Statistical simulation of the influence of the NAO on European winter surface temperatures: Applications to phenological modeling

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Received 31 October 2003; revised 24 May 2004; accepted 28 June 2004; published 31 August 2004.

[1] We develop a modeling framework to investigate the influence of the North Atlantic Oscillation (NAO) on phenological variability in Europe through its influence on the distribution of wintertime synoptic-scale surface temperature variability. The approach employs an eigendecomposition of NCEP daily winter surface temperature estimates from the latter twentieth century to represent the spatial structure in the surface temperature field. The subset of statistically significant principal components are modeled as first-order autoregressive AR(1) processes, while the residual variance is modeled as spatially uncorrelated AR(1) noise. For those principal component time series that exhibit a statistically significant seasonal relationship with the NAO index, the parameters of the AR(1) model are conditioned on the phase ("high," "neutral," or "low") of the NAO. This allows for realistic simulations of synoptic scale surface temperature variability over Europe as it is influenced by the NAO index. The model is applied to the simulation of trends in growing degree days (GDD) over Europe where simulated GDD variations are shown to agree well with growing degrees days from the data and evidence from available phenological records. Preliminary application of this model to a climate change scenario involving an increasing NAO 50 years into the future suggests the potential for a continued advancement of the start of the growing season. *INDEX TERMS:* 0317 Atmospheric Composition and Structure: Chemical kinetic and photochemical properties; 1615 Global Change: Biogeochemical processes (4805); 1620 Global Change: Climate dynamics (3309); 1630 Global Change: Impact phenomena; *KEYWORDS:* climate change, NAO, phenology

Citation: Cook, B. I., M. E. Mann, P. D'Odorico, and T. M. Smith (2004), Statistical simulation of the influence of the NAO on European winter surface temperatures: Applications to phenological modeling, *J. Geophys. Res.*, *109*, D16106, doi:10.1029/2003JD004305.

1. Introduction

[2] Much work has been done investigating the relationship between the North Atlantic Oscillation (NAO) and the timing of start of season phenological measures, such as budburst and leaf out [*Ottersen et al.*, 2001; *D'Odorico et al.*, 2002]. To date, however, the vast majority of studies have used coarse empirical analyses, applying standard statistical techniques (e.g., least squares regression) to identify significant relationships between the NAO and phenological metrics. In this paper we present a new modeling framework for investigating connections between the NAO and the growing season, employing a statistical empirical model to diagnose growing degree day (GDD) distributions based on the phase of the NAO and using these GDD distributions to predict phenological events.

[3] The NAO represents a meridional displacement of atmospheric mass between the Icelandic Low and Azores High. It is one of the primary modes of cold season climate variability in the Northern Hemisphere, explaining 31% of the variance in Northern Hemisphere winter temperatures (December through March) above 20°N [*Hurrell*, 1996]. When a winter is in the high or positive NAO phase, Europe and many other extratropical areas in Eurasia experience higher than normal temperatures; the converse is true during a low or negative NAO. Over the past 20–30 years the NAO has had a tendency to manifest in the positive phase, a trend associated with winter warming over much of the Northern Hemisphere extratropics [*Intergovernmental Panel on Climate Change* (*IPCC*), 2001, chapter 2, pp. 152–153]. This warming, in turn, has been correlated to changes in the timing of phenological events [*Post and Stenseth*, 1999; *Ottersen et al.*, 2001; *Walther et al.*, 2002].

[4] As part of a project to investigate the timing of onset and changes in the length of the growing season under different climate regimes (i.e., NAO forcings), we developed a technique for simulating the influence of the NAO on winter season (December through March) surface temperatures. The development of this technique is presented in section 2, and its application to phenological modeling is discussed in section 3.

2. Spatial Auto-Resampling Method (SPARM)

[5] To identify dominant spatial and temporal modes of variability in wintertime surface temperatures, we con-

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Table 1. Summary of Output From the Unrotated EOF Analysis of Daily Surface Temperatures[a]

Mode	Eigenvalue	Percent Variance	Cumulative Variance	Correlation With NAO
1	104.6062	0.4102	0.4102	**.766**
2	49.5552	0.1943	0.6046	**.333**
3	21.9452	0.0861	0.6906	**.470**
4	14.2485	0.0559	0.7465	**.553**
5	10.0683	0.0395	0.7860	.256
6	6.8648	0.0269	0.8129	.022
7	6.3585	0.0249	0.8378	**.514**
8	4.7029	0.0184	0.8563	.002
9	4.0383	0.0158	0.8721	**.295**
10	3.9588	0.0155	0.8876	**.762**
11	2.9800	0.0117	0.8993	.034
12	2.4042	0.0094	0.9087	.006
13	2.2225	0.0087	0.9175	**.416**

[a]The table shows the 13 modes retained using the Preisendorfer Rule-n test and correlations between the winter NAO and the seasonal average for each PC. Significant correlations ($p < .05$) are highlighted in boldface.

ducted a principal component analysis (PCA) on daily surface temperature anomalies from the NCEP/NCAR Reanalysis Data Set [*Kalnay*, 1996]. The NCEP/NCAR reanalysis project uses a state of the art data assimilation model to incorporate meteorological observations and generate data sets as complete as possible in space and time. Quality for different variables differs based on the relative influence of the model versus the data; surface temperature (used in this study) is listed as a type B variable, meaning it is influenced significantly by both the model and data. Sources of bias arising from changes over time in data assimilation in the NCEP reanalysis are likely to impact trends in surface temperatures over time [*Hurrell and Trenberth*, 1998], but are unlikely to have any significant impact on synoptic-scale temperature variability. For a more detailed discussion of the various strengths and weaknesses implicit in the reanalysis data, the reader is directed to *Kalnay* [1996]. We used data from winters (December through March, with the designated year referring to the year March falls in) 1949 through 1996, a period including both negative and positive trends in the NAO [*Hurrell*, 1995, 1996]. Our study area is mainland Europe, from 0° to 40°E longitude and 35° to 70°N latitude, a region strongly influenced by the winter NAO and witnessing significant phenological changes in the last half century [*Menzel and Fabian*, 1999; *Menzel*, 2000].

[6] A Preisendorfer Rule-n test truncated the output of the PCA at 13 eigenvectors and associated principal components, accounting for 91.75 % of the variance in the original data (Table 1). The remaining variance is contained in the residual temperatures, defined as the temperature anomalies leftover after the temperature anomaly projections from these 13 eigenvectors are subtracted from the original temperature anomalies. We retained the eigenvectors "as is" to define the spatial patterns in the surface temperature fields. To represent temporal variability in the model, we resampled from the distributions of the principal components using lag-1 autoregressive models (AR1),

$$x_{t+1} = \phi(x_t - \mu) + \varepsilon_{t+1} + \mu,$$

where x_{t+1} is the value of eigenscore x at time t + 1, x_t is the value of x at time t, ϕ is the autocorrelation coefficient (proportional variance explained by x at time t), μ is the mean for the principal component time series, and ε is a random quantity drawn from a gaussian distribution, defined by μ and the innovation variance (variance of the white noise).

[7] The seasonal means of eight of the principal components correlated significantly ($p \le .05$) with the winter NAO (PCs 1, 2, 3, 4, 7, 9, 10, 13) (Table 1): the associated eigenvectors for these PCs are shown in Figure 1. Combined, these 8 components describe 75.55% of the variance in the surface temperature data. We used the combination of these eight components to represent forcing by the NAO on European winter temperatures (December through March) as follows. A winter (normally 121 days long, 122 days during leap years) was demarked as occurring during a low, neutral, or high NAO depending on whether the value for the winter NAO index for that year fell below −1 standard deviation, within ±1 standard deviation, or above +1 standard deviation of the winter NAO time series (December through March) from winters for 1949–1996. We separately binned the daily eigenscores for these eight PCs, according to the phase of the NAO for that winter (low, neutral, or high). Then, for each of these eight principal components for each phase of the NAO, we fit an AR(1) model. In this way, parameters in the AR(1) model are biased by the phase of the NAO. Residual temperatures were modeled in a similar way. We can then use these new PCs, in conjunction with the eigenvectors, to project back into surface temperature anomaly space and generate new temperature distributions consistent with an a priori diagnosed phase of the NAO. We developed the AR(1) models for the remaining five principal components using the daily eigenscore distribution over the entire time period of the data, independent of the phase of the NAO. Using the resampled principal components and residual temperatures as our new time series, and the associated eigenvectors to define the spatial patterns, we back transformed the principal components into surface temperature anomaly space, added these anomalies back onto the mean temperatures, and reconstructed new temperature fields over Europe. Such a classification approach seeks to resolve the most coarse NAO influences on synoptic-scale variability in the face of a limited training data set. The approach is appropriate for NAO variability or trends within the range of those observed during the training interval, which likely includes the moderate changes expected in future decades due to anthropogenic forcing. The approach would not be appropriate in a "no analog" distant future or past climate state; for example, a situation with fundamentally altered boundary conditions where the relationship between the NAO and surface temperatures breaks down.

[8] To summarize, we used the principal components and associated eigenvectors to project back into surface temperature anomaly space. The eigenvectors give the modeled data spatial cohesiveness consistent with synoptic scale patterns seen over Europe in the NCEP reanalysis. New principal component time series are generated by resampling from the distributions of the original principal components as AR(1) processes. For those principal components that significantly correlate ($p \le .05$) with the NAO, the parameters for the AR(1) model are biased by the phase of the NAO (low,

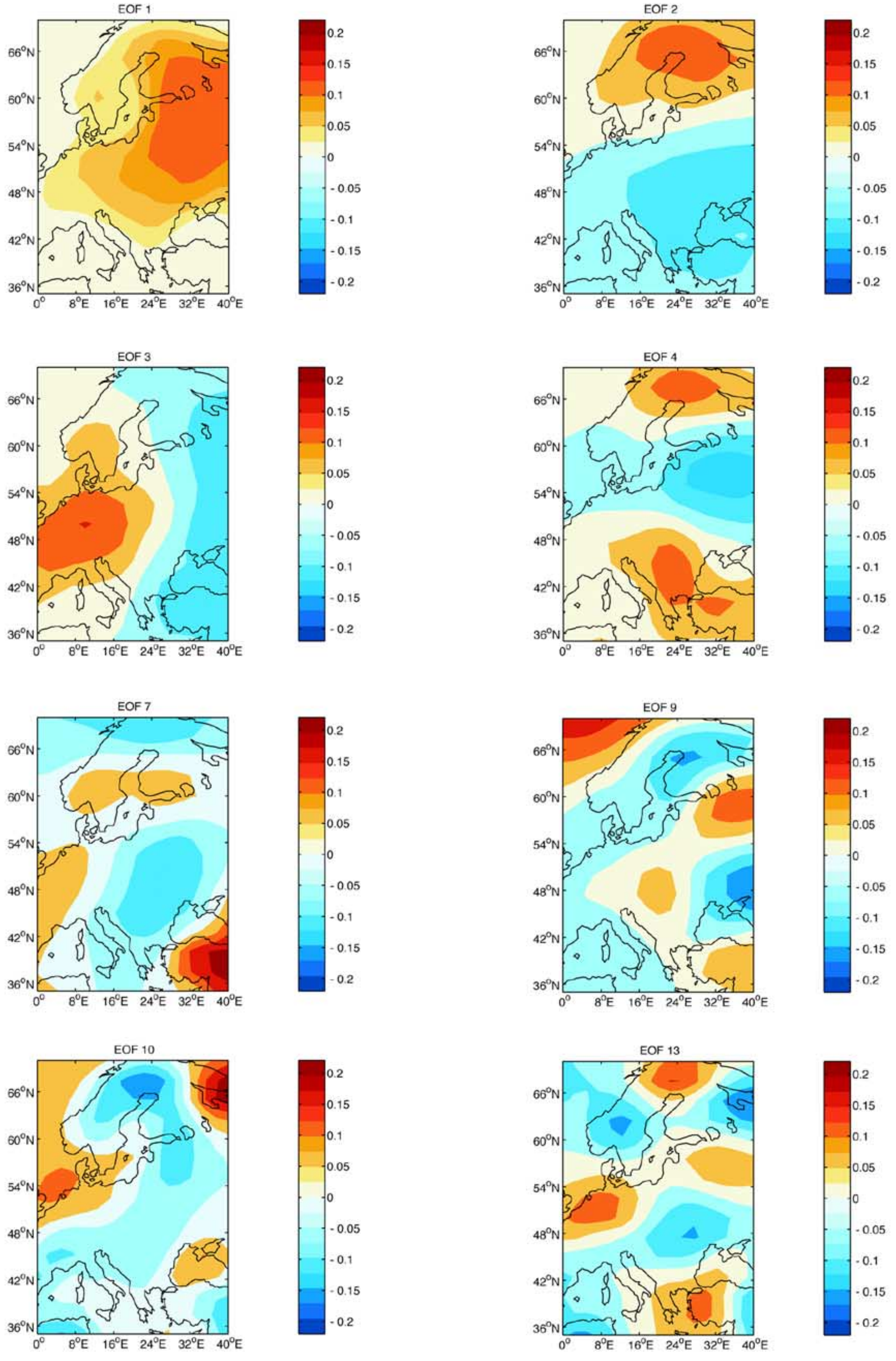


Figure 1. Loadings from the principal component analysis, projected over Europe, of the eight eigenvectors significantly correlated with the winter season NAO ($p < .05$).

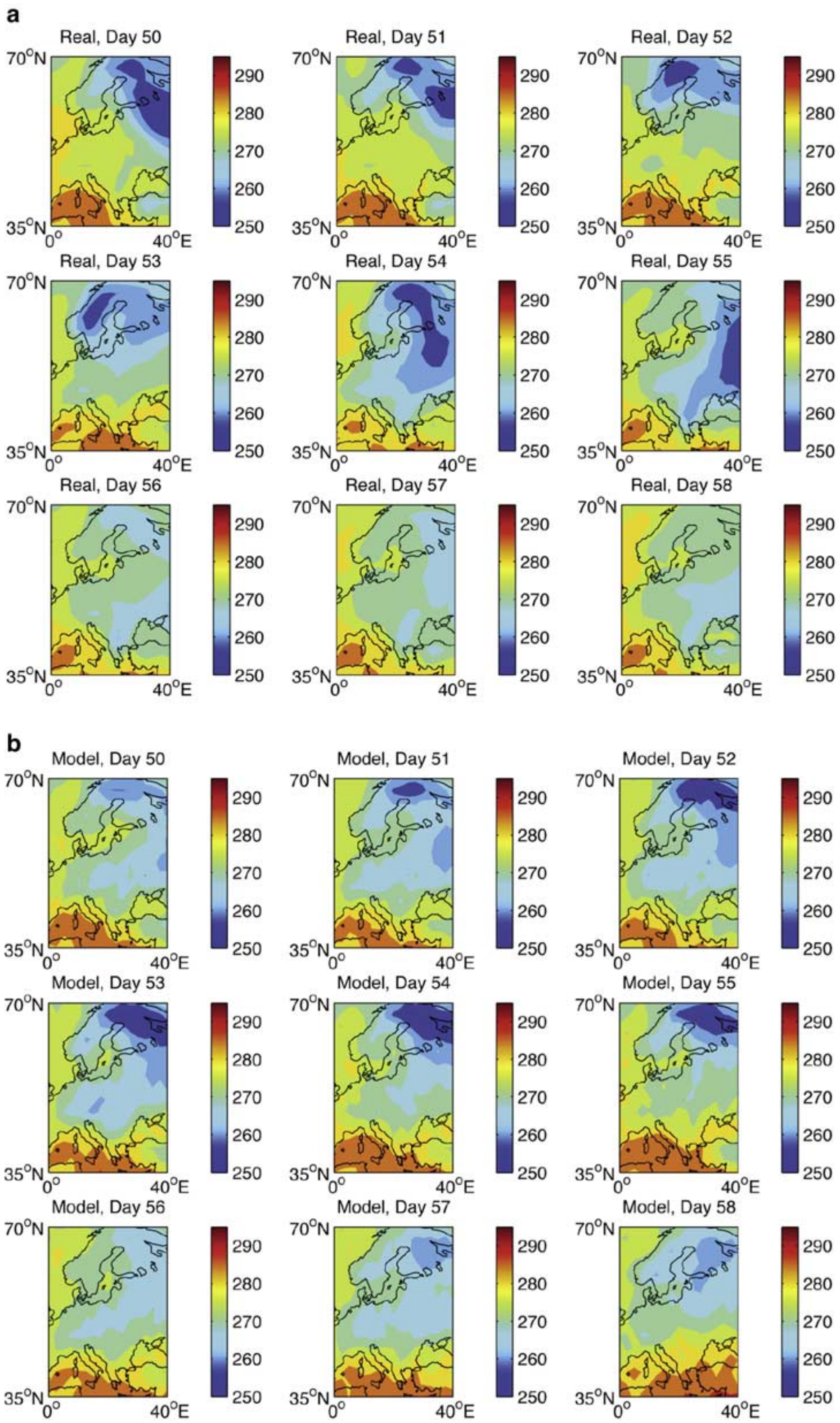


Figure 2. Surface temperature fields (in Kelvins) for nine consecutive days over Europe, from (a) data from the NCEP reanalysis and (b) one realization of the SPARM model.

Table 2. Parameters Describing the Distributions of Temperatures and Growing Degree Days for High, Neutral, and Low NAO Winters in the Data Set and From Three 10,000 Day Simulations of the Model[a]

	High (Data)	High (Model)	Neutral (Data)	Neutral (Model)	Low (Data)	Low (Model)
μ_{total}	274.998	274.986	273.733	273.776	273.103	273.110
σ_{total}	53.132	53.013	68.270	68.527	74.9874	73.745
μ_{GDD}	279.521	279.615	279.653	279.829	279.955	279.870
σ_{GDD}	20.2171	19.618	20.311	21.089	22.382	22.004
Percent GDD	61.2	61.1	55.1	54.9	50.7	51.3

[a]Subscript "total" refers to the total temperature distributions, subscript "GDD" refers to the growing degree day distributions, and percent GDD refers to the proportion of total days (in the data or model) that qualify as growing degree days.

neutral, or high). These new principal components are used to represent the temporal variability consistent with an a priori diagnosed NAO forcing.

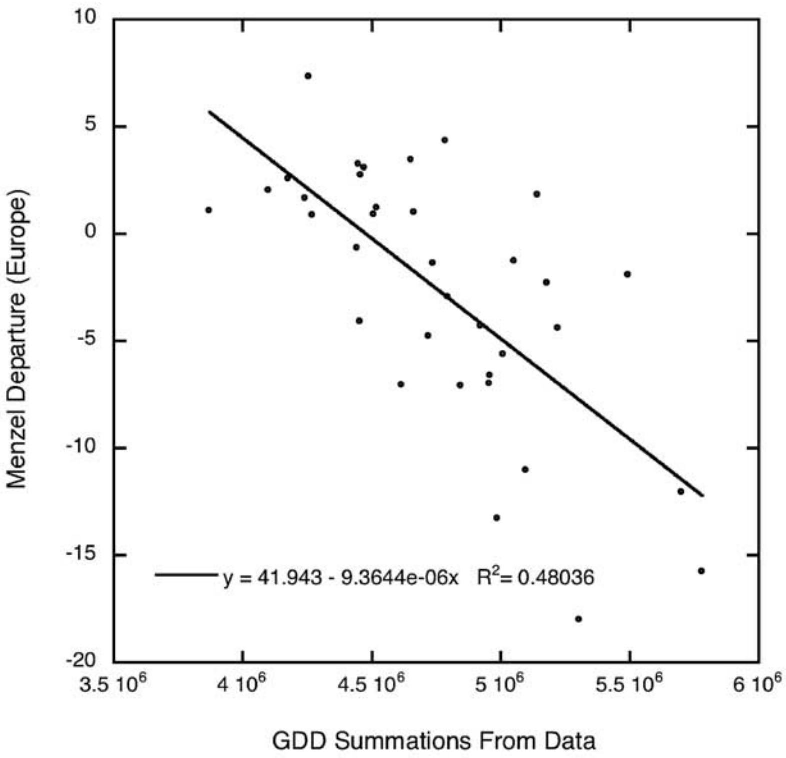
[9] Using this technique we have been able to realistically reproduce the spatial and temporal distributions of winter temperatures over Europe. Figures 2a and 2b show temperature fields over Europe for nine consecutive days from the actual data and one realization of the model, respectively. This qualitative comparison demonstrates how effectively simulated fields capture the synoptic scale variability in the actual data. Large-scale spatial features are reproduced, as is the day-to-day progression (persistence) of the temperature fields. Exact agreement is not expected because of the stochastic nature of the model; rather the expectation is that the coarse temporal and spatial features of the temperature fields are reconstructed in the model. A more quantitative verification of the method is shown in Table 2. In this table we compare daily temperature and growing degree day distributions between high, neutral, and low NAO years from the data and the model. The central tendency and variability in temperatures is well captured by the model for the various phases of the NAO. A student's t test shows that there is no significant difference between the modeled and actual distributions for the three phases at the $p = .05$ level of significance. Additionally, the distribution and occurrence of growing degree days (an important variable for phenological modeling; discussed in detail in section 3) is also well captured for the three phases of the NAO.

3. Applications to Modeling Phenology

[10] The study of phenology has recently gained new prominence in the global change research community, especially for its recognized relevance to carbon cycling and as a "fingerprint" for climatic change [*Parmesan and Yohe*, 2003]. Models used to predict the timing and occurrence of phenological events (e.g., budburst, leaf-out, first flowering, or more general ecosystem level metrics such as "onset") often use growing degree day approaches [*Hunter and Lechowicz*, 1992; *White et al.*, 1997, 1999; *Kramer et al.*, 2000]. In a typical growing degree day model, mean daily temperatures above a certain threshold ("growing degree days") are summed each day ("growing degree day summations") until a critical sum is reached, triggering the phenological event of interest. The threshold at which a day qualifies as a growing degree day usually represents some temperature that will elicit a biochemical response from the plants that will stimulate the occurrence of the phenological event. These models may also incorporate moisture or radiation summations [*White et al.*, 1997, 1999]. Our GDD summations represent cumulative summations of growing degree days over the entire winter, as this is the window of influence for our model.

[11] We compared growing degree day summations (hereafter, GDD summations) from the NCEP reanalysis data set and the NAO index against a phenological measure, the Menzel departure series for Europe [*Menzel*, 2000]. The departure series is a composite of phenological indicators reprocessed from the International Phenological Gardens. Each individual, species based series was converted to anomaly values relative to its mean value for the 1976–1980 period and then average values for all these anomaly series were calculated for each year. The departure series shows a general picture of the trend in the timing of the start of the growing season ("onset") for Europe, the period characterized by an actively photosynthesizing biosphere [*Menzel and Fabian*, 1999]. For our analyses, a day qualifies as a growing degree day if the mean temperature is above freezing (the threshold used in *White et al.* [1997, 1999]). GDD summations from the data explain a significantly higher amount of the variance in the departure series than the NAO index (R^2 values of 0.48 for GDD summations, 0.22 for the NAO), indicating that the NAO alone is not sufficient for predicting phenological variability (Figure 3).

[12] As a preliminary test of the applicability of our temperature model to phenological modeling, we compared GDD summations from the model for each winter period against the GDD summations from the data and the Menzel departure series (Figure 4). Also shown in the same figure is the Hurrell NAO, standardized to the same mean and variance as the GDD summations from the data. A large ensemble of 500 simulations was used to estimate the range of variability of GDD summations consistent with the stochastic nature of the weather forcing (the observed GDD series represents the result of just one of an infinite possibility of actual weather sequences consistent with the observed NAO forcing). The GDD summations from the data fall well within the resulting range of estimated variability in the model, as does the Menzel departure series (standardized to the same mean and variance as the GDD summations from the data). On average, our model performed better at predicting the Menzel departure series ($R^2 = 0.26$) than the NAO alone ($R^2 = 0.22$, as described above) (Figure 5). The biggest discrepancy appears to be two years, 1959 and 1961. These were two years in the data with negative and neutral index NAO values, but with high GDD summations and extremely negative Menzel departure values (−13.3 and −18 days for 1959 and 1961, respectively). It is likely, then, that the high GDD summations and extreme negative values for the Menzel departure series during these years may be driven by factors other than the NAO. When these values are dropped from the verification regressions, the R^2 value between the Menzel departure series and the Hurrel NAO improved to 0.26 and the R^2 value between the Menzel departure series and ensemble mean GDD Summations from the model improved to 0.40. The relationship between the GDD summations from the



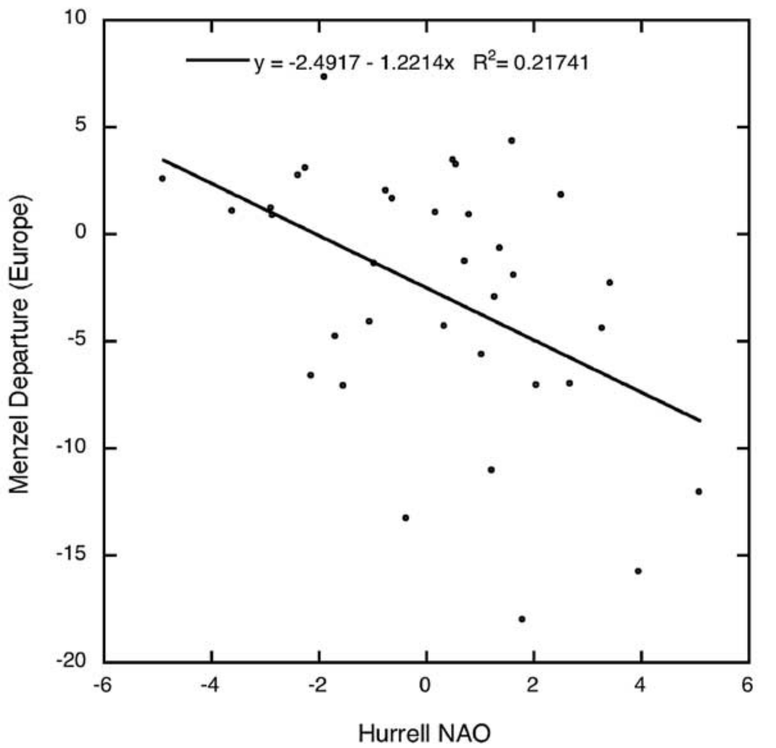


Figure 3. Regression of the Menzel departure series against wintertime growing degree day summations and the NAO index. This demonstrates the inadequacy of the NAO as a predictor and the necessity of using growing degree day summations.

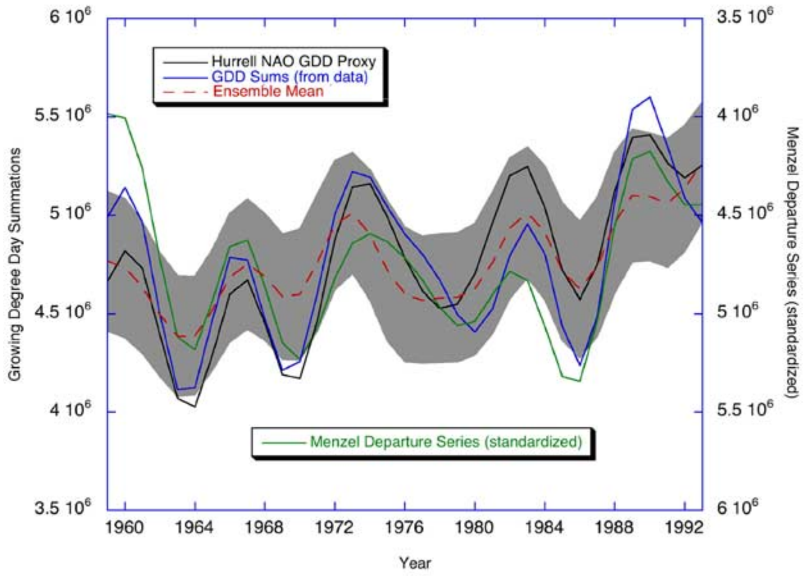


Figure 4. Smoothed curves (5-year low-pass butterworth filter) for GDD summations (model and data, in Kelvins, marked in scientific notation) and Menzel Departure series (standardized to the same mean and variance as the GDD summations from the data). The shaded area represents the ±1 standard deviation of the GDD summations for 500 realizations of the model, and the red dashed line is the ensemble mean of the GDD summations for those same realizations. The axis for the departure series is reversed because higher GDD summations are associated with an earlier onset date and therefore lower departure values.

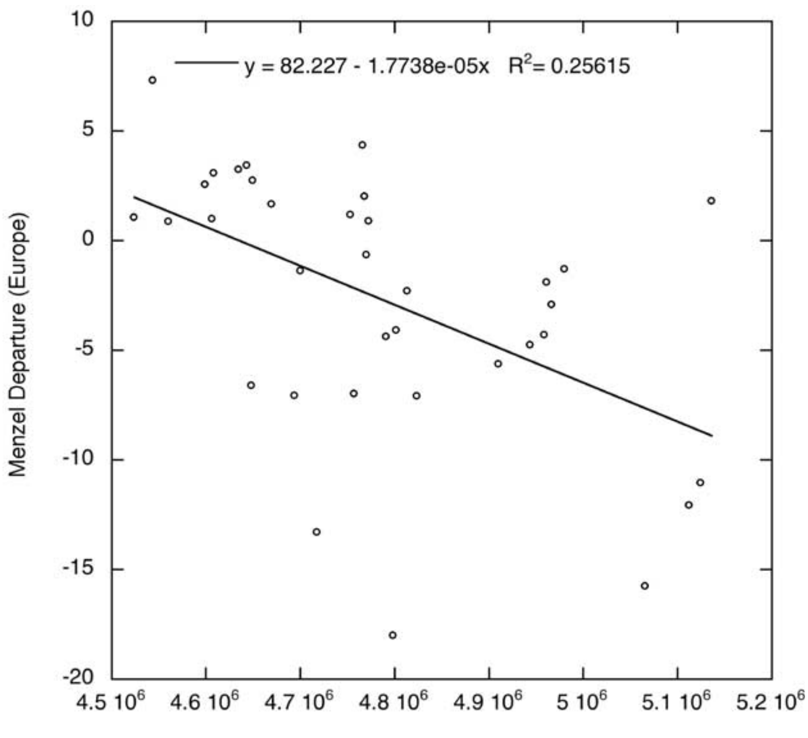


Figure 5. Regression of the Menzel departure series against ensemble mean growing degree day summations from the SPARM model.

Table 3. Summary of R^2 Values for the Verification Regressions Between the Menzel Departure Series and GDD Summations From the Data, the Hurrell NAO, and Ensemble Mean GDD Summations From the Model[a]

Regression	R^2, All Years	R^2, Without 1959 and 1961
GDD (data) versus Menzel	0.48	0.48
NAO versus Menzel	0.22	0.26
GDD (model) versus Menzel	0.26	0.40

[a]Included are the R^2 statistics for the regressions with and without years 1959 and 1961, the 2 years with low or neutral index NAO values but high GDD summations and low Menzel departure values.

data and the Menzel departure series remains the same (R^2 = 0.48) when these two years are dropped. The complete R^2 values for the verification regressions are summarized in Table 3. These results lend support for this technique as an appropriate framework for driving a phenology model designed to capture variability in the growing season associated with variability in the NAO.

[13] We also tested the model against two species based phenological indicators from the Marsham phenological record [*Margary*, 1926; *Sparks and Carey*, 1995] for a longer period outside the model calibration period (Figure 6). Because we lack data on GDD summations for this period, we used the standardized Hurrell NAO (from Figure 4) as a proxy. We use species based phenology time series rather than the Menzel departure series, because the latter covers only a relatively short time period (1959–1993). Excellent agreement is seen between the GDD simulations and one of the two long phenology series (Mountain Ash). Less close agreement is observed with the Hawthorn phenology series, but even here the observed phenological variations are well within the estimated variability due to weather noise.

[14] Recent modeling evidence suggests the distinct possibility that the trend towards increasing prevalence of the positive phase of the NAO during the Northern Hemisphere winter may indeed represent a signature of anthropogenic climate change [*Osborn et al.*, 1999; *Shindell et al.*, 1999]. We might speculate, in this scenario that the recent trend in the NAO will continue, for example, into the mid 21st century and beyond. For this preliminary climate change scenario, we generated a hypothetical NAO series, from 1949 to 2051 (Figure 7). From 1949 to 2002, the actual Hurrell NAO index is used. From 2003 through 2051 we generated a stochastic NAO series and superimposed on it the trend in the NAO from 1960 to 2000. We ran an ensemble of 500 model simulations, forced by the NAO index from Figure 6 and used the resulting GDD summations to predict phenological variability using the regression equation from a previous comparison of GDD summations and the Menzel departure series. Results from this simple experiment are shown in Figure 8. This simple modeling exercise suggests the potential for a continued advance in onset date, when compared to the average confidence intervals for the 1949 to 1960 period (the black dashed lines, representing a period when the NAO was more or less stationary, with a slight negative trend). Future changes are outside the bounds of variability during a period when the NAO was stationary or decreasing. While this represents only a very preliminary analysis (the true dependence of phenological variability on climate forcing is likely somewhat more complex than can be captured with these simple GDD summations and this relatively simple phenology series), these results nonetheless suggest the possibility of continued advances in the onset date of phenological spring

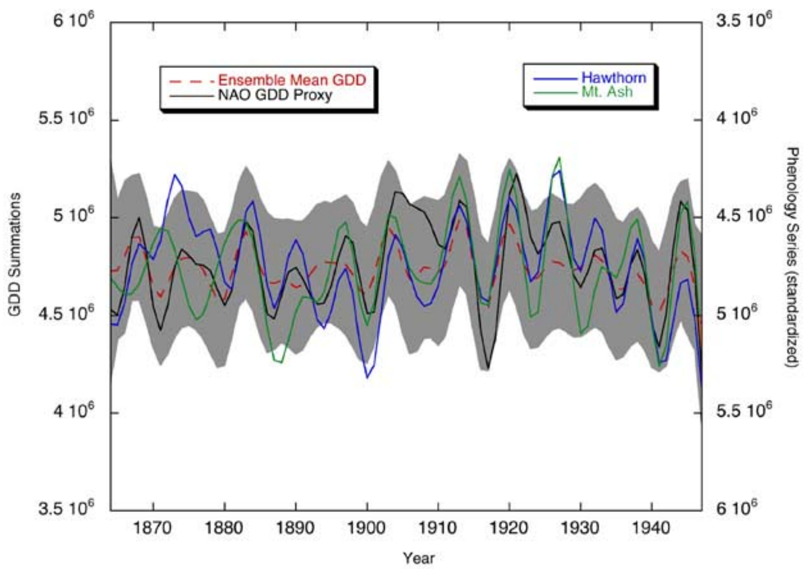


Figure 6. Same as Figure 4, but for two longer, species based phenological series (Hawthorn and Mountain Ash). Because these phenology series cover a period prior to the period we have GDD summations for, we used the standardized Hurrell NAO index (from Figure 4) as a proxy for GDD summations. As in Figure 3, the second y axis for the phenology series is reversed, as higher growing degree day summations are associated with earlier onset dates and thus lower values for the phenology time series.

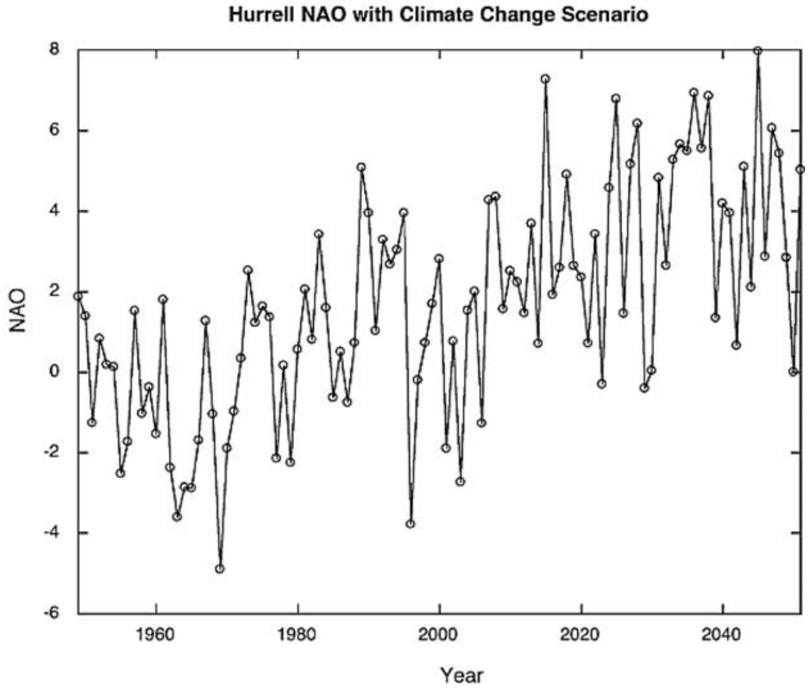


Figure 7. NAO series used to drive the preliminary climate change scenario. From 1949 to 2002, the Hurrell NAO series is used; for projections 50 years into the future (2003 to 2052) I stochastically generated a synthetic NAO series, superimposed over the same linear trend of the Hurrell series from 1960 to 2002.

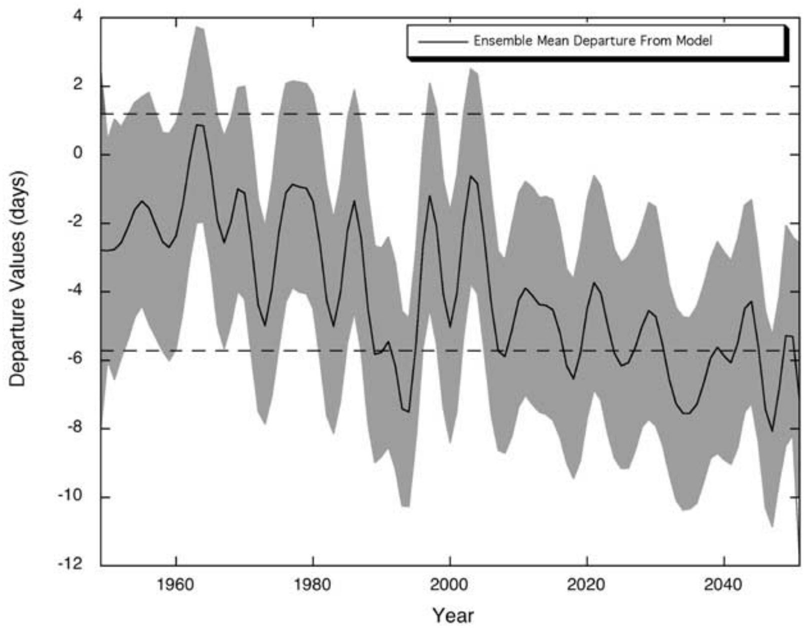


Figure 8. Onset departure values from a preliminary climate change simulation. The red line is the ensemble mean departure for the simulations, and the grey shaded area represents the ±1 standard deviation from the ensemble of model simulations. Black dashed lines represent the average ±1 standard deviation for the period 1949 to 1960. All curves represent 5-year low-pass butterworth filters.

in the Northern Hemisphere extratropics of up to a week or more in the next half century, as a result of a continued trend in the NAO.

4. Concluding Comments

[15] The technique we have outlined above represents a useful approach for simulating the influence of the NAO on European winter surface temperatures. Additionally it has been shown that, at least in a preliminary test, this approach is appropriate for phenological modeling applications and offers a novel way to investigate variability in the growing season that may be connected to variability in the NAO. Because the model is built using current climatologies of surface temperature and the NAO, we believe it will be most useful for investigations of moderate climate changes, such as those that may be associated with anthropogenic forcing. This is evidenced in our preliminary climate change scenario, which suggests the potential for a continued advance of the growing season, should the current trend in the NAO continue into the future. Because of the statistical/empirical nature of the model, we assume stationarity in the relationship between the NAO and daily surface temperatures when we apply the model. As stated previously, this framework would therefore be inappropriate for future or past climate states with fundamentally different boundary conditions.

[16] Future work will lead to the development of an ecosystem level phenology model for Europe, forced by this temperature model, with later applications toward using the phenology model to resolve variability in the terrestrial carbon cycle associated with changes in the growing season. As a final note, this technique could be applied with minor modification to other studies involving variability in climate indices and meteorological variables, e.g., the El-Nino Southern Oscillation and precipitation.

[17] **Acknowledgments.** The authors wish to thank Annette Menzel for providing her departure series for Europe and two anonymous reviewers for their helpful comments. NCEP Reanalysis data provided by the NOAA-CIRES Climate Diagnostics Center, Boulder, Colorado, USA, from their Web site at http://www.cdc.noaa.gov. This work was supported in part (M.E.M and B.I.C.) by the NOAA CIFAR program and the University of Virginia Fund For Excellence in Science and Technology (FEST).

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