Norwegian
Meteorological
Institute

METreport

No. 11/2016
ISSN 2387-4201
Climate

The effect of homogenized input data in gridding of daily temperature and precipitation

Ole Einar Tveito

Norwegian Meteorological Institute

METreport

Title The effect of homogenized input data in gridding of daily temperature and precipitation	Date 2016-05-31
Section Division for climate services	Report no. No. 11/2016
Author(s) Ole Einar Tveito	Classification ● Free ○ Restricted
Client(s) MET and Statkraft	Client's reference Gastón Santisteban-Martinez

Abstract

This report presents the results of a study analysing the effects of applying homogenized daily temperature and precipitation series as input to a spatial interpolation method. Daily homogenized series are derived from monthly series by a linear interpolation of the adjustment factors.

The analysis shows that applying homogenized input series in general have no systematic effect on the grid estimates. The noisy pattern of daily values and the uncertainty of the gridding methods are larger than the break adjustment amplitudes.

Keywords

Homogenization, spatial interpolation, gridding, precipitation, temperature

Hans Olav Hygen /s.

Disiplinary signature

Per-Ove Kjensli /s.

Responsible signature

Meteorologisk institutt
Meteorological Institute
Org.no 971274042
post@met.no

Oslo
P.O. Box 43 Blindern
0313 Oslo, Norway
T. +47 22 96 30 00

Bergen
Allégaten 70
5007 Bergen, Norway
T. +47 55 23 66 00

Tromsø
P.O. Box 6314, Langnes
9293 Tromsø, Norway
T. +47 77 62 13 00

www.met.no

Content

1 Introduction

When analysing trends and variability of climatic time series will the accuracy and consistency of the underlying observations be of extreme importance. A homogenous representation of climate only exists when variations in the time series are solely results of variations in weather and climate (Easterling et al, 1996). Changes in the technical and/or environmental conditions such as relocations, change in instruments and sensors, change of observers, change of observing practices, new buildings etc. at observation stations might seriously affect the measurements in such a way that sudden shifts (homogeneity breaks) in the time series will be introduced. Other conditions such as land use changes, urban development and changes in vegetation introduce trends in the time series that might deviate from the regional climate characteristics. Analysing and correcting for such external influences to achieve homogeneous climatic time series is therefore necessary before making an assessment of climatic change.

During the last 10-15 years gridded climate data has been introduced in order to provide a continuous and consistent spatial description of climate. For that purpose several methods for estimating gridded climate datasets have been developed. Tveito et al. (2008) gives an overview of the main methodical principles and examples of applications of such. Up to now datasets based on observation gridding and spatial statistics approaches have been the ones that have provided the most reliable and unbiased information. In that context it is natural to investigate whether homogenized input data will improve the estimations of the gridding methods.

This report presents an analysis of the effect of applying homogenised temperature and precipitation series for gridding. First are the theoretical backgrounds, basic assumptions and the data applied in the analysis presented. Thereafter the pre-processing of data and the analyses is described, before a presentation and discussion of the results. At the end final remarks and conclusions are presented.

1.1 Spatial interpolation and gridding

Given that (i) the gridding method is perfect and the observations are associated with correct and representative metadata gridded data should by nature be homogenous, and (ii) the observation network is representative for the entire gridding domain, gridded data should be spatially and temporally homogenous. Neither of these criteria can in practice be fully fulfilled, at least not in areas with strong climatic gradients and complex topography such as Norway.

When doing a spatial interpolation there are a few basic assumptions that need to be fulfilled. The most important are the assumptions that the process should be stationary in space, and that the co-variations between observation points can be explained by the distance between observations (a spatial covariance function). Normally isotropy is assumed, i.e. the spatial covariance is independent of geographical direction.

1.2 Spatial interpolation of temperature

The assumption of second order spatial stationarity for temperature is not possible to fulfil in Norway. Strong gradients and complex topography makes that rather impossible. Direct spatial interpolation of temperature is therefore not possible without converting the observed temperature fields closer to fulfilling the second order spatial stationary criteria (Tveito and Førland, 1999). The Norwegian Meteorological Institute has for more than a decade produced daily gridded temperature data based on a residual kriging approach according to Tveito et al. (2000). Residual kriging (often also called kriging with an external trend) consist of two components.

$$\hat{X} = X_S + X_D \tag{1}$$

where XD is a deterministic term, often described as a large scale global trend. This describes the temperature dependence of elevation, distance to sea etc. Tveito et al. (2000) suggested to apply five independent parameters to describe the deterministic trend; local elevation, average elevation within a 20 km circle, lowest elevation within the same circle, longitude and latitude. These five parameters are used to establish a linear relationship giving a climatological first guess field. In Tveito et al. (2000) are monthly trend expressions developed. When the trend component is removed from the observed values the result is a residual field that are close to fulfil the second order spatial stationarity assumption. The detrended values are then interpolated applying a spatial interpolation method e.g. kriging, which then is the stochastic term Xs in equation 1.

When the interpolated field is estimated the trend expression is added back. This can be expressed as:

$$\hat{T} = \sum_{i=1}^{n} \lambda_i T_i + \left(\alpha_0 + \sum_{j=1}^{m} \alpha_j x_j\right) \tag{2}$$

where the first term is the spatial interpolation. i denotes the n observations entering the spatial interpolation. λi are the interpolation weights for each station, Ti are the observed temperatures. The second term is the deterministic trend where α0 is a constant, αj regression coefficients and xj the external predictor parameters.

In this analysis the residual kriging algorithm established by Tveito et al (2000), and applied to produce the SeNorge v1.1. gridded data set (Mohr, 2008), been applied to assess the differences applying homogenised versus non-homogenised input data.

1.3 Spatial interpolation of precipitation

Spatial interpolation of precipitation is even more challenging. Precipitation is non-continuous in time and space, skewly distributed with an absolute lower boundary (zero). This means that the assumption of normality and spatial stationarity cannot be fulfilled, and that method relying on such assumption should not be applied. In hydrology the approach of using nearest (representative) neighbour been a widely applied concept. This geometrical method (Fig 1a) is in hydrology known as the Thiessen method (Thiessen, 1911), but are in other disciplines also known as the Voronoï-diagrams or Dirichlet diagram, a method that can be traced back to Descartes in the mid-17th century. The precipitation gridding applied in this study is based on the same geometrical principle, the Delaunay triangulation. The triangulation connects points with a three –dimensional mosaic of triangles (fig 1b) where the slope describes the spatial gradient of precipitation. In the MET Norway triangulation algorithm for precipitation a relative elevation factor compensating for orographic effects is included. See Mohr (2008) for further details.

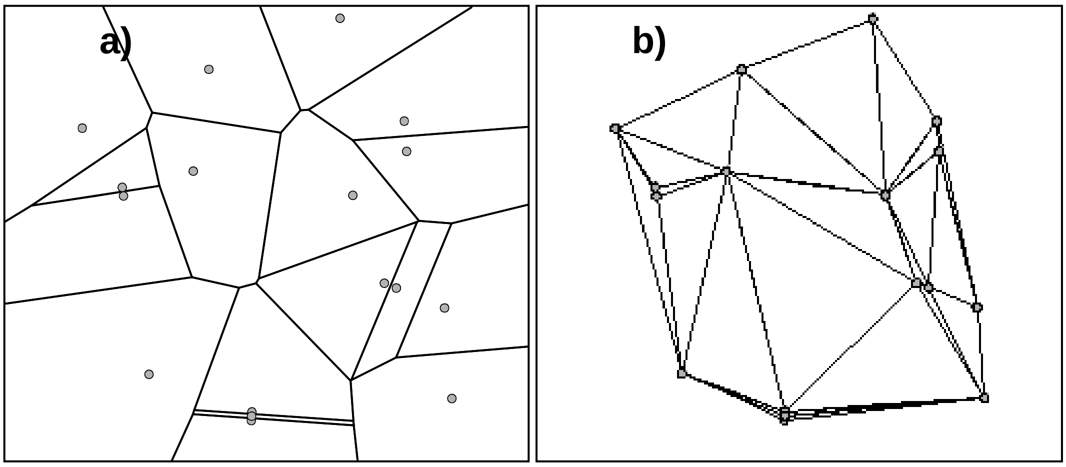

Figure 1. a) Thiessen polygones b) Delaunay triangles

2 Homogenised data

2.1 Homogenized temperature series

In this analysis estimations based on homogenised and non-homogenised temperature observations are compared. During the recent years a number of tools for assessing homogeneity of climate times have been developed (Lundstad and Tveito, 2016), and applied to adjust for inhomogeneities. Andresen (2011) performed a homogenisation analysis for 225 monthly temperature series in Norway applying the SNHT method (Alexandersson, 1986) and in this investigation the results from that analysis is applied as input data. Figure 3 shows the location of the 225 series.

In order to obtain daily homogenised data from the monthly homogenisation a linear interpolation of monthly adjustment factors into daily adjustments following the concept of Vincent (2002) has been applied. The linear interpolation was chosen even though the average daily adjustment factors are different from the monthly. The motivation for that is there is no scientific basis from the monthly analysis that the adjustments based on climatology should be more extreme than the monthly average when considering the entire temperature distribution. Figure 4 shows an example of the interpolation of daily adjustments factors for homogenisation at the series 24890 Nesbyen in 1961. The observations in 1961 where taken at a different location in 1961 (station ID 24860) than the current location 24890. Figure 5 shows the monthly coefficients for the entire length of the series.

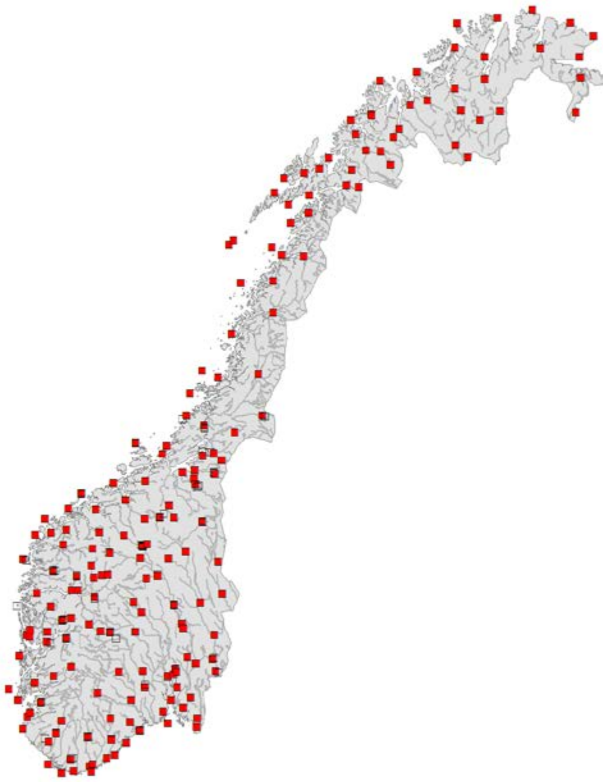

Figure 3: Location of the 225 climate series assessed by Andresen (2011). Open symbols indicate locations of stations that are merged with the candidate series.

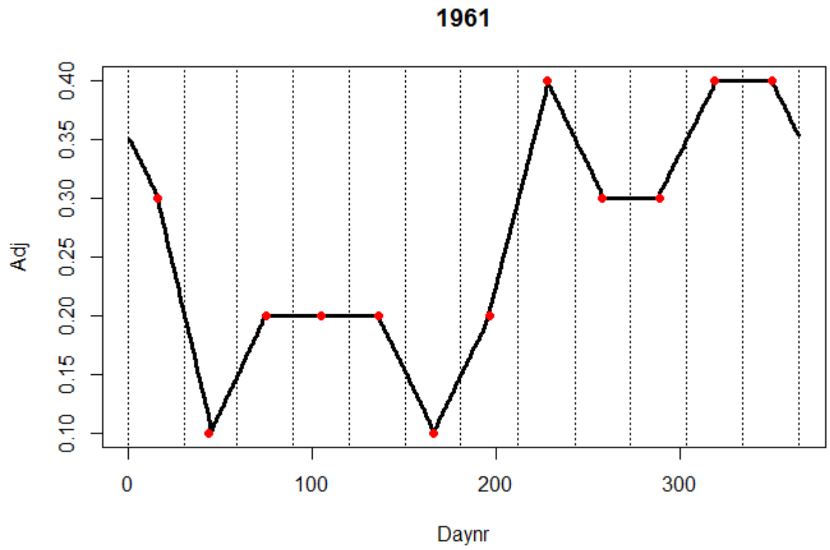

Figure 4: Daily adjustment factor at 24890 Nesbyen in 1961. The red dots indicate the monthly adjustments factors obtained by Andresen (2011).

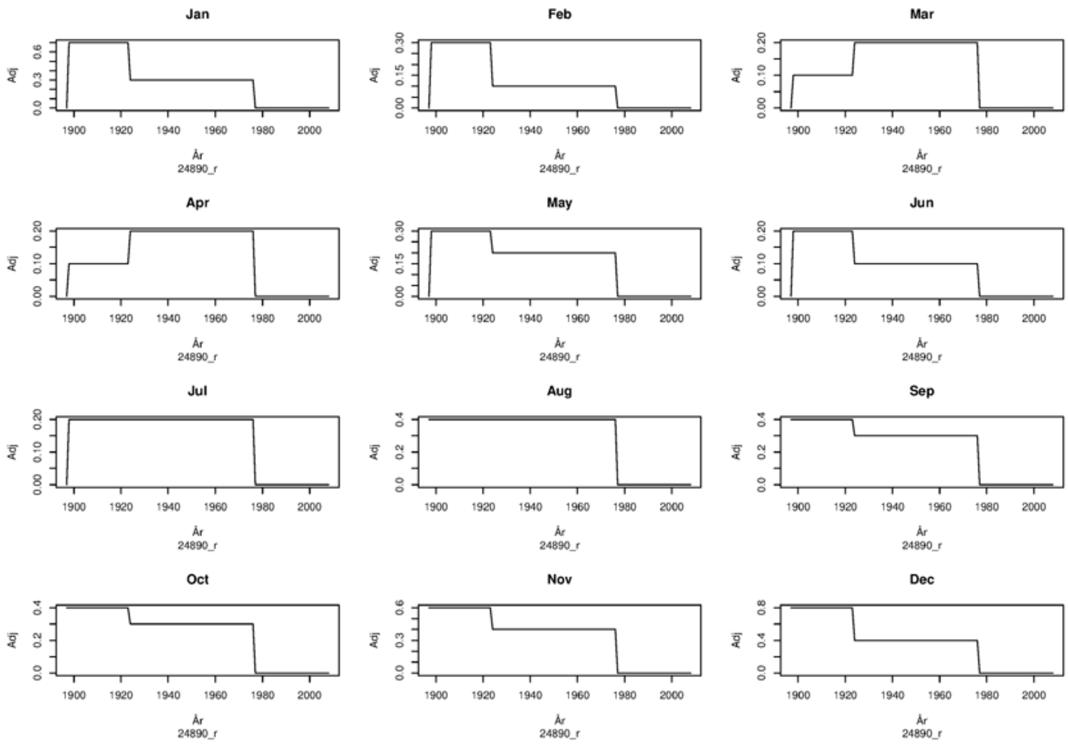

Figure 5: Monthly adjustment factors at the series 24890 Nesbyen 1897-2008.

2.2 Homogenized precipitation series.

The homogenized precipitation series applied are results of a preliminary analysis of long Norwegian precipitation series. 204 monthly precipitations series covering Norway south of 65°N and the period 1896-2015 have been analysed. These 204 series are based on 343 original precipitation observation series. Figure 6 show the locations of these 204 target series and if they are adjusted for inhomogeneities.

The MASH algorithm (Szentimrey, 2008,2011) was applied for the homogenization. This is an automatic procedure able to analyse large datasets fairly effectively. The analysis was done for three subregions; Eastern Norway, Southern and Western Norway, North-western Norway and Trøndelag) before the results were merged. The analysis identified inhomogeneities in 52% of the series.

The analysis was carried out on monthly, seasonal and annual basis. The adjustments have been inspected manually in order to remove single year inhomogeneities in the monthly series. This is an identified weakness of the MASH method, which seems to be very sensitive to single anomalies in the time series and often introduce short inhomogeneities with compensating adjustments in consecutive years. The results shows that the spatial distribution of homogenous and series adjusted for inhomogeneities are well blended.

The further analysis demand daily adjustment factors. These are achieved by applying the Vincent approach in the same way as for temperature.

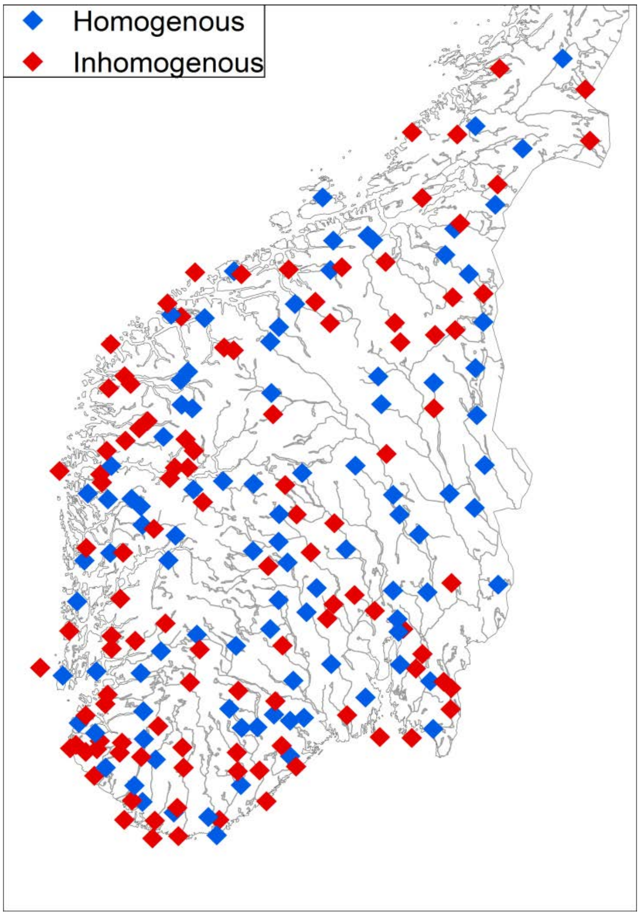

Figure 6: Location of the homogenized precipitation series. Blue markers indicate series without inhomogeneities, red markers indicate series adjusted for inhomogeneities.

3 The analysis

The analysis is carried out applying the ”leave-one-out” cross-validation version of the gridding methods. This a function normally applied to compare observations and independently spatially interpolated values to assess uncertainties of gridded fields. The concept is to remove the observation to be interpolated, and then use all remaining observations as input to the point estimation. This is repeated iteratively until all locations are independently estimated.

To assess the effect of homogenisation the cross-validation is done both for homogenised and raw (un-homogenised input). For the series where the homogenisation is due to relocations metadata describing locations and elevations will vary throughout the period. In order to assess that the analysis is carried out in two modes:

1. Keeping the metadata for the homogenised series for both the homogenised and un-homogenised series for the entire series. This means that metadata remain unchanged.
2. Apply metadata for the original series (observation sites) throughout the period for the un-homogenised series. This means varying metadata.

The principle is illustrated in figure 7, showing the changes in station elevation for the study period 1961-2008.

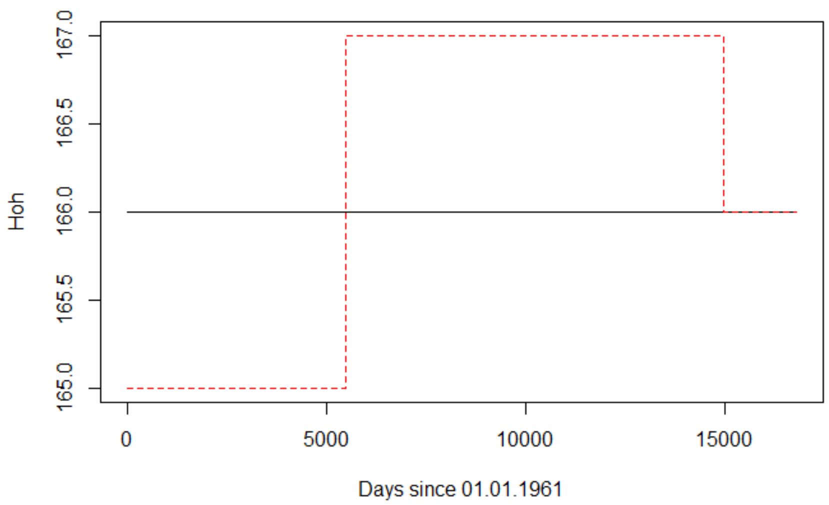

Figure 7: Metadata modes in the analysis. Mode 1 is represented by the black solid line, while the dashed red line illustrate mode 2. This example is from the 24890 Nesbyen.

4 Results

4.1 Temperature analysis

The analysis of temperature is carried out for the period 1961-2008, a period of 49 years. The results are summarized by statistical measures such as absolute bias (prediction error) and root mean square error (RMSE). The statistics are mostly presented as graphics.

Figure 8 and 9 presents an overall assessment of the effect applying the two modes of metadata for non-homogenized data for all the series. It shows the monthly spread of root mean square error, showing very small, almost negligible differences between the two setups.

Locally are the effects more visible. Figure 10 shows the elevation of the observation sites merged into series 29720 Dagali, series where the elevations have changed considerably during the analysis period. Figure 11 shows that for this location and locally will the use of correct metadata provide more robust gridded estimates (the red boxes shows generally smaller error values than the black).

The comparison of estimations applying non-homogenized and homogenized data respectively at all stations does not show significant differences.

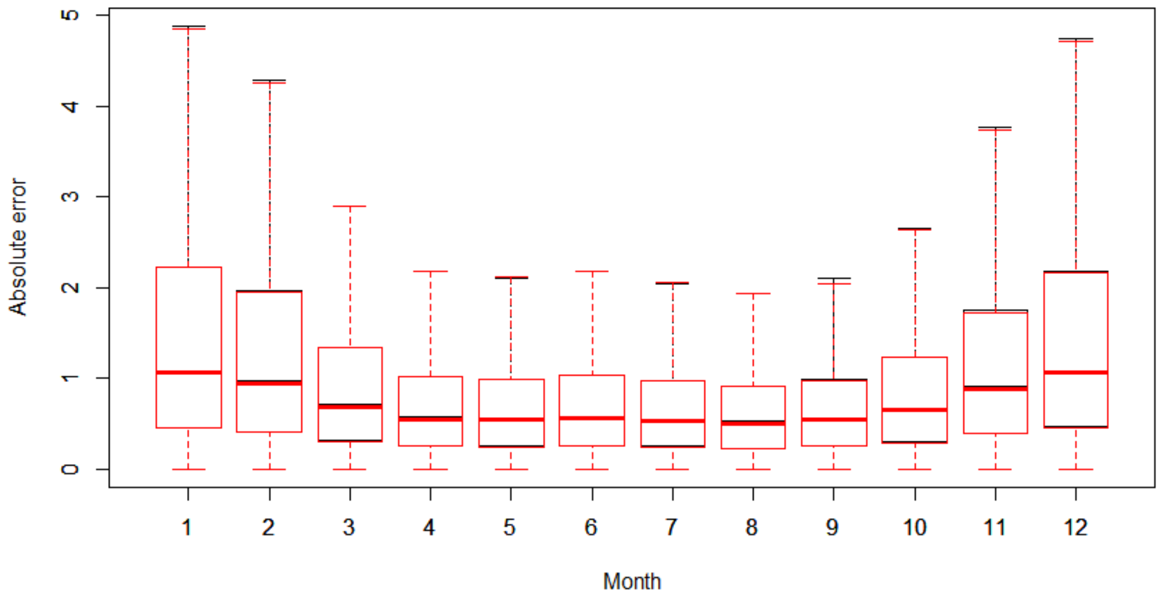

Figure 8: Box-whisker plots of monthly RMSE for non-homogenized input for all stations 1961-2008. Black boxes refer to constant metadata, red boxes refers to time variant metadata.

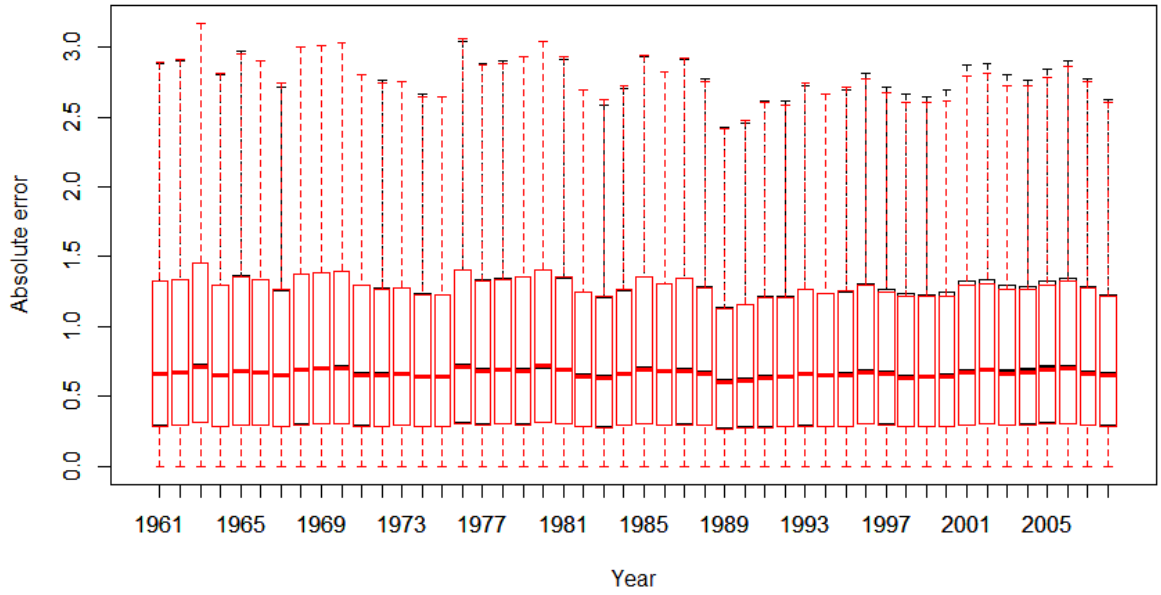

Figure 9: Box-whisker plots of annual RMSE for non-homogenized input for all stations. Black boxes refer to constant metadata, red boxes refers to time variant metadata.

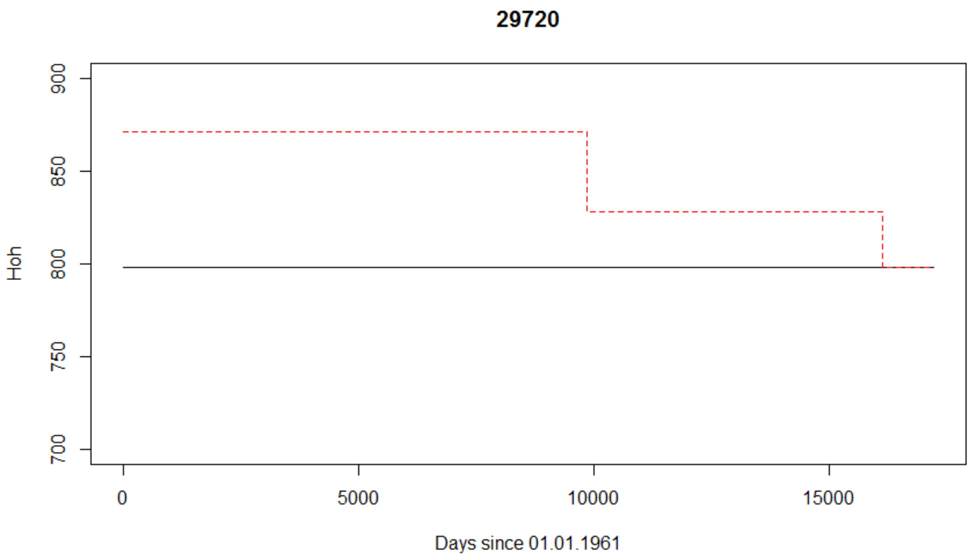

Figure 10. Elevations at the locations used to establish the long term temperature series 29720 Dagali.

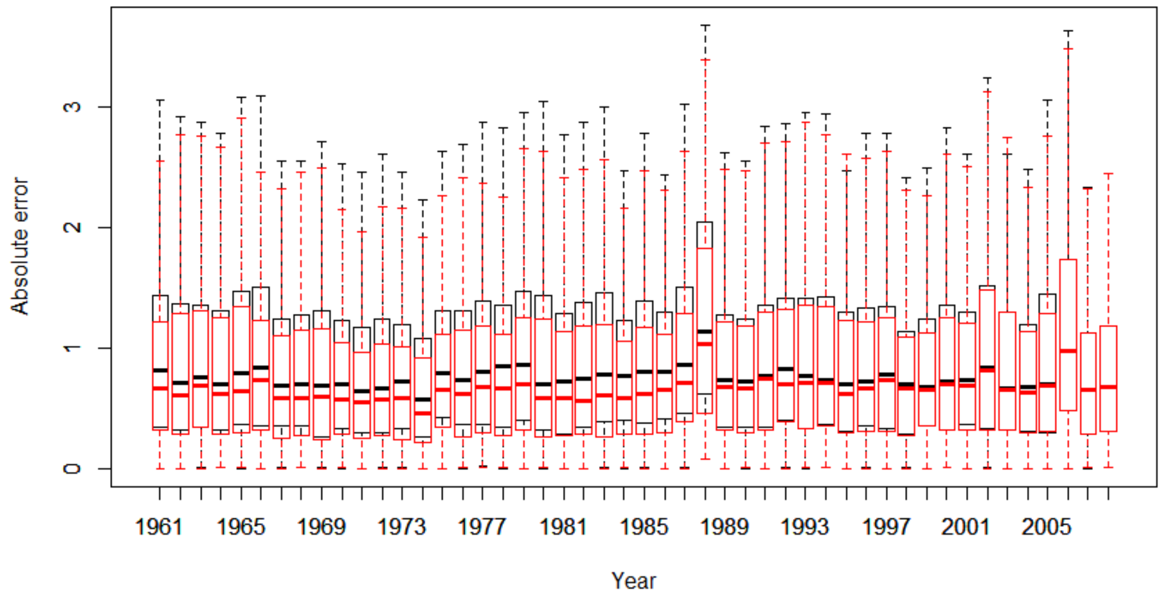

Figure 11 Box-whisker plots of annual RMSE 1961-2008 at Dagali. Black boxes refer to constant metadata, red boxes refers to time variant metadata.

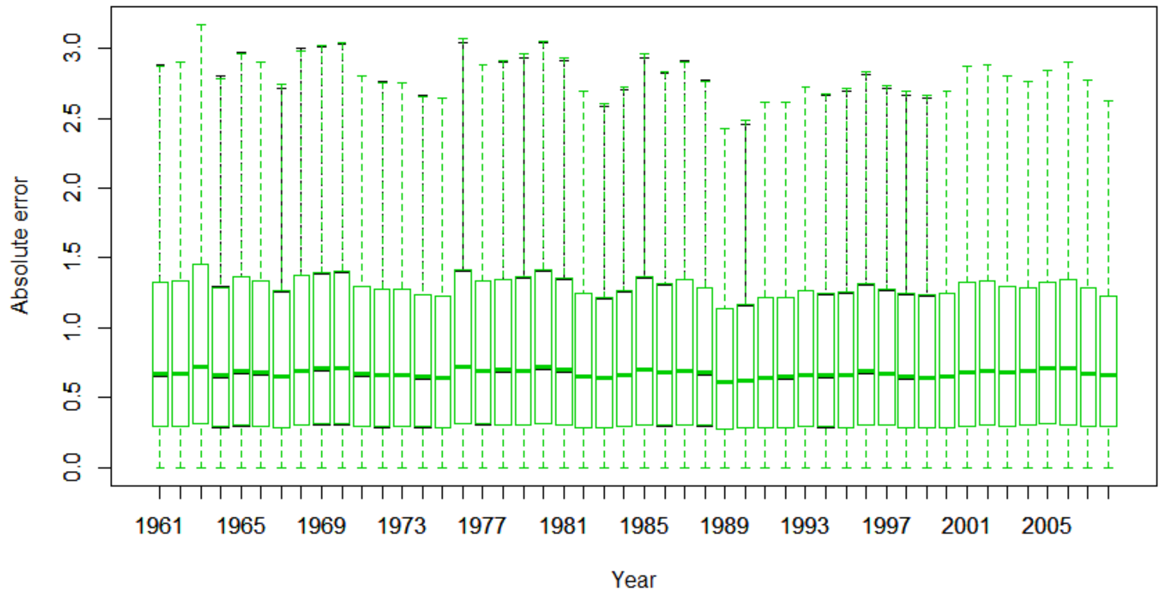

Figure 12. : Box-whisker plots of annual RMSE for all stations. Black boxes refer to nonhomognized series, green boxes refers to homogenized series.

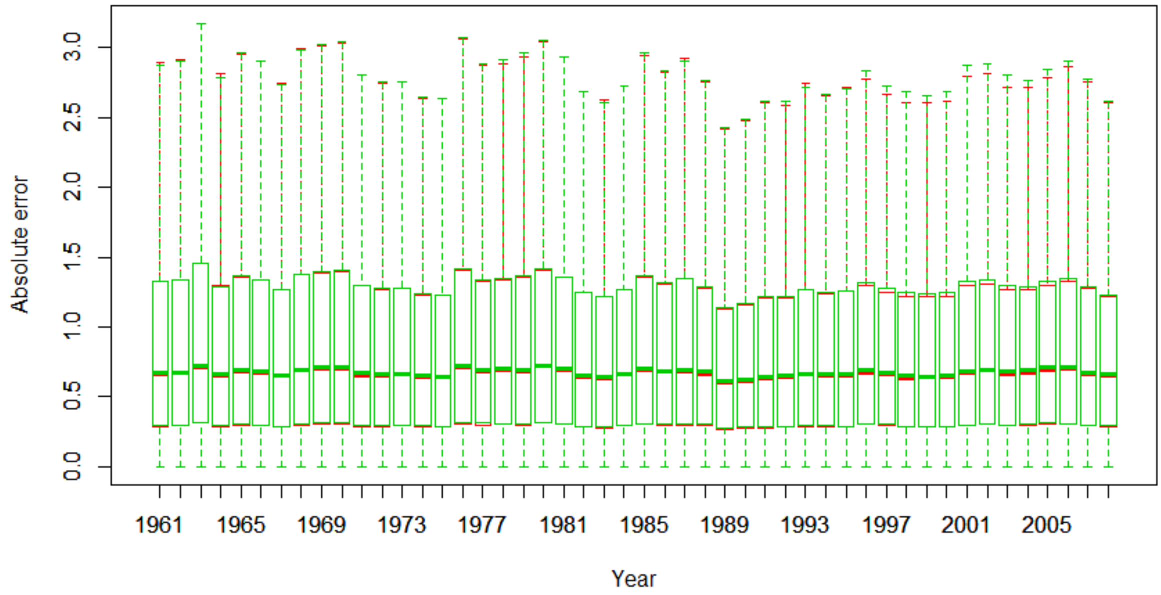

Figure 13: Box-whisker plots of annual RMSE for all stations. Red boxes refer to nonhomogenized series and time variant metadata, green boxes refers to homogenized series.

Figure 14 shows the annual variations in absolute error at Dagali. It shows that the use of correct metadata for the input series gives more significant improvement of the estimates than applying homogenized input series. An examination of the distribution of station-wise RMSE of the three setups also confirm that applying correct metadata on raw series give slightly better gridded estimates than both homogenized and non-homogenized merged series.

Figure 15 shows the frequency distribution of station wise estimation scores for all series. It can be seen that there are very small differences between the biases. The approach giving slightly better estimates are by applying raw data with correct description of metadata.

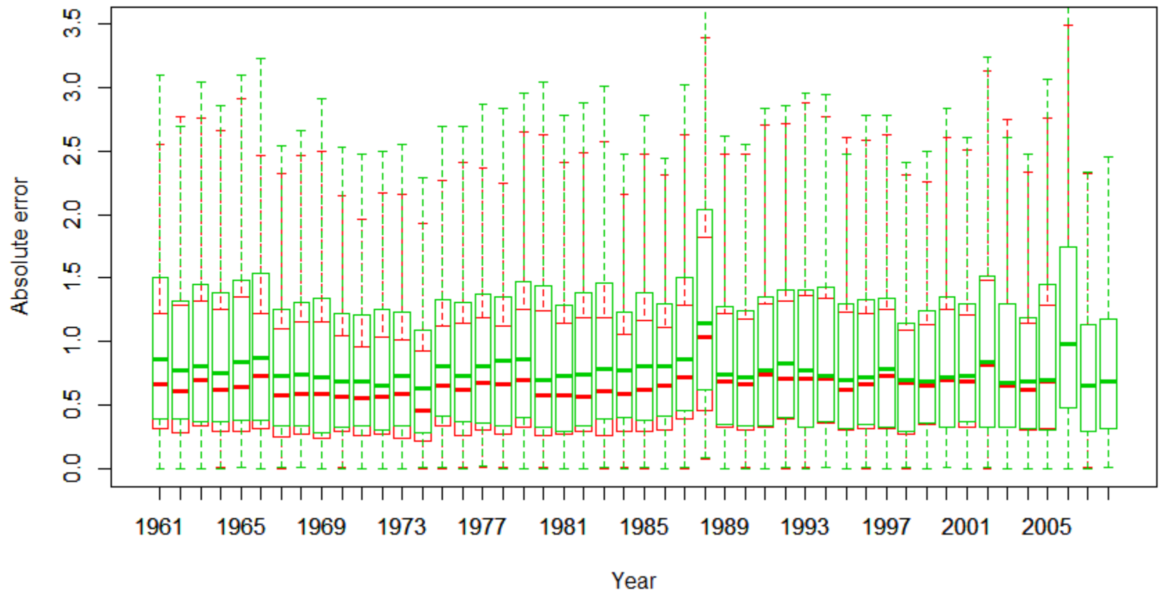

Figure 14: Spread of annual absolute biases 1961-2008 at Dagali. Red boxes refers to time variant metadata and non-homogenized input data, Green boxes refer to homogenized input data.

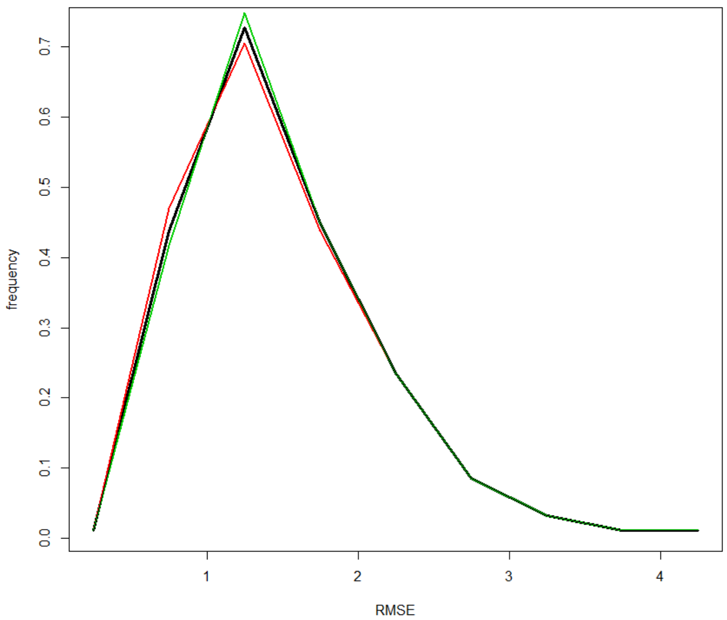

Figure 15: Distribution of station-wise RMSE's of grid estimates. Black curve represents merged non-homogenized input data, green curve merged homogenized data. Both these have static metadata. The red curve represents non-homogenized series with time-variant metadata.

4.2 Precipitation analysis

The precipitation analysis covers the period 1961-2015, a period of 55 years. In total 204 series are investigated. The number of analysed series varies though over the period. It is rather stable around 200 stations until the mid-1990'ies when the network begin to be reduced, with a rapid decrease after 2005. The maximum of 204 stations appear in the 70'ies and 80'ies, and the minimum of 156 long term series in 2015. Figure 16 shows the development of the network.

To be able to interpret and understand the results and effects of applying homogenized input series it is important to understand the performance characteristics of the spatial interpolation method itself.

For validation of precipitation the ability to estimate precipitation occurrence is essential. One commonly used score is the probability of detection, POD based on a contingency table:

	Precipitation observed, no=0	Precipitation observed, yes=1
Precipitation estimated, no=0	N(0,0)	N(1,0)
Precipitation estimated, yes=1	N(0,1)	N(1,1)

$$\mathrm{POD} = \frac{\mathrm{N}(1,1)}{\mathrm{N}(1,0) + \mathrm{N}(1,1)} \tag{3}$$

This criterion explains how many precipitation events observed that actually was estimated. It thereby tells how good the interpolation model is to model precipitation occurrence. It is a binary based indicator, and does not consider the precipitation amounts. Figure 17 shows the annual POD-scores for the entire network. It shows that more than in average almost 95 % of the precipitation events is estimated. The annual variability is between 92 and 96.2.

Another criterion is the chance to estimate precipitation that has not occurred. This is often expressed as the false alarm rate FAR:

$$\mathrm{FAR} = \frac{\mathrm{N}(0,1)}{\mathrm{N}(0,1) + \mathrm{N}(1,1)} \tag{4}$$

The annual variability of this score is shown in figure 18, showing that the FAR varies between 18.7 and 29.3, with an average of 22.4.

Daily precipitation is highly variable, and this large variability we have chosen to primarily to present the results as statistics based annually aggregated values. Then the noisy character of daily values will be supressed and the systematic biases, if any, become clearer.

However, in figure 19 all observed and estimated values are presented. If the plot is examined thoroughly pairs of back and red markers can be identified. These represent non-homogenized and homogenized values respectively and the plot do not reveal any systematic improvement of the estimates, meaning that the red dots should be closer to the diagonal line representing the prefect estimate. In figure 19 constant metadata are applied. Figure 20 present the similar plot but applying correct time-variant metadata. There is not possible to find any systematic improvement of the homogenized data in this analysis either.

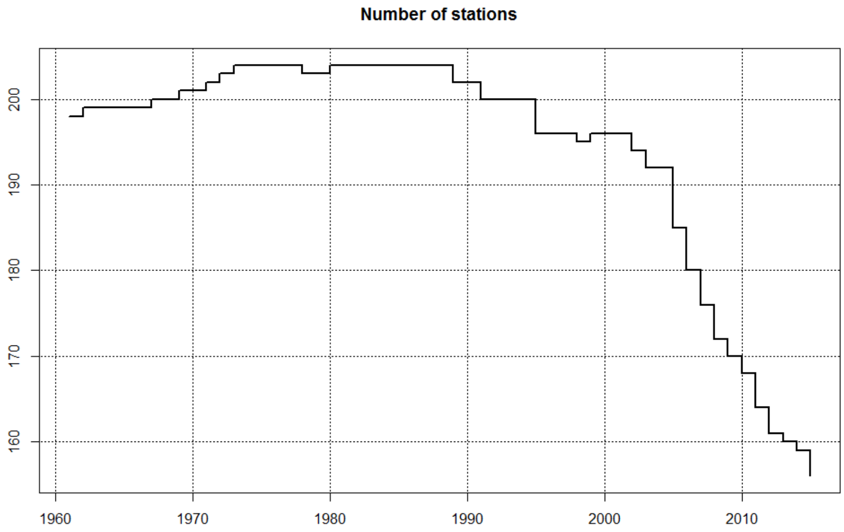

Figure 16: Station coverage during the precipitation analysis period.

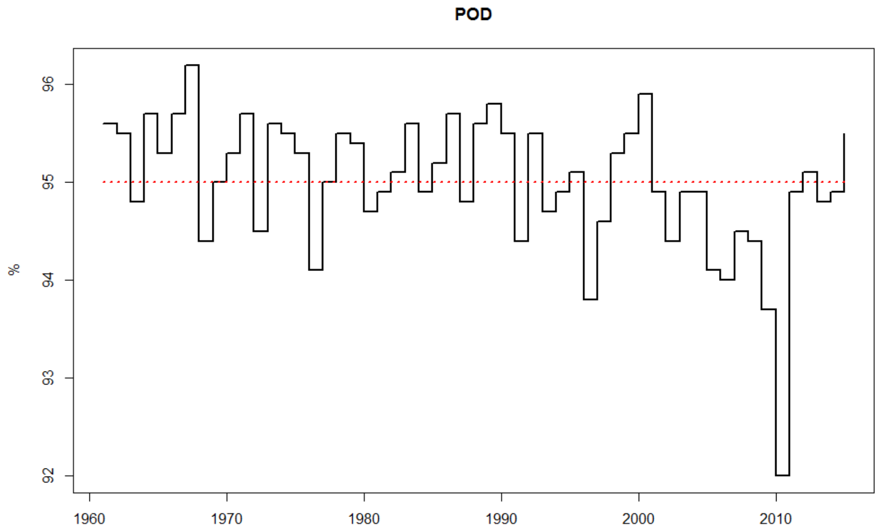

Figure 17: Annual probability of detection of precipitation

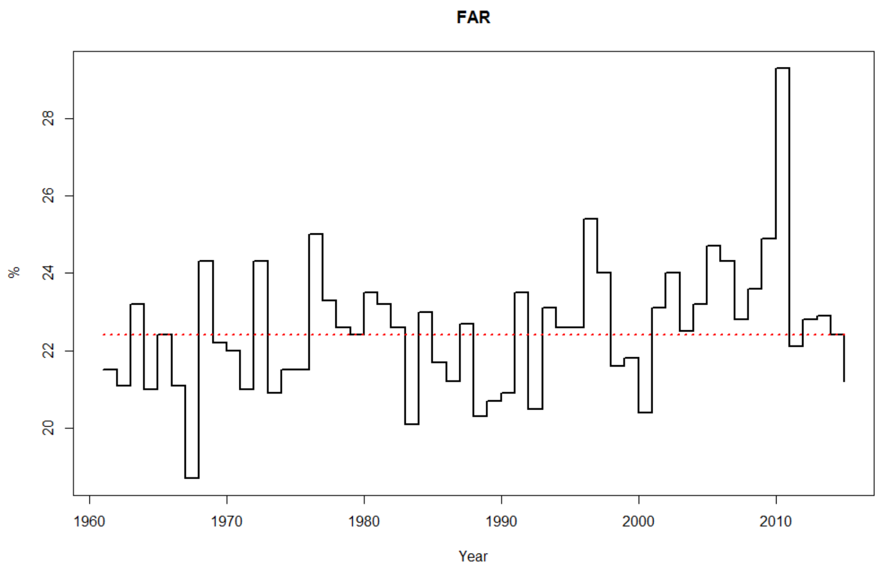

Figure 18. Annual false alarm rate (FAR) of precipitation

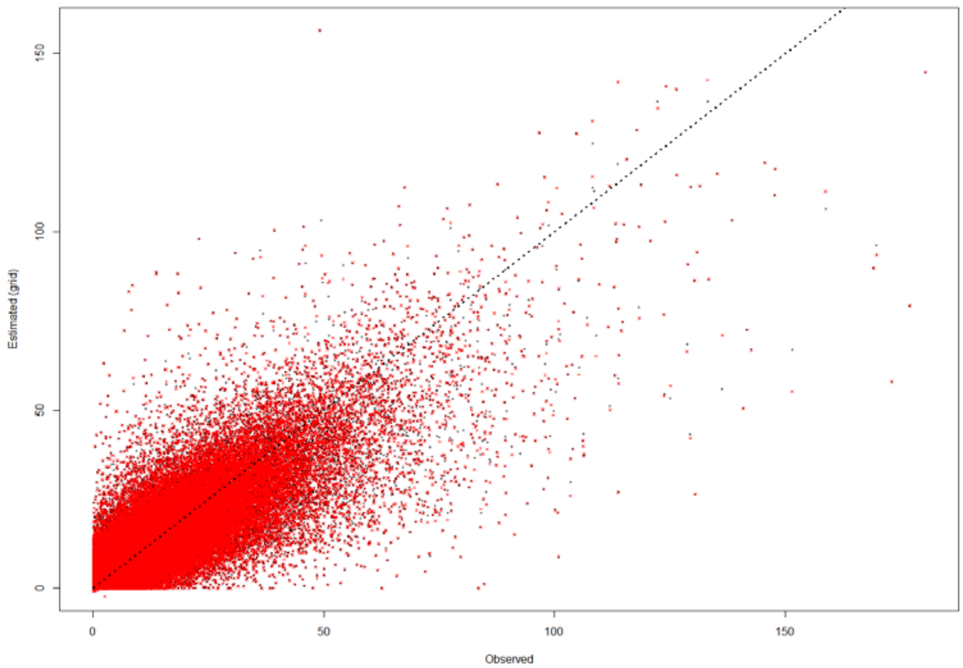

Figure 19: Scatterplot of observed and estimated precipitation when metadata are constant in time. Black markers represent non-homogenized values, red markers homogenized values.

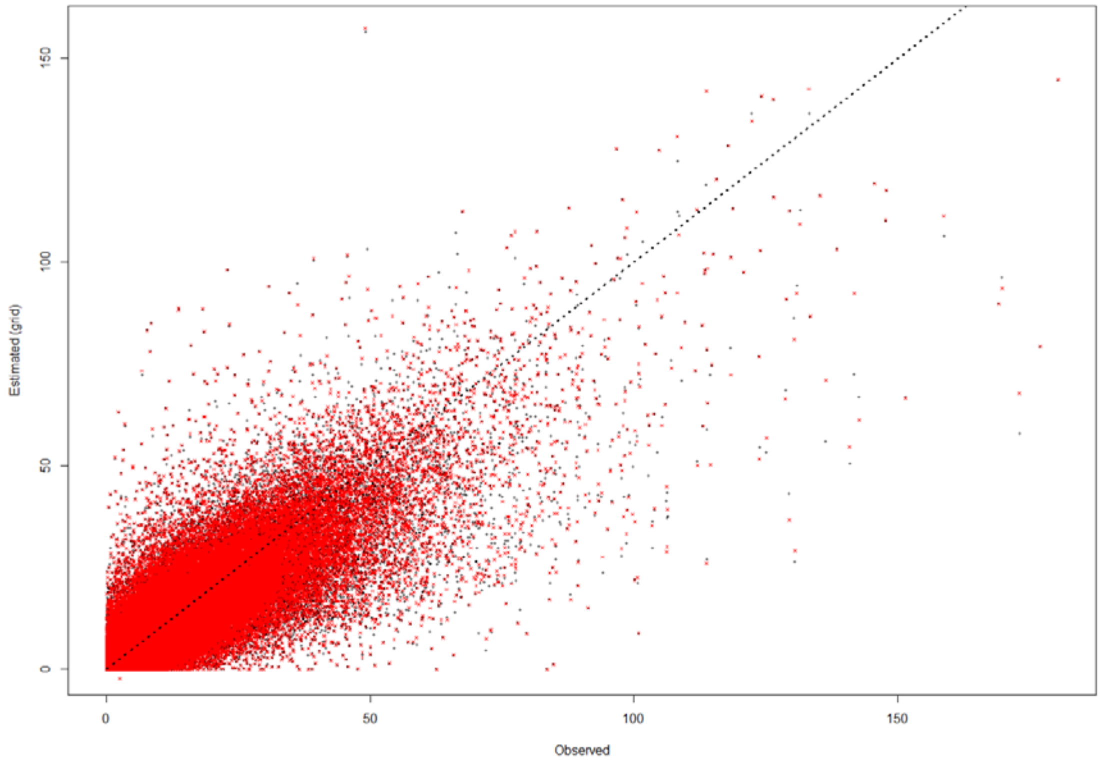

Figure 20: Scatterplot of observed and estimated precipitation when metadata are varying in time. Black markers represent non-homogenized values, red markers homogenized values

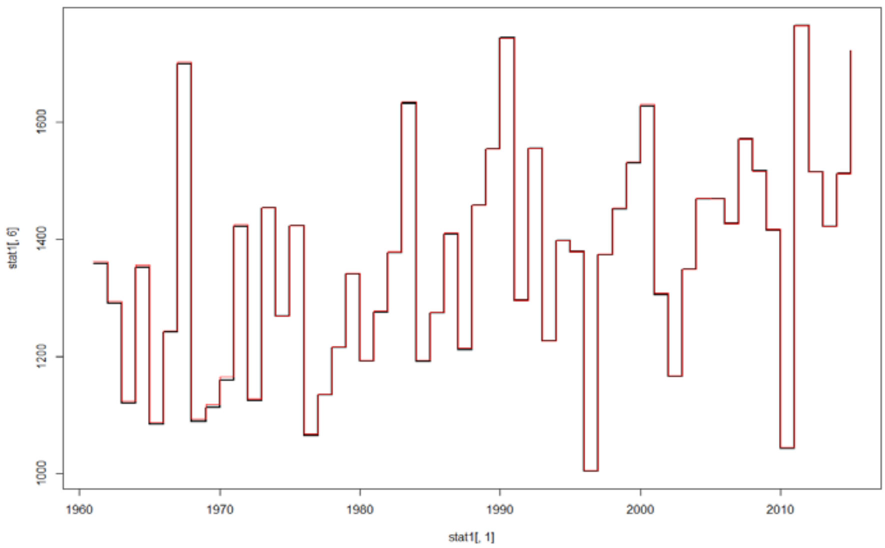

Figure 21: Annual mean sums of predicted precipitation for non-homogenized input data (black) and homogenized input data (red). Metadata are constant over time.

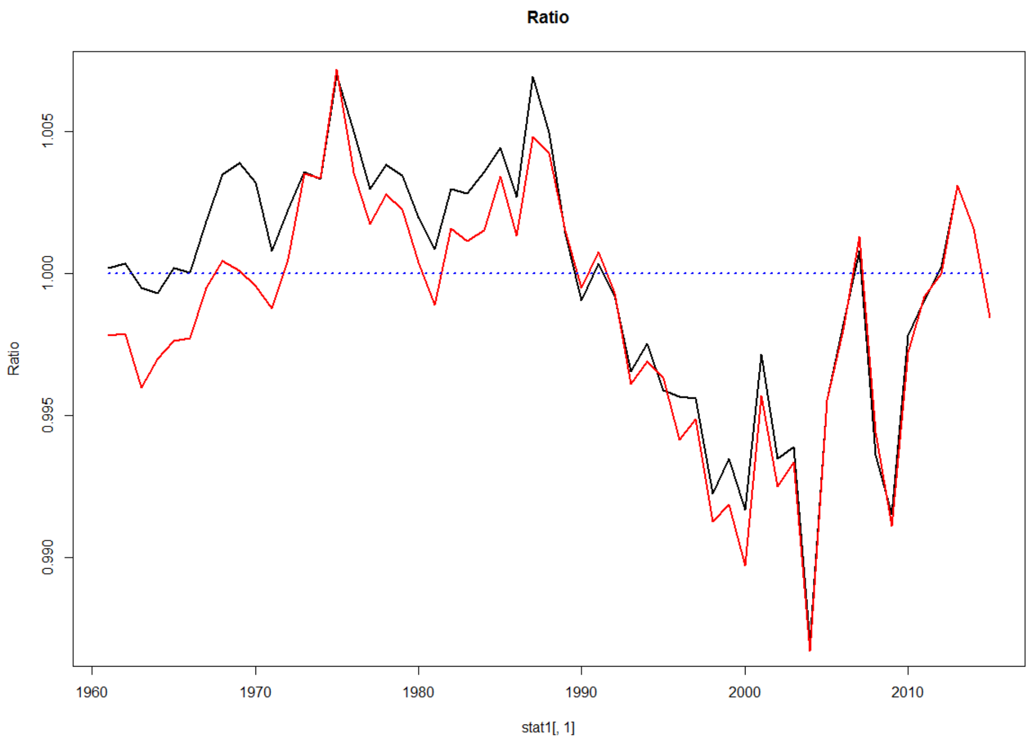

Figure 22: Annual ratio (obs/est) between observed and predicted precipitation. Black curve represent non-homogenized data, red curve homogenized data. Metadata are constant over time.

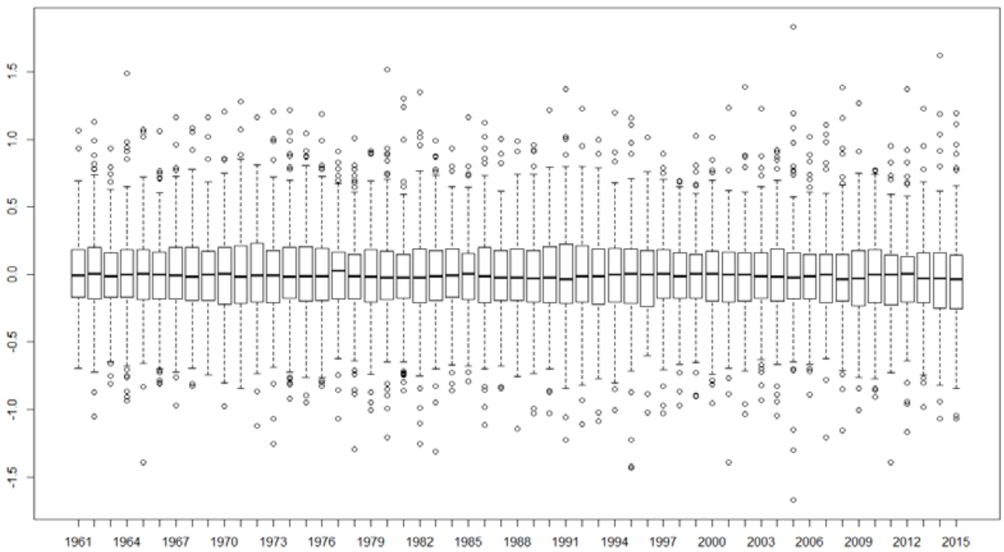

Figure 23: Annual variability in the two ratios described in figure 22.

When metadata varying in time is applied the general statistics shows the same characteristics. There is no systematic improvement of the estimates of precipitation when the input data are homogenized compared with estimations using non-homogenized data. Figure 24 shows the annual mean sums for all stations for the two input data series. There are only minor differences between them. Figure 25 shows the mean annual ratio between observed and estimated precipitation applying non-homogenized and homogenized input respectively. There are no systematic differences between the two series. In figure 26 and 27 are the mean ratios in relation to daily precipitation intensity presented. Figure 26 shows the result of the analysis applying constant metadata. There are small differences. Figure 27 compare ratios based on correct time variant and constant metadata. Also here are the differences small, but slightly in favour of the homogenized input.

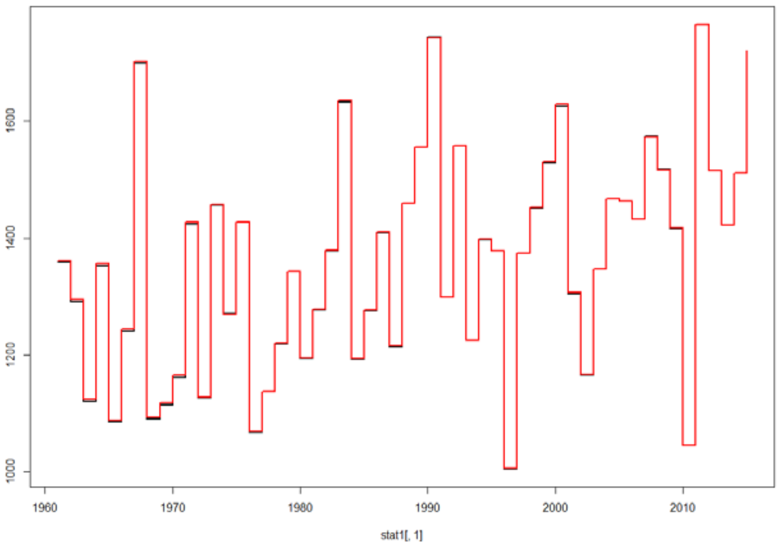

Figure 24. Annual mean sums of predicted precipitation for non-homogenized input data (black) and homogenized input data (red). Metadata are varying over time.

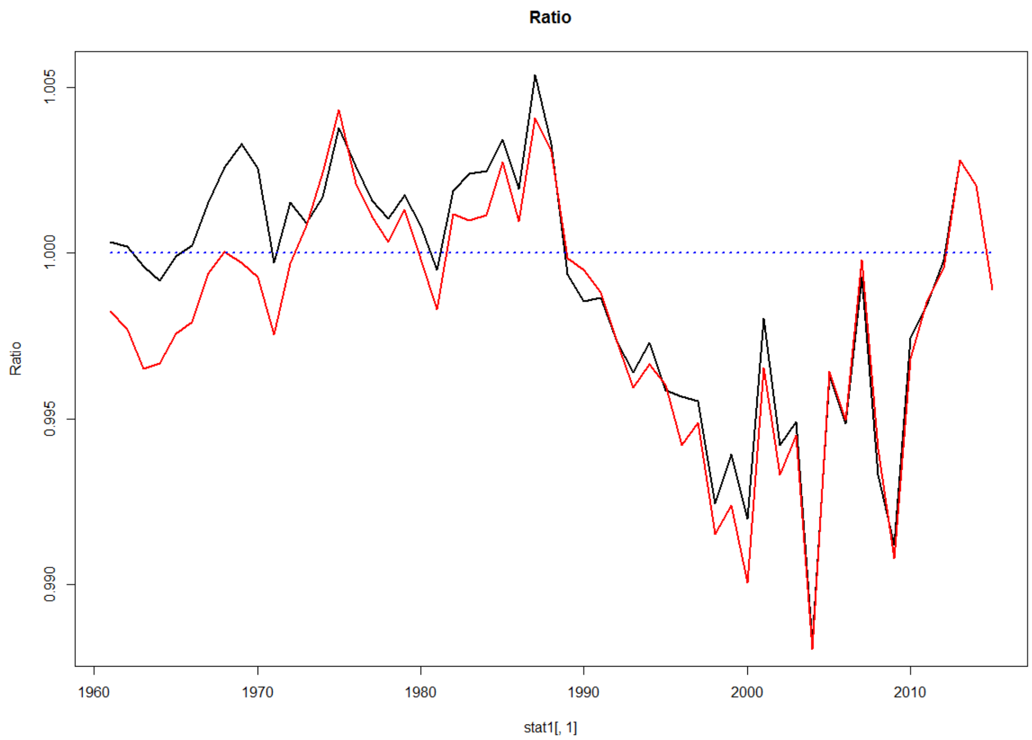

Figure 25: Annual ratio (obs/est) between observed and predicted precipitation. Black curve non-homogenized data, red curve homogenized data. Metadata are varying over time.

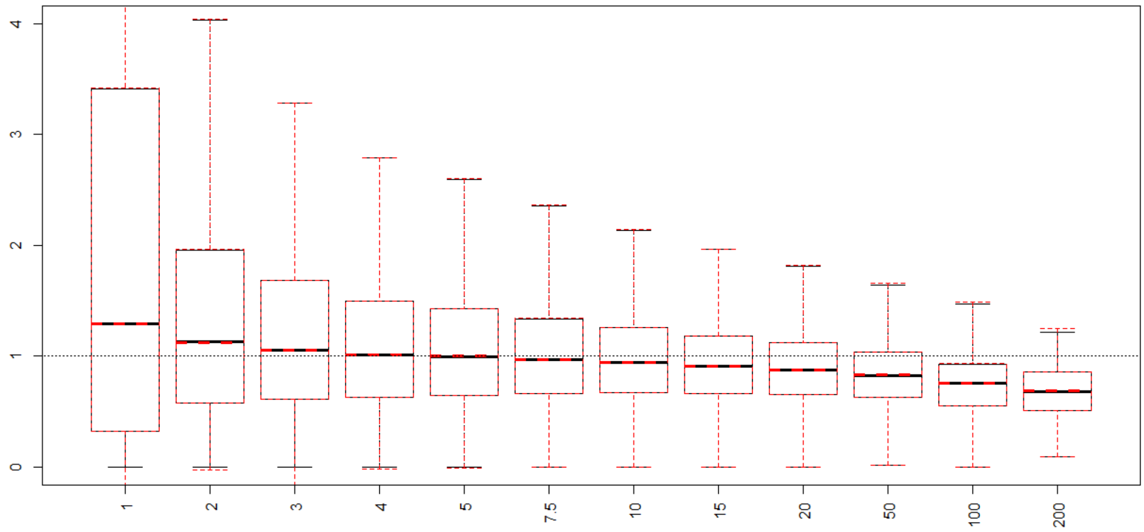

Figure 26: Distribution of ratio between observed and estimated precipitation applying constant metadata as function of precipitation intensity (mm/day). Black colour represent nonhomogenized data, red data homogenized data.

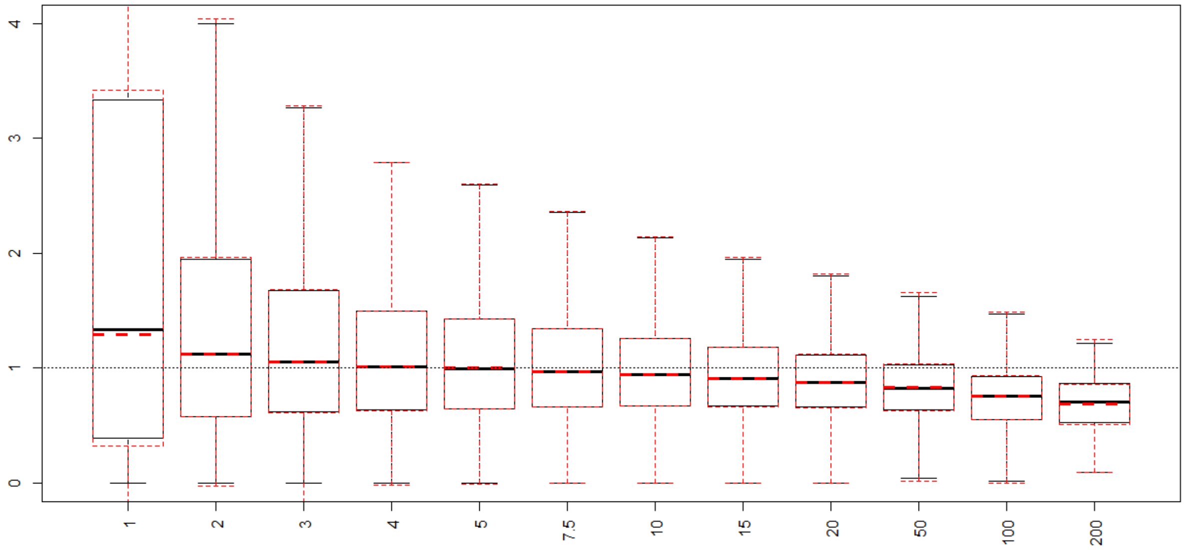

Figure 27: Distribution of ratio between observed and estimated precipitation as function of precipitation intensity (mm/day). Black colour represent non-homogenized data applying timevariant metadata, red data homogenized data applying time constant data.

5 Discussion and conclusions

This report presents an analysis of the effect of applying homogenized compared to non-homogenized input data for spatial interpolation with daily resolution. The results, based on leave one out independent cross validation shows very small differences between the different input data.

For temperature the best estimates are achieved when applying geographical metadata for the original non-homogenized observations. This indicates that the spatial interpolation algorithms in general better account for these characteristics than the homogenization procedures. Spatial interpolation algorithms are developed to describe local and regional spatial variations in temperature, while homogenization procedures are meant to better explain long-term variations.

For precipitation the differences for the input series also are small. The noise in the daily input series and the general uncertainty of the interpolation estimates are much larger than most homogeneity adjustments. On an annual scale they are about at the same order. Applying homogenized input for gridding does not generally improve the precision of the estimates.

Changes in the station network have locally a greater impact on gridding estimates than the homogeneity of the input series (Tveito, unpublished research), especially when the interpolation method include predictors representing local effects such as elevation. The effect of changes in the station network should be investigated further.

The homogenised data applied in this study are based on a homogenization of monthly temperature (Andresen, 2011) and precipitation series. The daily adjustments are linearly interpolated from monthly adjustment factors according to the principle presented by Vincent (2002). As described by Lundstad and Tveito (2016) are daily values related to the actual weather situation, and not to the climatology. The daily adjustment factors interpolated from monthly factors might therefore not be representative for all situations, and hence “weaker” when applied for spatial interpolation. Daily adjustment factors based on adjusting the temperature and precipitation distribution function should therefore be tested. So far only five Norwegian daily temperature series (Lundstad and Tveito, 2016) and five precipitation series (Lundstad, 2016) are homogenized according to this principle. It should be a goal to widen that analysis for all possible long daily temperature precipitation series.

Acknowledgements

Herdis Motrøen Gjelten and Elin Lundstad have contributed to this analysis by carrying out the homogenization of monthly precipitation series together with the author.

The study was carried out as a part of the collaborative MIST2 projects between STATKRAFT and MET Norway

References

Alexandersson, H., 1986. A homogeneity test applied to precipitation data, J. Climatol., 6, 661–675, 1986.

Andresen, L., 2011: Homogenization of monthly long-term temperature series of mainland Norway. Met.no Note 2/2011. Norwegian Meteorological Institute

Easterling, D.R. and Peterson,T.C., 1995. A new method for detecting undocumented discontinuities in minimum and maximum temperature, Atmos.Res, 37, 369-377

Lundstad, E. 2016. Homogenization of daily precipitation in Norway, MET Report 12/2016 Climate.

Lundstad, E. and Tveito, O.E. 2016. Homogenisation of daily mean temperature in Norway, MET Report 06/2016 Climate.

Mohr, M. 2008. New Routines for Gridding of Temperature and Precipitation Observations for “seNorge.no”, met.no NOTE 08/2008 (Available online: http://met.no/Forskning/Publikasjoner/metno_note_utgatt_serie/2008/filestore/NewRoutinesforGriddingofTemperature.pdf)

Szentimrey, T. 2008. Development of MASH homogenization procedure for daily data, Proceedings of the Fifth Seminar for Homogenization and Quality Control in Climatological Databases, Budapest, Hungary, 2006; WCDMP-No. 68, WMO-TD NO. 1434, 2008, pp. 116-125.

Szentimrey, T. 2011. Manual of homogenization software MASHv3.03, Hungarian Meteorological Service, pp. 64.

Tveito, O.E. and E. Førland. 1999. Mapping temperatures in Norway applying terrain information, geostatistics and GIS, Norsk geogr. Tidsskr. 53

Tveito, O.E., E.J.Førland, R.Heino, I.Hanssen-Bauer, H.Alexandersson, B.Dahlström, A.Drebs, C.Kern-Hansen, T.Jónsson, E.Vaarby-Laursen and Y.Westman. 2000. Nordic Temperature Maps, DNMI Klima 9/00 KLIMA

Tveito,O.E., Wegehenkel, M., Wel,F..v.d., Dobesch,H. 2008. “The Use Of Geographic Information Systems In Climatology And Meteorology”, COST Action 719 FINAL REPORT, COST Office, OPOCE 2008, ISBN-978-92-898-0045-7

Vincent L., Zhang X, Bonsal BR, Hogg WD. 2002. Homogenization of daily temperatures over Canada. Journal of Climate 15(11): 1322–1334