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Climate indices for Baltic States from principal component analysis

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Abstract. We used principal component analysis (PCA) to derive climate indices that describe the main spatial features of the climate in the Baltic States (Estonia, Latvia and Lithuania). Monthly mean temperature and total precipitation values derived from the ensemble of bias-corrected regional climate models (RCM) were used. Principal components were derived for years 1961-1990. The first three components describe 92% of the variance of the initial data and were chosen as climate indices in further analysis. Spatial patterns of these indices and their correlation with the initial variables were analyzed and it was observed that higher values of each index corresponded to: (1) less distinct seasonality, (2) warmer and (3) wetter climate. The loadings from the chosen principal components were then further used to calculate values of the climate indices for years 2071-2100. Overall increase was found for all three indices with minimal changes in their spatial pattern.

1 Introduction

Spatial representation of the climate e.g. mapping of climatic zones is a useful tool in climate analysis. First, it can be used to better convey information about the climate features of the region, for applications in climate change adaptation and mitigation. Second, the spatial patterns can give insight both into the possible relationship and the impacts of the climate to other fields, e.g., phenological processes and vegetation distribution (Feng et al. 2012). Third, they illustrate geographical features that influence climate, such as hillsides, coastal zones etc. There is a wide variety of approaches for creating spatial representation of climate, but usually they belong to either rule-driven or data-driven methods. Rule-driven methods are used more often, the most popular being Köppen-Geiger classification (Peel et al. 2007). These methods are based on some predefined rules, for example, thresholds of meteorological variables or frequency of events. Climate zones derived from classifications of this type usually correspond to vegetation distributions, in the sense that each climate type is dominated by one vegetation zone or eco-region (Belda et al. 2014). However, predefined rules make these methods subjective. Alternatively, the spatial pattern can be derived from data-driven or analytical methods. These include principal component analysis (PCA, Benzi et al. 1997, Estrada et al. 2008) and cluster analysis (Bieniek et al. 2012) or a combination of both methods (Briggs and Lemin 1992, Fovell and Fovell 1993, Baeriswyl and Rebetez 1997, Malmgren et al. 1999 Fan et al. 2014, Forsythe et al. 2015). Analytical methods, depending on the chosen variables, can give results that are similar to those of rule-driven methods, but results are more homogenous (Netzel and Stepinski 2016). Analytical methods provide a spatial pattern that must be interpreted before it can be linked with possible applications.

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Principal component analysis or empirical orthogonal function analysis has two important applications. First, it can reduce the number of variables that are used to describe regional climate while still retaining most of the variation seen in the initial data. Second, PCA provides new indices that are the linear combination of chosen variables. The loadings of chosen principal components are the coefficients that define the newly created indices, which then describe the main features of climate. Variables for PCA can be chosen and indices calculated with a specific purpose in mind, for example, indices for the classification of different types of winters (Hagen and Feistel 2005) or estimation of crop yield based on the climate (Cai et al. 2013). Indices can also be chosen to describe climate of the region in general (Estrada et al. 2008). However, the problem with the indices that are derived using analytical methods is that their meaning is not known beforehand, so their interpretation may require further analysis.

For many practical applications temperature and precipitation are the two main variables of interest for a certain region. They are usually sufficient for representing vegetation types in corresponding climate zones (Zhang and Yan 2014). Vegetative production, organic matter decomposition, and cycling of nutrients are strongly influenced by temperature and moisture (Briggs and Lemin 1992). Distinct changes of temperature and precipitation are to be expected in future (BACC 2015). Thus, consequently, any climate patterns based on these two variables also will be affected, leaving significant impact on living organisms. For instance, plant species inhabiting regions subjected to climate change might have too little time to adapt (Mahlstein et al. 2013).

The Baltic States region exhibits significant spatial and temporal climatic variability, with influence of air masses from arctic to subtropical origin (Jaagus and Ahas 2000, Rutgersson et al. 2014). The terrain is mostly flat, with the highest elevations extending slightly above 300 meters. The Baltic Sea and the shape of its coastline have an important role in the climate of the region. PCA has been used to describe precipitation pattern in the Baltic countries with atmospheric and landscape variables (Jaagus et al. 2010).

To study effects of climate change on climate patterns regional climate model (RCM) data can be used (Mahlstein and Knutti 2010, Tapiador et al. 2011, Fan et al. 2014). RCM models are continuously improving and correspond rather well to climate observations (Castro et al. 2007). Other advantages of using RCM data are that (a) their data are regularly spaced while PCA applied on irregularly spaced data can produce distorted loading patterns (Karl et al. 1982) and (b) RCM data are available also as future projections giving insight into manifestation of climate change. Additionally, the spatial representativeness of the network of observation stations in the Baltic States has been reported to be problematic (Remm and Jaagus 2011).

The aim of this work is to define climate indices which represent the main features of Baltic States climate in a compact form. The study consists of several parts. First, RCM data for temperature and precipitation were bias-corrected. Second, monthly average values for the reference period 1961-1990 were calculated and standardized. Third, PCA analysis was performed and main principal components were identified. Acquired principal components and their spatial patterns were analyzed. Fourth, loadings of chosen principal components were used to calculate indices for years 2071-2100 and compared to reference data.

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2 Data and Methods

2.1 Climate data and methods

The source of the RCM ensemble data is the ENSEMBLES project (van der Linden and Mitchell 2009). Model data sets for the A1B scenario are given for the time period 1961 – 2100. 22 model runs were considered (shown in Table 1). We used time series of daily average air temperature at 2m height and daily precipitation. RCM models are known to show systematic biases (Teutschbein & Seibert 2012). Bias correction method (Sennikovs and Bethers 2009) that uses quantile mapping was chosen and the cumulative distribution function was calculated for each day of the year using 11-day running average – the data for five days before and five days after the day of interest. The control period for bias correction was 1961-1990 and the locations of observation stations used for bias correction are shown in Fig. 1. Bias corrected data was then interpolated to a regular grid because it has been shown that PCA applied to irregularly spaced data can produce distorted loading patterns (Karl et al. 1982).

Two time periods were chosen – 1961-1990 (as reference climate) and 2071-2100 (as future climate projections). For each time period monthly average temperature and precipitation were calculated for each grid point. In total 24 variables were used - 12 monthly precipitation and 12 monthly average temperatures. The spatial distribution of these variables is shown in Fig. 2 and Fig. 3. Figure 2 shows north-south gradient of monthly precipitation during April-June and east-west gradient of monthly precipitation during October-January. Figure 3 shows east-west gradient of monthly temperatures during October-February and north-south gradient of monthly temperatures during April-June. This implies that some of the variables can be combined in seasons (as it is done by (Malmgren et al. 1999) and (Forsythe et al. 2015)) and that for some months temperature and precipitation is correlated. A better insight of variables with similar patterns can be gained by examining the correlation matrix in Fig. 4. The matrix areas that represent strongly correlated variables are marked in this figure and they show following relationships:

1 - Very strong correlation (above 0.8) between precipitations in winter months – more precipitation in, e.g., December is clearly linked to more precipitation in January. Thus, entire winters are either dry or humid.

2 - Strong correlation (above 0.5) between precipitation and temperature in spring months. Thus, colder springs are also dryer, whilst warmer springs are rainy.

3 - Strong negative correlation (below -0.5) between precipitation in autumn and late spring/early summer temperature – more precipitation in autumn corresponds to colder spring.

4- Very strong correlation (above 0.8) between temperatures of autumn and winter months – warmer autumn corresponds to warmer winter.

Figure 4 shows that 24 monthly variables contain redundant information and through PCA we can summarize information and create new variables.

2.2 PCA method

The aim of PCA is to create a new set of uncorrelated variables that are linear combination of initial variables and explain as much as possible of the initial variation. An extensive description of PCA can be found in Jolliffe (2002), and its applications to climate are described in Preisendorfer (1988).

An important choice must be made when applying PCA: whether to use correlation matrix or covariance matrix in the calculation of coefficients that define principal components (eigenvectors). If the covariance matrix is used then a second choice must be made – if and what standardization to use. When performing data standardization following issues should be taken into account:

1 – Variables should be of similar scale, otherwise variables with considerably larger variance will dominate the principal components. Different scales are usually a consequence of different units of measurement. In our case the variance for precipitation measured in millimeters is considerably larger than that of temperature that is measured in degrees Celsius.

2 – In case of variables that are measured in same units variances contain useful information and can improve interpretation of PCA (Overland and Preisendorfer 1982). Therefore, for variables that are measured in same units (for example, average temperature of different months) we wish to keep the ratio between variances of different months. This means that correlation matrix, where each variable is divided by its square root of variance, should not be used, as it would bring the variances of all 24 variables to 1.

3 – As we are planning to use the acquired loadings as coefficients for climate index calculation for future data and compare then with the reference climate it is necessary that the same standardization process is used for the data of the future time period.

Taking into account the issues described above we propose to use standardization in Eq. (1), where the spatial mean is subtracted for each variable as usual, but the average variance of all temperature or precipitation variables is used for scaling:

$$\frac{T_k-\bar{T}_k}{\sqrt{\bar{V}(T)}}, \qquad \frac{P_k-\bar{P}_k}{\sqrt{\bar{V}(P)}}, \qquad k = 1, \dots ,12, , \tag{1}$$

where $\bar{V}(T)$ – average variance of 12 temperature variables and $\bar{V}(P)$ – average variance of 12 precipitation variables.

The variances before and after such standardization for reference period are shown in Table 2. The ratio of variances for different months is retained. For data representing the future time period the standardization is performed by using the mean values and average variances from the reference period. Results of data standardization for future time period are shown in Table 3. It should be noted that in the future the variance of precipitation data will increase and the variance of temperature data will decrease. However, the proportion of variances in different months is similar.

Another detail that must be considered when using PCA is the choice of method for determining the number of principal components that describe data variation sufficiently well and can be used in further analysis. There are multiple methods to choose from (Preisendorfer 1988), however in our case one of the most common methods – scree-plot – gives excellent and clear results. A scree plot is a graph of explained variances of acquired principal components and the number of principal components is decided based on the break point in such a graph. Components to the left of the break point are retained.

3 Results

3.1 Principal components for control period (1961-1990)

Explained variance and loadings of first 3 principal components are shown in Table 4. The scree-plot of all principal components is shown in Fig. 5. First two components already describe 78% of variance of initial variables, while first three components describe 92% of variance. According to Jolliffe (2002) the cutoff point should be between 70% and 90% explained variance. However, the scree-plot clearly shows that first 3 principal components can be retained, so we chose to further analyze first 3 components.

Figure 6 shows the spatial pattern of the first three principal components for the reference climate. They should be analyzed together with the correlation coefficients between the new variables and initial variables shown in Table 5, where the bright red or blue colors mark high positive or negative correlation.

Correlation coefficient values (Table 5) show that the first principal component (PC1) has a high positive correlation with the autumn-winter temperature and precipitation and high negative correlation with temperature and precipitation in late spring and early summer months. This means that higher values of PC1 correspond to warmer winters with more precipitation (snow or rain) and colder summers with less precipitation. Such relationship between PC1 and original variables implies that high values of PC1 describe climate in which seasons are more similar to each other. From the spatial distribution (Fig. 6) we can see that PC1 has an east – west gradient implying less distinction between seasons at the seaside. The spatial distribution of PC1 is similar to the spatial patterns of mean start date of winter (see results for Estonia in Jaagus and Ahas (2000)) with higher PC1 values corresponding to later winters.

Second principal component (PC2) is positively correlated with all monthly temperatures and negatively correlated with precipitation in autumn. This means that high PC2 values correspond to regions that are generally warmer than others and have low precipitation in autumn. For PC2 a north – south gradient is evident with the warmer climate in south. However, this pattern is slightly influenced by geographical features (elevation) and the shape of the coast. The patterns exhibited by PC2 therefore can be expected to be similar to the spatial distribution of phenological events where the temperature is the main driving factor. For example, the spatial pattern of PC2 shows similarities to spring and summer start dates in the Baltic Sea region and to more specific phenological events, such as apple tree blossoming and beginning of the vegetation of rye (Jaagus and Ahas 2000) or strawberry blooming and harvest (Bethere et al. 2016). In general, higher values of PC2 correspond to earlier phenological processes.

PC3 is mainly positively correlated with precipitation for most of the year (December – August) and spring temperature (April – May). This means that high PC3 values correspond to overall high precipitation and warm spring, or in other words – overall wetter year. High values of winter precipitation and high temperatures in spring can be interpreted in the context of

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spring floods – however additional analysis is needed to account for the snow cover. The map of PC3 spatial distribution is similar to the map of average annual precipitation. Interestingly, the precipitation in autumn months (September – October) has a little contribution to PC3 (Table 5).

When the spatial patterns of PC2 and PC3 are analyzed the effect of orography can be seen, especially, the location of highlands is clearly visible, while for PC1 the terrain seems to have little impact.

Conclusions based on spatial pattern and correlation coefficient analysis are summarized in Table 6.

3.2 Climate indices for future climate (2071-2100)

To calculate indices for future climate (corresponding to period 2071-2100) and analyze the change in their patterns we used loadings acquired from past climate data (see Table 4) and calculated the indices from bias-corrected and standardized data for period 2071-2100. In Fig. 7 the correlation coefficients between indices and initial variables are shown and it can be seen that they are similar to those for past climate. Therefore, they have the same interpretation and it is possible to analyze the change in spatial patterns between the past and future climate. The spatial distributions of future indices are shown in Fig. 8. Statistical descriptors, e.g., minimal, maximal and mean value of past and future indices are summarized in Table 7.

All indices have higher values in future climate. This can be interpreted as lower difference between seasons (increase of PC1), an overall warmer climate (increase of PC2) and wetter climate (increase of PC3).

For PC1 it is shown that the values corresponding to coastal regions in reference climate will “move” to the eastern part of Baltic States in the future projections. The expected changes of PC2 are the largest – the maximum values of PC2 for reference climate (in southern Lithuania) are lower than the minimum values for future climate (in central Estonia). Statistics in Table 7 show that the reference range of this index does not overlap with the range of future values. The expected overall increase of PC3 is similar to that of PC1. The climate corresponding to reference values of PC3 in western Lithuania (Zhemaichiai highland) will in future be observable in plateaus in central and north-eastern part of Baltic States.

4 Discussion

The methodology used in this study has been able to reduce 24 climate variables to 3 new indices that more efficiently and compactly represent the main features of the climate in the Baltic countries. The methodology can also be applied to the future climate data and therefore the impacts of climate change can be analyzed. Additional analysis is needed for the interpretation of the acquired indices. To some extent such interpretation is provided in this study. The methodology could be further improved to better link acquired indices with phenological processes or seasons by either rotating acquired principal components (Jolliffe 2002) or performing correlation or regression analysis with other variables, such as crop yield (Cai et al. 2013). Another approach that could be used to describe spatial variability of climate in the Baltic States is clustering based on chosen principal component values (Fovell and Fovell 1993, Forsythe et al. 2015).

If variables other than temperature or precipitation are used for the principal components analysis, in some cases the standardization procedure should be modified. However, it should be taken into account that when more than one data set is used, e.g., when past and future climate is compared, the same values used for standardization should be applied to all of them.

5 Conclusions

Most of the spatial variability of monthly average temperature and precipitation over the Baltic countries can be represented by three principal components both for past and future climate. These components can be considered as climate indices, where higher values of each index correspond to (1) climate with less distinct seasons, (2) warmer climate, (3) climate with more precipitation. Each component has a distinct spatial pattern. The index related to seasonality exhibits clear east-west (or inland) gradient with less distinct seasonality at seaside (West). The second index (warmer climate) shows north-south gradient with warmer climate in south. This index also reflects orography with colder climate in hilly regions. The third index reflects the overall precipitation. Its spatial distribution is mainly dominated by elevation, with maxima at the highlands and less precipitation in plains and at the seaside. Specific standardization of data allows calculation of such indices also for the future climate. Change in the component values in future implies less distinct seasons, warmer and wetter climate.

For all three indices changes in spatial pattern are minimal. For the first and third component regions can be identified where future climate will be similar to the climate currently in other regions.

Acknowlegments

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References

The BACC II Author Team ed.: Second assessment of climate change for the Baltic Sea basin, Regional Climate Studies, doi: 10.1007/978-3-319-16006-1, 2015.

Baeriswyl, P.A. and Rebetez, M.: Regionalization of precipitation in Switzerland by means of principal component analysis, Theor. Appl. Climatol., 58(1-2), 31-41, doi:10.1007/bf00867430, 1997.

Earth Syst. Dynam. Discuss., doi:10.5194/esd-2017-34, 2017
Manuscript under review for journal Earth Syst. Dynam.
Discussion started: 6 April 2017

Belda, M., Holtanová, E., Halenka, T., and Kalvová, J.: Climate classification revisited: from Köppen to Trewartha, Clim. Res., 59(1), 1-13, doi:10.3354/cr01204 , 2014.

Benzi, R., Deidda, R., and Marrocu, M.: Characterization of temperature and precipitation fields over Sardinia with principal component analysis and singular spectrum analysis, Int. J. Climatol., 17(11), 1231-1262, doi:10.1002/(sici)1097-0088(199709)17:11<1231::aid-joc170>3.3.co;2-1, 1997.

Bethere, L., Sile, T., Sennikovs, J., and Bethers, U.: Impact of climate change on the timing of strawberry phenological processes in the Baltic States, Est. J. Earth Sci., 65(1), 48-58, doi: 10.3176/earth.2016.04, 2016.

Bieniek, P.A., Bhatt, U.S., Thoman, R.L., Angeloff, H., Partain, J., Papineau, J., Fritsch, F., Holloway, E., Walsh, J.E., Daly, C., and Shulski, M.: Climate divisions for Alaska based on objective methods, J. Appl. Meteorol. Climatol., 51(7), 1276-1289, doi:10.1175/jamc-d-11-0168.1, 2012.

Briggs, R.D. and Lemin Jr, R.C.: Delineation of climatic regions in Maine, Can. J. For. Res., 22(6), 801-811, doi:10.1139/x92-109 , 1992.

Cai, R., Mullen, J.D., Bergstrom, J.C., Shurley, W.D. and Wetzstein, M.E.: Using a climate index to measure crop yield response, J. Agr. Appl. Econ., 45(4), 719, doi:doi.org/10.1017/s1074070800005228, 2013.

De Castro, M., Gallardo, C., Jylha, K., and Tuomenvirta, H.: The use of a climate-type classification for assessing climate change effects in Europe from an ensemble of nine regional climate models, Clim. Chang., 81(1), 329-341, doi:10.1007/s10584-006-9224-1, 2007.

Estrada, F., Martinez-Arroyo, A., Fernández-Eguiarte, A., Luyando, E., and Gay, C.: Defining climate zones in Mexico City using multivariate analysis, Atmósfera, 22(2), 175-193, 2009.

Fan, F., Bradley, R.S., and Rawlins, M.A.: Climate change in the northeastern US: regional climate model validation and climate change projections, Clim. Dyn., 43(1-2), 145-161, doi:10.1007/s00382-014-2198-1, 2014.

Feng, S., Ho, C.H., Hu, Q., Oglesby, R.J., Jeong, S.J., and Kim, B.M.: Evaluating observed and projected future climate changes for the Arctic using the Köppen-Trewartha climate classification, Clim. Dyn., 38(7-8), 1359-1373, doi:10.1007/s00382-011-1020-6, 2012.

Forsythe, N., Blenkinsop, S., and Fowler, H.J.: Exploring objective climate classification for the Himalayan arc and adjacent regions using gridded data sources, Earth Syst. Dynam., 6(1), doi:10.5194/esd-6-311-2015, 311-326, 2015.

Fovell, R.G. and Fovell, M.Y.C.: Climate zones of the conterminous United States defined using cluster analysis, J. Clim., 6(11), 2103-2135, doi:10.1175/1520-0442, 1993.

Hagen, E. and Feistel, R.: Climatic turning points and regime shifts in the Baltic Sea region: the Baltic winter index (WIBIX) 1659-2002, Boreal Environ. Res., 10(3), 211-224, doi:doi.org/10.1109/baltic.2014.6887870, 2005.

Jaagus, J. and Ahas, R.: Space-time variations of climatic seasons and their correlation with the phenological development of nature in Estonia, Clim. Res., 15(3), 207-219, doi:10.3354/cr015207, 2000.

Jaagus, J., Briede, A., Rimkus, E., and Remm, K.: Precipitation pattern in the Baltic countries under the influence of large-scale atmospheric circulation and local landscape factors, Int. J. Climatol., 30(5), 705-720, doi:10.1002/joc.1929 , 2010.

Jolliffe, I.: Principal component analysis, John Wiley & Sons, Ltd, doi:10.1007/b98835, 2002.

Karl, T.R., Koscielny, A.J., and Diaz, H.F.: Potential errors in the application of principal component (eigenvector) analysis to geophysical data, J. Appl. Meteorol., 21(8), 1183-1186, doi:10.1175/1520-0450(1982)021<1183:peitao>2.0.co;2, 1982.

Mahlstein, I., Daniel, J.S., and Solomon, S.: Pace of shifts in climate regions increases with global temperature, Nat. Clim. Chang., 3(8), 739-743, doi:10.1038/nclimate1876, 2013.

Mahlstein, I. and Knutti, R.: Regional climate change patterns identified by cluster analysis, Clim. Dyn., 35(4), 587-600, doi:10.1007/s00382-009-0654-0, 2010.

Malmgren, B.A. and Winter, A.: Climate zonation in Puerto Rico based on principal components analysis and an artificial neural network, J. Clim., 12(4), 977-985, doi:10.1175/1520-0442, 1999.

Netzel, P. and Stepinski, T.: On Using a Clustering Approach for Global Climate Classification, J. Clim., 29(9), pp.3387-3401, doi:10.1175/jcli-d-15-0640.1 , 2016.

Overland, J.E. and Preisendorfer, R.W.: A significance test for principal components applied to a cyclone climatology, Mon. Weather Rev., 110(1), pp.1-4, doi:10.1175/1520-0493(1982)110<0001:astfpc>2.0.co;2, 1982.

Peel, M.C., Finlayson, B.L., and McMahon, T.A.: Updated world map of the Köppen-Geiger climate classification, Hydrol. Earth Syst. Sci. Discuss., 4(2), 439-473, doi:10.5194/hessd-4-439-2007 , 2007.

Preisendorfer, R. W. and Mobley, C.D.: Principal component analysis in meteorology and oceanography, Amsterdam: Elsevier; doi: , 1988.

Remm, K., Jaagus, J., Briede, A., Rimkus, E., and Kelviste, T.: Interpolative mapping of mean precipitation in the Baltic countries by using landscape characteristics, Est. J. Earth Sci., 60(3), 172, doi:10.3176/earth.2011.3.05, 2011.

Rutgersson, A., Jaagus, J., Schenk, F., and Stendel, M.: Observed changes and variability of atmospheric parameters in the Baltic Sea region during the last 200 years, Clim. Res., 61(2), 177-190, doi:10.3354/cr01244 , 2014.

Sennikovs, J., Bethers, U.: Statistical downscaling method of regional climate model results for hydrological modelling, Proc.18th World IMACS / MODSIM Congress, Cairns, Australia 13-17, 2009.

Tapiador, F.J., Angelis, C.F., Viltard, N., Cuartero, F., and De Castro, M.: On the suitability of regional climate models for reconstructing climatologies, Atmos. Res., 101(3), 739-751, doi:10.1016/j.atmosres.2011.05.001, 2011.

Teutschbein, C. and Seibert, J.: Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods. J. Hydrol., 456, 12-29, doi:10.1016/j.jhydrol.2012.05.052, 2012.

Van der Linden, P. and Mitchell, J. E.: ENSEMBLES: Climate Change and its Impacts: Summary of research and results from the ENSEMBLES project, Met Office Hadley Centre, Exeter, 160, 2009.

Zhang, X. and Yan, X.: Spatiotemporal change in geographical distribution of global climate types in the context of climate warming, Clim. Dyn., 43(3-4), 595-605, doi:10.1007/s00382-013-2019-y, 2014.

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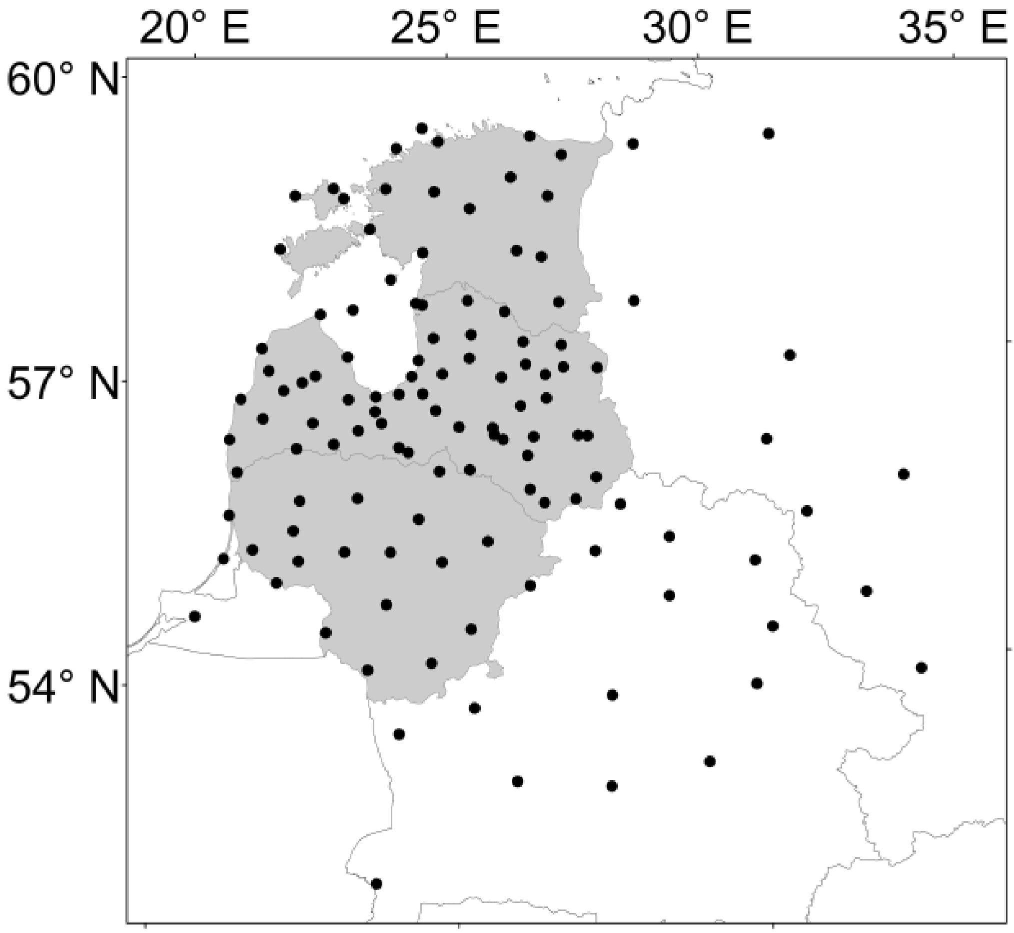
Figures and Tables

Figures



5 **Figure 1: Locations of meteorological stations used for bias-correction of RCM data.**

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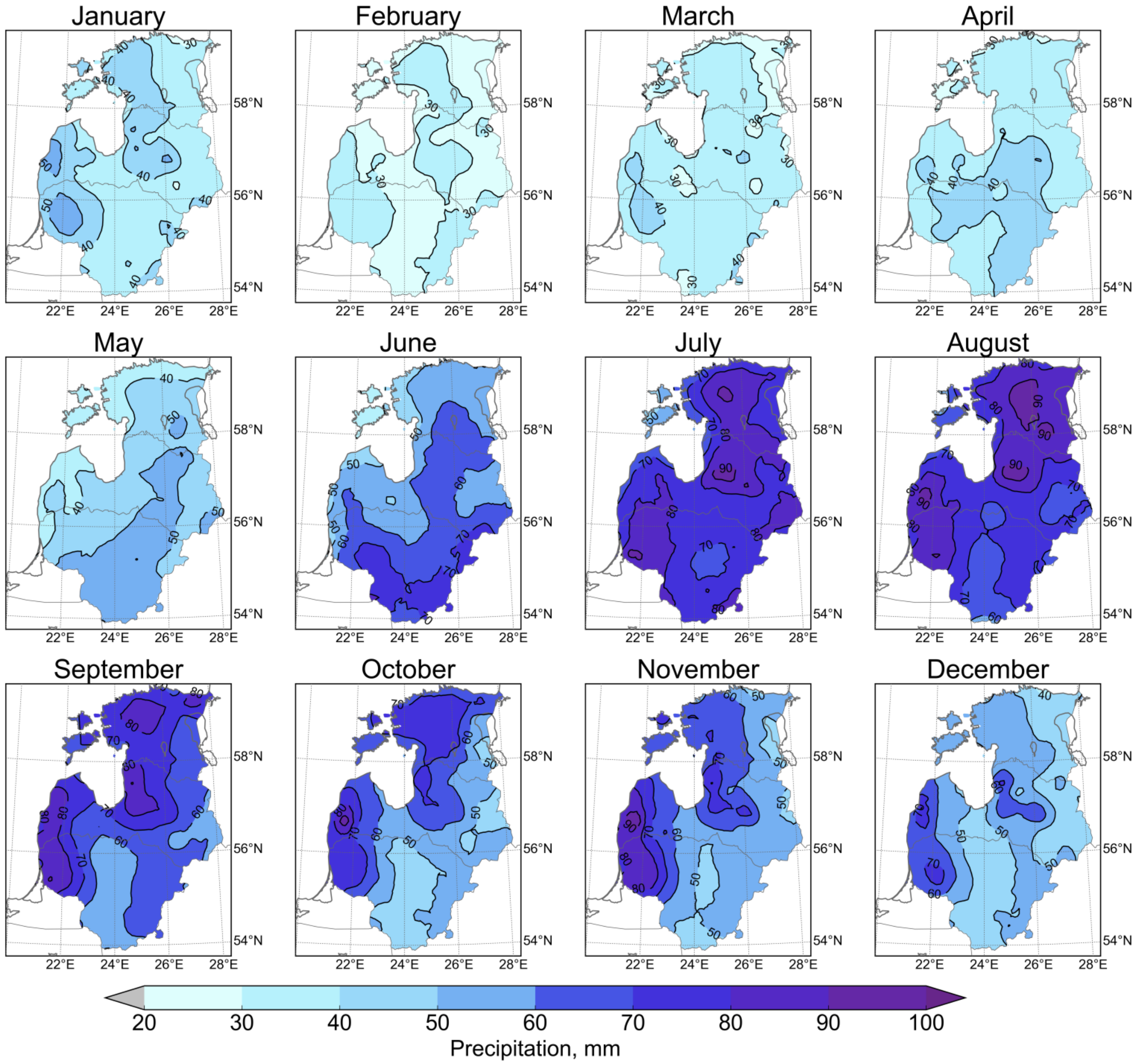

Figure 2: Monthly precipitation 1961-1990, bias-corrected median of RCM ensemble.

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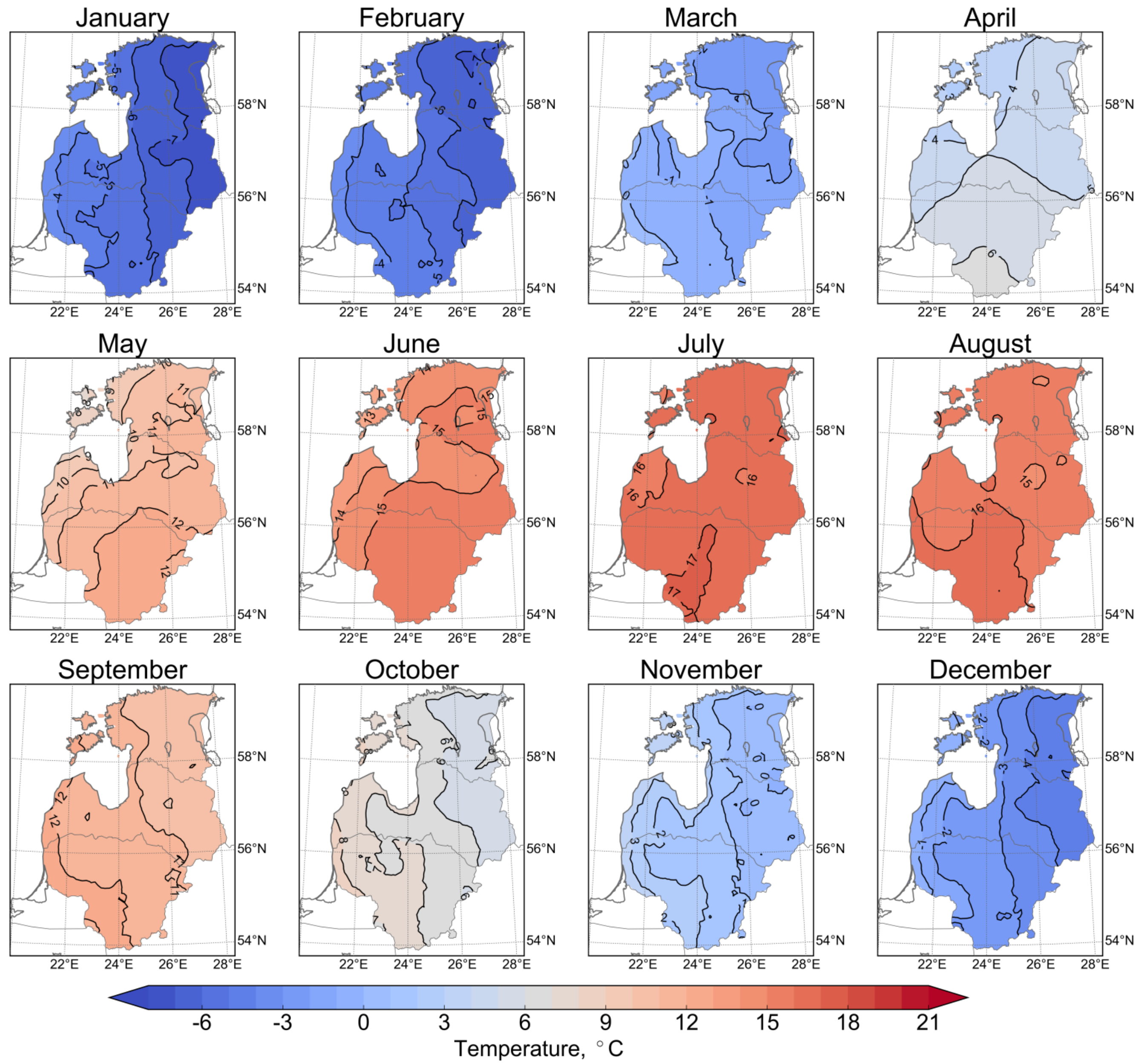

Figure 3: Monthly average temperature 1961-1990, bias-corrected median of RCM ensemble.

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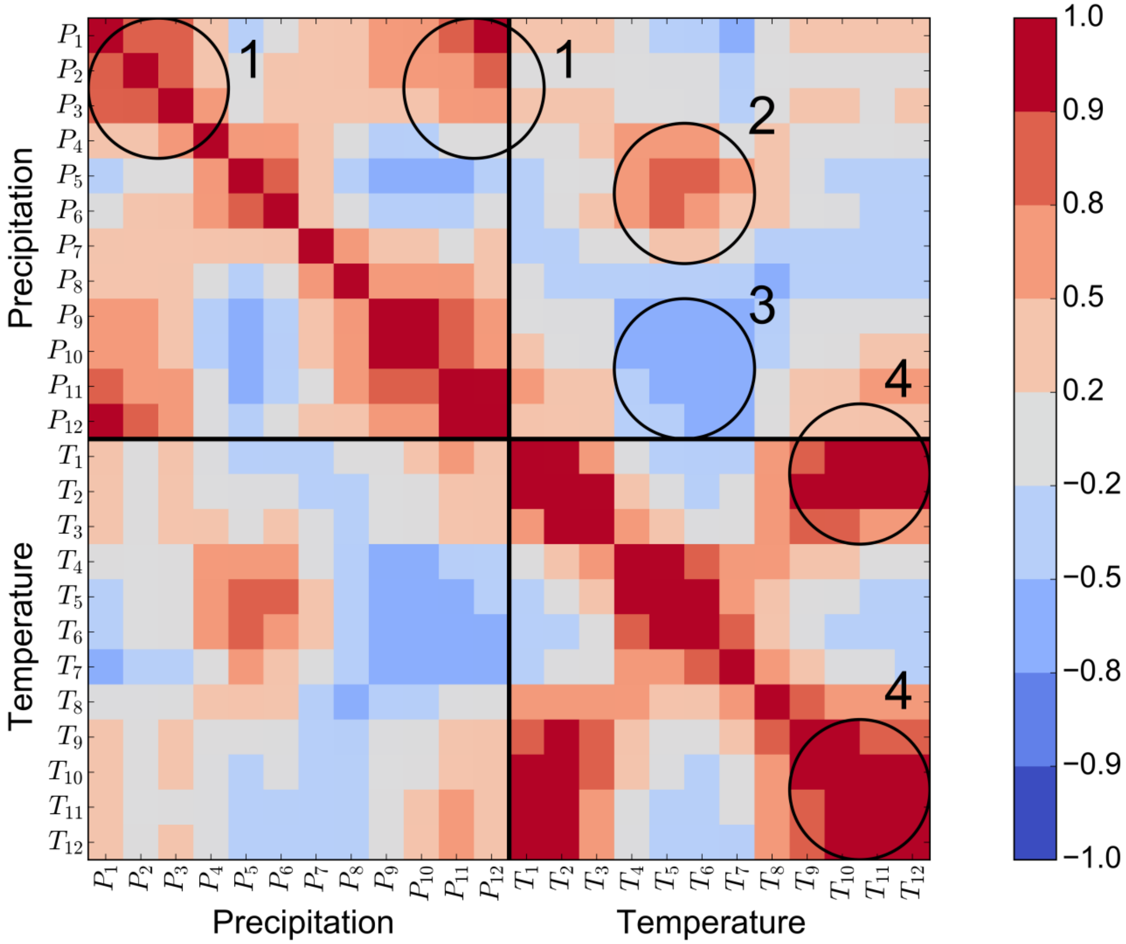

Figure 4: Temperature-precipitation correlation matrix, bias-corrected data. Marked and numbered features show especially high absolute correlation: 1- strong correlation between precipitation in winter months; 2- strong correlation between precipitation and temperature in spring months; 3- strong negative correlation between precipitation in autumn and spring temperature; 4- strong correlation between temperatures of autumn and winter months.

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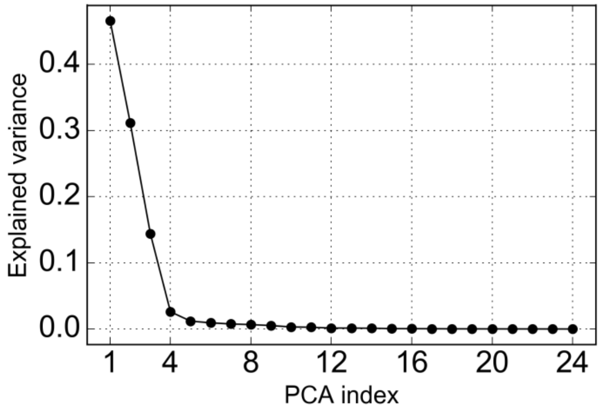

Figure 5: Scree plot (explained variance of each principal component), calculated for reference (1961-1990) climate.

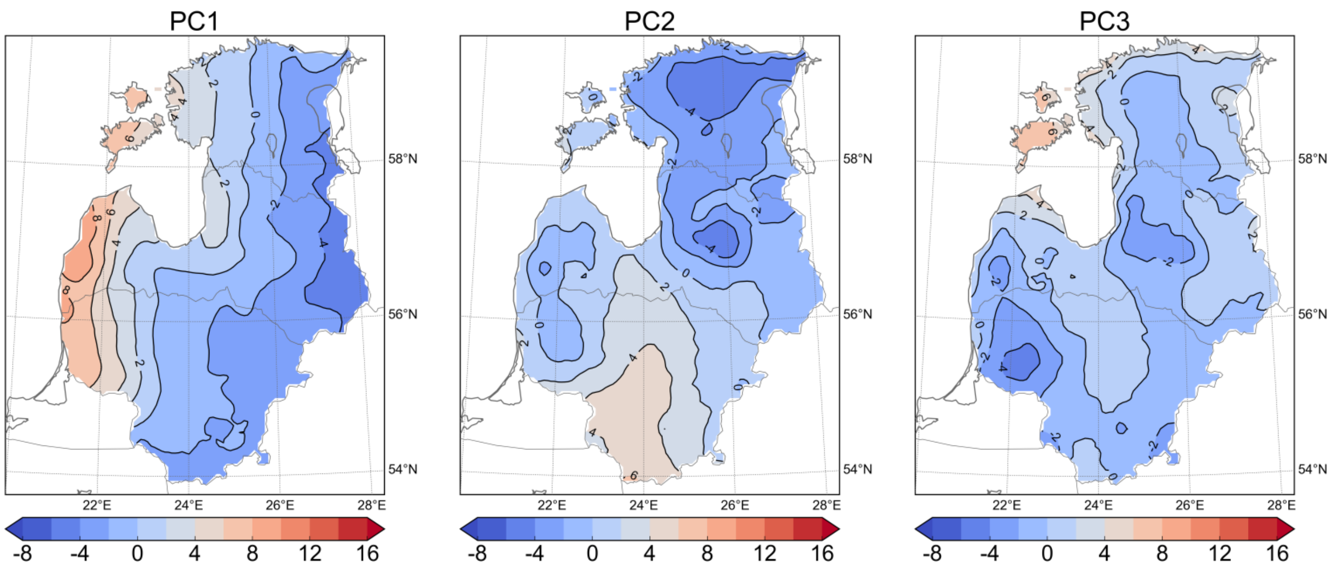

Figure 6: Spatial pattern of first three principal components based on monthly temperature and precipitation data for years 1961-1990.

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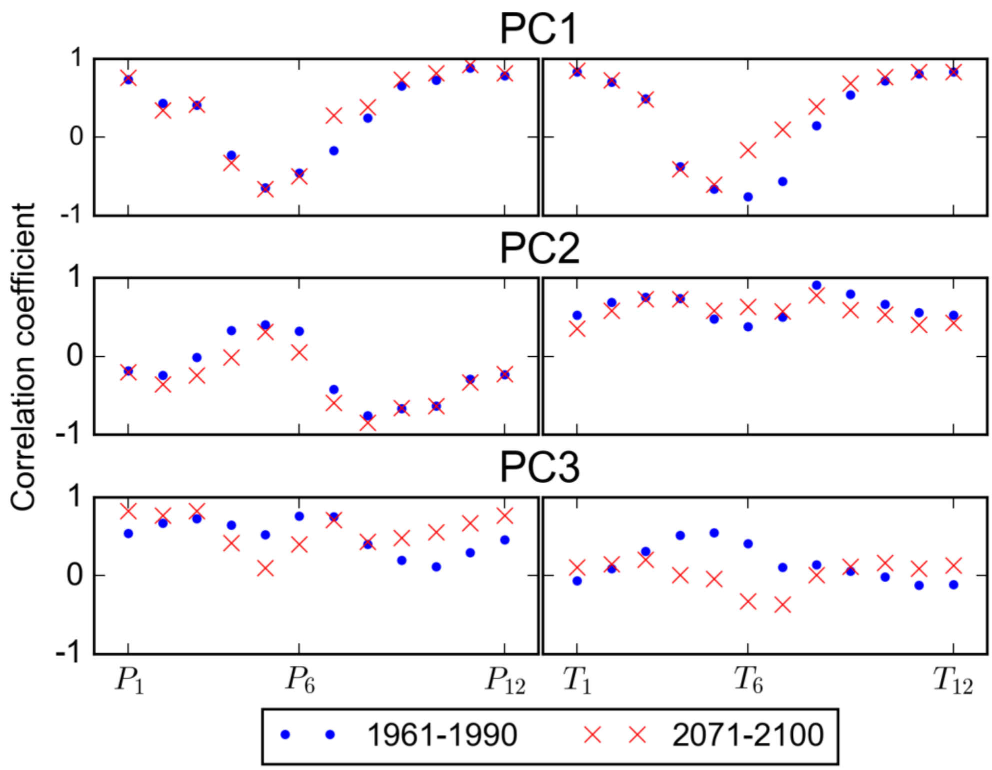
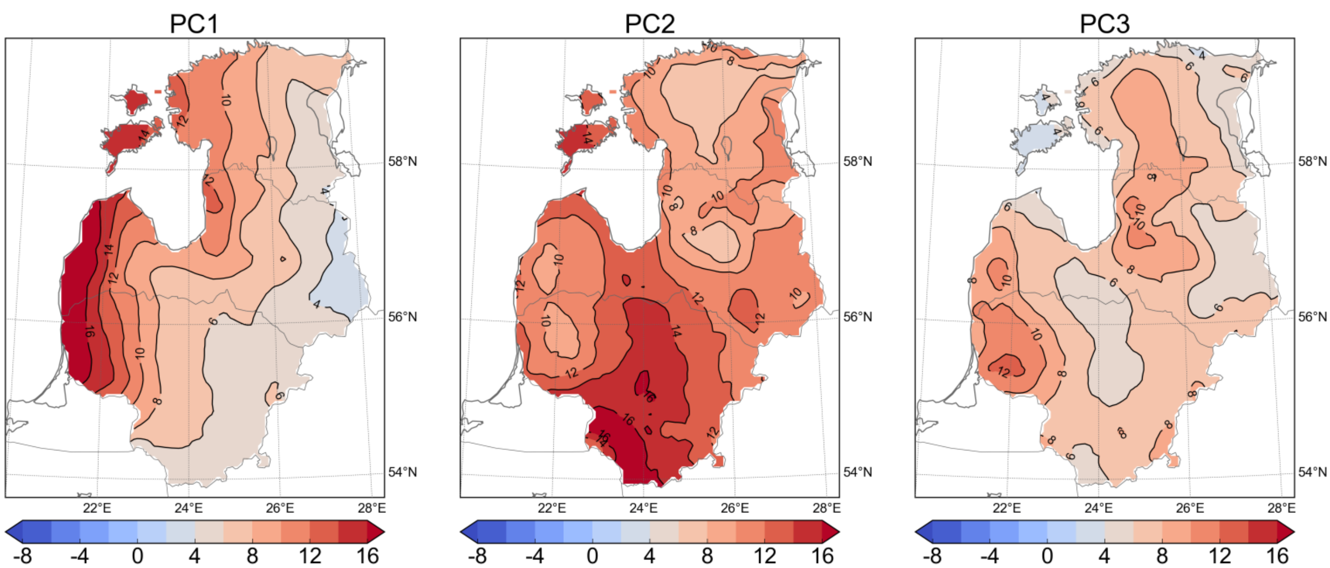


Figure 7: Correlation coefficients between indices (principal components) and initial variables for reference and future climate.



5 **Figure 8: Climate indices (based on principal components from 1961-1990) for years 2071-2100.**

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Tables

Table 1: List of the Regional Climate Model (RCM) ensemble members used (ENSEMBLES), showing the originating institution, the name of RCM, the driving General Circulation Model (GCM). For explanation of abbreviations see van der Linden & Mitchell (2009).

Institution	GCM	RCM
C4I	HadCM3Q16	RCA3
CNRM	ARPEGE	Aladin
CNRM	ARPEGE_RM 5.1	Aladin
DMI	ARPEGE	HIRHAM
DMI	ECHAM5-r3	DMI-HIRHAM5
ETHZ	HadCM3Q0	CLM
GKSS	IPSL	CLM
HC	HadCM3Q0	HadRM3Q0
HC	HadCM3Q16	HadRM3Q16 (high sensitivity)
HC	HadCM3Q3	HadRM3Q3 (low sens.)
ICTP	ECHAM5-r3	RegCM
KNMI	ECHAM5-r3	RACMO
KNMI	ECHAM5-r3	RACMO
KNMI	MIROC	RACMO
METNO	BCM	HIRHAM
METNO	HadCM3Q0	HIRHAM
MPI	ECHAM5-r3	REMO
SMHI	BCM	RCA
SMHI	ECHAM5-r3	RCA
SMHI	HadCM3Q3	RCA
UCLM	HadCM3Q0	PROMES
VMGO	HadCM3Q0	RRCM

Table 2: Variances of climate variables before and after standardization for years 1961-1990.

1961-1990												
Before standardization												
P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}	P_{12}	Mean
28.85	7.45	13.03	13.66	31.93	63.40	47.20	65.65	86.22	110.43	114.47	50.60	52.74
T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}	T_{11}	T_{12}	Mean
1.36	0.95	0.60	0.62	0.93	0.41	0.09	0.19	0.39	0.54	0.83	1.27	0.68
After standardization												
P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}	P_{12}	Mean
0.55	0.14	0.25	0.26	0.61	1.20	0.89	1.24	1.63	2.09	2.17	0.96	1.00
T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}	T_{11}	T_{12}	Mean
2.00	1.40	0.88	0.91	1.37	0.60	0.14	0.27	0.57	0.80	1.22	1.86	1.00

Table 3: Variances of climate variables before and after standardization for years 2071-2100.

2071-2100												
before standardization												
P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}	P_{12}	Mean
52.78	12.33	22.68	27.02	33.84	52.5	42.87	72.7	126.1	154.3	204.3	85.6	73.92
T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}	T_{11}	T_{12}	Mean
1.08	0.92	0.37	0.25	0.26	0.12	0.11	0.2	0.45	0.51	0.84	1.08	0.52
after standardization												
P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}	P_{12}	Mean
1.00	0.23	0.43	0.51	0.64	1.00	0.81	1.38	2.39	2.93	3.87	1.62	1.40
T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}	T_{11}	T_{12}	Mean
1.59	1.35	0.55	0.36	0.38	0.18	0.16	0.3	0.67	0.74	1.23	1.58	0.76

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Table 4: Explained variance and loadings of first 3 principal components, calculated from temperature and precipitation data for years 1961-1990.

	PC1	PC2	PC3	sum
Explained variance	0.47	0.31	0.14	0.92
Loadings				
P_1	0.16	-0.05	0.22	
P_2	0.05	-0.03	0.14	
P_3	0.06	0.00	0.20	
P_4	-0.03	0.06	0.18	
P_5	-0.15	0.12	0.22	
P_6	-0.15	0.13	0.45	
P_7	-0.05	-0.15	0.38	
P_8	0.08	-0.31	0.24	
P_9	0.25	-0.31	0.13	
P_{10}	0.32	-0.33	0.09	
P_{11}	0.39	-0.16	0.24	
P_{12}	0.23	-0.08	0.24	
T_1	0.35	0.27	-0.04	
T_2	0.25	0.30	0.06	
T_3	0.14	0.26	0.16	
T_4	-0.11	0.26	0.27	
T_5	-0.23	0.21	0.35	
T_6	-0.18	0.11	0.17	
T_7	-0.06	0.07	0.02	
T_8	0.02	0.17	0.04	
T_9	0.12	0.22	0.02	
T_{10}	0.19	0.22	-0.01	
T_{11}	0.27	0.23	-0.07	
T_{12}	0.34	0.27	-0.08	

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Table 5: Correlation coefficients between principal components and standardized initial data for years 1961-1990. High positive correlation corresponds to darker red color and high negative correlation corresponds to darker blue color.

	PC1	PC2	PC3
P_1	0.73	-0.18	0.54
P_2	0.44	-0.24	0.68
P_3	0.41	-0.01	0.73
P_4	-0.22	0.33	0.65
P_5	-0.65	0.4	0.53
P_6	-0.45	0.33	0.76
P_7	-0.17	-0.42	0.75
P_8	0.25	-0.75	0.41
P_9	0.66	-0.67	0.2
P_{10}	0.73	-0.63	0.12
P_{11}	0.89	-0.29	0.3
P_{12}	0.78	-0.23	0.46
T_1	0.83	0.53	-0.06
T_2	0.7	0.69	0.1
T_3	0.49	0.76	0.32
T_4	-0.38	0.74	0.52
T_5	-0.66	0.48	0.55
T_6	-0.76	0.38	0.41
T_7	-0.57	0.5	0.11
T_8	0.15	0.91	0.14
T_9	0.54	0.8	0.06
T_{10}	0.72	0.67	-0.01
T_{11}	0.81	0.56	-0.12
T_{12}	0.83	0.53	-0.11

Table 6: Description and interpretation of climate indices base on PCA.

Name	High values correspond to	Possible interpretation of high values
PC1	Warm winter with high precipitation, cold summer with low precipitation	Less distinct seasonality
PC2	High overall temperature, low precipitation in autumn	Warmer climate
PC3	High annual precipitation, warmer springs	More humid climate

Table 7: Statistics of climate indices (based on PCA) for past and future data.

		1961-1990	2071-2100
PC1	mean	0.00	8.38
	min	-4.84	3.17
	max	8.95	18.24
PC2	mean	0.00	11.38
	min	-5.62	6.24
	max	6.14	17.05
PC3	mean	0.00	7.13
	min	-8.43	1.54
	max	4.84	12.28