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Exploring two methods for statistical downscaling of Central European phenological time series

Received: 10 March 2003 / Revised: 19 June 2003 / Accepted: 3 July 2003 / Published online: 2 September 2003
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Abstract In this study we set out to investigate the possibility of linking phenological phases throughout the vegetation cycle, as a local-scale biological phenomenon, *directly* with large-scale atmospheric variables via two different empirical downscaling techniques. In recent years a number of methods have been developed to transfer atmospheric information at coarse General Circulation Model's grid resolutions to local scales and individual points. Here multiple linear regression (MLR) and canonical correlation analysis (CCA) have been selected as downscaling methods. Different validation experiments (e.g. temporal cross-validation, split-sample tests) are used to test the performance of both approaches and compare them for time series of 17 phenological phases and air temperatures from Central Europe as microscale variables. A number of atmospheric variables over the North Atlantic and Europe are utilized as macroscale predictors. The period considered is 1951–1998. Temporal cross-validation reveals that the CCA model generally performs better than MLR, which explains 20%–50% of the phenological variances, whereas the CCA model shows a range from 40% to over 60% throughout most of the vegetation cycle. To show the validity of employing phenological observations for downscaling purposes both methods (MLR and CCA) are also applied to gridded local air temperature time series over Central Europe. In this case there is no

obvious superiority of the CCA model over the MLR model. Both models show explained variances from 40% to over 70% in the temporal cross-validation experiment. The results of this study indicate that time series of phenological occurrence dates are very compatible with the needs of empirical downscaling originally developed of local-scale atmospheric variables.

Keywords Empirical downscaling · Phenological phases · Vegetation cycle · CCA · MLR

Introduction

The main aim of this study is to investigate the possibility of linking phenological phases throughout the vegetation cycle, as a local-scale biological phenomenon, *directly* with large-scale atmospheric variables via two different downscaling approaches: multiple linear regression (MLR) and canonical correlation analysis (CCA).

The effect on the biosphere of a future climate with possibly higher air temperatures and changed precipitation patterns constitutes one of the great concerns of community studying the climate impact. Although the spatial resolution of the GCM is continuously being enhanced, downscaling of atmospheric information from the GCM scale to the regional scale and individual points is still necessary to provide input for ecological models, such as forest-gap models or biogeochemical models. Basically there are two strategies to connect large-scale atmospheric variables with local-scale atmospheric variables: dynamical and empirical downscaling; large-scale atmospheric information is transferred to local-scale atmospheric variables that describe the biophysical environment and represent the input for models simulating biological processes (for example, forest-gap models, e.g. Lexer et al. 2002; Price et al. 2001; Bolliger et al. 2000; or phenological models, e.g. Menzel 1997; Osborne et al. 2000).

In recent years a number of empirical downscaling methods have been developed that link the large-scale

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atmospheric circulation with the local-scale atmosphere (von Storch et al. 2000). If a local-scale biosphere phenomenon and large-scale atmospheric variables can be linked *directly* through an empirical relationship, statistical downscaling techniques might be applied without the effort of modelling between the local-scale biosphere phenomenon and the local-scale atmosphere.

There are a number of biospheric variables that, for instance, reveal a strong link with the large-scale 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 be particularly suited to statistical downscaling procedures (e.g. Heyen et al. 1998; Kröncke et al. 1998; Maak and von Storch 1997).

To evaluate the usefulness of local-scale phenological time series in empirical downscaling a set of macroscale variables has been selected, which represent the variability of the large-scale field distribution. These are linked with the local-scale phenological series by means of an empirical relationship, which is derived from observations on both scales.

Maak and von Storch (1997), using the flowering of *Galanthus nivalis* and CCA, demonstrated the potential of such an approach. In this study we selected 17 phenological phases throughout the seasons covering most of the vegetation cycle over a greater part of Central Europe as local-scale variables, so that the usefulness of phenological phases in empirical downscaling could be assessed from very early spring to autumn phases. This differs from the few similar studies, which have so far been restricted to certain selected phases (e.g. Maak and von Storch 1997; Chmielewski and Rötzer 2001).

The following two sections are devoted to the data and the methods respectively. Subsequently the phenological phases considered, which are distributed over the vegetation cycle, are linked via MLR and CCA to large-scale atmospheric processes. In Results the two methods are evaluated in different validation experiments and compared. Split-sample tests and temporal cross-validation serve as validation procedures. The methods are also applied to local-scale air temperature. Consequently the performance of the *direct* downscaling procedures can be compared with those of a *classical* application of empirical downscaling. Thus the usefulness of the phenological phases as local-scale variables can be assessed. In the case of the flowering of *G. nivalis* we compare our results with those of Maak and von Storch (1997).

Materials and methods

Data

On the large scale, monthly fields of atmospheric variables (Table 1) over an area from 50°W to 30°E and 35°N to 65°N are used. The dataset spans the period from 1951 to 1998 and was provided by the National Centre for Atmospheric Research (NCAR) reanalysis project (Kalnay et al. 1996).

Table 1 List of large-scale atmospheric variables

No.	Variable	Pressure level (hPa)
1	Relative humidity	850, 700, 500
2	Specific humidity	850, 700, 500
3	<i>u</i> and <i>v</i> components of the wind	850, 700, 500, 200
4	Air temperature	850, 700, 500, 200
5	Geopotential height	850, 700, 500, 200
6	Vorticity	850, 700, 500, 200
7	Divergence	850, 700, 500, 200
8	Sea-level pressure	
9	Relative topography 700–850 hPa	

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

No.	Phase	Month
1	<i>Corylus avellana</i> beginning of flowering	March
2	<i>Galanthus nivalis</i> beginning of flowering	March
3	<i>Tussilago farfara</i> beginning of flowering	March
4	<i>Anemone nemorosa</i> beginning of flowering	April
5	<i>Larix decidua</i> leaf unfolding	April
6	<i>Betula pendula</i> leaf unfolding	April
7	<i>Aesculus hippocastanum</i> leaf unfolding	April
8	<i>Taraxacum officinale</i> beginning of flowering	April
9	<i>Fagus sylvatica</i> leaf unfolding	April
10	<i>Picea abies</i> May sprouting	May
11	<i>Aesculus hippocastanum</i> beginning of flowering	May
12	<i>Syringa vulgaris</i> beginning of flowering	May
13	<i>Sambucus nigra</i> beginning of flowering	June
14	<i>Sambucus nigra</i> ripe fruit	September
15	<i>Aesculus hippocastanum</i> autumn colouring	October
16	<i>Betula pendula</i> autumn colouring	October
17	<i>Fagus sylvatica</i> autumn colouring	October

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 (Fig. 1) for the period 1951–1998, collected for the EU-funded project POSITIVE (<http://www.forst.tumuenchen.de/EXT/LST/METEO/positive>). The data have been checked for consistency and outliers with methods described in Scheifinger et al. (2002). In order to facilitate further analysis, the observations have been interpolated to a 1° × 1° grid, covering much of Germany, Switzerland, Austria and Slovenia (Fig. 1).

The downscaling procedures are also applied to time series of monthly air temperature deviations for comparative purposes. The time series are from the ALPCLIM project (Environmental and Climate Records from High Elevation Alpine Glaciers, funded by the European Commission, <http://crusoe.iup.uniheidelberg.de/glacis/ALPCLIM>), where long instrumental air temperature time series from Alpine countries have been collected (Böhm et al. 2001). In this work, monthly anomaly series are used and referred to the monthly means of the period 1901–1998, interpolated to a 1° × 1° grid, overlapping with the POSITIVE grid (Fig. 1).

Methods

Empirical orthogonal functions (EOF) of two-dimensional fields of atmospheric variables over a certain area are frequently used to represent the main fraction of the field variance (von Storch and Zwiers 1999). Hence, their time coefficients (principal components, PC) often serve as predictors in empirical relationships (e.g.

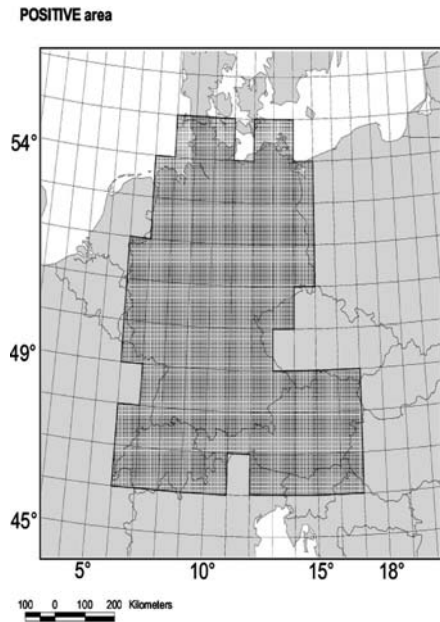


Fig. 1 $1^\circ \times 1^\circ$ grid of the phenological observation area. Phenological time series have been interpolated to this grid

Hewitson and Crane 1992; Matulla et al. 2002). In the multiple linear regression (MLR) approach, PC are actually utilized as predictors. Canonical correlation analysis (CCA) is performed after separately transforming the observations on both scales to EOF coordinates (von Storch and Zwiers 1999).

Multiple linear regression

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

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

whereby $b_{i,k}$ represent the regression coefficients, j is the index for the grid point, t that 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 EOF are calculated for each of the 12 months. In order to enlarge the sample size, and hence obtain less ambiguous 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 EOF and the time expansion coefficients (PC) 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 year days, 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 five EOF 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 air-temperature totals accumulated over a longer period preceding the phenological event (Menzel 1997). To

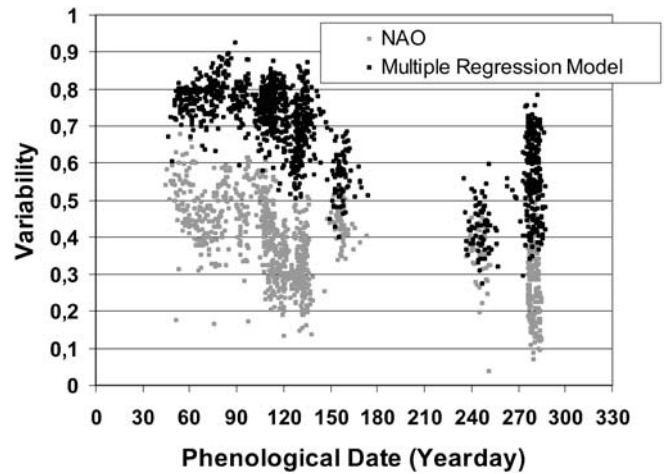


Fig. 2 *Grey dots* The common variability between the North Atlantic Oscillation (NAO) time series of Jones et al. (1997) and phenological time series at the $1^\circ \times 1^\circ$ grid as a function of mean entry date of the phenological phase. *Black dots* The variance explained by the multiple regression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

accommodate this, instead of 1 month, 2 months – the month of occurrence and the previous month – were entered into the analysis, resulting in 20 independent variables for the regression model. We use a stepwise multiple regression (IMSL routine RBEST) procedure to assist in determining the best regression model for each group of independent variables. For comparative purposes, monthly air-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 EOF from one or two atmospheric variables, such as 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 EOF and their associated PC to explain a higher fraction of the variance of the local-scale phenological series than a regression model based on the NAO index alone. Figure 2 compares the success of MLR when the NAO index (Jones et al. 1997) and the above-mentioned PC are used. Both models have been calibrated over the period 1951–1998. The use of PC mainly improves the modelling of early spring and autumn phases and, to a lesser degree, that of late spring and summer phases.

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

Only a few EOF seem to dominate the regression relation. The most important appear to be the first EOF of the 850 hPa air-temperature distribution of the month previous to the phenological occurrence date and the same EOF of the actual month of occurrence. The success of the different EOF entering the MLR via their associated PC depends on the actual phase. Hence, there is a seasonal cycle whereby the influence of the two temperature EOF is reduced as the year advances. Towards late spring and summer an unclear composition of EOF replaces the dominance of the two temperature EOF. Because of its importance, the first EOF of the 850 hPa temperature fields is depicted in Fig. 3.

Figure 3 describes the air-temperature difference between the northeastern Atlantic and Europe. This air-temperature EOF is strongly linked with the first two EOF 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).

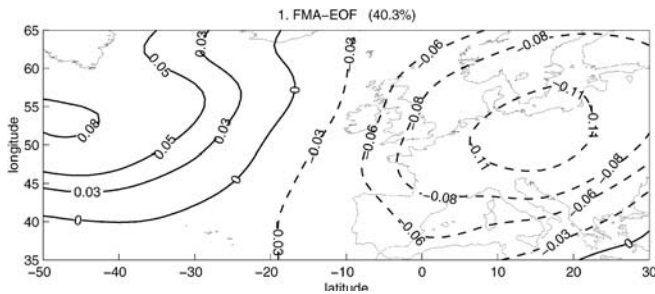


Fig. 3 The first empirical orthogonal function (EOF) of the February, March and April 850 hPa air temperature field explaining 40.3% of its variance

Canonical correlation analysis

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; Busuioac and von Storch 1996) and downscaling of phenological phases (e.g. Table 2).

Phenological occurrence dates serve as local-scale variables. Combinations of two large-scale atmospheric fields serve as large-scale variables. In the first step, both the macro- and microscale variables are subjected to an EOF analysis, resulting in the amount of data required to continue the work being greatly reduced and the signal in the time series retained. In the second step the correlation structure between the remaining random fields, derived from the phenological phases and the large-scale field combinations under consideration, is analysed with CCA. CCA is constructed to find those patterns in which the time coefficients show maximal correlation.

Maak and von Storch (1997) explained 72% of the flowering date variance of *G. nivalis* in Northern Germany with the first pair of canonical correlation patterns. As the large-scale field they used the 2 m air temperature. Table 3 shows results from our study of the flowering date of *G. nivalis* and compares these to findings of Maak and von Storch (1997). Chmielewski and Rötzer (2001) found that the spatial patterns of the first three CCA pairs between the 2 m air temperature and the beginning of growing season, as marked by the beginning of leafing of four species (*Betula pubescens*, *Prunus avium*, *Sorbus aucuparia* and *Ribes alpinum*, data from International Phenological Gardens), are closely linked over Europe. Taken together, the first three canonical correlation patterns explain 73% of the yearly variability of the beginning of the growing season. In our 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, were

tested. The results indicate that quite a number of combinations of independent variables perform equally well. The interdependence of the atmospheric variables might explain that observation. For the large-scale variables the number of EOF is chosen such that a minimum of 80% of the variance is explained. The maximum number of EOF allowed has been set to 16.

For most phenological phases the first one or two leading EOF explained more than 85% of the variability. Only autumn phases required up to ten or more. Figure 4 illustrates the spatial pattern of the first CCA pair of relative humidity and air temperature anomaly fields during February, March and April in 850 hPa, on the one hand, and the phenological phase: the beginning of flowering of *Taraxacum officinale*, on the other. One finds a temperature dipole over the selected area with positive anomalies centred over Northern Germany and Southern Scandinavia and negative anomalies over the North Atlantic. This pattern is comparable with the 2 m air-temperature anomaly pattern shown in Fig. 4 in Maak and von Storch (1997). Positive temperature anomalies seem to coincide with negative anomalies of relative humidity. Higher air temperatures cause *T. officinale* to flower 5–10 days earlier, the greatest advancement being in the area of the greatest temperature anomalies in the north and the least advancement at the southern boundary of the area.

Results

First, the general ability of downscaling methods to link phenological phases with large scale atmospheric variables is evaluated. Second, the performance of both downscaling methods, MLR and CCA, is compared. Third, both techniques are applied to local-scale air temperature. Hence the usefulness of phenological series can be compared to a “classical” local-scale variable in empirical downscaling. The findings, based on the flowering of *G. nivalis*, are compared (see Table 3) with those of Maak and von Storch (1997).

Three different validation approaches are applied to compare the performance of the statistical models. 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 to 1980 and an independent validation period from 1981 to 1998. In the third validation case, temporal cross-validation is applied, where the model is calibrated over 48 different 47-year periods, successively skipping 1 independent year, for which the model is applied. This results in a

Table 3 Results of a comparison of multiple linear regression (MLR) and canonical correlation analysis (CCA) for the beginning of flowering of *Galanthus nivalis*. *c* Calibration period, *v* validation period

Beginning of flowering of the snowdrop <i>G. nivalis</i>	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, <i>c</i> 1971–1990, <i>v</i> 1951–1970	0.55	
This work 1951–1998		
MLR <i>c</i> 1951–1998 <i>v</i> 1951–1998	0.78	100
MLR <i>c</i> 1951–1980 <i>v</i> 1981–1998	0.48	98
MLR temporal cross-validation: 1951–1998	0.41	100
CCA <i>c</i> 1951–1998 <i>v</i> 1951–1998	0.60	100
CCA <i>c</i> 1951–1980 <i>v</i> 1981–1998	0.62	100
CCA temporal cross-validation: 1951–1998	0.53	100

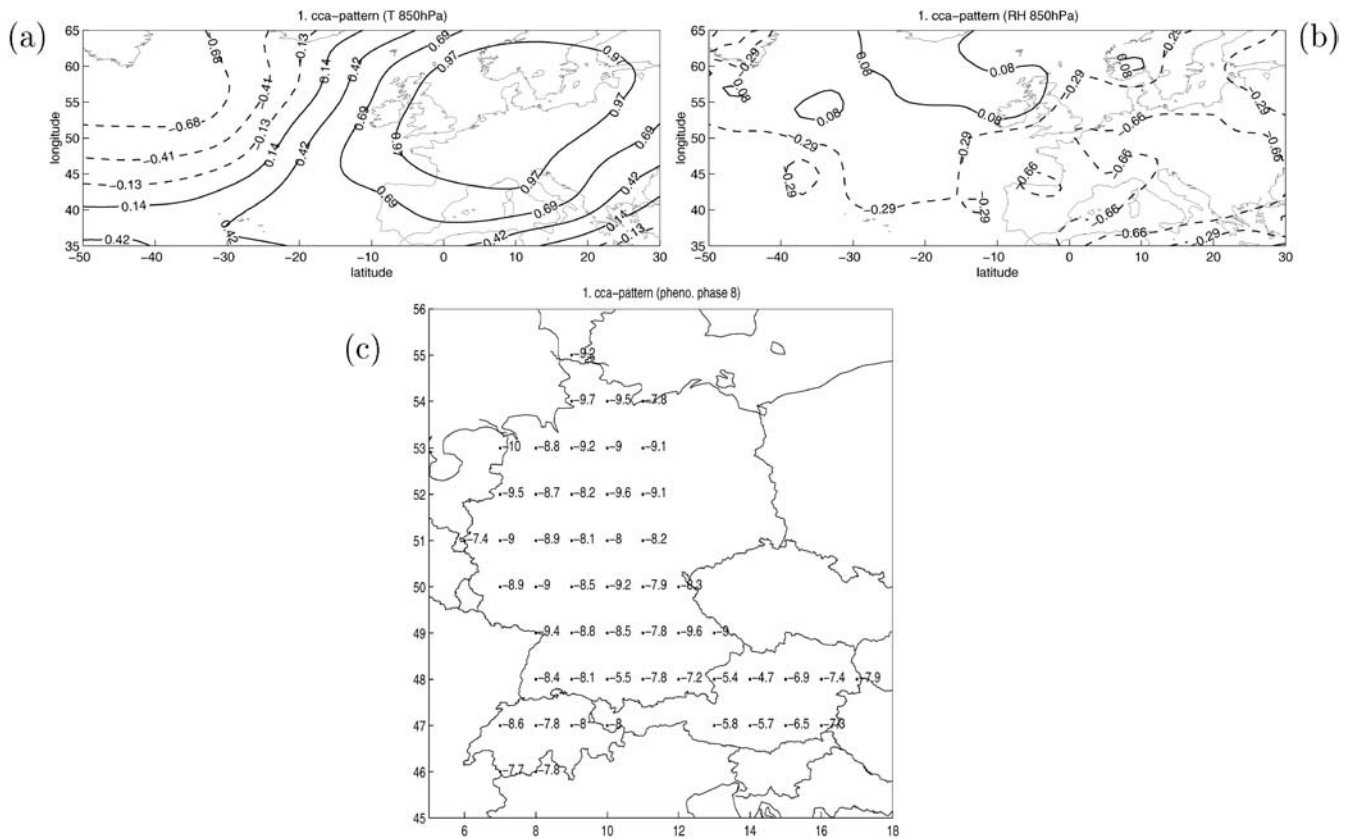


Fig. 4a–c First canonical patterns for the predictors (**a**, **b**) and for the dependent variable (**c**). **a** Air temperature. **b** Relative humidity. **c** The pattern of the phenological phase: the beginning of flowering of *Taraxacum officinale*. The first ten predictor EOF and the first

two EOF of the phenological phase were used, explaining 82% and 88% of the respective total variances. The correlation coefficient between the time coefficients is 0.92

modelled time series over the total period of 48 years, which is compared with the observed series. As evaluation parameter the variance explained by the models is calculated.

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

Phenological phases

Figures 5 and 6 show the results of the validation approach described above. The most striking features are:

1. The decreasing level of the MLR performance from the first experiment to the temporal cross-validation and then to the split-sample test. This is not 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 when in the calibration period values of

70%–80% are achieved, and, at the same time, in the other two validation experiments the values remain below 50% (Fig. 5).

2. The deficiencies of MLR and CCA in their 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.
3. MLR is much more sensitive to the differences in time span available for calibration. Reducing the calibration period by 17 years (temporal cross-validation has 47 years for calibration and the split-sample case 30 years) reduces the MLR performance much more than that of the CCA (Figs. 5 and 6).
4. In the case of phenological phases as local-scale variables and temporal cross-validation (see Fig. 7), CCA generally performs better than MLR. Specifically, the phases during April improve by between 15% and over 30%. For all phases from the very early spring (March) to early summer (June), CCA results are, in contrast to those of MLR, statistically significant at all gridpoints.
5. There is a seasonal cycle in the explained variance: earlier phases achieve a higher amount of explained variance than the later ones. During March and April

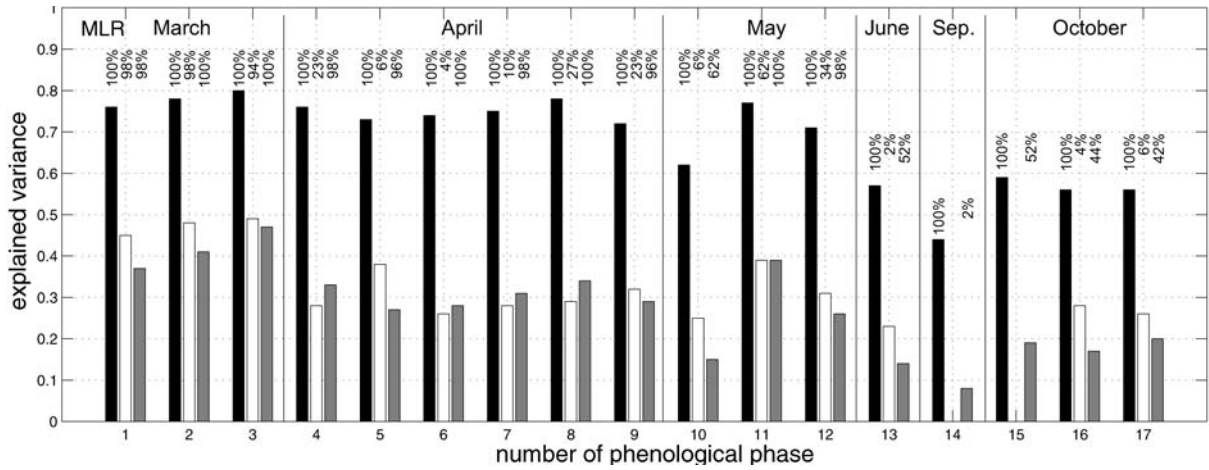


Fig. 5 Results of the three validation procedures for the multiple regression model (*MLR*). Calibration period identical with validation period 1951–1998 (*black*); split-sample test: calibration 1951–1980, validation 1981–1998 (*white*); temporal cross-validation (*grey*). Mean squared correlations between measured and modelled

time series are separately plotted for each of the 17 phenological phases (see Table 2). Only significant correlations ($P < 0.05$) enter the analysis. Percentages of grid points with significant correlations are displayed above the bars

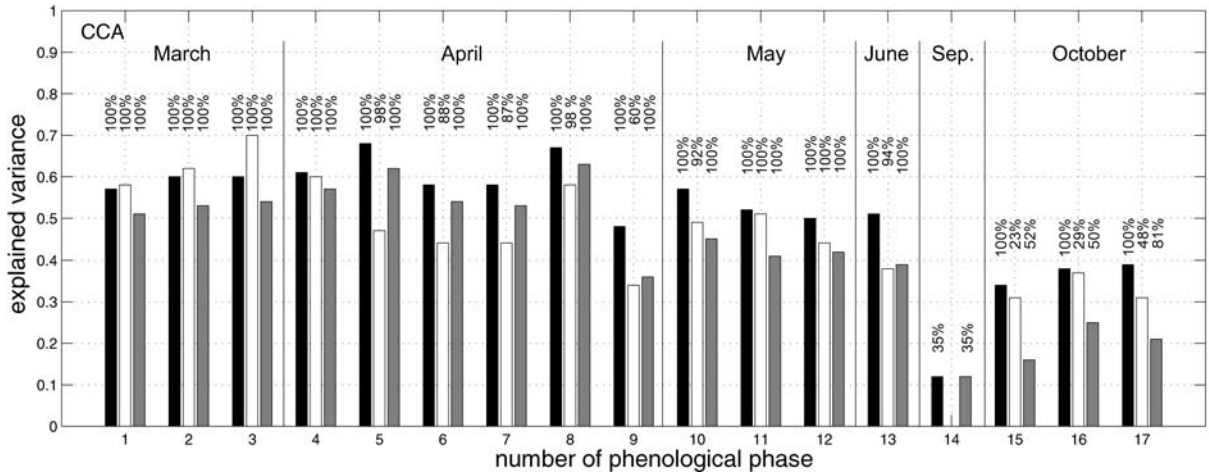


Fig. 6 Same as Fig. 5 but for canonical correlation analysis (*CCA*)

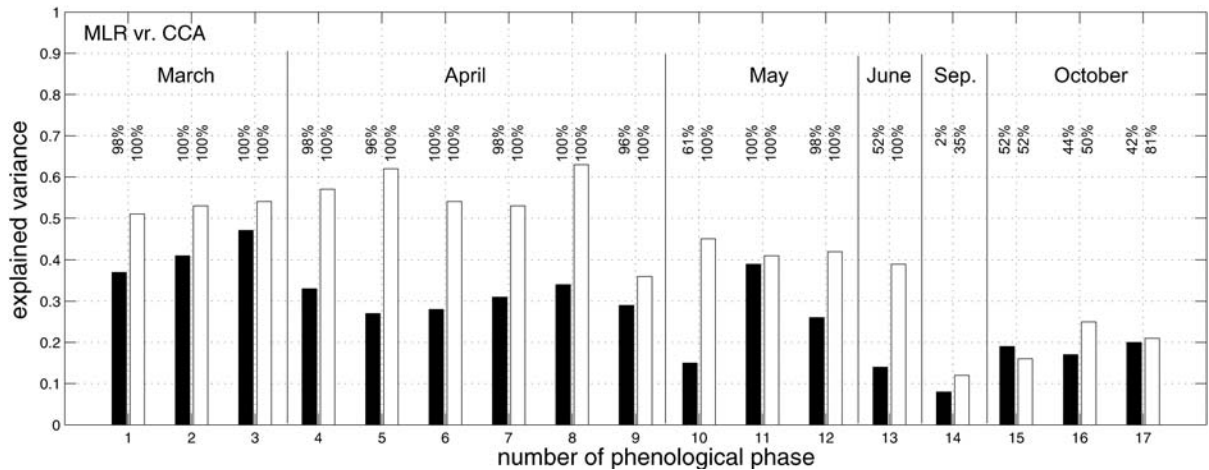


Fig. 7 Comparing the results of the temporal cross-validation procedure between *MLR* (*black*) and *CCA* (*white*) for the phenological phases 1951–1998. Results are plotted for each of the 17 phenological phases (see Table 2) separately. *Bars* Mean

squared correlation between measured and modelled time series ($P < 0.05$). Percentages of grid points with significant correlations are written above the corresponding bar

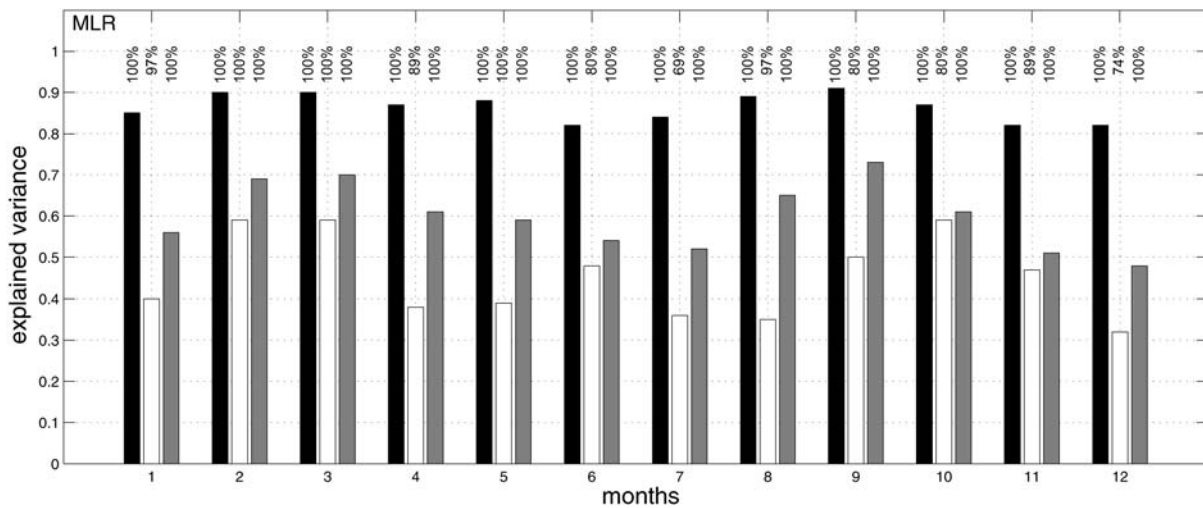


Fig. 8 Results of the three validation procedures for the multiple regression model (MLR), calibration period identical with validation period 1951–1998 (black), calibration period 1951–1980 and validation period 1981–1998 (white) and temporal cross-validation

(grey). Results are plotted for each month of the year separately. Bars Mean squared correlation between measured and modelled time series ($P < 0.05$). The percentage of grid points with significant correlations is written above the corresponding bar

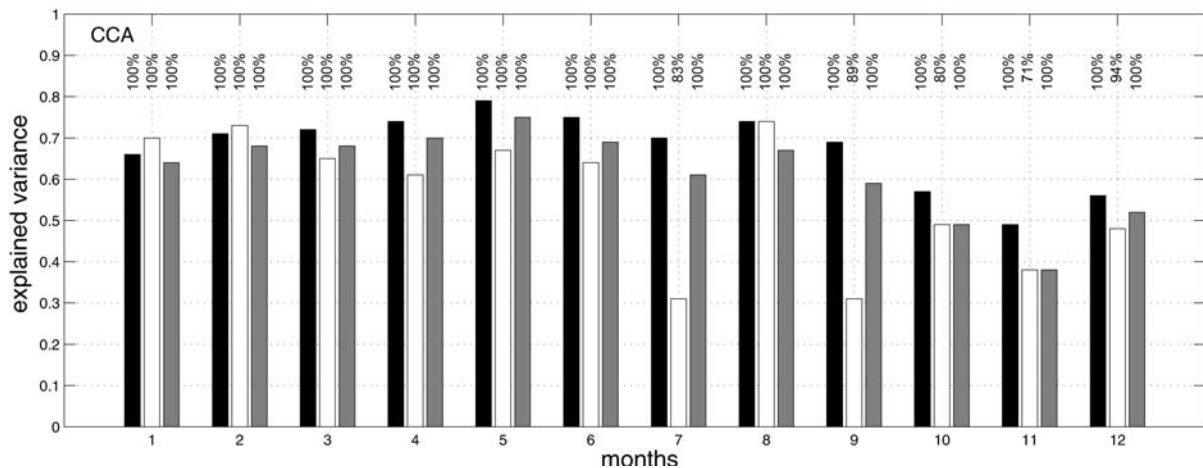


Fig. 9 Same as Fig. 8 but for canonical correlation analysis (CCA)

explained variances of more than 50% are the rule in the 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. This might be related to an increasing uncertainty with time and is in accordance with Menzel (2002), for example. In the case of MLR the seasonal pattern in performance is not so pronounced (Fig. 7). However, compared to the other phases, the performance during early and full autumn is clearly reduced.

Air temperature

Both techniques, MLR and CCA, are better at modelling local-scale air temperature (Figs. 8 and 9) than are

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 decreased success in the case of air temperature appears less than that for the phenological phases. The performance variables of the CCA do not display any systematic difference between the three validation procedures. Moreover, the pattern of seasonality in explained variance is clearly different for air temperature, if compared with that of the phenological phases.

Figure 10 reveals a slightly better performance by the CCA model (see also Fig. 7). The reason for both observations might be associated with the restricted geographical extent of the air temperature data set, which involves only the POSITIVE area covered south of 49°N

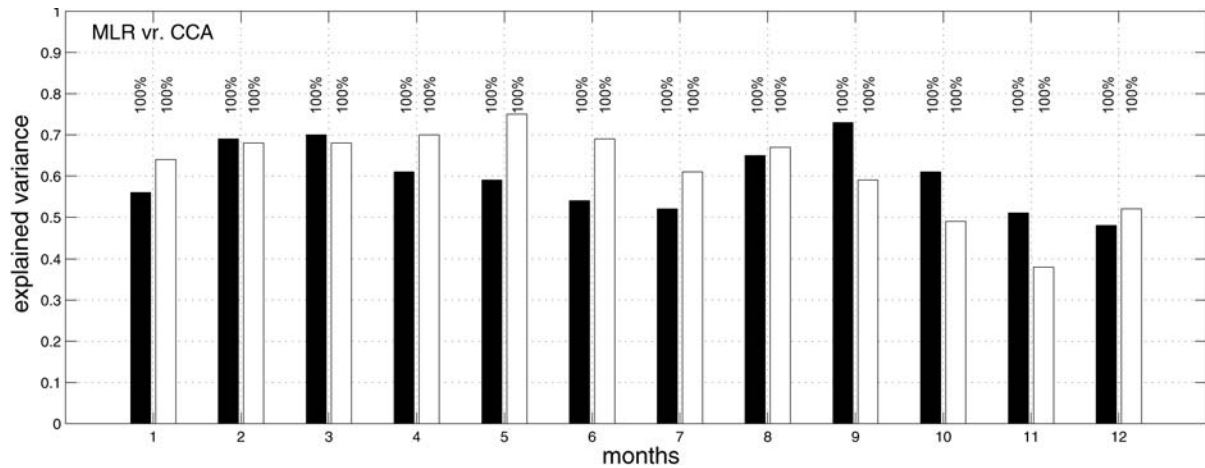


Fig. 10 Comparing the results of the temporal cross-validation procedure between MLR (*black*) and CCA (*white*) for air temperature, 1951–1998. Results are plotted from January to December

separately. Mean squared correlation between measured and modelled time series. Correlations are significant ($P < 0.05$) at all grid points

and therefore does not provide enough spatial variability for the CCA.

Conclusions

We have tested 17 phenological phases throughout the vegetation cycle as local-scale predictors in empirical downscaling relationships and compared them to local-scale air temperature, a predictor for which empirical downscaling was originally designed. As empirical techniques we utilized MLR and CCA, hence our findings have implications for both the local-scale variables and the downscaling techniques.

Local-scale variables

The analyses indicate that phenological observations as non-atmospheric independent variables perform comparably to local-scale air temperature. Hence they are no less suited for the purpose of downscaling than other local-scale atmospheric variables. This is perhaps because, in middle and higher latitudes, the seasonal cycle of plants, especially in spring to summer, is mainly governed by the local-scale air temperature.

To date, in many studies linking phenological series to large-scale atmospheric processes, regressions, made up of the NAO index, are used. As a result of our analyses one might generalize that transfer functions based on a number of EOF of one or two large-scale atmospheric variables perform better than regressions based on the NAO time series alone (see Fig. 2).

Downscaling techniques

Temporal cross-validation reveals that the CCA model performs generally better than the MLR model. MLR can explain 20%–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%–30%. Phases occurring after April are more difficult to model for both of the two models. The inclusion of the spatial information of the microscale variable seems to make CCA superior to MLR.

For air temperature the CCA model is not obviously better than 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 the case of temporal cross-validation. It appears that the CCA model can extract more information from the independent variables over the time available than can the MLR model. It might be the case that the MLR models require a longer time for calibration than the CCA models. Consequently, if data are available only over restricted periods, CCA should be the model of choice.

The results of this study indicate that 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 that CCA should be used 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, which might be related to the increasing amount of uncertainty during the vegetation cycle.

Acknowledgements 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) and by the Austrian Federal Ministry of Education, Science and Culture within the research project: "Usability of different downscaling methods in complex terrain". MeteoSwiss, the German Weather Service and the Hydrometeorological Service of Slovenia are thanked for providing phenological observations. The Austrian Weather Service provided the ALPCLIM dataset. We would like to thank H. Matulla, S. Wagner and D. Bray for fruitful discussions and for helping us with the manuscript. The manuscript was improved by the comments of two anonymous referees.

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