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A) Projektdaten

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B) Projektübersicht

1 Kurzfassung

Tägliche homogenisierte Daten bekommen für Studien über das Klima und den Klimawandel immer größere Bedeutung. Während der letzten Jahre wurden unterschiedliche Methoden entwickelt und getestet um tägliche Temperatur- und Niederschlagswerte zu homogenisieren. Doch auch andere Parameter gewinnen an Bedeutung. In diesem Projekt wurden unterschiedliche Homogenisierungsmethoden auf ihr Vermögen Tagesmittelwerte der relative Feuchte zu homogenisieren untersucht. Die relative Feuchte wurde ausgewählt, da dieser Parameter der Feuchteparameter ist, der von den Stakeholdern des Projektes am meisten genutzt wird.
Vier unterschiedliche Homogenisierungsmethoden, die schon in der COST-Action ES0601 für Temperatur und Niederschlag getestet wurden, wurden hier verwendet. Da die meisten dieser Methoden unterschiedliche Einstellungsmöglichkeiten bieten, wurden insgesamt 17 unterschiedliche Ergebnisdatensätze zum Evaluieren der unterschiedlichen Homogenisierungsmethoden erzeugt. Um eine objektive Einschätzung der Fähigkeiten der einzelnen Methoden zu bekommen, wurden Surrogatedatensätze mit unterschiedlichen Schwierigkeitsgraden erzeugt. Diese Datensätze spiegeln die statistischen Eigenschaften der relativen Feuchte und potentieller Brüche wider. Diese statistische Information wurde anhand von Parallelmessungen und Metadaten von Österreichischen Stationen gewonnen. Die Fähigkeit der Methoden zur Bruchdetektion und Bruchkorrektur wurde untersucht und die Methode mit den besten Ergebnissen verwendet um reale Stationsdaten zu homogenisieren.

Die besten Ergebnisse für die Bruchdetektion zeigten ACMANT und HOMOP. Für die Abschätzung der Qualität der von den einzelnen Methoden durchgeführten Korrekturen wurde der RMSE, die Varianz und der Trend genutzt. Im realistischen Fall zeigten dabei MASH und ACMANT die besten Ergebnisse.
Auf Grund der Ergebnisse in den Surrogate-Tests wurde ACMANT gewählt um 34 österreichische Stationen zu homogenisieren. Ungefähr die Hälfte der gefundenen Brüche konnte mit Metadaten in Übereinstimmung gebracht werden, ohne Einträge „Stationskontrolle“ zu berücksichtigen. Die Stationen beginnen analog zu den im ACRP-Projekt HOM-START homogenisierten Daten, je nach Messbeginn der Station, frühestens jedoch in 1948.
Die Analyse dieser Daten zeigte, dass die Trends sich durch die Homogenisierung verstärken, wobei eine negative Steigung besteht. Die Homogenisierung führte auch zu höheren Medianen der relativen Feuchte in den unterschiedlichen Monaten.
Gemeinsam mit den Stakeholdern wurden Analysen der relativen Feuchte in Kombination mit Temperatur, Globalstrahlung und Schadstoffen durchgeführt. Für einige der Auswertungen war nur eine Datenbereitstellung notwendig.
In Zukunft werden noch weitere Verbesserungen in den Homogenisierungsmethoden notwendig sein. Im Moment berücksichtigt ACMANT noch keine Metadaten und es gibt keine Möglichkeit den Zeitpunkt des Bruches zu beeinflussen. Außerdem gibt es keine Information über die Unsicherheit der Ergebnisse. Eine Kombination der Vorteile von ACMANT mit denen von HOMOP scheint daher wünschenswert. Außerdem wären Untersuchungen notwendig, über die gemeinsame Verwendbarkeit von unabhängig voneinander homogenisierten Parametern wünschenswert.

2 Executive Summary

Daily homogenisation is of more and more importance for climatological studies. During the last years, the abilities of different methods to homogenise daily data of temperature and precipitation have been developed and tested. Nevertheless, other parameters such as humidity can also be important and therefore different methods have been tested in this project for their ability to homogenise this parameter. From all the possible humidity parameters, relative humidity (daily average) was chosen, as this parameter is the most widely used by the stakeholders of the project. Humidity is not only of climatological importance, but also has an influence on building materials, different plants and the ability to produce artificial snow.

The four different homogenisation methods used have been used in the past in the COST-Action ES0601 and tested for temperature and precipitation. As most of the methods can be used with different settings 17 different results for the homogenisation tests have been produced. In order to get an objective estimate of the ability of the different methods, a surrogate dataset containing different difficulties, was created. This dataset reproduced the statistical characteristics of relative humidity (daily average) and possible breaks. This statistics resulted from

studies of parallel measurements and the available metadata of the Austrian stations (including number of relocations and instrumentations changes). The ability of break detection and correction has been analysed. Afterwards the best of these methods has been implemented to homogenise real Austrian station data.
Furthermore, the relative humidity data, together with the homogenised temperature data of the ACRP HOM-START project (K09AC0K00025) was used for different analyses done together with the stakeholders and in climatological studies showing the effect of the homogenisation.

Due to the small break signal in the relative humidity time series, the detection of these breaks is challenging using all the methods. The highest efficiency in detecting breaks was found for ACMANT and HOMOP. For the assessment of the quality of the correction of time series the parameters RMSE, variance and trend deviations have been used as criteria. ACMANT and MASH showed the best correction results in the realistic case of the surrogate data.
Due to its ability to accurately detect and correct, ACMANT was chosen for homogenising the Austrian relative humidity data. A homogenisation of 34 stations was possible. Without taking individual station inspection into account, about half of the breaks found in the time series could be confirmed by metadata like relocation or instrumentations changes.
The analyses of the homogenised data showed that the trend in most of the time series grew stronger, having a negative slope during the measuring period of the individual time series, starting in 1948 in the earliest for these homogenisations. This is in agreement with the dataset homogenised in HOM-START, where the same maximal starting year was used and the same pool of stations was homogenised. The homogenisation led to higher medians of relative humidity during all months of the year.
For the analyses of the stakeholders data of relative humidity, minimum and maximum temperature and global radiation data was prepared. For some of the stakeholders, only data preparation was done (including the choice of possible stations), as they preferred not to give away their own data. For the others, correlations to pollutants and the height gradients of relative humidity were analysed.
In the future, further improvements in homogenisation methods might be needed. At the moment, metadata is not included in ACMANT and there is no possibility to influence the break timing chosen by the software. Moreover, no uncertainty measures are available. A combination of the advantages of ACMANT with the advantages of HOMOP seems desirable. Additional analyses of the possibility to use datasets of different parameters homogenised with different methods together would be necessary.

3 Hintergrund und Zielsetzung

To achieve reliable results on the development of the past climate, it is necessary to use well-homogenised data. Homogeneous datasets are influenced by climate alone. Original observational data includes effects caused by station location, used instrumentation, the observer, etc. (Aguilar et al. 2003).
To remove those effects, statistical methods are applied to adjust data from earlier periods to the current situation of the station. This process is called homogenisation.
Homogenisation has already been performed for different parameters on monthly resolution since about 20 years. During the last years the interest in and the activity for homogenised daily data increased (e.g.: COST-Action ES0601 www.homogenisation.org)
In contrast to temperature and precipitation, which have been in the focus of daily homogenisation until now, relative humidity shows a strict upper and lower limit of possible values and the values have limited range. Therefore only small, but nevertheless potentially important, breaks are to be expected, as bigger breaks can be found by data quality control and technical support easily and have been removed earlier. Moreover, instrumentation of relative humidity measurements is changed more frequently than that of other parameters. Therefore homogenisation methods for relative humidity have to be able to detect small but potentially frequent breaks.
This project aimed to test different methods used for homogenisation of daily data and used within the COST-Action ES0601 on their ability to meet the requirements for homogenising daily relative humidity. If a successful method could be identified, a set of Austrian stations (STARTCLIM-dataset) was to be homogenised. As for those stations where daily temperature extremes and precipitations were already homogenised, this additional homogenised parameter is especially valuable.
In addition, analyses with these data concerning climate change and the effect of the homogenisation itself have been done as well as analyses that were performed in cooperation with stakeholders.

4 Projektinhalt und Ergebnis(se)

In this project a surrogate dataset for relative humidity was created, different homogenisation methods tested and one of them chosen for homogenising Austrian relative humidity data.

A surrogate dataset is a dataset of artificially created data, that has the statistical properties of real data. The characteristics of the homogeneous data are the statistical probability distribution and the cross- and auto-correlations. Inhomogeneities are added to this data.

- *Analysis of real station*

In order to get information on the size of possible inhomogeneities, parallel measurements for different stations in Austria were analysed to collect information on differences in the distribution of measured values during the different seasons and the year. The stations used are listed in Table 1.

Table 1: List of stations used for analyses of parallel measurements

station	***start***	***End***	***station***	***start***	***End***
Kremsmünster	19880101	20081231	Amstetten	19701001	19771130
Salzburg	19920201	20060331	Retz	19940101	19950531
Innsbruck	19920701	20130526	St.Pölten	20030701	20050630
Bregenz	19930101	20130331	Waidhofen	20021001	20041231
Feuerkogel	19891001	20081231	Jauerling	19940101	19950630
Patscherkofel	19930819	20080101	Mallnitz	19870220	20020801
Sonnblick	19881101	20081231	Sillian	19960901	19990930
Kufstein	19920601	20021231	Leibnitz	19941203	20041231

Additionally, the number and temporal distribution of breaks (based on station relocations and changes of instrumentation) was analysed by the study of metadata for the stations distributed over Austria.

Moreover, 6 networks of 4 to 6 highly correlated Austrian stations were created, which represent different regions of Austria (Figure 1). For those networks, a homogeneity test was executed on the monthly data with HOMER (Mestre et al., 2013), created within the COST-Action ES0601. This data was used in the following to create surrogate datasets with 100 years of length in different complexities by the project partner Victor Venema at the University of Bonn. For details on the creation of the surrogate dataset see chapter 6 in part C.

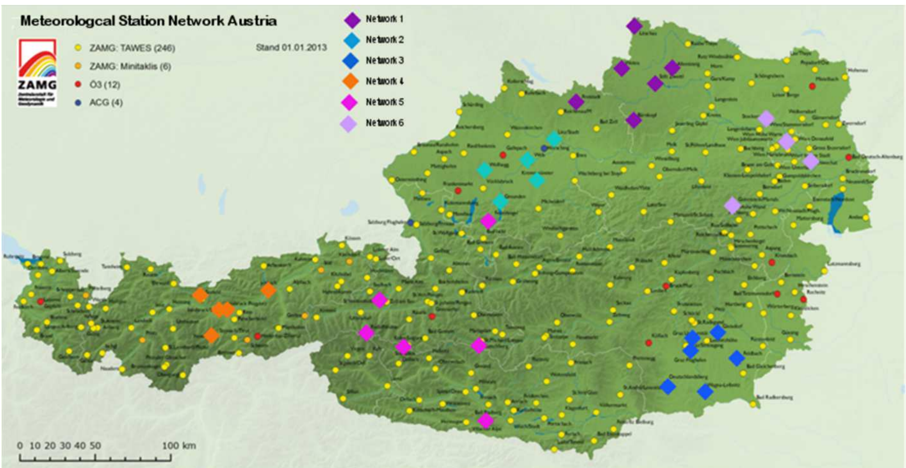

Figure 1: Networks used for Surrogate dataset

- *Handling of simultaneous breaks*

At the turn of the year 1970 to 1971, the evening observation in the whole meteorological network of Austria was changed from 9pm to 7pm. As this was done simultaneously, no relative homogenisation can be applied. Therefore an alternative method for adjusting these breaks was developed using hourly data for training and validation. To adjust the 9pm value, different methods like spline interpolation, similarity approach (Brandsma and Können, 2006), linear interpolation between the adjacent measurements, multiple linear regression model and seasonal multiple linear regression model were tested. The best results were achieved using the seasonal multiple regression model, using the measurements of this day and the 7am measurement of the following day as well as the time of sunrise and sunset. The original range of RMSE for those stations was reduced from -0.5% to 3% to the range of -0.5% to 0.5%.

Nevertheless, the coefficients seem to depend on small scale features, so that no general coefficients could be found. Therefore only those stations for which hourly values are available before and after 1971 could be corrected. Only 17 stations have been corrected in this manner. The corrections vary between ±11%, with one third of the corrected data points needing no correction (Figure 2).

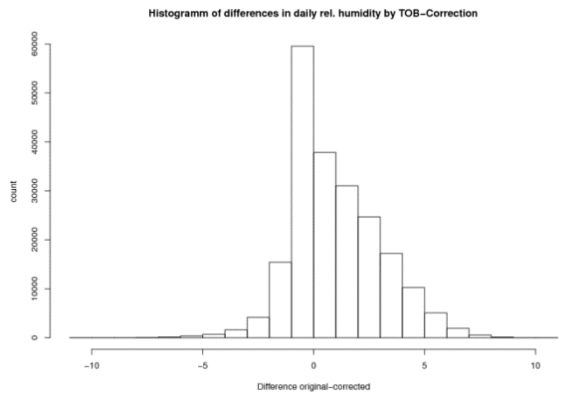

Figure 2: Histogram of differences between time of observation bias corrected data points and original measurements of daily relative humidity

- *Break detection*

For details on the different homogenisation methods have a look at chapter 6 in part C.

In Figure 3, an example of the break detection for a time series in the deterministic surrogate dataset is shown. In the upper part of the figure, the inhomogeneities of the different breaks of this time series is shown as a function of the measured value and for the different seasons. The timing of the breaks can be found on the x-axis. The multicolour circles in the middle part of the plot show which method detected this specific break and in the lower part all the breaks detected by the different methods are displayed (colours following the same code as the multicolour cycles. A break is defined as detected as soon as the detection takes place in the according year or +/- 1year. The detection, e.g. in MASH, is done for each month separately; therefore the number of detected breaks is higher than e.g. for HOMOP. This was taken into account by only using one break per year for MASH. Breaks in neighbouring years were not counted as more than one if they could be attached to one and the same break of the surrogate dataset.

The ability in detection was calculated using the detection efficiency (Domonkos et al., 2011). The efficiency is defined as the ratio of correctly and falsely detected breaks to the number of searched (inserted) breaks:

$$E_D = \frac{\#breaks_{correct} - \#breaks_{false}}{\#breakes_{inserted}}$$

In the case that all breaks are correctly detected and no additional breaks are detected, E_D is 1. For those methods that detect the breaks for each month separately (PROCLIM, MASH), the E_D-values are strongly negative (Figure 5). A distinct improvement can be noted between MASH and MASHeingriff. Nevertheless, the efficiency stays negative for most of the time series. There are differences between the different detection methods of PROCLIM. In contrast to the other methods, the bivariate method shows a positive efficiency for most of the time series.

Looking at differences in the different networks, it can be noted that the homogenization of network 5 gave the worst results and the homogenization worked best for network 4 and 8 in the deterministic case. Regardless, network 5 shows the best, but still negative results, for 2 methods. MASHeingriff improves all the networks in comparison to MASH.

In accordance with expectations, the detection efficiency for realistic networks is less than for the deterministic ones, as the detection is rendered more difficult by missing values, additional noise and different length of the time series.

In the deterministic and the realistic case the methods ACMANT and HOMOP show the highest detection efficiency.

All the methods classified some of the series as homogeneous. Most time series wrongly described as homogeneous occurred with HOMOP taking into account the deterministic and the realistic networks. Taking a look at the deterministic networks alone, MASHeingriff classified more time series wrongly.

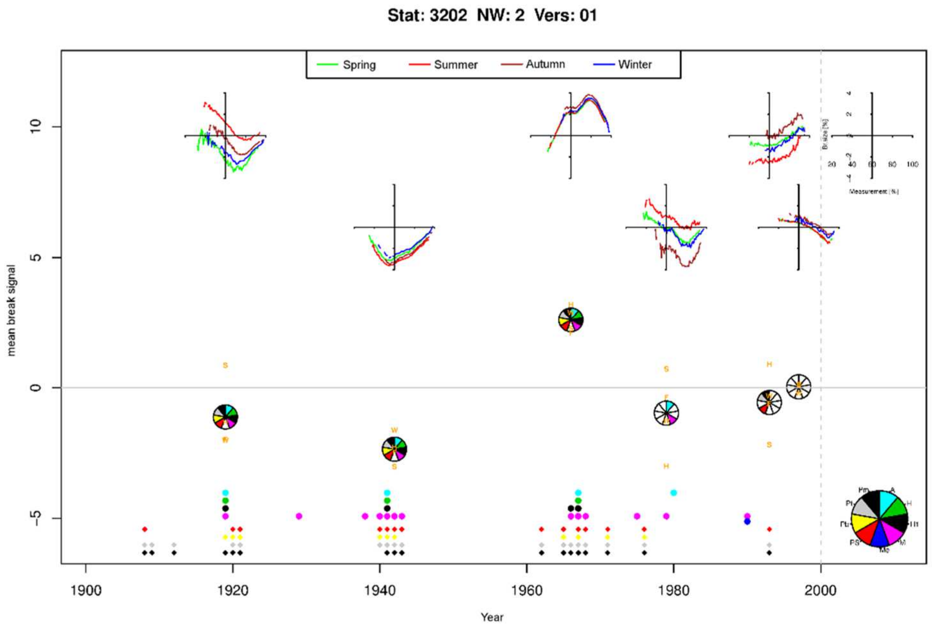

Figure 3: Examples of break detection of different methods: line plots in the upper part: structure of the induced break for different seasons (legend above) for the different breaks in the year (x-axis), in which the centre of the plot is plotted. The legend for the axis of the plots can be found on the right of the vertical line in 2000). Middle part: Colours of this pie chart show which of the methods have detected a break in this year (± 1year). The height of the centre of the circles indicates the yearly mean break size (see y-axis for the value) for the year. The orange letters give the mean break size for the seasons (F…spring, S…summer, H…autumn, W…winter). The legend for the pie chart is given on the lower right site of the vertical line in 2000.

Abbreviations for the Methods: A…ACMANT, H…HOMOP, H1…HOMOP with changed break criteria, M…MASH, Me…MASH with interaction, PS….PROCLIM , Pb….PROCLIM bivariate, Pt…PROCLIM t-Test, Pm…PROCLIM merged). The lines of dots in the lower part give the information about all detected breaks by the methods (colours are the same as in the pie chart, diamonds indicate the 4 PROCLIM versions).

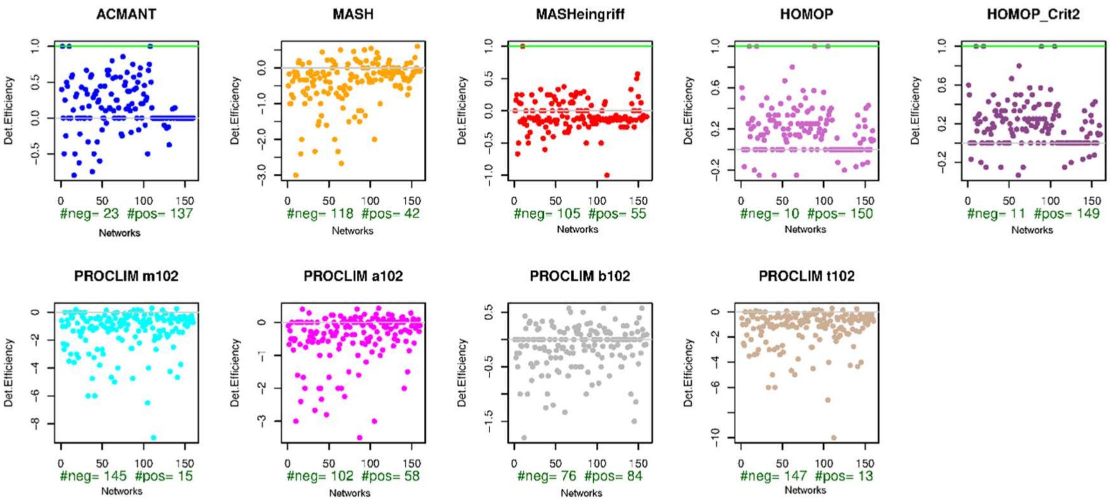

Figure 4: Detection efficiency for all time-series for the different detection methods in the deterministic cases

Additionally, an analysis using ACMANT, MASH (automatic version only) and HOMOP was performed on the homogeneous time series, to see if those would be defined as homogeneous by the methods. All of the methods detected breaks, but their number was roughly an order smaller than in the inhomogeneous case.

- *Break characteristic*

A further analysis was done in order to gain understanding of which characteristics the breaks found by the different methods would have to meet. The size of the break signal, the correlation within the network and the clustering of the breaks within the time series itself and in combination with breaks of the reference stations were taken into account. In order to keep this idea as simple as possible, only the deterministic validation datasets were used. The break was classified as “clustered” if more than one break lay within a time window of 5 years.

Only 4 breaks in the surrogate dataset were not clustered with breaks in the reference time series and those occurred at the beginning of the time series (between 1901 and 1909). Half of them were not detected by any method, the other half was detected by 3-4 methods. About ¾ of all the breaks were additionally clustered with breaks of the time series itself.

The percentage of correctly detected breaks increases with the correlation within the network. Moreover, the ratio of correctly detected breaks increases with the absolute value of the ratio of break size to the variance of the time series. In the case of the surrogate dataset of relative humidity most of the breaks have a signal about the same size as the variance.

- *Break correction*

Not all methods have been able to provide complete solutions for all the networks, as for some methods and stations the correlation of the reference series was not sufficient. In the realistic case, the final quality control by MASH had to be skipped as the number of reference stations was not sufficient in these cases. The number of not solvable stations stays nearly the same in the deterministic and realistic case. Most problems had ACMANT and PROCLIM. However PROCLIM was not used in the realistic case for break correction as it gave the worst results in the deterministic case and moreover did not work satisfactorily on all computers.

The improvement by homogenization of RMSE, variance (time series with removed annual cycle were used in this case) and trend of the homogenized time series were analysed. For RMSE and variance, only the part of the time series in which differences should/did occur was taken into account. Therefore the data between the newest break point (first detected or introduced in the surrogate dataset) and the beginning of the time series (oldest data point) was used. This causes slight differences in the length of the analysed time series with the different methods, but as only means are compared these differences seem of no consequence. The advantage of this method is that long homogeneous parts at the end of the time series (most current data) do not influence the results. All time series for which a homogenization result was achieved were taken into account, including time series classified as homogeneous by the homogenization method.

Trends in relative humidity are (if existing) very small and not significant, but as the improvement of trends is one of the declared goals of homogenization, this parameter was also looked at.

Following Domonkos et al. 2011 the RMSE-efficiency and the trend-efficiency were calculated:

$$RMSE_{Efficiency} = \frac{RMSE_{original} - RMSE_{homogenised}}{RMSE_{original}} * 100$$

$$Trend_{Efficiency} = \frac{(\Delta Trend_{original}) - (\Delta Trend_{homogenised})}{(\Delta Trend_{original})} * 100$$

Only ACMANT could solve the bigger part of the stations with a positive RMSE-efficiency (Figure 5) in the deterministic cases. The ratio between positive and negative efficiencies is similar between HOMOP and MASH. PROCLIM gives the worst values of RMSE-efficiency and only a small portion of the stations can be improved.

In the realistic case ACMANT results in the highest number positive influenced time series (about half of the time series). All other methods did not improve a single time series.

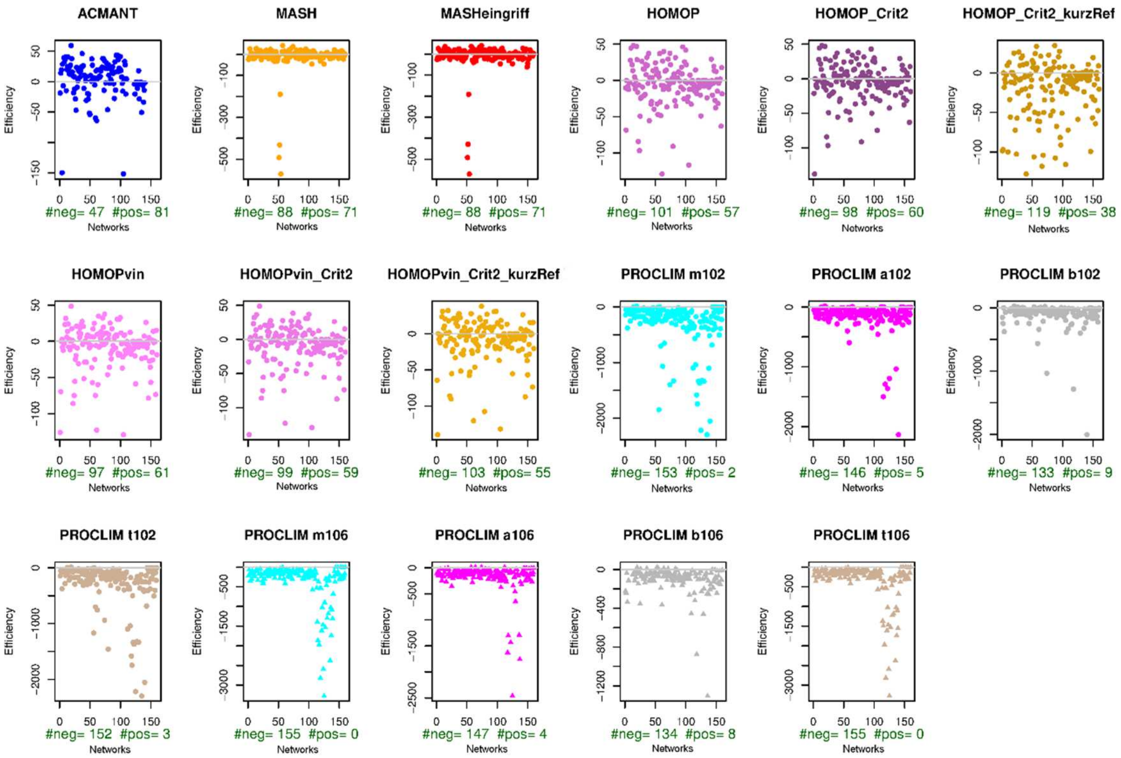

Figure 5: RMSE-Efficiency for all time-series in the deterministic networks for the different homogenisation methods. Green shows the number of time series with negative and positive efficiency. Time series with no change in the RMSE are not included there.

In the case of trend-efficiency, all the methods improved about 1/2 to 2/3 of the time series. The best results are reached by ACMANT and HOMOP using spline corrections with the complete reference period. The highest number of negatively influenced time series resulted from PROCLIM using monthly correction with the breaks resulting from the break detection methods t-test and merged. In the realistic case MASH improves most time series (improved: 116/worsened: 44).The ratio of ACMANT is comparable, but less stations have been homogenised by this method (improved: 91/worsened: 43). HOMOP shows the worst results with only about half the stations improved.

A comparison of the differences of the variance between the optimal solution and the homogenised time series resulted in the deterministic cases in nearly no changes compared with the inhomogeneous data for MASH, MASHeingriff and HOMOP with Vincent correction, short reference period and the lighter break definition. All the other methods show a broader distribution with more extreme differences in the variance of the optimal solution.

In the realistic case, it is still MASH that shows the smallest median of differences, but MASH is also worsening some of the time series. Once again, the human influence made MASH results slightly worse. When using ACMANT, the median of the homogenised series is similar to the median in the inhomogeneous cases, but some outliers show distinctly higher differences. The HOMOP methods give the worst results, showing an increase of variance in most of the time series.

- *Homogenisation of Austrian time series*

As can be seen in the results of the tests with surrogate data, only MASH and ACMANT show an ability for homogenising daily averages of relative humidity. Therefore those methods were tried for homogenising real station data.

Networks of 4 stations were built, of which all had a correlation of at least 0.6 and were located within a radius of 200km horizontal and 200m vertical. The period for homogenisation was chosen according to the already available data, starting in 1948 when possible. The period had to be shortened for some stations.

MASH and ACMANT were able to provide solutions for those networks. The choice of the final homogenisation method used in this project was therefore taken somewhat subjectively, as MASH detected the first breaks right at the beginning of the time series, which resulted in very short reference periods. Moreover, the test showed that ACMANT improves the RMSE better than MASH and gives similar results in the improvement of the trends. As relative humidity is often used in combination with other parameters, the improvement of RMSE seems quite important. *Thus, although MASH has the advantage of including information on metadata and therefore of possible break points, ACMANT was chosen.*

Table 2: Information on the homogenised stations and the homogenisation result: For breaks written in orange colour meta-information within +/-1year can be identified (in case of Hohenau, no long term metadata was available). As valid metadata changes in the humidity instrumentation, changes in the observer and relocations (or the documented construction of building in the surrounding) were used. Station numbers written in blue mark those stations for which a correction of the change in observation time has been done. The subjectively determined quality of the homogenisation is given in colour code (green: ok, orange: ~, red: bad)

Station Nr.	Station (lon,lat,height[m])	# stat in network	quality & comment	# breaks
90500 (1948-2013)	Retz (15°57‘,48°46‘,320)	15		6 (1977,1990,1992,1994,1997,2000)
140100 (1960-2013)	Kollerschlag (13°50‘,48°36‘,714)	14		9 (1967,1973,1979,1981,1988,1991, 2001,2002)
160100 (1948-2013)	Freistadt (14°30‘,48°30‘,539)	11		7 (1953,1958,1971,1989,1991,1998, 2001)
240000 (1956-2013)	Laa/Thaya (16°23‘,48°44‘,184)	19		11 (1963,1967,1968,1979,1983,1986, 1991,1993,1997,2003,2009)
260000 (1949-2013)	Hohenau (16°54‘,48°37‘,154)	16		6 (1949,1952,1959,1962,1969,2007)
290000 (1949-2013)	Reichersberg (13°23',48°20',351)	12		12 (1950,1955,1958,1962,1965,1976, 1979,1985,1988,1995,2000,2004)

341000 (1948-2013)	Pabneukirchen (14°40',48°21',554)	14		6 (1954,1957,1976,1982, 1989,2004)
380500 (1948-2013)	Krems (15°37',48°25',203)	22		2 (1973,1995)
501200 (1948-2013)	Kremsmünster (14°08',48°03',382)	17		8 (1954,1962,1989,1992,1996,2001, 2004,2008)
590400 (1948-2013)	Wien Hohe Warte (16°21',48°15',198)	16		5 (1962,1970,1987,1991,1993)
599000 (1948-2013)	Schwechat (16°34',48°07',183)	13		4 (1971,1983,1994,2011)
630000 (1948-2013)	Salzburg (13°,47°48',430)	18		9 (1954,1962,1968,1971,1979,1987, 1994,1998,2010)
691000 (1953-2000)	Großraming (14°31',47°54',379)	8	few ref. in early years	6 (1956,1968,1973,1983,1985,1997)
770400 (1976-2013)	Eisenstadt (16°32',47°52',184)	15		4 (1985,1988,1996,2003)
964000 (1963-2013)	Bad Aussee (13°46',47°37',743)	12		4 (1975,1979,1983,1995)
1180300 (1948-2013)	Universität Innsbruck (11°23',47°16',577)	9	few ref. in early years	2 (1971,1979)
1190100 (1956-2013)	Jenbach (11°45',47°23',530)	14		11 (1962,1968,1970,1976,1977,1982, 1986,1997,2003,2009,2010)
1232200 (1948-2013)	Zell/See (12°48',47°20',751)	17	few ref. in early years	7 (1968,1975,1985,1989,1996,2001, 2005
1500100 (1948-2013)	Mayrhofen (11°51',47°10',640)	11		8 (1955,1964,1967,1976,1980,1992, 2004)
1540200	Rauris (13°,47°13',941)	16	few ref. in early years	8 (1961,1964,1977,1984,1989,1993, 1999,2003)
1571200 (1984-2013)	Tamsweg (11°35',47°08',1025)	7		3 (1997,2008,2010)
1591000 (1952-2013)	Stolzalpe (14°11',47°07',1291)	8	few ref. in early years	3 (1980,1997,1999)
1630000 (1961-2007)	Lobming (15°11',47°03',414)	9		4 (1975,1985,1994,1999)
1640000	Flughafen Graz	13		4

The networks

were

(1965-2013)	(15°26',47°,340)			(1971,1990,1997,2000)
1641200 (1965-2013)	Universität Graz (15°27',47°05',367)	12		10 (1968,1973,1978,1980,1983,1986,1992,1996,1999,2003)
1650000 (1961-2013)	Gleisdorf (15°42',47°07',377)	14		5 (1977,1984,1992,1998,2005)
1671100 (1955-2013)	Wörterberg (16°06',47°14',404)	19		7 (1963,1973,1981,1986,1997,2003,2008)
1770000 (1948-2013)	St. Jakob/Defreggental (12°21',46°55',1383)	5	too few ref.	2 (1996,1997)
1790100 (1948-2013)	Lienz (12°48',46°50',661)	13	few to no ref. in early years	7 (1965,1973,1986,1990,1995,1998,2004)
1810000 (1955-2001)	Kolbnitz (13°19',46°52',603)	12		4 (1957,1963,1967,1988)
1880500 (1951-2013)	Preitenegg (14°55',46°56',1034)	8	few ref. in early years	7 (1969,1993,1998,2001,2004,2007,2009)
1980000 (1961-2013)	Reisach (13°09',46°39',646)	9	few ref. in current years	5 (1971,1974,1986,1988,1995)
2021200 (1964-2013)	Klagenfurt (14°19',46°39',450)	16		7 (1967,1975,1976,1998,2006,2008,2010)
2040000 (1961-2013)	St. Michael ob Bleiberg (14°46',46°34',532)	19		5 (1980,1986,2007,2009,2011)

expanded with further reference stations to improve the homogenisation results.

In Table 2, the stations for which a homogenisation was possible are displayed along with their coordinates, the number of reference stations used (not all of them where available through the whole period) and some information on the homogenisation and the data series.

Some stations were excluded as the available time series was too short, too incomplete or because a sufficient number of reference stations was not found. An example of the homogenisation is displayed in

Figure 6.

The quality of the homogenisation has not been assessed by the software so far. Therefore all time- series are to be called homogenised; nevertheless the quality of the homogenisation was subjectively determined by the length and number of available reference series.

The change in the observation time in 1971 may still be found in some of the stations. This is especially true for those stations that have been corrected for this change. As ACMANT doesn't offer the possibility to influence the used break points, the influence of the not corrected stations cannot be counteracted.

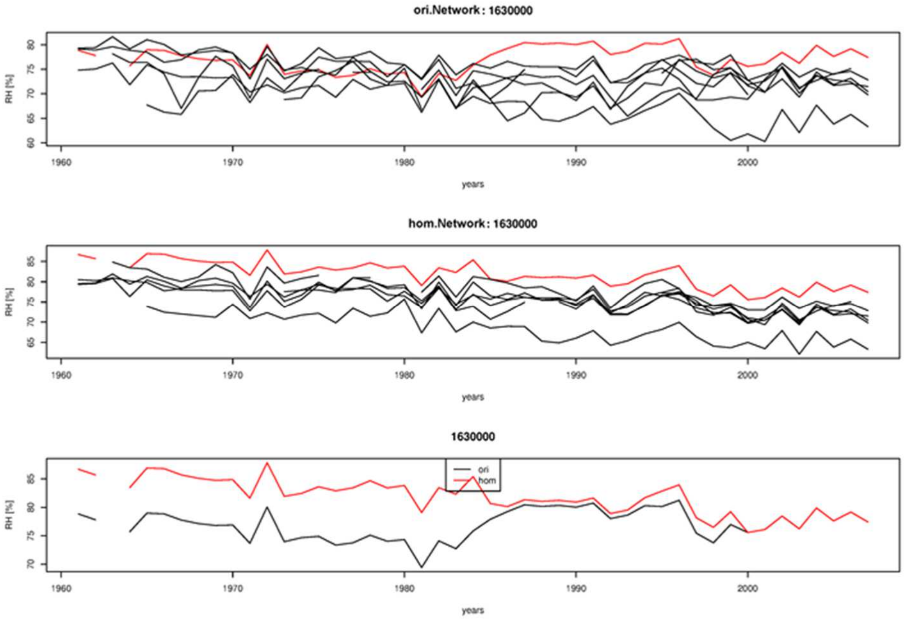

Figure 6: Example of a real homogenised time series (Lobming). Upper panel: original data (Lobming: red) and reference series (black); middle panel: as upper panel but homogenised data; lower panel: Lobming original data (black) and homogenised (red). Displayed annual means.

- *Analyses of relative humidity*

In cooperation with 4 stakeholders analyses of relative humidity showing the large potential of humidity series.

Where possible and necessary, homogenised temperature values of the project HOM-START (www.zamg.ac.at/cms/de/forschung/klima/datensaetze/homstart; Nemec et al. 2012) have been used and were prolonged by original data for the recent years. Daily mean temperature was calculated by averaging T_{min} and T_{max}. For relative humidity in the original data, time correction was applied where possible and necessary.

The annual cycle (on daily base) and trend has been removed for all time-series (if not stated otherwise below) for correlations. Both actions have been taken to remove "wrong" correlation information as all parameters are influenced by the annual cycle and trends. Without removing those effects, the correlation would be higher than by looking at the signal of the parameter itself (Table 4). As not all the parameters are normally distributed, the spearman's rank correlation has been used. The statistical significance is given by the p-value.

The analyses were repeated with the homogenised data if necessary, but no essential changes occurred.

The first cooperation took place with Prof.DI.Dr. Hans-Peter Hutter of the Medical University of Vienna. He was interested in the influence of relative humidity and temperature on the concentration of air pollutants NO2 and PM10 in urban regions. The cities of Graz, Linz and Vienna were chosen. Further investigation concerning physical health indicators like the number of discharges from hospital and mortality (cardiovascular and respiratory), will be done by the stakeholder himself if necessary.

The data on NO2 and PM10 was provided by the Federal government of Styria, Upper Austria and the Conservation department of the Vienna city administration.

Information on NO2 and PM10 concentrations is not available at the same locations as the meteorological data. The locations of the stations used are given in Table 3.

Table 3: Location of stations used for investigation of pollutants and meteorological parameters

city	meteorological	NO2	PM10
Graz	Graz airport	Graz/Sued Tiergartenweg	

Linz	Hörsching	Traun/Tischlerstraße	
Vienna	Hohe Warte	Hohe Warte	Wien/Schafbergbad

The correlations between the meteorological parameters and the pollutants have been calculated (Table 4) for the time period for which the data of the pollutant was available.

Differences in the correlation can be seen according to seasons. Additionally, a delay can be found for some of the time series, resulting in higher correlations when calculating the correlation between the pollutant and the meteorological value of the following day. The influence of season and shift differs for the different locations.

Table 4: Spearman correlation between the time series of relative humidity/temperature and air pollutants (first value in column "correlation" and "significance" for original data, second value for time series with removed annual cycle and trend; statistically not significant correlations are marked with an "-")

city (pollutant)	Investigation period	Correlation (RH)	Significance (RH)	Correlation (T)	Signifi-ance (T)
Graz (NO2)	20030425 - 20140531	-0.60/-0,01	0,1%/-	0.31/-0,05	0,1%/0,5%
Vienna (NO2)	19880101 - 20140531	-0.30/0,07	0,1%/ 0,1%	0.22/0,07	0,1%/ 0,1%
Linz (NO2)	19900101 - 20140531	-0.44/0,01	0,1%/ -	0.24/-0,05	0,1%/ 0,1%
Graz (PM10)	20030425 - 20140531	-0.51/0,07	0,1%/ 0,1%	0.29/-0,04	0,1%/5%
Vienna (PM10)	20020412 - 20140531	-0.26/-0,00	0,1%/-	0.15/0,08	0,1%/ 0,1%
Linz (PM10)	20001212 - 20140531	-0.20/0,04	0,1%/0,5%	0.01/-0,13	-/ 0,1%

The correlations between meteorological data and concentration of air pollutants do not include quite important processes that influence the air pollutants. In the case of PM10, the main influencing factors are distant sources of air pollutants and their advections by large-scale atmospheric conditions, or also neighbouring sources like construction sites or winter road gritting. Moreover, in this analysis no distinction between potential periods with and without temperature inversions was drawn.

In the case of NO2, chemical reactions have an influence on the concentration of the pollutant as well as local influencing factors (e.g. road traffic, which might explain the period of small concentration around Christmas holidays)

The second analysis was done for Dr. Meinhard Breiling of the Technical University of Vienna. His research is focused on the artificial snow production and therefore his interest lies in the climatological information on the conditions to produce snow. In this project an analysis on monthly and seasonal (winter half-year: October to March) basis of vertical gradients of air temperature and relative humidity between stations pairs (Table 5) was done.

To reduce the possibility of breaks in the high level station, for which no homogenised data is available, a common period (19970101-20081231) was chosen for all stations for which no relocations took place.

Table 5: Information on stations used for vertical gradients

Low level station	Height [m]	High level station	Height [m]
Graz university	366	Schöckl	1436
Innsbruck university	578	Patscherkofel	2251
Rauris	934	Sonnblick	3109

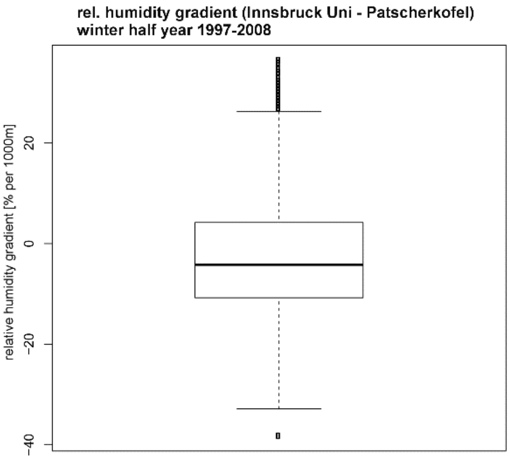

Figure 7: Boxplot of daily gradients of relative humidity [%/1000m] for Innsbruck University and Patscherkofel for winter half year

Looking at the differences between high and low level stations the medians for the months and season are, with the exception of January, negative for Rauris and Sonnblick, meaning that relative humidity is predominantly higher at high elevations. The lowest medians are exhibited in February and March.

For temperature, as expected, values at higher stations are lower than at lower stations. Negative values occur only seldom and are small. As only two stations have been used for these analyses no information about the height of inversions was available. As radio sounding data cannot be used easily as a comparison for daily means, no further attempts in this direction were made. The station pair Graz/Schöckl shows the highest percentage of positive temperature gradients (10% of the days). The height between these stations seems therefore to be not too far from the height of usual temperature inversions, as the effect was not counterbalanced by the usual temperature reduction by height. The most/strongest temperature inversions occur in December and January.

As only the winter half year was analysed no correction for annual cycle and trends have been done when calculating the correlations (Spearman) between temperature and relative humidity gradients.

For the other two stakeholders (Dr. Thomas Bednar of the Technical University of Vienna, and Dr. Thomas Cech of the Federal forest research centre (BFW)), only data preparation was necessary, as both of them wanted to use the data not available for the public within their own software.

In the case of Dr. Bednar, the topic of the investigation was the influence of daily T_{min} and T_{max}, relative humidity and global radiation on construction materials.

The topic of Dr. Cech is the dieback of ash trees in Austria and therefore correlation with relative humidity is of importance. The investigations focus on Lower Austria, as monitoring data of the dieback is available there for 2000 to 2006. Moreover, regional gradients from west to east should be analysed.

Stations were chosen that were located as closely as possible to the BFW monitoring areas in a similar elevation distributed across Lower Austria from west to east.

Beside analyses done in cooperation with stakeholders additional analyses have been performed. The trend of all stations is influenced by the homogenisation (Figure 8). All trends in this figure are calculated using all available data for the stations, therefore the differences in the trends are influenced by the time span that was available.

Before homogenisation, more than 10 stations showed a positive trend, and after homogenisation only three stations (1500100, 177000 and 964000) show a positive trend signal. 964000 is the only station for which the trend changed from a negative sign to a positive one by homogenisation. For all the other stations the trend became more negative. Nevertheless the slope is less than 0.2% per year. The biggest change took place for 1571200 (~0,3% per year). All trends are statistically significant in the homogenised dataset. Using a 95%-confidence interval the trend change is only statistically significant for 25 stations.

Looking at the different seasons, the most positive trends occur in autumn and winter while nearly no positive trend can be found in spring and summer. The change to a positive trend for 9640000 can be found in each season. For 4 other stations changes to positive sign can only be found in one to two seasons.

Taking into account only those stations for which the time series starts in 1948, the homogenised and original trend can be seen in Figure 9. In the beginning of this homogenised time series an increasing or constant level of relative humidity can be found. Between 1970 and 1990 a decrease can be observed, afterwards a relatively constant value is reached again. The original time series start with a lower value of relative humidity. Therefore the decrease is smaller after 1970, ending in a slight increase after 1980 and a constant value in the present.

The annual cycle of relative humidity shows only slight changes (Figure 10). For all months, the median shows higher relative humidity in the homogenised data than in the original data. The difference is larger in the warmer months (May-July |median of differences|>3%) than in the cooler (Dec-Feb |medians of differences|<=2%) ones.

No height dependence seems to occur in the median and variability of relative humidity in the different months.

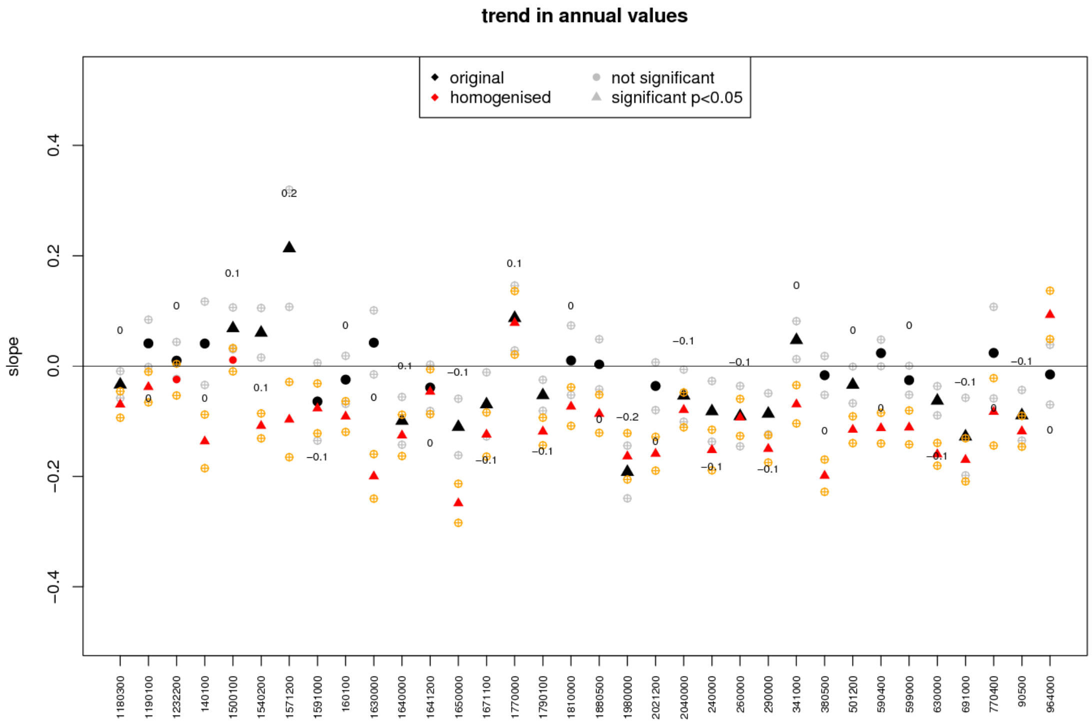

Figure 8: Information on annual trends of original and homogenised dataset. Station numbers given on the x-axis, the slope [% per year] on the y-axis. Black and grey points give original values, red and orange show the homogenised data. Grey and orange crossed circles give the 95%-confidence interval. The values give the original trend values.

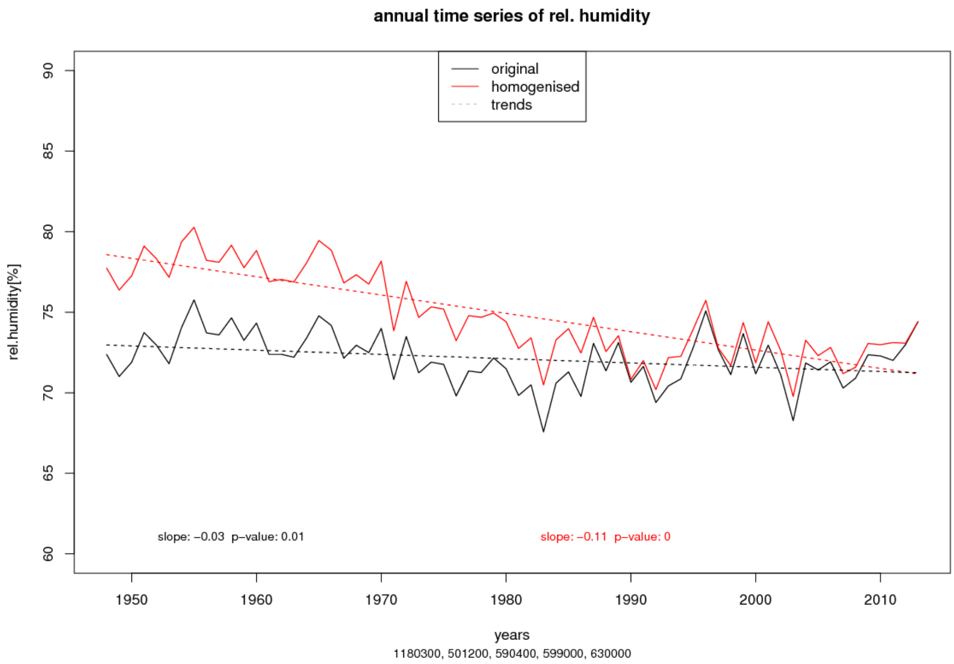

Figure 9: Annual time series for 5 stations (given on the lower part of the figure) starting 1948 and trends. Slopes [% per year] and p-values for the slopes are given at the lower part of the figure.

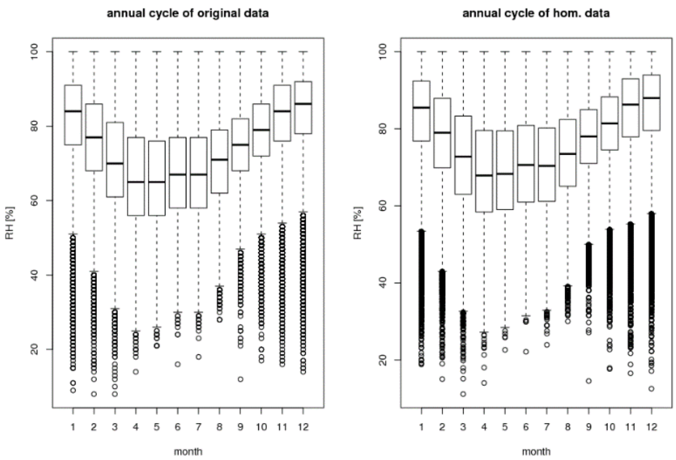

Figure 10: Annual cycle of relative humidity values for original (left) and homogenised (right) data

A comparison between the monthly RH-data homogenised within the framework of HISTALP in 1997 and the daily homogenised data from this project (averaged over the single months for equal resolution) was done for all 4 stations that are available in both datasets (Innsbruck University, Kremsmünster, Wien Hohe Warte, Graz University). The differences between the original data (CC-IMPATY minus HISTALP) have values between -7% and 5% (mean: -3%) due to different calculation of monthly means in both datasets (using daily means in CC-IMPATY and all observation-time measurements of the months for the HISTALP-data). Comparing the homogenised time series from the beginning of the available series until 2013 (using unhomogenised data before 1997 for HISTALP) showed that the differences have a range of -15% and 14% (Table 6)(mean: -4%). In most months, mean monthly humidity is higher in HISTALP than in CC-IMPATY, with negative mean relative humidity values. Only in Kremsmünster did roughly half the months show means indicating that relative humidity is lower in HISTALP. No common seasonal cycle can be seen between the differences of HISTALP and CC-IMPATY in the different stations. When looking at trends for the single months, they are very similar for three of the stations having mean absolute errors of 0.05%/y. Only Graz University has differences of >=0.1%/y for each month.

Table 6: Distribution of differences (CC-IMPATY minus HISTALP) for each month (M1-M12) for homogenised monthly data

	Kremsmünster			Wien Hohe Warte			Innsbruck Uni			Graz Uni		
	mean	min	max	mean	min	max	mean	min	max	mean	min	max
M1	-2	-6	2	-1	-5	1	-4	-8	-1	-6	-13	-1
M2	-3	-5	1	-5	-12	0	-5	-9	-2	-7	-13	-2
M3	-3	-6	-1	-5	-10	-2	-6	-11	-4	-8	-13	-3
M4	-3	-10	5	-10	-15	-2	-6	-12	-2	-9	-14	-4
M5	5	-4	10	-6	-10	-2	-5	-12	0	-5	-12	-1
M6	6	-4	14	-3	-9	1	-5	-11	-2	-5	-13	0
M7	2	-5	10	-5	-10	-2	-5	-11	1	-5	-14	-1
M8	-3	-8	5	-5	-10	-2	-5	-11	-1	-7	-14	-1
M9	0	-5	5	-2	-5	6	-5	-9	4	-5	-12	-1
M10	0	-4	5	-2	-6	3	-4	-8	-2	-7	-13	-2
M11	-3	-5	2	-2	-9	3	-3	-7	-1	-6	-14	-2
M12	-1	-4	4	-1	-5	2	-5	-7	-2	-5	-11	-1

5 Schlussfolgerungen und Empfehlungen

Homogenisation methods:

*) The tests using surrogate data showed that in break detection ACMANT and HOMOP performed best with fewer time series wrongly classified as homogeneous by ACMANT.

*) The number of breaks was reduced significantly by human interaction with MASH in comparison to the automated version. That led to most wrongly as homogeneous classified time series in the deterministic case. In the realistic case the number of wrongly classified time series was similar to the automatic version.

*) MASH and PROCLIM detect more breaks than ACMANT and HOMOP, although their characteristic to detect the breaks in each month separately was taken into account by summing up each break within 1 year as only 1 break.

*) The location of the network (inner alpine, stations located nearby or farther from each other,…) seems of less importance to the break detection than the characteristic of missing data, noise,…

*) All methods tested on their ability to recognise homogeneous time series found breaks in the homogeneous, deterministic surrogate dataset. Nevertheless, the number of breaks was significant (1 order) smaller than in the inhomogeneous cases.

*) Almost all breaks in the surrogate networks were located within 5 years of at least one break in the reference series and more than 2/3 of the breaks lay within 5 years of a break in the candidate time series itself.

*) The probability of detection increases with increasing correlation of the candidate station and the reference stations and the size of the break signal in comparison to the noise.

*) ACMANT was the method that provided solutions for the least number of stations.

*) The network with the most problems was network 8, with only 4 stations.

*) Of all the methods, only MASH solved all stations for all networks.

*) In which networks some stations could not be solved depended on the methods and not on the network.

*) In the realistic case, the quality control usually done by MASH could not be used due to “too few reference stations”.

*) The RMSE can be improved in the deterministic case (by ACMANT, MASH and HOMOP in 2/3 to 1/2 of the stations), but ACMANT is able to improve the time series (~1/2 of them) in the realistic case.

*) The trend is improved by all methods for about 2/3 to 1/2 of the stations. The ability to improve the trend decreases in the realistic case, but still about ½ of the stations are positively influenced.
*) There is nearly no influence in the performance of HOMOP with different correction methods, break detection criteria and length of reference period.
*) The influence of human interaction in MASH is high. Profound induction training is therefore necessary to use this homogenisation tool and should not be done without knowledge of metadata.

Homogenisation of real data:
*) Daily relative humidity data of 34 Austrian stations has been homogenised.
*) About half of the breaks can be explained by metadata.
*) The positive effect of the correction of the bias due to observing time changes was counter acted by the homogenisation due to the higher number of reference stations without this correction.

Analyses:
*) The homogenisation has an important influence on the trend of the relative humidity in the last years, by making the trend negative in most of the cases. This influence should be checked by other homogenisation methods, e.g. on monthly base.
*) While the median values of relative humidity in the different months increase, the annual cycle remains similar, with a minimum in April and May and the highest values in winter.
*) No height dependence seems to exist in the median of original and homogenised relative humidity values.
*) A comparison with monthly HISTALP-data showed that the difference between the two datasets increased by the homogenisation.
*) Most mean monthly relative humidity values are higher in HISTALP than after the daily homogenisation.
*) The consistency in trend analyses in individual months is varying. While some month at some station show absolute differences of 0.01%/year, other months at other stations can have differences up to 0.19%/y.

C) Projektdetails

6 Methodik

Different homogenisation methods were tested for their applicability to homogenise daily data of relative humidity. The methods chosen have been tested on their ability to homogenised daily temperature and precipitation data within the COST-Action ES0601:

HOMOP: (Gruber et al., 2009, Nemec et al., 2012)

Break detection is done with PRODIGE (Caussinus & Mestre, 2004), applying a penalised likelihood method comparing the candidate stations with as many reference series as possible. Three different penalty-terms are used. And in this project two different criteria were applied to decide if a break signal is strong enough to indicate a break. The usual criterion for a break, is that the signal is shown by at least half of the reference stations in at least two seasons by at least 2 penalty term versions. With the second criterion used in this project, only the results of one penalty term has to indicate a break in two seasons for more than half of the reference stations.

Two different break correction methods have been applied: In one case, the correction was done by SPLIDHOM (Mestre et al, 2011) using a spline regression, resulting in different corrections for different values. Outside of the data range of the reference period, a constant correction was applied.

The second correction method is INTERP (Vincent et al. 2002), calculating daily adjustments by interpolation of monthly adjustments.

Moreover, two different options of reference periods have been tested: in one case the maximum possible reference length was used, and in the other case the reference period was reduced to a maximum of 5 years to minimize the possibility of breaks in the reference series within this period.

ACMANT: (Domonkos, 2011)

This fully automatic method was developed for temperature data in mid- and higher latitudes. Composite data of at least 30years length are used as reference. The detection is based on PRODIGE (Caussinus & Mestre, 2004), but there are some differences:

1) the reference series are prehomogenised

2) a bivariate detection (for annual values and the seasonal amplitude) is used

3) homogeneous parts of the time series longer than 3 years are detected separately from inhomogeneities that have a strong signal, but result in a short homogeneous part of the time series (only 3-60month between two breaks)

4) a composite reference is used instead of pairwise comparison of stations

The correction is based on ANOVA, excluding breaks that are not significant and correcting only those significant ones. The adjustments are calculated from monthly correction values.

The stations of the whole network are homogenised using this method.

MASH: (Szentimrey, 1999)

This iterative method uses all stations as candidate stations and reference stations. In each iteration, the homogenisation is based on the results of the last step. The homogeneity test is done using test statistics. Daily adjustments are based on monthly ones.

To apply this method it was necessary to divide the measurements by 10.

The method was applied in two ways: In one version a fully automatic script was started, which is not recommended by the authors, and in the second version the homogenisation was done interactively, changing break points if they seemed unrealistic. As no metadata was available for the tests of the benchmark dataset, it seemed possible that the fully automatic process might lead to better results than a human without any additional information on the breaks.

PROCLIM: (Štěpánek, 2008)

This software combines many different detection and correction methods. Following the recommendation of P. Štěpánek, 3 different break detection methods (SNHT, bivariate, t-test) and their combination and 2 correction methods where chosen. One of the corrections used daily adjustments based on monthly corrections and the second one used the q-q-method for directly determining daily adjustments.

A total of 17 different methods (including different options for one and the same algorithm) were applied to a surrogate dataset in order to find the method best suited for homogenisation of relative humidity.

As no evaluation can be done when using original measurements, a surrogate data set was created, that has the statistical properties of the relative humidity data (data range, cross correlation, seasonal cycle,...). But in contrast to real data, timing and size of break signals are known. The homogenisation is done without using this knowledge, as the project partner creating the dataset did not pass this information on, before the homogenisation was finished. Therefore an objective testing of the different methods was possible. The statistical information needed for creating the surrogate dataset was gathered using metadata and analysing parallel measurements.

A stochastic simulation method (IAAFT, iterative amplitude adjusted Fourier transform, Schreiber und Schmitz, 1996, Schreiber und Schmitz, 2000, Venema et al., 2006a-c) was used to create the long-term homogeneous surrogate dataset from short homogeneous station data. The method allows simulating the exact distribution of the data, which is especially important for relative humidity, where the maximal value of 100% must not be exceeded.

The autocorrelations are constrained by reproducing the power spectrum. The empirical distribution of the measurement is used as input to the IAAFT algorithm. The seasonal cycle is modelled by simulating an empiricial distribution for every month. The distribution of the difference time series (cross-correlations) also has a seasonal cycle this way and together with the power spectrum models the cross-correlation matrix.

Judging from the way the spectrum is computed from short time series, variability on decadal scales is likely too weak. Therefore we explicitly model the decadal variability smooth noise time series with a power law power spectrum with exponent -4. This time series is normalised to a mean of zero and its standard deviation is about 6% of the variability of the homogeneous data. The same variability was added to every time series in one network.

The statistical properties of the century long surrogate datasets accurately match those of the stations they are based on. This means that the autocorrelation function and the distribution match well and only the cross correlations between the stations are too low over the entire seasonal cycle. This indicates that the convergence of the iterative algorithm was not ideal, which is likely due to the strongly non-Gaussian distribution of the humidity data. The deviations seem acceptably small for this application, however. The cross correlations of the surrogate data could represent a network with a slightly different geographical configuration. Nevertheless, higher correlations can also be found for some networks and months..

Three different kinds of inhomogeneities have been created: “deterministic”, “stochastic” and “realistic”.

In the realistic case, three kinds of missing data are included: 1) The number of stations increasing with time. 2) During the Second World War (1940-1946) more data are missing than during other periods. In 1946 75% of stations have missing data and stations with missing data in one year have a 75% probability of having missing data in the preceding year as well. 3) Random missing data was inserted. The probability of one new missing data value being inserted is 0.0016. The next day has a 75% probability of also being missing.

Inhomogeneities are modelled as a power law power spectrum with exponent -4. In addition they have a seasonal cycle, which is generated by repeatedly smoothing white noise (periodic boundary conditions) and normalising it. After adding the perturbations, tapering is applied to avoid relative humidity values above 100%.

In the case of the stochastic and realistic dataset, white noise was added to the inhomogeneities. The standard deviation of this white noise was modelled in the same way as the deterministic inhomogeneities.

In the first two datasets, breaks are inserted with a frequency of 1 break/13years. In the realistic dataset the breaks are more frequent in the beginning of the time series.

The mean of the break size changes linearly in time to create a bias in the relative humidity of 2% over the century. To reduce problems with the upper level, it was assumed that old values were biased 2% too low. Information on real long term biases is not available, but including a bias was seen as desirable to be able to assess how well the methods would handle a trend if there was one.

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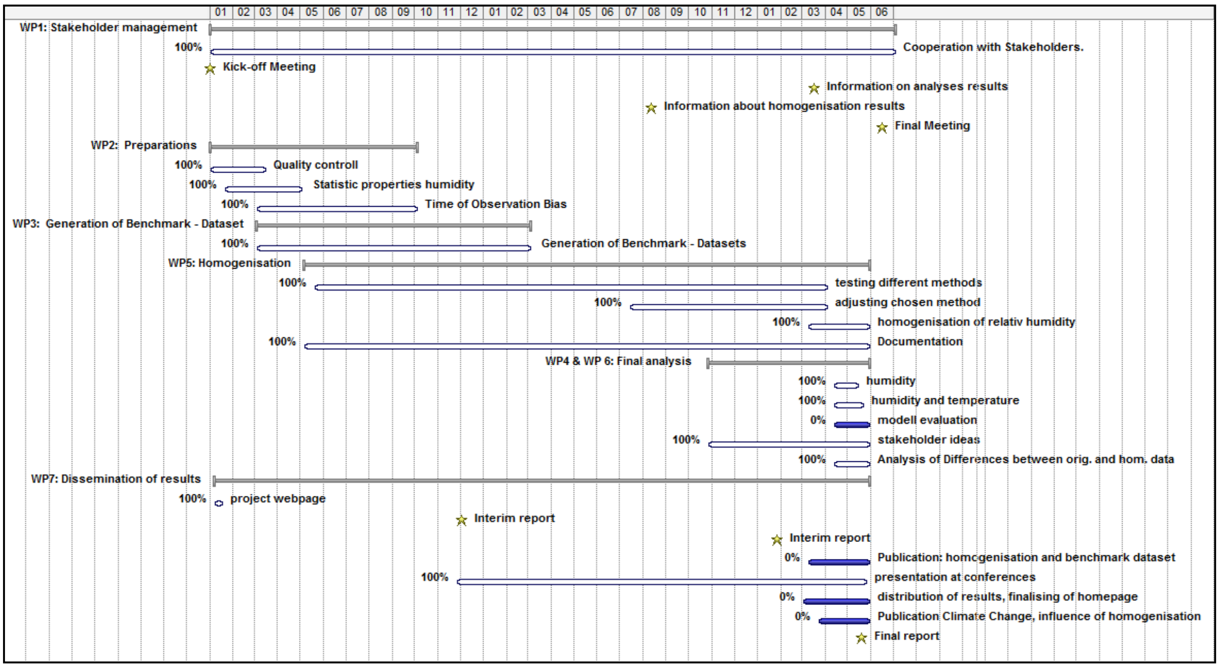
7 Arbeits- und Zeitplan



8 Publikationen und Disseminierungsaktivitäten

During the project the project was represented at the following conferences:

- Österreichischer Meteorologentag 2013, Feldkirch
- Österreichischer Klimatag 2014, Innsbruck
- Österreichischer Klimatag 2015, Wien
- EGU 2014, Wien
- EGU 2015, Wien