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ISSN 0344-9629

GKSS 2003/7

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ISSN 0344-9629

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Direct downscaling of Central European phenological time series using two empirical techniques

Christoph Matulla, Helfried Scheifinger, Annette Menzel, Elisabeth Koch

22 pages with 11 figures and 3 tables

Abstract

In recent years it became increasingly clear that phenological data are a powerful tool for the investigation of the connection between ecosystems and climate. Using biosphere phenomena, the response of ecosystems to human activities can be assessed.

In this study we explore two empirical downscaling techniques that linklarge scale atmospheric variables to local scale phenological occurrence data and, for comparative purposes, the local scale temperature.

The results of this study indicate time series of biospheric variables are very compatible with the needs of empirical downscaling that was originally developed of local scale atmospheric variables.

Anwendung zweier empirischer Downscaling-Methoden auf phänologische Zeitreihen in Zentral-Europa

Zusammenfassung

In den letzten Jahren ist die Bedeutung phänologischer Daten zur Untersuchung der Beziehung zwischen atmosphärischen Feldern und Ökosystemen zunehmend erkannt worden.

Diese Studie untersucht die Fähigkeit zweier empirischer Downscaling-Methoden, den Zusammenhang zwischen grossskaligen atmosphärischen Feldern und den Eintrittsdaten phänologischer Phasen sowie zum Vergleich der Temperatur, auf der regionalen Skala zu beschreiben.

Die Ergebnisse bestätigen diese Fähigkeit. Insbesondere die kanonische Korrelationsanalyse ist als gut geeignet einzustufen, um etwa Auswirkungen von Szenarien auf untersuchte Pflanzen direkt abschätzen zu können.

Manuscript received / Manuskripteingang in TDB: 12. März 2003

1 Introduction

The effect of a future climate with possibly higher temperatures and changed precipitation patterns on the biosphere constitutes one of the great concerns of the climate impact community. Apart from the question of the reliability of the General Circulation Models (GCMs) scenarios for the future climate, the scale problem is not yet satisfactorily solved. Although the spatial resolution of the GCMs is continuously being enhanced, downscaling of atmospheric information from GCM scale to regional scale and individual points is still necessary to provide input for ecological models, like forest gap models or biogeochemical models. For this purpose a number of downscaling methods have been developed in recent years, which link the large scale atmospheric circulation with the local-scale atmosphere (von Storch et al. 2000).

There are two principal strategies applied to connect large-scale atmospheric variables with local scale impact phenomena. Via dynamical or statistical downscaling large scale atmospheric information is transferred to local scale atmospheric variables, which describe the biophysical environment and represents the input for models simulating biological processes, for instance, as for forest gap models (e.g. Lexer et al. 2002; Price et al. 2001; Bolliger et al. 2000) or for phenological models (Menzel 1997; Osborne et al. 2000).

If a local scale biosphere phenomenon and large scale atmospheric variables can be linked directly via an empirical relationship, statistical downscaling techniques might be applied without the detour via models between the local scale biosphere phenomenon and the local scale atmosphere. There are a number of biospheric variables, which, for instance, reveal a strong link with the North Atlantic Oscillation phenomenon (c.f. Post and Stenseth 1999; Chmielewski and Rötzer 2001; Straile 2002; Ottersen et al. 2001; Scheifinger et al. 2002) Such biospheric variables should particularly be suited for statistical downscaling procedures (e.g. Heyen et al. 1998; Kröncke et al. 1998; Maak and von Storch 1997).

For that purpose a set of macro-scale variables is selected, which represent the variability of the large-scale field distribution. These are linked with the micro-scale variables by means of an empirical relationship, which is derived between observations on both scales. Empirical Orthogonal Functions (EOFs) of 2D fields of atmospheric variables over a certain area are frequently used to represent the main fraction of the field variance. Hence, their time coefficients (Principal Components, PCs) often serve as predictors in empirical relationships (e.g. Hewitson and Crane 1992; Matulla et al. 2002). However, there are a number of statistical methods at hand to relate both sets of variables, for example, Canonical Correlation Analysis (CCA) or multiple linear regression (MLR). Assuming the validity of the empirical relation derived from instrumental time series also for the future climate, time series of micro-scale variables are calculated from the difference of the GCM scenario run for the future climate and the GCM control run for the present climate. The downscaled anomalies are then added to the presently observed mean values in order to provide an assessment of possible future climate conditions. Although the methods developed here can be applied to scenarios of future climate, this investigation is restricted to the derivation and evaluation of empirical transfer functions.

In this study Empirical Orthogonal Functions (EOFs) of 2D fields of atmospheric variables serve as macro-scale variables, which are related to local scale phenological observations and, for comparison purposes, also to temperature by MLR and CCA. 17 phenological phases throughout the season serve as local-scale variables, thus covering the complete vegetation cycle. The few similar studies have so far been restricted to certain phases (e.g. Maak and von Storch 1997; Chmielewski and Rötzer 2001).

2 Data

On the large scale monthly fields of atmospheric variables (Table 1) over an area from 50^oW to 30^oE and 35^o to 65^oN are used. The dataset spans the period from 1951 to 1998 and is provided by the National Center for Atmospheric Research (NCAR) reanalysis project (Kalnay et al. 1996).

Table 1: List of large scale atmospheric variables.

Nr.	variable	pressure level
1	Relative humidity	850, 700, 500 hPa
2	Specific humidity	850, 700, 500 hPa
3	u and v components of the wind	850, 700, 500, 200 hPa
4	Temperature	850, 700, 500, 200 hPa
5	Geopotential height	850, 700, 500, 200 hPa
6	Vorticity	850, 700, 500, 200 hPa
7	Divergence	850, 700, 500, 200 hPa
8	Sea level pressure	
9	relative topography 700-850hPa	

Monthly North Atlantic Oscillation (NAO) time series are from the data set publicly available from the Climate Research Unit in the UK (Jones et al. 1997).

On the local scale observations of 17 phenological phases (see Table 2) are available from Germany, Austria, Switzerland and Slovenia (Figure 1) for the time period 1951–1998, collected for the EU funded project POSITIVE (www.forst.tu-muenchen.de/EXT-/LST/METEO/positive). The data have been checked for consistency and outliers with methods as described in Scheifinger et al. 2002. In order to facilitate further analysis, the observations have been interpolated to a $1^o \times 1^o$ grid, covering much of Germany, Switzerland and Austria (Figure 1).

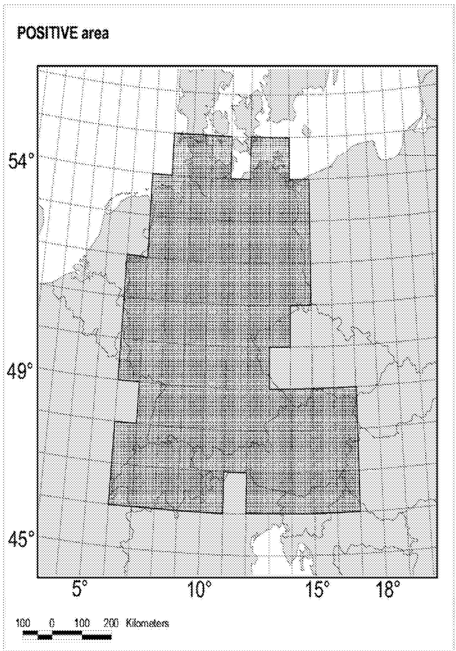

Figure 1: $1^o \times 1^o$ grid of the phenological observation area. Phenological time series have been interpolated to this grid.

The downscaling procedure is also applied to time series of monthly temperature deviations for comparison purposes. They originate from the ALPCLIM project (Environmental and Climate Records from High Elevation Alpine Glaciers funded by the European Commission, http://crusoe.iup.uni-heidelberg.de/glacis/ALPCLIM), where long instrumental temperature time series from Alpine countries have been collected (Böhm et al. 2001). In this work monthly anomaly series are used, referenced to the monthly means of the time period 1901–1998, interpolated to a $1^o \times 1^o$ grid and overlapping with the POSITIVE grid (Figure 1).

Table 2: List of phenological phases and their mean month of occurrence in Central Europe.

Nr.	Phase	month
1	*Corylus avellana* beginning of flowering	March
2	*Galanthus nivalis* beginning of flowering	March
3	*Tussilago farfara* beginning of flowering	March
4	*Anemone nemorosa* beginning of flowering	April
5	*Larix decidua* leaf unfolding	April
6	*Betula pendula* leaf unfolding	April
7	*Aesculus hippocastanum* leaf unfolding	April
8	*Taraxacum officinale* beginning of flowering	April
9	*Fagus sylvatica* leaf unfolding	April
10	*Picea abies* May sprouting	May
11	*Aesculus hippocastanum* beginning of flowering	May
12	*Syringa vulgaris* beginning of flowering	May
13	*Sambucus nigra* beginning of flowering	June
14	*Sambucus nigra* ripe fruit	September
15	*Aesculus hippocastanum* autumn colouring	October
16	*Betula pendula* autumn colouring	October
17	*Fagus sylvatica* autumn colouring	October

3 Methods

3.1 Multiple linear regression

Multiple regression is a widely applied transfer function to link macro with micro scale variables at individual points (e.g. Hewitson and Crane 1992). The empirical relationship between the PCs (X_i) of the macro scale variables and time series of the micro scale variables (Y_i) is described by following multiple regression model:

$$Y_{j,t} = b_{j,0} + \sum_{k=1}^{N} b_{j,k} X_{k,t}$$

whereby the $b_{i,k}$ represent the regression coefficients, j is the index for the grid point, t for the time step and k refers to the independent variable.

After subtracting the mean seasonal variation from the time series of the atmospheric fields, the EOFs are calculated for each of the 12 months. In order to enlarge the sample size and hence obtain less ambivalent results (von Storch and Hannoschöck 1985), the data of the previous and following months have been added to support the analysis, resulting in a moving data window spanning 3 months. The methods for deriving the EOFs and the time expansion coefficients (PCs) are described in detail in von Storch and Zwiers (1999).

In order to apply the regression model to phenological data, phenological occurrence dates, which are given in yeardays, have to be related to a certain month. This is achieved by taking the 48 year (1951–1998) mean occurrence date of the phenological phase at each individual grid point. Phases occur mainly in March, April, May, June, August, September and October. As independent variables the time expansion coefficients of the first 5 EOFs of temperature in 850 hPa and geopotential height in 850 hPa are selected as predictors for the MLR model. Plant phenological events are related to temperature sums accumulated over a longer time period preceding the phenological event (Menzel 1997). Hence, it was decided that two months – the month of occurrence and the previous month – should enter the analysis, resulting in 20 independent variables for the regression model. The stepwise multiple regression (IMSL routine RBEST) procedure assists in determining the best regression model for each group of independent variables. For comparison purposes, monthly temperature time series have been regressed with the same set of independent variables.

The first and second EOF of the sea level pressure field (SLP) are highly correlated with the NAO index (e.g. Fyfe et al. 1999). Consequently a set of EOFs from one or two atmospheric variables, like those mentioned above, should describe a higher fraction of the atmospheric variability over the North Atlantic and Europe than the NAO index alone. Therefore one would expect, for instance, the MLR model based on such EOFs and their associated PCs to explain a higher fraction of the variance of the local scale variables. Figure 2 compares the MLR skill using the NAO index (Jones et al. 1997) and the above mentioned PCs. Both models have been calibrated over the period 1951–1998. The use of PCs mainly improves the modeling of early spring and autumn phases and to a lesser degree that of late spring and summer phases.

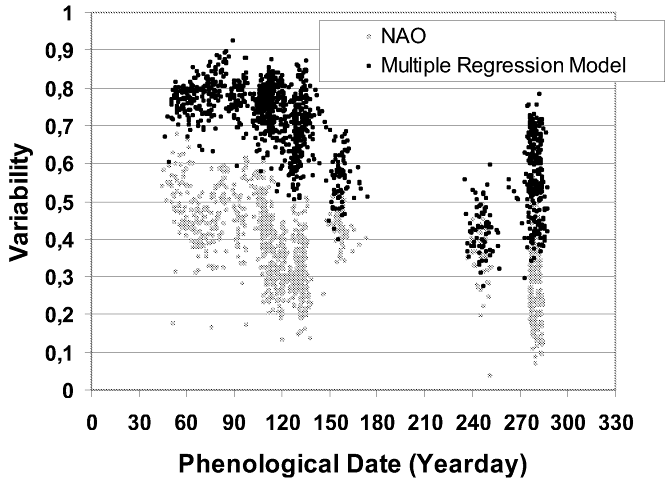

Figure 2: Grey dots indicate the common variability between the NAO time series of Jones et al. 1997 and phenological time series at the $1^o \times 1^o$ grid as function of mean entry date of the phenological phase. Black dots indicate the variance explained by the multiple regression model with 20 independent variables (calibration period = validation period).

The spatial differentiation of the explained variance appears rather low, because the differences are small between the Southern and Northern or the Eastern and Western half of the observation area (not shown).

Only a few EOFs seem to dominate the regression relation. The most important appear to be the first EOF of the 850 hPa temperature distribution of the month previous the phenological occurrence date and the same EOF of the actual month of occurrence. The skill of the different EOFs entering via their associated PCs the MLR depend on the actual phase. Hence, there is a seasonal cycle, whereby the influence of the two temperature EOFs is reduced with increasing yearday. Towards late spring and summer an unclear composition of EOFs replaces the dominance of the two temperature EOFs. Because of its importance the first EOF of the 850 hPa temperature fields is depicted in Figure 3.

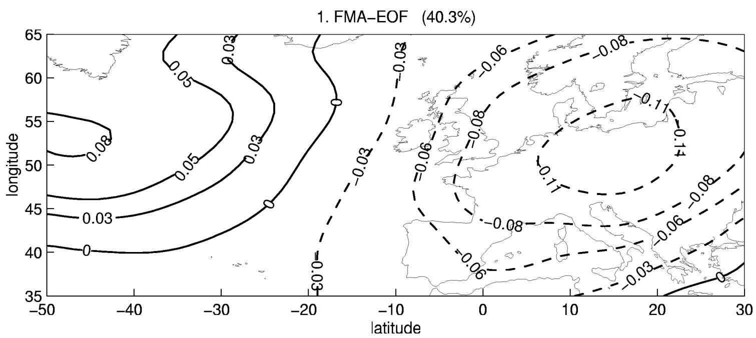

Figure 3: The first EOF of the February, March and April 850 hPa temperature field explaining 40.3 % of its variance.

Figure 3 describes the temperature difference between the northeastern Atlantic and Europe. This temperature EOF is strongly linked with the first two EOFs of the 850 hPa geopotential height fields (Matulla et al. 2002), which themselves are highly correlated with the NAO index (e.g. Fyfe et al. 1999).

3.2 Canonical correlation analysis

In a first step, both, the macro and micro scale variables, are subjected to an EOF analysis, resulting in the amount of data to continue the work being greatly reduced and the signal in the time series almost retained. Phenological occurrence dates serve as local scale variables and combinations of two large-scale fields as large scale variables. In a second step the correlation structure between the remaining random fields, derived from the phenological phases and the considered large scale field combinations, is analysed with Canonical Correlation Analysis. CCA is constructed to find those patterns whose time coefficients show maximal correlation. CCA has found wide application as an analysis and downscaling technique in the field of meteorology, including precipitation downscaling (von Storch et al. 1993; Gyalistras et al. 1994; Busuioc and von Storch 1996) and downscaling of phenological phases (e.g. Table 2).

Maak and von Storch (1997) explained 72 % of the flowering date variance of *Galanthus nivalis* in Northern Germany with the first pair of canonical correlation patterns. As large scale field they used 2 m temperature. Table 8 shows results from this study concerning the flowering date of *Galanthus nivalis* and compares it to findings of Maak and von Storch (1997). Chmielewski and Rötzer (2001) found that the spatial patterns of the first 3 CCA pairs between the 2 m temperature and the beginning of growing season as marked by the beginning of leafing of 4 species (*Betula pubescens, Prunus avium, Sorbus aucuparia* and *Ribes alpinum*, data from International Phenological Gardens) are closely linked over Europe. Taken together, the first 3 canonical correlation patterns explain 73 % of the yearly variability of the beginning of the growing season. In this work CCA describes the simultaneous variations of local appearances of phenological phases in central Europe and two large scale atmospheric variables over the North Atlantic and Europe. In order to obtain the best CCA model, all possible combinations of independent variables, listed in Table 1, have been tested. The results indicate that quite a number of combinations of independent variables performs equally well. The interdependence of the atmospheric variables might explain that observation. For the large scale variables the number of EOFs is chosen such that a minimum of 80 % of the variance is explained. The maximum number of EOFs allowed has been set to 16.

For most phenological phases the first 1 or 2 leading EOFs explained more than 85 % of the variability. Only autumn phases required up to 10 or more. Figure 4 illustrates the spatial pattern of the first CCA pair of relative humidity and temperature anomaly fields during February, March and April in 850 hPa on the one hand and the phenological

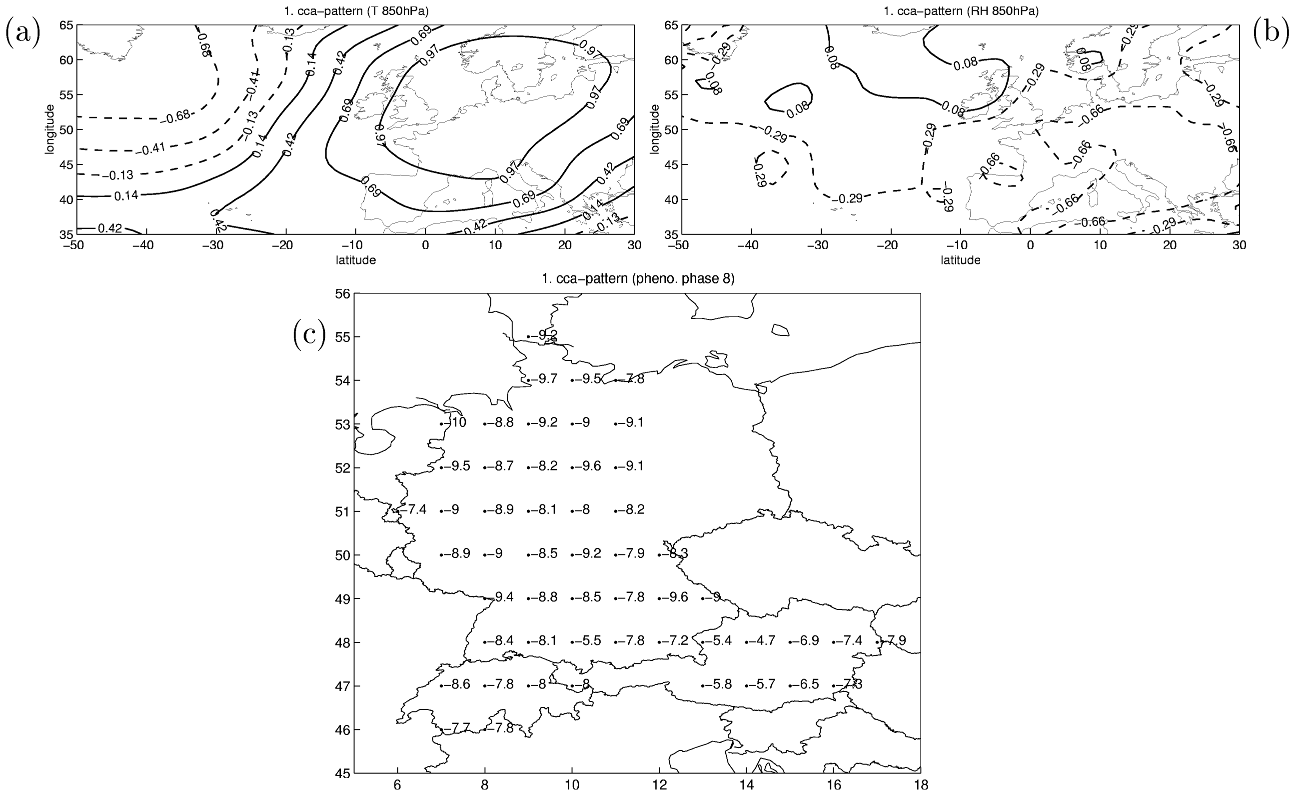

Figure 4: First canonical patterns for the predictors (a, b) and for dependent variable (c). (a) and (b) correspond to temperature and relative humidity subpattern, respectively. (c) shows the pattern of the phenological phase *Taraxacum officinale* beginning of flowering. The first ten predictor EOFs and the first two EOF of the phenological phase were used, explaining 82 % and 88 % of the respective total variances. The correlation between the time coefficients is 0.92.

phase phase *Taraxacum officinale* beginning of flowering on the other. One finds a temperature dipole over the selected area with positive anomalies centered over northern Germany and southern Scandinavia and negative anomalies over the north Atlantic. This pattern is comparable with the 2 m temperature anomaly pattern of Figure 4 in Maak and von Storch (1997). Positive temperature anomalies seem to coincide with negative anomalies of relative humidity. Higher temperatures cause an earlier flowering of *Taraxacum officinale* by 5 to 10 days, with the greatest advancement in the area of the greatest temperature anomalies in the north and the least advancement at the southern boundary of the area.

4 Comparison of MLR and CCA

Using 3 different validation approaches, the performance of the statistical models are compared. In the first experiment the model calibration and validation period span the total period for which data are available (1951–1998). The second validation experiment is a split sample test with a calibration period from 1951–1980 and an independent validation period from 1981–1998. In the third validation case, temporal cross validation is applied, where the model is calibrated over 48 different 47–year periods, successively skipping one independent year, for which the model is applied. This results in a modeled time series over the total time period of 48 years, which is compared with the observed series. As evaluation parameter the variance explained by the models is calculated.

The correlations, on which the explained variances are based on, must be significant at the 95 % level, otherwise the explained variance value is rejected for further statistical treatment. Therefore one has to consider not only the achieved mean explained variance but also the numbers above the bars, showing the percentage of grid points with significant correlations.

4.1 Phenological phases

Figure 5 and 6 show the results of the above described validation approach. The most striking features are: (i) The decreasing level of the MLR performance from the first experiment to the the temporal cross validation and then to the split sample test. This is not to be observed in case of the CCA Model, where the explained variances remain within a restricted range. The drop in explained variance for the phenophases is especially pronounced where for the calibration period values of 70 to 80 % are achieved, when at the same time in the other two validation experiments the values remain below 50 % (Figure 5). (ii) The deficiencies of MLR and CCA in the ability to describe the autumn phases. For these phenophases both measures of skill, the explained variance as well as the percentage of gridpoints with a significant correlation, clearly take values below the others. (iii) MLR is much more sensitive to differences in time span available for calibration. Reducing the calibration period by more 17 years (temporal cross validation has 47 years for calibration and split sample case 30 years) reduces the MLR performance much more than that of the CCA (Figure 5 and 6). (iv) In the case of phenological phases as local scale variables and temporal cross validation (see Figure 7), CCA performs generally better than MLR. Specifically, the phases during April improve

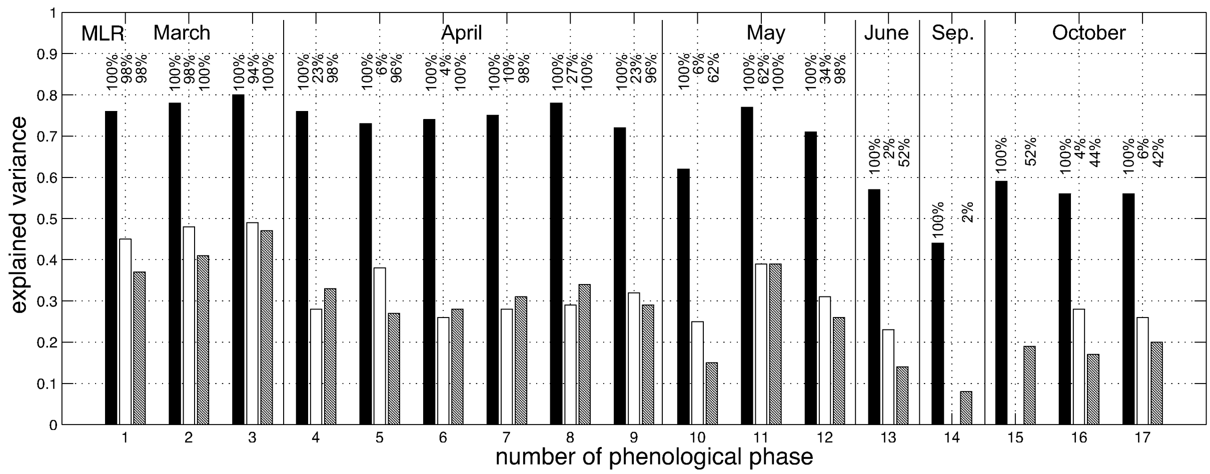

Figure 5: Results of the 3 validation procedures for the multiple regression model. Calibration period identical with validation period 1951–1998 (black), split sample test: calibration: 1951–1980, validation: 1981–1998 (white) and temporal cross validation (grey). Mean squared correlation between measured and modeled time series are separately plotted for each of the 17 phenological phases (see Table 1). Only significant correlations ($p<0.05$) enter the analysis. Percentage of grid points with significant correlations are displayed above the bars.

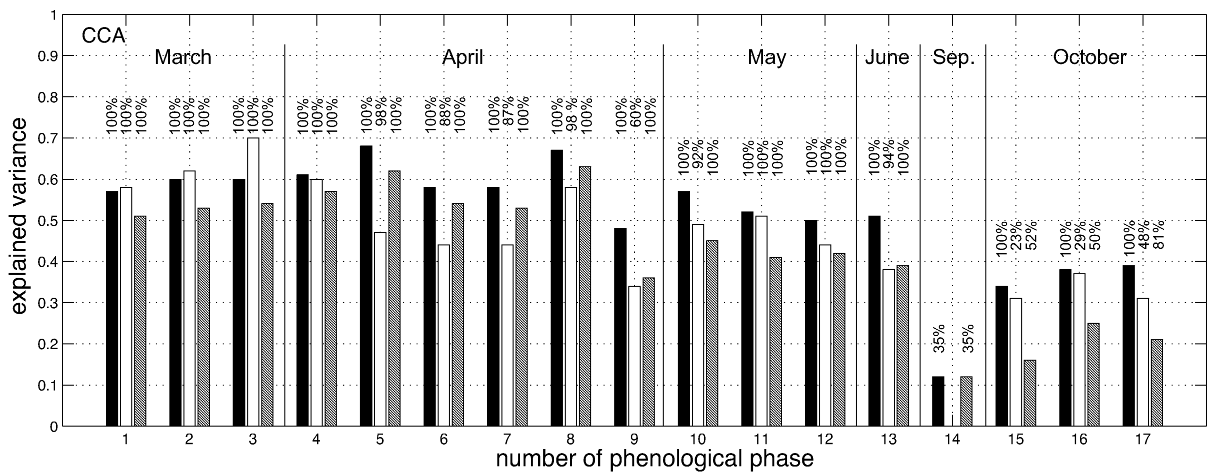

Figure 6: Same as Figure 5 but for canonical correlation analysis.

by an amount varying between 15 to over 30 %. For all phases from the very early spring (March) to early summer (June), CCA results are, in contrast to MLR, significant at all gridpionts. (v) There is a seasonal cycle in explained variance to be observed, whereby the earlier phases achieve a higher amount of explained variance than the later ones. During March and April explained variances of more than 50 % are the rule in case of CCA. The fraction of explained variance is relatively high during March and April, decreases in May and June and decreases even further during early and full autumn. In case of MLR the seasonal pattern in performance is not so pronounced (Figure 7). However, compared to the other phases, the performance during early and full autumn is clearly reduced.

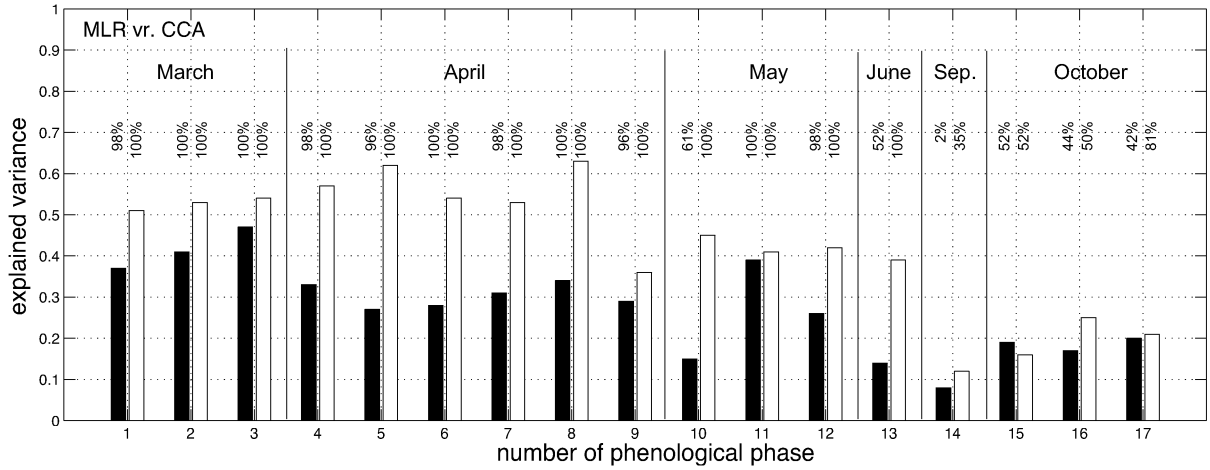

Figure 7: Comparing the results of the temporal cross validation procedure between MLR (black) and CCA (white) for the phenological phases, 1951–1998. Results are plotted for each of the 17 phenological phases (see Table 1) separately. bars: mean squared correlation between measured and modeled time series ($p<0.05$). Percentages of grid points with significant correlations are written above the corresponding bar.

Table 3: Results of MLR and CCA in comparison for *Galanthus nivalis* beginning of flowering. c. ... calibration period, v. ... validation period

Snow drop *Galanthus nivalis* beginning of flowering	explained variance at local grid points or stations (mean value)	Percentage of grid points with p<0.05
Maak and von Storch (1997) 1971–1990 CCA, c.:1971–1990, v.: 1951–1970	0.55	
this work 1951–1998		
MLR c.:1951–1998 v.:1951–1998	0.78	100
MLR c.:1951–1980 v.:1981–1998	0.48	98
MLR temporal cross validation:1951–1998	0.41	100
CCA c.:1951–1998 v.:1951–1998	0.60	100
CCA c.:1951–1980 v.:1981–1998	0.62	100
CCA temporal cross validation:1951–1998	0.53	100

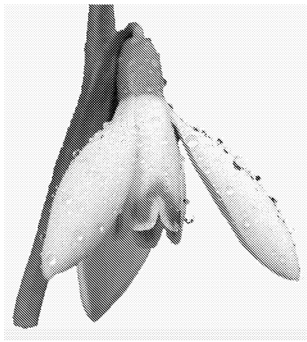

Figure 8: Flower of *Galanthus nivalis*

4.2 Temperature

Both techniques, MLR and CCA, show improved skills in modeling local scale temperature (Figure 9 and 10) as compared with phenological phases as local scale variables. As was the case with phenological phases the MLR model shows a much larger drop in explained variance from the calibration case to the other validation cases. However, the decrease of skill for temperature appears less then that for the phenological phases. The performance variables of the CCA do not display any systematic difference between the 3 validation procedures. Moreover, the pattern of seasonality in explained variance is clearly different for temperature, if compared with that of the phenological phases.

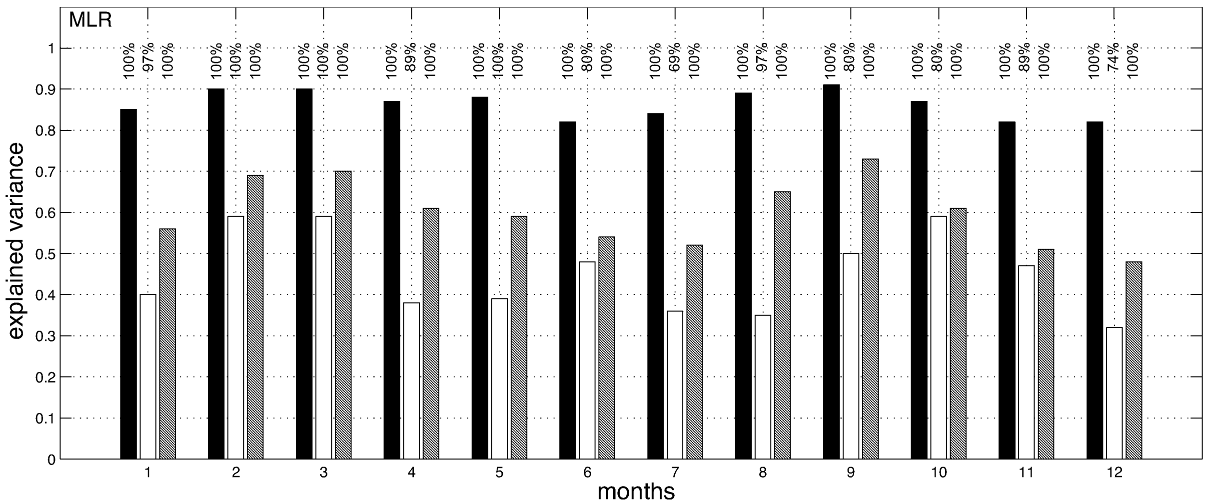

Figure 9: Results of the 3 validation procedures for the multiple regression model, calibration period identical with validation period 1951–1998 (black), calibration period 1951–1980 and validation period 1981–1998 (white) and temporal cross validation (grey). Results are plotted for each month of the year separately. bars represent: mean squared correlation between measured and modeled time series ($p<0.05$). The percentage of grid points with significant correlations is written above the corresponding bar.

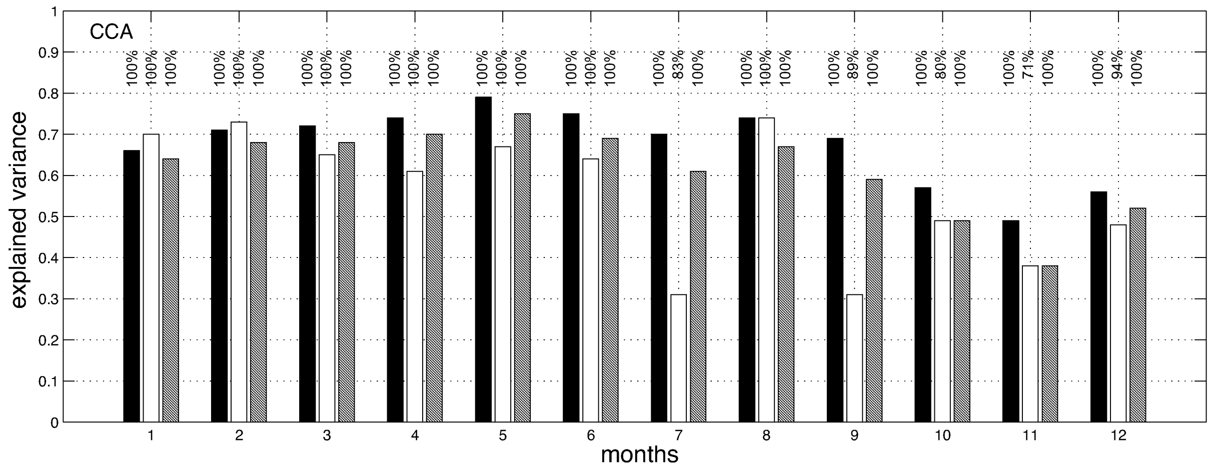

Figure 10: Same as Figure 9 but for canonical correlation analysis.

Figure 11 reveals a slightly higher skill of the CCA model (see also Figure 7). The reason for both observations might be associated with the restricted geographical extent of the tmperature data set, which has only the POSITIVE area covered south of 49^{o}N and therefore does not provide enough spatial variability for the CCA.

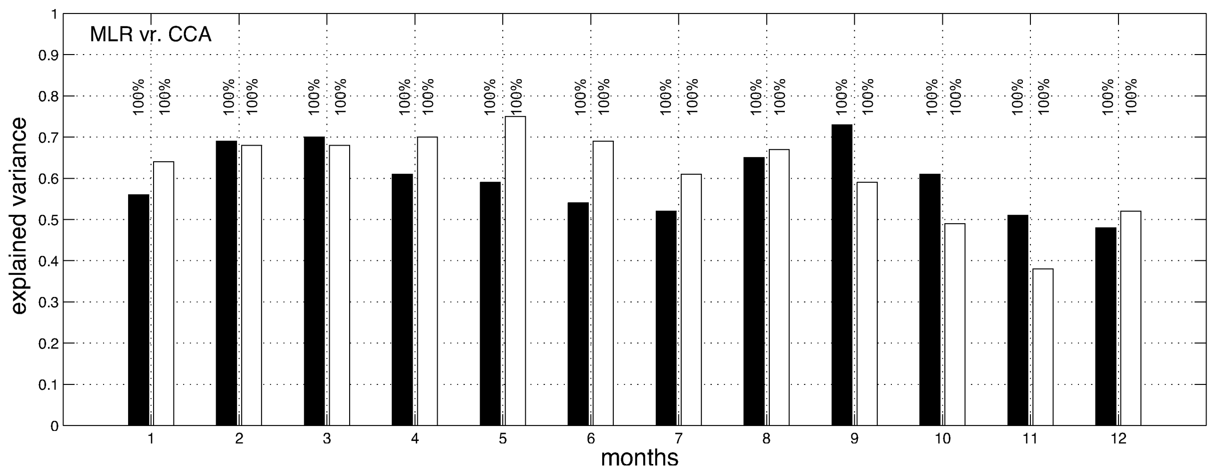

Figure 11: Comparing the results of the temporal cross validation procedure between MLR (black) and CCA (white) for temperature, 1951–1998. Results are plotted from January to December separately. Mean squared correlation between measured and modeled time series. Correlations are significant (p<0.05) at all grid points.

5 Conclusions

Phenological observations as non - atmospheric independent variables are no less suited for the purpose of downscaling than any local scale atmospheric variable, because in middle and higher latitudes the seasonal cycle of plants, especially in spring to summer, is mainly governed by the local scale temperature.

As a result of this work one might generalise that transfer functions based on a number of EOFs of one or two large scale atmospheric variables show a superior performance to regressions based on the NAO time series alone. Temporal cross validation reveals that the CCA model performs generally better than the MLR model. MLR can explain 20 to 50 % of the temporal variance of the phenological phases, whereas the CCA model shows a range from 40 to over 60 %. Especially for phenological phases during April, the CCA model achieved an improvement of 15 to 30 %. Phases occurring after April are more difficult to model for either of the two models. The inclusion of spatial information of the micro scale variable seems to make CCA superior to MLR.

For temperature there is no obvious superiority of the CCA model over the MLR model, which might be related to the restricted spatial range of the temperature data. Both models show better performances for temperature than for phenological phases ranging from 40 to over 70 % explained variability in case of temporal cross validation. It appears that the CCA model can extract more information from the independent variables over the available time period than the MLR model. It might be the case that the MLR models require longer time periods for calibration than the CCA model. Consequently, if data are available only over restricted time periods, CCA should be the model of choice. What is the added value of this study? The results of this study indicate time series of biospheric variables (e.g. phenological occurrence dates) are very well suited for empirical downscaling, which was originally developed for local scale atmospheric variables. Moreover the findings suggest the use of CCA in preference to MLR or the NAO index alone in order to transfer information between the scales. However, autumn phases are more difficult to model than spring phases. This confirms the current state of knowledge (e.g. Menzel 2002).

Acknowledgments This study was funded by the 5th Framework Programme of the European Commission under the key action Global Change, Climate and Biodiversity (POSITIVE, EVK2-CT-1999-00012). MeteoSwiss, the German Weather Service and the Hydrometeorological Service of Slovenia are thanked for providing phenological observations. We want to thank D. Bray, B. Hünicke and B. Gardeike for helping us with this manuscript.

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