

# PATTERNS OF PRECIPITATION VARIABILITY IN THE GREATER ALPINE REGION

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**Abstract:** A recently set up and homogenised new precipitation dataset for the Greater Alpine Region (GAR) is presented here with some first preliminary analyses. Climate change patterns within the study region are analysed in terms of regionally different evolutions, seasonality, and short to long-term trends. It will be shown that precipitation presents pronouncedly different variability patterns in space as well as in terms of seasonality and at different time scales.

**Keywords** – *Precipitation, PCA, Trends*

## 1. INTRODUCTION

The paper investigates precipitation variability in the Greater Alpine Region (GAR) (4°E-19°E, 43°N-49°N) based on 192 instrumental homogenised and outliers checked series of monthly precipitation and on the 1-deg gridded version of the same data set (for details about the datasets see Auer et al., 2005). The data set was clustered into climatically homogeneous regions by means of a Principal Component Analysis. The principal component analysis was applied also in Q-mode to investigate the most recursive precipitation patterns that characterize the examined area. Yearly and seasonal trend analysis were performed both on regional average series and on the mean GAR series. Trend analysis was applied to study short period changes too, but these last result will be shown in the poster presentation.

## 2. PRINCIPAL COMPONENT ANALYSIS

The precipitation dataset has been clustered into homogeneous precipitation areas by means of a principal component analysis (PCA).

PCA allows the identification of a small number of variables known as principal components (PCs), which are linear functions of the original data, and which maximize the amount of their explained variance.

The technique was applied to the correlation matrix R calculated from the monthly anomalies series (expressed as the ratio respect to the 1961-1990 period), in order to avoid the dominance of the annual cycle in the analysis results.

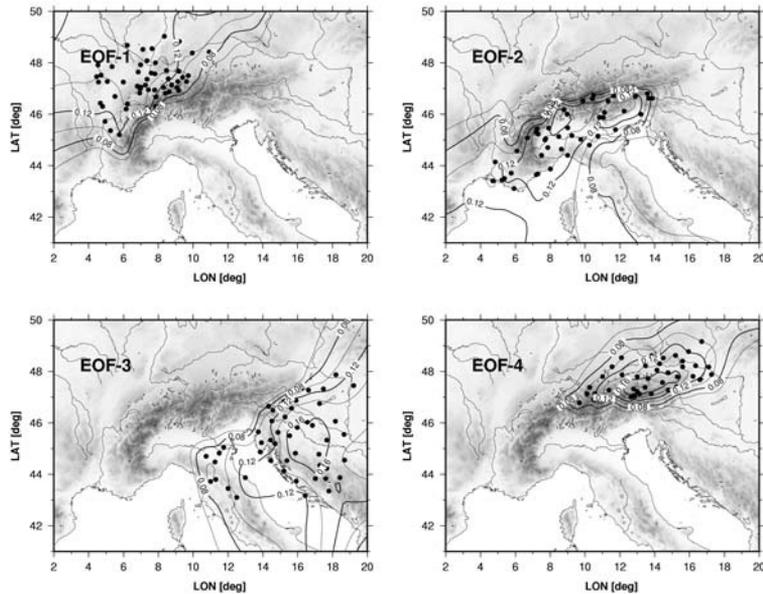
R was calculated both for the whole year (by including all the 12 months per year) and separately for each season (winter: DJF; spring: MAM; summer: JJA; autumn: SON).

The analysis was applied to the sub-period 1927-2002, for which all 192 series are available (figure 1).

The eigenvalues of R (table 1) reveal that 18 EOFs account for more variance than the original variables (having eigenvalues greater than 1) and that these explain globally the 80% of the variance of the whole dataset (last column of table 1).

In fig. 1 the factor loadings of the first four rotated (by a VARIMAX rotation) normalized EOFs are plotted on geographic maps, by drawing contours through the points with the same loadings.

The stations with the highest loading in the correspondent EOF are plotted too.



**Figure 1.** First four rotated EOFs

**Table 1.** Eigenvalues and explained variance of the first 18 not-rotated EOFs obtained from the PCA applied to the monthly anomaly series

	Eig.val.	Var. [%]	Tot. Var. [%]
1	63.25	32.94	32.94
2	28.32	14.75	47.69
3	18.68	9.73	57.43
4	9.17	4.77	62.20
5	6.80	3.54	65.74
6	4.67	2.43	68.17
7	3.59	1.87	70.04
8	2.54	1.32	71.37
9	2.43	1.27	72.63
10	2.17	1.13	73.76
11	2.12	1.10	74.87
12	1.80	0.94	75.80
13	1.61	0.84	76.64
14	1.49	0.78	77.42
15	1.30	0.68	78.10
16	1.18	0.62	78.72
17	1.15	0.60	79.31
18	1.01	0.53	79.84

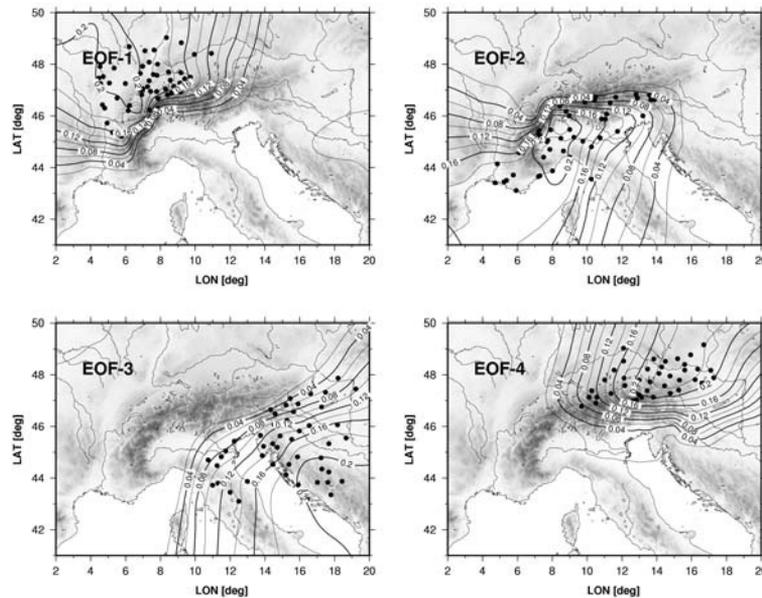
The loadings patterns allow the following regions to be identified:

- The *North-West* (NW): A region of mainly maritime influences from the Atlantic, and framing the Alps in the north;
- The *South-West* (SW): A region covering most of the northern continental part of Italy, and having maritime influence from the Atlantic and the Mediterranean. It has definite borders in the North (towards the Alps) in contrast with the situation in the East, which is characterized by a gentle transition into the Adriatic cluster;
- The *South-East* (SE): A region covering the Adriatic coast;
- The *North-East* (NE): A region of mainly continental features framing the Alps in the north, and covering the most part of Austria.

The analysis was applied also to the seasons. In winter and autumn there is a higher spatial coherence than in spring and summer, this is evident from the lower number of eigenvalues greater than 1 (17 for winter and autumn, 22 and 29 for spring and summer respectively).

To verify that the PCA result is not affected by the spatial distribution of the stations over the GAR area, the analysis was performed also on the 1-deg resolution gridded version of the data set.

In fig. 2 the first 4 rotated EOFs obtained by applying the PCA to the gridded version of the data-set are shown.



**Figure 2.** First four yearly rotated EOFs obtained from the gridded version (1 deg resolution) of the data-set. The location of the stations clustered by the first 4 rotated yearly EOFs in station mode are indicated too.

### 3. PRINCIPAL COMPONENT ANALYSIS IN Q-MODE

The PCA is usually applied to time series to extract typical patterns of variability.

It is a sort of “variable reduction procedure” that extract from  $N$  linearly dependent time series, a set of  $N'$  independent series (with  $N' \ll N$ ), the PCs.

The Q-mode approach consists of a sort of exchange between the two variables *space* and *time*.

The basic idea is as follows. We have  $N$  time series  $n_y$  years long. Their temporal behaviour can be characterised by some spatial patterns that repeat themselves more and more times (but not necessary with a periodical behaviour) over the spanned time period. We can summarize the variability of our precipitation field by collecting all the similar patterns together into one single pattern.

In this case the eigenvalues represent the multiplicity of each pattern (i.e. the number of times it happens) and the sum of all of them is  $n_y$ .

In the standard PCA, the PCs are time series of the most typical mode of variability of the system. In the Q-mode approach they represent the spatial patterns, while their time occurrence is described by the EOFs.

In this case the data series consist of the spatial variability of each single temporal instant, for this reason it is more suitable the gridded version of the data-set, being it complete (all the 112 grid points) for a longer period (124 years from 1880 to 2003) than the station-mode data-set (which is complete only over the 1927-2002 period).

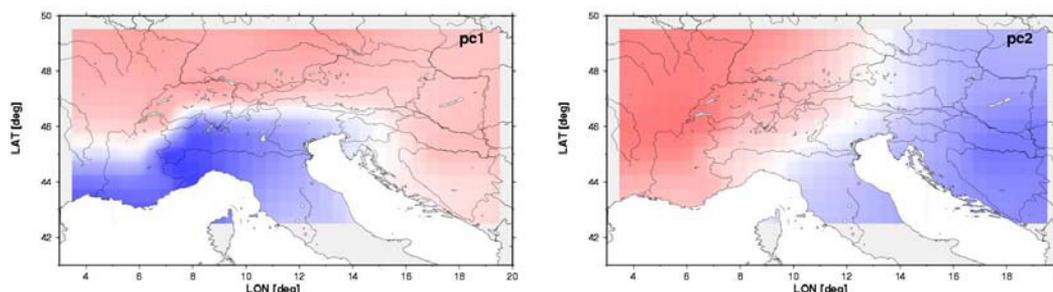
For each year from 1880 to 2003 we extract the series consisting of each single grid value of the annual precipitation. So, we have 124 series (the number of years) each one having 112 values (the number of grid points).

By looking at the eigenvalues it is evident that the first pattern happens about 36 times in the 1880-2003 period, the second one 27 times, the third one about 14 times, and so on (being the first three eigenvalues 36, 27, and 14 respectively).

In QPCA the EOFs represent the temporal behaviour of the spatial patterns described by the corresponding PCs, being the PCs 112 element vectors (one element per grid point) composed by the weights of each grid point in the corresponding EOF.

The PCs corresponding to the two highest eigenvalues are shown in fig. 3.

It is evident from the first panel of fig. 3 that the most frequent configuration is a di-polar north-south pattern, with the Alps playing a primary role as separation border for dry/wet areas. The second configuration (second panel of fig. 3) corresponds to an east-west di-polar pattern.



**Figure 3.** First two principal components obtained from the QPCA

More than the 50% of the time (over the 1880-2003 period) the GAR precipitation lie in one of the first two patterns shown in figure 10.

In winter, due to the higher spatial coherence of atmospheric circulation, the permanence in the first two patterns is also higher, with 44 years in the first one and about 24 years in the second one, corresponding to more than the 55% of the time (over the 1880-2003 period).

#### 4. CONCLUSION

A new precipitation dataset for the Alpine region was analysed.

The principal component analysis identified 4 climate regions, two north of the Alps and two south of the Alps. The most typical spatial patterns were identified by applying the PCA in its Q-mode approach, by exchanging space and time. The results highlighted the dominance of two di-polar patterns characterising the precipitation of the region: a north-south di-pole and an east-west one. These two patterns take into account more than the 50% of the events over the examined period.

More results about long and short-term trend will be presented at the conference, the preliminary results highlight a different behaviour for northern and southern regions, the Alps playing a fundamental role in separating different precipitation patterns.

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