

Classifying reconstructed daily pressure patterns for the period 1850 to 2003 in the North-Atlantic - European region by simulated annealing clustering

Andreas Philipp, Jucundus Jacobeit, Paul M. Della-Marta

Angaben zur Veröffentlichung / Publication details:

Philipp, Andreas, Jucundus Jacobeit, and Paul M. Della-Marta. 2007. "Classifying reconstructed daily pressure patterns for the period 1850 to 2003 in the North-Atlantic - European region by simulated annealing clustering." In *COST Action 733: proceedings from the 5th annual meeting of the European Meteorological Society; Session AW8 – Weather types classifications, Utrecht, Netherlands, 12-16 September 2005*, edited by Ole Einar Tveito and Massimiliano Pasqui, 17–25. Berlin: European Meteorological Society.

Nutzungsbedingungen / Terms of use:

licgercopyright

Dieses Dokument wird unter folgenden Bedingungen zur Verfügung gestellt: / This document is made available under these conditions:

Deutsches Urheberrecht

Weitere Informationen finden Sie unter: / For more information see:

<https://www.uni-augsburg.de/de/organisation/bibliothek/publizieren-zitieren-archivieren/publiz/>



Classifying reconstructed daily pressure patterns for the period 1850 to 2003 in the North-Atlantic - European Region by Simulated Annealing Clustering

A. Philipp (1), J. Jacobeit (1) and P.M. Della-Marta (2)

(1) University of Augsburg, (2) University of Bern

Abstract

In order to assess long-term changes of daily circulation variability, different classification methods are applied to a recently reconstructed Sea Level Pressure (SLP) dataset reaching back to 1850. Both the reconstruction and the classification is part of the ongoing EU project EMULATE (European and North Atlantic daily to MUL-Tidecadal climATE variability) which has the final aim to examine changes of circulation-climate-relationships with particular respect to extreme climatic events. This study deals with classification methods suitable for assessing long-term changes in the SLP fields. In order to account for the varying reconstruction skill, an error weighting scheme is applied to the SLP fields before submitting them to the classification procedure. Since statistical methods applied to the classification results (e.g. trend analysis of pattern frequencies) may be quite sensitive to small changes in the classification, robust results have to be achieved. Conventional Cluster Analysis (e.g. k-means clustering) does not meet these requirements: Depending on the dataset as well as on the number of clusters, the resulting partition is a matter of chance, and thus no robust evidence on long-term changes can be provided. In order to find a stable solution for this classification problem, a clustering method based on so called simulated annealing and multistart techniques is used. This allows for a reliable examination of circulation changes which are shown in their relevance for temperature variability as an example of applying results of this classification.

1. Introduction

In the context of assessments of climate change dynamics it is important to extend the study period on climatic variability back into time as far as possible. In order to keep a minimum level of data quality, the temporal resolution of most reconstruction approaches have been limited to monthly or seasonal time scales. Within the EU project EMULATE (European and North Atlantic daily to MULTidecadal climATE variability) a new dataset has been generated by reconstructing sea level pressure (SLP) fields on a daily basis for the period 1850 to 2003. This new dataset is expected to allow improved insights into long-term changes of high frequency variability of the North-Atlantic – European circulation. Therefore one objective of EMULATE is to identify leading atmospheric circulation patterns for assessing their trends and variations in time.

A very fundamental approach in this context is to create a pressure-pattern-classification which allows a sound analysis of the complex variability within the dataset based on well-defined categories. This approach is similar to so called weather-type-classifications but

differs in using only one parameter for classification (SLP) instead of attempting to represent the weather as a whole.

The classification method applied here is a non-hierarchical Clustering technique whose methodological aspects may affect similar classification techniques as well and therefore might have relevance to weather-typing approaches in general.

2. Data

The gridded SLP reconstruction has been done by Ansell et al. (2005) applying the Reduced Space Optimum Interpolation (RSOI) method (Kaplan et al. 2000) to quality checked and homogenized historical station time series and ICOADS marine data. The product provides a $5^\circ \times 5^\circ$ spatial grid for the daily mean SLP from the 1st of January 1850 in the sector 70°W - $50^\circ\text{E}/25^\circ\text{N}$ - 70°N . Additionally, RSOI-error estimates are provided for each grid point and each day (for further details see Ansell et al. 2005).

Before applying the classification scheme, all SLP-fields were weighted by the square root of the cosine of latitude to account for area differences in grid cells. Additionally the RSOI-error estimates have been used to weight the data in order to account for the varying confidence in the reconstructed data. The RSOI-error weight was calculated as the inverse of the mean RSOI-error divided by the standard deviation (both in hPa) of each grid point for the whole period 1850-2003. As an example, Figure 1 shows the error weighting field for the winter (DJF) season. With the highest values over western and central Europe the classification scheme is most sensitive to pressure configurations in these areas of high confidence on reconstructed SLP.

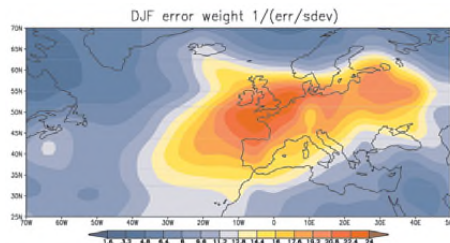


Figure 1: Error weights for the winter season as applied to the daily pressure patterns prior to their classification.

3. Classification by k-means cluster analysis

A conventional approach for classifying a set of objects (e.g. the daily pressure patterns of the reconstructed dataset) is to use non-hierarchical k-means cluster analysis (CA) which tries to find an optimal assignment of each pattern to a particular cluster by minimising the within cluster variances. Within cluster variance can be measured by the so called Explained Cluster Variance (ECV): $ECV = 1 - WSS / TSS$, where WSS is the sum of squares of distances between all objects within a cluster and the corresponding cluster centroid and TSS is the sum of squares of distances between all objects and the total centroid of the dataset.

The process can be split up into three steps:

1. Produce a starting partition, i.e. an assignment of each object to initial clusters.
2. Iteratively rearrange objects from one cluster to another if this reassignment increases the cluster quality (reduces within cluster variance).
3. Stop the iterations if no enhancement by reassigning objects is possible anymore. This means that a final convergence of the optimisation process has been reached.

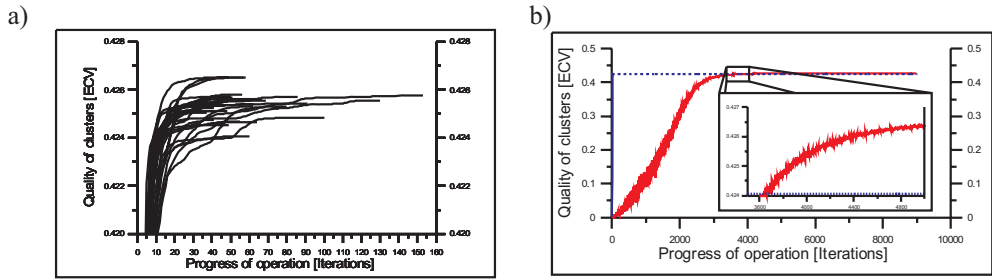


Figure 2: Visualisation of optimisation processes by k-means cluster analyses (CA) showing cluster quality as a function of progress of operation: a) several runs of conventional CA differing just by starting partition and ordering of objects (see text); b) Simulated Annealing CA run (the blue line indicates a conventional k-means CA run). ECV is a measure of cluster quality and is calculated as 1 minus the within cluster variability (sums of squares of distances between objects and their cluster centroid) scaled by total variability (sums of squares of distances between all objects and the overall mean).

The result is always an optimized partition. But the main problem of this method – at least if a complex dataset is used as in our case – arises with the fact that there is a various number of possible solutions, called local optima, which are more or less different and generally worse than the so called global optimum which is the best one possible. Any dataset may be called 'complex' in the context of classification problems if it does not show clearly separated groups of objects inherent in the dataset .

In order to illustrate the behavior of conventional CA when applied to a complex dataset, figure 2a exemplarily presents the optimization process of different k-means CA runs differing just by two initial conditions:

1. The starting partition has been determined by different methods (hierarchical CA, PCA and by random),
2. The ordering of objects (days) has been changed by random.

The latter initial condition leads to a different ordering of checks to determine whether an object has to be moved to another cluster which in turn has a large impact on the outcome of all subsequent checks.

In figure 2a each single optimization process can be depicted by an individual line representing cluster quality (ECV) as a function of the progress of operation. If the method would be stable, all these lines would end up in one single point which should be the best solution, but conventional k-means CA is not able to realize this. Instead we can see that the result is unpredictable and found by chance. Thus, different ordering of objects and different starting partitions lead to different clustering results.

No method is known to determine the global optimum directly but only the brute force method of testing all possible combinations of objects, which is impossible for large datasets.

A method explicitly designed to approximate the global optimum (regardless of the ordering of objects or starting partitions) is the Simulated Annealing technique. This method can be utilized for k-means CA and systematically avoids bad local optima because it allows small steps backward (in terms of overall ECV) during the optimization process and therefore is able to get over these pitfalls as it is indicated in figure 2b. The idea behind this approach is to

move all objects randomly between the clusters like in a hot melt of particles and slowly reduce the probability of objects moving into a ill-suited cluster which is simulating the process of slow cooling. By moving all objects initially, the result should be ideal for the whole of the objects, in contrast to any approach looking just at the momentary advantage of each single reassignment (for details see Philipp et.al. 2006).

The computational effort of using Simulated Annealing for clustering a large dataset is relatively high, thus the question arises whether it is worth doing so. In order to give an answer, figure 3 shows an example of a cluster equivalently derived by conventional k-means (figure 3 upper panel) and by simulated annealing clustering (figure 3 lower panel). The centroid patterns in both cases show a blocking situation over the British Isles, but the simulated annealing result provides a better defined anticyclonic pattern which seems to be the product of a better assortment of daily patterns. Furthermore, the differences are even more significant if we look at the time varying seasonal frequencies of this cluster (Fig. 3, right column). Not only short-term variability, but especially the long term changes show remarkable differences: while the simulated annealing cluster has a significantly positive trend (Mann-Kendall-trend test at the 95% confidence level), this long-term change (also apparent from the time series of cumulative anomalies in figure 2) is not detected by conventional k-means CA. These differences are a direct result of the sub-optimal classification of the latter method. As a rule of thumb, the danger of achieving non-optimal results increases with the number of objects, with the number of clusters, and with the complexity (no clearly defined natural clusters) of the dataset, because all these factors tend to enlarge the number of local optima.

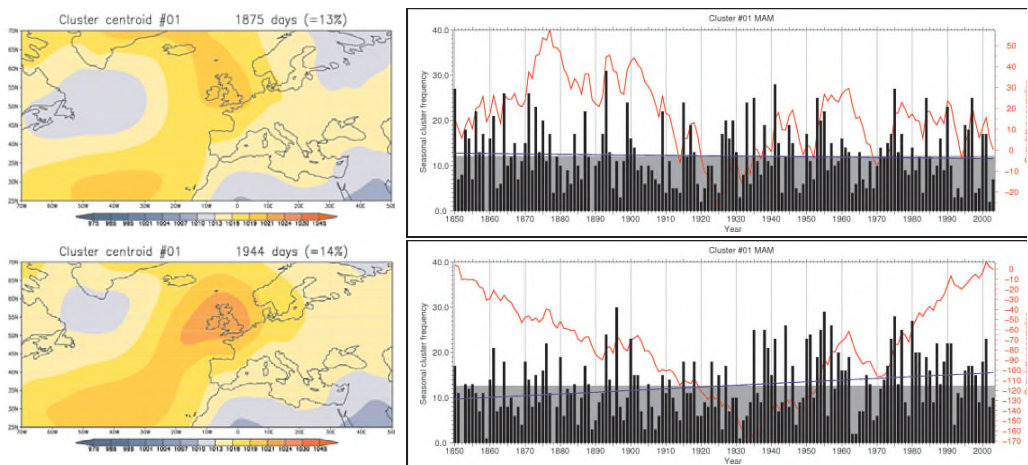


Figure 3: First of 11 cluster centroids and seasonal cluster frequencies derived for an example in spring by conventional k-means cluster analysis (upper level) and by cluster analysis using the simulated annealing technique (lower panel). The patterns (left column) are the mean raw data from the cluster members. The time series plots (right column) include in gray the overall long-term means, as blue lines the linear trends, and as red lines the cumulative anomalies of cluster frequencies.

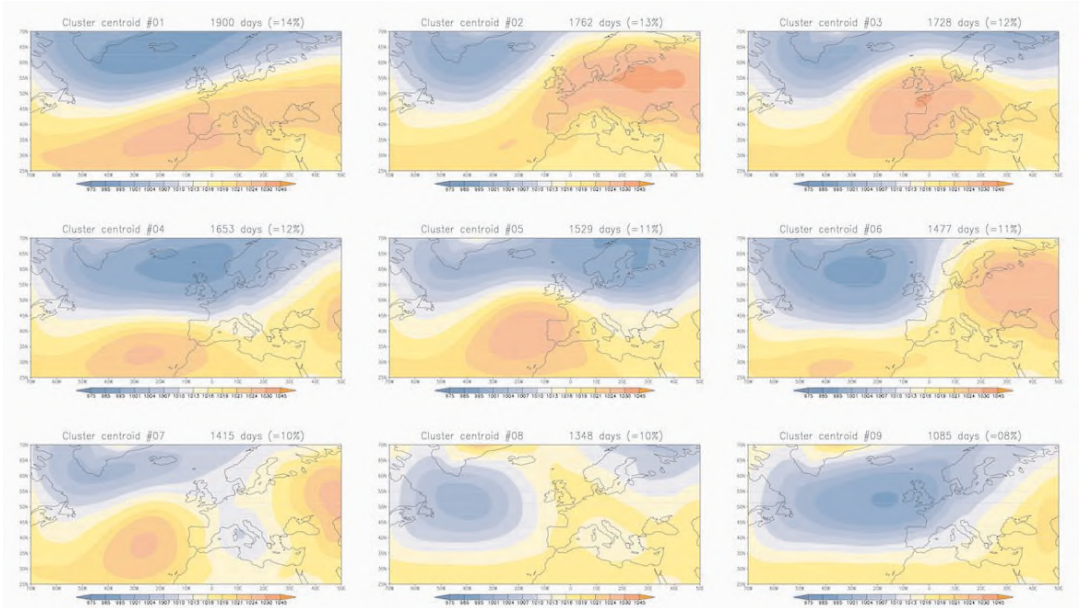


Figure 4: *Simulated Annealing Cluster centroid patterns for clusters 1 to 9 in winter (DJF) 1850-2003. Patterns represent the average of all cluster members using non-weighted data in order to aid the interpretation of these patterns.*

The numbers of clusters chosen to represent the winter season (DJF) was 9. While all commonly used indices for an appropriate number of clusters failed to give a reliable hint for this dataset (probably another consequence of the complexity of the dataset), it was determined by a PCA approach. This method tries to estimate the number of uncorrelated patterns fitting into the dataset. The detailed description of this method is beyond the scope of this report and will be published elsewhere.

The resulting classification for the winter (DJF) season is represented in figure 4 by the cluster centroid patterns. While the CA itself was performed with weighted data, the centroids are shown with original raw data for better interpretation. A wide range of pressure configurations is obtained comprising of zonal ones (clusters 1, 2 and 5) as well as anticyclonic and generally meridional ones. The temporal information for these patterns is given in figure 5 in terms of the seasonal cluster frequencies (SCF): significant long-term positive trends are indicated for the zonal flow pattern (cluster 4) and negative trends for cluster 6 - a pressure configuration of mainly meridional air flow and high pressure influence over Europe. The zonal cluster 1 resembles the recent positive phase of the North Atlantic Oscillation which is outbalanced by another positive phase at the very beginning - in the 1850s and 1860s. Therefore no significant overall linear trend is indicated for this cluster.

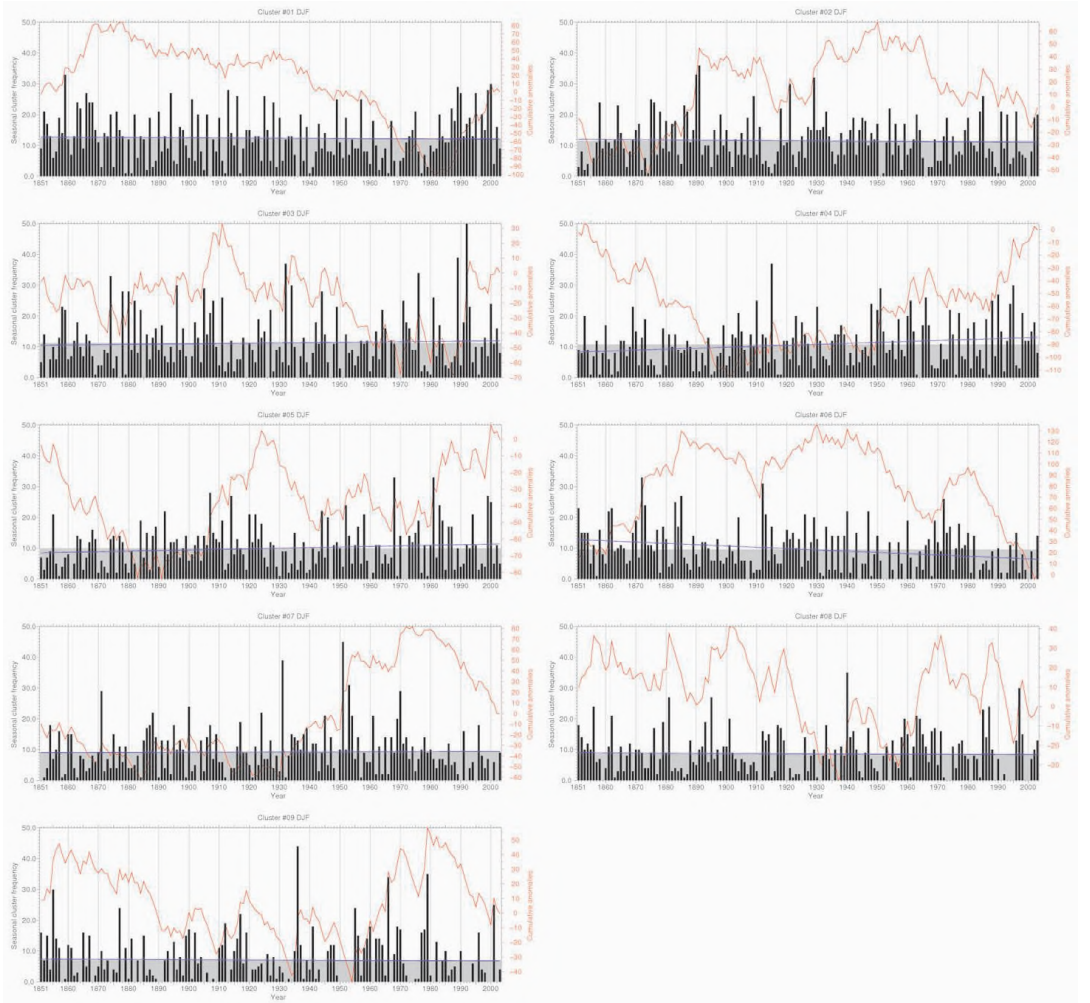


Figure 5. Seasonal cluster frequencies (black bars) of clusters 1 to 9 (see Fig. 4) in winter (DJF) for the period 1851 to 2003. The gray fields indicate the overall long term means, the blue lines the linear trends, and the red lines the cumulative anomalies of cluster frequencies.

4. Application for assessments of European winter temperatures

An example application of the SLP pattern classification is given in figure 6. The information about mean daily temperature conditions associated with each SLP cluster can be used to set up a simple descriptive model for assessing the seasonal mean temperatures from cluster frequencies within each season. For this purpose NCEP/NCAR reanalysis data for the period 1948 to 2003 have been used to calculate for each cluster the average daily temperature anomaly (relative to the monthly mean of the reference period 1961 to 1990) covering the area 5°E to 20°E and 45°N to 55° N. This area covers most of Central Europe and implies convenience because reconstructed and observational monthly mean temperature data exist back to 1851 with the prominent CRUTEM2v dataset from Jones and Moberg (2004). Therefore this region offers the possibility to compare temperatures modeled by SCF against 'observed' data. Past monthly means of temperature were modeled just by summing up the associated mean temperature anomalies for each cluster occurring in that month and dividing this sum by the number of days in this month.

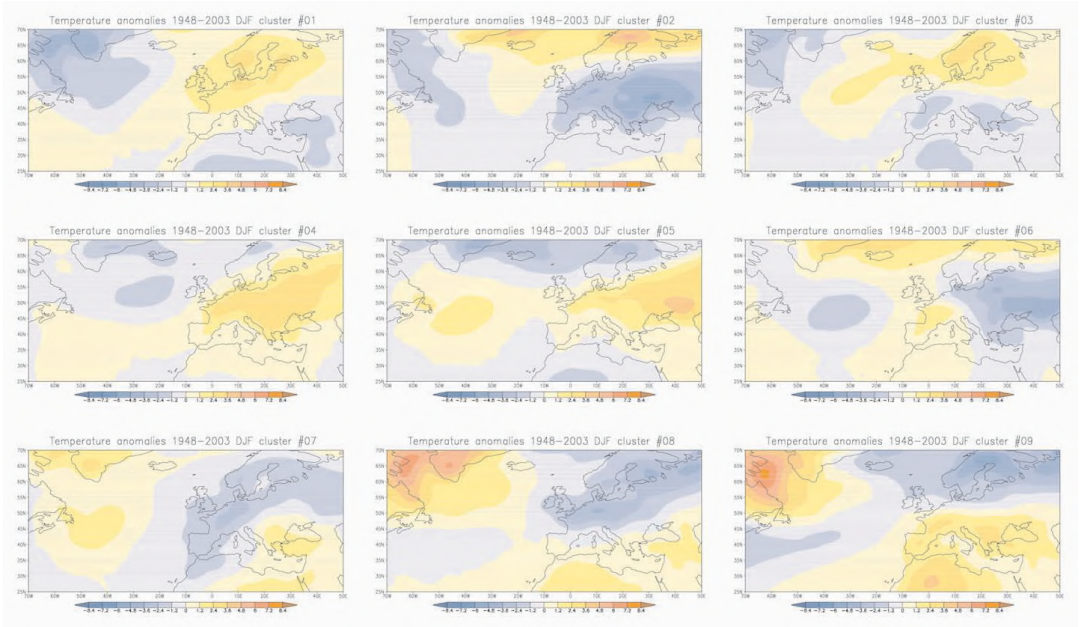


Figure 6. Associated temperature anomaly fields for clusters 1 to 9 (see Fig. 4) in winter (DJF) within the modern reanalysis period 1948 to 2003. Data represent the average anomaly of all days within each cluster related to the monthly long-term mean of the period 1961 to 1990.

The simplicity of this model is obvious: no information about previous history (e.g. persistence of a particular circulation pattern) was introduced into the model which would allow for a more appropriate temperature assessment. However, the only purpose of this simplified model is to describe the varying influence of pressure patterns onto regional temperature. The results can be seen from Fig. 7.

Although of rather low skill, this descriptive model reveals that some parts of temperature variability can be explained by pure SCF data. Remarkably this is also true for low- frequency temperature variability (see the cumulative anomalies in figure 7). This is also true for the recent warming period since about 1985 which is reproduced. However, as the most outstanding exception we find a tendency for overestimation of the temperatures in the very first part of the period (especially between 1852 to 1865) which means that there could have been some other influences than seasonal SLP cluster frequencies which caused the unusual cold conditions.

5. Discussion and Conclusions

Results presented in this report indicate that conventional cluster analysis is limited in finding optimal and stable results for large and complex datasets. Therefore we use the simulated annealing technique to approximate the best solution possible (the global optimum) and to ensure a robust solution of the classification problem. As an example the results for the winter (DJF) season 1851-2003 are presented in terms of SLP cluster centroid patterns, seasonal cluster frequencies and additionally by the associated mean daily temperature fields in the modern reanalysis period. A simple descriptive modelling approach of central European

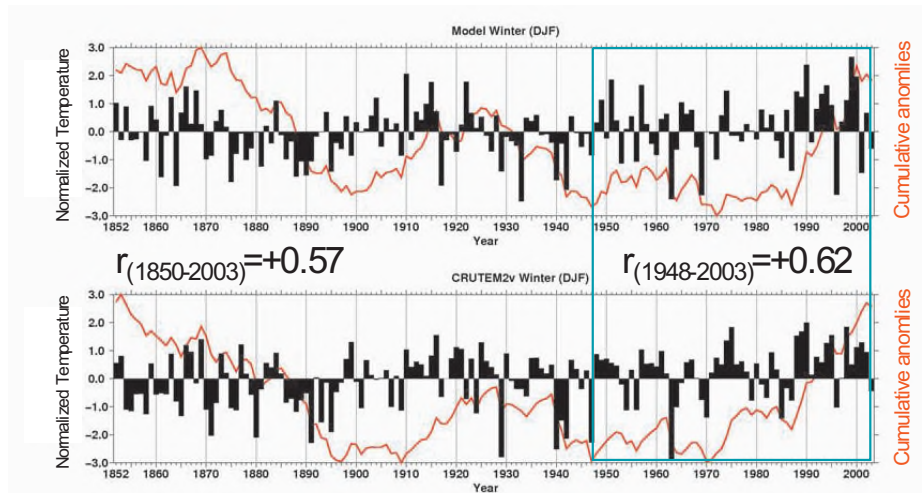


Figure 7. Comparison between Central European seasonal temperature anomalies modeled by SCF (upper panel, for detailed explanation see text) and reconstructed from observations (lower panel, data from Jones and Moberg 2003). The calibration period 1948 to 2003 is boxed by the green frame. Its pearson correlation coefficient is $r = 0.62$, while the correlation for the whole period is $r=0.57$. The red lines represent the cumulative anomalies.

temperature based exclusively on circulation cluster frequencies is presented as an example of applying results of this SLP classification. Temperature variations can be explained by SLP cluster frequencies in large parts for most of the period concerning the tendencies of warming and cooling, but not concerning the absolute extend due to the simplicity of the estimation approach. However, during the second half of the 19th century conditions have been colder than it would be expected from the circulation based model. Possible factors relevant for this overestimation of temperatures in the second half of the 19th century – beside random fluctuations - might be decreased solar activity, a weaker thermohaline ocean circulation, or a smaller greenhouse forcing due to lower concentrations of greenhouse gases at this time compared to the modern calibration period. In contrast the recent warming period since the mid 1980s is reflected more or less adequately by the model, suggesting that it is partly due to circulation changes. This is in good accordance with the increase of the westerly pattern of cluster 1 showing warm conditions for central Europe and the decrease of the continental high of cluster 6 with cold conditions during this period. In order to allow more detailed estimations of the role of circulation pattern frequencies for long-term temperature changes the statistical modelling based on circulation classification should be enhanced in the future.

References

Ansell, T.J., P.D. Jones, R.J. Allan, D. Lister, D.E. Parker, M. Brunet, A. Moberg, J. Jacobeit, P. Brohan, N.A. Rayner, E. Aguilar, H. Alexandersson, M. Barriendos, T. Brandsma, N.J. Cox, P.M. Della-Marta, A. Drebs, D. Founda, F. Gerstengarbe, K. Hickey, T. Jónsson, J. Luterbacher, Ø. Nordli, H. Oesterle, M. Petrakis, A. Philipp, M.J. Rodwell, O. Saladie, J. Sigro, V. Slonosky, L. Srnc, V. Swail, A.M., García-Suárez, H. Tuomenvirta, X. Wang, H. Wanner, P. Werner, D. Wheeler and E. Xoplaki (2005): 'Daily mean sea level pressure reconstructions for the European – North Atlantic region for the period 1850-2003', Journal of Climate (in press).

Jones, P. and A. Moberg (2003): Hemispheric and large-scale surface air temperature variations: an extensive revision and an update to 2001., *Journal of Climate*, 16, 206–223.

Kalnay, E., M. Kanamitsu, R. Kistler, W. Collins, D. Deaven, L. Gandin, M. Iredell, S. Saha, G. White, J. Woollen, Y. Zhu, M. Chelliah, W. Ebisuzaki, W. Higgins, J. Janowiak, K. Mo, C. Ropelewski, J. Wang, A. Leetmaa, R. Reynolds, R. Jenne and D. Joseph (1996): The ncep/ncar 40-year reanalysis project, *Bulletin of the American Meteorological Society* 77(3), 437–471.

Kaplan, A., Y. Kushnir and M.A. Cane (2000): Reduced space optimal interpolation of historical marine sea level pressure: 1854-1992', *J. Climate*, 13, 2987-3002.

Kistler, R., E. Kalnay, W. Collins, S. Saha, G. White, J. Woollen, M. Chelliah, W. Ebisuzaki, M. Kanamitsu, V. Kousky, H. van den Dool, R. Jenne and M. Fiorino (2001): The ncep-ncar 50-year reanalysis: Monthly means cd-rom and documentation, *Bulletin of the American Meteorological Society*, 82(2), 247–267.

Philipp, A., P.M. Della-Marta, J. Jacobeit, D.R. Fereday, P.D. Jones, A. Moberg, H. Wanner (2006): Long term variability of North Atlantic-European pressure patterns since 1850 classified by simulated annealing clustering. *Journal of Climate*. Submitted.