COMPARATIVE ANALYSIS OF SPATIAL AND SEASONAL VARIABILITY: AUSTRIAN PRECIPITATION DURING THE 20TH CENTURY

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ABSTRACT

The purpose of this investigation is to demonstrate the usability of objective methods to study the variability of precipitation and hence to contribute to a better understanding of spatial and seasonal variability of Austria’s precipitation climate during the 20th century.

This will be achieved by regionalizing the intra-annual variability of seasonal precipitation distributions during three non-overlapping 33 year samples (1901–33, 1934–66, 1967–99). Monthly precipitation totals were extracted at 31 Austrian stations from a homogenized long-term climate dataset provided by the Austrian weather service. Three statistical techniques, namely cluster analysis (CLA), rotated empirical orthogonal functions (REOFs) and an unsupervised learning procedure of artificial neural networks (ANNs), were utilized to find homogeneous precipitation regions.

The results of summer (June, July, August (JJA)) and winter (December, January, February (DJF)) seasons are presented. The resulting homogeneous precipitation regions depend on season, period and method in this order. Hence, differences introduced by using different methods are small compared with those inferred by investigating different episodes and especially with those related to the seasons.

During winter, three homogeneous precipitation regions are found, independent from the period considered. These regions can be assigned to different airflows dominating Austria’s climate and triggering precipitation events during the cold season. The situation during summer is more complicated. Thus, at least four clusters are necessary to record the circumstances, which are caused by spatially inhomogeneous convective events such as thunderstorms. Copyright © 2003 Royal Meteorological Society.

KEY WORDS: homogeneous regions; REOFs; cluster analysis; ANNs; Austria’s precipitation climate

1. INTRODUCTION

Precipitation is one of the main climatic elements and its distribution can be highly variable in space and time, particularly over complex terrain. Long-term fluctuations of precipitation affect the composition of vegetation directly (Lexer et al., 2002). Hence, recording of past variations and simulation of future variations and changes of homogeneous precipitation regions are principal tasks of climate research.

This work pursues two aims. First, to illustrate objective methods to detect homogeneous precipitation regions and thereby to contribute to a better understanding of the spatial and seasonal variability of precipitation climate in Austria. Second, to study precipitation behaviour during the 20th century. These goals appear to be of value, since Austria’s precipitation climate is marked by complicated patterns of spatial and seasonal variability (Auer, 1993). Nevertheless, the results of the study are limited by the difficulties of measuring precipitation in high mountains.

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Austria’s landscape is complex. It ranges from basins with low altitudes of only a few hundred metres to high mountains from 2000 m up to more than 3500 m and deep valleys along the Alpine chain (see Figure 1).

The weather in Austria is dominated by three main airflows, originating from the Atlantic, from the Mediterranean and from eastern Europe. The Alpine crest separates Austria into several climatic provinces. The northern and central Alps form a barrier for the northwesterly airflow. From Vorarlberg across the Bavarian Alps to the Salzburger Alps, mean annual precipitation totals reach values of more than 3000 mm (Schwab et al., 2001), having a maximum, as in all parts of Austria, during summer. The precipitation totals decrease eastwards, and inner alpine valleys like the Inntal and the Ötztal, located at the lee side, are not so wet. The eastern parts of Austria, including the Mühl-, Wald- and Weinviertel, as well as the Burgenland and areas in the Steiermark, are relatively dry, with mean annual totals from less than 500 to 700 mm. The climatic impact in this region is conditioned by the continent and shows large differences between summer and winter seasons. Areas south of the main alpine peaks, such as the Klagenfurter valley and the east-Styrian uplands receive higher amounts of precipitation than the eastern region. This is mainly due to the advection of humid air masses from the Adriatic Sea during the summer months. In this part of the country the frequency of occurrence of thunderstorms and hail is higher than in any other part of Austria.

To identify different homogeneous regions, precipitation distributions are regionalized using different methods. The application of methods is repeated for different periods during the 20th century. Three samples of equal length were allocated (1901–33, 1934–66, 1967–99). This was done to fulfil the World Meteorological Organization (WMO) recommendation of using periods of at least 30 years for climate analysis (WMO, 1992). Moreover, this arbitrary choice matches typical research conditions.

Some practical applications of homogeneous precipitation regions are: (i) application in downscaling and impact studies; (ii) use for climatological and forecasting models; (iii) comparison of different statistical methods; (iv) detection of climatic fluctuations; and (v) station network design.

This paper is organized in the following way. The high-quality homogenized long-term climate dataset called ALOCLIM (Austrian long-term climate; Auer et al., 2001), which serves as the basis of this study, is introduced in Section 2. In Section 3, the three different methods used (rotated empirical orthogonal functions (REOFs), cluster analysis (CLA) and an artificial neural networks (ANNs) technique) are presented. Section 4 contains the results and a comparative synopsis for winter and summer. Section 5 contains the discussion. Finally, the conclusions are drawn in Section 6.

2. DATA

ALOCLIM (Auer et al., 2001) is one of the first datasets that meets all the necessary requirements to describe climate and its variability. Such requirements are: (i) high density and long-term station records; (ii) multiple-element datasets; and (iii) high data quality in terms of non-climatic inhomogeneities.
All time series entering the ALOCLIM dataset have been investigated for breaks and systematic biases in the long-term station records. This is achieved by a homogenizing procedure (Auer et al., 2001; Böhm et al., 2001) using meta data information and mathematical homogeneity tests. Owing to the fact that the Austrian weather service collaborates with national weather services of most neighbouring countries, the quality of the ALOCLIM data is homogeneous in space (i.e. not limited by the borders of the Austrian territory). ALOCLIM contains precipitation, temperature, pressure and sunshine duration on a monthly basis.

Monthly precipitation totals from 31 stations (see Table I and Figure 1 for their spatial distribution), spread over Austria, were extracted from the ALOCLIM dataset for the 20th century. Only 0.6% of these data are missing. To simplify matters, they are replaced by their 100-year monthly means.

### 3. METHODS

Three techniques are used in order to group the stations into homogeneous precipitation regions. These are outlined in this section. The mathematics of the methods are not introduced, as they are given in...
various statistical publications (e.g. Haykin, 1994; von Storch and Zwiers, 1999). However, the main ideas are presented.

The methods utilized are: (i) a principal component analysis (PCA) performed on seasonal correlation matrices of precipitation data followed by a varimax rotation (REOFs); (ii) a cluster analysis (CLA) and (iii) a subgroup of artificial neural networks (ANNs) using the process of 'competitive learning'.

3.1. Rotated empirical orthogonal functions

Rotation was introduced to meteorology by Richman (1986) and its goal is to derive simple but meaningful patterns. Ehrendorfer (1987) used REOFs to identify homogeneous regions for summer and winter half-years from 1951 to 1980 in Austria. He utilized networks with somewhat less than 30 stations and found three precipitation regions of Austria for both winter and summer half-years. Widmann (1996) regionalized Swiss precipitation from 1961 to 1990 and Alpine precipitation from 1978 to 1991 using REOFs.

PCA is used to identify a low-dimensional subspace of the original data-space that contains most of its variability. This subspace is spanned by the leading eigenvectors, termed empirical orthogonal functions (EOFs). The rotation procedure usually follows a PCA in order to separate the noise from the signal.

The required ‘simple’ patterns are obtained by applying an orthonormal transformation to the EOFs. The required transformation solves a variational problem, which minimizes a cost function (von Storch and Zwiers, 1999). The form of the cost function characterizes the shape of the REOFs.

Simplicity can be achieved for the REOFs or their time coefficients, but not for both at the same time; hence, the REOFs can be orthogonal or the coefficients can be uncorrelated. In this study, the so-called ‘varimax’ method (Richman, 1986) is used to determine the form of the cost function.

3.2. Cluster analysis

Woth (2001) used a hierarchical CLA to find homogeneous regions of winter (DJF) precipitation on the Iberian Peninsula and in the south of France. Ramos (2001) investigated autumn and spring precipitation distribution patterns in northeastern Spain for the period 1889–1999 by applying hierarchical and non-hierarchical CLA techniques. Jackson and Weinand (1994) classified tropical precipitation stations distributed over the globe, using PCA and a clustering procedure. They utilized daily data records of different lengths, ranging from 5 to >50 years.

The purpose of a CLA is to sort objects into clusters according to different aspects. Clusters are units containing objects. Following Woth (2001), a hierarchical type of CLA is used to identify different homogeneous precipitation regions.

A hierarchical CLA is situated between two extreme states. One at its beginning, where every object forms a cluster on its own, and another at its end, where all objects are joined into one cluster. Between these extremes the objects are onwardly aggregated into clusters. In this study, the objects under investigation are normalized anomalies of seasonal precipitation totals at Austrian stations. CLA offers many possibilities of grouping objects. This wide choice corresponds to the ways of answering the following questions:

1. How can similarity between the objects/clusters be quantified?
2. When should two objects/clusters be joined into one?

Both questions deal with fuzziness — different objects or clusters become indistinguishable with increasing fuzziness. In this work, the correlation coefficient was selected to quantify fuzziness and thereby to answer the above questions. With reference to question 1, a high correlation coefficient between two objects accounts for much similarity between them. With reference to question 2, two clusters are not joined together until the correlation coefficient between their most dissimilar objects is lower than the fuzziness considered. This intersection technique is called the ‘complete linkage method’. It does not combine different clusters until the Euclidean distance between the most dissimilar objects underruns a given value. The utilization of the correlation coefficient $\rho$ advises the use of normalized anomalies $(X, Y)$ as objects, mainly because it permits
the formulation of the correlation coefficient as a simple function of the distance:

$$\rho(X, Y) = 1 - \frac{1}{2} ||X - Y||^2$$

An effective CLA should provide clusters inheriting a high degree of inner homogeneity and outer separation, i.e. the correlation coefficients between the objects inside the clusters should be high and between different clusters the corresponding correlation coefficient should be low.

### 3.3. Self-organizing networks

ANNs have been used for a wide range of applications. Foody (1999), for example, used ANNs to classify vegetation data in environmental sciences, Michaelides et al. (2001) and Hewitson and Crane (2002) applied them to the climatological domain. Michaelides et al. (2001) used ANNs to classify rainfall variability in Cyprus. They found that ANNs perform more realistically than a CLA.

Self-organizing networks are a subgroup of ANNs intended to perform a mapping of arbitrarily distributed data (input patterns) on a low-dimensional space. More precisely, it is an ‘unsupervised learning’ procedure. There are many types of self-organizing network applicable to a wide area of problems. Hewitson and Crane (2002) recently used ‘self-organizing feature maps’ to describe changes of synoptic circulation and discuss in detail their performance and application within the climatology domain. Here, another technique, ‘competitive learning’ (Rumelhart and Zipser, 1985), which is related to ‘self-organizing feature maps’, is used. This kind of self-organizing network divides a set of input patterns into groups.

The architecture of the neural network used in this paper consists of an input layer containing $n$ nodes and an output layer with $n_0$ nodes, where $n$ corresponds to the dimension of the input vector, which in our case equals the length of the time series, and $n_0$ is the desired number of clusters. Each node of the output layer is connected to all nodes of the input layer through the connection weights. The input data are generally arranged as a matrix of $m \times n$ dimension, where $m$ and $n$ denote the number of observations and variables respectively. The data are assigned to the output nodes through an iterative process. An iteration consists of selecting an observation (input vector) at random, finding its ‘best matching’ output node (the one having the smallest Euclidean distance with the input vector) and updating the connection weights. The updating formula is a function of one learning rate $\eta$. In total, there are two learning rates $\eta$ and $\eta' (\eta \gg \eta')$, which are fixed during the whole process: $\eta$ is used to update the weights of the ‘best matching’ node and $\eta'$ for all others. $\eta'$ is used to prevent the situation of only one node being the ‘best matching’ node. If further iterations cause no alteration of the compositions of each node, then the learning process is complete. All stations mapped onto the same node form a group.

### 4. RESULTS

#### 4.1. Rotated empirical orthogonal functions

In this study, the seasonal totals at the stations in their standardized form are entered in the rotation approach, which is explained in Section 3.

The first step is to perform a PCA on the standardized random variable, i.e. to diagonalize the correlation matrix. The corresponding eigenvectors (EOFs) form an orthogonal basis and their time coefficients are uncorrelated. The resulting eigenvalues are utilized, via the so called ‘logarithm of eigenvalue plots’ (Preisendorfer, 1988), to determine the dimension of the subspace containing the main fraction of variance.

In case of DJF, the subspaces spanned by the first three (four) EOFs contain more than 75% (80%) of the intra-annual variance. During the summer season (JJA), the first four (five) EOFs explain more than 65% (70%); see Table II.

However, the quality of the EOFs declines with increasing index; hence, including more and more EOFs will not solve the problem. Von Storch and Hannoschöck (1985) showed that the variance of the eigenvalue estimates is large and biased. In general, large eigenvalues are overestimated and small ones...
Table II. Fraction of variance explained by the leading DJF and JJA EOFs

<table>
<thead>
<tr>
<th>Period</th>
<th>DJF 3EOFs</th>
<th>DJF 4EOFs</th>
<th>JJA 4EOFs</th>
<th>JJA 5EOFs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1901–33</td>
<td>77.4</td>
<td>81.9</td>
<td>70.8</td>
<td>74.8</td>
</tr>
<tr>
<td>1934–66</td>
<td>81.1</td>
<td>85.6</td>
<td>74.4</td>
<td>79.0</td>
</tr>
<tr>
<td>1967–99</td>
<td>76.2</td>
<td>81.9</td>
<td>67.4</td>
<td>72.3</td>
</tr>
</tbody>
</table>

are underestimated. These errors become considerably large if the degree of freedom exceeds the sample size. Hence, it was decided to take the first three DJF EOFs and the first four JJA EOFs. Ehrendorfer (1987), who investigated the period 1951–80, took three EOFs for both the winter and summer half-years. Subsequently, the varimax rotation that provides the REOFs is applied. With respect to subsequent applications (e.g. downscaling), it was decided to keep the time coefficients of the rotated patterns uncorrelated, which implies that the REOFs are not orthogonal. Thus, the EOFs and their coefficients have to be renormalized prior to rotation (von Storch and Zwiers, 1999).

Stations that share the highest value at the same rotated vector are combined into one group. Hence, the maximum number of regions is given by the dimension of the subspace retained, i.e. three (four) for the winter (summer) season. Figure 2 displays the regions found during the winter (left-hand side) and the summer seasons (right-hand side).

4.2. Cluster analysis

As mentioned in Section 3, we apply the ‘complete linkage method’ as an intersection technique and the normalized time series at the stations are entered in the cluster analysis.

The results of the cluster analysis is displayed in a so-called dendogram. An example of a dendogram is given in Figure 3. The abscissa displays the stations and the ordinate the correlation coefficient. At the beginning the correlation coefficient is equal to unity (i.e. uniqueness). Thus, two objects form a cluster only if they are identical. Along the y-axis, fuzziness (the correlation coefficient) is increasing (decreasing). Hence, the number of clusters is decreasing. At an arbitrary value of the correlation coefficient the aggregation is truncated and the effectiveness of the analysis (inner homogeneity and outer separation) is evaluated (e.g. Table III). If the result is not acceptable then a further union of clusters or a cutoff at a higher correlation coefficient is necessary.

Table III displays the inner homogeneity and outer distinctiveness (i.e. the quality measures of the analysis). At the end of the procedure, the precipitation regions are plotted (see Figure 4). A drawback of the method is that it depends critically on the initial state. Hence, objects that are actually related, although situated in different clusters (at the beginning), may not be combined until the end of the CLA. Knowledge of precipitation climate groupings is a prerequisite for the application of the method.

4.3. Self-organizing networks

As input data we used standardized seasonal anomalies of monthly precipitation at the stations considered. They are arranged as an $m \times n$ matrix, as mentioned previously. The connection weights are randomly initialized between $-1$ and $+1$ and the learning rate parameters $\eta$ and $\eta'$ are fixed to 0.08 and 0.001 respectively. The desired number of clusters are chosen as three and four for winter and summer respectively. During the winter seasons, convergence is reached after 2000 iterations. In the case of the summer seasons, 5000 iterations are necessary. Figure 5 shows the regions found by the ANNs technique used.
4.4. Comparative synopsis for winter

Period 1901–33: the findings of CLA and ANNs are identical. Differences in the REOFs appear only along the edge between the region defined by a square (□), lying in the northeast of Austria, and the region defined by a circle (O), covering the territory in the north of the main alpine peaks from Vorarlberg to the Mühlviertel. The third region, defined by a triangle (△), runs along the alpine chain and includes all stations to its south.

Period 1934–66: during this period, the results of REOFs and ANNs are strongly linked more so than to the results of CLA. All techniques combine stations in the northern plateaus (Wein-, Wald- and Mühlviertel) with stations in and around Salzburg (□). Additionally, ANNs and REOFs show a connection to stations in Vorarlberg. Unit (△) extends from stations in the vicinity of the southern basins (Grazer and Klagenfurter basin) to the northeast. The remaining stations (O) form a group, which runs from Vorarlberg across Tirol to the southern edge of Salzburg. Noticeable differences between the techniques appear around the Hohe Tauern.

Period 1967–99: the situation is related to the first period. During this period, results of REOFs and CLA are sightly closer to each other than to findings of ANNs. However, differences occur only in the vicinity of the Hohe Tauern. One feature appears worth mentioning, i.e. the extension of the northeastern group (□) into Steiermark, which is found by all methods.
Table III. Assessment of CLA results for the winter season. Fischer and Pearson correlation coefficients measure the homogeneity inside the clusters. The correlation matrix determines the similarity between the clusters.

<table>
<thead>
<tr>
<th>Period</th>
<th>Measure</th>
<th>Cluster 1</th>
<th>Cluster 2</th>
<th>Cluster 3</th>
<th>No clustering</th>
</tr>
</thead>
<tbody>
<tr>
<td>1901–33</td>
<td>Fischer</td>
<td>1.01</td>
<td>1.01</td>
<td>0.75</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td>Pearson</td>
<td>0.77</td>
<td>0.76</td>
<td>0.64</td>
<td>0.45</td>
</tr>
<tr>
<td></td>
<td>Correlation Matrix</td>
<td>1.00</td>
<td>0.42</td>
<td>0.24</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.42</td>
<td>1.00</td>
<td>0.44</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.24</td>
<td>0.44</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>1934–66</td>
<td>Fischer</td>
<td>0.90</td>
<td>0.92</td>
<td>0.91</td>
<td>0.59</td>
</tr>
<tr>
<td></td>
<td>Pearson</td>
<td>0.72</td>
<td>0.72</td>
<td>0.72</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td>Correlation Matrix</td>
<td>1.00</td>
<td>0.58</td>
<td>0.41</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.58</td>
<td>1.00</td>
<td>0.71</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.41</td>
<td>0.71</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>1967–99</td>
<td>Fischer</td>
<td>1.12</td>
<td>0.77</td>
<td>0.82</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td>Pearson</td>
<td>0.81</td>
<td>0.65</td>
<td>0.68</td>
<td>0.45</td>
</tr>
<tr>
<td></td>
<td>Correlation Matrix</td>
<td>1.00</td>
<td>0.57</td>
<td>-0.01</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.57</td>
<td>1.00</td>
<td>0.50</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.01</td>
<td>0.50</td>
<td>1.00</td>
<td></td>
</tr>
</tbody>
</table>

During all episodes investigated, three regions can be distinguished. A rough classification might be: one region covers Austria’s south, another comprises the stations in the northeast and the third contains the western parts of Austria. The agreement among the methods is satisfying. Two features appear worth mentioning: the large region covering the northern plateaus (□) during the second period (1934–66), and the combination of the northeastern part with stations in the Steiermark (1967–99) are both detected by all methods. The patterns found in the first (1901–33) and third (1967–99) episodes share more similarities than those found in period 1934–66.
4.5. Comparative synopsis for summer

**Period 1901–33:** REOFs and ANNs detect four groups, and CLA defects six. Similar regions are: (□) which covers large parts of the northern plateaus and extend westwards; (Δ) combining stations along the southern border of Austria; and (Ο) running along and north of the alpine crest from Salzburg to Vorarlberg. ANNs and CLA find groups, labelled (Δ), (*) and (□), that are (almost) identical.

**Period 1934–66:** the northern region (□), as well as the cluster in Austria’s southeast, labelled (Δ) in the case of REOFs and CLA or (*) in the ANNs case, are found by all methods. Moreover, REOFs and CLA rearrange stations in Vorarlberg to a unit (+).

**Period 1967–99:** REOFs findings are almost in perfect agreement with those derived by ANNs. Both methods show four regions: one in Vorarlberg (+), another (Ο) stretches from Tirol to Salzburg, the third (Δ) follows the alpine crest eastwards and covers basins in its south and the Vienna basin and the last one (□) combines large parts of the northern plateaus. The picture drawn by CLA differs.

The situation during summer is more complex than during winter, and the methods show differences. However, similarities outweigh the differences. Three regions are almost always detected: one covering the northern plateaus, one combining areas in Austria’s southeastern part and one forming a unit in Vorarlberg. In detail, several groups of stations can be found, which are always joined together.
5. DISCUSSION

The findings of the different techniques agree relatively well. Moreover, from a climatological point of view, the results derived are reasonable and hence the techniques appear suitable for these kinds of problem. However, the quality of the results is heavily dependent upon the quality of the data.

The findings of all three techniques show the main precipitation-modulating effects in Austria. Accordingly, the Alps is a barrier for the main airflows, concerning north and southward advection. The continental influence in the east is captured owing to a quasi-permanent easterly high. During the warm season, convective processes dominate the precipitation regime. Independently from the periods considered, all techniques separate Austria into three regions during winter. Differences emerging between the periods are reproduced by all techniques in a very similar way.

During the first period, the winter season shows a ‘classical’ pattern. The first region covers alpine areas in Vorarlberg and runs eastwards to the western edge of Niederösterreich; the second one combines the alpine chain with basins in its south; and the third region lies in Austria’s northeast. In this succession they reflect the Atlantic, Mediterranean and continental influences respectively.

During the second period, large fractions of the 1901–33 western and eastern groups are joined into one. This might be the most striking result of the whole analysis. In order to find the sea-level pressure (SLP) pattern, that is associated with precipitation in this region during the 20th century, the geographical sector
from 50°W to 30°E and 35°N to 65°N is extracted from the Northern Hemisphere SLP dataset (Trenberth and Paolino, 1980) and investigated by means of PCA and multiple linear regression. The most important features found are: (i) a negative anomaly over large parts of Europe having its minimum over Scandinavia; (ii) almost zero values south of Iceland and a poorly developed positive anomaly in the west of Spain. This points to air mass advection from the northwest leading to precipitation at the northern border of the entire Alps. However, another region, more clearly influenced by the Atlantic, can be found in the central Alps.

The third period only shows a small region influenced by the Mediterranean and a larger one under continental influence. During this period the region influenced by the Atlantic is similar to the first period. Although Ehrendorfer (1987) uses other data, another period (1951–80) and investigates half-years, his results are similar to our results.

During the summer season, Austria’s precipitation pattern is more patchy. Not all regions can be easily related to different air flows or precipitation regimes. Contrary to winter, only three regions are almost similar for all techniques. The first one is located in the central Alps (Tyrolian Alps and Hohe Tauern), an area that is known for low convective precipitation compared with other parts in Austria. The second one covers areas from Salzburg to the Waldviertel in the north of the Alps, and the third region is situated in the southeast of Austria. The differences between the periods are of the same magnitude as the differences produced by different techniques within the periods. Thus, a comprehensive meteorological interpretation is not possible.

Taking into account the different rain-producing mechanisms, it is not surprising that precipitation during summer is highly variable in comparison with winter precipitation. Precipitation events during winter are mainly triggered by large-scale advective processes, with sizeable temporal extent. During summer, precipitation is dominated by local-scale short-term convective processes. These differences are responsible for the precipitation distribution depending on the seasonal cycle.

6. CONCLUSIONS

The techniques are able to reveal the seasonal dependence of Austria’s precipitation patterns. Differences among the methods are larger during summer than during winter. In the case of CLA the differences between summer and winter can be seen directly in the dendrograms. During summer, it is difficult to distinguish clearly between different groups, and this leads to a reduced outer separation and inner homogeneity of the final regions. In the case of REOFs, the dimension of the subspace, required to comprise approximately the same fraction of variance as in winter, is higher. Hence, the corresponding patterns are likely to be more complicated than in winter. In the case of ANNs, during winter, only one choice of parameters was sufficient for all episodes. During summer, these parameters had to be adjusted for each period separately. Hence, differences between the methods are more pronounced in summer than in winter.

To summarize, the results found by the different techniques are in agreement. This is particularly true for the winter season, but even during summer there are common features. This fact inspires confidence in the usefulness of the methods.

CLA, REOFs and ANNs depend on the objective of the research: CLA offers many possibilities of quantifying similarity, i.e. to measure how two stations are alike and how they differ; REOFs depend on the number of EOFs retained and the rotation method, and in ANNs several parameters (e.g. learning rates, distance weighting, etc.) can be adjusted.

The results of this work are now being used in downscaling studies. For every region a single downscaling model is established (Woth, 2001), to infer information from larger to smaller scales. Further goals might be the application of the techniques presented to: (i) larger amounts of station data, which generally comprise only a short period in comparison with the total period available in this work; (ii) larger regions, e.g. the whole alpine area; and (iii) detection of homogeneous regions with respect to time.

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