STARDEX

STAtistical and Regional dynamical Downscaling of EXtremes for European regions

EVK2-CT-2001-00115

Deliverable D15

Improved statistical downscaling methodologies: description of the STARDEX methods

FOREWORD

The STARDEX project on STAtistical and Regional dynamical Downscaling of EXtremes for European regions is a research project supported by the European Commission under the Fifth Framework Programme and contributing to the implementation of the Key Action "global change, climate and biodiversity" within the Environment, Energy and Sustainable Development.

STARDEX will provide a rigorous and systematic inter-comparison and evaluation of statistical and dynamical downscaling methods for the construction of scenarios of extremes. The more robust techniques will be identified and used to produce future scenarios of extremes for European case-study regions for the end of the 21st century. These will help to address the vital question as to whether extremes will occur more frequently in the future.

For more information about STARDEX, contact the project co-ordinator Clare Goodess (c.goodess@uea.ac.uk) or visit the STARDEX web site:
http://www.cru.uea.ac.uk/projects/stardex/

STARDEX is part of a co-operative cluster of projects exploring future changes in extreme events in response to global warming. The other members of the cluster are MICE and PRUDENCE. This research is highly relevant to current climate related problems in Europe. More information about this cluster of projects is available through the MPS Portal:
http://www.cru.uea.ac.uk/projects/mps/

STARDEX PROJECT MEMBERS

UEA	University of East Anglia, UK
KCL	King's College London, UK
FIC	Fundación para la Investigación del Clima, Spain
UNIBE	University of Berne, Switzerland
CNRS	Centre National de la Recherche Scientifique, France
ARPA-SMR	Servizio Meteorologico Regionale, ARPA-SMR Emilia-Romagna, Italy
ADGB	University of Bologna, Italy
DMI	Danish Meteorological Institute, Denmark
ETH	Swiss Federal Institute of Technology, Switzerland
FTS	Fachhochschule Stuttgart – Hochschule für Technik, Germany
USTUTT-IWS	Institut für Wasserbau, Germany
AUTH	University of Thessaloniki, Greece

D15 Summary

This report provides a compilation of descriptions of the downscaling methodologies developed by STARDEX partners and listed in the summary table. The descriptions were written in January/February 2005 and finally compiled into this one file in August 2011.

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Table 1: List of STARDEX downscaling methodologies

Method	***Predictand(s)*** ***(Unless otherwise indicated, predictands are station series)***	***Predictor(s)*** ***(See STARDEX Deliverable D10 for selection procedure)***	***Description*** ***(See STARDEX Deliverable D15 for details)***
ADGB_HYPER4	Regional DP index	GPH anomalies at 500 hPa, RH at 700 hPa, geostrophic wind at 500 hPa & precipitable water	Random sampling within the 4-dimensional hyperspace of the 4 predictors which defines conditions for high precipitation
ARPA_CCA	PIE, TIE	SLP, SH at 1000, 950, 850 and 700 hPa, and T at 850 hPa	Canonical Correlation Analysis
ARPA_MLR	PIE, TIE	Z500: First 4 PCs of 500 hPa GPH anomalies T850: First 4 PCs of 850 hPa T	Multiple Linear Regression
AUTH_ANN	DP, DT	500 hPa GPH & 1000-500 hPa thickness	Artificial Neural Network
AUTH_CCA	DP, DT	500 hPa GPH & 1000-500 hPa thickness	Canonical Correlation Analysis
AUTH_MREG	DP, DT	Circulation types for 500 hPa, 1000-500 hPa thickness	Multiple Linear Regression
CNRS_PPCI	DP	Large Scale Circulation patterns defined using 700 hPa GPH	Random selection of an analogue within a set of training days having the same ‘Potential Precipitation Circulation Index’ category
DMI_CWG	DP	SLP	Conditional weather generator, conditional on quantile values of a circulation index, in which precipitation occurrence and amount are modelled separately
ETH_DYN	DP – station data or mesoscale grids	Grid-box precipitation	As ETH_LOC, but with flow-dependent scaling factors
ETH_DYNI	DP – station data or mesoscale grids	Grid-box precipitation	As ETH_LOCI, but with flow-dependent scaling factors
ETH_LOC	DP – station data or mesoscale grids	Grid-box precipitation	Local scaling of GCM simulated precipitation
ETH_LOCI	DP – station data or mesoscale grids	Grid-box precipitation	Local scaling of GCM simulated precipitation with correction of precipitation frequency and intensity bias
FIC_ANAL2	DP, DT	Geostrophic fluxes at 1000 & 500 hPa, low tropospheric humidity and thickness	Two-step analogue method, in which (1) the ‘n’ most similar days to the day being simulated are selected from a

(2SA in some figures)			reference data set and (2) regression is performed using predictand/predictor relationships from the 'n' days data set
KCL_ANN_GA_RBF	DP	The SDSM set of predictors	Genetic algorithm used to optimise the Radial Basis Function network structure and parameters
KCL_ANN_IRBF	DP	The SDSM set of predictors	Individual Radial Basis Function artificial neural network model (i.e., applied to individual sites in each region)
KCL_ANN_MLP	DP	The SDSM set of predictors	Multi Layer Perceptron artificial neural network model
KCL_ANN_RBF	DP	The SDSM set of predictors	Radial Basis Function artificial neural network model (applied across all sites for each region)
KCL_CR	DP	The SDSM set of predictors	Conditional resampling of area average precipitation, conditional on the large-scale atmospheric forcing and a stochastic error term, and daily precipitation amounts at a 'marker site' (generated using SDSM).
UEA_ANN_GAMMA *(GAM in some figures)*	DP	The SDSM set of predictors	Bayesian multilayer perceptron artificial neural networks, using the hybrid Bernoulli/Gamma data misfit term
UEA_ANN_GAMMAMC	DP	The SDSM set of predictors	Bayesian multilayer perceptron artificial neural networks, using the hybrid Bernoulli/Gamma data misfit term and Monte-Carlo simulation
UEA_ANN_SSE	DP	The SDSM set of predictors	Bayesian multilayer perceptron artificial neural networks, using the sum-of-squares data misfit term
UEA_CCA	PIE	CCA1: MSLP CCA4: MSLP + GPH, RH, T at 500, 700 & 850 hPa	Canonical Correlation Analysis
UNIBE_CCA	DT	SLP and GPH, T, SH & RH at 100, 850, 700, 500 and 300 hPa	Canonical Correlation Analysis
USTUTT_MAR	DP	Objective circulation patterns (CPs) and: - eastward moisture flux at 700 hPa (for precipitation) - GPH at pressure level corresponding to the CP	Multivariate Auto-Regressive model
USTUTT_MLR	PIE, TIE	GPH, RH, T, divergence and vorticity at several levels, eastward moisture flux at 700 hpa level and objective circulation patterns	Multiple Linear Regression

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Improved Statistical Downscaling methodologies

ADGB Contribution

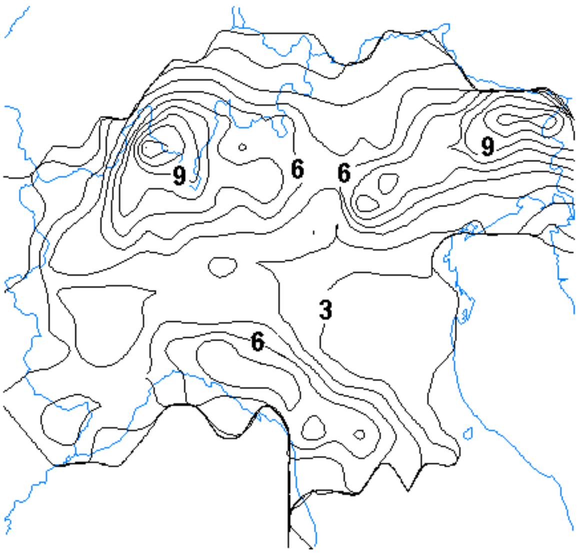
Ennio Tosi and Stefano Alberghi

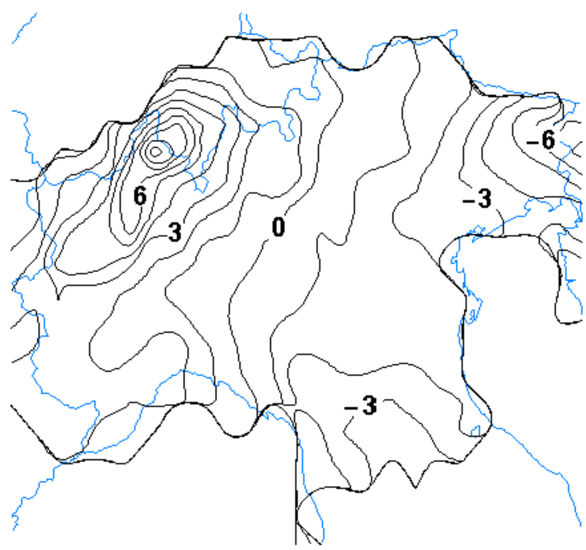
ADGB_Hyper4

Detailed description of ADGB statistical downscaling method "HYPER4"

The assumptions at the base of the method derive from the consideration that the observations at a single station are too much influenced by local weather conditions to be sufficiently correlated to large scale parameters, and that, due to the high small scale variability of the topography in Northern Italy, the precipitation field is highly variable in space. The consequences of this high variability are that some areas, like the delta of the river Po, have a 90th percentile of 16 mm while the areas of maximum precipitation, the area between Switzerland and Italy around the lake of Como, the area between Austria, Slovenia and Italy, and the eastern side of the gulf of Genoa have the 90th percentile of 42 mm. The characteristics of the extreme events are therefore quite different, and the occurrence of an event in an area may be associated to “normal” precipitation in another area. Moreover two very similar large scale patterns can produce extreme events in different areas, usually the areas where the mean precipitation is higher.

To have a good compromise between good links with large scale parameters, and good representation of small scale precipitation features, the model uses a single index of precipitation for all Northern Italy, which has a strong link with large scale predictors and a good correlation with precipitation events over Northern Italy. Index chosen is the sum of squares of the first two adimensional PCs of rain on Northern Italy, computed using the gridded data produced by ETH in the MAP project. This is a daily index, and it has been computed from 1966 to 1990, beyond this interval rain data on Italy become unreliable. As figs 1 and 2 show, high values of PC1 give maximum precipitations both in the Western and Eastern part of Northern Italy, high values of PC2 give high precipitation either in the West or in the East, depending on the sign.





Figures 1-2 – EOF1 and EOF2 of total precipitation, each multiplied by the root of its eigenvalue.

The definition of the events takes into account that we are interested in precipitation extremes linked to large scale circulation patterns and therefore associated with synoptic scale systems, and not deriving from intense convection associated with thunderstorms.

The identification of a day with precipitation is made in two steps: first it is required the presence of at least 1 mm of rain in 25 adjacent grid points, second, considering that the grid point value is obtained by interpolating station values, and therefore a high value is "distributed" over nearby grid points, isolated precipitation peaks have been eliminated if their value is greater than 4 times the minimum value of the 8 closest points. If there are only isolated (as defined above) precipitations the day is classified as a no rainy day.
The precipitation value for a day classified as precipitation day is the maximum over the whole area.

This procedures produces a series of daily precipitation values and the 95th percentile value has been chosen as the threshold for extreme precipitation. Extreme events occur when large scale parameters fall into a reduced range of values, the choice of the 95th percentile allows a significant restriction of this range.

The predictand has been chosen considering that the first two principal components of the precipitation over Northern Italy have a strong relation with the extreme precipitation events, that are always located in correspondence of the maxima of the two PC. The correlation between large scale features and the amplitude of the two PC is good. The square root of the sum of the squares of the two PC is strongly linked to intensity of the precipitation (as defined above), the correlation coefficient is .85 (see Fig.3), and, therefore has been chosen as predictand. The method derives separately the amplitude of PC1 and PC2, and the predictand is computed afterwards.

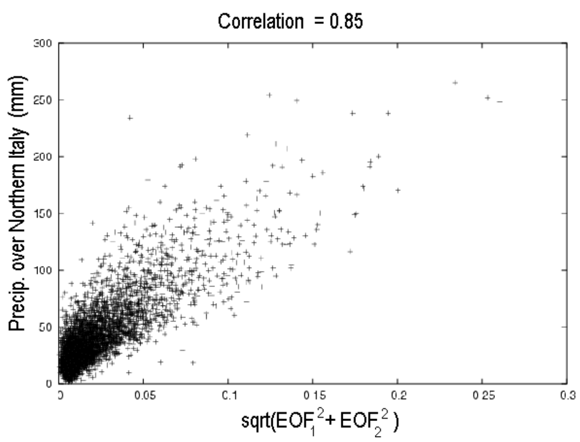


Figure 3

The choice of the predictors has been made firstly considering that when extreme events occur, large scale parameters fall within a restricted range of values. Specifically: the GPH anomalies at 500 hPa around the point of maximum correlation are below 60 m. The relative humidity at 700 hPa in the point of maximum correlation is above 33%. The geostrophic wind at 500 hPa over Northern Italy comes from South-West. The 500-1000 thickness gradient is directed in a North- South direction. The total precipitable water is above 13 mm. The

selection criteria for the 95th percentile are more restrictive than those for 90th. These selection criteria allow to decide a priori if a precipitation extreme can occur in a given day.
The choice of the large scale parameters to be used for the selection of the days has been made a priori taking into account the fact that high precipitation events are usually associated with cyclogenesis in the lee of the Alps, and relative humidity and precipitable water have been added to add information about the saturation state of the atmosphere and the amount of water available. After the choice their effective selection capability has been tested.

The determination of the grid points to be used for the values of the predictors cannot be made only using linear correlation coefficient. For instance the direction of the geostrophic wind at 500 hPa, being a periodic parameter, does not correlate with PC1 or PC2, the scatter plot shows points crowding in correspondence of the South-West direction showing that there is a non linear dependence of the amplitude of the PCs from the direction of the wind. The points to be used have therefore been chosen analyzing the scatter plots and selecting the point whose plots showed the highest variation of the PC amplitude as a function of the parameter under examination, i.e. points that show maximum discriminating power (fig.4).

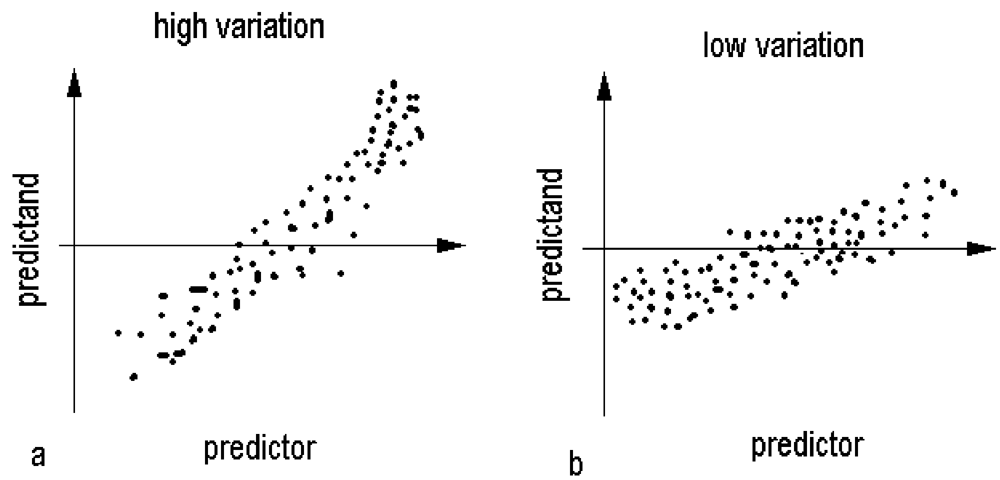


Figure 4

The verification of the predictive ability of the predictors has been made using them separately and then, starting with the most powerful, introducing one predictor at a time to test an effective increase of prediction skill. At the end of the procedure the 4 predictors chosen are:
1.GPH anomalies at 500 hPa. The anomaly has been computed subtracting at each grid point value the zonal mean at that latitude. This allows a good definition of the position of high and low centers.
2.Relative humidity at 700 hPa
3.Precipitable water
4.Direction of the geostrophic wind at 500 hPa
The downscaling is done separately for EOF_1 and EOF_2. The grid points used for each EOF are obviously different. After the two separate downscaling the final predictor is computed

The downscaling method begins with the selection of the days with condition favorable for high precipitation. If the large scale parameters are in requested range their values identify a point in the 4 dimensional hyper space of the 4 predictors. The distribution of observed PC amplitude in the neighborhood of this point varies as a function of the region. An histogram is constructed with the PC amplitudes contained inside a hyper sphere in the space of predictors whose radius is chosen to contain 150 points. Various bin size of the histogram have been tested to assure stability of the results. Given the histogram, a value is chosen for the PC amplitude using a random number generator. Figure 5 exemplifies the technique for a 2 dimensional space. The final output is the number of occurrences of a value of the index ($PC1^2$ +$PC2^2$)exceeding the given threshold.
The results of the model are sensitive to the choice of the random number, as expected for rare events, so the results are given as a mean of 99 runs of the model.

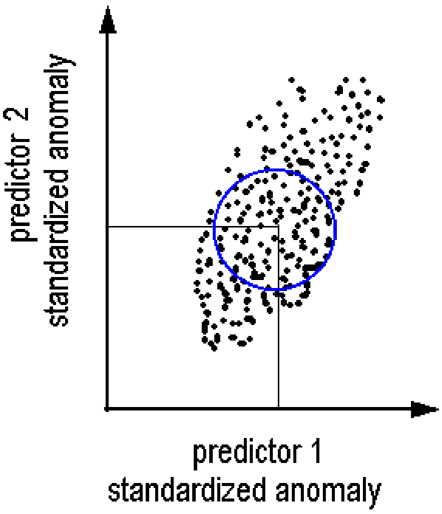


Figure 5

It has been chosen to use always full year data, without considering different seasons. The main reasons are that during summer the total number of data (rainy days) is reduced, and therefore the exclusion of some years for testing the downscaling method could produce a statistic too poor. The second reason is that introducing a season dependent statistic based on observed seasons forces the observed annual cycle of future climate scenarios, and does not allow to detect shifts of the annual cycle.

As already mentioned, the precipitation data on Italy are unreliable after 1990, thus, to have a sufficient statistic to compute skills (e.g. rank correlation), all the years from 1966 to 1990 have been downscaled for verification one at a time, using in turn the remaining 24 years for training.

As the model is based on a pre-selection of days favourable to extreme precipitations, it produces a non-continuous time series of values for the downscaled index. Thus it is not possible to produce indexes like consecutive dry days

A short summary of the method with some details

Characteristics:
- a “type 2” method (daily downscaling, then calculation of indices)
- downscales precipitation
- calculates number of extremes over 90th perc. of rainy days in the whole period (index Pnl90)
- Calibration period: 1966-1990. Verification period: cross validation on 1966-1990
- not seasonally-based, but a unique full-year calibration (to eventually allow annual cycle shifts)
- gives a unique index of precipitation for all Northern Italy, not indexes on single stations

The method uses precipitation data from MAP. A "rainy day" on Northern Italy is defined as a day in which at least 1mm of precipitation falls in at least 25 neighbouring grid points, excluding thunderstorms, i.e. peaks in the precipitation pattern. Using daily maximum precipitation values on Northern Italy a list of observed extreme events days (with precipitation greater than 95th percentile of the entire distribution) is drawn.
Afterwards EOF analysis is performed and a daily series of the first two precipitation PCs is used in the subsequent DS method. An index is computed from the "observed" PCs (sum of squares of adimensional PCs), that is well correlated (>0.85) with max. precipitation value on Nortern Italy. 90th percentile of this index in rainy days is used as a threshold for Pn90 calculation.

NCEP parameters used are:
- 500hPa geopotential height anomaly (2 grid points)
- 500hPa geostrophic wind direction
- 700hPa relative humidity
- 500-850hPa thickness gradient direction
- precipitable water (calculated from specific humidity at 500, 700 and 850hPa)

Except that geopotential height anomaly, other parameters are considered in only 1 grid point (the most selective, or the most "predictive" one).

The method consists of a two-steps algorithm:
- First, a preselection of "potentially extreme" days, based on the range of values that large-scale NCEP parameters undertake in the observed extreme events list. This "pre-selections" allows to discard about 60% of days
- Second, a resampling (random) procedure in the 4-dimensional hyper-space of parameters (thickness is not used) to reproduce correctly the statistics of precipitation events for a given set of large-scale parameters values. PC1 and PC2 are separately downscaled for each pre-selected day, then the 'sum of squares of PCs' index is computed. Finally Pn90 is calculated. The procedure is iterated 100 times to have a better stability of results. Mean values are considered.

Note that:
- rainy days on Northern Italy (as defined above) are about 55% of total days
- a 90th percentile calculated on rainy days only is used
- BIAS and RMSE are dimensional quantities, thus comparison with other methods for this region is not really fair (on a single Northern Italy station, rainy days are less than one third of total)

What is new with the method

The spatial distribution of the precipitation in the area under study is strongly influenced by orography. Its distribution has two distinct peaks, one in the western part of the domain and the other in the eastern part and this structure is well captured by the first two EOFs of the field. The distribution of extreme events follows the same pattern (almost all the extremes are placed in the areas of the two maxima of precipitation) and therefore has a strong correlation with the first two EOFs. The method exploits this strong correlation and the high correlation of the EOFs with the large scale parameters. This is a clear strength of the method, when applied to areas where these strong correlation occur.

Another important characteristic, particularly important in areas with a strong seasonal cycle, is that the downscaling does not aggregate data per season. This avoids two problems: it does not force the observed seasonal cycle on downscaled data and does not use an unnatural grouping (e.g. the seasonal cycle of precipitation in northern Italy is not captured by using DJF, MAM, JJA and SON).

Strenghts	Weaknesses
not seasonally dependent	downscales only selected days (not full series)
good link with large scale	only one index and not on a station scale
high skill in correlation with observed	doesn't predict precipitation directly

Application critera table

Method provides:	Y/N	Comments/Notes
Station-scale information	N	
Grid-box information	N	
European-wide information	N	only one series, representative of all Northern Italy
Daily time series	Y	but about half of total days are not downscaled (because of extreme events calibration)
Seasonal indices of extremes	Y	but only n. days > 90th perc.
Temporally consistent temperature and precipitation[1]	N	only precipitation index downscaled
Spatially consistent multi-site information[2]	N	only one downscaled series
Temporally consistent multi-site information[3]	N	only one downscaled series
Information at sites with no observations	/	

Method requirements :	**Relatively high/medium/low**	**Comments/Notes**
Computing resources Volume of data inputs Availability of input data	relatively low medium medium	

[1] i.e., the temperature/precipitation co-variance is similar for the downscaled validation series and observed series
[2] i.e., the downscaled validation series has a similar spatial pattern to the observed series
[3] i.e., the downscaled validation series has similar daily inter-site correlations to the observed series

Improvements

A longer observed precipitation record could certainly improve the performances of the method.

The increasing availability of high resolution climate models (T106 typically) requires the recalibration of the method with higher resolution analyses, like ERA40.

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Improved Statistical Downscaling Methodologies: description of the STARDEX methods

R.Tomozeiu , A.Morgillo, C.Cacciamani ,V.Pavan

ARPA-SIM, Bologna

ARPA_CCA & ARPA_MLR

The statistical downscaling methods developed by ARPA–SMR in order to downscale the extreme events are :

1. Multivariate regression based on Canonical Correlation Analysis (CCA)
2. Multiple Linear Regression based on the principal components (PCs) derived from EOF analysis

1.Statistical Downscaling model based on CCA

Description of the method

The statistical model based on the *Canonical Correlation Analysis* (CCA) was introduced in the climate research by Barnett and Preisendorfer (1987). This technique finds pairs of patterns in a way that the correlation between two corresponding pattern is maximized. A description of the methods is presented in the following.

CCA is a statistical method that enables an expansion of two multivariate, observed vectors (**X** and **Y**) into a finite set of vectors, called *canonical correlation patterns* ($\mathbf{F}_X$ and $\mathbf{F}_Y$):

$$\vec{\mathbf{X}}_t = \sum_{k=1}^{K} \alpha_k(t)\vec{\mathbf{F}}_X^k \text{ and } \vec{\mathbf{Y}}_t = \sum_{k=1}^{K} \beta_k(t)\vec{\mathbf{F}}_Y^k .$$

The canonical correlation patterns are derived by $\mathbf{f}_X$ and $\mathbf{f}_Y$, respectively the eigenvectors of the matrices $\mathbf{A}_X = \mathbf{S}_X^{-1}\mathbf{S}_{XY}\mathbf{S}_Y^{-1}\mathbf{S}_{XY}^T$ and $\mathbf{A}_Y = \mathbf{S}_Y^{-1}\mathbf{S}_{XY}^T\mathbf{S}_X^{-1}\mathbf{S}_{XY}$:

$$\vec{\mathbf{F}}_X^k = \mathbf{S}_X\vec{\mathbf{f}}_X^k \text{ and } \vec{\mathbf{F}}_Y^k = \mathbf{S}_Y\vec{\mathbf{f}}_Y^k$$

where $\mathbf{S}_X$ and $\mathbf{S}_Y$ are, respectively, the covariance matrices of **X** and **Y,** while $\mathbf{S}_{XY}$ is the cross-covariance matrix of **X** and **Y**. It can be shown that canonical correlation patterns are chosen such that:

- Canonical correlation coefficients, α and β, defined by projection of two data sets onto these patterns, are optimal in a least square sense, i.e. for given patterns $\mathbf{F}_X$ and $\mathbf{F}_Y$ the norms $\left\|\vec{\mathbf{X}}_t - \sum_{k=1}^{K}\alpha_k(t)\vec{\mathbf{F}}_X^k\right\|$ and $\left\|\vec{\mathbf{Y}}_t = \sum_{k=1}^{K}\beta_k(t)\vec{\mathbf{F}}_Y^k\right\|$ are minimised. This condition implies: $\alpha_k = \left\langle \mathbf{S}_X^{-1}\vec{\mathbf{F}}_X^k, \vec{\mathbf{X}}_t \right\rangle$ and $\beta_k = \left\langle \mathbf{S}_Y^{-1}\vec{\mathbf{F}}_Y^k, \vec{\mathbf{Y}}_t \right\rangle$, where $\mathbf{S}_X$ and $\mathbf{S}_Y$ are, respectively, the covariance matrices of **X** and **Y.**

The canonical coefficients, defined by projection of two data sets onto canonical patterns exhibit maximum correlation, Corr[α_1, β_1] ≥ Corr[α_2, β_2] ≥ … ≥ Corr[α_K, β_K] ≥ 0, but are

- uncorrelated with the projections of the data onto any of the other patterns: Corr[α_k, α_l], Corr[β_k, β_l], Corr[α_k, β_l] and Corr[α_l, β_k] are equal zero for all $k \neq l$.

- the canonical coefficients, also called *canonical correlation coordinates,* are orthonormalized: Var[α_k] = Var[β_k] = 1.

In order to simplify mathematics and to reduce the noise of fields involved, observation vectors are transformed into a low-dimensional EOF-space (EOF stands for Empirical Orthogonal Functions) before computing CCA:

$$\vec{\mathbf{X}}_t \cong \sum_{k=1}^{K} \tilde{\alpha}_k(t)\sqrt{\lambda_k^X}\,\vec{\mathbf{e}}_X^k \text{ and. } \vec{\mathbf{Y}}_t \cong \sum_{k=1}^{K} \tilde{\beta}_k(t)\sqrt{\lambda_k^Y}\,\vec{\mathbf{e}}_Y^k$$

The numbers λ_k^X and λ_k^Y are the eigenvalues, whereas $\vec{\mathbf{e}}_X^k$ and $\vec{\mathbf{e}}_Y^k$ the empirical orthogonal functions. In EOF coordinates, because of $\mathbf{S}_X$ and $\mathbf{S}_Y$ are both identity matrices, CCA matrices are of the simpler and the non-negative definite symmetric form: $\mathbf{A}_X = \mathbf{S}_{XY}\mathbf{S}_{XY}^T$ and $\mathbf{A}_Y = \mathbf{A}_X^T$.

Construction of the model

In order to estimate the predictand anomalies from the predictor anomaly field, the first step is to connect α_1(t) and β_1(t) with a simple linear model: $\beta_1(t) = \rho_1\alpha_1(t)$, and since α_1(t) and β_1(t) are normalised to unit variance, ρ_1 is the canonical correlation coefficient. The predictand anomalies are forecast as:

$$\vec{\mathbf{Y}} = \beta_1(t)\vec{\mathbf{F}}_Y^1 = \rho_1\alpha_1(t)\vec{\mathbf{F}}_Y^1$$

If the most important canonical correlation patterns are taken into account, predictand anomalies can be described by a multiple linear model:

$$\vec{\mathbf{Y}} = \sum_{k=1}^{K} \beta_k(t)\vec{\mathbf{F}}_Y^k = \sum_{k=1}^{K} \rho_k\alpha_k(t)\vec{\mathbf{F}}_Y^k$$

Description of why this method is improved/new

CCA especially finds the optimum linear-combination of the predictor data vector that will explain the most variance in the predictand data vector

A table listing up to three general strengths and three weakness of the method as bullet points

Strengths:

- Canonical correlation analysis is a multivariate statistical technique that objectively define the most highly related patterns of potential predictors and predictands;
- CCA can be viewed as an extension of the multiple regression;

- Canonical correlation analysis enables to define a local climate, through a statistical relationship that relates large-scale atmospheric features (predictors), usually well predicted by GCMs, to local ones (predictand).

Weakness:

- CCA and all other statistical downscaling models (such as MLR) underestimate the temporal variance;

- CCA is sensitive to the number of EOFs/CCP used in the downscaling model, such as many test have to be done as far as the best combination is found;

- The model skill depends on the spatial area over which predictors are taking into account.

Specific suggestions for further improvements to/developments of the method

In order to solve the problem of underestimation of the temporal variability, technique such as those suggested by von Storch (1999), namely, adding to the downscaled series a white noise, is necessary.

2. Statistical Downscaling model based on MLR

Description of the method

Multiple Linear Regression analysis, so useful in diagnostic and predictive studies of data sets, attempts to model the relationship between two or more variables by fitting a multi-linear equation to observed data (Wilks, 1995). One variable is considered to be an explanatory variable (the predictand), and the other is considered to be dependent variables (the predictors).
The model may be expressed by the following equation:

$$Y = a_0, + a_1X_1 + a_2X_2 + \ldots\ldots + a_nX_n$$

where: Y is the predictand;
a_i are the regression coefficients that are estimated using the observed data;
X is the predictors.

The regression coefficients are determined by using the least squares methods. To avoid the multicollinearity of the predictors the choice of this had to be made carefully because we had to be sure to choose indipendent variable. One way to do this is first to study the correlation between the predictors and selected only the predictors less correlated.

In order to filter the noise from the data and to reduce the dimensionality of the predictors the regression model could be constructed based on PCs derived from EOFs analysis, that are shortly described in the CCA methods. We consider retaining in the MLR only the number of PC's that have a meaningfully contribution to total variance and that make significant the regression coefficients.

Description of why this method is improved/new

The MLR methods has been tested in two steps:

a) using only the first 4PCs of the predictors;
b) increasing the number of PCs of predictors, such as the explained variance to be 97% from the total variance.

The skill of the model has been slightly improved in the second situation for some extrems.

A table listing up to three general strengths and three weakness of the method

Strengths:

- MLR is enables to define a local climate, through a statistical relationship that relates large-scale atmospheric features to local one;
- MLR is very simple method to be implemented.

Weakness:

- MLR underestimate the temporal variability, such in the CCA case;
- MLR need to test before the construction of the model, the relationships between predictors and predictand;
- The model skill depends on the spatial area over which predictors are taking into account.

Specific suggestions for further improvements to/developments of the method

Same solution like in the CCA techniques

References

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Improved Statistical Downscaling Methodologies: description of the STARDEX methods

AUTH, Greece

AUTH_ANN, AUTH_CCA & AUTH_MREG

AUTH DOWNSCALING METHODS

Introduction

AUTH has developed three statistical downscaling models a) **Multiple Linear Regression Model using the circulation type approach** b) **Canonical Correlation Analysis (CCA) Model** c) **Artificial Neural Network Model**, in order to simulate the extreme indices of temperature and precipitation. The models are described in detail in the next paragraphs. They were applied on an annual and seasonal basis using as predictors the **500hPa geopotential heights** in the case of the extreme precipitation indices (predictants) and the **(1000-500hPa) thickness field** (predictors) for the simulation of the extreme temperature indices (predictants).

For all three models initially the calibration period is 1958-1978+ 1994-2000 and the validation period is 1979-1993 using the NCEP/NCAR reanalysis data. In the case of the GCM output the calibration period is 1958-2000 (NCEP data) and the validation period is 1960-1990 (GCM control run) or 2070-2100 (GCM scenarios).

Multiple Linear Regression Model using the circulation type approach

AUTHs Multi Linear Regression Model is based on a daily catalogue of 14 circulation types, which is constructed for each calibration period. The automated classification scheme is based on standardized 500hPa and 1000-500hPa (thickness) daily geopotential height data of the NCEP/NCAR reanalysis data achieve (Kalnay et al., 1996) with a spatial resolution of 2.5^o x 2.5^o within the European region of 20^oN -65^oN and 20^oW-50^oE.

Six anticyclonic types (Anw (A1), Ane (A2), A (A3), Asw (A4), Ase (A5) and Ae (A6)) and eight cyclonic types (C, Cs, Csw, Cnw, Cne, Cse, Cn and Cw) are defined. The characterization of Anticyclonic or Cyclonic circulation types refers to the locations of the positive or negative anomaly centre ($z_i = \frac{x_i - \bar{x}}{\sigma}$, where z_i = the standardized daily values for each grid, x_i = the daily values of geopotential height for each grid (i), $\bar{x}$ = the mean monthly value for each grid for the period 1958-2000 and σ = the corresponding standard deviation) in relation to the Greek area.

For example, the positive anomaly centre of the anticyclonic type A locates over Greece, while the location of the negative anomaly centre of Csw (cyclonic type) is in southwest of the Greek area. More details on the classification method are provided by Maheras et al. (2000) and Maheras and Anagnostopoulou (2003).

After developing the daily calendar for the two fields, the multi linear regression method is used for all possible combinations of the circulation types (fig1). On a second step, the best for each group of circulation types (each ct separately, each pair of ct, each triplet, each quadruplet, etc) was selected using the highest R^2. Continuously, the simulated data from these "best R^2" groups were compared with the observed data and the best of these "best R^2" groups was selected based on the highest correlation coefficient. Finally, for each station and for each season, one ct group was chosen, which was then applied to the MLR Model (fig 1).

For the validation period a new daily calendar was developed, computing the frequencies of the new circulation types. Then, the MLR model is applied in the same way as in the calibration period (fig 1).

Referencies:

Kalnay E, Kanamitsou M, Kistler R, Collins W, Deaven D, Gandin L, Irebell M, Saha W, White G, Woolen J, Zhu Y, Leetman A, Reynolds R, Chelliah M, Edisuzaki W, Huggins W, Janowiak J, Mo KC, Ropelewski C, Wang J, Jenne R, Joseph D. 1996. The NCEP/NCAR 40-year Reanalysis project. *Bulletin of American Meteorological Society* **77**: 437-471.

Maheras P, Patrikas I, Karacostas Th, Anagnostopoulou Ch. 2000. Automatic classification of circulation types in Greece: Methodology, description, frequency, variability and trend analysis. *Theoretical and Applied Climatology* **67**: 205-223.

Maheras P, Anagnostopoulou Chr. 2003. Circulation Types and their Influence on the Interannual variability and precipitation changes in Greece, Mediterranean Climate-Variability ad Trends. *Springer Verlag, Berlin, Heidelberg*, 215-239.

Input for Predictors:
Data NCER/NCAR for
- 500hPa geopotential heights
- thickness field 1000-500hPa
in grid points 2.5x2.5
(Kalnay et al., 1996)

Input for Predictands:
- Daily rainfall totals of precipitation
- Daily Maximum and minimum temperature for stations or grid points

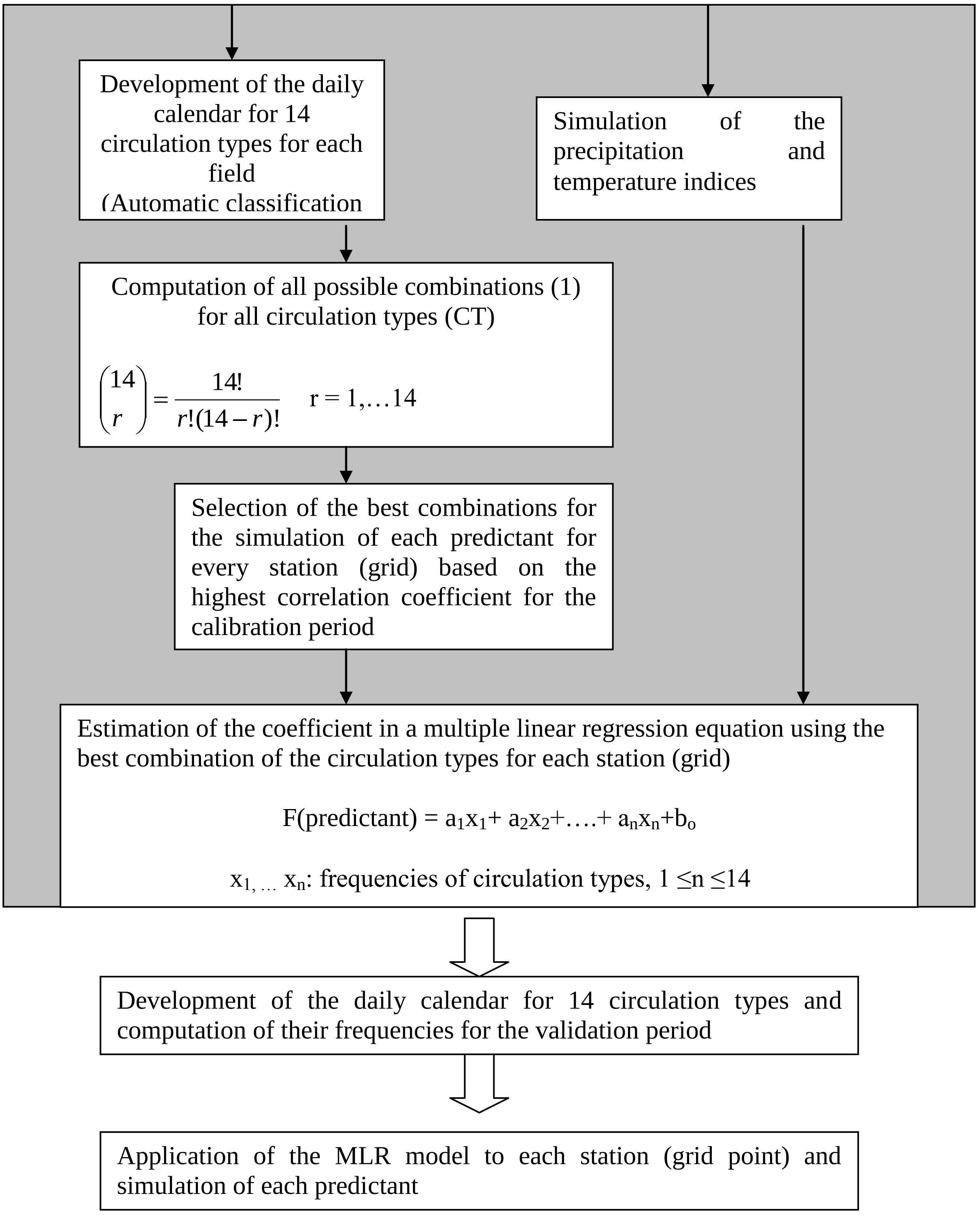

Figure 1. The Multi Linear Regression Model based on a circulation type approach

Canonical Correlation Analysis Model

AUTHs Canonical Correlation Analysis Model is based on CCA (Barnett and Preisendorfer 1987; von Storch and Zwiers, 1999), which selects pairs of spatial patterns of two space-time dependent variables.

Initially the S-mode unrotated PCA method was applied to the predictors (500 hPa and (1000-500) hPa thickness geopotential heights) in order to reduce the dimensionality of the original data. The PCs retained explained more than 80% of the total variance. The scores of these Principal Components were used in CCA method and all the canonical pairs were computed. The predictants are the precipitation and temperature indices for all stations (or grid points).

On a second step, these CCA pairs were used in a multiple regression model in order to estimate the predictants from the large scale predictors. Finally, this model is applied again using as predictors the GCM output (fig 2).

References:

Barnett T and Preisendorfer R (1987) Origin and levels of monthly and seasonal forecast skill for United States surface air temperatures determined by canonical correlation analysis. Monthly Weather Review 115: 1825-1850.

Von Storch H, and Zwiers FW (1999) Statistical Analysis in Climate Research. Cambridge University Press. pp 484

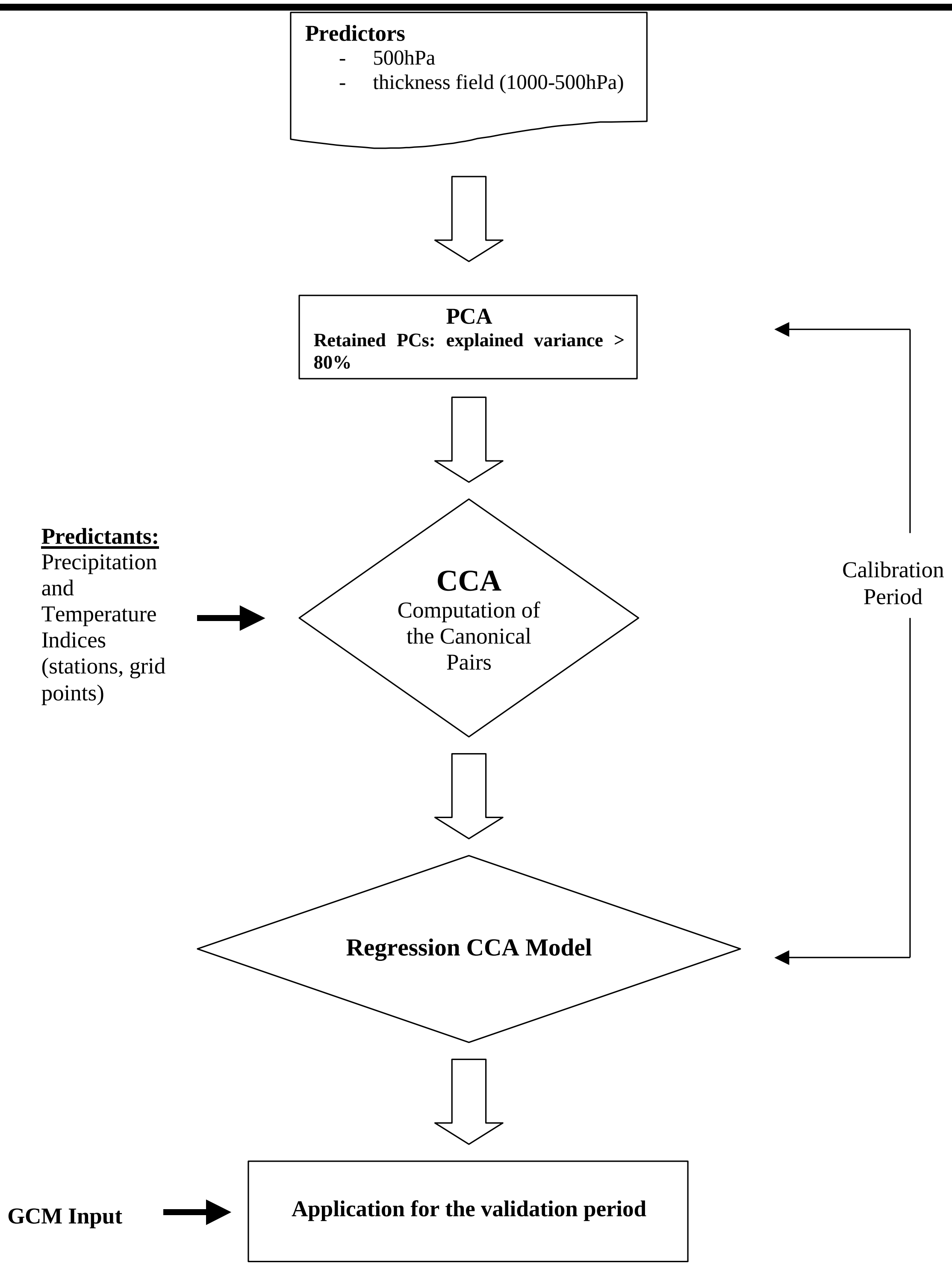

Figure 2. Block diagram of the CCA model used

Downscaling Technique using an ARTIFICIAL NEURAL NETWORK

The AUTHs ANN Model is based on the **quickprop** algorithm created by Scott Fahlman using in the beginning Common Lisp and then translated in C by Terry Regier (University of California, Berkley). This algorithm is described in detail by Fahlman 1988.

The neural net that was used is a **feed – forward type** of neural network and its learning process is based on **back – propagation** method. After having constructed many configurations for this neural network, it was concluded, on a trial and error basis, that the best results were obtained with only one hidden layer, with 12 nodes (figure 3).

The chosen predictors for the simulation of **precipitation** and **precipitation indices** (predictants) are:

- Scores of the 500hPa field (S-mode PCA unrotated)

The chosen predictors for the simulation of **temperature** and **temperature indices** (predictants) are:

- Scores of the thickness (1000-500hPa) field (S-mode PCA unrotated)

The neural net is trained for the years of the calibration period and is validated for the years of the validation period. Before the training process begins, the weights (w) were initialized to small number using a random seed generator. The NET signal:

$$NET = \sum x_n w_n$$

is processed by the transfer (activation) function:

$$F(NET) = \frac{1}{1 + \exp(-NET)}$$

to produce the output signal.

This transfer function is a “sigmoid function” which values are ranging between 0 and 1 and so the target vector of the predictants are “normalized” taking values between these limits in order to be compared with the F(NET) signal.

The error between the predicted output (F(NET)) and the target vector is estimated using the RMSE (root mean square error):

$$RMSE = \sqrt{\frac{\sum (F(NET) - t\arg etvector}{N}}$$

This calculated error is then back-propagated and the weights are determined again in order to minimize the error in the next “training year”. This procedure ends when the error reaches a minimum.

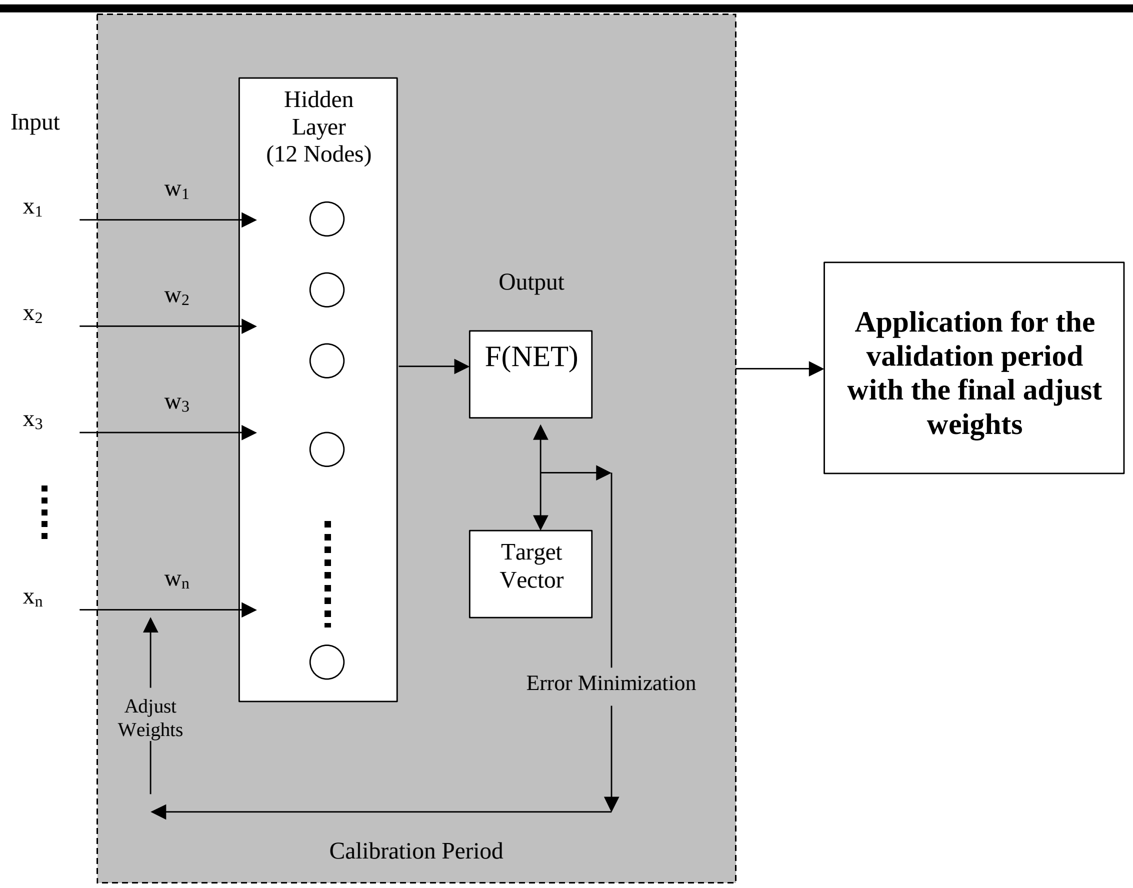

Figure3. The artificial neural network model used.

Reference:

Fahlman S., 1988: Faster Learning Variations on Back-propagation. An Empirical Study. Proceedings of 1988 Connectionist Models Summer School, published by Morgan Kaufmann.

STARDEX

STAtistical and Regional dynamical Downscaling of EXtremes for European regions

EVK2-CT-2001-00115

Deliverable D15

Improved Statistical Downscaling Methodologies: description of the STARDEX methods

Guy Plaut

CNRS

CNRS_PPCI

D15: Improved Statistical Downscaling Methodologies: description of the STARDEX methods

1.Main steps of the algorithm.

- Definition of **IPE**s (Intense Precipitation Events) over the station of interest.
- Definition of **PR**s (Precipitation Regimes), an extension of **WR** s(Weather Regime) concept.
- Construction of the **ppci**, a linear index depending on **LSC**s (Large Scale Circulation patterns), **PR**s, and **WR**s.
- Description of the **DS** (Downscaling) scheme.
-

2.Definition of IPEs.

-

Many definitions of local Intense Precipitation Events may be given. We choose to define **IPE**s as those days with a precipitation in excess of a fixed threshold. The threshold value is choosen in such a way that one is left with about 10 **IPE**s per year. Witth such a definition, **IPE**s occur preferentially during wet seasons if any, generally fall and winter in southern Europa. The **PR**s and ultimately the **DS** scheme appear to be very insensitive to the precise value of the threshold.

3.Definition of PRs.

-

Once **IPE** days have been selected, we extract the corresponding **Z700** height maps over an euro-atlantic sector and like in [Plaut et al., 2001], we classify these maps into clusters. We call Precipitation Regimes (**PR**s) the central patterns of these clusters.

This new naming is a natural extension of the naming Weather Regimes (**WR**) which commonly refers to the central patterns of the clusters one obtains when classifying all the **LSC** patterns. Unlike **WR**s, **PR**s highly depend on the particular station (or gridpoint) of interest. **PR**s are most often robust and may own a high **discriminating power**: this peculiar quality manifests through the fact that whenever the anomaly pattern correlation coefficient (**apcc**) of any day **LSC** with a given **PR** is high enough (close enough to 1), the probability of this day being an **IPE** gets high.

-

10. Construction of a ppci..

- The **potential precipitation circulation index** is a linear daily precipitation index.
- Its value is defined as the best regression of (daily)precipitation against the **apcc**s of the corresponding **LSC** with the **PR**s and **WR**s.

- Since classification may have been performed into various numbers of **PR**s or **WR**s, the *optima*l number of **PR**s and **WR**s are looked for in a cross-validation way; (please, note that *optimality* may be defined in various ways).
- The **ppci** appears extremely robust and over-constrained, with almost similar *learning* and *verification* scores if one uses a *cross-validation* approach.
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5.Description of the Downscaling algorithm.

- Our previously defined **ppci** is the basic tool of our stochastic scheme. We first compute the **ppci**s of any learning period day (see above). Then we classify the values of these **ppci**s into 20 categories (20 is better than 10; higher numbers of categories bring no more improvement!). Using categories to find analogs is a pretty way to take into account the non-linear link between precipitation and the **ppci:** precipitation almost never occur with negative **ppci** values, whereas **IPE**s mostly occur together with the highest **ppci** categories [Plaut, 2004].
- Our scheme is a true **DS** one (no small scale parameter involved)
- Starting from the **LSC** of any involved day, we compute its **ppci**. And the category into which it enters.
- Then we randomly choose an *analog* within the subset of *learning period* days having a **ppci** belonging to the same category, and assign this analog *precipitation* to the involved *day*
- In this way complete daily precipitation series may be easily generated and any seasonal extreme index (like **Pav**, **PQ90**, **P5DMAX**, **PCDD**, etc...) may be computed.
- Given the stochastic component of our scheme, a large number of precipitation series may be downscaled from a single **GCM** run, in a way somewhat rench s to ensemble technics.
- Given the different dynamical processes involved in the generation of different season precipitation, the best **ppci** are looked for independently for the four (DJF, MAM, etc...) seasons. Therefore the exact model differ from season to season.

10. Some strength of the ppci DS scheme.

- Robustness
- Truely a **DS** scheme: no small scale (often less accurately forecast) parameter involved
- Pretty good description (high Spearman correlation) of seasonal precipitation (alpine stations, except during summer; western rench stations, winter, spring) or drought duration indices (Alps: fall and winter; West Iberia: spring and winter).

10. Some weaknesses of the ppci DS scheme.

- Summer indices badly reproduced, likely due to smaller scale precipitation mechanisms during summer.
- Except for **Pav**, the interannual variability is most often highly underestimated
- Low quality **PQ90**, better **P5DMAX** and **PCDD**..

•No spatial coherence at the daily time scale (imdependent models for 2 different stations).

8. Application criteria for statistical and dynamical downscaling

Method provides:	Y/N	Comments/Notes
Station-scale information	Y	
Grid-box information	Y	provided it learns with gridbox precipitation
European-wide information	N	
Daily time series	Y	
Seasonal indices of extremes	Y	
Temporally consistent temperature and precipitation[1]	N	only precipitation is downscaled
Spatially consistent multi-site information[2]	Y	at seasonal level, not at daily level
Temporally consistent multi-site information[3]	N	
Information at sites with no observations	N	
Method requirements :	**Relatively high/medium/low**	**Comments/Notes**
Computing resources	**medium**	The algorithm may be simplified without noticeable loss of skill
Volume of data inputs	**medium**	
Availability of input data	**high**	

9. Suggestions for further improvement, development.

•Large Scale domain adaptive size.

•The bulking of menth into standard seasons (DJF, etc...) may not be the best.

•For future climate change investigations,it seems that our model may be simplified in a way that would allow much faster numerical investigations [Plaut, 2005].

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10. References.

•[Plaut et al., 2001]: Plaut, G., Schuepbach, Evi, and Doctor, M.: **Heavy precipitation events over a few alpine sub-regions and the links to large-scale circulation: 1971-1995**, *Climate Research* 17, CR Speial 9 **ACCORD**, pp285-302, 2001.

•[Plaut, 2004]: Plaut G., **Downscaling algorithms for precipitation: The "potential precipitation circulation index" or "ppci", an adaptive predictor to downscale extreme precipitation on the rench Alpes Maritimes**, STARDEX partner 5 (CNRS-INLN) deliverable report **D10**, 2004, available on

•STARDEX web site or http://www.inln.cnrs.fr/~plaut/STARDEX.CNRS.reports/D10

•[Plaut, 2005]: **Downscaling of extremes for precipitation over 10 alpine and 16 iberian stations: Application of a stochastic algorithm based on a "potential precipitation circulation index" ("ppci") defined using NCEP reanalysed large scale Z700 geopotential field (1958-2000)**, STARDEX partner 5 (CNRS-INLN) deliverable report **D12**, 2005, available on

•STARDEX web site or http://www.inln.cnrs.fr/~plaut/STARDEX.CNRS.reports/D12

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STARDEX

STAtistical and Regional dynamical Downscaling of Extremes for European regions

EVK2-CT-2001-00115

Deliverable D15

Improved Statistical Downscaling Methodologies: description of the STARDEX methods

Torben Schmith

DMI, Denmark

DMI_CWG

A conditional weather generator

DMI partner report for deliverable D15
Torben Schmith, Danish Meteorological Institut

Description of method

We apply a weather generator approach for hindcasting daily precipitation amounts, where the parameters in the generator are dependent on daily values of an index describing the large scale circulation on which the probabilistic characteristics of the precipitation are quantified. The relation between the circulation and the precipitation characteristics is calculated for each station and for each season.
For calibrating the model to a given station, a surface pressure pattern is obtained as the average pressure difference between rainy days and dry days measured at that station. The circulation index is then calculated by projecting the daily surface pressure anomaly field onto this pattern.
The parameters in the weather generator are: the probability for wet/dry days, the probabilities for a wet/dry day following a dry/wet day, and the two parameters describing the gamma-distribution that best approximates the probability density of the rain amount (only wet days). The dependence of these parameters on the circulation index is then determined by 'binning' into 5-10 bins.
When applying the model, the daily circulation index is calculated by projection the daily surface pressure anomaly field onto the pattern found above. Using the dependence of the probabilities on the circulation index a two-state Markov process is used to obtain the sequence of dry/wet days. Then, for each wet day the rain amount is drawn from a gamma-distribution with the parameters corresponding to the circulation index of that day.

Why this method is improved.

Conditional weather generator approaches for downscaling daily precipitation values have been previously applied (Wilby et al., 1998), but in that work the circulation idex is evaluated at a point. The improvement of the present method is that the index is defined as projection onto an 'optimal' pattern.

Strengths/weaknesses

Strengths:

- Few parameters (thresholds, geographical domains etc.) to be specified.
- Calculates daily values of predictor
- Calculates distribution of daily values

Weaknesses:

- Does not - in the present formulation - take vertical stability or humidity content explicitly into account.
- Single site method – does not exploit spatial correlations.

Application criteria table

Method provides:	Y/N	Comments/Notes
Station-scale information	Y	
Grid-box information	N	
European-wide information	Y	
Daily time series	Y	
Seasonal indices of extremes	Y	
Temporally consistent temperature and precipitation[1]	Y	
Spatially consistent multi-site information[2]	N	
Temporally consistent multi-site information[3]	N	
Information at sites with no observations	N	
Method requirements :	**Relatively high/medium/low**	**Comments/Notes**
Computing resources	**Low**	
Volume of data inputs	**Low**	
Availability of input data	**High**	

[1] i.e., the temperature/precipitation co-variance is similar for the downscaled validation series and observed series
[2] i.e., the downscaled validation series has a similar spatial pattern to the observed series
[3] i.e., the downscaled validation series has similar daily inter-site correlations to the observed series

Specific suggestions for further improvements to/developments of the method

One immediately applicable improvement to the model would be to include a measure of vertical stability. Changes in vertical stability are known to influence the typical scale and development times of baroclinic disturbances which could probably lead to precipitation changes.

One candidate is the approximate expression for the growth rate of the fastest growing baroclinic disturbance:

$$\sigma_{BI} = 0.31\frac{f}{N}\frac{\partial|v|}{\partial z} = -0.31\frac{1}{T}\left(\frac{1}{g\theta}\frac{\partial\theta}{\partial z}\right)^{-0.5}|\nabla T| \text{ (Lindzen and Farrell (1980)),}$$

which is combination of horizontal circulation and vertical stability.

References

Lindzen, R: S:, and B. Farrell, 1980: A simple approximate result for maximum growth rate of baroclinic instabilities. J. Atmos Sci., 37, 1648-1654.
Wilby, R. L., T. M. L. Wigley, D. Conway, P. D. Jones, B. C. Hewitson, J. Main, and D. S. Wilks, 1998: Statistical downscaling of general circulation model output: A comparison of methods. Water resources res., 34, 2995-3008.

STARDEX

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EVK2-CT-2001-00115

Deliverable D15

Improved Statistical Downscaling Methodologies: description of the STARDEX methods

Juerg Schmidli and Christoph Frei

ETH, Switzerland

ETH_LOC & ETH_LOCI

D15 Method Description - ETH

The ETH downscaling method is based on the procedure of Widmann and Bretherton (2003) and uses GCM-simulated precipitation as a predictor for regional/local precipitation. The basic idea of both the original (LOC) and the new (LOCI) downscaling method is to rescale the GCM-simulated precipitation with a spatially varying, but time-invariant factor, which compensates for the longterm bias of the GCM at the station. (A variant of both methods allows for a scaling factor which
depends on the season of the year).

Within STARDEX a more refined variant of the original scheme was implemented.
The new method improves on the original method by including a bias correction for precipitation frequency and intensity. The positive impact of this bias correction is shown clearly by the validation experiments.

The downscaled precipitation $\hat{P}$ for a given station can be written as

$$\hat{P}(t) = \begin{cases} 0 & \text{if } P^m(t) < P^m{}_{WDT} \\ s\,P^m(t) & \text{if } P^m(t) \geq P^m{}_{WDT} \end{cases}$$

where P^m is the GCM-simulated precipitation, $P^m{}_{WDT}$ is the model wet-day threshold,

$$s = \frac{\langle P^o : P^o \geq P^o{}_{WDT} \rangle}{\langle P^m : P^m \geq P^m{}_{WDT} \rangle}$$

is the station-dependent scaling factor, P^o is the observed precipitation, and $P^o{}_{WDT}$ is the wet-day threshold for the observations. The angle brackets indicate the climatological mean precipitation intensity over the calibration period at each grid point, and $P^o{}_{WDT}$ is defined to be equal to 1 mm per day. The idea of the new method is to define the model wet-day threshold $P^m{}_{WDT}$ such that the model precipitation frequency equals the observed precipitation frequency. For further details on the ETH downscaling method see Schmidli and Frei (2005).

Strengths of the ETH downscaling methods are:
- Easily transferable to different regions

4. Easy implementation and low data requirements (no daily observations required at station, but only mean precipitation frequency and mean precipitation intensity)
6. Strong predictor/predictand relationship and therefore potentially less prone to stationarity problems

Weaknesses are:

2. Downscaling skill depends crucially on quality of GCM data
3. Non-responsive to changes in mesoscale processes that are not resolved by the GCM

The scheme may be considered as the grafting of a GCM (rather than a full downscaling technique) that serves as a useful benchmark, against which other downscaling methods are compared.

References

Schmidli, J., and C. Frei, 2005:
Statistical precipitation downscaling over the European Alps using model precipitation as a predictor. (in preparation).

Widmann, M., and C. S. Bretherton, 2003:
Statistical precipitation downscaling over the Northwestern Unites States using numerically simulated precipitation as a predictor, J. Climate, 16, 799--816.

STARDEX

STAtistical and Regional dynamical Downscaling of EXtremes for European regions

EVK2-CT-2001-00115

Deliverable D15

Improved Statistical Downscaling Methodologies: description of the STARDEX methods

FIC, Spain

FIC_ANAL2

AUTHORS AND VERSION HISTORY

Lead author:
Jaime Ribalaygua, FIC

Contributing authors:
Lucía Benito, FIC
Luis Torres, FIC

Version 1.0: 27 February 2005

1. Data.

The downscaling method works on a daily basis. The low resolution predictors have been selected from NCEP/NCAR Reanalyses. In the verification phase, the calibration period is 1958-1978 and 1995-2000, and the verification period is 1979-1994. For the final application of the method to HadAM3p output, the reference period is 1958-2000.

A good diagnostic capability in the daily scale is required, to ensure the statistical relationships stability. In this regard some ideas must be kept in mind:

1. The statistical tool must be "non-linear" enough to handle the strong non-linear relationships that link predictors with most of the local surface weather predictands.
2. Predictors must present clear physical linkages with the predictand. That points towards the need of using as predictors (whenever is possible) direct forcings of the predictand.
3. The predictors must cover, as much as possible, all the direct forcings of the predictand.

The statistical downscaling method has been developed trying to consider the previous conceptual framework.

1.1. Predictors for precipitation.

Precipitation is forced by upwards movements of air. The most important forcings of upward movements are:

- o Dynamic forcing
- o Topographic lift
- o Convection

- Dynamic forcing at the synoptic scale is determined by geopotential configurations at 1000 and 500 hPa (see “ω” equation, Holton, 1975).
- Topographic lift could be considered attending at surface winds, which are strongly related to geostrophic flux at 1000 hPa.
- Convection occurs due to triggering factors (differential surface heating, topographic or frontal lifts) on a more or less unstable atmospheric profile.

Beside this, low troposphere humidity is related with the amount of precipitation due to upwards movements.

The predictors used for precipitation are:

- Geostrophic flux direction at 1000 hPa, obtained from 1000 hPa geopotential height.
- Geostrophic flux velocity at 1000 hPa, obtained from 1000 hPa geopotential height.
- Geostrophic flux direction at 500 hPa, obtained from 500 hPa geopotential height.
- Geostrophic flux velocity at 500 hPa, obtained from 500 hPa geopotential height.

Another predictor has been tested, but the final version of the method does not use it:

- Low troposphere relative humidity, obtained from 1000, 925 and 850 hPa relative humidity.

Convective precipitation downscaling can be improved attending also to instability predictors (instability indexes, low level thermal advection…). This could be very important for extremes simulation, since some of the extreme precipitation events in certain regions are related to convective precipitation.

1.2. Predictors for temperature.

Two meter air temperature is influenced both by low troposphere temperature and by soil surface temperature:

- Low troposphere temperature is well resembled by low troposphere thickness (for example 1000/850, 1000/700 or 1000/500 thickness) that are good predictors for surface temperature. 1000/850 hPa can be also sensitive to land-sea mask in coastal regions.
- Regarding soil temperature:
    - Soil surface temperature is driven by heat fluxes at the surface layer.
    - The insolation angle affects soil temperature, and it can be considered using sine functions of the day of the year. This influence depends on cloudiness.
    - Soil temperature is strongly influenced by cloudiness, because it modifies radiation cooling/heating of the surface. Cloudiness is forced by upwards movements of air, like precipitation, and the precipitation predictors are perfectly suitable for cloudiness.
    - The thermal inertia of the soil could be considered using previous days temperature as predictors.
    - Snow cover strongly modifies radiative cooling / heating of the surface so it should be also used.
- The influence of both low troposphere temperature and soil temperature, on two meter temperature, depends on atmospheric stability: under unstable conditions, there are more vertical heat fluxes, and two meter temperature is more dependant on low troposphere temperature.

Most of the predictor / predictand relationships are strongly non linear. For example, the relationship between the maximum two meter temperature and low troposphere thickness is very non linear, depending on the cloudiness conditions: under covered skies, low troposphere thickness almost determines the maximum two meter temperature; but if the sky is clear, the maximum temperature is driven by solar radiation, and the influence of low troposphere thickness is much lower. A previous stratification attending to cloudiness conditions makes these relationships much more linear, an then, much more easily and robustly captured.

The predictors used for temperature are:

- Geostrophic flux direction at 1000 hPa, obtained from 1000 hPa geopotential height.
- Geostrophic flux velocity at 1000 hPa, obtained from 1000 hPa geopotential height.
- Geostrophic flux direction at 500 hPa, obtained from 500 hPa geopotential height.
- Geostrophic flux velocity at 500 hPa, obtained from 500 hPa geopotential height.
- 1000/500 Hpa thickness, obtained from 1000 and 500 hPa geopotential heights.

Two other predictors are used, in this case not obtained from NCEP/NCAR Reanalyses:

- Low troposphere relative humidity, obtained from 1000, 925 and 850 hPa relative humidity.
- A sine function of the day of the year
- The mean temperature of the previous days, obtained as follows:

$$Tm = \sum_{i=1}^{10} (11 - i) \cdot (T\max_{d-i} + T\min_{d-i}) / 2$$

where *d-i* is the *i* previous day of the problem day. The maximum and minimum temperature are those downscaled for the previous days

2. Description of the method.

The method estimates high-resolution surface meteorological fields for a day “X”, in two steps (see figure 1): in the first step, the “n” most similar days to the “X” day, attending to their low-resolution atmospheric fields, are selected from a reference dataset. In the second one, high-resolution surface information is estimated in a different way for precipitation and temperature. Rainfall estimations for a point are done by means of a simple average of the observed precipitation amounts in the “n” analogous days, in that point. It was also tested to select (in the “n” day’s population) the most similar days attending to low troposphere humidity. Temperature is obtained applying a further multiple linear regression analysis that searches for relationships (in the “n” day’s population) between the predictors and the surface maximum and minimum temperature (predictand).

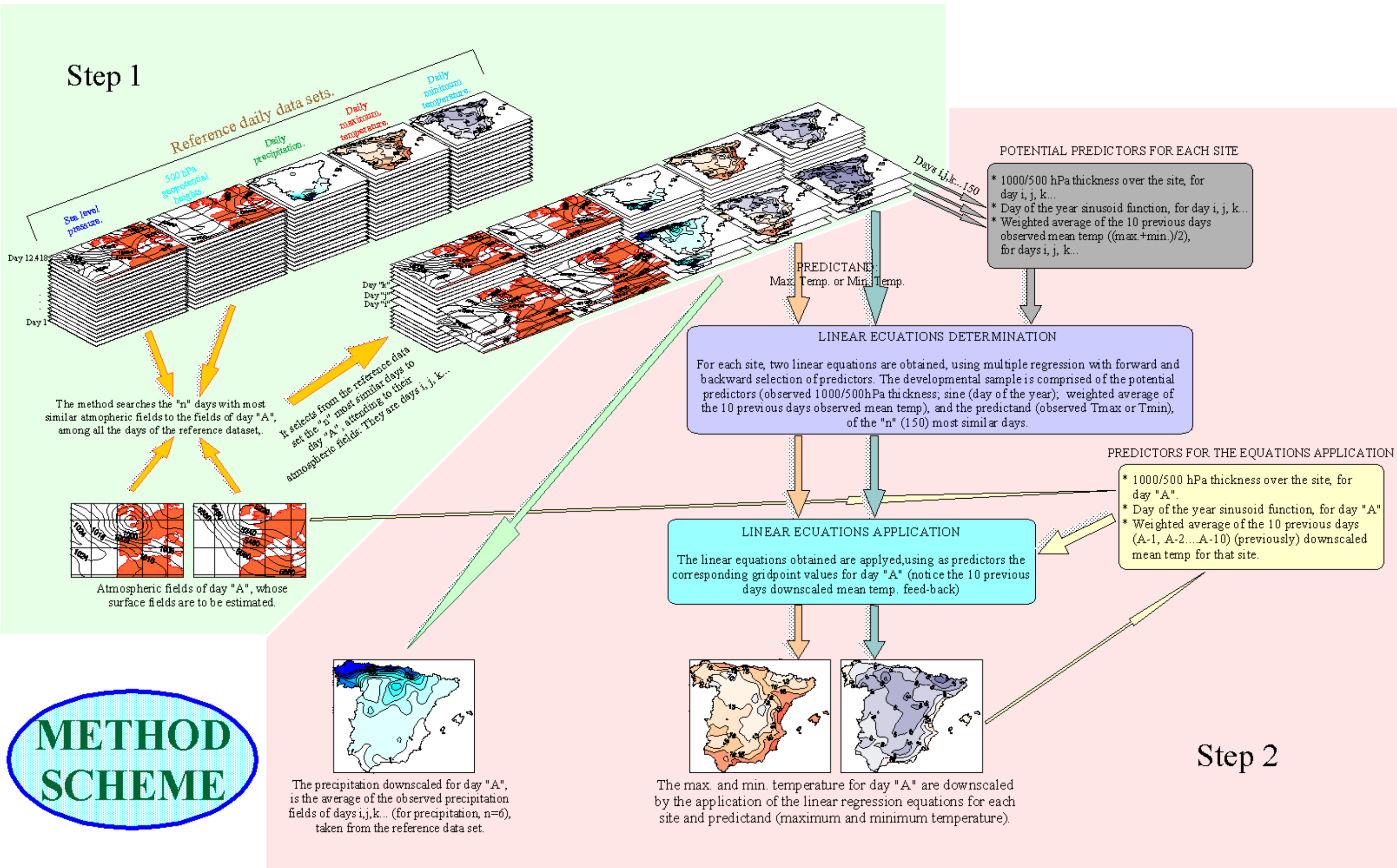

Figure 1

2.1. First step: the analogical technique

As pointed earlier, in the first step, the "n" most similar days to the "X" day, attending to their low-resolution atmospheric fields, are selected from a reference dataset. The similarity measure must contain diagnostic capability regarding high-resolution precipitation fields. In this sense, the similarity measure must assess the likeness of as many as possible precipitation forcings associated to the low resolution atmospheric configurations of the days being compared.

<u>The analogical predictors: mean daily geostrophic flux fields on 1000 and 500 hPa.</u>

It must be highlighted that predictor variables are not point, but field values (what increases trustworthiness of the predictor). 32 sets of atmospheric windows have been defined. Each set consists of three windows. The first set covers the area 55ºN-30ºN 27.5ºW-15ºE, and the grid points belonging to each of the three windows of that first set are shown in figure 2.

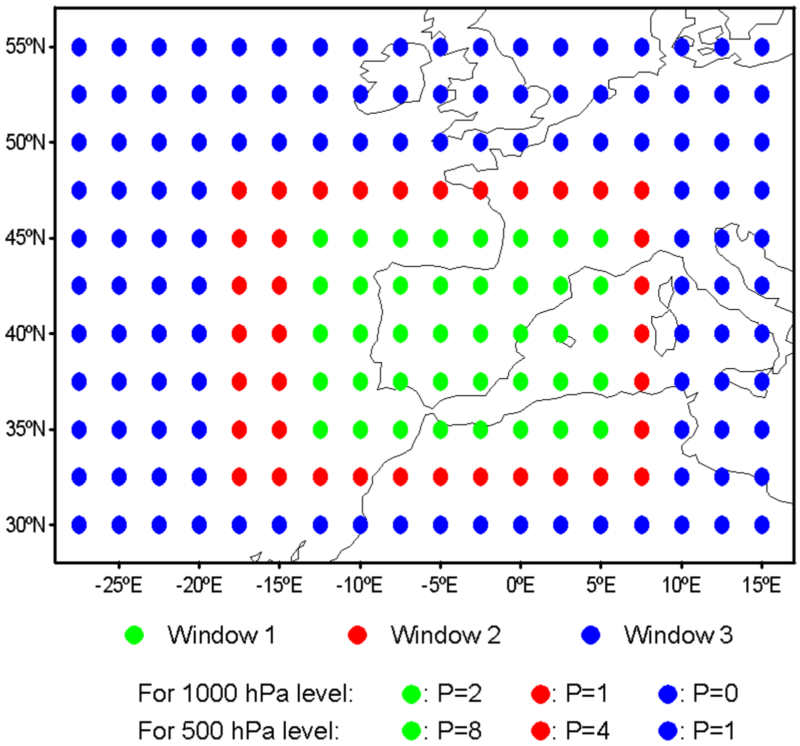

Figure 2

The other window sets are obtained moving the window 10 degrees northwards, and 10 degrees eastwards. So window 3 of each of the 32 sets cover the following areas:

Window 3 of set 1: 55ºN-30ºN 27.5ºW-15ºE
Window 3 of set 2: 65ºN-40ºN 27.5ºW-15ºE
Window 3 of set 3: 75ºN-50ºN 27.5ºW-15ºE
Window 3 of set 4: 85ºN-60ºN 27.5ºW-15ºE
Window 3 of set 5: 55ºN-30ºN 17.5ºW-25ºE
Window 3 of set 6: 65ºN-40ºN 17.5ºW-25ºE
Window 3 of set 7: 75ºN-50ºN 17.5ºW-25ºE

Window 3 of set 8: 85ºN-60ºN 17.5ºW-25ºE
Window 3 of set 9: 55ºN-30ºN 7.5ºW-35ºE
Window 3 of set 10: 65ºN-40ºN 7.5ºW-35ºE
Window 3 of set 11: 75ºN-50ºN 7.5ºW-35ºE
Window 3 of set 12: 85ºN-60ºN 7.5ºW-35ºE
Window 3 of set 13: 55ºN-30ºN 2.5ºE-45ºE
Window 3 of set 14: 65ºN-40ºN 2.5ºE-45ºE
Window 3 of set 15: 75ºN-50ºN 2.5ºE-45ºE
Window 3 of set 16: 85ºN-60ºN 2.5ºE-45ºE
Window 3 of set 17: 55ºN-30ºN 12.5ºE-55ºE
Window 3 of set 18: 65ºN-40ºN 12.5ºE-55ºE
Window 3 of set 19: 75ºN-50ºN 12.5ºE-55ºE
Window 3 of set 20: 85ºN-60ºN 12.5ºE-55ºE
Window 3 of set 21: 55ºN-30ºN 22.5ºE-65ºE
Window 3 of set 22: 65ºN-40ºN 22.5ºE-65ºE
Window 3 of set 23: 75ºN-50ºN 22.5ºE-65ºE
Window 3 of set 24: 85ºN-60ºN 22.5ºE-65ºE
Window 3 of set 25: 55ºN-30ºN 32.5ºE-75ºE
Window 3 of set 26: 65ºN-40ºN 32.5ºE-75ºE
Window 3 of set 27: 75ºN-50ºN 32.5ºE-75ºE
Window 3 of set 28: 85ºN-60ºN 32.5ºE-75ºE
Window 3 of set 29: 55ºN-30ºN 42.5ºE-75ºE
Window 3 of set 30: 65ºN-40ºN 42.5ºE-75ºE
Window 3 of set 31: 75ºN-50ºN 42.5ºE-75ºE
Window 3 of set 32: 85ºN-60ºN 42.5ºE-75ºE

Window 2 and 1 of each set are located as shown in figure 2, inside window 3.

For each site, the most skilful set of windows downscaling precipitation was selected, and used to downscale both precipitation and temperature

The similarity measure: average of standardised Euclidean distances among 1000 and 500 hPa daily geostrophic flux fields.

As pointed earlier, the downscaling method should perform as good as possible at the daily scale. The similarity measure between two days must be a scalar magnitude (to allow sorting), that summarises the resemblance of this two days with regard to their mean 1000 and 500 hPa geostrophic wind fields.

The similarity between two days is calculated determining (and standardising) independently those days likeness regarding each of the final four predictor fields “p”: 1000 hPa geostrophic wind speed field, 1000 hPa geostrophic wind direction field, 500 hPa geostrophic wind speed field and 500 hPa geostrophic wind direction field.

The similarity of days “i” and “j” regarding each predictor field “p” (for example, 1000hPa geostrophic wind speed), is calculated as an euclidean distance with:

$$D_{spd1000}(i,j) = \sqrt{\frac{\sum_{k=1}^{N}\left(Spd1000_{ik} - Spd1000_{jk}\right)^2 \cdot P_k}{\sum_{k=1}^{N} P_k}}, \ (*)$$

where $Spd1000_{ik}$ is the value of the 1000 hPa geostrophic wind speed of the day “i”, at the grid point “k” of the grid used to represent atmospheric fields (see figure 2); P_k is the weighting coefficient of the “k” grid point. P_k coefficients are different for 1000 and 500 hPa predictors (see figure 2). And “N” is the number of the atmospheric grid points (198), that is determined by the spatial domain (55ºN-30ºN 27.5ºW-15ºE for the first set) and the resolution (2,5º x 2,5º; lat. x lon.) of the referred grid.

Once $D_{spd1000}(i,j)$ has been calculated, it has to be standardised. The standardisation is done by means of substituting $D_{spd1000}(i,j)$ by $cent_{spd1000}$, that is the closest centil of the reference population of Euclidean distances among predictor fields *“spd1000”*, to the $D_{spd1000}(i,j)$ value. The centil values are previously determined, obiously independently for each “p” predictor field, over a reference population of more than 1.000.000 values of D_p, calculated applying the previous formulae, with the same P_k values, to randomly selected days (i.e., days multiple of 10). If the closest value to $D_{spd1000}(i,j)$ is $cent_{spd1000}$ = c, that means that about the c% of the 1.000.000 $D_{spd1000}$ values are lower than $D_{spd1000}(i,j)$.The use of centil instead of the original distance allows to consider adimensional and initially equally weighted variables, in the measure.

After the four $D_p(i,j)$ independent calculation and standardisation (determination of the closest four $cent_p$), the final similarity measure between days “i” and “j” is:

$$sim(i,j) = w_{spd1000}cent_{spd1000} + w_{dir1000}cent_{dir1000} + w_{spd500}cent_{spd500} + w_{dir500}cent_{dir500},$$

where w_p is the weighting coefficient of the predictor field “p”. The w_p combination finally selected is: $w_{spd1000}$ = 0,25; $w_{dir1000}$ = 0,25; w_{spd500} = 0,25; w_{dir500} = 0,25;

The equal value of the four w_p coefficients indicates that the four predictors (1000 and 500 hPa geostrophic wind speed and direction), are equally important in precipitation diagnosis. The P_k selected coefficients stress the fact that closer wind features exert higher influence over precipitation. 1000 and 500 hPa “windows” are large enough to capture full sized synoptic waves, but 1000 hPa window is slightly shorter than 500 hPa one, resembling that precipitation is affected by closer structures at 1000 than at 500 hPa.

Categorical estimation of daily precipitation field for a day “X” is obtained by means of a weighted average of the observed 6 (“n”=6) most analogous day’s observed precipitation in that site. The weighting coefficient of each analogous day’s field is the inverse of its similarity to the problem day “X”.

2.2. Second step: the multiple linear regression analysis.

The estimation procedure for temperatures requires, after the selection of the “n” analogous days described above, a further diagnosis by multiple linear regression. Although predictor/predictand relationships determined in this second step are linear, an important part of the non-linear links of free atmosphere variables with surface temperatures is considered with the previous (analogical) stratification. For example, the two steps procedure allows to consider the strong non-linear influence of cloudiness on surface temperature, because the previous selection of very similar days regarding precipitation, is implicitly guarantying also very similar cloudiness conditions for the selected days, what makes the further diagnosis by multiple linear regression very accurate.

The multiple linear regression employs a forward and backward stepwise selection of predictors. The potential predictors are three:

1. Mean daily 1000/500 hPa thickness over the site, to include the strong relationship between lower troposphere and surface temperatures (meteorological factor),
2. A sinusoid function of the day of the year with maximum in June 22nd, to consider the clear sky radiation influence on the warming/cooling of the surface air (seasonal factor),
3. And a weighted average of the surface grid-point mean daily temperatures of the ten previous days, to account for the soil thermal inertia influence (soil memory factor). Weighting coefficients decrease linearly from a value of 10 for the D-1 day to a value of 1 for the D-10 day.

The non-linear influence of other important meteorological factors, like cloudiness, precipitation and low troposphere wind speed, is considered through the previous analogical stratification. In fact, the regression is performed over a population of “n” days that present very similar precipitation conditions, and subsequently, very similar cloudiness conditions. As the analogical selection searches for days with similar 1000 and 500 hPa geostrophic wind fields to the problem day, low troposphere wind speed fields of the “n” days also tend to be very like.

For each site (and each problem day), this regression is performed twice, using as predictands maximum and minimum temperatures. So, two diagnostic equations are developed (using the predictand and predictor values of the “n” analogous days population) and applied to estimate both daily temperatures, for each site and problem day. It is important to highlight that, in the equations application, even for the validation period, the 10 previous days temperature values used are the method previously estimated values for that gridpoint, and not the observed ones. This last option clearly improves the validation results but, obviously, couldn’t be applied for future climate prospects. For the “averaged temperature of the ten previous days” predictor for the first days of the period to be downscaled, sensibility tests to several ºC modifications of the initial condition temperature values showed no influence over the mean estimated temperatures on multiyear scale, so the observed temperature values of 1961 January the 1st was finally used as the initial condition field.

The number “n” of most similar days used in the operational calculus is 6 for precipitation estimation, and 150 for the temperature further linear analyses appliance. Although the higher the “n”, the lower is the global similarity among the selected days and the problem day, relatively big samples are necessary in order to keep low the risk of overfitting in the multiple linear regression process. In this regard, the F-to-enter threshold was set to 4. The F-to-enter parameter is a statistic employed to assess the risk of including a non-significant potential predictor in the regression equation. When F-to-enter is set to 4, and when working with three potential predictors this risk is some 10%.

Although the set of windows for each site and the centil values for each of the 32 sets and each of the four predictor fields (gestrophic wind speed and direction at 1000 and 50 hPa), can be obtained using the procedure described, the values used in FIC's application of the method are available for anyone that would like to get them.

STARDEX

STAtistical and Regional dynamical Downscaling of EXtremes for European regions

EVK2-CT-2001-00115

Deliverable D15

Improved Statistical Downscaling Methodologies: description of the STARDEX methods

Malcolm Haylock

UEA

UEA_ANN & UEA_CCA

UEA Contribution to D15

Malcolm Haylock, UEA

Introduction

This document describes a downscaling method devised by UEA to model seasonal indices of extreme rainfall using mean large-scale circulation.

Data and Methodology

Canonical correlation analysis (CCA) is used to model the seasonal precipitation indices directly using seasonal means of circulation variables. Four potential predictors were chosen by examining correlations between the indices and the circulation variables. These are sea level pressure, relative humidity at 700hPa, specific humidity at 700hPa and temperature at 700hPa. For each season and precipitation index a CCA was carried out using all 15 possible combinations of the four predictors. The best set of predictors was selected using cross validation in the training period, whereby each year was removed and the model trained on the remaining years. The missing year was then hindcast and the skill measured by averaging across all stations the Spearman correlation between the observed and hindcast indices. Therefore the predictor set varies between indices and seasons but is the same for all the grid points in the region.

The canonical patterns and series were calculated using a singular value decomposition of the cross-covariance matrix of the principal components (PCs) of the two fields. This is numerically more stable than the more common method of working with the joint variance-covariance matrix (Press et al., 1986) and also incorporates the pre-filtering of the data by using just the significant PCs (Barnett and Preisendorfer, 1987). The number of PCs retained for the analysis was selected by a Monte Carlo process, whereby 1000 PC analyses were carried out using data randomly resampled in time from the original series (Preisendorfer et al., 1981). In each of the 1000 analyses the eigenvalues were calculated. Each of the eigenvalues of the real observations was then compared against the distribution of the 1000 randomly generated values to determine if they were greater than the rank 50 eigenvalue (equivalent to $p<0.05$). Therefore the number of eigenvectors retained was different for each predictor, predictand and season.

Innovation

Previous approaches to downscaling precipitation have modelled the entire daily precipitation distribution. By modelling indices of extremes we focus just on the extremes, which may have a different relationship to predictors than the lower magnitude events.

Strengths

- Computationally efficient.
- Transparent with easily accessible diagnostics.
- Reveals orthogonal statically-coupled modes.

Weaknesses

- No downscaled daily data.
- Models large-scale behaviour of entire network at once, which means that statistically independent stations will be poorly reproduced.

Improvements

Currently 95% of the computation is taken up with the scree test for assessing the number of significant PCs to include in the CCA. This could be reduced by using a different approach e.g. selecting the number of PCs that account for 90% of the total variance. This would greatly speed up the cross-validation for predictor selection thereby enabling a larger set of potential predictors to be included.

References

Barnett TP, Preisendorfer R. 1987. Origins and Levels of Monthly and Seasonal Forecast Skill for United-States Surface Air Temperatures Determined by Canonical Correlation-Analysis. *Monthly Weather Review*. **115.** 1825-1850

Preisendorfer RW, Zwiers FW, Barnett TP. 1981. *Foundations of Principal Component Selection Rules*. *SIO Reference Series 81-4*. Scripps Institution of Oceanography, 192 pp.

Press WH, Flannery BP, Teukolsky SA, Vetterling WT. 1986. *Numerical Recipes : The Art of Scientific Computing*. Cambridge University Press, 818 pp.

Method provides:	**Y/N**	**Comments/Notes**
Station-scale information	Y	
Grid-box information	Y	
European-wide information	Y	
Daily time series	N	
Seasonal indices of extremes	Y	
Temporally consistent temperature and precipitation[1]	Y	
Spatially consistent multi-site information[2]	Y	
Temporally consistent multi-site information[3]	Y	
Information at sites with no observations	N	
Method requirements :	**Relatively high/medium/low**	**Comments/Notes**
Computing resources	medium	
Volume of data inputs	low	
Availability of input data	high	

Application criteria for statistical and dynamical downscaling

STARDEX

STAtistical and Regional dynamical Downscaling of EXtremes for European regions

EVK2-CT-2001-00115

Deliverable D15

Improved Statistical Downscaling Methodologies: description of the STARDEX methods

USTUTT, Germany

USTUTT_MLR & USTUTT_MAR

1. Multiple linear regression model

This model is implemented for the downscaling of the standard seasonal extreme precipitation and temperature related indices from seasonal measures of a set of large scale circulation variables.

Each index is expressed as a linear function of a set of predictors selected from a range of potential predictors. The potential predictors for the precipitation and temperature indices were selected from correlation analysis of the indices and the large scale circulation variables as part of D10. Since the indices to be downscaled are measures of extremes of the meteorological variables, measures of extremes of the large scale variables were also used in the regression equation as predictors. In addition to the seasonal mean values of the predictor variables, their seasonal 90^{th} and 10^{th} percentiles were considered as potential predictor variables. Predictors corresponding to each index are then selected among the potential predictors using the forward selection method. The predictor values in the regression equation are taken as the average over the nearest four grid points to the target location.

The potential predictor variables include relative humidity, geopotential height, temperature, vorticity, and divergence at 500, 700, and 850 hPa levels as well as eastward moisture flux at 700hPa level and objective circulation patterns constructed by classifying sea level pressure. Since the circulation pattern is not a numerical variable, the seasonal frequency of circulation patterns associated with wet days is used in the regression equation.

The important improvement in this approach is that measures of extremes of the predictor variables are used instead of the mean of their distribution to predict indices related to extremes of precipitation and temperature.

The strengths of the method lie in that:

- it is simple in its structure and is fast.

- it provides better skill in downscaling indices since it is calibrated against the indices themselves.

Weaknesses of the model are:

- It doesn’t take the spatial structure of the indices into account making it weaker as a tool for multi site downscaling

- Doesn’t give any information about the time series of the precipitation and temperature making it of limited use for hydrological impact assessment.

Further development of the method by extending it to include the spatial structure of the variables would result in a better tool for multi-site downscaling.

Table 1: Application criteria for the mlr model

Method provides:	Y/N	Comments/Notes
Station-scale information	Y	
Grid-box information	Y	
European-wide information	-	Not verified
Daily time series	N	
Seasonal indices of extremes	Y	
Temporally consistent temperature and precipitation[1]	-	
Spatially consistent multi-site information[2]	N	Spatial structure is not taken into account
Temporally consistent multi-site information[3]	-	
Information at sites with no observations	N	
Method requirements :	**Relatively high/medium/low**	**Comments/Notes**
Computing resources	low	
Volume of data inputs	relatively high	Uses many predictors
Availability of input data	relatively high	

[1] i.e., the temperature/precipitation co-variance is similar for the downscaled validation series and observed series
[2] i.e., the downscaled validation series has a similar spatial pattern to the observed series
[3] i.e., the downscaled validation series has similar daily inter-site correlations to the observed series

2. Mutivariate autoregressive model

This is a classification based downscaling approach based on the modified version of the space-time model described in Bárdossy and Plate (1992). The model is used to generate daily series of both precipitation and temperature at multiple locations simultaneously by taking into account the spatial correlation of the observed series between observation locations. Atmospheric circulation patterns are used to condition the model parameters. Any kind of classification of the circulation patterns can be used. Objective circulation patterns defined by classifying the distribution of anomalies of sea level pressure or geopotential heights of other pressure levels using a fuzzy rule-based classification scheme (Bárdossy, et al, 1995; 2002) are implemented in this work. Different criteria were used to classify circulation patterns for precipitation and temperature downscaling (Bárdossy, et al, 2002) and therefore the circulation patterns used for downscaling of precipitation and temperature are different.

The important development in this model is that the spatial structure of the variable is taken in to account and maintained in downscaling them, rendering the method a suitable tool for multi-site downscaling. Besides the impact of moisture flux on the precipitation amount is taken account of in downscaling daily series of precipitation.

2.1 Precipitation model

Usually, the probability of occurrence of dry days is relatively high and the rainfall amounts on days with precipitation are described by means of continuous distribution. Therefore, random variables with mixed (discrete-continuous) distributions are required to describe daily precipitation. Dry and wet days generally occur in cluster, which is caused by persistence of atmospheric circulation patterns.

Let $\mathbf{A} = \{\alpha_1, ..., \alpha_m\}$ be a set of possible atmospheric circulation patterns. Let $\tilde{A}_t$ be the random variable describing the actual atmospheric circulation pattern, taking its values from **A.** Let the daily precipitation amount at time *t* and point *u* in the region *U* be modelled as the random function $Z(t,u)$. The distribution of rainfall amounts at a selected location is skewed. In order to relate this mixed distribution to a simple normally distributed random function $W(t,u)$, the following power transformed relationship is introduced:

$$Z(t,u) = \begin{cases} 0 & \text{if } W(t,u) \le 0 \\ W^{\beta}(t,u) & \text{if } W(t,u) > 0 \end{cases} \qquad 2.1$$

Where β is an appropriate positive coefficient, which is introduced to account for the skewed nature of the distribution of daily precipitation. This transformation is done since multivariate processes can be modelled much easier if the process is normal. The problem of intermittence of occurrence of precipitation is also handled by this transformation, as the negative values of *W* are declared as dry days and dry locations. As the process $Z(t,u)$depends on the atmospheric circulation pattern, so does$W(t,u)$.

From earlier analysis, it was found that there is a strong relationship between the precipitation amount and moisture flux. For stations located in the Rhine basin, the highest relationship was found for the eastward moisture flux at 700hPa level. Therefore, in addition to the circulation pattern type, the moisture flux is used as an additional variable to estimate the expected value of the daily precipitation amount. The expected value of $W(t,u)$ for a given circulation pattern α_i and moisture flux $MF(t,u)$ is therefore given by:

$$w_{\alpha_i}(t,u) = E\left[W(t,u) \mid \tilde{A}_t = \alpha_i ; MF(t,u)\right] = w'_{\alpha_i}(t,u) + \delta_{\alpha_i}(u) MF(t,u)$$
2.2

Where $\delta_{\alpha_i}(u)$ is a circulation pattern dependent coefficient. The first term of the above equation, $w'_{\alpha_i}(t,u)$, is assumed to have a circulation pattern dependent annual cycle, which is expressed using a Fourier series:

$$w'_{\alpha_i}(t^*,u) = \frac{a_0(w_{\alpha_i},u)}{2} + \sum_{k=1}^{K}\left(a_k(w_{\alpha_i},u)\cos(k\omega t^*) + b_k(w_{\alpha_i},u)\sin(k\omega t^*)\right) \qquad 2.3$$

Where t^* is the Julian date and the frequency ω is $2\pi/365$.

Using the following notation for the multivariate random variables:

$$\mathbf{W}(t) = (W(t,u_1),...,W(t,u_n)) \qquad 2.4a$$
$$\mathbf{Z}(t) = (Z(t,u_1),...,Z(t,u_n)) \qquad 2.4b$$
$$\mathbf{w}_{\alpha_i}(t) = (w_{\alpha_i}(t,u_1),...,w_{\alpha_i}(t,u_n)) \qquad 2.4c$$

The random process describing $\mathbf{W}(t)$ is described by using the following multivariate AR(1) model:

$$\mathbf{W}(t) = r(t^*)\left(\mathbf{W}(t-1) - \mathbf{w}_{\alpha_{i'}}(t-1)\right) + \mathbf{C}_{\alpha_i}(t^*)\mathbf{\Psi}(t) + \mathbf{w}_{\alpha_i}(t) \qquad 2.5$$

Where $\mathbf{\Psi}(t) = (\psi(t,u_1),...,\psi(t,u_n))$ is a random vector of independent $N(0,1)$ random variables. α_i and $\alpha_{i'}$ are the circulation pattern types on day *t* and the previous day respectively. $r(t^*)$ is the lag-1 day autocorrelation function. The lag-1 autocorrelation of daily precipitation doesn't vary strongly in space and therefore it is assumed in the model to be equal at all locations. It doesn't also depend on the circulation pattern, but has an annual cycle which is approximated by a Fourier series:

$$r(t^*) = \frac{A_0}{2} + \sum_{k=1}^{K}\left(A_k \cos(k\omega t^*) + B_k \sin(k\omega t^*)\right)$$
2.6

The advantage of Fourier series approximation (instead of simple polynomial fit) is that adding new A_k and B_k parameters does not change the values of the former ones. For very large K, the Fourier approximation is identical with the observed series. Usually the first three Fourier parameters are enough to simulate the annual cycle of the autocorrelation.

$\mathbf{C}_{\alpha_i}(t^*)$ is an $n \times n$ matrix that takes the spatial variability of the process into account, where n is the number of locations at which downscaling is done. It is related to $\mathbf{W}(t)$ through (Bras and Rodriguez-Iturbe, 1985):

$$\mathbf{\Gamma}_{0\alpha_i}(t^*) = E\left[\left(\mathbf{W}(t) - \mathbf{w}_{\alpha_i}(t)\right)\left(\mathbf{W}^T(t) - \mathbf{w}_{\alpha_i}^T(t)\right)\right] \quad 2.7$$

$$\mathbf{\Gamma}_{1\alpha_i}^T(t^*) = E\left[\left(\mathbf{W}(t-1) - \mathbf{w}_{\alpha_i}(t-1)\right)\left(\mathbf{W}^T(t) - \mathbf{w}_{\alpha_i}^T(t)\right)\right] \quad 2.8$$

$$\mathbf{C}_{\alpha_i}(t^*)\mathbf{C}_{\alpha_i}^T(t^*) = \mathbf{\Gamma}_{0\alpha_i}(t^*) - \mathbf{\Gamma}_{1\alpha_i}(t^*)\mathbf{\Gamma}_{0\alpha_i}^{-1}(t^*)\mathbf{\Gamma}_{1\alpha_i}^T(t^*) \quad 2.9$$

Where $\mathbf{\Gamma}_{0\alpha_i}(t^*)$ is the spatial covariance matrix and $\mathbf{\Gamma}_{1\alpha_i}(t^*)$ is the space-time covariance matrix for the time lag of one day. Assuming these two matrices are related to each other through:

$$r(t^*)\mathbf{\Gamma}_{0\alpha_i}(t^*) = \mathbf{\Gamma}_{1\alpha_i}(t^*) \quad 2.10$$

Leads to:

$$\mathbf{C}_{\alpha_i}(t^*)\mathbf{C}_{\alpha_i}^T(t^*) = \left(1 - r^2(t^*)\right)\mathbf{\Gamma}_{0\alpha_i}(t^*) \quad 2.11$$

Parameter estimation

The expected value of the transformed daily precipitation amount $W(t,u)$ is expressed as the sum of a term which has a CP dependent annual cycle and a term which accounts for the effect of the moisture flux (eq.2.2). Substituting eq. 2.3 into eq 2.2:

$$w_{\alpha_i}(t,u) = w'_{\alpha_i}(t^*,u) + \delta_{\alpha_i}(u)MF(t,u) = \delta_{\alpha_i}(u)MF(t,u) + \frac{a_0(w_{\alpha_i},u)}{2} + \sum_{k=1}^{K}\left(a_k(w_{\alpha_i},u)\cos(k\omega t^*) + b_k(w_{\alpha_i},u)\sin(k\omega t^*)\right) \quad 2.12$$

The standard deviation of the transformed precipitation amount is also assumed to have a CP dependent annual cycle, which is approximated by a Fourier series:

$$\sigma_{\alpha_i}(t^*,u) = \frac{c_0(w_{\alpha_i},u)}{2} + \sum_{k=1}^{K}\left(c_k(w_{\alpha_i},u)\cos(k\omega t^*) + d_k(w_{\alpha_i},u)\sin(k\omega t^*)\right) \quad 2.13$$

Where t^* is the Julian date corresponding to t. The parameters in the above two equations can then be estimated using the maximum likelihood method together with a numerical optimisation algorithm.

The spatial structure of the rainfall is described using a circulation pattern dependent covariance structure of the matrix $\boldsymbol{\Gamma}_{0\alpha_i}\left(t^*\right)$ as shown in eq. 2.11. The covariance structure is assumed to be translation invariant but depends on time of the year:

$$\mathrm{cov}\left[Z_x, Z_y\right]_{\alpha_i}\left(t^*\right) = p_{\alpha_i}\left(t^*\right)e^{-h(x,y)q_{\alpha_i}\left(t^*\right)}$$

Where *h(x,y)* is the distance between points *x* and *y*. The parameters $p_{\alpha_i}\left(t^*\right)$ and $q_{\alpha_i}\left(t^*\right)$ depend on the circulation pattern and day of the year and are modelled by means of Fourier series. The parameters of the spatial covariance matrix are estimated using the least squares approach.

Once the parameters related to the annual cycle of the distribution of the transformed daily precipitation and the spatial covariance are estimated, the precipitation series are generated on the daily basis for a set of points simultaneously using eq. 2.5 and the transformation given in eq. 2.1.

2.2 Temperature model

For temperature downscaling, the daily temperature is related to the average elevation of a pressure level (such as 700 or 500hPa). Average elevation of the 700hPa pressure level is used in this work. The circulation patterns are also classified based on the elevation field of the same pressure level. In addition to the circulation pattern and the average elevation of the pressure level, the daily temperature depends on the previous day’s temperature and the precipitation on the same day.

$$T(u,t) = F\left(u, H_p(t), \tilde{A}_t, T(u,t-1), Z(u,t)\right) \qquad 2.14$$

The link between precipitation and temperature is established using an indicator $I_z(t)$, which takes a value of 1 if the areal precipitation at location *u* is greater than a certain threshold value z_0 defined to distinguish between dry and wet days and 0 otherwise. The areal precipitation can be estimated either using kriging techniques from nearby precipitation stations or as a mean precipitation from stations located within a certain distance from *u*.

Using the following notations:

$$\mathbf{T}(t) = \left(T(u_1,t),...,T(u_m,t)\right) \qquad 2.15a$$
$$\mathbf{c}\left(I_z(t)\right) = \left(c_1\left(I_z(t)\right),...,c_m\left(I_z(t)\right)\right) \qquad 2.15b$$
$$\mathbf{d}\left(I_z(t)\right) = \left(d_1\left(I_z(t)\right),...,d_m\left(I_z(t)\right)\right) \qquad 2.15c$$

The relationship between the daily temperature and the average elevation of the pressure level can be expressed as:

$$E\left[\mathbf{T}(t)\right] = \mathbf{c}\left(I_z(t)\right)H_p(t) + \mathbf{d}\left(I_z(t)\right) + \mathbf{R}_{\alpha_i}(t) \qquad 2.16$$

Where $\mathbf{R}_{\alpha_i}(t)$ is a circulation pattern dependent residual, which has an annual cycle, whose components are expressed with Fourier series:

$$R_{\alpha_i}(u,t) = \sum_{k=0}^{K} \left(a_k \left(R_{\alpha_i}, u \right) \sin(k\omega t) + b_k \left(R_{\alpha_i}, u \right) \cos(k\omega t) \right) \quad 2.17$$

The daily temperature is then simulated using the multivariate AR(1) model:

$$\begin{aligned} \mathbf{T}(t) = {} & \mathbf{c}(I_z(t))H_p(t) + \mathbf{d}(I_z(t)) + \mathbf{R}_{\alpha_i}(t) + \\ & \mathbf{P}_{\alpha_i} \left\{ \mathbf{T}(t-1) - \left[\mathbf{c}(I_z(t-1))H_p(t-1) + \mathbf{d}(I_z(t-1)) + \mathbf{R}_{\alpha_i}(t-1) \right] \right\} + \mathbf{S}_{\alpha_i} \mathbf{\Psi}(t) \end{aligned} \quad 2.18$$

Where $\mathbf{\Psi}(t) = (\psi(t,u_1),...,\psi(t,u_m))$ is a random vector of independent *N(0,1)* random variables; $\mathbf{P}_{\alpha_i}$ is the circulation pattern dependent matrix of the autoregressive part of the process. $\mathbf{S}_{\alpha_i}$, like in the precipitation model, takes the spatial covariance structure into account.

In the autoregressive model above, one should notice that the expectation of the previous day is calculated using the circulation pattern of the current day.

Parameters of the model are estimated in a similar fashion as in the precipitation model. As no transformation of variables is required, the temperature model is simpler than the precipitation model.

The model was originally used to downscale mean daily temperature. As both daily minimum and maximum are of interest in this work, a simultaneous downscaling of the minimum and maximum daily temperature is done by the model. In order to keep the minimum always less than the maximum, a circulation pattern dependent annual cycle of the difference between the maximum and minimum temperatures is used to correct the simulated difference if the model gives inconsistent maximum and minimum.

2.3 Further comments on the model

Specifically, the strength of the model lies in that:

- The spatial covariance structure of the daily precipitation and temperature are maintained.
- It can be used to generate areal values of precipitation and temperature on grids using the spatial structure from observation locations, which can be used for hydrological impact study.

The weakness of the model is:

- Performance of the model in estimating extremes is not as good as that of the mean.

Further development of the model in such a way that more emphasis is given to the extreme part of the distribution of the daily precipitation would improve the estimation of the indices related to extremes. Work is underway on this issue.

Table 2: Application criteria for the mar model

Method provides:	**Y/N**	**Comments/Notes**
Station-scale information	Y	
Grid-box information	Y	
European-wide information	-	Not verified
Daily time series	Y	
Seasonal indices of extremes	Y	Calculated from the downscaled daily series
Temporally consistent temperature and precipitation[1]	Y	
Spatially consistent multi-site information[2]	Y	
Temporally consistent multi-site information[3]	Y	
Information at sites with no observations	Y	Computed from the spatial-temporal structure
Method requirements :	**Relatively high/medium/low**	**Comments/Notes**
Computing resources	Relatively high	
Volume of data inputs	low	
Availability of input data	relatively high	

[1] i.e., the temperature/precipitation co-variance is similar for the downscaled validation series and observed series
[2] i.e., the downscaled validation series has a similar spatial pattern to the observed series
[3] i.e., the downscaled validation series has similar daily inter-site correlations to the observed series

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