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Ensemble empirical mode decomposition for analyzing phenological responses to warming

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ABSTRACT

Numerous studies conducted over the past decade have revealed that plant phenophases have shifted in many temperate ecosystems. Although the consensus is that these shifts reflect plant responses to rise in temperatures, we have yet to match unequivocally the phenological and temperature trends. More importantly, little is known about warming's effects on and contributions to phenophase variability. The key to accomplishing both tasks lies in a proper separation of a trend from natural variability. Based on ensemble empirical mode decomposition, this study shows that, over the past 30 years, the advancing trends in the first flowering dates (FFD) of apple (*Malus domestica*) in Austria and blackthorn (*Prunus spinosa*) in Germany unequivocally correspond to the respective regional winter/spring warming trends. The variability of both FFD series before 1981 was almost entirely due to natural variability. In contrast, warming since 1981 contributed 4% and 21% toward the total phenophase variability of apple and blackthorn, respectively. Furthermore, while contributing to both the temperature and FFD overall variability, recent warming also lowers the FFD natural variability by modulating the temperature natural oscillation amplitudes. Thus, warming can affect both the timing and the natural variability of a phenophase development. As concurrently shifting the timings and reducing the natural variability of phenophase developments may have important ecological and evolutionary consequences, it will be of great interest and importance to examine whether the conclusion holds for other phenophases and species in various regions as well. The introduced approach will be a valuable tool for answering the question.

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1. Introduction

Analyses based on spatially extensive phenological data have revealed that in many temperate ecosystems, plant phenophases have shifted (Parmesan and Yohe, 2003; Root et al., 2003), especially those of spring events (Badeck et al., 2004; Schwartz et al., 2006). These shifts could potentially generate a chain of adverse effects that would cascade throughout ecosystems (Memmott et al., 2007; Walther, 2010; Donnelly et al., 2011; Diez et al., 2012). Because plant phenophase variations mainly reflect thermal environment variability in temperate ecosystems, the consensus is that such shifts are biological responses to anthropogenic warming (Cleland et al., 2007; Rosenzweig et al., 2008; Parmesan et al., 2011).

Temperature variability may arise from both natural variability and human activity (Badeck et al., 2004; Rosenzweig et al., 2008; Polgar and Primack, 2011). By definition, the influences of the former on temperature (and thus, plant phenophase developments) should be oscillatory, whereas those of the latter should be a non-cyclic trend over the time span considered. Otherwise, we cannot distinguish these types of influences from one another. In practice, however, low-frequency natural variation could complicate the matter, as a portion of the variation might resemble and therefore be indistinguishable from a trend caused by anthropogenic forcing. Notwithstanding the cause of recent warming, be it anthropogenic or natural variability, if this warming is indeed responsible for the observed plant phenophase shifts, then the trends of phenophase development and recent warming should correspond closely.

However, although significant progress has been achieved in identifying and quantifying phenophase shifts (*e.g.*, Dose and Menzel, 2006; Menzel, 2006; Parmesan, 2007; Schleip et al., 2008; Amano et al., 2010), an unequivocal correspondence between these two types of trends remains to be demonstrated. More importantly,

Abbreviations: edf, effective degrees of freedom; EEMD, ensemble empirical mode decomposition; EMD, empirical mode decomposition; FFD, first flowering dates; IMF, intrinsic mode function; NAO, Northern Atlantic Oscillation; OC, oscillatory component; SSA, singular spectrum analysis; T_{max}, monthly mean of the daily maximum temperature; T_{mean}, monthly mean of the daily mean temperature.

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Table 1
Summary of phenological and temperature data.

Series	Site	Longitude (°E)	Latitude (°N)	Elevation (m)	Period
	Phenological records				
Apple	Weiz, Austria	15.63	47.22	465	1951–2003
Blackthorn	Germany[a]	8.65–10.47	49.42–50.95	190–290	1951–2011
	Average February to April T_{max}[b]				
T_{max}-A	Austria	13.0–16.0	47.0–49.0		1951–2011
T_{max}-G	Germany	8.5–10.5	49.0–51.0		1951–2011

[a] A composite series from eight stations. See Appendix A for the details.
[b] Based on the European Climate Assessment & Dataset Ensembles Observations E-OBS 5.0 gridded dataset, resolution 0.25°.

we have yet to examine warming's effects on and contributions to phenophase variability. Because changes in phenophase variability can have important ecological and evolutionary consequences (Diez et al., 2012), such an undertaking is crucial for our understanding and assessment of how warming affects ecosystems.

The key to accomplishing both tasks lies in a proper separation of a trend from natural variability (*i.e.*, oscillatory component, OC). Three interrelated issues, however, have impeded us from achieving the goal until recently. First, both phenophase development and temperature exhibit substantial year-to-year variability (Badeck et al., 2004; Polgar and Primack, 2011), which makes it difficult to identify and extract the embedded trends. Second, phenological and temperature data are typically non-linear and non-stationary, which renders the classical time series methods invalid. Third, it is preferable and more acceptable if no external information (*e.g.*, an *a priori* model structure) is injected during the separation process.

A potentially useful approach for separating a trend from OC embedded in temperature and phenological data is ensemble empirical mode decomposition (EEMD; Wu and Huang, 2009). EEMD is an improvement of empirical mode decomposition (EMD), an empirical but highly efficient and adaptive method for processing non-linear and non-stationary signals (Huang et al., 1998; Huang and Wu, 2008). As a part of the Hilbert-Huang transform, EMD views a complex signal as superimpositions of a finite and small number of simple intrinsic oscillatory functions (the intrinsic mode functions, IMFs) with significantly different frequencies and a residual (trend). EMD seeks to separate the IMFs and trend adaptively and intrinsically in time domain, while satisfying the completeness, orthogonality, and uniqueness properties required by a decomposition method (Huang and Wu, 2008).

Using two long-term European first flowering date (FFD, day of the year) series and the corresponding regional winter/spring temperature data as examples, this study shows that EEMD can resolve the three issues simultaneously and demonstrates how the phenophase timings and variability responded to recent warming.

2. Materials and methods

2.1. Phenological data

The apple (*Malus domestica*, medium cultivar) FFD anomaly series (1951–2003) was obtained in Weiz, Austria (Pan European Phenology station ID 6594; Table 1 and Fig. 1) and with respect to the 1961–1990 base period mean FFD (the 117th day of the year). The FFD of this species is considered to be controlled by spring temperature alone (Cook et al., 2012).

The blackthorn (*Prunus spinosa* L.) FFD anomaly series (1951–2011) was the annual average of 8 German FFD series (Table 1, Fig. 1, and Appendix A), without adjusting for elevation differences and with respect to the 1961–1990 base period mean FFD (the 110th day of the year). In contrast to apple, the FFD of blackthorn is considered to be controlled by both spring and previous fall/winter temperatures (Cook et al., 2012).

The FDD data were from the PEP725 Pan European Phenology Project (2012) data archive. For the species and regions examined, this study only included stations with uninterrupted observations in analyses.

2.2. Climate data

The February to April (FMA) thermal regime plays a large role in governing the spring phenophase development of plants in Europe (Chmielewski and Rötzer, 2001; Menzel, 2003; Dose and Menzel, 2006; Amano et al., 2010). It has been suggested in the literature that the spring phenophase development of plants in Europe is controlled by the average FMA monthly mean of the daily mean temperature (T_{mean}). A preliminary analysis, however, indicated that the FFD of both species had a stronger correlation with the average FMA monthly mean of the daily maximum temperature (T_{max}) than with T_{mean}. Thus, this study examined two long-term (1951–2011), regional average FMA T_{max} anomaly series (base period 1961–1990), denoted T_{max}-A and T_{max}-G for the apple and blackthorn study regions, respectively (Table 1 and Fig. 1).

The Northern Atlantic Oscillation (NAO) is a major natural climate phenomenon that influences the winter/spring temperature and plant spring phenophase developments in Europe (Jones et al., 1997; Chmielewski and Rötzer, 2001; Menzel, 2003; Osborn, 2011). Hence, this study examined the correlations between the NAO Gibraltar–Stykkishólmur (NAO_{GS}) index and the four anomaly series as well.

The average FMA T_{max} anomaly series were derived from the E-OBS 5.0 gridded T_{max} datasets (0.25° resolution) from the EU-FP6 ENSEMBLES project (Haylock et al., 2008). All of the gridded datasets and the NAO_{GS} index were obtained from the Royal Netherlands Meteorological Institute Climate Explorer website (http://climexp.knmi.nl).

2.3. Ensemble empirical mode decomposition

Let $x(t)$ be a time series, and the objective of EMD is to decompose $x(t)$ into a small and finite number of IMFs and a residual (trend), that is, $x(t)=\sum_{i=1}^{k}\mathrm{IMF}_i(t)+R(t)$, where k is the number of IMFs, $\mathrm{IMF}_i(t)$ is the ith IMF, and $R(t)$ is the residual or trend. The number of IMFs is a function of data length, $k=\log_2(\text{length})-1$, rounded toward zero. An IMF is an oscillatory function that satisfies the conditions (1) the numbers of extrema and zero crossings must be equal or differ at most by one, and (2) the envelopes defined by the local maxima and minima average to zero (Huang et al., 1998; Huang and Wu, 2008).

The IMFs are extracted from high to low frequencies using a spline-based iterative sifting process. EMD first finds the local extrema in $x(t)$ and generates a pair of upper and lower envelopes by interpolating local maxima and local minima using a cubic spline. It then takes the average of the two envelopes and subtracts the average from the original signal $x(t)$, producing an oscillatory series $x'(t)$. Treating $x'(t)$ as the new signal and by repeating the

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