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Complete and homogeneous monthly air temperature series for the construction of 1981–2010 climatological normals in Croatia

Irena Nimac and Melita Perčec Tadić

Meteorological and Hydrological Service, Zagreb, Croatia

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Providing climatological normals is one of the most important tasks for national meteorological services. Estimating the statistical characteristics of climate variables from incomplete and inhomogeneous data can result in biased estimations; thus, it is necessary to fill in missing values and remove inhomogeneities. Though it is very important, the homogenization procedure is still not a part of data quality-check procedures. In this work, monthly temperature data from 39 meteorological stations in Croatia for the period 1981–2010 were examined for missing data and inhomogeneities. Stations were divided into three climatic regions, and homogenization was performed for each one separately. The performance of the homogenization method was tested by: (1) comparison of correlation coefficients amongst stations and (2) changes in rotated principal components for datasets before and after homogenization. Obtained homogeneity breaks were compared with metadata and published literature. Changes in the statistical characteristics of temperature climate normals 1981–2010 (*e.g.*, long-term means and decadal trends) were observed at annual and seasonal scales between original and homogenized series. The significance of the changes in mean was tested using the Student's t-test, while the significance of trends was tested with the Mann-Kendall test. The homogenization software used was the R package, c*limatol*.

Keywords: completeness, homogeneity, monthly air temperature, principal component analysis, climatological normal

1. Introduction

A measure that recent or current observations can be compared to is called the climatological normal. As defined by the WMO (1988), the climatological normal (CLINO) is an average value of a climatological variable computed for a relatively long period (at least 30 years), while normals that are calculated for consecutive 30-year periods (*e.g.*, 1901–1930, 1931–1960) are called climatological standard normals. When calculating the CLINO for a meteorological station, the data record for a 30-year period should be complete and homogeneous (WMO, 2011). A climate variable is homogeneous when variations are only of climatic origin (Mitchell et al., 1966). However, apart from climate variations, measurements are also affected by artificial influences such as changes in instruments, observers, observational procedures, relocations and/or changes in environment (Peterson and Vose, 1997; Aguilar et al., 2003). Sometimes, such information is documented in the metadata, but often it is missing or incomplete. Even when available, it is difficult to quantify the non-climatic influence on data. Due to different influences from a certain change, the nature of the inhomogeneity is also different. While gradual change in a surrounding environment (*i.e.*, planting the trees or continuous build-up of the surrounding environment) causes a gradual artificial trend, a station relocation results in an abrupt shift in the mean when comparing to the average prior to relocation (Pandžić and Likso, 2009). In larger cities, stations are often relocated to the periphery to avoid the effects of urbanisation. As a result of gradual urbanisation, climate variables measured at those stations become different from those in outlying suburban neighbourhoods (Mitchell et al., 1966). An example of the influence of urbanisation to a temperature series is presented in Staudt et al. (2007), where a strong connection between an increase in population for Madrid and an increase in the minimum temperature difference between Madrid and Toledo was detected, so an empirical correction for the Madrid urban heat island was introduced on a monthly time scale.

Different statistical tests can be applied to test the homogeneity of a series. They can be classified into two groups: absolute and relative homogeneity tests (Pandžić and Likso, 2009). In the first approach where homogeneity test is applied to a particular time series, it is hard to separate inhomogeneities from regional climate variation. When using relative tests, testing the candidate time series is done according to a reference time series with the same natural climate variation assumption. Since relative tests are more appropriate when dealing with non-stationary time series, these kinds of tests are more frequently used, especially recently due to climate change. In Easterling et al. (1996), Peterson and Vose (1997) and Peterson et al. (1998), several quality control and homogenization methods and techniques were reviewed, including one not dependent on the metadata. That work mainly supported the development of a U.S. Historical Climatology Network monthly dataset and a highly appreciated Global Historical Climatology Network (GHCN) dataset. One of the most widely used homogeneity tests is the Standard Normal Homogeneity Test (SNHT) developed by Alexandersson (1986), which showed to be one of the most efficient tests for homogeneity according to Ducre-Robitaille et al. (2003). Eight homogenization techniques were compared in Ducre-Robitaille et al. (2003), where SNHT and multiple linear regression performed slightly better than the others. Another interesting method of homogenization was presented in a study by Costa and Soares (2009), where they used a geostatistical simulation approach to detect inhomogeneities.

The importance of performing homogenization procedures for station data are further appreciated when deriving grids for temperature, precipitation and other climatic parameters, similar to the CRU TS global gridded dataset with a 0.5° spatial resolution (Mitchell and Jones, 2005). In Europe, part of the ENSEMBLES project was devoted to the automatic detection of inhomogeneities in a climatological time series for temperature, precipitation and air pressure (Begert et al., 2008). The procedure combined the VERAQC (Vienna Enhanced Resolution Analysis Quality Control) output with Alexandersson's SNHT and was performed on an European Climate Assessment (ECA) dataset (Klein Tank et al., 2002) to prepare high quality input data for gridding. The result of the ENSEMBLE project served as an input to produce well known E-OBS gridded data on 0.25° and 0.5° resolutions (Haylock et al., 2008).

In Perez-Zanon et al. (2015), they compared HOMER (HOMogenization softwarE in R, Mestre et al., 2013) and ACMANT (Adapted Caussinus-Mestre Algorithm for Networks of Temperature series, Domonkos, 2011), multiple break point homogenization methods, on a central Pyrenees monthly temperature dataset. The results showed that the automatic method (ACMANT) gave credible results, while HOMER was more dependent on the user skill and was therefore more sensitive to subject errors, though it was able to include the consideration of metadata. Several homogenization methods were adopted in the AnClim software (Štěpánek, 2008).

Homogeneity of an annual temperature series in Croatia have been investigated in some studies. In Likso (2003), the average annual air temperature for 10 stations in Croatia was tested for homogeneity using SNHT. Most of the breaks were explained from the metadata. In Pandžić and Likso (2009), average annual air temperature series for 22 stations were tested for homogeneity as part of a preliminary study for statistical analysis and mapping for the Climate atlas of Croatia for the periods 1961–1990 and 1971–2000 (Zaninović et al., 2008; Perčec Tadić, 2010). The more general version of SNHT was used, which includes artificial linear trends for temperature time series in addition to abrupt breaks in homogeneity. Additionally, in Cindrić et al. (2010), a basic test of homogeneity was conducted for 25 annual precipitation series using the SNHT, while in Zahradníček et al. (2014) monthly precipitation was tested with the ProClimDB/Anclim software (Štěpánek, 2010) on 137 stations.

Calculating climatological normals is an important task to prepare for the new Climate atlas of Croatia for 1981–2010; therefore, data "cleaning" is necessary since missing or inhomogeneous data can significantly alter the estimated statistical properties of a whole series. Due to incomplete metadata information, the automatic homogenization procedure was preferred, and the R (R Core Team, 2015) package c*limatol* (Guijarro, 2016) was introduced for interpolation of missing data and homogenization of climatological series for monthly temperatures in Croatia.

2. Area of interest

As a Mediterranean country, Croatia is situated in one of the most vulnerable areas regarding global warming, according to the IPCC (Barros et al., 2014). Due to the Mediterranean influence and position along the Adriatic Sea, the openness of NE Croatia to the Pannonian Plain, and the complex orography of the Dinarides, three main climate regions occur: maritime, continental and mountainous. Factors that primarily influence air temperature are warming or cooling of the

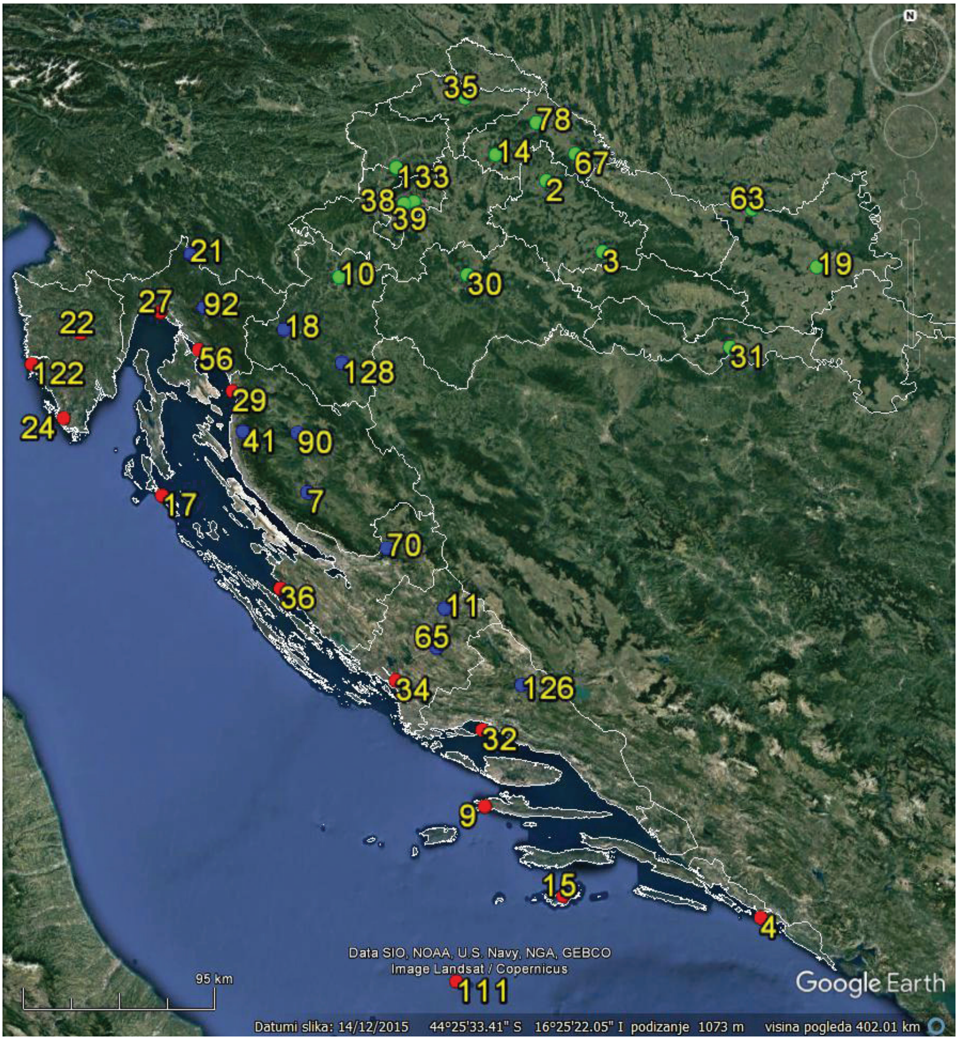


Figure 1. Spatial distribution of selected meteorological stations divided into 3 regions: continental (*green*), mountainous (*blue*) and coastal (*red*).

air from the surface and heat radiation of the air itself. Therefore, spatio-temporal characteristics of air temperature in Croatia are mainly influenced by land-sea distribution, elevation and latitude and longitude (Zaninović et al., 2008). For this study, 39 meteorological stations that are part of the Meteorological and Hydrological Service of Croatia (DHMZ) network were selected. Selection of these stations represented and divided regions according to climate similarity (Fig. 1 and Tab. A1 in the Appendix). In each region, there was approximately the same number of the stations: 11 in the mountainous region, 14 in the continental region and 14 in the coastal region. Although the largest distance between stations in the coastal region was up to 500 km, this division was justified since changes in temperature are much larger in the west-east direction than the south-north direction due to sea influence. This kind of a division of climatic regions is preferred due to the requirements for the applied homogenization method.

3. Data

Data used in this study were monthly temperatures for the period 1981–2010 from 39 meteorological stations. There are 26 stations consisting of full 30-year series, nine stations had less than 10% of data missing, and between 10% and 19% of data were missing at four stations (Fig. 2). On a monthly scale, those values ranged from 3% up to 23% of missing data (Tab. 1). The longest breaks over several years occurred at three stations (Slunj (marked with code 128 in Fig. 1), Gračac (70) and Drniš (65)) during the war in the 1990's, which complicates the homogeneity analysis due to the very complex orography of those regions (Fig. 1). Palagruža (111), the island station in the middle of the Adriatic, also had a break during the 1990's. Two stations had longer breaks during the late 1980's (Rovinj (122) and Stubičke Toplice (133)).

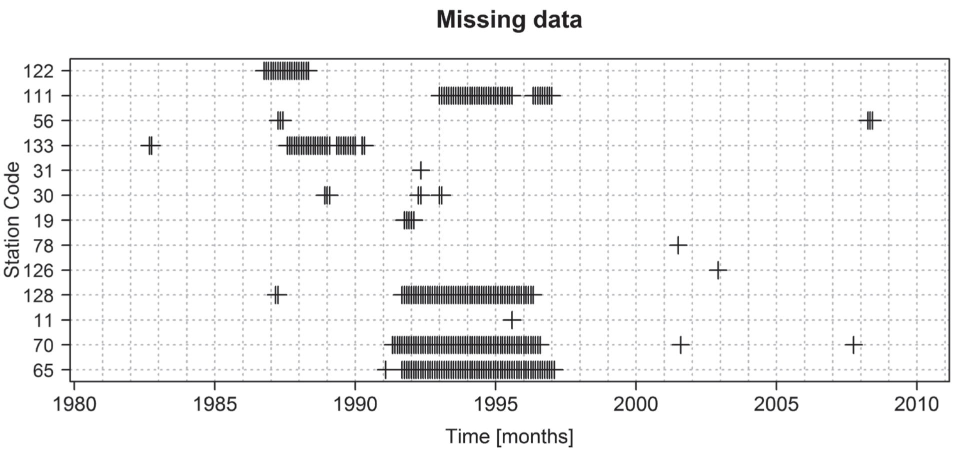


Figure 2. Temporal distribution of missing data.

Table 1. Amount of missing data (%) for each month.

Station (Code)	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Drniš (65)	20	23	17	17	17	17	17	17	20	20	20	20
Gračac (70)	17	17	17	17	20	20	20	23	17	20	17	17
Knin (11)	0	0	0	0	0	0	0	3	0	0	0	0
Slunj (128)	17	17	20	20	17	13	13	13	17	17	17	17
Sinj (126)	0	0	0	0	0	0	0	0	0	0	0	3
Koprivnica (78)	0	0	0	0	0	0	3	0	0	0	0	0
Osijek (19)	3	3	0	0	0	0	0	0	0	3	3	3
Sisak (30)	7	7	0	3	3	0	0	0	0	0	0	3
Slavonski Brod (31)	0	0	0	0	3	0	0	0	0	0	0	0
Stubičke Toplice (133)	10	7	3	7	10	7	7	10	13	13	10	10
Crikvenica (56)	0	0	0	7	7	7	0	0	0	0	0	0
Palagruža (111)	13	10	10	10	13	13	13	13	10	10	10	10
Rovinj (122)	7	7	7	7	7	3	3	3	3	7	7	7

4. Methods

4.1. Complete, non-homogenized dataset

A complete and non-homogenized dataset was created for validation of the homogenization procedure. Normals calculated from incomplete datasets can be biased and, therefore, it is necessary to fill in missing values before calculation. The procedure must be robust in a sense that it does not affect the statistical property of the long term mean. The interpolation technique was based on a random selection of a sample from original station data with a normal distribution. This interpolated dataset in the following analysis represents the non-homogenized data.

4.2. R package climatol

Temperature homogeneity was tested with *climatol* (Guijarro, 2016), an R package used for the interpolation and homogenization of a climatological series. The goal was to remove perturbations due to changes in observation conditions or in nearby environments to allow the series to reflect only climatic variations (Guijarro, 2014). A relative homogenization method was used in order to avoid the assumption of climate stability, which is unrealistic, especially for air temperature (Guijarro, 2014). Therefore, stationarity tests were applied not to the original temperature data but to a series differences between the observations and the reference series, which was constructed as a weighted average series from nearby stations. Since the selection of these stations was based only on proximity by disregarding the correlation criterion in order to use as much data as possible, the region under study should be climatically homogeneous. This is especially important in Croatia where sharp terrain boundaries, such as the Dinarides mountain range, introduce large differences in climatic series even across short distances. As a result, homogenization was applied to every climate region independently. Prior to homogenization, normalisation of the temperature data was performed. The first obstacle with calculating incomplete series was that we could not compute means and standard deviations for the whole period. The creation of data estimates, or "estimated series", was based on neighbouring stations and was used to fill in missing values in a candidate series, as proposed. The procedure was iterative until the change in mean before and after the process was less than chosen amount (detailed in Guijarro, 2014).

For every candidate series, estimated series were created as a weighted average of selected number of the nearest available stations (weights could all be the same, or they could be an inverse function of distance between the observing sites).

4.3. Outliers and sharp shift detection and correction

After the estimated series were created, tests for the detection of outliers and shifts in means were applied to a series of anomalies, which was the difference between the normalized, original data and the estimated data. An outlier here is defined as a standardized anomaly greater than five standard deviations, though this default value can be changed by the user. The outliers detected resulted in the deletion of their original data.

The SNHT was applied to detect shifts in mean of anomaly series in two stages: first in windows of 120 terms (10 years) that moved forward in steps of 60 terms and then on the whole series. If the greatest SNHT value was higher than a certain threshold, then the series split from that point to the end of the series, and those values were transferred to a new series with the same coordinates and removed from the original one. This way, two split series were created instead of just the original one. This procedure continued on the newly created series, with new possible inhomogeneities detected. This way, all resulting series were presumably homogeneous. The decision was made to choose the final, corrected series for each station based on one of the suggested criteria: (a) the series reconstructed from the last sub-period, which is usually chosen for climate monitoring, (b) the series from the period with the highest percentage of original data, (c) the series with the lowest final SNHT value, or (d) all of them, when there was no a priori knowledge on which sub-period was more representative. It was decided to take the series reconstructed from the last sub-period, since we assume that the quality in observations is improving over time. For series created according to those criteria, temperature normal means and trends are compared and differences have been discussed.

A final, third stage was devoted to the missing data recalculations, which included the removed outliers and data transferred into a split series.

The detected breaks in homogeneity were compared with documented and published breaks from the metadata or breaks detected by using different methods, such as ACMANT.

4.4. Validation of the homogenization procedure

Statistical characteristics of non-homogenized (IHs) and homogenized (Hs) datasets were compared in several ways. The improvement in spatial homogeneity before and after homogenization was tested with a correlation coefficient and root mean square error. Correlation coefficients were calculated for monthly anomalies between each station and all the stations in the region. As shown in the box plot, the average correlation coefficient was expected to increase, while the spread of values was expected to decrease due to an expected improvement in spatial homogeneity.

Another indicator of a more compact spatial structure after homogenization is the principal component analysis (PCA), which was performed for the entire area. PCA is a widely used technique in meteorology and climatology (Molteni et al., 1983; Benzi et al., 1997). It allows for the decomposition of a climate parameter into linearly independent spatial components (*e.g.*, eigenvectors, EVs) and time dependent components (*e.g.*, principal components, PCs). While physical interpretation, rather than data compression, is the primary goal of PCA, it is often desirable to rotate a subset of the initial eigenvectors into a second set of new coordinate vectors (Wilks, 1995). As a result, a second set of new variables is produced, called rotated principal components (RC). Here, the *principal* function from the R package *psych* (Revelle, 2017) was applied to perform a PCA with VARIMAX rotation. The input into the principal component analysis was a correlation matrix calculated from the data. The physical interpretation was performed based on EV coefficients and by looking at reconstructed temperature anomalies based on PC amplitudes. Reconstructed temperature anomalies (departures from average station temperatures) from the EV coefficients and RC amplitudes allow for the physical interpretation of the rotated principal components. The comparison of both EVs and PCs for statistically interpolated (IHs) and homogenized (Hs) data allows us to discuss the improvements in spatial temperature structure after data homogenization. For PCA terminology, we refer to Tab. 9.3 in Wilks (1995), where different terminology is summarized for the same technique used.

Changes in mean temperature and temperature trends were also observed amongst IHs and Hs datasets. The significance of a difference in means was tested using the Student's t-test for the change in mean, while trend significance was tested with the Mann-Kendall trend test at significance level of 0.05 (Wilks, 1995).

5. Results

5.1. Outliers and sharp shift detection and correction

Only four outliers defined as standardized anomalies greater than five standard deviations were detected and replaced with suggested values at the stations: Slunj (128), Gospić (7), Rovinj (122) and Senj (29) (Tab. 2).

Detected breaks (time and maximum SNHT value) are given in Tab. 3. A maximum of four breaks were detected in Križevci (14) and Bjelovar (2). Two breaks were detected in seven stations, and there were eleven stations with just one break. The remaining 19 stations showed no breaks in homogeneity during the period 1981–2010.

According to available metadata, the detected breaks were mostly due to relocation, urbanisation and changes in environment. The times of the breaks that corresponded to the relocation of a station, such as Zadar (36), Karlovac (10) and Osijek (19) were supported with metadata; if not the exact month, then the few months surrounding the month of relocation. Compared to breaks in Pandžić and Likso (2009), where annual temperature series for 22 stations in Croatia for the 1961–2000 period were analysed, some breaks were detected in the same year. Compared to breaks obtained by the ACMANT software (D. Rasol, personal communication) (column "Break_AC" in Tab. 3), eleven breaks were discovered in the same month (*climatol* reports the first month after the break, and ACMANT reports the last month before the break), but there were still some differences due to different algorithms in the homogenization methods and different periods of data tested.

After homogenization was finished, due to outlier and sharp shift detection and correction, the new split series was created, and the series reconstructed from the last sub-period was retained.

Table 2. Stations with a detected outlier. Data show the moment the outlier was detected, the amount detected and a suggested correction.

Reg	Station (Code)	Month/Year	Observed	Suggested	St. Dev.
1	Slunj (128)	1/1997	–1.7	1.4	–5.13
1	Gospić (7)	1/2002	–3.7	–1.4	–5.38
3	Rovinj (122)	11/1989	10.9	8.7	5.01
3	Senj (29)	2/1986	0.9	3.7	–5.26

Table 3. For stations with detected breaks, the following results are shown: the maximum SNHT, the moment of observed breaks in homogeneity (Break_CL for climatol and Break_AC for ACMANT method) and potential cause.

Reg	Station (Code)	SNHT	Break_CL	Break_AC	Potential cause
1	Knin (11)	28.6	1/1992	12/1994	War
1	Sinj (126)	28.6	12/1999	1/2003	
1	Parg (21)	30.7	12/1998	11/1998	
1	Gospić (7)	30.8	10/2000	11/1995 11/2006	
1	Gračac (70)	84.0	8/1989	7/1989	Pine trees 20 m from the station
1	Lokve Brana (92)	35.6	1/1984	10/1983	
1	Lokve Brana (92)	38.5	6/2006	12/2003	
2	Karlovac (10)	41.5	11/1992	1/1993	Relocation on 9/11/1992
2	Karlovac (10)	27.7	10/2001	9/2001	Relocation in 2001
2	Stubičke Toplice (133)	25.3	1/1983	7/1981	
2	Stubičke Toplice (133)	41.6	10/1991	8/1982	
2	Križevci (14)	25.9	10/1981	9/1981	Fruit tree planting in 1980s
2	Križevci (14)	29.5	6/1987		
2	Križevci (14)	28.3	8/1995	7/1995	
2	Križevci (14)	37.8	2/2001	3/2001	
2	Osijek (19)	38.0	7/1991	10/1990	Relocation on 17/10/1991
2	Bjelovar (2)	35.6	12/1988	3/1983	Change in environment
2	Bjelovar (2)	36.5	1/1995		
2	Bjelovar (2)	29.1	2/2002	2/1999	
2	Bjelovar (2)	49.3	7/2004	6/2004	
2	Daruvar (3)	31.2	9/1988		
2	Daruvar (3)	38.2	10/1996		
2	Sisak (30)	28.3	9/1985	9/1985	Urbanisation and change in environment
2	Sisak (30)	27.5	11/1995	10/1996	
2	Zagreb Maksimir (39)	87.3	5/1992	10/1987	Urbanisation in 1990s
2	Donji Miholjac (63)	28.2	11/1983	10/1983	Buildings and fruit trees
2	Donji Miholjac (63)	83.2	2/1997	2/1997	
3	Rovinj (122)	43.5	10/1986	11/1986	
3	Pula (24)	42.5	11/1995	7/1995	
3	Šibenik (34)	36.6	6/1998	8/1997	Urbanisation
3	Zadar (36)	32.7	8/1995	6/1988 11/1991	Relocation on 27/06/1995
3	Crikvenica (56)	48.6	10/1991	9/1991	
3	Crikvenica (56)	53.2	3/1997	6/1996	

5.2. High-quality stations

There are some stations that retained 99% or 100% of the original data after the homogenization process (Tab. 4). These stations were mostly the main meteorological stations with professional observers and a first order of quality. The largest percentage of these stations with a homogeneous monthly temperature series was in the coastal region, where 50% of them retained 100% of the original data after the homogenization process; Senj (29) had just one change due to a detected outlier. In the continental region, 36% of the stations retained either all or all but one of the original values; in the mountainous/hinterland region, 27% of them were of such high quality. Two continental stations (Koprivnica (78) and Slavonski Brod (31)) also retained 99% of the original data, except for the one replacing a missing monthly value.

Table 4. Stations with the highest percentage of original data (pod) after the homogenization process and SNHT values for the homogenized series (SNHT).

Reg	Station	pod (%)	SNHT	Reg	Station	pod (%)	SNHT
1	Ličko Lešće	100	7.3	3	Dubrovnik	100	7.1
1	Ogulin	100	14.4	3	Hvar	100	7.2
1	Zavižan	100	13.3	3	Lastovo	100	13.8
2	Đurđevac	100	16.8	3	Mali Lošinj	100	2.6
2	Varaždin	100	11.3	3	Pazin	100	31.6
2	Zagreb-Grič	100	8.2	3	Rijeka	100	31.9
2	Koprivnica	99	22.8	3	Split-Marjan	100	6.4
2	Slavonski Brod	99	16.4	3	Senj	99	3.3

5.3. Validation using correlation coefficients

The homogenization process decreased the number of outliers (Fig. 3, circles in box-plots). The medians of r were larger while the spread of r decreased, which led to smoother temperature fields and improved spatial correlation. The largest average r and smallest r spread was in the continental region (Reg2) as a result of lower temperature variability, while the opposite situation (lower r, larger spread in r) was in the mountainous/hinterland area (Reg1). Drniš (65), Gračac (70), Slunj (128) and Zavižan (41) had the lowest correlation coefficients out of the remaining stations in Reg1 before the homogenization process, mainly due to the large amount of missing data. After the homogenization process, an increase in r was noticeable for those stations. In continental Reg2, station Stubičke Toplice (133) showed a lower correlation with other stations, which was also due to the large amount of missing data that were replaced by the "statistical-normal"

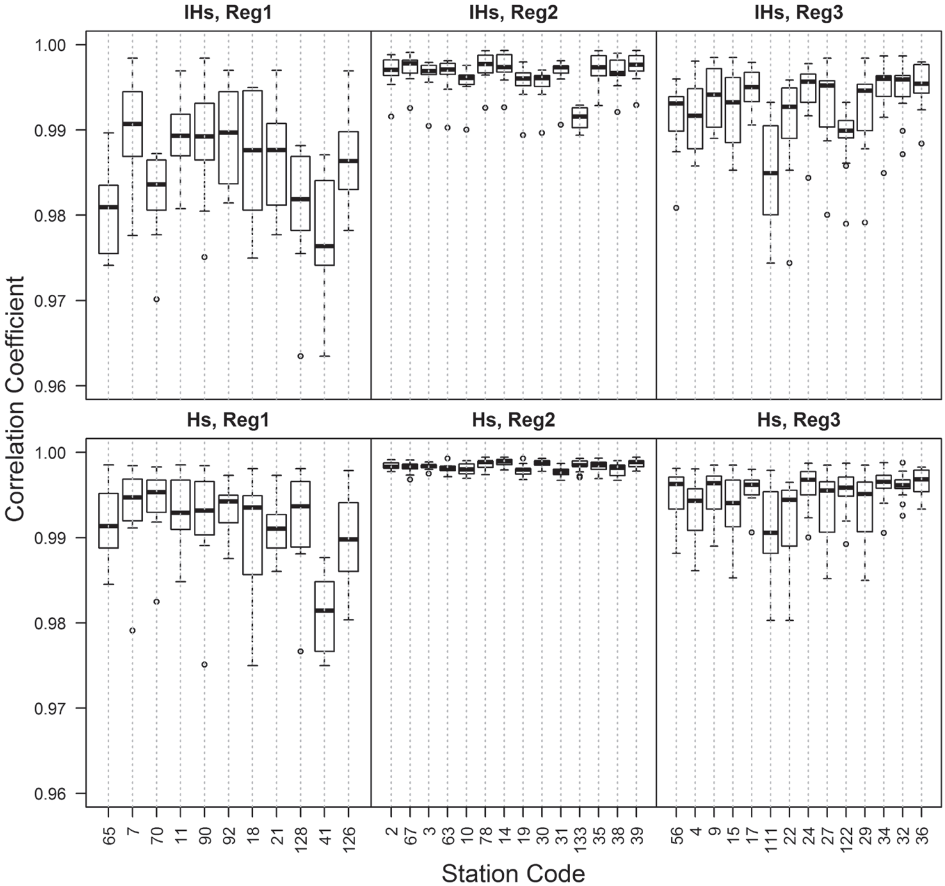


Figure 3. Box-plots of correlation coefficients for non-homogenized IHs (*top*) and homogenized Hs (*bottom*) data for mountainous/hinterland (Reg1), continental (Reg2) and coastal (Reg3) regions.

method; there were also noticeable outliers at the rest of the stations. After homogenizing, the temperature field in the region became smoother with lower variability in *r*, larger average *r* values and almost no outliers. In coastal region (Reg3), stations Palagruža (111) and Rovinj (122) also had more missing values, which was again apparent from a lower *r*. The same improvement was achieved after homogenization, where there was an increase in the average *r* and decrease in both *r* variability and the number of outliers.

Even if we tried to perform this type of analysis on the entire study area the correlation coefficients amongst the stations would be high. The lowest correlation coefficient for non-homogenized data ($r = 0.938$) was found between island station Palagruža (111) and continental station Stubičke Toplice (133), while for homogenized data, the lowest correlation coefficient ($r = 0.947$) was found between Palagruža (111) and continental station Bjelovar (2). Such results are expected, as those stations are representative of the maritime and continental effects. Therefore, variations in monthly temperature over this area were in strong connection and influenced by common factors (Pandžić, 1986).

5.4. Validation using the root mean square error

For additional insight into station quality or climatic singularity, a root mean square error (*RMSE*) was calculated for every series by taking differences between the observed and estimated data (the reference series was derived using surrounding stations). Higher *RMSE* values indicated either: (a) poor quality of the original series or (b) uniqueness of the station in a special microclimate. On average, the lowest RMSE values (Fig. 4) were in the continental region (Reg2), where the spatio-temporal characteristics of temperature were similar, so it was easier to describe conditions at one station using a series from surrounding stations. In coastal region (Reg3), the largest *RMSE*s at certain stations were due to climatic singularities, such as in Palagruža (111), which is the island station quite distant from the coast and in Pazin (22), which is situated in a basin in Istria's hinterland at an altitude of 291 m and is a well-known local cold spot based on the annual number of days with frost (Zaninović, 2008). Additionally, in Senj (29) and Mali Lošinj (17), strong bora events can significantly alter air temperature compared to surroundings, which leads to a larger *RMSE*. On average, the highest *RMSE* values were in the mountain/hinterland region (Reg1) due to a very complex terrain and a larger variability of climate conditions. The largest *RMSE* value (1.4 °C) was obtained from the highest altitude station, Zavižan (41). Because this station is a synoptic meteorological

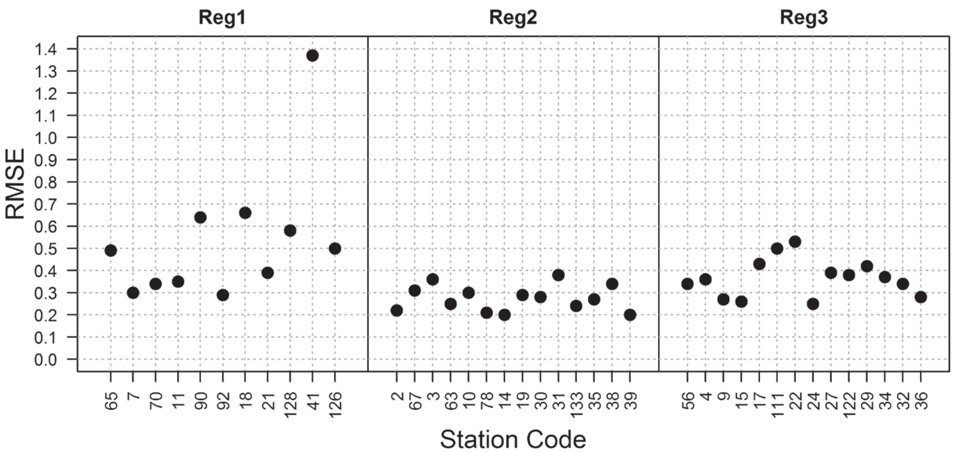


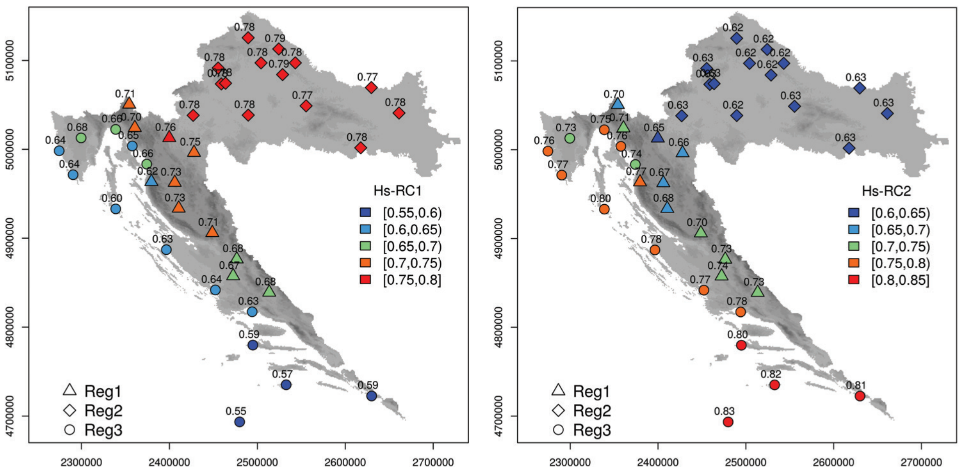
Figure 4. Root mean square error (*RMSE*) between original and estimated series for each station in mountainous/hinterland (Reg1), continental (Reg2) and coastal (Reg3) regions.

station with high quality measurements, the change in temperature development was mainly driven by the elevation difference, which was the main reason for a large RMSE.

5.5. Validation using a principal component analysis

The physical interpretation of spatial patterns in temperature was performed based on the EV coefficients (loadings in *psych*) (Fig. 5) while the interpretation of inter-annual temperature variations was performed on the amplitudes of rotated PCs, denoted as RCs for clarity (scores in *psych*) (Fig. 6).

The first rotated principal component (RC1) had the largest correlation (loading) with continental stations (maximum at Bjelovar (2)) but had the smallest



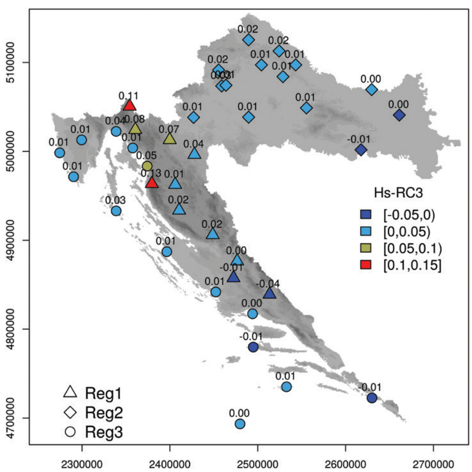


Figure 5. Eigenvalue coefficients for homogenized Hs data from three rotated principal components: RC1, RC2 and RC3.

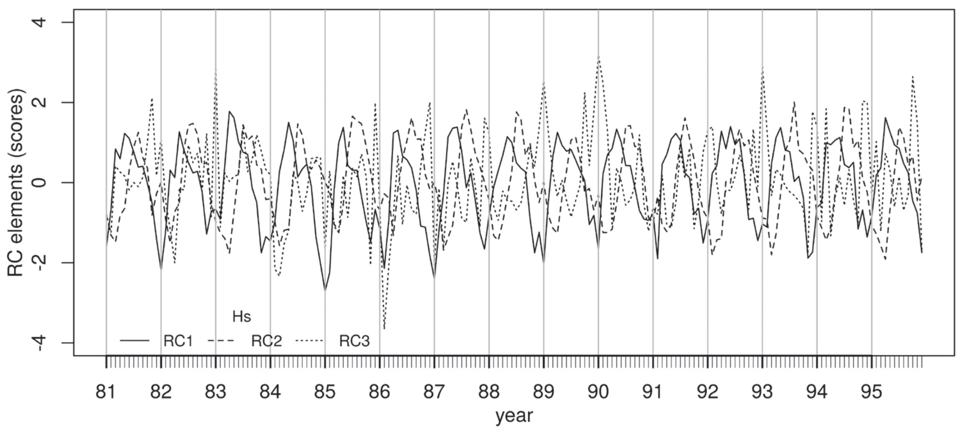


Figure 6. Amplitudes of rotated PCs from RC1, RC2 and RC3 for Hs homogenized data.

correlation with maritime stations (minimum at Palagruža (111)) (Fig. 5, top left). When examining the RC amplitudes (Fig. 6), the maximum RC1 amplitudes occurred during spring (53% in May, 30% in April) and sometimes in Jul (17% of cases), while the minimums occurred during winter (40% in January, 37% in December). This reflects the thermal difference in mainland heating, which is faster and stronger during spring and early summer compared with maritime areas that are still under the maritime cooling effect.

There was an opposite correlation for data series RC2, where the largest correlation was at island Palagruža and the smallest was at continental station Bjelovar (2) (Fig. 5, top right). The RC2 amplitudes (Fig. 6) were at a maximum during summer (53% in Aug and 43% in July) and sometimes in autumn (3% in September), while minimums occurred during March (47%) and April (33%); in other words, approximately 2–3 months after the maximums and minimums for RC1.

Hence, RC1 can be interpreted as heating from the ground, or more correlated with the solar year, while RC2 was correction due to heating/cooling from the sea. A similar result was discussed in Pandžić (1986) for the first two rotated components, while the third one was discussed in relation to cold front frequencies.

Here, we noticed that the maximum for RC3 (Fig. 5, bottom left) was related to mountain areas (maximum in Zavižan (41) and other elevated stations), while the minimum for RC3 was in Sinj (126), Dubrovnik (4), Slavonski Brod (31) and a few other extremely hot stations in eastern continental Croatia and Dalmatia; thus, we suspect that this third mode could be related with both extremes, cold and warm.

Looking at annual maximum RC3 amplitudes (Fig. 6), most maximums were reached during either Nov, Dec or Jan (more than 20% of cases in each month), while more than 15% of cases with minimum RC3 amplitudes occurred in February, March or April. It is interesting that all months in some years had a minimum or maximum value from RC3 except for May, which could be considered the calmest month.

Here, the three RCs can be related to climatic factors by RC1 and RC2 each explaining almost 50% of the variance, while less than 1% of the variance was explained by RC3. Without rotation, the first component alone explained 98.7% of the variation in temperature and can be used to efficiently reconstruct the data, but without the ability to explain the physical background.

RC loadings, which are spatial components, were similar before and after homogenization (not shown), even though there was a change in spatial locations of the minimum/maximum loadings. Prior to homogenization, the minimum RC3 values were in Gračac (70), Drniš (65), Sinj (126), Slunj (128) and Palagruža (111). All but Sinj had a large amount of missing data, so after homogenization, the minimum shifted to Sinj, Dubrovnik and Slavonski Brod.

Before homogenization, the fraction of variance explained by the first mode (RC1) was 49.788%, and it increased to 49.847% after homogenization. This increase was mainly due to differences in interpolation technique in *climatol* (Hs dataset) and the "statistical-normal" method that was used to create IHs inhomogeneous datasets, which had noticeably large differences in RC amplitudes during years when some of the data were missing (compare Fig. 7 and Fig. 2). Differences in the second mode, when compared non-homogenized and homogenized datasets, were similar to those from the first mode (*i.e.*, the largest differences occurred when data were missing). The fraction of variance explained by

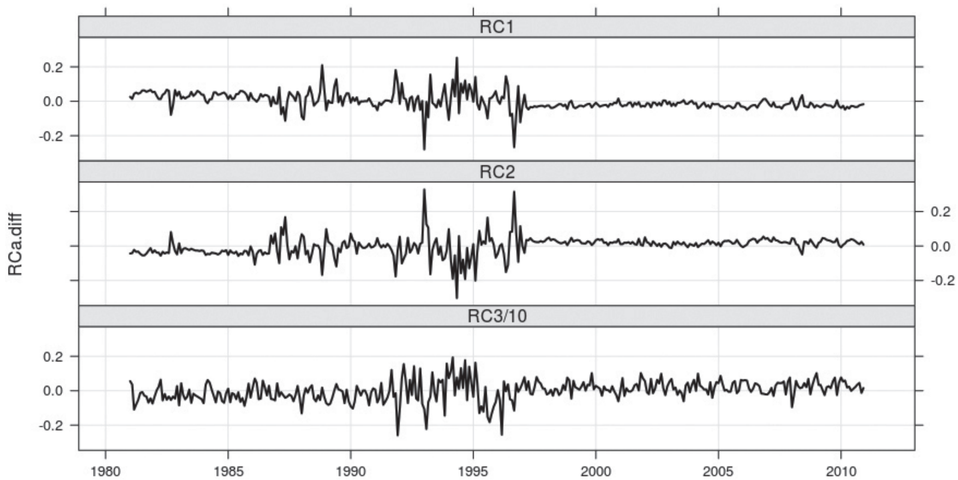


Figure 7. RC amplitude differences between IHs and HS datasets. Note that amplitudes of RC3 were divided by 10 in order to plot all three of them on the same scale.

RC2 slightly increased after the homogenization process (from 49.566% to 49.744%). The fraction of variance explained by the third component also increased from 0.123% to 0.135%. Overall, explained variance increased from 99.476% for IHs to 99.726% for Hs dataset.

When comparing RC amplitudes between homogenized and non-homogenized data, which had temporal components from the temperature field and coefficients from the spatial components, changes in the temporal components were noticeable (Fig. 7), while the spatial coefficients were more stable. These PC analysis results were another indicator of a more compact, spatio-temporal structure of the temperature field after the homogenization process.

5.6. Influence of filling missing data and homogenization on the long-term mean temperature

To examine the changes in statistical properties of the datasets due to filling the missing data and homogenization, the mean temperature and decadal trend on annual and seasonal scales were calculated. Differences in mean annual and seasonal temperatures amongst homogenized and non-homogenized series are shown in Fig. 8, and the significance of changes was tested with the Student's t-test at the 0.05 significance level.

The largest, as well as the only significant difference occurred at the Karlovac station, where mean annual temperature from the homogenized dataset was –0.5 °C lower compared to the measurements. This annual decrease was mainly a result of negative and significant changes in all seasons, except in winter when negative change was not significant. Relatively lower mean values compared to the non-homogenized series occurred in the eastern continental and hinterland part of the middle Adriatic, while somewhat higher values occurred in the north-central and northern Adriatic region, but those differences were not significant.

The spread of annual normal means in the Hs dataset was reduced compared to the IHs dataset due to improved homogeneity of the series in the study area.

The decision to use a homogenized series reconstructed from the last subperiod (decision criteria from section 4.3) as the series recommended for climate monitoring was examined for the influence on annual normal mean values. The comparison of mean values for specified regions showed that differences in the regional means, depending on the decision criteria, were not higher than 0.1 °C for Reg1 and Reg2 and not higher than 0.3 °C for the coastal Reg3.

5.7. Influence of filling the missing data and homogenization on temperature trends

For each station, a decadal temperature trend was estimated using linear regression, while significance of the trend was tested using a Mann-Kendall test at the 0.05 significance level. There were slight changes when comparing tem-

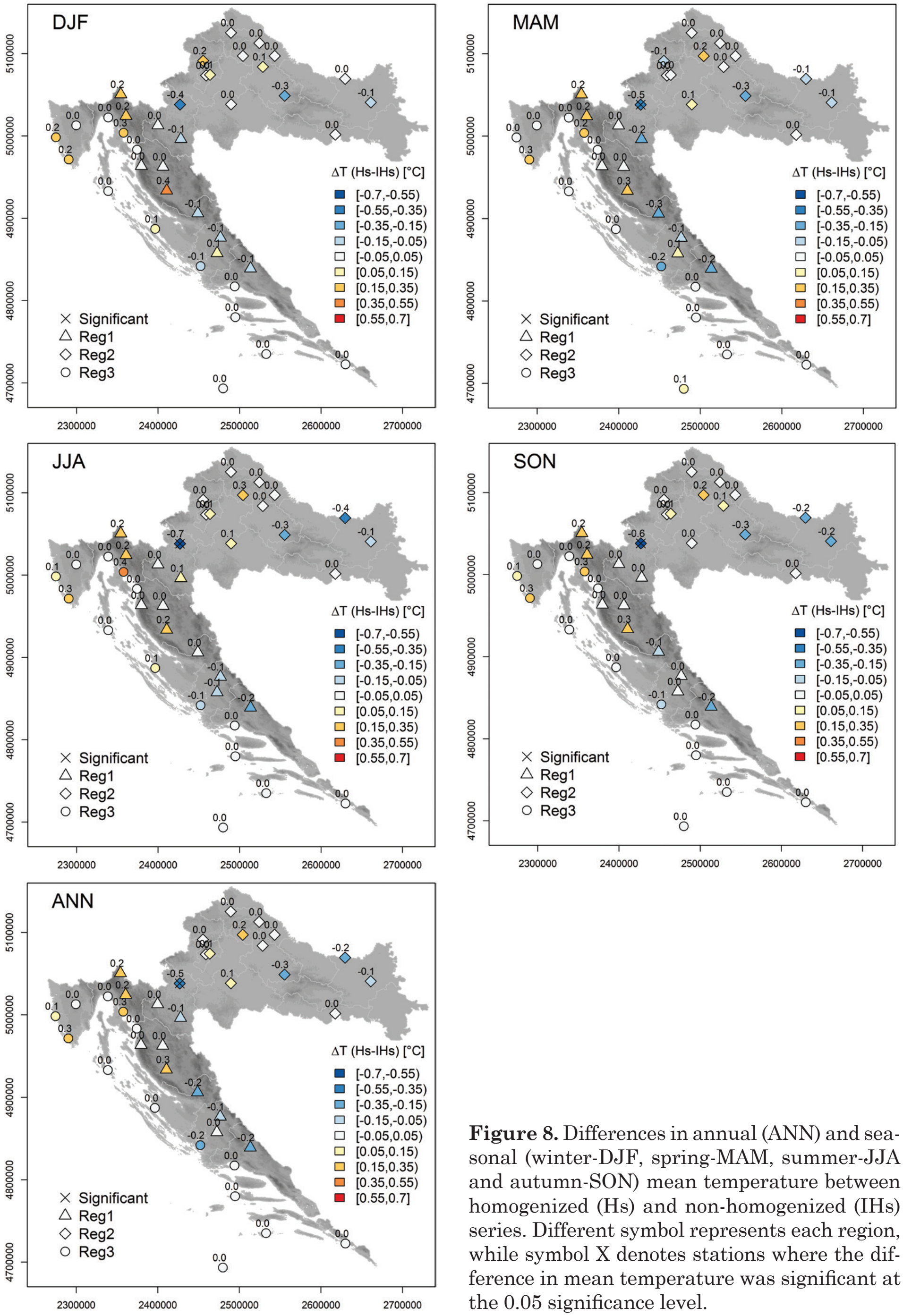


Figure 8. Differences in annual (ANN) and seasonal (winter-DJF, spring-MAM, summer-JJA and autumn-SON) mean temperature between homogenized (Hs) and non-homogenized (IHs) series. Different symbol represents each region, while symbol X denotes stations where the difference in mean temperature was significant at the 0.05 significance level.

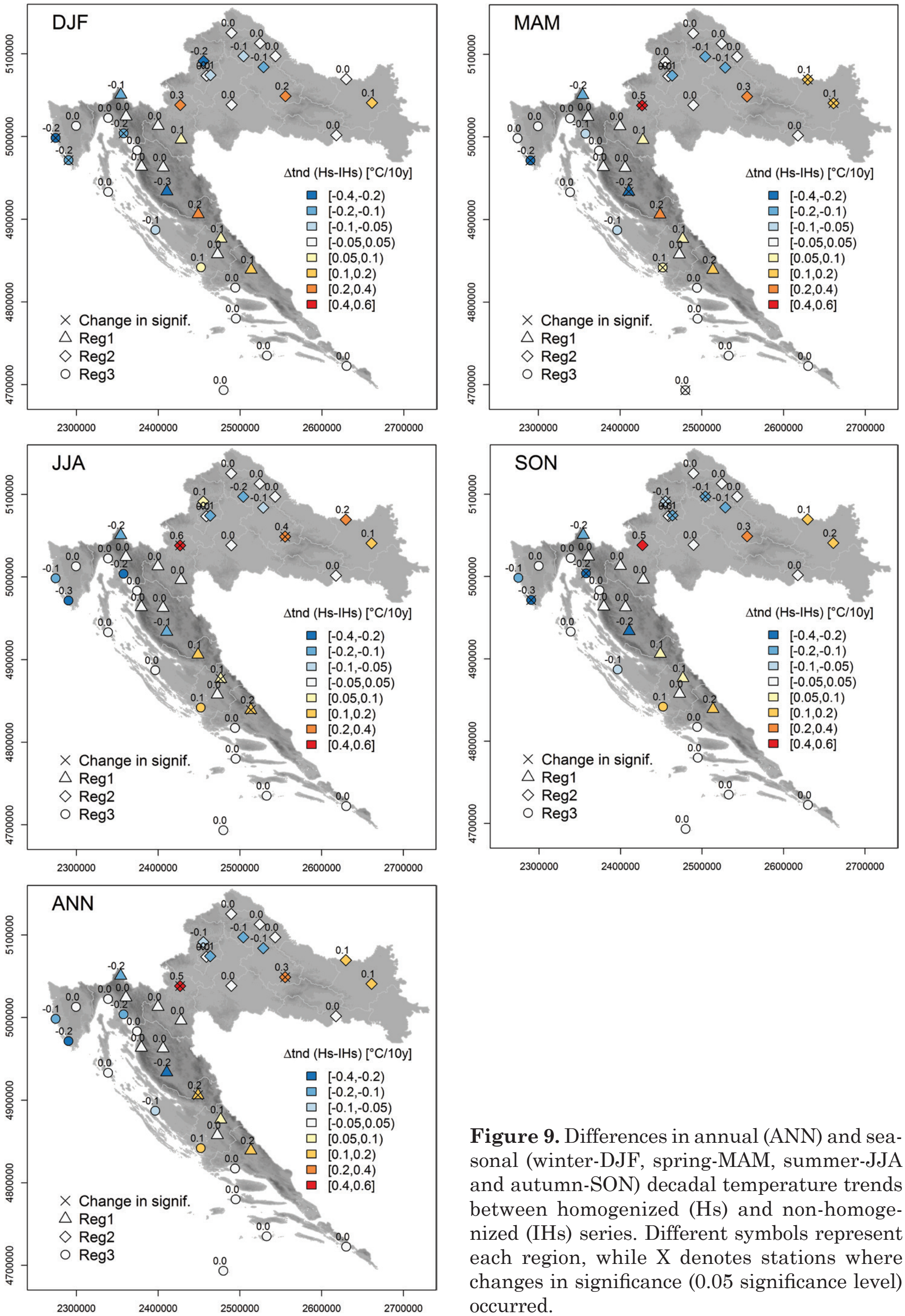


Figure 9. Differences in annual (ANN) and seasonal (winter-DJF, spring-MAM, summer-JJA and autumn-SON) decadal temperature trends between homogenized (Hs) and non-homogenized (IHs) series. Different symbols represent each region, while X denotes stations where changes in significance (0.05 significance level) occurred.

perature trends among Hs and IHs datasets, not only in trend rate but also in trend significance. The annual temperature trends for homogenized stations were positive (from 0.2 to 0.6 °C/10 y) in the study area, with slightly decreased spread compared to the trends in non-homogenized data. The trend rate did not depend on the selection criteria of the final corrected data series.

For the Hs dataset the obtained annual decadal trend was positive and significant at all selected stations, except at the highest altitude station Zavižan where positive trend was not significant (not shown). Higher trend values were located in continental inland and lower trend in mountain regions, as well as along the coast. Trend was strongest in the warmest part of the year, especially in summer when it was significant at almost all stations, except at the station Pazin situated in a basin in Istria's hinterland. Changes in seasonal and decadal annual trends at each station between Hs and IHs datasets are shown in Fig. 9 (ANN). In those figures, X denotes a station where a change in significance occurred. Due to in general positive temperature trend in relatively all seasons, an increase in trend rate with mark X denotes that at that station trend became significant after homogenization process, while it was not before. In accordance, decrease in trend rate with mark X stands for transition from significant to non-significant trend after homogenization. Again, Karlovac station stood out with the highest amplitude of change and change in significance; *i.e.*, the estimated trend from the homogenized dataset was significant, while the trend obtained from the non-homogenized dataset was not. The increase in annual trend rate was mainly due to an increase in trend rate during warmer parts of the year when a change in significance was also present. Two more stations experienced a change in significance for annual decadal trends: continental station Daruvar (0.3 °C/10 y) and mountain/hinterland station Gračac (0.2 °C/10 y). At a seasonal scale, a few more stations had changes in trend significance. It is noticeable how the increase in northern Adriatic temperature during colder parts of the year is no more significant, as well as the increase in autumn in the central part of the continental region. Spring temperature trend became significant after homogenization for easternmost stations. The exception from this, in general positive, temperature trend characteristic occurred in autumn and winter at a few stations (not shown). A negative trend is obtained at Zavižan station in autumn (–0.3 °C/10 y), while there was no trend in winter. In autumn, a negative temperature trend also occurred in Drniš (–0.1 °C/10 y), while there was no trend on the southernmost part of the Adriatic and two stations in the northern Adriatic. For all those mentioned stations with negative or no temperature trend, there was no change in trend rate after homogenization.

6. Conclusion

Testing the homogeneity of monthly temperature series gave quite a new insight into station data quality. Data from 39 stations in Croatia showed that half of the coastal stations had homogeneous monthly temperature series with no breaks. The largest number of breaks were detected at continental stations (Reg2), where Bjelovar and Križevci had up to four detected break points. Potential break sources (where there were traces in the metadata) are the relocation stations or changes in environment (*e.g.*, urbanisation or planting trees in the vicinity, respectively). Compared to breaks obtained by the ACMANT software, some of the breaks were close in time, but there were still some differences due to different algorithms in the homogenization methods and a different period of tested data. Evaluation of the homogenization process using correlation coefficients showed that monthly temperature fields across the study area became smoother, which will also improve the spatio-temporal interpolation procedure and grid production in the next step of the climatological analysis. The principal component analysis confirmed this statement through an increase in overall variance, explained by rotated principal components over the entire area. The results show that changes in PCA temporal components were more noticeable than changes in spatial components comparing IHs and Hs datasets. In conclusion, homogenization with the *climatol* package algorithm gave break-points supported with metadata (when they are available), and it proved especially useful for the interpolation of missing monthly temperature values.

Looking at the statistical characteristics of the series, some significant changes were obtained after filling missing data and homogenization. Changes in mean annual temperature had the largest amplitude in Karlovac (–0.5 °C), which was significant at the annual scale and in spring, summer and autumn. On average, slightly lower mean values compared to non-homogenized series were in the easternmost part of the continental region and in the southern mountainous/hinterland stations. Somewhat higher average values occurred at northern coastal and northern mountainous/hinterland stations. A similar spatial distribution of differences also occurred in all seasons. The estimation of decadal trends from homogenized data showed that trends were positive and significant at almost all stations and were spatially smoother than the non-homogenized data. The exception was the highest altitude station Zavižan, where an increase of 0.2 °C/10 y was not significant. When comparing temperature trends for homogenized and non-homogenized series, the homogenized data showed a reduced spread, with Karlovac station experiencing the largest change (0.5 °C/10 y). Decadal trend at that station became significant, as well as for stations Gračac and Daruvar. On a seasonal scale, changes in trend rates were in accordance with annual ones, but some stations also experienced changes in the significance of trend. For instance, at the northern coastal station of Pula, the trend rate decreased and was no longer significant for all seasons (except for summer). A similar change was also obtained in the colder part of the year at Crikvenica station but was also observed in autumn at a few northern continental stations. In spring, the increase in trend rate occurred in the easternmost part of Croatia and in Šibenik, making the temperature trend significant. In summer, two southern mountainous stations also experienced this increase and significance change.

Overall, calculated mean values were not as sensitive to inhomogeneities in data as was determining the trend or calculating correlation coefficients between station series. The original Karlovac data series showed to be unreliable due to two station relocations combined with instrument changes.

The selection criteria of the final estimated series slightly influenced the homogenized annual means but did not influence the homogenized temperature trends. Our selection was justified as today's observation techniques, methods and instruments are much more accurate than before.

This study serves as an insight into the homogenization of monthly temperature data, which will be used to make climate maps for the period of 1981–2010. In future work, the intention is to include all available stations and time series. The variation of parameters, such as distance or number of nearby stations used in the homogenization process, could yield even better results, especially for stations in a complex terrain. Other long-term climatological series for the upcoming climate atlas for the 1981–2010 normal period also plan on being adjusted for inhomogeneities, starting with monthly precipitation amounts.

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SAŽETAK

Potpuni i homogeni nizovi mjesečnih temperatura zraka za konstruiranje klimatskih normala 1981.–2010. za Hrvatsku

Irena Nimac i Melita Perčec Tadić

Pružanje informacija o klimatskim normalama pripada u najvažnije zadatke nacionalnih meteoroloških službi. Statistička obilježja klimatskih varijabli određena iz nepotpunih i nehomogenih podataka daju pristranu procjenu te je nedostajuće podatke nužno nadopuniti i ukloniti nehomogenosti. Homogenizacija podataka, iako vrlo važna, još uvijek nije dio procedura za kontrolu kvalitete podataka. U radu je ispitan obim nedostajućih podataka i homogenost na nizovima mjesečnih temperatura zraka s 39 meteoroloških postaja u Hrvatskoj iz razdoblja 1981.–2010. Postaje su podijeljene prema pripadnosti klimatskim područjima i homogenizacija je provedena za svako područje posebno. Uspješnost metode homogenizacije testirana je: (1) usporedbom koeficijenata korelacije mjesečnih temperatura na postajama i (2) usporedbom rotiranih glavnih komponenti prije i nakon homogenizacije. Prekidi u homogenosti uspoređeni su s meta podacima i objavljenom literaturom. Promjene u statističkim obilježjima temperaturnih klimatskih normala 1981.–2010. kao što su višegodišnji srednjak i dekadni trend uočene su na godišnjoj i sezonskim skalama između originalnih i homogeniziranih nizova. Značajnost razlika u srednjaku testirana je Studentovim t-testom dok je značajnost trenda testirana Mann-Kendalovim testom. Za homogenizaciju je korišten *R* paket *climatol*.

Ključne riječi: potpunost, homogenost, mjesečne temperature zraka, metoda glavnih komponenata, klimatska normala

Corresponding author's address: Irena Nimac, Meteorological and Hydrological Service, Grič 3, HR-10 000 Zagreb, Croatia; tel: +385 1 456 5623; e-mail: irena.nimac@cirus.dhz.hr

Appendix

Table A1. Selected meteorological stations with code, altitude, geographical location and the climatological region to which they belong.

Region	Station	Code	h (m)	lon (°)	lat (°)
Reg 1 – mountainous region	Drniš	65	324	16.16	43.87
	Gospić	7	564	15.37	44.55
	Gračac	70	567	15.86	44.31
	Knin	11	255	16.21	44.04
	Ličko Lešće	90	463	15.31	44.81
	Lokve Brana	92	774	14.72	45.36
	Ogulin	18	328	15.22	45.26
	Parg	21	863	14.63	45.59
	Slunj	128	254	15.58	45.12
	Zavižan	41	1594	14.98	44.81
	Sinj	126	308	16.67	43.70
Reg 2 – continental region	Bjelovar	2	141	16.87	45.91
	Đurđevac	67	121	17.06	46.03
	Daruvar	3	161	17.21	45.59
	Donji Miholjac	63	97	18.17	45.77
	Karlovac	10	110	15.57	45.49
	Koprivnica	78	141	16.81	46.17
	Križevci	14	155	16.55	46.03
	Osijek	19	89	18.56	45.50
	Sisak	30	98	16.37	45.50
	Slavonski Brod	31	88	18.00	45.16
	Stubičke Toplice	133	180	15.92	45.98
	Varaždin	35	167	16.36	46.28
	Zagreb Grič	38	157	15.97	45.81
	Zagreb Maksimir	39	123	16.03	45.82
Reg 3 – coastal region	Crikvenica	56	2	14.69	45.17
	Dubrovnik	4	52	18.09	42.64
	Hvar	9	20	16.44	43.17
	Lastovo	15	186	16.90	42.77
	Mali Lošinj	17	53	14.47	44.53
	Palagruža	111	98	16.25	42.39
	Pazin	22	291	13.95	45.24
	Pula	24	43	13.85	44.87
	Rijeka	27	120	14.44	45.34
	Rovinj	122	20	13.63	45.10
	Senj	29	26	14.90	44.99
	Šibenik	34	77	15.91	43.73
	Split Marjan	32	122	16.43	43.51
	Zadar	36	5	15.21	44.13