case separately.

Example of use of the method

An interpolation of daily minimum air temperature at Ljubljana airport in the period 2003–2007, based on the reference period 1995–2002, will be discussed as an example of the method. Computer programme selected five best-correlated stations, whereas the explanatory variable was also daily minimum air temperature. For the gropu of similar days we considered temperatures at 21:00 LT the day before, at 7:00 LT and 14:00 LT on the given day and the minimum and maximum temperatures. The parameters p_1 and p_2 were set to 1, while p_3 was set to 2. The results of the most simple method with monthly correction factors used on the data from the whole reference period at meteorological station Ljubljana (best-correlated, 17 km SSE of the target station) are added for comparison.

The first interesting detail in the presented case, which is worth of analysis, is the role of the k_{dev} factor. In Fig. 3 we can see the monotonous reducing of the standard error as k_{dev} is increasing. In other words, the best result is obtained when only the second kind of similarity (similar temperature range and spatial pattern) is taken into account.



Figures 3 and 4. Dependence of the standard error to k_{dev} (left) and comparison of the standard error through year between the methods (right)

Another question, which has not been discussed yet, is the optimal size of the group of similar days and the number of days from the reference period to be considered for each target day. Some testing revealed a huge difference from case to case, meaning that the magnitude of sample error (large when only few days are considered) and the error caused by the inclusion of "non-similar" days (limiting to the most simple methods) is very different for each case. Results for 20 and 200 days for the presented case are shown in Fig. 4.

If we take a look inside a part of the interpolated series, we can notice some systematic difference between the simplest method and the method discussed in this paper (Fig. 5). The former method is better in most days, though the error remains quite high in some days.

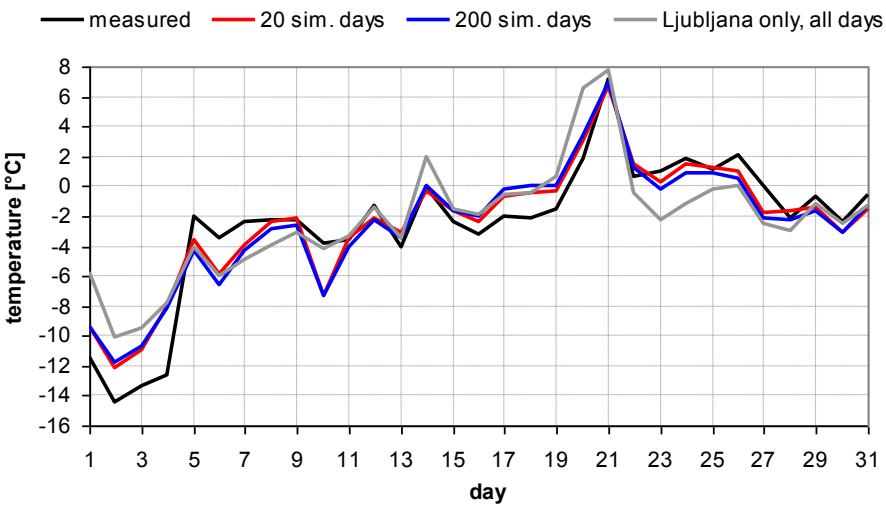


Figure 5. Comparison of the measured and the interpolated series for March 2004

CONCLUSION

The method described in the paper is able to decrease the interpolation error, but the lack of other meteorological data still prevents it to make an adequate estimation of the temperature when there is a local phenomenon at the target station we can not infer on using only available temperature data. Such cases are the main reason for the large part of the variance being unexplained. Thus, inclusion of other meteorological data from the reference as well as

from the target station (if possible) would probably result in further significant reduction of the error.

Another issue which has to be solved or at least minimized is the choice of the model's parameter values. There is no simple answer to weighting factors, the size of the group of similar days and variables to be included. Test runs have shown that at least some of the optimal parameters differ strongly from case to case, while in most cases inclusion of more variables and stations yields better results. Iterative process could minimize the problem but then the method could become time-inefficient.

The most significant disadvantage or restriction of the method is the necessity of using more or less homogenous series at nearby stations. Artificial jumps and temperature trends can otherwise seriously influence both the choice of the most similar days and the interpolation results. On the other hand this problem is marginal for quality control where small interpolation error is not of big importance.

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AIR HUMIDITY IN CRACOW IN THE PERIOD 1863-2007 – DAILY DATA QUALITY CONTROL AND HOMOGENIZATION METHODS

Agnieszka Wypych, Katarzyna Piotrowicz
Institute of Geography and Spatial Management, Jagielonian University,
Gronostajowa 7, 30-387 Krakow, Poland, 12 664-53-25, 12 664-53-85,
awypych@geo.uj.edu.pl; k.piotrowicz@geo.uj.edu.pl

INTRODUCTION

Air humidity, in other words water vapour content in the air, is characterized by various factors. They include, among others: relative humidity, vapour pressure, moisture deficit, dew point temperature or specific and absolute humidity. Air humidity is one of the more important weather and climate components. It plays a key role in defining the climate conditions of a given area. Water vapour content in the air has a decisive influence on evaporation intensity, occurrence of precipitation and certain phenomena, such as fog.

Variations of humidity parameters over several years are very seldom analysed (Dubicka et al. 2003, Wypych 2003). This is caused, among others, by lack of long-term hygrometric or psychrometric measurements. The impact of urban areas on the annual and spatial variability of air humidity has been researched much more frequently (Ackerman 1987, Hage 1975, Holmer, Eliasson 1999, Lee 1991). Relatively short series of measurements (3-10 years) have been used for this purpose (Chandler 1967, Murinova 1978, Unger 1999).

The research station of the Institute of Geography and Spatial Management of the Jagiellonian University in Krakow, Poland, was established in 1792. It has got one of the longest, regular series of measurements and observations of various meteorological elements conducted in the same location. The complete documentation of the station, together with the metadata, constitutes unique research material.

The only measurement series to have undergone homogeneity testing thus far are series of air temperature, atmospheric pressure and precipitation (Twardosz 1997, Ustrnul 1997). The homogeneity of air humidity parameters has not been investigated, mainly due to the methodical difficulties related to the analysis of numerical material.

The paper presents the stages and the methods used in order to examine the quality of Krakow's air humidity measurement series. Daily values of selected air humidity parameters calculated on the basis of psychometric measurements were verified.

DATA SOURCES

Air humidity measurements in Krakow commenced at the time of the station's creation. Initially, hair hygrometers were implemented, including a Saussure hygrometer, which operated until 1830. Since 1834, all measurements have been carried out by means of an August psychrometer. Thermometers are located in a Stevenson shelter next to a window with NNW exposure, second floor level (12 m AGL) of the Śniadecki College building in the Botanical Garden of the Jagiellonian University (Fig. 1). Alas, from 1856 until November 1862, there is a gap in measurements of meteorological elements under analysis. Within the last 145 years (1863-2007), all observations of water vapour content in the air have been uninterruptedly performed in the same location and using consistently the same method, three or four times per every 24 hours (Tab. 1).

Figure 1. The Historical Station in Krakow (Śniadecki College building)

Tab. 1. Observation hours in Krakow in the period 1792-2007

Years	The hours of observation	Time of observation
1792-1825	6-7, 14-15, about 21	Krakow local*
1826-1836	7, 12, 15, 21	Krakow local
1837-1891	6, 14, 22	Krakow local
1892-1902	6, 14, 22	Cental-European
1903-1911	7, 14, 21	Cental-European
1912-1956	7, 14, 21	Krakow local
1957-1970	7, 13, 21	Cental-European
1971- to today	1, 7, 13, 19	Cental-European
* Krakow local time is put back at 20 minutes in relation to Central-European time. Measurements were performed in Krakow local time between 6-7 a.m, 2-3 p.m and about 9 p.m., that is Central-European time: 5.40-6.40 a.m., 1.40-2.40 p.m. and about 8.40. p.m.		

METHODS

The first stage of the analysis encompassed a comparison of air temperature (T), whose homogeneity had previously been checked, with the appropriate readings of a wet bulb thermometer (T'). Doubtful T' values were verified on the basis of the records of current meteorological phenomena (fog, horizontal visibility, precipitation). Such doubtful values were scarce in the entire series of long-term observations. They were caused, among others, by converting the temperature scale, as temperature was measured in the Réaumur scale until 1876.

After conversion from Réaumur to Celsius, some readings of a wet-bulb thermometer were 0.1-0.2°C higher than readings of a dry-bulb thermometer. Therefore, wet-bulb temperature was assumed to be the same as dry-bulb temperature, especially if it was accompanied by fog, mist or precipitation. Negative temperatures, when T' values may be higher than T values, were kept unchanged.

Subsequently, all the missing data concerning the state of the cambric during the measurements (water/ice) were completed. Unfortunately, before 1950 it had not always been recorded in the cold half of the year whether the cambric wetting the thermometer was covered with ice or water. The presence of ice/water on the cambric has a significant influence on measurement results. It is also related to using an appropriate psychrometric constant (Tab. 2). Absence of such information means that the resulting humidity parameters would be subject to excessive error. On the basis of data from the years 1863-1900, for

relative air humidity the estimated error for extreme T' values was ±3.6-4.4% (Fig. 2). It is slightly higher for positive temperatures of the wet-bulb thermometer and this is why relative humidity could be overestimated even by 4.4%. For negative T' values, relative humidity would be underestimated up to ca. 3.6%.

Tab. 2. Psychrometric formulas used to calculate air humidity parameters (Robitzsch 1949; modified)

ice	water
$e = ET' - 0{,}7060(T - T')$	$e = ET' - 0{,}7946(T - T')$
$ET' = 6{,}107 \times 10^{\frac{9{,}5T'}{265{,}5+T'}}$	$ET' = 6{,}107 \times 10^{\frac{7{,}4366T'}{235+T'}}$
e – vapour pressure; E – saturation vapour pressure; T – air temperature; T' – wet-bulb temperature	

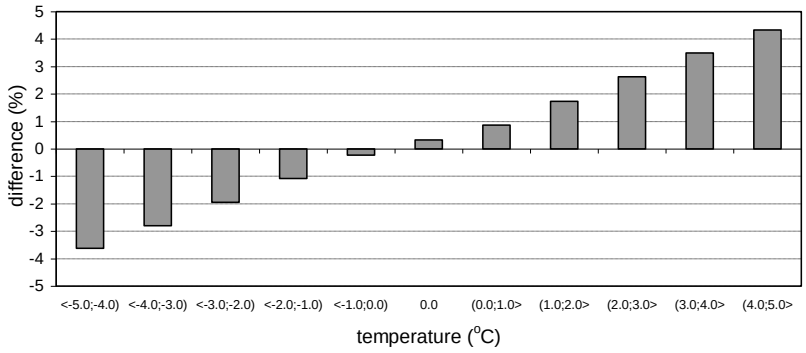

Figure 2. Difference (%) between relative air humidity values counted using „ice formulas" and „water formulas" (-5≤t≤5°C) (Krakow 1863-1900)

To prevent such differences in calculations, the frequency of occurrence of ice and water on the cambric for individual air temperatures was estimated. For that purpose, a series of measurements from 1971-2000 was used, when the condition of the cambric was conscientiously recorded and when thermal and air humidity conditions in Krakow were very diverse. This 30-year period included both extremely warm winters, e.g. in 1972/73, when T' was seldom covered with ice, and very severe ones (e.g. 1962/63) when temperature was very often below 0°C.

Psychrometric patterns permit the presence of ice or water on the cambric when the wet-bulb temperature is from -10°C to 8°C. In Krakow, from 1971-2000, at three observation times ice was always (100%) reported on the cambric when T was below -4°C and with declining frequency until 4°C (0.4%) (Fig. 3). Water appeared on the cambric for temperatures T from -4°C (0.4%) to 4°C (96.6%). For temperatures above 4°C, the bulb of the wet-bulb thermometer was always wet with water (Fig. 3).

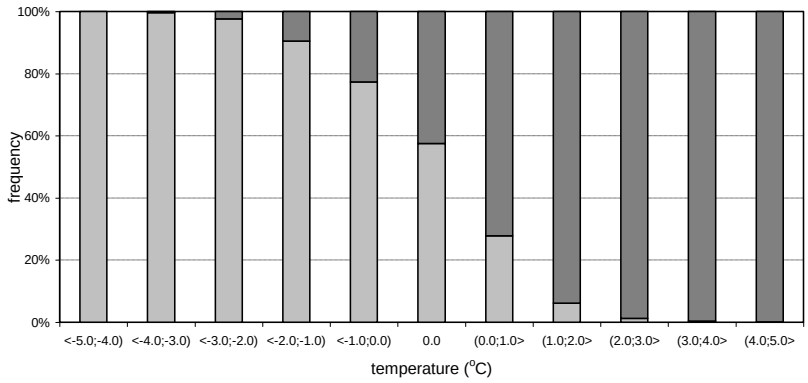

Figure 3. Frequency of ice/water cambric state (Krakow 1971-2000)

Those results enable us to fill in missing cambric status information and reduce the miscalculation of relative humidity to ±1.5%. It has been assumed that for air temperatures T<-3.0°C, cambric on the bulb of the wet-bulb thermometer was covered with ice, similarly for temperatures in the range -3.0°C<T<-2.0°C when T'<-2.0°C. Presence of water on the cambric was assumed for air temperatures T>2.0°C while all temperatures in the range -1.9°C≤T≤1.9°C were compared with current weather conditions. Current synoptic situation and cloud cover were taken into account, and 24h time series of air temperature was analysed on the basis of hygrograms. Ice on the cambric was reported for all days when temperatures remained below zero.

Psychometric models, identical for the entire series, were used to calculate the value of air humidity parameters (Rojecki 1959). On the basis of readings of T and T', they help obtain values of four humidity parameters: vapour pressure, relative humidity, saturation deficit and dew point temperature. At further stages of homogeneity testing of series of data only relative humidity was investigated as it is the most frequently analysed humidity parameter. It might be assumed that if relative humidity proves homogeneous, other humidity parameters will be homogeneous, too, because they had been calculated on the basis of the same T and T' values.

The results obtained in consequence were compared with the values read from hygrograms and the readings of the hair hygrometer. At the same time as psychrometric measurements, relative humidity was measured using a hygrometer or hygrograph. Extreme cases, which gave rise to doubts, were analysed with regard to the records about the state of the atmosphere: circulation conditions, the occurrence of foehn and some atmospheric phenomena. Krakow is exposed several times a year to effects of operation of foehn in the Tatra Mountains which are some 80 km away in a straight line. Krakow's relative humidity was then even ca. 15%.

RESULTS

The performed homogeneity tests (modified form of SNHT Alexandersson – Stepanek, 2007) did not find any cases which would clearly indicate that the series was not homogeneous. The controversial values identified in the analysis were subjected to further verification. To achieve that, archival records of measurements and meteorological observations were used. Corrections of numerical data were not performed. The content of air vapour in the air is a resultant of the interaction of numerous factors and processes, which need to be taken into account before correcting the values. In light of the lack other objective possibilities of verification of air humidity in Krakow, the analysed data were considered as relatively homogeneous.

Figure 4a shows long-term mean annual relative air humidity in Krakow in the years 1863-2007. Values have been calculated on the basis of observation times averages (as the arithmetic mean of 3 daily readings).

The turn of the 20th century saw a marked decline in Krakow's relative air humidity (Wypych 2007). The mean annual relative humidity in that period ranged from 85% in 1871 to 72% in 1911. Until the 1960s, relative humidity stood at ca. 79% and did not undergo significant changes on a year-on-year basis. Then a marked drop of this meteorological element was observed. At the turn of the 21st century, average annual relative humidity was ca. 70% and was the lowest since the beginning of the period under analysis. To make sure that fluctuations in relative humidity were related to fluctuations of Krakow's climate and not to the non-homogeneous quality of the series of data, results were compared with long-term air temperature variation and urban development.

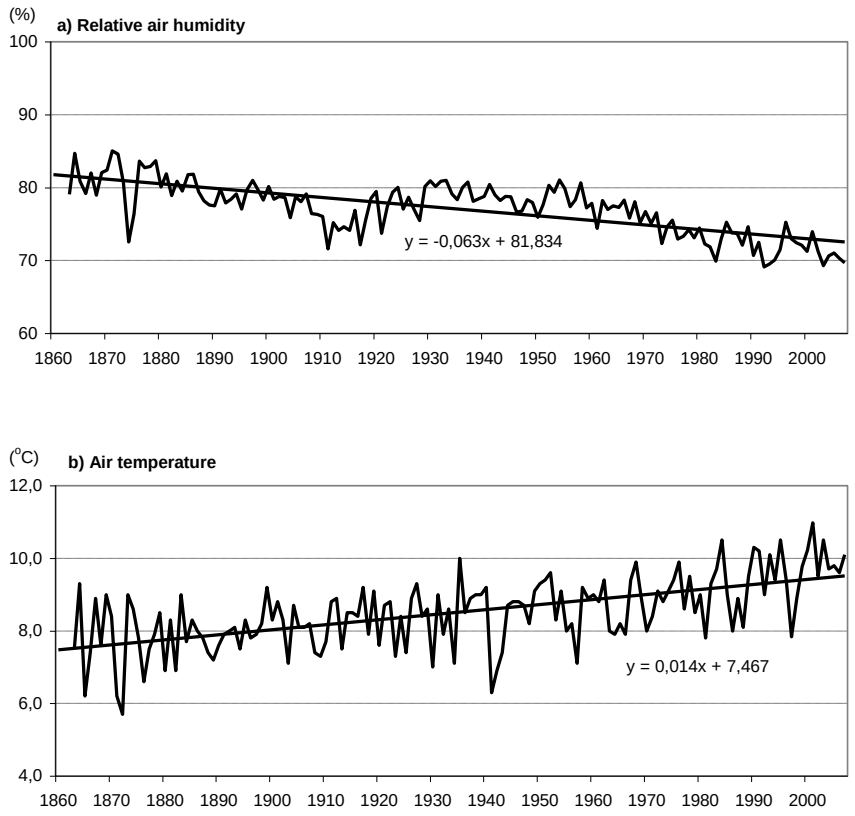

Figure 4. Mean annual relative air humidity and air temperature in Krakow in the period 1863-2007

Until the beginning of the 20th century, the station was located outside the city, to the east. At that time Krakow's industrial function was weak. From 1792 until 1900, city area changed only slightly, from ca. 5 to 8.9 km^2 (Matuszko et al. 2004). The number of inhabitants changed to a much higher extent – it rose from 10,100 in 1785 to more than 85,000 in 1900. Now the city has a population of ca. 800,000 inhabitants living on an area of 327,000 km^2. The years 1918–1939 brought a gradual rise in Krakow's economic and urban growth, with the greatest changes occurring after the Second World War. The 1950s saw the establishment of a centre of heavy industry with a steel mill and residential area with services to the east of the city – Nowa Huta.

The probable causes of Krakow's high relative air humidity until the beginning of the 20th century were local conditions: location in a weakly ventilated, damp Vistula river valley and limited air circulation due to deposition of thermal inversion layers in the concave terrain (Matuszko et al. 2003). The gradual rise in the number of inhabitants and higher development density contributed to the decline in the city's air humidity. After Second World War, land improvement of waterlogged areas and expansion of industrial areas resulted in a significant drying of the city's air (Matuszko et al. 2004). Artificial heat emission into the atmosphere contributed to a rise in the dry day's rate (Piotrowicz, Wypych 2006; Fig. 5).

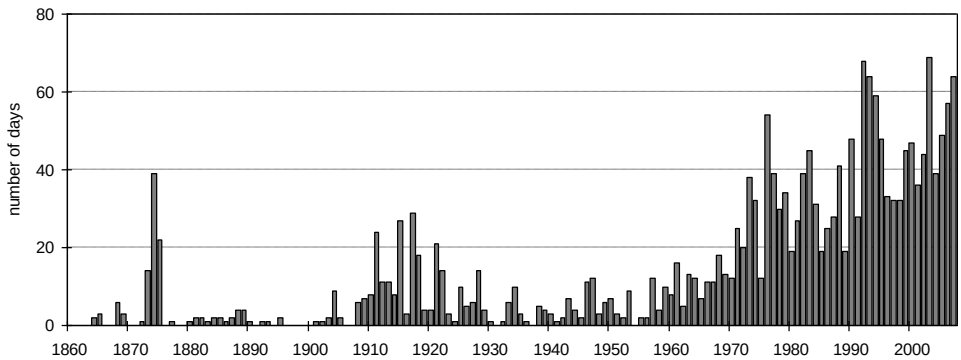

Figure 5. Number of dry days in Krakow in the period 1863-2007

The decline in relative humidity observed in the period under analysis is well correlated with the rise in the average annual air temperature (Fig. 4b). Since the end of the 19th century, Krakow has observed a constant rise in temperature of 1.5°C every 100 years. The causes of changes in meteorological elements under analysis should be also attributed to natural factors, mainly to variation of atmospheric circulation reinforced by the operation of anthropogenic factors.

CONCLUSIONS

The content of air vapour in the air is a resultant of the interaction of numerous factors and processes. Measurement of air humidity, especially using a psychrometer, is prone to a variety of errors. The most common reason seems to be erroneous temperature readings – relatively easy to correct – and defective maintenance of the psychrometer. It is essential to maintain a wet-bulb thermometer in appropriate condition: the cambric should be changed at appropriate intervals, the cambric should be the required length and only distilled water should be used to wet the thermometer. To obtain objective measurement results, the psychrometer should be located away from a water region or any other evaporating surface. An analysis of archival and contemporary materials of Krakow's climate station indicates that measurements were conducted in accordance with recommendations and the status of the wet-bulb thermometer was frequently checked.

The uncommon layout of instruments and change of observation times may give rise to many more doubts about data quality. Non-standard conditions at the level of 12 m AGL play an essential role in modifying temperature-humidity relationships. In the 18th and 19th centuries, meteorological equipment was very often located in such places, e.g. in the Prague Klementinum station. However, it is extremely important that Krakow's Stevenson shelter has never been moved. In 1958, a new instrument shelter was added, now at the standard height of 2 m AGL. Therefore, it is possible to compare both series for the last 50 years.

Changed times of readings are especially important for summer humidity measurements. Heino (1994) proved that evening and morning observation times have the greatest importance. Differences in calculations of the mean daily relative humidity may reach 3-4%. In Krakow, reading times in periods of air humidity measurements changed eight times, with the greatest differences relating to the evening reading (180 minutes).

Another important factor affecting the quality of available source material are the surroundings of the meteorological station. The Krakow station has never changed location. When observations were started, the area was located on the outskirts of the city, enclosed only by scattered buildings. Now, due to the city's dynamic growth, it is situated in the centre, at the crossroads of busy arterial roads. Additionally, it is within the Botanical Garden founded in 1783. With the passage of time, the garden expanded (from 2.4 to 9.6 hectares) and its development changed too – the number and diversity of species grown there rose as well.

Due to potential measurement and calculation errors described, results obtained should be appropriately verified. Quite often it is not possible on account of new observation times and station's environment. Therefore, existing air humidity variation studies have been in general based on short series which provide a relative guarantee of homogeneity. However, they are not sufficiently representative to define development trends.

Global climate change, widely discussed in recent years, can be described only thanks to in-depth studies aimed at an analysis of long-term variation of basic meteorological elements. The big-city location of meteorological stations which have long measurement sequences leads to error-prone readings, with the error being related to the dynamic change in local conditions. Studies based on data from relocated stations also raise a variety of concerns – on account of more or less successful attempts at standardization of material.

An in-depth analysis of source material, which encompasses 145 years of meteorological observations carried out without a break in one place in Krakow, enables to say that data available is relatively homogenous. With such a long-term series of data, ranging from the beginnings of instrumental measurement, it is impossible to completely avoid certain inhomogeneities. However, any attempts at data improvement could be erroneous and destroy the originality and substantive value of the series.

Acknowledgements

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HOMOGENIZATION OF WATER VAPOUR DATA FROM VAISALA RADIOSONDES AND OLDER (MARZ, RKZ) USED IN POLISH AEROLOGICAL SERVICE

Barbara Brzóska
Institute of Meteorology and Water Management, Centre of Aerology, Poland,
Barbara.Brzoska@imgw.pl

Abstract

The water vapour content in the atmosphere has got fundamental meaning for the ozone chemistry and photochemical processes of its destruction. Thus the research of its variability is of crucial importance, particularly in the levels of upper troposphere and lower stratosphere (UTLS). Another important issue is to investigate the processes of water vapour transport through the troposphere. The most reliable source of information on the relative humidity (RH) the results of the radiosonde measurements conducted in Poland since the 30-ties of the 20th century. Unfortunately, the numerous changes of radiosonde types influence the homogeneity of the RH series. The registers of RH obtained from the simple humidity sensors (MARZ, RKZ) used in Polish aerological service till the 90-ties are somewhat greater than the data from the following period. Since 1992 in Poland Vaisala radiondes are used to measure RH in the profile of atmosphere. However, the change of the radiosonde type in June 1999 (RS-80A to RS-90) caused the break of homogeneity of the series.

For correction of RS-80A's relative humidity (RH) data series, four methods have been used, available in the literature. The correction equations result from comparison of measurements of different sensors or of laboratory measurements. The results of the comparisons show that the method evaluated in Lindenberg (Germany) for dr Leiterer's team, is the best one for our series correction purposes.

For correction of MARZ's and RKZ's relative humidity data series (measurements from before 1992), method dr Leiterer's team from Lindenberg have been used. Values of RH with correction expending more reliability, but still the data series are not homogeneous in all isobaric levels in troposphere.

INTRODUCTION

Water vapour is measured in the atmosphere from multiple platforms with a large variety of sensors. The instruments developed in more recent years. The measurement of upper tropospheric water vapour by radiosondes is, however, fraught with numerous problems. In the stratosphere, the most commonly used *in situ* water vapour measurement instruments have shown significant biases between each other. As a result of correlative measurement programs, special intercomparison activities and algorithm improvements, discrepancies between measurement systems have been better quantified.

HUMIDITY CORRECTION METHODS FOR RS-80A RADIOSONDE

In the first step of homogenisation, data from Vaisala radiosondes was smoothed using a 12-month moving average. The figure 1 presented the humidity row and smoothed series for three polish radiosounding stations – Leba, Legionowo and Wroclaw.

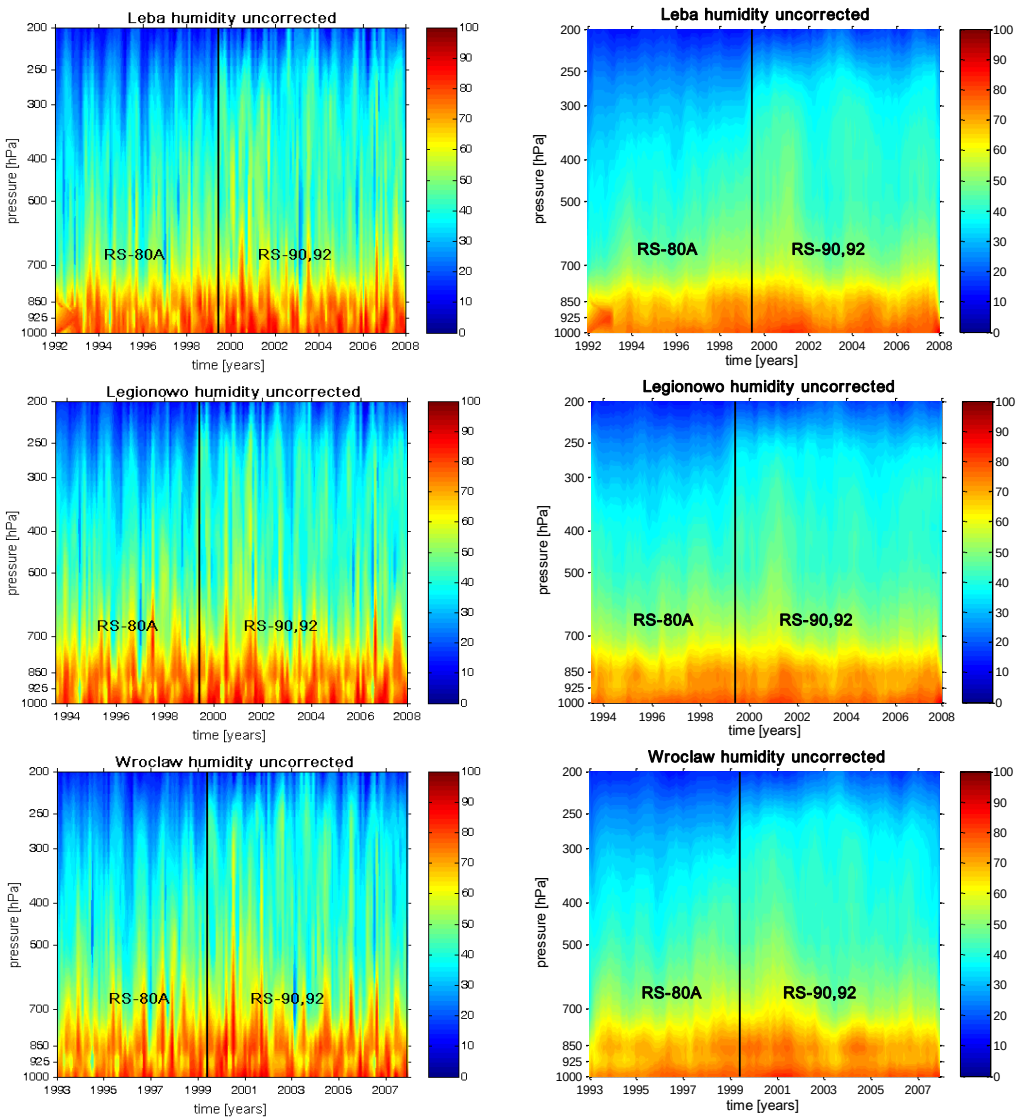

Figure 1. Humidity series for Leba, Legionowo and Wroclaw for row (left) and smoothed (right) data

For correction of RS-80A's humidity series, four methods have been used, available at literature. The correction equations are results of comparison of measurements from different sensors or of laboratory measurements. Two of correction methods depend not only on temperature, but also on actual humidity. One of these methods (Leiterer, 2002), taking into account climatological data (Lindenberg, Germany), seems to be best one. Only this correction 'repairs' acceptably, smaller values of humidity, detected by RS-80A radiosonde. Applied correction formulas have been inserted in Appendix A.

The Figure 2 shows humidity series for Leba (January 1992 – December 2007), Legionowo (July 1993 - December 2007) and Wroclaw (January 1993 - December 2007) at 00 UT for uncorrected and corrected series using the all correction methods.

Humidity series looks better with, than without correction. It seems that majority corrective methods rest on simple shift to part of highest value only. They behave better in bottom tropospheric levels and worst heigher. The corrective methods dependent on more of factor have been checked much better than dependent on only temperature. The 'Wang' and 'Leiterer' methods, especially in the UTLS region, where underestimated values of humidity from RS-80A have increased after correction, making the series less inhomogeneous than

others. And so farthers verification methods have been employed only for these two corrections.

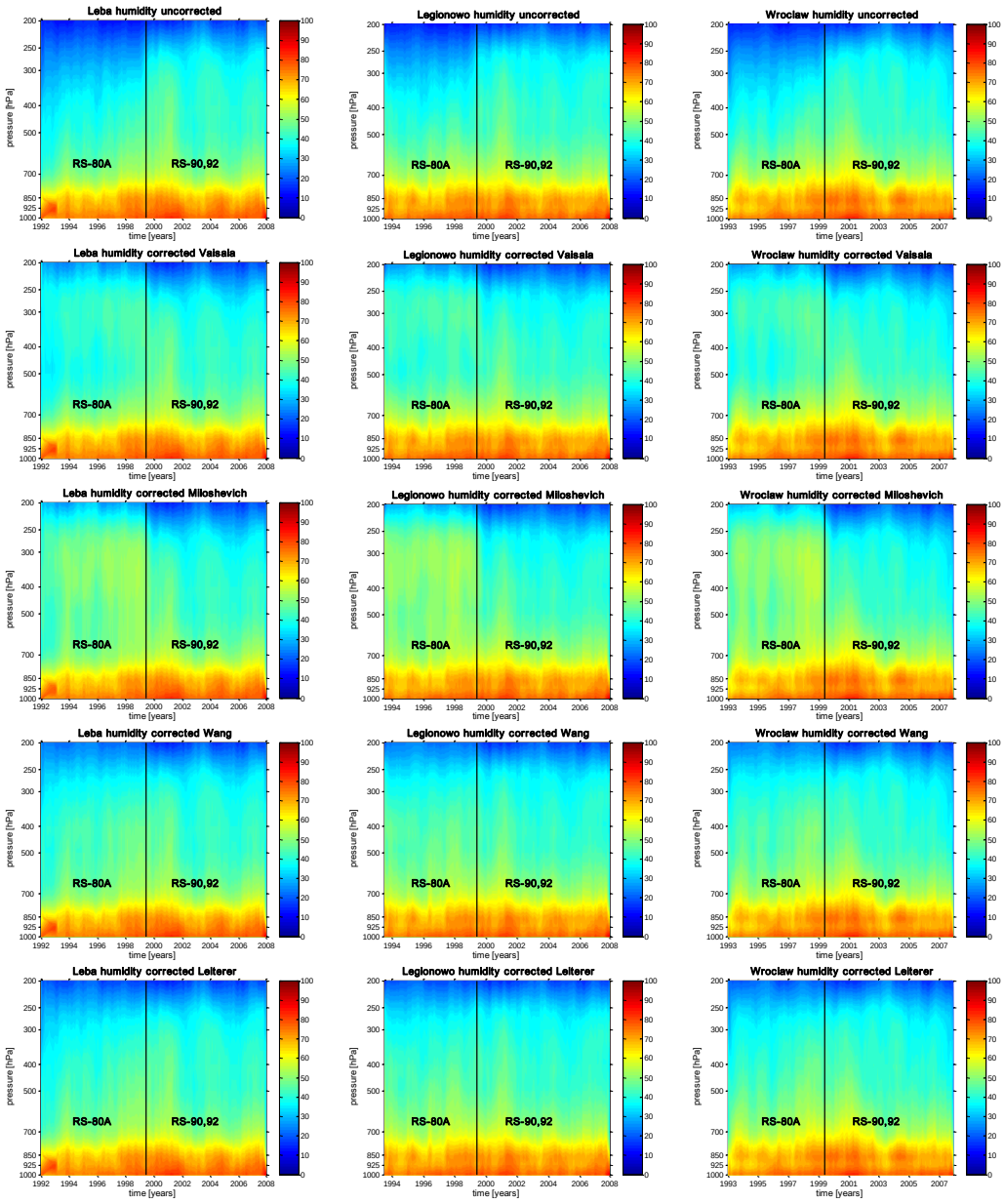

Figure 2. Humidity series for Leba 01.1992 – 12.2007 (left column), Legionowo 06.1993 – 12.2007 (middle column) and Wroclaw 01.1993 – 12.2007 (right column) at 00 UT

The subsequent step of choice of most reliable correction method was observing the humidity data at the 9 geopotential surfaces from 1000hPa up to 200 hPa and counting trend for all of these levels [% / year]. The figure 3 presents humidity series with trend at three chosen surfaces with 'Wang' and 'Leiterer' correction. The dominance of 'Leiterer' correction over 'Wang' one is observed. Values of humidity measured with RS-80A sensor corrected by 'Wang' method seem to be overestimated than the humidity series form radiosondes RS-90 and RS-92, particularly at higher altitudes. Humidity series data with 'Leiterer' correction seems to be compact with humidity measured with RS-90's sensors.

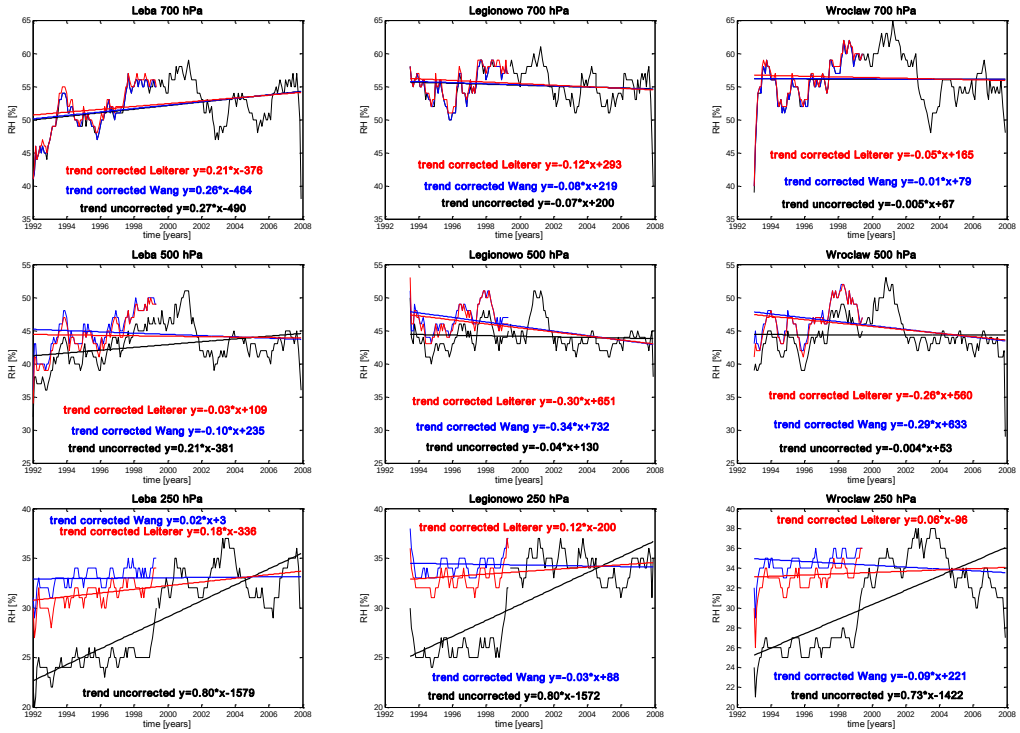

Figure 3. Humidity series for Leba (left panels), Legionowo (middle panels) and Wroclaw (right panels) 00 UT. The figures present humidity series with trends uncorrected (black line), corrected 'Wang' (blue line) and 'Leiterer' (red line) methods at three chosen goepotential surfaces: 700hPa, 500hPa and 250hPa.

HUMIDITY CORRECTION METHODS FOR MARZ AND RKZ RADIOSONDES

In view of good quality of corrective method processed by dr Leiterer's group (Lindenberg, Germany) for measurements execute with radiosounds RS-80A for correction of quality data from soviet radiosounds MARZ and RKZ, the corrective method processed also by Leiterer's group have been used. This method emerge on base of comparison humidity data from radiosonding and satellite measurements.

The Figure 4 shows humidity series for Leba (January 1973 – December 2007), Legionowo (March 1971 - December 2007) and Wroclaw (August 1990 - December 2007) at 00 UT for uncorrected and corrected. We saw that correction methods correct quality of data. After correction there is lack of distribution for uncorrected and corrected series.

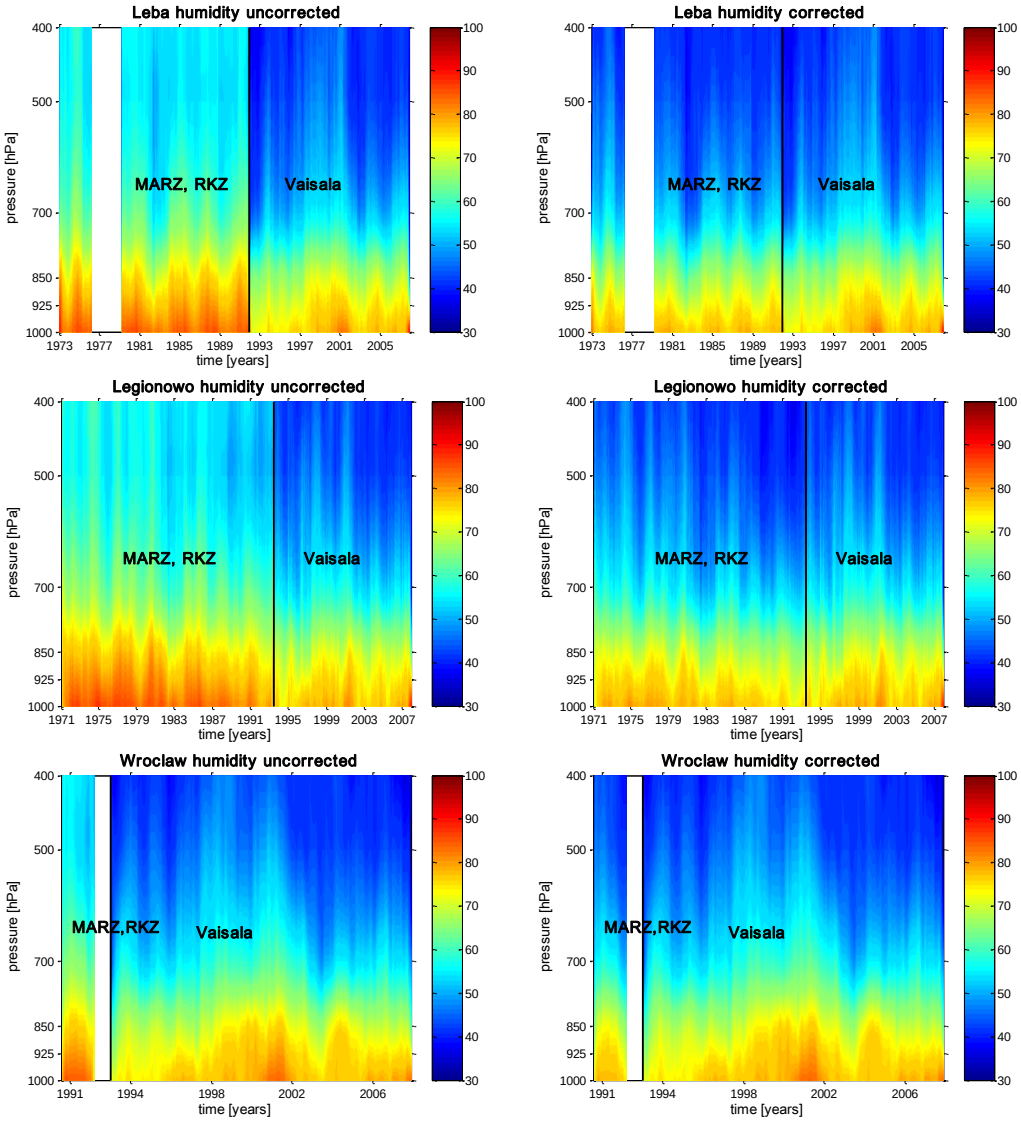

Figure 5. Humidity series for Leba, Legionowo and Wroclaw at 00 UT for uncorrected (left column) and corrected (right column) data

The next step was observing the humidity data at the 5 geopotential surfaces from 1000hPa up to 400 hPa and counting trend for all of these levels [% / year]. The figure 5 presents humidity series with trend at three chosen surfaces. Humidity series looks better with, than without correction. Unfortunately, received results have exerted, that employed corrective method, it does not eliminate completely the differences among data from soviet and Finnish radiosounds. Results are different for each geopotential level and each station however, it get no completelely similar series. Additional opposite sign of trend of humidity from soviet and finnish radiosounds on many surfaces have been visible, that makes impossible obtainment of similar series. In final effect still has been show that series of measurement of humidity is uncontinuous at change of sensor.

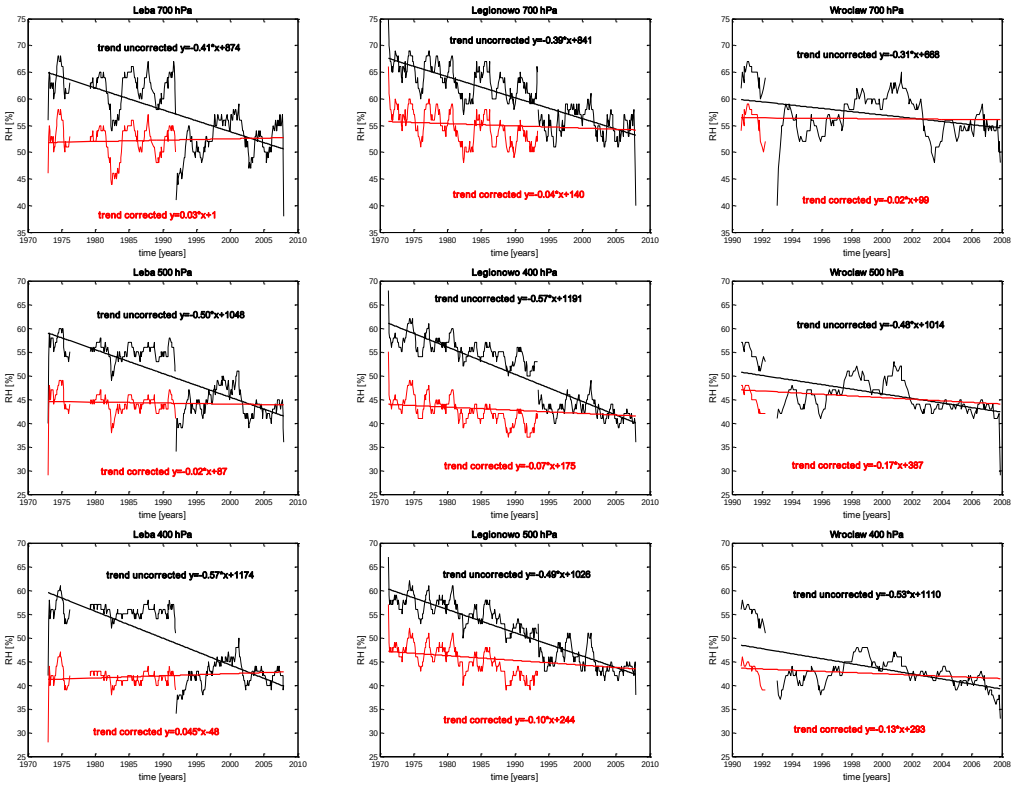

Figure 6. Humidity series for Leba (left panels), Legionowo (middle panels) and Wroclaw (right panels) 00 UT. The figures present humidity series with trends uncorrected (black line) and corrected (red line) data at three chosen goepotential surfaces: 700hPa, 500hPa and 400hPa.

CONCLUSIONS

- For homogenisation of humidity data from Vaisala radiosounds (RS-80A, RS-90 and RS-92) four correction methods have been chosen for correction data from RS-80A radiosounds.
- Two methods (‘Wang’ and ‘Leiterer’) were submitted for further studies.
- Analyses of humidity trends on different goepotential surfaces show dominance of ‘Leirerer’ correction over ‘Wang’ one.
- For homogenisation of humidity data from soviet (MARZ and RKZ) and Finnish (RS-80A, RS-90 and RS-92) radiosounds the correction methods execute by Leiterer’s group have been chosen for correction data from soviet radiosounds.
- Adopted method ameliorates quality of data however, there is still not so good so as data after correction can become subject climatic analyses.

APPENDIX A: MATHEMATICAL BACKGROUND

The RS80-A is subject to several sources of measurement error, and correction of the individual measurement errors is an alternative approach for correcting RS80-A data that is under development. A "temperature-dependence error" is caused by using a linear approximation in the data processing algorithm to represent the actual non-linear temperature dependence of the sensor calibration, and is, in general, the largest RS80-A measurement error at cold temperatures.

The first correction factor for temperature-dependence error has been derived from laboratory measurements conducted at Vaisala. The magnitude of the correction factor is about 1.1 at –35°C, 1.4 at –50°C, 1.8 at –60°C, and 2.5 at –70°C. (Sparc, 2000)

$H_{corr} = (-2\cdot10^{-5}\cdot t^3 - 0.0021\cdot t^2 - 0.089\cdot t - 0.3)\cdot H$ 'Vaisala' (A1)

A recent study by Miloshevich *et al.* [2001] characterised RH measurements from Vaisala RS80-A radiosondes, the most frequently used radiosonde in the world, and developed a correction for the measurements in the temperature range 0˚C to –70˚C.

$H_{corr} = H \cdot G(t)$ 'Miloshevich' (A2)

$G(t) = (3.9407\cdot10^{-8})\cdot t^4 + (1.8179\cdot10^{-6})\cdot t^3 + (1.5783\cdot10^{-4})\cdot t^2 + (-5.9662\cdot10^{-3})\cdot t + 0.9278$ (A3)

Another correction methods were processed by Wang *et al.* [2002] on base of measurement collected during the Tropical Ocean and Global Atmosphere (TOGA) Coupled Ocean–Atmosphere Response Experiment (COARE). The temperature dependence error for the RS-80A results from an approximation of a linear function of temperature to the actual nonlinear temperature dependence of the sensor, and also introduces a dry bias.

$$H_{corr} = \frac{H + 2.22168 - 0.11108\cdot t}{0.999634 + (1.83105\cdot10^{-5})\cdot t}$$ 'Wang' (A4)

A new measuring and evaluation method has been developed at the Meteorological Observatory Lindenberg by Leiterer *et al.* [2002]. Research reference humidity radiosondes are the experimental basis using the new measuring and evaluation method of so-called "standardised frequencies".

$$H_{corr} = H + [5.6\% \cdot \frac{H}{100\%}] + $$
$$+ [0.005\cdot t^2 + 0.112\cdot t + 0.404]\cdot[\frac{H + (5.6\% \cdot \frac{H}{100\%})}{H_w(t,100\%ice) - (0.005\cdot t^2 + 0.112\cdot t + 0.404)}]$$

'Leiterer' (A5)

$$H_w(t,100\%ice) = \frac{e_i(T)}{e_w(T)}\cdot 100\%$$ (A6)

T = 273.16K+t	temperature in Kelvin (K)	(A7)
t	temperature in Degree Celsius (°C)	
$e_i(T)$	saturation vapour pressure with respect to ice in hPa	
$e_w(T)$	saturation vapour pressure with respect to water in hPa	

$\ln e_i(T) = (-6024.5282)\cdot T^{-1} + 24.7219 + (1.0613868\cdot10^{-2})\cdot T +$
$+ (-1.3198825\cdot10^{-5})\cdot T^2 + (-0.49382577)\cdot \ln T$ (A8)

$\ln e_w(T) = (-6096.9385)\cdot T^{-1} + 16.635794 + (-2.711193\cdot10^{-2})\cdot T +$
$+ (1.673952\cdot10^{-5})\cdot T^2 + 2.433502\cdot \ln T$ (A9)

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HOMOGENIZATION OF ITALIAN PRECIPITATION SERIES

Andrea Toreti[1,2,3], Franco Desiato[1], Guido Fioravanti[1], Walter Perconti[1]
[1] ISPRA, Istituto Superiore per la Protezione e la Ricerca Ambientale (ex APAT),
[2] Institute of Geography, Climatology and Meteorology, University of Bern,
[3] Oeschger Centre for Climate Change Research (OCCR) and National Centre of Competence in Research on Climate (NCCR Climate), University of Bern, tel: +390650072567,
fax: +390650072657
andrea.toreti@apat.it

INTRODUCTION

The analysis of precipitation series is crucial in the assessment of climate change in the Mediterranean area, in order to understand its impacts on ecosystems and human activities, and to provide reliable information for the definition of adaptation strategies. In this context the Italian Research Institute for the Environment – ISPRA (formerly National Environmental Agency APAT) developed a computerized system for the collection and elaboration of statistical data on the Italian climate, denominated SCIA (Desiato et al., 2007). In this system rough data, coming from national and regional meteorological networks, are collected and quality checked; the outputs, e.g. ten-daily, monthly and annual indicators, are available on the web site: www.scia.sinanet.apat.it.

In this study a set of 59 stations (fig. 1), belonging to the Air Force Weather Service and some regional environmental agencies and characterized by temporal continuity and high quality, was selected. Data underwent a quality control procedure and outliers were discarded; afterwards monthly series were elaborated. Time series of climatic variables, as temperature and precipitation, may be affected by non-climatic factors, that can hide or alter the climatic signal; therefore, a 3-step homogenization procedure was applied to monthly series.

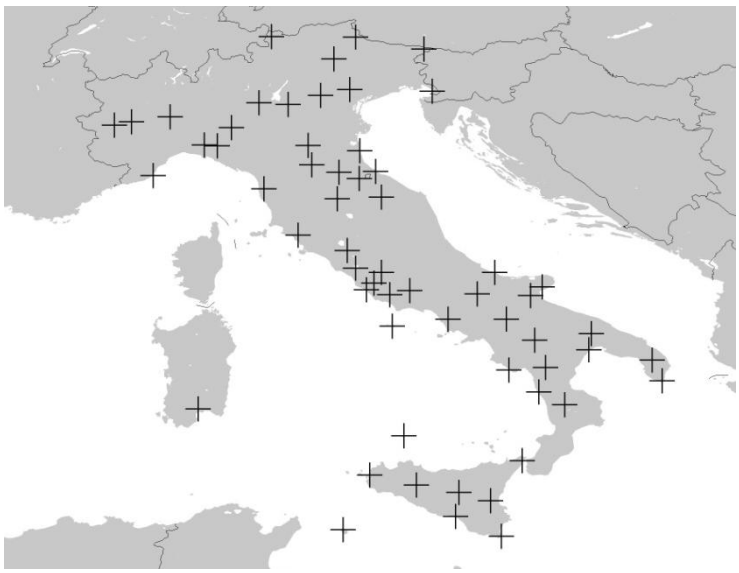

Figure 1. Map of the 59 stations

METHODS

Hourly data underwent a weak climatological control and a consistency control, through the check of a variable with other related variables (e.g. temperature and dew point temperature). Outliers were detected applying filters, build up as a function of latitude and season, and performing a spatial comparison (Baffo et al. 2005, Eisched, 1995). Monthly values were calculated only if 90% of daily precipitation data are valid.

The homogenization of precipitation still remains a difficult task, moreover it is important to avoid over-correction; therefore a 3-step procedure was applied to the monthly series. First of all, in order to obtain a preliminary idea of the behaviour of the log series, an absolute method was chosen: the Kolmogorov Zurbenko Adaptive filter KZA (Zurbenko et al., 1996). It is an iterative moving average filter that dynamically adjusts its moving length.

$$Y_t = (q_{H(t)} + q_{T(t)})^{-1} \sum_{i=-q_{T(t)}}^{q_{H(t)}} X_{t+i}$$

where X denotes the original series and $q_{H(t)}$ and $q_{T(t)}$ depend on $f(D(t)) = 1 - \{D(t)/\max[D(t)]\}$; D is a function of the Kolmogorov Zurbenko filter (Rao and Zurbenko, 1994; Zurbenko, 1986) applied to X. The possible inhomogeneities are located in correspondence of the sample variance peaks. Figure 2 shows an example of this method applied to a series recorded at Latronico, a synoptic station located in Southern Italy. In the upper plot the thin line denotes the log series of monthly precipitation, while the thick line represents the KZA output; the lower plot shows the sample variance and a significant peak in 1957/8 is evident.

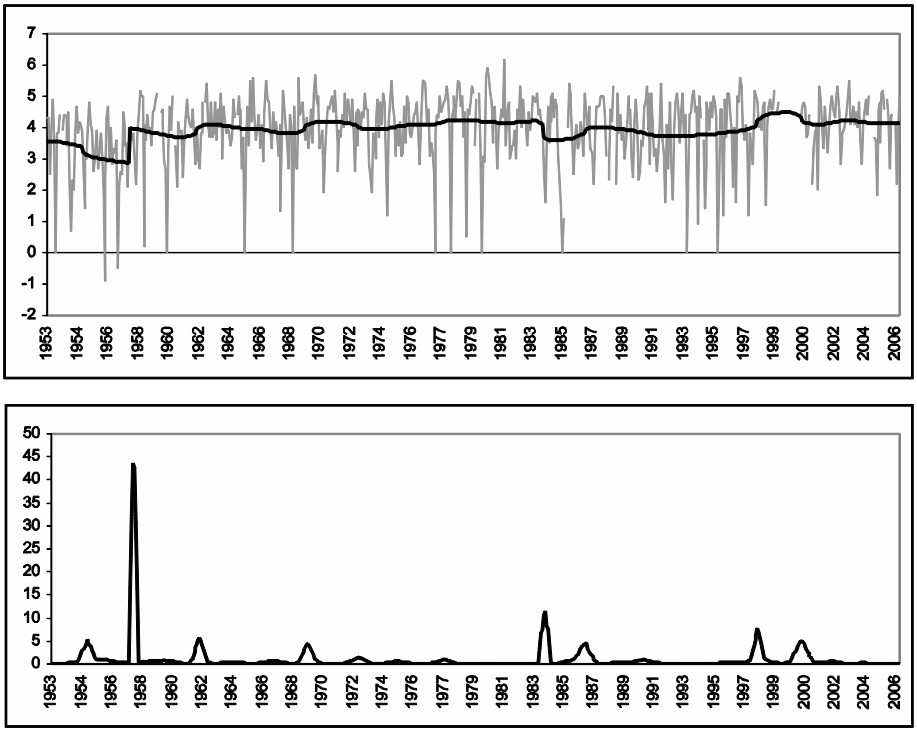

Figure 2. An example of the KZA application

The second step involves a modified version of the well-known Standard Normal Homogeneity Test (Alexandersson and Moberg, 1997). A moving window approach was implemented, using a window length of 12 years, but discarding the inhomogeneities detected in the first/last four years. The modified SNHT was applied to the log ratio series, building up the reference series with at least three stations, chosen using the best correlation criterion (Peterson and Easterling, 1994) and putting some geographical limitations.
The identified shifts underwent the third step of our procedure: the Multi Response Permutation Procedure MRPP (Easterling and Peterson, 1994; Mielke et al., 1981). It is non parametric and it was implemented choosing a window length of 96 values (centred at the inhomogeneity point). It is based on a standardized version of the following statistic and on a partition of K elements in g subgroups:

$$\delta = \sum_{i=1}^{g} C_i \xi_i \ , \ C_i = n_i / K$$

Where n_i denotes the cardinality of the i-th subgroup, ξ_i the average distance (using the Euclidean distance) for all elements belonging to the i-th subgroup. Figure 3 illustrates an example: the synoptic station Enna in Sicily before (red line) and after (grey line) the homogenization, indeed an inhomogeneity was detected by the procedure in November 1964.

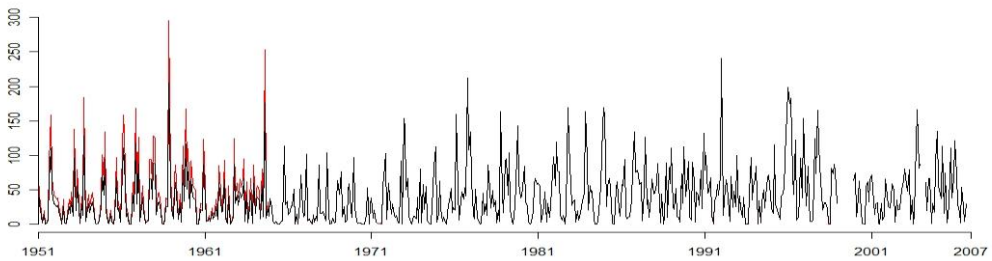

Figure 3. Enna series before (red line) and after (grey line) the homogenization

RESULTS

After the homogenization of the 59 monthly precipitation series, they were transformed in standardized anomaly series (Jones and Hulme, 1996), using as reference period 1971 – 2000. Afterwards, annual and seasonal series were calculated; the former considering the year from December to November, the latter applying the meteorological definition of seasons. Finally, the series were aggregated, in order to achieve three series for the following sub-areas: Northern, Central and Southern Italy. In the case of annual series no significant trends were identified. On the contrary, Northern winter series has a decreasing trend since 1961 and Centre winter series is characterized by a positive trend since 1998 (it might be confirmed in next years, when more data will be available).

The same calculations were carried out also for the original series, trying to understand the impact of the homogenization on the final output, which was used for trend identification and further climatological analysis. As for annual standardized series, absolute values of differences (between homogenized and original series) do not overcome 0.5, with greatest values in Central Italy and smallest values in Southern Italy (fig. 4 and fig. 5).

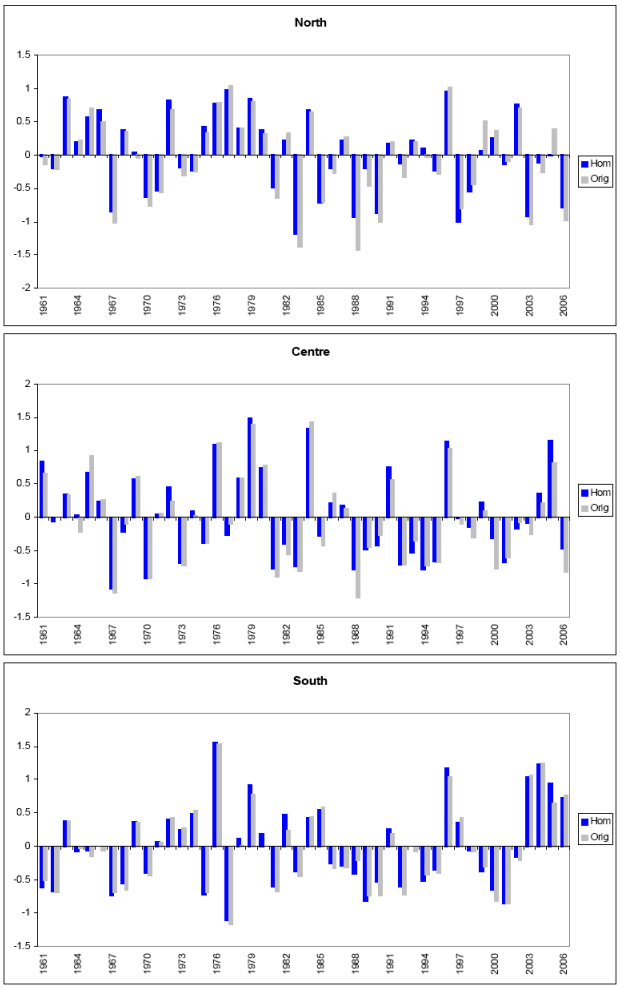

Figure 4. Comparison of annual standardized series before and after the homogenization

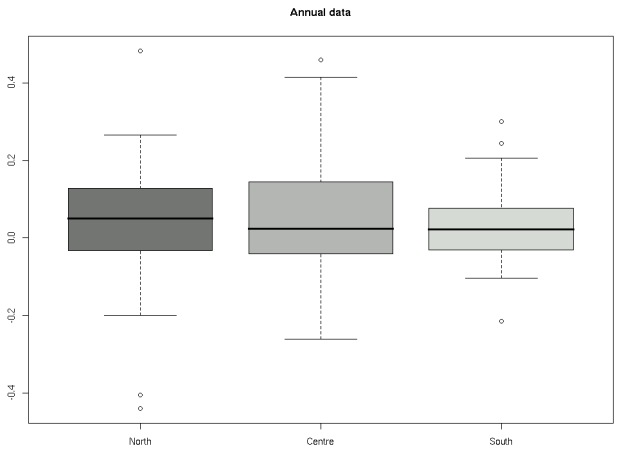

Figure 5. Boxplot of the differences between original and homogenized annual series

In Northern Italy there are not great differences between homogeneous and original series, especially during autumn (fig. 6, fig. 7 and fig. 8); all values belong to (-0.5, 0.3).

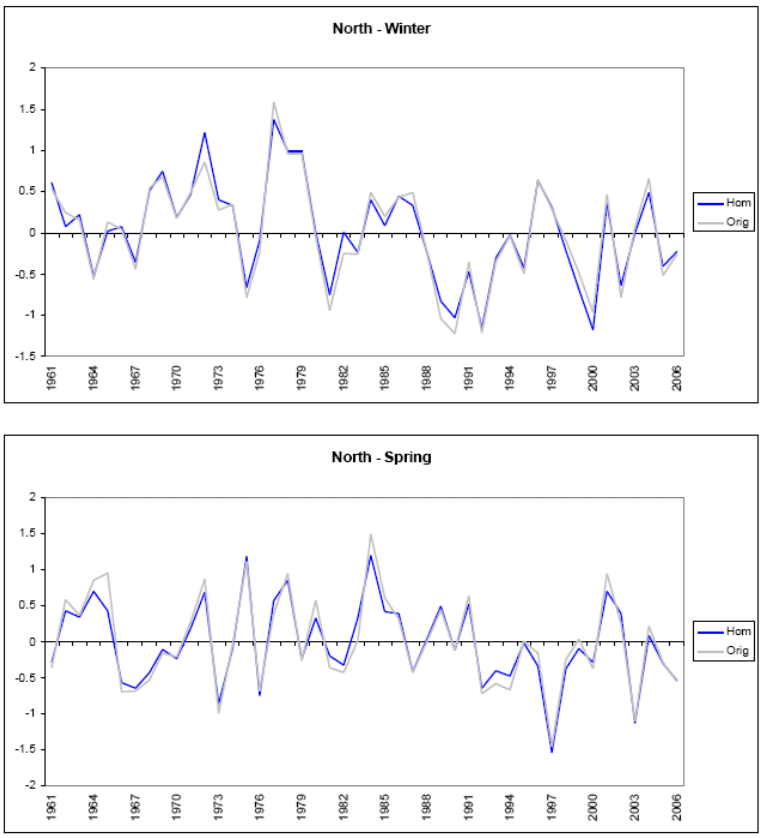

Figure 6. Comparison of seasonal standardized series, before and after homogenization in Northern Italy (winter and spring)

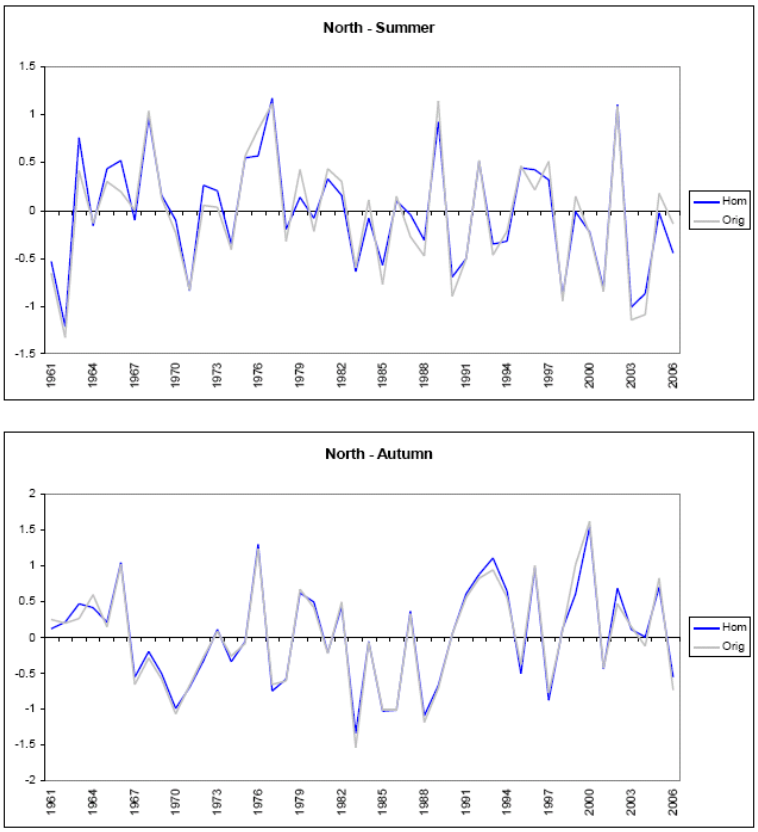

Figure 7. Comparison of seasonal standardized series, before and after homogenization in Northern Italy (summer and autumn)

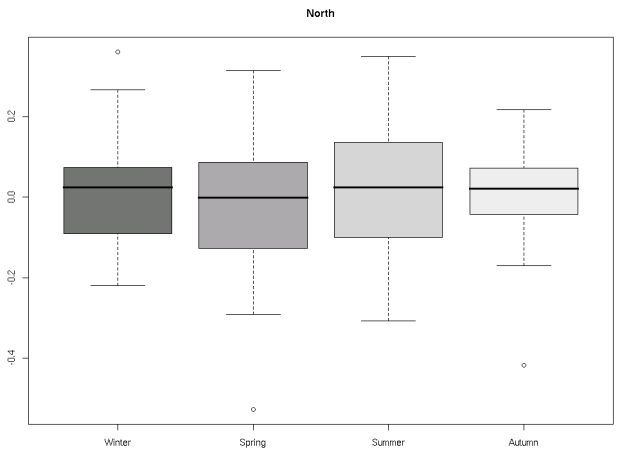

Figure 8.**Boxplot of the differences between original and homogenized seasonal series in Northern Italy**

In Central Italy differences are small, but winter 2000 with a value of about 0.6; spring values, with three exceptions, are concentrated around zero (fig. 9, fig.10 and fig. 11).

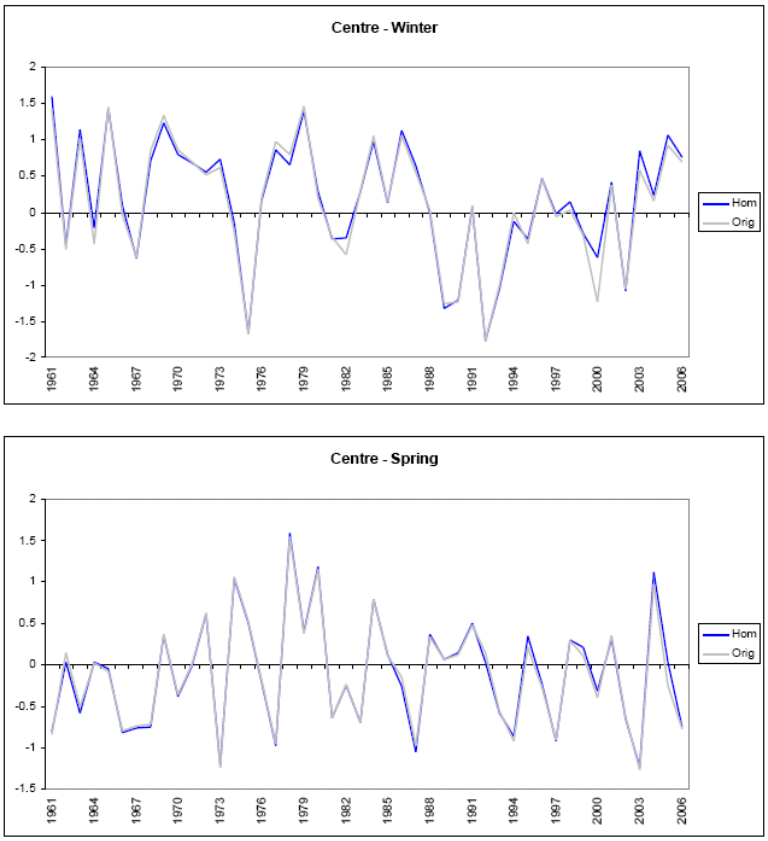

Figure 9. Comparison of seasonal standardized series, before and after homogenization in Central Italy (winter and spring)

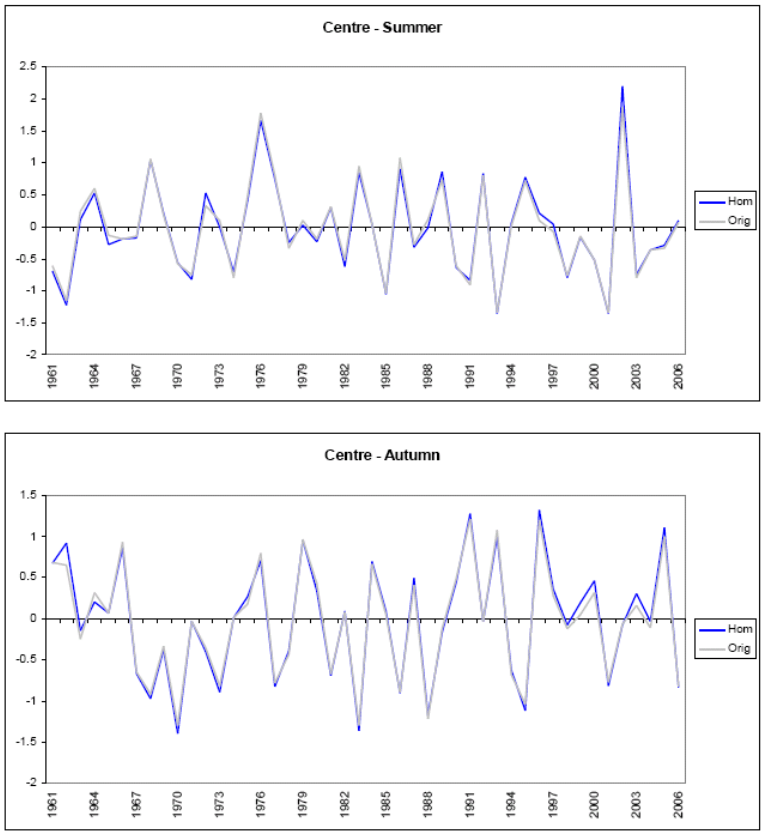

Figure 10..**Comparison of seasonal standardized series, before and after homogenization in Central Italy (summer and autumn)**

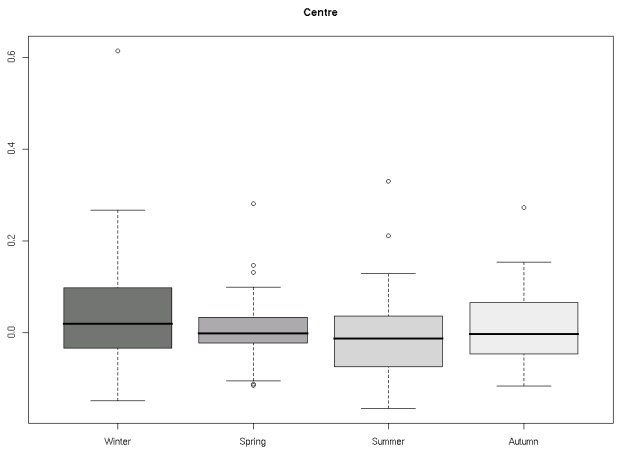

Figure 11. **Boxplot of the differences between original and homogenized seasonal series in Central Italy**

Finally, in Southern Italy there are not remarkable differences, except some high values, as summer 1999 (with a value of about 1) and winter 1996 (with a value of about 0.6). Figures 12, 13 and 14 show these results.

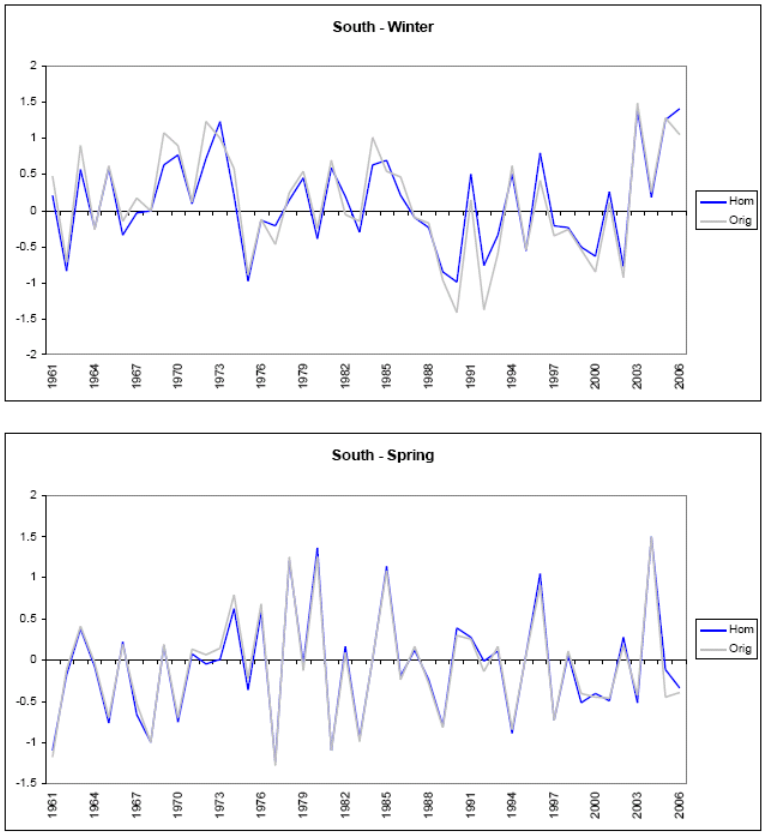

Figure 12. Comparison of seasonal standardized series, before and after homogenization in Southern Italy (winter and spring)

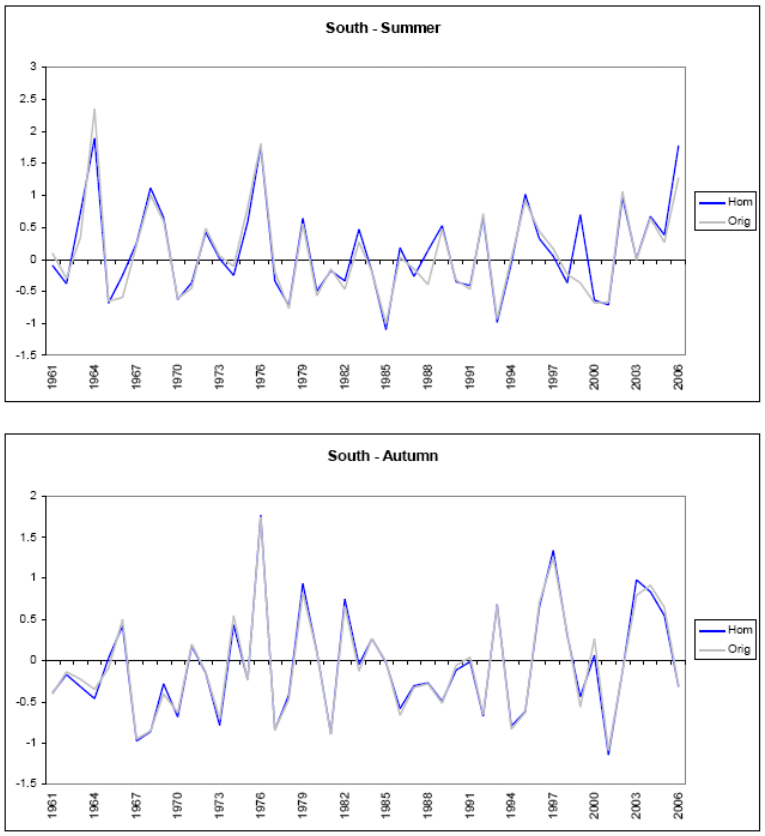

Figure 13. Comparison of seasonal standardized series, before and after homogenization in Southern Italy (summer and autumn)

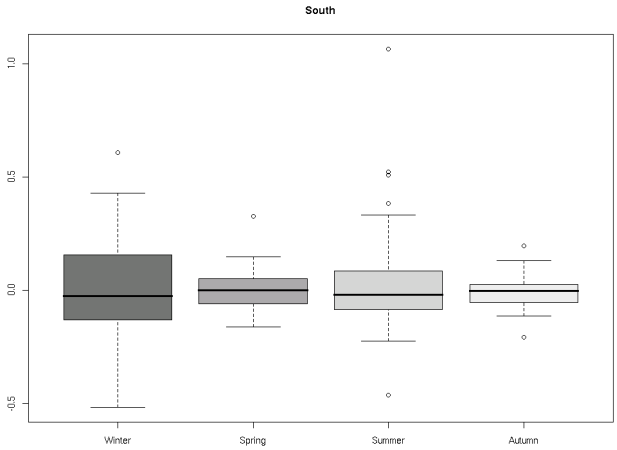

Figure 14. Boxplot of the differences between original and homogenized seasonal series in Southern Italy

CONCLUSIONS

In order to obtain a set of high quality precipitation series for climatological analysis, 59 monthly series well distributed over the Italian territory were homogenized applying a three steps procedure: KZA, modified SNHT and MRPP. The application of these different methods should avoid overcorrection, preserving the true climatic signal. However, it is important to underline that the homogenization of precipitation is still a tricky question. Our ongoing research concerns the investigation of other methods, the introduction of pairwise comparison in the procedure and the homogenization of daily series.

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HOMOGENISATION OF TEMPERATURE TIME SERIES IN CROATIA

Dubravka Rasol, Tanja Likso, Janja Milković
DHMZ, Grič 3, HR-10 000 Zagreb, Croatia,
rasol@cirus.dhz.hr

Abstract

The use of homogenized meteorological data time series is very important for all climate analyses because artificial shifts can cause misleading conclusions that do not correspond to real climate changes. Until recently, the homogenization of Croatian meteorological data series was carried out only sporadically. However, since Croatia joined the HOME COST Action ES0601, we have started dealing more intensively with the issue of homogenization.
This paper outlines the preliminary results of homogenization of some Croatian temperature data series. Two methods of homogenization were used and the results were compared. One of the methods used was Multiple Analysis of Series for Homogenization - MASH v3.02 and the other one was Standard Normal Homogeneity Test - SNHT applied with the AnClim software. Those two methods were applied on the data series from nine stations situated in the northwestern part of Croatia. Both methods gave similar results in detecting break points with quite a high accordance with the existing metadata. Furthermore, three stations were chosen for comparison of homogenized data series. Differences between values obtained by each method were negligible, but more detailed analysis of those results is required in the future.

INTRODUCTION

Homogeneous time series of climatic elements are essential for all studies concerning climate variability. Inhomogeneities caused by station relocation, instrumentation changes, changes in methods of calculating monthly means, etc. (e.g. Peterson and Easterling 1994; Jones 1995) can mask real trends and variability. In practice, it is difficult to preserve the permanence of all observation elements. Because of that many long-term time series contain inhomogeneities that must be adjusted before any comprehensive analysis for climatic variations (Alexandersson 1986; Karl and Williams 1987; Peterson and Easterling 1994; Jones 1995; Heino 1997; Peterson et al. 1998).
The intention of this paper is to compare two different homogenization methods *Multiple Analysis of Series for Homogenization* (MASH) and *Standard Normal Homogeneity Test* (SNHT) in order to evaluate the effectiveness of the procedures for breakpoints detection and time series adjustment.

Homogenisation in Croatia

Until recently, the homogenisation of Croatian meteorological data series was carried out only sporadically (Volaric 1982, Juras 1993, Likso 2004). Lately, in the Meteorological and Hydrological Serivce (MHC) of Croatia none of the methods of homogenisation is applied operationally. Recently meteorologists from the MHS have joined the COST Action ES0601 - *Advances in homogenisation methods of climate series: an integrated approach* (HOME, 2007-2011), and also have started a bilateral cooperation with the Hungarian Meteorological Service the project "*Harmonization of homogenisation and interpolation methods*" (2007-2009). As a consequence meteorologists in Croatia have started dealing more intensively with the issue of homogenization.

Croatian meteorological network

The meteorological observations in Croatia date back to the second half of the 19th century. Figure 1 shows how the network of stations developed from 1850 to 2000. A big drop in number of stations that occurred in 1991 is due to the war in Croatia which started at that time. Nowadays, the network consists of 41 main meteorological stations, 116 climatological and 336 precipitation stations. Some of them have series of more than a hundred years of observations. There are also 2 upper-air stations, 8 radars and 34 automatic stations. Figure 2 shows the spatial distribution of main and climatological stations.

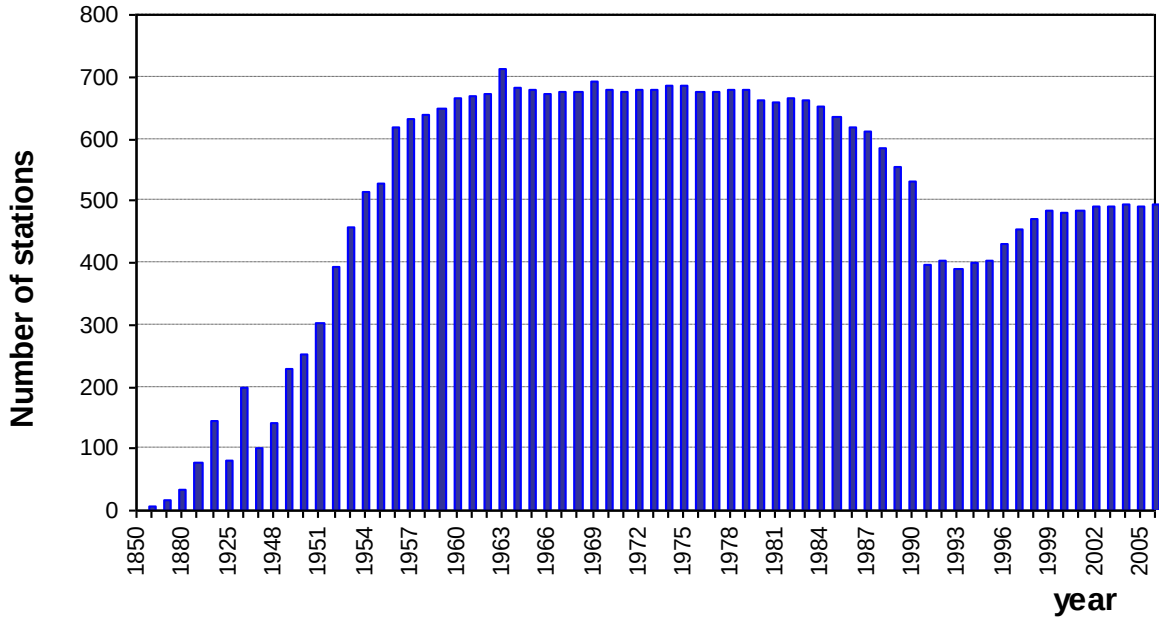
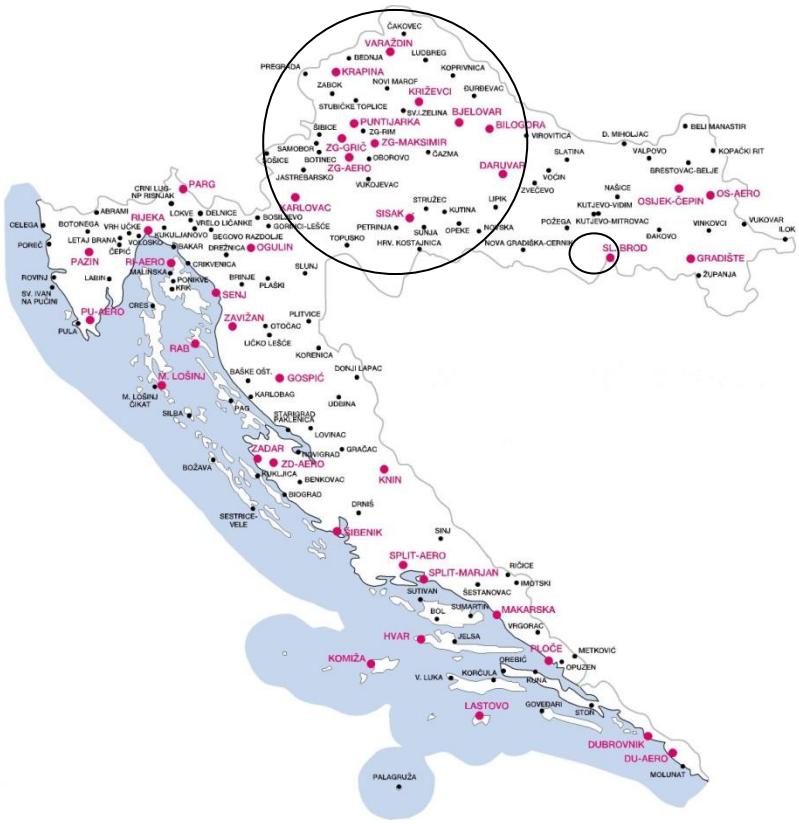


Figure 1. Temporal evolution of Croatian meteorological network

DATA AND METHODS

In this study monthly mean air temperature series from 9 stations from the northwestern part of Croatia were chosen for analysis (Figure 2). The period 1961-2006 was chosen as the longest one for which the data was available for all the stations. The data series were quality controlled according to the MHS quality control procedure (Rasol et al. 2007).



Bjelovar
Karlovac
Koprivnica
Krizevci
Sisak
Slavonski Brod
Zagreb Gric
Zagreb Maksimir
Varazdin

Figure 2. Spatial distribution of main (red) and climatological (black) stations and the list of stations chosen for this study

Break points were found and data was homogenized with two methods for relative homogeneity testing and the results obtained by each method were compared.

One method used here for the homogenization of temperature data is *Multiple Analysis of Series for Homogenization*, developed by Tamas Szentimrey in the Hungarian Meteorological Service (Szentimrey 1994, 1995, 1996). That procedure does not assume a reference series is homogeneous. Break points are detected and adjusted through mutual comparisons of series within the same climatic area. The candidate series is chosen from the available time series and the remaining series are considered as reference series. Several difference series are constructed from the candidate and weighted reference series.

The other method is described in Alexandersson (1986) and Alexandersson and Moberg (1997), known as the *Standard Normal Homogeneity Test* applied with the AnClim software (Stepanek, 2005). This procedure requires a homogeneous reference series. The reference series should ideally consist of meteorological data from several stations where the climate variations resemble those at the test station. Reference station should be located in a region with the same climatic characteristics as the test station. The number of reference stations should be large enough to eliminate eventual inhomogeneities in the reference data. In general, reference series have been constructed as a weighted average of the data from reference stations. The weight factors are the correlation coefficients between the test series and the series from reference stations.

As the testing was performed on the temperature time series, the differences between test and reference series were considered. The SNHT test is based on the likelihood ratio test with the assumption that there is at most one break point in the series. The test for a single shift cannot properly handle series with many break points (Alexanderson and Moberg 1997). In this paper, if a break point was detected, it was adjusted by calculating an adjustment factor (the

difference between the test series and the reference series). The test was repeated to detect further break points, until the series is considered homogeneous. For a homogeneous time series, the test statistic should not exceed a critical t-value on a specified confidence level.

RESULTS

Table 1 shows the breakpoints detected by MASH and SNHT. Quite a lot of breakpoints were found by both methods. The years for which there is a justification for the breakpoint in the metadata are bolded. Both methods detected all, from metadata known breakpoints, as well as additional ones. The accordance between mentioned procedures for breakpoint detection was very high. There were some minor changes found in the metadata that were not detected, but we can not be sure that those changes could really cause significant breaks in data series.

Table 1: Breakpoints detected by MASH (blue) and SNHT (red)

Bjelovar	1969 1981 1983 1989 1998 2001 2003 2004 1969 1983 1989 1998 2001 2004
Karlovac	**1992** 1993 1994 1999 2000 **2001** 1965 1984 **1992** 2000 **2001**
Koprivnica	1964 **1967** 1999 1965 **1967** 1980 1998
Krizevci	1980 1982 1984 1994 1995 **2000** 1981 1986 1993 1997 **2000**
Sisak	1964 1969 1971 1984 1989 1996 1964 1969 1979 1984 1996 2001
Slavonski Brod	**1969** 1974 1986 1991 1994 1996 **1969** 1986 1991 1996 1998
Zagreb Gric	1982 1989 1992 1998 1967 1972 1984
Zagreb Maksimir	**1981** 1987 1989 1991 **2002** **1981** 1991 1995 **2002**
Varazdin	**1971** 2000 **1970** 1987 1989 2000

Figure 3 shows the results of adjusting with MASH and SNHT method for Zagreb Gric station. Zagreb Gric temperature series is almost homogeneous, there were some very small changes in series but none of the breakpoints have justification in metadata.

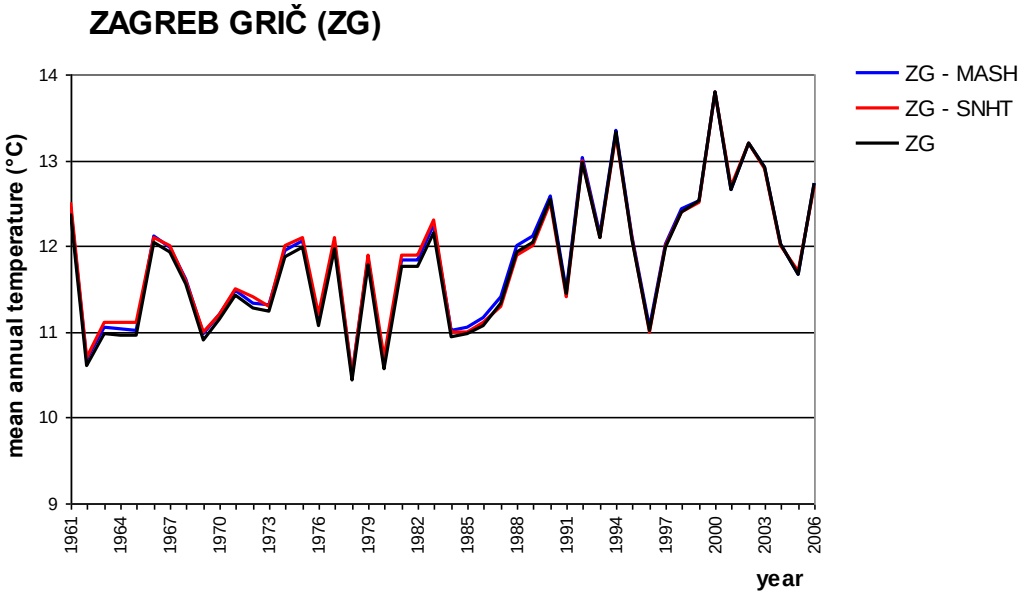


Figure 3: row data (black), SNHT homogenized data (red) and MASH homogenized data (blue) for Zagreb Gric station

The same for Zagreb Maksimir station is shown in figure 4. Both methods detected two breakpoints documented in the metadata. The first one was in 1981 when an annex to a factory near the station was built. The second one occurred in 1991, when indoor sport facilities were built near the station.

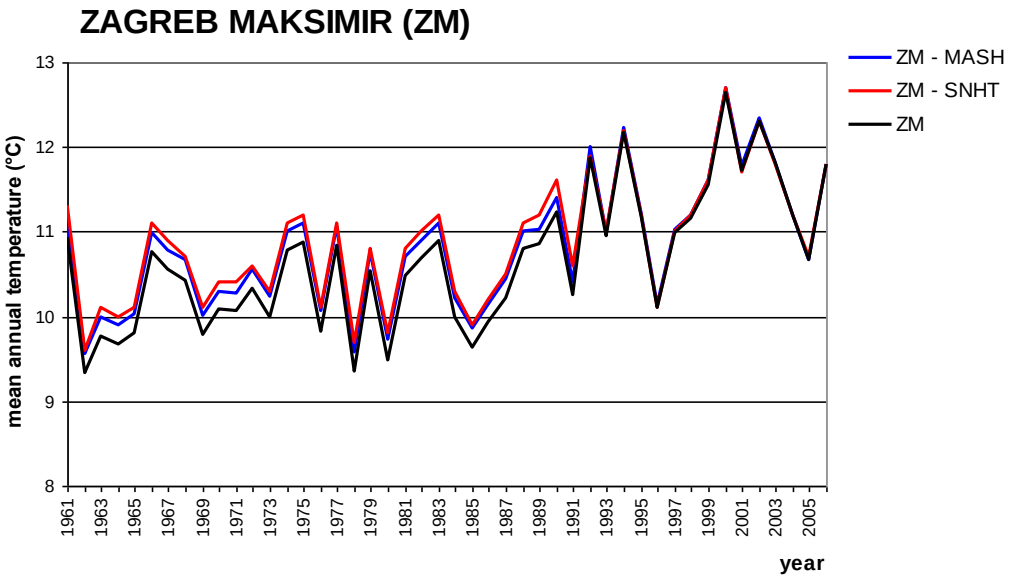


Figure 4: row data (black), SNHT homogenized data (red) and MASH homogenized data (blue) for Zagreb Maksimir station

Figure 5 shows the results of adjusting for Karlovac station. Both methods have made very similar adjustments and detected two break points documented in the metadata. The first one was in 1992 when the station was relocated from the city center to a suburban area. That relocation caused a huge inhomogeneity. The second one occurred in 2001 when the instruments screen was moved around 50 m from the previous location.

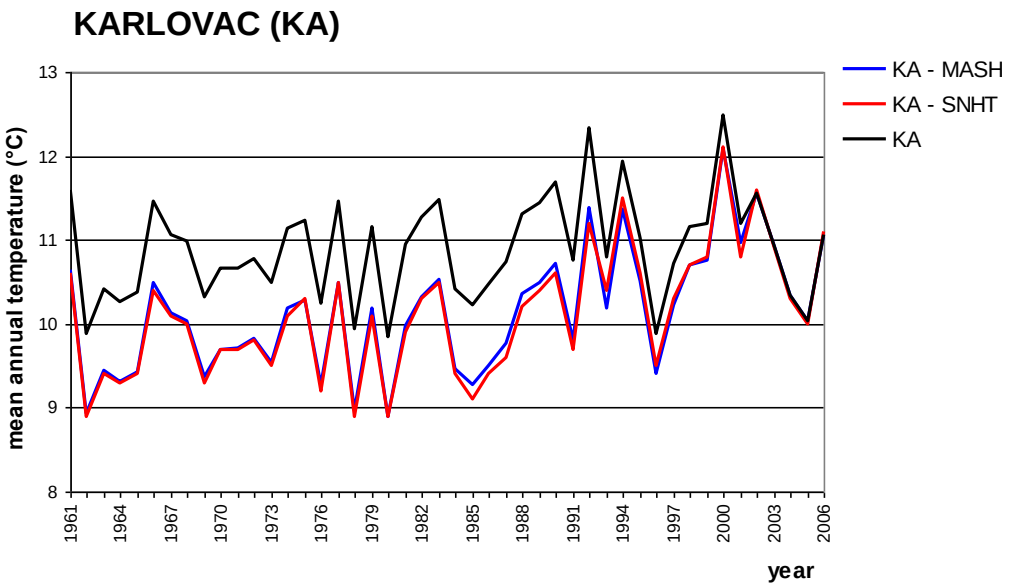


Figure 5: row data (black), SNHT homogenized data (red) and MASH homogenized data (blue) for Karlovac station

The differences between the MASH homogenized and SNHT homogenized series (Figure 6), for all three stations are very small, mostly less than 0.1°C and the largest is 0.2°C what is still very good accordance. From this it cannot be said which method would be better to use.

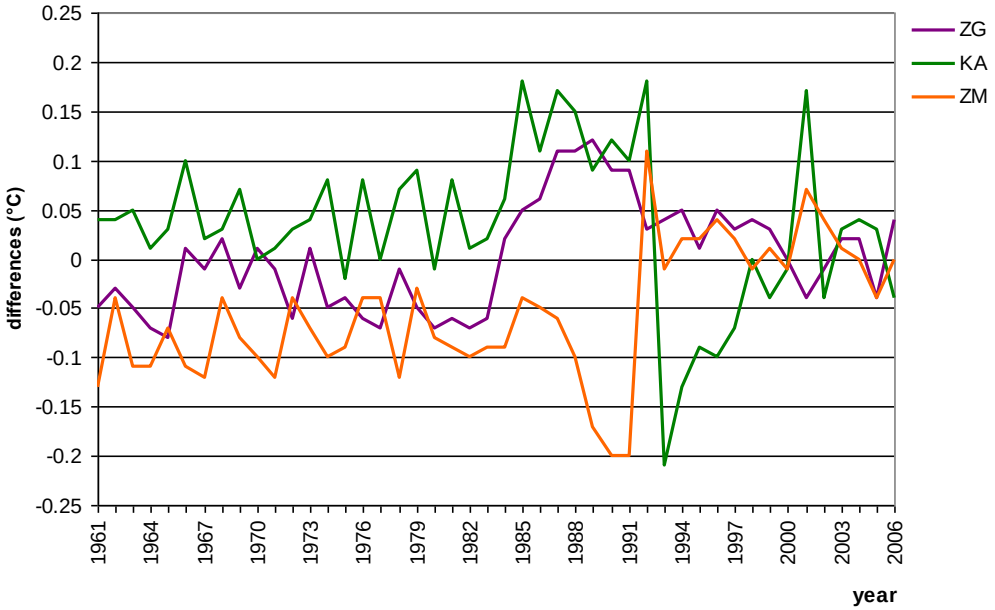


Figure 6: Differences between MASH and SNHT homogenized for Zagreb Gric (violet) Zagreb Maksimir (orange) and Karlovac (green) stations

Figure 7 up shows the place where Karlovac station was situated until 1992, it was in the middle of the city with the high urban impact, and the figure 7 down shows the new position after the relocation in 1992. The green arrow shows the position of the instruments screen in the period from 1992 to 2001 and the red one the position after 2001 which is around 50 m from the previous one. It is obvious that the position after 1992 is completely different, being out in the fields and far from any urban impact.

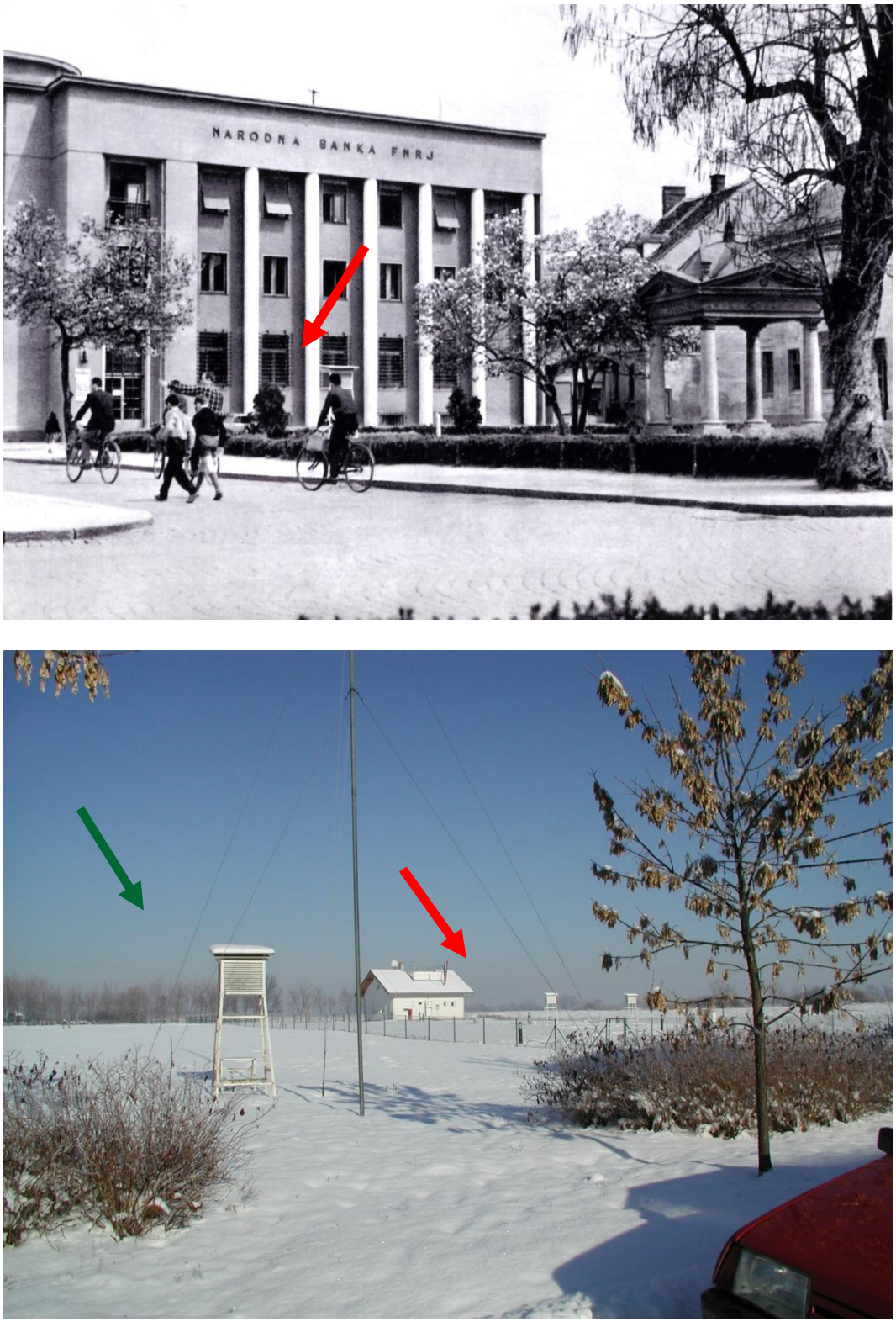


Figure 7: Position of the Karlovac station until 1992 (up) and after 1992 (down)

Figure 8 shows differences between yearly mean temperatures at Karlovac station and at all reference stations. There is a big drop in 1992 and another one in 2001. It is obvious that after relocation temperatures at Karlovac station became higher what is in accordance with the location differences.

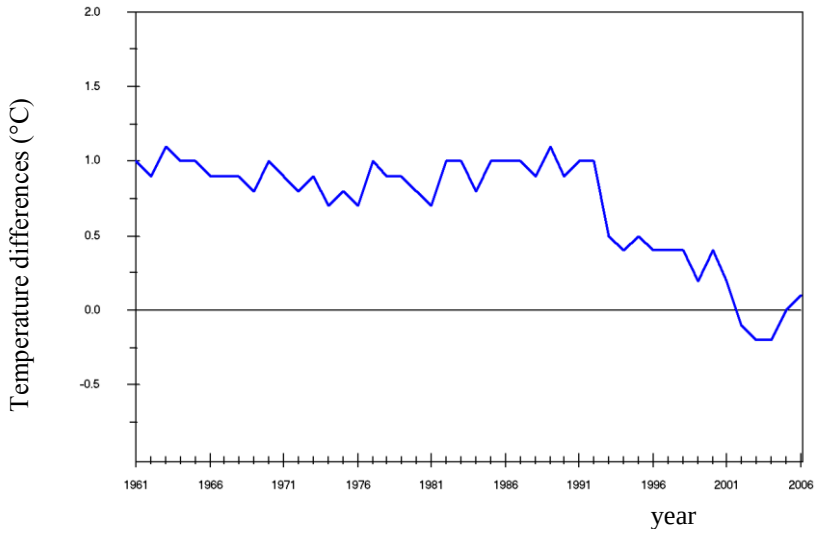


Figure 8: Differences between yearly mean temperatures at Karlovac station and at all reference stations

Trends

To get an impression of the difference between using original and homogenized data linear trends for Karlovac station are shown in figure 9. The slope of homogenized data is much steeper what shows the importance of homogenization of meteorological time series.

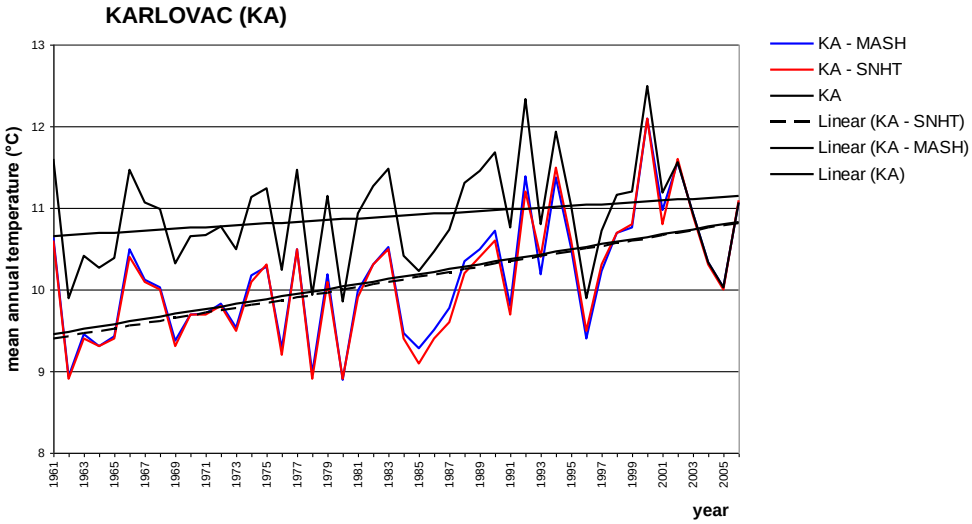


Figure 8: Linear trends for row and homogenized temperature time series for Karlovac station

CONCLUSIONS

Both MASH and SNHT methods for all studied stations detected all breakpoints known from metadata, as well as some other undocumented discontinuities. The differences between homogenized series obtained by each method were negligible. For Karlovac station it is still to be discussed if it is better to homogenize the series according to the most recent data or the data before the relocation in 1992. The question to be addressed is which part of the series is more representative for the region so the more detailed analysis of the presented results is required in the future.

Acknowledgements

Authors would like to thank Tamas Szentimrey for his valuable help regarding the MASH homogenization method. This study was supported by the Ministry of Science, Education and Sports of Croatia (project: "Harmonization of homogenization and interpolation methods") and the Hypo Alpe-Adria bank d.d. donation "Ten for ten".

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TOWARDS THE ASSESSMENT OF INHOMOGENEITIES OF CLIMATE DATA SERIES, RESULTING FROM THE AUTOMATION OF THE OBSERVING NETWORK IN MAINLAND PORTUGAL

Mendes M., Nunes L., Viterbo P., Neto J.
Instituto de Meteorologia, Rua C do Aeroporto, 1749-077 Lisboa, Portugal,
Tel: (351) 218447000, Fax: (351) 218402370
manuel.mendes@meteo.pt

INTRODUCTION

Climate data series are based on meteorological observations, following a set of rules, with regard to type of instruments, exposure, representativeness of station location and data recording procedures, amongst others. The history and evolution of observing networks show examples of a variety of changes, for instance, changes on instrument type, on instrument performance (calibration) and data procedures.
In recent years, Portugal, following a global trend, introduced changes in meteorological observation methods, especially due to the automation of the data acquisition and transmission procedures. Parallel observations with co-located conventional and automatic instruments in several sites, result in sets of overlapping data for various meteorological elements, now available for analysis.
In the present work, we study possible impacts on time series continuity originated by changes in observation procedures.
The present work plans to extend studies developed for the maximum temperature for two locations and years (Nunes, 1996) and for minimum and maximum temperatures and precipitation for a pair of years (Silva, 2001), by characterizing significant differences between automated and conventional stations in space and time. With the extended series of records analysed here, based on a set of 30 sites, we can start to estimate the impact of observation changes on climate series and monthly values. Comparisons with 1961-1990 Normal values and statistical indices were made to evaluate the significance of differences between both series.

DATA

The data used were acquired from 30 stations chosen from the Portuguese Network, in places were there was a overlap exposure of both automated and conventional systems, for periods ranging from 5 to 10 years.
In Figure 1 we can observe the station spatial distribution, type, and climatic classification. Principal or synoptic stations, operated by professional personnel and for synoptic hours, are represented in black. Simpler stations, operated by volunteers with a more basic background in observing procedures, are represented in blue. The observing time in this station type is 09 UTC.
The climatic classification assured a relatively good special resolution and representativeness.
Table 1 represents the overlapping period for each station and the date of beginning of operations for the conventional stations.

It is possible to observe that the overlapping periods are different for different stations and one can evaluate the importance of the present work from the date of the beginning of some of the Conventional Weather Station (CWS), which, in some cases, date from the 19th century.

Parameters presented in the present work are air temperature at 09 UTC (T009), minimum (Tmin) and maximum (Tmax) air temperatures, recorded between 09-09 UTC.

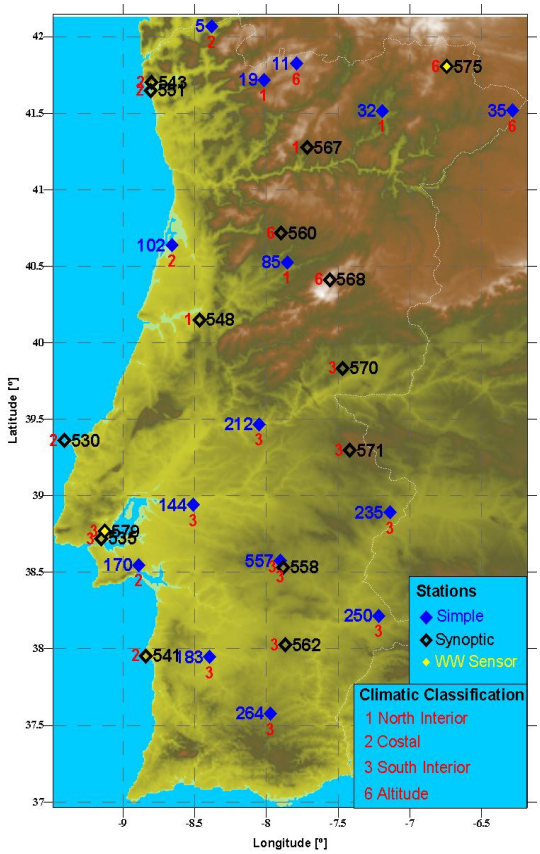


Figure 1. Distribution of the station type and climatic classification

Table 1. Stations and overlapping periods

Nr.	Begin CWS	Overlap start	Overlap end	End CWS
531	07/1922	07/1997	12/2006	
535	01/1836	07/1999	12/2007	
541	11/1988	07/1997	12/2007	
543	07/1969	06/1998	02/2006	02/2006
548	04/1995	06/1998	12/2007	
551	11/2005	11/2006	12/2007	
557	01/1869	01/2002	12/2007	
558	04/1995	06/1997	12/2007	
560	04/1991	06/1997	12/2007	
562	01/1873	07/1997	04/2004	04/2004
567	02/1992	06/1997	12/2007	
568	01/1931	01/1998	12/2007	
570	05/1985	05/1998	12/2007	
571	01/1932	06/1997	12/2007	
575	03/1931	06/1998	12/2007	
579	01/1982	06/1997	12/2007	
605	08/1967	06/1998	12/2007	
611	01/1879	01/2000	12/2007	
619	01/1980	07/1997	12/2007	
632	01/1924	01/2000	12/2007	
635	01/1932	01/2000	11/2001	11/2001
685	01/1954	06/1998	08/2002	08/2002
702	10/1980	07/1998	12/2007	
744	05/1977	05/1997	08/2007	
770	01/1924	05/1997	12/2007	
783	11/1933	05/1997	12/2006	
812	01/1948	01/2000	12/2007	
835	01/1927	05/1997	12/2007	
850	05/1963	05/1997	06/2007	
864	06/1982	05/1997	12/2004	

MISSING DATA

One of the most significant problems that the present study faced was related to missing data. In fact, both systems had a significant number of missing data. In the Automatic Weather Stations (AWS) the problem is related to power supply and data communications. On the other hand, in CWS the problem is related to the decreasing number of professional personnel handling the principal stations. Overall, data failure is lower for principal stations than in the simple stations. The main factor for this difference is related with power supply in simple stations, which are solar powered. In winter days, the exposure of the solar panels is shorter, therefore, the batteries have a lower autonomy.

METHODOLOGY

Statistics, such as average, standard deviation, root mean square error (RMSE), and correlation coefficients, were computed for both automated and conventional series, as well as for the difference between them.

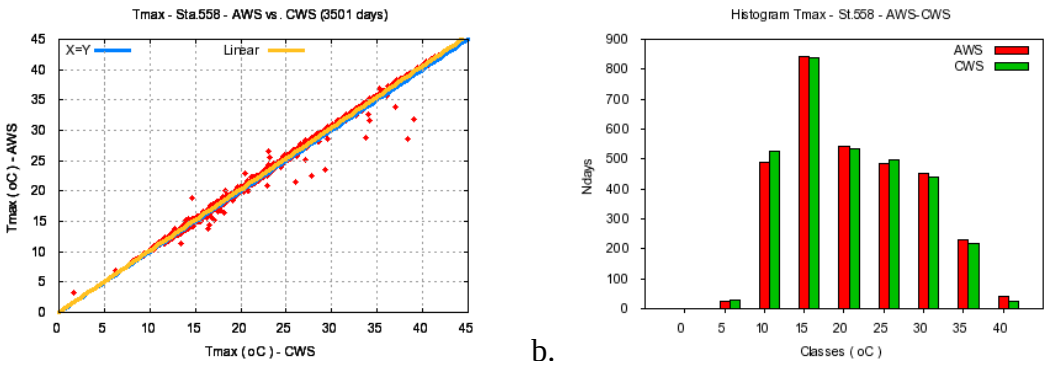
To compare these indices, statistical tests were made, especially over the mean values. A subjective analysis was made over the stability of the differences and the spatial distribution of the bias during the overlapping periods, based on visual inspection of results.

For climatic purposes, it became necessary to compare monthly data, retrieved from both series. Mean and extreme values were compared trough statistical testing for significance

levels of 1 and 5%. These values were also compared with the proportions obtained from several climatic indices retrieved from 1961-1990 Normal values.

RESULTS

Results are presented in two parts: An heuristic part, with analysis of figures, and an objective part, including tables with statistics.



a. b.

Figure 2. Scatter plot of AWS and CWS Tmax series at station 558 (Evora) (a), and the correspondent distribution histogram (b)

Figure 2 presents, in the left panel, an example of a scatter plot of the maximum temperature in CWS and AWS in station number 558, Evora, and, in the right panel, the correspondent histogram. In Evora, as seen in most of the cases inspected, the regression line as an almost 1:1 slope. The histogram shows a slight tendency for the AWS to be colder than CWS for the lower range of temperatures and the reverse tends to happen for upper range. Careful inspection of similar plots for all the stations did not reveal any clear regional pattern of differences. We cannot rule out the possibility of smaller spatial patterns for the differences, not detectable with current station density.

In several cases a seasonal pattern was identified, such as the one presented in Figure 3. The box-plot diagrams per class of values, displayed in Fig. 4, show a clear dependency on the temperature range of the AWS-CWS differences. This was a common result for temperature data.

To objectively characterize the differences AWS-CWS a statistical approach was made. The following analysis shows the percentage of the statistical tests that confirmed that AWS and CWS series are not, in most cases, significantly different. Table 2 summarizes, for the 3 temperature parameters, the differences AWS-CWS in all stations, stratified in terciles.

Figures 3 and 4 display examples of the seasonal evolution of the differences and their dependency on classes of values,, respectively.

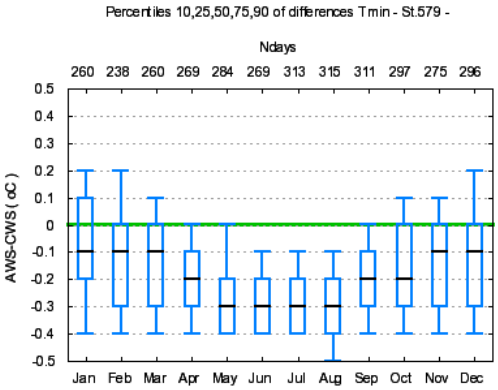


Figure 3. Box-plot of the monthly percentiles of the differences of Tmin of station 579 (Lisboa)

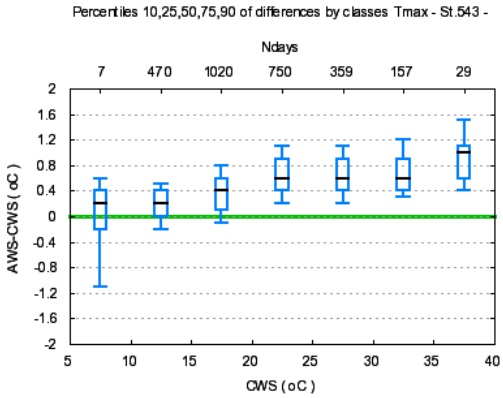


Figure 4. Box and whiskers representation of of Tmin AWS-CWS differences by classes of values of station 543 (Viana do Castelo). Boxes represent the 25 to 75 percentile, whiskers at 5 and 95 percentile and the black line is the median

In the T009 case, more than 50% of the bias values are on the 3rd tercile, corresponding to positive values. On the other hand, minimum and maximum temperatures have the larger percentage values over the 2nd tercile that correspond to the central values, near zero.

In the statistical tests corresponding to overall monthly averages and monthly series, calculated when possible, the global results show, in more than 60% of the test values, differences between the overall monthly averages and the monthly data series of AWS and CWS that are not significant (Table 3).

Table 2. Distribution of AWS-CWS differences in tercile values

Var	Nr.cases	1st T	2ndT	3rd T
T009	30	23%	23%	53%
Tmax	30	23%	43%	33%
Tmin	30	30%	53%	17%

Table 3. Percentage of non-significant differences of overall monthy average and monthly series at 99% significance level

	Daily time series			Montlhy time series		
	T009	Tmax	Tmin	T009	Tmax	Tmin
Jan	87	83	93	96	92	100
Feb	87	90	93	95	93	100
Mar	90	93	97	100	96	100
Apr	83	97	90	97	100	98
May	83	97	100	98	100	100
Jun	80	97	93	97	97	100
Jul	80	97	90	97	100	98
Aug	63	97	87	91	100	96
Sep	67	97	87	90	100	96
Oct	80	93	93	99	98	94
Nov	80	87	93	96	94	100
Dec	83	80	93	93	97	96

Anomalies of the AWS and CWS with respect to the 1961-1990 monthly normals show a very similar behaviour of the two observation systems, *i.e.*, the test values were rejected/accepted with similar threshold values. This fact is shown in Tables 4a to 4c.

Table 4 reveals that that in the latest years, all the three studied temperatures have higher values than the 1961-1990 normals. This fact is shown by the larger number of significant

differences between AWS (CWS) and normals for positive anomalies (rejections of the hypothesis of statistical equal values).

The following step was to test the differences for extreme values. Climatic indices (WMO Nr.100, 1983) such as the 10th an 90th percentiles of the minimum and maximum temperatures (TNpp and TXpp, 1961-1990 Normal values), the cold days (CD, Tmin<-10ºC), tropical nights (TN, Tmin>20ºC), warm days WD, Tmax>20ºC), summer days (SD, Tmax>25ºC), tropical days 1 (TD1, Tmax>30ºC) and tropical days 2 (TD2, Tmax>35ºC).

We assessed if the proportion of days above or below the indices between AWS and CWS series was significantly different. Table 5 shows, for more than 90% of months, proportions are not significantly different at the 1% significance level.

Table 4. Contingency tables with the number of rejected months of AWS and CWS series when compared with 1961-1990 Normal values: (a) T009, (b) Tmax and (c) Tmin

a		CWS							
	T009	Rej(-)	1	5	10	90	95	99	Rej(+)
AWS	Rej(-)	68	9	4	9	3	0	1	0
	1	10	9	3	4	1	0	0	0
	5	4	4	4	6	6	1	0	1
	10	11	12	5	58	21	1	2	3
	90	3	6	5	64	115	8	16	15
	95	0	0	0	8	20	7	8	9
	99	1	1	0	5	34	10	10	20
	Rej(+)	1	3	1	10	39	17	64	307

b		CWS							
	Tmax	Rej(-)	1	5	10	90	95	99	Rej(+)
AWS	Rej(-)	24	2	0	1	1	0	0	0
	1	5	5	0	2	0	0	0	0
	5	0	3	2	5	0	1	0	0
	10	5	6	4	52	11	2	0	0
	90	1	2	0	31	72	3	10	9
	95	2	0	0	0	16	2	4	2
	99	0	0	0	3	14	14	20	12
	Rej(+)	0	0	0	1	10	4	24	154

c		CWS							
	Tmin	Rej(-)	1	5	10	90	95	99	Rej(+)
AWS	Rej(-)	42	7	1	2	0	0	0	0
	1	6	6	2	5	0	0	0	0
	5	0	3	3	9	0	0	0	0
	10	11	2	4	58	25	0	0	0
	90	3	4	1	10	80	14	10	2
	95	1	0	0	2	5	6	6	6
	99	1	0	0	4	3	1	16	20
	Rej(+)	1	0	0	1	3	1	5	133

Table 5. Percentage of months that rejected proportions between AWS and CWS indices were significantly different at 1% confidence level

		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Tmin	CD	100	100	100	100	100	100	100	100	100	100	100	100
	TN	100	100	100	100	100	100	100	97	100	100	100	100
	TN10	100	100	100	100	100	97	100	90	93	93	97	97
	TN90	97	97	97	100	100	97	100	100	97	97	100	100
Tmax	WD	97	97	97	97	97	100	100	100	100	97	97	100
	SD	100	100	100	97	97	100	100	93	100	97	97	100
	TD1	100	100	100	97	97	97	100	100	97	100	100	100
	TD2	100	100	100	100	100	97	97	100	100	100	100	100
	TX10	97	93	100	97	100	100	97	97	97	93	93	97
	TX90	97	93	97	100	100	97	100	100	100	97	97	93

In order to determine in an objective way the pattern of each difference, we devised an heuristic method to detect the existence of dependency of differences on classes of values. For each parameter, differences were stratified in classes of values and a box and whiskers representation created for each class (see Figure 4 as an example). In such a figure, a linear increase (decrease) with class of values can be idealized as a straight line with positive (negative) slope; $\pm\sigma/(x_{max}- x_{min})$, where sigma, xmax, and xmin are, respectively, the sample

standard deviation, minimum value and maximum value. In the following we refer to this as the reference slope. Next we compute the linear fits to the dependency of each of the 10, 25, 50, 75 and 90th percentiles with class of values, obtaining in this way 5 slopes for each variable. If two of the absolute values of the slopes were higher the reference slope, the parameter difference was considered value-dependent. Tables 6a-b show the percentage of cases in which the slope value was higher than the reference slope, for positive values (+m) and negative values (-m). Table 6c, summarizes the absolute number of cases that are value-dependent (Val) and non value-dependent (NVal). Overall, results from Table 6, suggest that the number of cases that are value-dependent (Val) are between 15 and 30% of the total number of cases. It is interesting to note, on panels (A) and (B) of Table 6, that the slopes of minimum and maximum temperatures have opposite sign.

Table 6. (A) Percentage of negative slopes that are lower than the reference slope; (B) Percentage of positive slopes that are higher than the reference slope; (C) Absolute number of cases classified as value-dependent (Val) and non value-dependent(NVal)

A

-m	p10	p25	p50	p75	p90
T009	18	4	4	0	4
Tmax	4	0	0	0	0
Tmin	21	11	14	14	21

B

+m	p10	p25	p50	p75	p90
T009	7	7	14	21	14
Tmax	14	18	18	21	25
Tmin	0	0	0	0	0

C

	Val	NVal
T009	6	22
Tmax	8	20
Tmin	5	23

CONCLUSIONS

Overall, for meteorological surveillance and monthly reporting, the main operational use of data at IM, the differences between AWS and CWS are not significant. Most of the tests reveal that for daily or monthly data, differences are acceptable and do not compromise continuity of the data series. We identified patterns on some of the differences shown, which can lead to a statistical or algorithm correction. The value-dependent differences are very likely related to exposure factors such as the effect of the different type of shelters/screens used to cover the AWS and CWS sensors (Perry *et al*, 2007).
Nevertheless, if the goal is to study long series of data, its extremes and tendencies, the raw data needs to be corrected prior to the merge of the time series.

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HOMOGENIZATION OF DAILY DATA SERIES FOR EXTREME CLIMATE INDECES CALCULATION

Lakatos, M., Szentimrey, T., Bihari, Z., Szalai, S.
Hungarian Meteorological Service,
lakatos.m@met.hu

INTRODUCTION

Extreme climate indices calculations require at least daily resolution of homogeneous time series. In many cases the characteristics of the estimated linear trends are unambiguously unlike on the original and homogenized time series. It is a frequent occurrence that the sign of the slope implies decreasing or increasing on the data with artificial breaks, while the fitted trend to homogenized data implies adverse character.
The ECA&D indices and some other special temperature and precipitation indices of our own development were built in to the Climate Database of the Hungarian Meteorological Service. Long term daily maximum, minimum temperature and daily precipitation sums series were homogenized and the climate indices series based on daily data has been derived and analyzed for the period 1901-2007. The extreme climate indices calculation results and the fitted linear trend statistics were tested on the original as well as on the homogenized daily data series. The differences are exposed in this paper.

DATA AND METHOD

Deriving the extreme climate indices the gaps in the data series and the inhomogeneities caused problems. Therefore the homogenization of observation series is crucial to get correct consequences on changes of extremes.
The necessity of homogenization is demonstrated in *Figs. 1 and 2* which show the annual number of frost days (daily minimum temperature < 0°C) for Szeged station in original and the homogenized daily minimum temperatures. Both the magnitude and the sign of the estimated linear trend are different in the two cases.

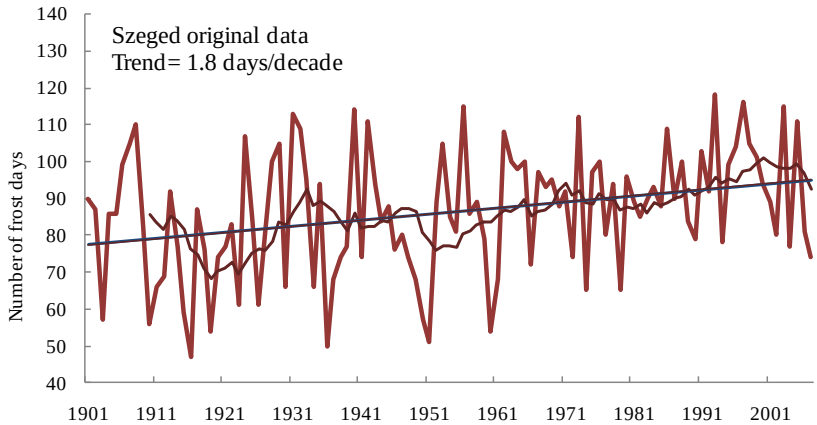

Figure 1. Annual number of frost days with the ten-years moving average for Szeged station in the period of 1901-2007 using the original data

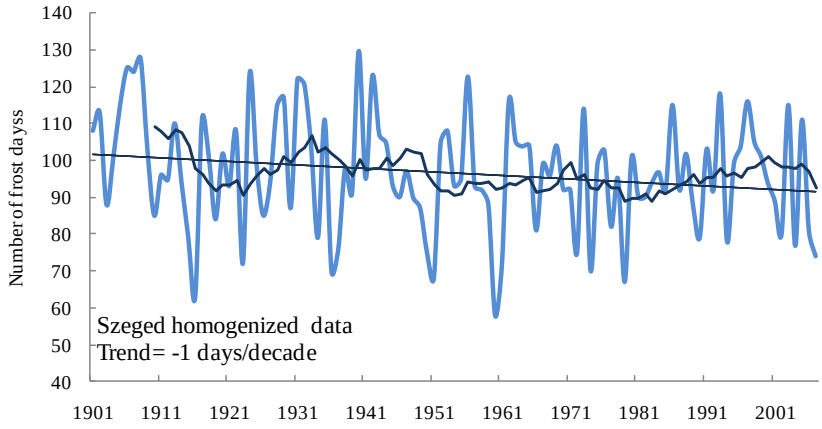

Figure 2. Annual number of frost days with the ten-years moving average for Szeged station in the period of 1901-2007 using the homogenized data

The computations implemented in this work are based on long term daily data in the period of 1901-2007. Daily maximum and minimum temperatures of 15 observation stations and daily precipitation sum of 58 precipitation stations were taken into account in the analysis. In the preparation phase the homogenization and quality control of the daily measurements were carried out. The homogenization of daily data was performed with the procedure MASH (Multiple Analysis of Series for Homogenization) (*Szentimrey*, 1999).

The main features of MASHv3.02 (Szentimrey, 2007)

The software consists of two parts.
Part 1: Quality control, missing data completion and homogenization of monthly series:
Relative homogeneity test procedure.
Step by step procedure: the role of series (candidate or reference series) changes step by step in the course of the procedure.
Additive (e.g. temperature) or multiplicative (e.g. precipitation) model can be used depending on the climate elements.
Providing the homogeneity of the seasonal and annual series as well.
Metadata (probable dates of break points) can be used automatically.
Homogenization and quality control (QC) results can be evaluated on the basis of verification tables generated automatically during the procedure.
Part 2: Homogenization of daily series:
Based on the detected monthly inhomogeneities.
Including quality control (QC) and missing data completion for daily data. The quality control results can be evaluated by test tables generated automatically during the procedure.

VERIFICATION OF THE HOMOGENIZATION RESULTS AND QUALITY CONTROL

During the execution of MASH procedure the quality control and homogenization test results e.g. detected errors, degree of inhomogeneity, number of break points, estimated corrections and certain verification results are documented in the automatically generated tables which make the evaluation efficient. The Tables 1-3 contains the homogeneity test results for the different meteorological elements which were analyzed in this work. In the case of daily minimum temperature series the degree of inhomogeneity of the stations are high values,

multiples of the critical value even in average. The test statistics proximate the critical value after homogenization (Table 1.). Lower but still high degree of inhomogeneity is typical of the daily maximum temperatures (Table 2.). The MASH procedure reduced the test statistics in the case of daily maximum temperatures substantially. The inhomogeneity of the raw precipitation data series is less, although the MASH procedure more decreased the test statistics (Table 3.).

Table 1. Test results for daily minimum temperatures

VERIFICATION OF HOMOGENIZATION (MINIMUM)

TEST STATISTICS for ANNUAL SERIES (OUTPUT of MASH)
Critical value (significance level 0.05): 21.73

Test Statistics Before Homogenization(TSB)

Station	TSB	Station	TSB	Station	TSB
5	2024.83	12	1232.54	13	843.11
10	735.77	3	644.61	15	631.40
6	617.90	1	579.59	2	496.33
7	438.06	8	390.13	11	384.80
4	317.23	14	309.52	9	99.56

AVERAGE: ***649.69***

Test Statistics After Homogenization(TSA)

Station	TSA	Station	TSA	Station	TSA
14	36.56	2	35.15	13	31.27
4	30.55	1	30.02	8	29.43
9	28.10	5	27.74	3	24.01
6	23.30	7	22.87	10	22.37
12	22.09	15	21.68	11	17.68

AVERAGE: ***26.85***

Table 2. Test results for daily maximum temperatures

VERIFICATION OF HOMOGENIZATION (MAXIMUM)

TEST STATISTICS for ANNUAL SERIES (OUTPUT of MASH)
Critical value (significance level 0.05): 21.73

Test Statistics Before Homogenization(TSB)

Station	TSB	Station	TSB	Station	TSB
12	1106.40	6	1031.97	5	488.03
8	360.65	13	314.53	7	311.95
11	284.94	10	206.09	1	158.15
14	145.63	4	135.56	2	133.73
15	130.89	9	79.72	3	46.26

AVERAGE: ***328.97***

Test Statistics After Homogenization(TSA)

Station	TSA	Station	TSA	Station	TSA
1	60.91	7	49.90	5	44.96
2	44.82	14	34.28	8	32.99
6	31.73	9	28.31	11	25.28
10	22.59	3	21.89	13	21.44
15	21.21	4	20.36	12	19.39

AVERAGE: ***32.00***

Table 3. Test results for daily precipitation

VERIFICATION OF HOMOGENIZATION (PRECIPITATION)

TEST STATISTICS for ANNUAL SERIES (OUTPUT of MASH)
Critical value (significance level 0.05): 21.73

Test Statistics Before Homogenization(TSB)

Station	TSB	Station	TSB	Station	TSB
13	175.11	10	170.34	27	137.97
17	110.87	3	81.79	20	80.32
4	76.88	18	60.28	1	59.43
56	17.15	36	15.07	24	11.06

AVERAGE: ***43.10***

Test Statistics After Homogenization(TSA)

Station	TSA	Station	TSA	Station	TSA
2	66.34	18	59.33	37	54.23
58	51.60	20	51.54	51	48.02
1	44.91	44	43.98	52	43.85
8	15.27	56	14.62	36	12.82

AVERAGE: ***29.13***

The quality control part of the MASH demonstrates the detected errors. The Table 4 points a rough error in May 1941 on Kecskemét station. These very low daily maximum values appear as extremes in the original data. Extreme high daily minimum temperatures were registered in the climatological database in Túrkeve station to the date 18-19 February 1907 (Table 5.). The MASH quality control part detected the mistaken daily data. In case of precipitation we present only the summary of results in the Table 6.

Table 4. Quality Control results of daily maximum temperatures

Maximum temperature (1901-2007)
Result of automatic Quality Control By MASH
Total number of errors: 3319
Maximal positive error: 12.35
Minimal negative error: -20.91
Example: Kecskemét(46401), 26-31 May 1941

	48101	47100	46401	58104	55706	64704	44121
1941 525	22.4	24.6	26.0	24.6	24.8	24.2	25.3
1941 526	23.9	23.8	***2.4***	24.0	24.0	23.8	25.6
1941 527	24.2	24.2	***2.4***	25.6	23.3	23.8	22.8
1941 528	26.9	26.6	***2.7***	28.2	26.7	25.4	27.8
1941 529	25.8	24.0	***2.4***	27.0	26.5	24.6	24.2
1941 530	24.7	24.6	***2.5***	25.5	24.0	22.4	23.8
1941 531	25.0	25.2	***2.7***	26.5	25.8	25.4	25.9
1941 6 1	22.1	21.5	21.0	19.7	17.6	18.8	22.8

Table 5. Quality Control results of daily minimum temperatures

Minimum temperature (1901-2007)
Result of automatic Quality Control by MASH
Total number of errors: 2058
Maximal positive error: 14.03
Minimal negative error: -10.55
Example: Túrkeve(55706), 18-19 February 1907

48101	47100	46401	58104	55706	64704	44121

1907	217	-9.0	-13.0	-16.4	-10.8	-15.0	-17.9	-10.50
1907	218	-6.0	-5.1	-10.0	-3.9	***5.0***	-7.2	-5.50
1907	219	-1.5	-2.5	-6.4	-4.6	***10.6***	-13.2	-0.60
1907	220	-1.0	-1.5	-2.4	-0.1	-0.2	-1.9	-0.40

Table 6. Quality Control results of daily precipitation sum

Precipitation (1901-2007)
Result of automatic Quality Control by MASH
Total number of errors: ***854***
Maximal positive error: ***84.0***
Minimal negative error: ***-33.4***

CLIMATE INDICES

Extreme climate indices calculation started in the frame of project named „Regional Climate Modeling" 2005 – 2007 (NKFP-3A/082/2004, National Office for Research and Technology) in Hungary. The index definitions mainly are based on the ECA&D and Climdex definitions. The indices listed in the Table 7-9 were calculated in the climate database of The Hungarian meteorological Service. All of them were derived on original as well as on homogenized, quality controlled and complemented daily data. The changes raised in the extreme index series are estimated by linear trend fitting in three, partly overlapping time periods: 1901-2007, 1961-2007 and 1976-2007. The longest period goes back to the beginning of the 20th century to detect long term changes; the period from the mid 20th century turns up in IPCC reports, therefore that interval is analyzed. The last 30 years is chosen, because that is the most intense warming period, and it mostly characterizes the present climate.

Table 7. Extreme warm temperature indices in the climate database of HMS

Index/unit	Warm extremes
txx / °C	absolute Tmax
dtx25/day	summer days Tmax > 25 °C
dtx30e/day	hot days Tmax ≥30 °C
dtx35e/day	very hot days Tmax ≥35 °C
dtn20/day	tropical nights Tmin > 20 °C
ditxgnr/day	heat wave duration index
ditgnr90/day	warm spell days
itxgnr90/day	maximum duration of warm spell
TN90p /%	Tmin > 90th percentile of normal period
TX90/%	Tmax > 90th percentile of normal period

Table 8. Extreme cold temperature indices in the climate database of HMS

Index/unit	Cold extremes
tnn/°C	absolute Tmin
dtn0/days	frost days Tmin < 0°C
itn0x/days	maximum number of frost days Tmin < 0°C
t17s/°C	heating degree days
dtx0/day	ice days Tmax < 0°C
ditnlnr/day	cold wave duration index
ditlnr10/day	cold spell days
itnlnr10/day	maximum duration of cold spell
TN10p /%	Tmin < 10th percentile of normal period
TX10p /%	Tmax < 10th percentile of normal period

Table 9. Extreme precipitation climate indices in the climate database of HMS

Index/unit	Precipitation
rs/mm	precipitation sum
dr1/day	number of wet days
r1a/mm/day	mean wet-day precipitation
ir1xd/day	length of longest dry period R <1 mm
ir1xw/day	length of longest wet period R ≥ 1 mm
dr5/day	number of days R ≥ 5 mm
dr10 day	number of days R≥ 10 mm
dr20/ day	number of days R≥ 20 mm
rx1/mm	naximum daily sum
rx5/mm	naximum sum in 5 days long period
pr95gnr/%	proportion of prec. days R> 95% of normal period in the total annual precipitation
pr99gnr/%	proportion of prec. days R> 99% of normal period in the total annual precipitation

The estimation of trend values and testing of theirs significance are performed both on original while complemented data and on quality controlled, complemented and homogenized data. The MASH method was used for the data quality control, completion and for homogenization. In the Fig. 3 the changes of two indices based on daily minimum: TN10p (Tmin < 10th percentile of the 1961-1990 normal) and TN90p (Tmin > 90th percentile of 1961-1990 normal) are shown. The significant changes on 0.9 confidence level are colored according to the sign of the slope. The coloration of the cells indicates the significant increasing (red) and decreasing (blue) trends on the original and on the homogenized data. The decreasing tendency is dominant in the case of index TN10p, but there is inexplicable increasing on Szeged station in all the examined period. Kecskemét and Debrecen also show increased values on the longest series from 1901-2007. The adverse characteristics of the changes are caused by the artificial breaks in the data series. The positive values are eliminated after homogenization. The less extremely cold days rather agree with the global changes. Similarly in the case of index TN90p the presence of the wrong data and inhomogeneites result significant decreasing on the stations Kecskemét, Szeged and Debrecen from the beginning of the 20th century to 2007. The higher than the 90th percentile minimum temperatures are reassuringly dominant at all the stations and period.

TN10p orig	1901-2007	1961-2007	1976-2007
Sopron	-15.5	-11.1	-4.5
Szombathely	-0.5	-6.5	-6.7
Keszthely	-1.3	-7.6	-4.7
Mosonmagyaróvár	2.3	2.6	0.4
Siófok	-23.9	-7.7	-8.5
Pécs	1.2	-4.7	-5.2
Baja	-11.6	-5.4	-7.6
Kalocsa	-8.5	0.0	-2.7
Kecskemét	5.8	-2.0	-2.9
Szeged	6.1	9.4	8.2
Túrkeve	-1.4	-14.0	-19.4
Miskolc	-10.3	-5.2	-5.7
Debrecen	9.6	-0.6	-3.9
Nyíregyháza	-9.8	-5.6	-7.3
Budapest	-15.7	-4.9	-6.9

TN10p homogenized	1901-2007	1961-2007	1976-2007
Sopron	-7.3	-6.3	-6.4
Szombathely	-4.5	-5.3	-6.0
Keszthely	-4.0	-2.8	-3.6
Mosonmagyaróvár	-3.8	-3.3	-3.3
Siófok	-7.8	-6.2	-7.7
Pécs	-5.4	-4.9	-5.4
Baja	-6.0	-3.8	-5.4
Kalocsa	-5.6	-1.5	-4.4
Kecskemét	-3.4	-2.0	-3.5
Szeged	-2.2	0.0	-0.5
Túrkeve	-5.1	-6.2	-11.4
Miskolc	-6.7	-3.9	-5.7
Debrecen	-2.5	-2.8	-5.3
Nyíregyháza	-6.1	-4.3	-6.1
Budapest	-6.2	-4.9	-6.6

TN90p orig	1901-2007	1961-2007	1976-2007
Sopron	15.3	17.8	10.6
Szombathely	5.8	14.4	13.8
Keszthely	6.1	14.1	11.6
Mosonmagyaróvár	-0.2	0.0	3.8
Siófok	21.0	16.5	17.4
Pécs	-1.2	11.8	12.4
Baja	13.1	12.7	13.9
Kalocsa	9.0	8.0	11.5
Kecskemét	-6.2	8.8	10.7
Szeged	-3.9	-2.5	-1.0
Túrkeve	6.7	24.0	28.9
Miskolc	11.6	10.9	12.1
Debrecen	-7.8	5.9	8.9
Nyíregyháza	10.0	9.6	11.8
Budapest	14.5	10.4	13.8

TN90p homogenized	1901-2007	1961-2007	1976-2007
Sopron	6.4	10.4	10.2
Szombathely	10.0	11.8	12.2
Keszthely	7.9	9.1	9.4
Mosonmagyaróvár	8.6	9.0	9.3
Siófok	8.0	13.8	15.4
Pécs	8.1	11.5	12.2
Baja	9.0	10.4	11.2
Kalocsa	7.1	9.4	13.0
Kecskemét	7.7	9.1	11.2
Szeged	8.6	10.5	11.0
Túrkeve	10.4	5.6	9.3
Miskolc	8.1	9.2	12.1
Debrecen	10.7	9.3	11.2
Nyíregyháza	6.3	6.7	9.0
Budapest	5.9	9.7	12.8

Figure 3. Percentage change of the original and homogenized extreme indices based on daily minimum temperature for 15 Hungarian stations in three different time intervals

TX10p orig	1901-2007	1961-2007	1976-2007
Sopron	-9.4	-8.1	-10.0
Szombathely	-5.1	-8.2	-7.6
Keszthely	-6.9	-5.2	-5.7
Mosonmagyaróvár	-6.3	-4.4	-4.1
Siófok	-4.3	-4.6	-5.0
Pécs	-1.6	-4.5	-3.9
Baja	-5.3	-1.9	-2.9
Kalocsa	-5.7	-3.5	-7.4
Kecskemét	-5.8	-4.2	-5.3
Szeged	-8.7	-3.9	-5.7
Túrkeve	-11.7	2.8	-3.1
Miskolc	-7.3	-4.0	-6.8
Debrecen	-6.2	-3.1	-5.0
Nyíregyháza	-3.6	-2.4	-6.0
Budapest	-5.0	-2.6	-6.1

TX10p homogenized	1901-2007	1961-2007	1976-2007
Sopron	-5.9	-7.1	-8.9
Szombathely	-4.8	-5.9	-6.2
Keszthely	-5.1	-5.3	-5.6
Mosonmagyaróvár	-5.5	-5.1	-4.8
Siófok	-6.9	-6.0	-5.8
Pécs	-4.2	-3.8	-4.2
Baja	-5.7	-4.6	-5.7
Kalocsa	-4.3	-3.6	-6.6
Kecskemét	-5.2	-3.8	-5.7
Szeged	-4.2	-4.1	-4.8
Túrkeve	-3.6	-4.1	-8.8
Miskolc	-3.6	-3.0	-6.3
Debrecen	-4.4	-3.3	-5.2
Nyíregyháza	-5.7	-4.3	-6.7
Budapest	-5.1	-3.9	-7.8

TX90p orig	1901-2007	1961-2007	1976-2007
Sopron	11.4	13.0	14.3
Szombathely	9.4	12.9	12.7
Keszthely	7.9	9.9	12.1
Mosonmagyaróvár	5.7	10.3	10.7
Siófok	-0.7	11.7	13.7
Pécs	2.7	10.5	9.2
Baja	5.6	8.5	8.3
Kalocsa	5.2	10.9	15.1
Kecskemét	4.6	11.0	10.9
Szeged	10.7	11.3	13.6
Túrkeve	6.0	0.9	7.0
Miskolc	6.5	10.0	12.0
Debrecen	7.0	8.1	8.7
Nyíregyháza	0.8	7.7	12.4
Budapest	3.5	6.9	9.5

TX90p homogenized	1901-2007	1961-2007	1976-2007
Sopron	8.8	11.3	13.0
Szombathely	8.7	10.0	10.7
Keszthely	7.1	9.8	12.0
Mosonmagyaróvár	5.5	11.3	12.1
Siófok	2.4	12.8	14.8
Pécs	5.9	9.9	9.3
Baja	7.2	12.1	12.8
Kalocsa	4.1	10.9	14.3
Kecskemét	4.4	9.9	10.7
Szeged	7.5	11.8	12.3
Túrkeve	6.0	9.2	14.6
Miskolc	4.0	8.5	11.2
Debrecen	5.3	8.3	9.1
Nyíregyháza	3.3	9.8	13.0
Budapest	4.3	8.8	12.1

Figure 4. Percentage change of the original and homogenized extreme indices based on daily maximum temperature for 15 Hungarian stations in three different time intervals

In the Fig. 4 the changes of the indices TX10p and TX90p are shown. Both of them are calculated with using daily maximum temperatures. The differences between original and homogenized changes are less apparent than in Fig. 3, but the necessity of homogenization is obvious.

The columns in the Fig. 5 indicate also the degree and the trend of the indices which were examined in this study. Note that in many cases not only the degree but the sign of the estimated trend are discrepant. The diagrams are consistent with the test statistics introduced in the section 3. The degree of inhomogeneity of the indices based on daily minima is large, especially in the periods 1901-2007, but artificial breaks also were founded in the subsequent periods.

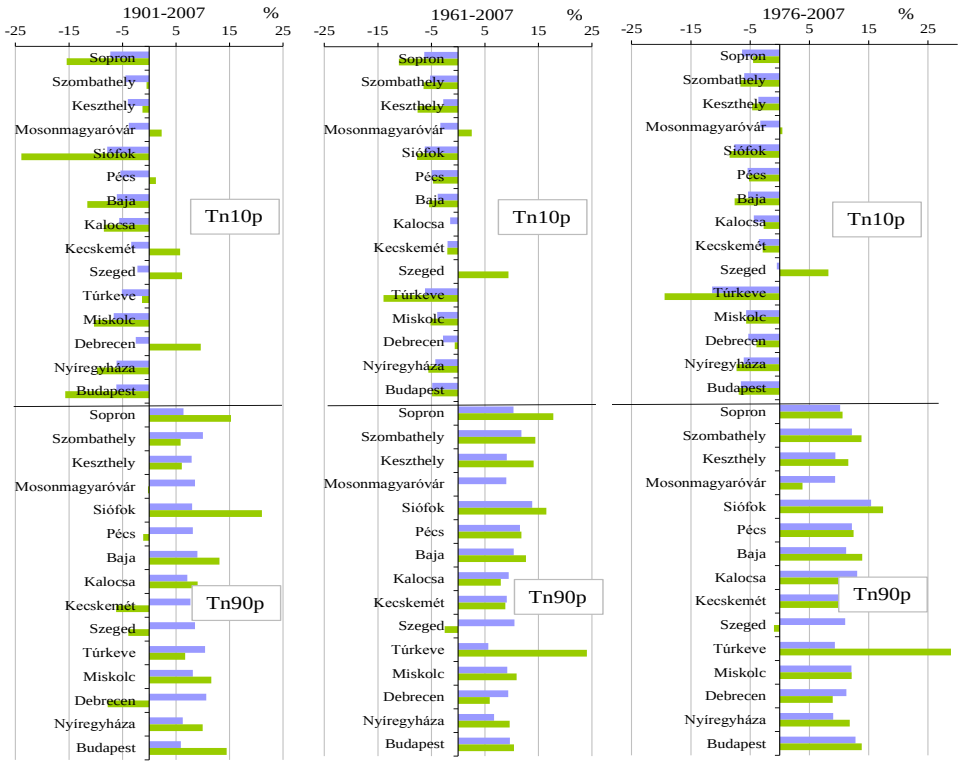

Figure 5. Comparative chart of the change arise in the series of TN10p and TN90p extreme climate indices for 15 Hungarian stations in three different time intervals

The precipitation is more variable climatological element than the temperature in time and in space as well. The extreme precipitation index which were examined in this paper is the proportion of precipitation days R> 95% of the 1961-1990 periods in the total annual precipitation (R95pTOT). The variability is manifested in Fig 6. which contains the changes of R95pTOT in the examined periods. The significant tendencies confirm that the fraction of the short term precipitation in the yearly sum is increased near to the present, but the measure of the changes is variant. The differences of the fitted original trend and homogenized trend are not so obvious than in the case of temperature. It follows from the fact that the MASH procedure is more cautious in the case of precipitation data.

R95pTOT (%)	homo	orig	homo	orig	homo	orig
	1901-2007	1901-2007	1961-2007	1961-2007	1976-2007	1976-2007
Sopron	-0.3	-1.0	3.3	3.2	6.9	6.8
Fertőszentmiklós	2.1	2.0	0.3	0.5	7.3	7.2
Szombathely	4.2	1.3	-0.4	-0.4	0.4	0.6
Felsőszölnök	3.0	-3.2	-0.9	-0.9	-3.1	-3.1
Mosonmagyaróvár	-3.3	-1.5	-2.7	-2.1	9.3	9.9
Ravazd	1.2	-2.8	1.5	1.6	6.7	6.8
Pér	3.3	3.1	2.5	3.6	-0.1	0.0
Beled	1.7	2.1	-1.8	-0.9	6.8	8.1
Bakonyszentkirály	0.5	2.0	2.6	2.8	10.1	10.3
Kemenesszentmárton	-0.5	2.3	-3.9	-5.5	4.7	4.2
Kerta	1.2	0.7	-7.3	-7.3	5.7	5.6
Bakonybél	4.2	4.1	1.1	1.3	10.9	11.0
Városlőd	0.9	4.1	-1.0	3.9	4.3	6.0
Herend	-3.5	-2.7	-1.8	-1.9	0.7	0.6
Türje	0.8	0.5	-6.0	-6.1	3.7	3.6
Sümeg	0.7	0.6	-3.2	-3.2	6.2	6.0
Nagyvázsony	1.2	-2.8	-2.2	-2.3	3.4	3.4
Keszthely	-1.2	-0.8	1.3	1.8	1.7	1.0
Balatonkeresztúr	-5.2	-4.1	1.7	2.4	2.3	3.0
Marcali	3.9	5.8	-0.3	-0.3	6.0	6.1
Mernye	8.5	8.4	1.2	1.2	6.6	7.3
Iharos	-6.6	-6.9	-5.1	-5.1	-3.0	-3.0
Rinyakovácsi	-4.2	-4.7	-1.4	-1.2	-0.7	-0.5
Márianosztra	1.8	1.8	-2.7	-2.6	7.2	7.3
Kápolnásnyék	-6.2	-6.7	1.5	1.5	5.1	5.1
Balatonalmádi	-2.2	-3.9	-6.0	-7.9	-8.5	-8.4
Siófok	1.5	0.8	2.6	2.2	0.6	0.4
Tab	-0.9	-0.6	-0.5	1.0	2.8	3.6
Pincehely	-0.6	-0.6	4.7	4.5	19.3	19.3
Tengelic	3.1	4.5	5.6	6.1	9.3	9.8
Gölle	-2.6	-1.6	-1.8	-2.1	13.5	13.5
Szálka	13.3	13.7	4.0	4.2	11.0	11.1
Pécs	6.5	5.0	6.1	6.1	12.2	12.0
Pásztó	-3.7	-0.7	-2.8	-2.4	3.9	4.4
Budapest	1.8	1.6	1.1	1.1	4.4	4.2
Tápiószele	0.4	0.7	-0.2	0.0	2.1	2.6
Kecskemét-kült	-0.9	-1.0	3.5	4.0	6.8	7.8
Kalocsa Öregcsertő	2.6	2.4	4.1	3.8	15.4	14.3
Baja	1.4	1.3	4.7	4.2	14.7	14.9
Felsőszentiván	6.4	5.7	3.7	2.2	14.9	15.0
Miskolc	-0.2	0.4	2.0	1.4	5.0	5.5
Bogács	-3.8	-3.9	0.3	0.3	3.1	3.1
Poroszló	-1.7	0.4	0.4	0.0	6.9	3.0
Fegyvernek	-5.3	-5.4	-6.3	-7.2	-4.7	-4.6
Túrkeve	8.9	8.8	8.7	8.8	13.3	13.5
Cibakháza	1.2	0.5	4.9	4.9	1.9	1.9
Kunszentmárton	3.3	4.2	-2.1	-2.2	3.0	3.2
Kondoros	5.7	5.5	0.5	0.9	6.9	7.6
Szeged	1.5	1.1	3.9	4.6	1.3	2.1
Karcsa	3.2	2.5	3.1	3.4	-0.7	-1.9
Nyíregyháza	1.6	1.2	3.5	3.5	7.9	7.7
Téglás Hadháztéglás	5.3	3.0	9.1	9.5	7.0	7.3
Hajdúszoboszló	8.4	7.7	4.1	4.2	5.9	6.0
Debrecen	7.7	7.2	6.2	6.7	6.5	6.8
Méhkerék	9.9	11.1	8.2	8.2	-0.8	-1.0
Battonya	4.6	4.5	1.3	1.3	5.6	5.7
Nyírmada	3.1	3.0	4.6	4.6	-0.2	-0.2
Vásárosnamény	7.9	7.6	0.3	1.5	3.4	3.4

Figure 6. Changes of R95pTOT extreme precipitation index for 58 Hungarian stations in three different time intervals

CONCLUSION

The majority of long data series is inhomogeneous, and often contains shifts in the mean or in the variance due to site-relocations, changes in instrumentation or in observing practices. Amongst the observation series there are good quality data as well, but sorting them out requires the execution of a homogenization procedure first. Neglecting the inhomogeneous series causes a huge loss of valuable information. Long term daily maximum, minimum

temperature and daily precipitation sums series were homogenized and the extreme climate indices series were derived and analyzed in the period of 1901-2007, 1961-2007 and 1976-2007 in this paper. In many cases the changes of indices series according to original data and homogenized data implies adverse character. According to our investigations the importance of homogenization is undeniable in climate change studies.

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PROGRAMME

BUDAPEST, HUNGARY

26 – 30 MAY 2008

Venue:

The Headquarters of the Hungarian Meteorological Service (1 Kitaibel Pál street, Budapest)

Monday, 26 May

8:30-9:30 Registration

9:30-12:00
Openning addresses by
the President of HMS
the Organizers
Introduction about COST HOME
Monday is dedicated to specific results obtained within COST HOME
WG1:
Aguilar, E. (SE): Results of WG1, Bibliography
Venema, V. (DE): Results of WG1, Benchmark dataset

Lunch break

13:30-18:00

WG2-3:

Mestre, O., Domonkos, P., Lebarbier, P., Picard, F., Robin, S. (FR, HU): Comparison of change-point detection methods in the mean of Gaussian processes

Prohom, M. (ES): Steps followed to create a climate dataset for Catalonia and Andorra (18th-21st centuries). Analysis of Catalan, Andorran and French temperature series from the early 20th century to the present using different homogenisation approaches

Menne, M. (US): Automated Homogenization of Monthly Temperature Series via Pairwise Comparisons

Szentimrey, T. (HU): Methodological questions of series comparison

WG4:

Gruber, C., Auer, I. (AT): Comparison of daily homogenization methods using parallel measurements for evaluation

Stepanek, P.,Zahradníček, P. (CZ): Experiences with homogenization of daily and monthly series of air temperature, precipitation and relative humidity in the Czech Republic, 1961-2007

18:00 Welcome party

Tuesday, 27 May

9:00-17:00
WG2-3 Round Table and presentations, discussions(with participation of non Cost members):

Jourdain, S., Mestre, O. (FR): Use and misuse of absolute homogeneity tests

Grimvall, A., Sirisack, S., Burauskaite-Harju, A., Wahlin, K. (SE): Unifying mixed linear models and the MASH algorithm for breakpoint detection

Brázdil, R., Stepanek, P., Macková, J. (CZ): Homogenisation of Brno climatic series 1799-2007: Example of the use of early instrumental records

Venema, V., Mestre, O., Rust, H.W. (DE, FR): Inhomogeneities in temperature records deceive long-range dependence estimators

Domonkos, P. (HU): Quantifying efficiency of homogenisation methods

Guijarro, J.A. (ES): Climatol 2: Interactive and automatic R functions for homogenisation of climatological series

Bari, B. (MA): Breakpoints detection in Temperature Time Series in Morocco using the Ellipse Test

Lizuma, L., Protopopova, V., Briede, A. (LV): Experience regarding detecting inhomogeneities in temperature time series using MASH

Lunch break: 12:00-13:30

Wednesday, 28 May

9:00-12:00

WG4 Round Table and presentations, discussions (with participation of non Cost members):

Stepanek, P., Zahradníček, P. (CZ): Quality control of daily data on example of Central European series of air temperature, relative humidity and precipitation

Aguilar, E., Brunet, M., Sigró, J. (ES): Different approaches for the homogenisation of the Spanish Daily Temperature Series

Brandsma, T. (NL): Understanding inter-site temperature differences at the KNMI terrain in De Bilt (the Netherlands)

Petrović, P., Curley, M. (RS, IE): Detected Inhomogeneities In Wind Direction And Speed Data From Ireland

Lunch break

13:30-18:00
Management Committee of COST HOME

19:00 Seminar banquet

Thursday, 29 May

9:00-12:00

Vertačnik, G. (SI): A method for daily temperature data interpolation and quality control based on the selected past events

Li, Z. and co-authors (CN): Effects of site-change and urbanisation in the Beijing temperature series 1977-2006

Wypych, A., Piotrowicz, K. (PL): Air humidity in Cracow (Poland) in the period 1863-2007 – daily data quality control and homogenization methods

Brzóska, B. (PL): Homogenization of water vapour data from Vaisala radiosondes and older (MARZ, RKZ) used in Polish aerological service

Toreti, A., Desiato, F., Fioravanti, G., Perconti, W. (IT): Homogenization of Italian precipitation series

Lunch break

13:30-17:00

Cheval, S., Szentimrey, T., Manea, A. (RO, HU), : Homogenization of monthly temperature series in Romania (1901-2005) using metadata

Wieczorek, A.M., Jourdain, S., Desmaizières, L., Grimal, D., Tamburini, A. (FR): Monthly Air Temperature Homogenization over France

Rasol, D., Likso, T., Milkovic, J. (HR): Homogenisation of temperature time series in Croatia

Mendes, M., Neto, J., Silva, Á., Nunes, L., Viterbo, P. (PT): Characterization of data sets for the assessment of inhomogeneities of climate data series, resulting from the automation of the observing network in Mainland Portugal

Adamczyk, R., Lupikasza, E. (PL): Comparison of re-analysis gridded and station cloudiness data over Europe

Lakatos, M., Szentimrey, T., Bihari, Z., Szalai, S. (HU): Homogenization of daily data series for extreme climate indeces calculation

Friday, 30 May

Excursion to Hollókő

Meeting point: HMS, 1, Kitaibel P. street at **7:45**

LIST OF PARTICIPANTS

AUSTRALIA

ROGER STONE
University of Southern Queensland
stone@usq.edu.au

AUSTRIA

INGEBORG AUER
Zentralanstalt für Meteorologie und Geodynamik
ingeborg.auer@zamg.ac.at

CHRISTINE GRUBER
Zentralanstalt für Meteorologie und Geodynamik
christine.gruber@zamg.ac.at

LEOPOLD HAIMBERGER
leopold.haimberger@univie.ac.at

BULGARIA

TANIA MARINOVA
National Institute of Meteorology and Hydrology, Bulgarian Academy of Sciences
Tania Marinova@meteo.bg

ALEXANDROV VESSELIN
Vesselin.Alexandrov@meteo.bg

CHINA

LI ZHEN
Institute of Atmospheric Physics
lizhen@tea.ac.cn

CROATIA

TANJA LIKSO
Meteorological and Hydrological Service of Croatia
likso@cirus.dhz.hr

JANJA MILKOVIĆ
Meteorological and Hydrological Service of Croatia
milkovic@cirus.dhz.hr

DUBRAVKA RASOL
Meteorological and Hydrological Service of Croatia
rasol@cirus.dhz.hr

ANA ŠANTIĆ
Meteorological and Hydrological Service of Croatia
santic@cirus.dhz.hr

CZECH REPUBLIC

RUDOLF BRÁZDIL
Institute of Geography, Masaryk University, Brno
brazdil@geogr.muni.cz

PETR ŠTĚPÁNEK
Czech Hydrometeorological Institute
petr.stepanek@chmi.cz

CYPRUS

FOKIANOS KONSTANTINOS
fokianos@ucy.ac.cy

FINLAND

TIETAVAINEN HANNA
hanna.tietavainen@fmi.fi

HEIKKI TUOMENVIRTA
heikki.tuomenvirta@fmi.fi

FRANCE

VALERIE DAUX
Valerie.Daux@cea.fr

OLIVIER MESTRE
Météo-France
olivier.mestre@meteo.fr

ANNE-MARIE WIECZOREK
METEO-FRANCE
anne-marie.wieczorek@meteo.fr

GERMANY

VICTOR VENEMA
Meteorologisches Institut Universitaet Bonn
Venema@uni-bonn.de

GERHARD MÜLLER-WESTERMEIER
Deutscher Wetterdienst
Gerhard.mueller-westermeier@dwd.de

GREECE

ATHANASSIOS ARGIRIOU
athanarg@upatras.gr

GEORGE KALOGERAS
Hellenic National Meteorological Service
gkalogeras@hnms.gr

HUNGARY

ZITA BIHARI
Hungarian Meterological Service
bihari.z@met.hu

PETER DOMONKOS
dopeter@t-online.hu

MÓNIKA LAKATOS
Hungarian Meterological Service
lakatos.m@met.hu

SÁNDOR SZALAI
Hungarian Meterological Service
szalai.s@met.hu

TAMÁS SZENTIMREY
Hungarian Meterological Service
szentimrey.t@met.hu

IRELAND

SEAN BONNER
Met Éireann
bonner@met.ie

MARY CURLEY
Met Éireann
mary.curley@met.ie

MICHAEL MCDONNELL
Met Éireann
michael.mcdonnell@met.ie

PROF. JOHN SWEENEY
Department of Geography
National University of Ireland, Maynooth
John.Sweeney@nium.ie

ITALY

FIORELLA ACQUAOTTA
University of Turin
fiorella.acquaotta@unito.it

MICHELE BRUNETTI
Institute of Atmospheric Sciences and Climate, Bologna
m.brunetti@isac.cnr.it

SIMONA FRATIANNI
University of Turin
simona.fratianni@unito.it

MAURIZIO MAUGERI
maurizio.maugeri@unimi.it

TERESA NANNI
t.nanni@isac.cnr.it

SILVIA UGHETTO
CNMCA-ITALY
ughetto@meteoam.it

ANDREA TORETI
APAT / UNIBERN
toreti@apat.it

LATVIA

ARGITA BRIEDE
Agrita.Briede@lu.lv

LITA LIZUMA

Latvian Environment, Geology and Meteorology Agency
lita.lizuma@lvgma.gov.lv

MOROCCO

DRISS BARI
Chef Adjoint du Service de Banque de données et Climatologie Direction Régionale Météorologique du Centre Casablanca
bari.driss@gmail.com

NETHERLANDS

THEO BRANDSMA
Royal Netherlands Meteorological Institute
Theo.Brandsma@knmi.nl

ALBERT KLEIN TANK
Royal Netherlands Meteorological Institute
kleintan@knmi.nl

NORWAY

LARS ANDRESEN
Norwegian Meteorological Institute
larsa@met.no

OYVIND NORDLI
Norwegian Meteorological Institute
oyvind.nordli@met.no

POLAND

ROMANA ADAMCZYK
University of Silesia, Faculty of Earth Sciences, Department of Climatology
r_adamczyk@op.pl

BARBARA BRZÓSKA
Institute of Meteorology and Water Management Centre of Aerology
Barbara.Brzoska@imgw.pl
basik@igf.fuw.edu.pl

JANUSZ FILIPIAK
University of Gdansk
geojf@univ.gda.pl

EWA ŁUPIKASZA
University of Silesia, Faculty of Earth Sciences, Department of Climatology
ewa.lupikasza@us.edu.pl

MIROSLAW MIETUS
miroslaw.mietus@imgw.pl

KATARZYNA PIOTROWICZ
Institute of Geography and Spatial Management, Jagiellonian University
k.piotrowicz@geo.uj.edu.pl

ZSUZSANNA VÍZI
Nicolaus Copernicus University
vizi@uni.torun.pl

AGNIESZKA WYPYCH
Institute of Geography and Spatial Management, Jagiellonian University
awypych@geo.uj.edu.pl

PORTUGAL

MANUEL MENDES
Instituto de Meteorologia
manuel.mendes@meteo.pt

ANA MONTEIRO
anamonteirosousa@gmail.com

LUIS NUNES
Instituto de Meteorologia
nunesl@meteo.pt

ROMANIA

CONSTANTA BORONEANT
boroneant@meteo.inmh.ro

SORIN CHEVAL
sorincheval@fulbrightweb.org

SERBIA

PREDRAG PETROVIĆ
Republic Hydrometeorological Service of Serbia
predrag.petrovic@hidmet.sr.gov.yu

SLOVAKIA

OLIVER BOCHNÍČEK
Slovak Hydrometeorological Institute
oliver.bochnicek@shmu.sk

PETER KAJABA
Slovak Hydrometeorological Institute
peter.kajaba@shmu.sk

JOZEF PECHO
Slovak Hydrometeorological Institute
jozef.pecho@shmu.sk

SLOVENIA

MIHA DEMŠAR
University of Ljubljana, Faculty of Mathematics and Physics
miha.demsar@gov.si

GREGOR VERTAČNIK
Environmental Agency of the Republic of Slovenia
gregor.vertacnik@gov.si

SPAIN

ENRIC AGUILAR
University Rovira i Virgili de Tarragona
enric.aguilar@urv.cat

JOSÉ ANTONIO GUIJARRO
Agencia Estatal de Meteorología
jaguijarro@inm.es

MARC PROHOM
mprohom@meteocat.com

SWEDEN

ANDERS GRIMVALL
Linköping University
angri@mai.liu.se

AGNE BURAUSKAITE-HARJU
Linköping University
agbur@ida.liu.se

HANS LINDERHOLM
University of Gothenburg
hansl@gvc.gu.se

SWITZERLAND

MISCHA CROCI-MASPOLI
Mischa.Croci-Maspoli@meteoswiss.ch

PAUL DELLA-MARTA
paul.della-marta@meteoswiss.ch

FRANZ GUNTHER KUGLITSCH
Oeschger Centre for Climate Change Research, University of Bern
kugl@giub.unibe.ch

UNITED KINGDOM

ROBERT ALLAN
Met Office Hadley Centre
rob.allan@metoffice.gov.uk

PHILLIP JONES
p.jones@uea.ac.uk

USA

MATTHEW MENNE
NOAA/National Climatic Data Center
Matthew.Menne@noaa.gov

For more information, please contact:

World Meteorological Organization

Observing and Information Systems Department

Tel.: +41 (0) 22 730 82 68 – Fax: +41 (0) 22 730 80 21

E-mail: wcdmp@wmo.int

7 bis, avenue de la Paix – P.O. Box 2300 – CH 1211 Geneva 2 – Switzerland

www.wmo.int