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Detecting and predicting spatial and interannual patterns of temperate forest springtime phenology in the eastern U.S.

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[1] We performed a diagnostic analysis of AVHRR-NDVI and gridded, temperature data for the deciduous forests of the eastern U.S., calibrating temperature accumulation model with satellite data for 1982–1993. The model predicts interannual variability in onset date based upon year-to-year changes in springtime temperature. RMS error over the period ranges from 6.9 days in the northern portion of the domain to 10.7 days in the south. The analysis revealed a relationship between temperature accumulation and satellite derived onset date (rank correlation = 0.31–0.62). The required temperature accumulation threshold can be expressed as a function of mean temperature (R^2 of 0.90) to facilitate predictive analysis of phenological onset, or when remote sensing data are unavailable. *INDEX TERMS:* 1640 Global Change: Remote sensing; 1615 Global Change: Biogeochemical processes (4805); 9350 Information Related to Geographic Region: North America; *KEYWORDS:* interannual NDVI, phenology, ecosystem models. **Citation:** Jenkins, J. P., B. H. Braswell, S. E. Frolking, and J. D. Aber, Detecting and predicting spatial and interannual patterns of temperate forest springtime penology in the eastern U.S., *Geophys. Res. Lett.*, *29*(24), 2201, doi:10.1029/2001GL014008, 2002.

1. Introduction

[2] The timing of seasonal cycles of vegetation activity, or phenology, is important for predicting ecosystem carbon fluxes. However, our knowledge of the subject comes primarily from observation of the externally visible phases of plant development instead of from a mechanistic understanding of the biochemical controls within plants [*Larcher*, 1995]. Variability in growing season length is likely to have a direct impact on the ecosystem carbon balance [*Black et al.*, 2000; *Frolking*, 1997; *Goulden et al.*, 1996; *White et al.*, 1999] and energy balance [*Fitzjarrald et al.*, 2001]. Vegetation phenophases are sensitive to certain environmental controls [*Kemp*, 1983; *Larcher*, 1995] and in temperate systems, onset is highly correlated with temperature [*Hänninen*, 1994].

[3] Since deciduous canopy development is linked to ecosystem level fluxes of carbon, nutrients and water, its timing is critical and must be prescribed in models [*Aber et al.*, 1995; *McGuire et al.*, 1992; *Parton et al.*, 1988; *Running and Hunt Jr.*, 1993]. The availability of multi-year *in situ* data from native vegetation is limited, and spatially explicit observations are very rare [*Schwartz*, 1998]. Many extant datasets, like the comprehensive USDA-derived lilac phenology dataset [*Schwartz*, 1997], are specific to a single canopy or an understory species and are difficult to relate to whole-ecosystem behavior. There also is no *a priori* link between reported phenophases and the simplified representation of onset in the models.

[4] Reflectance-based remote sensing products like NDVI have been used to specify ecosystem growing season dynamics [*Reed et al.*, 1994; *Schwartz*, 1997; *White et al.*, 1997]. NAVI is correlated with the column integral of chlorophyll in the canopy [*Myneni and Williams*, 1994], though the strength of this relationship is highly variable for different ecosystems [*Baret and Guyot*, 1991]. Though NDVI should be an indicator of the "seasonal wave" of vegetation activity, canopy reflectance depends on a variety of factors including variability in atmospheric conditions (eg. the presence of water vapor and aerosols), and observation conditions (eg. solar and viewing geometry, spatial sampling and temporal recompositing) [*Gutman*, 1999; *Los et al.*, 2000; *Privette et al.*, 1995]. While forest NDVI has a high dynamic range for spatial and seasonal patterns, interannual changes in the signal are at least an order of magnitude smaller and thus more difficult to detect.

[5] We develop a relationship using the remote sensing data which links vegetation seasonality to mean climatic conditions and we reparameterize this algorithm as a function of local temperature, which is appropriate for prognostic modeling. We also evaluate the ability of the optical remote sensing to capture spatial and interannual variability in vegetation seasonality within the studied domain.

2. Methods

2.1. Domain Selection

[6] We examined the seasonality and maximum greenness of the dominant vegetation in all 0.5° grid cells in the contiguous U. S. (Figure 1). Agriculture-dominated cells were identified with VEMAP land cover classification data [*Kittel et al.*, 1995; *VEMAP Members*, 1995] and excluded from the analysis. The VEMAP classes which comprise the template forests of the eastern U.S. exhibit moderate to high greenness and some degree of seasonality, providing a measure of consistency between the remote sensing and the land cover types. We selected these vegetation classes for the analysis domain, forming a set of 653 grid cells.

2.2. Climatology

[7] We extracted monthly mean temperature from the VEMAP Phase 2 climate data set [*Kittel et al.*, 1997] for the years 1982–1993. VEMAP temperature data are based on an interpolation of monthly observations at more than 1000 station locations. Daily temperature values were obtained using a spline interpolation of the monthly values.

[8] We used the growing degree day (GDD) sum, an integration of daily mean temperature above 0°C from Jan.

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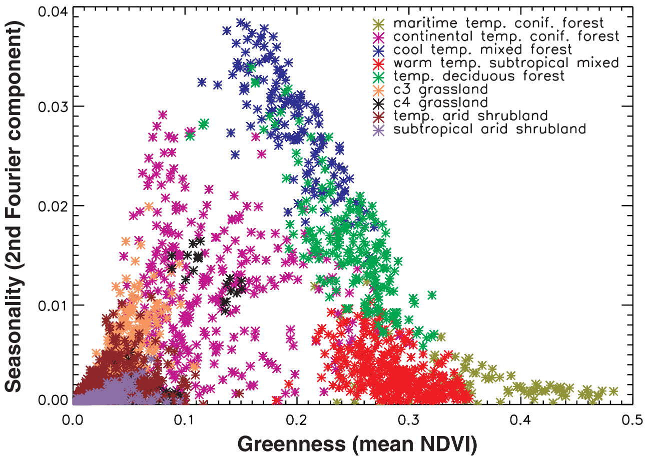

Figure 1. The greeness and degree of seasonality of a 12-year NDVI timeseries is used to identify the three VEMAP land cover classes: cool temperate forest, warm temperate forest and temperate deciduous forest, which are appropriate for the study.

1 to the predicted initial day of the growing season, as a measure of energy accumulation required for onset. Some studies have proposed variations to the GDD approach to fit site or vegetation specific measurements such as using a threshold of 5°C [*von Wuehlisch et al.*, 1995] [*Hänninen*, 1994] or including a chilling requirement [*Heide*, 1993; *Hunter and Lechowicz*, 1992]. However, for simplicity and because our study domain spans a broad climate and species range, we chose a simple temperature accumulation trigger with a threshold of 0°C.

2.3. Remote Sensing

[9] Twelve complete years (1982–1993) of available NDVI from the pathfinder AVHRR Land (PAL) composite date set were selected because of the extent of their spatial and temporal coverage, and for their high processing standards, which includes partial atmospheric correction [*Agbu and James*, 1994]. Data were recomposed from 10-day to monthly values using the maximum of the 3 observations per month and aggregated from 8 km to 0.5° by averaging. Re-gridded 0.5° cells containing fewer than 50% valid 8-km samples were excluded from the study domain reducing the total number of cells from 653 to 530.

2.4. Algorithm Description

[10] We selected a common NDVI threshold of 0.45 for the entire domain. For each grid cell and for each year, we identified onset as the day the NDVI threshold was crossed. A 12-year mean GDD sum was then calculated for each cell, thus defining onset as a climatological function.

2.5. Interannual Variability

[11] We performed a cross validation test of the algorithm by computing mean GDD sums for each grid cell, excluding each year in turn. We then used the mean GDD sums to obtain 12 predicted onset values, which we compared to observed onsets extracted directly from the remote sensing data for each respective year. This explicitly tests the relationship between interannual variability in the NDVI-based phenology and observed temperature. We examined the rank correlation in addition to RMS error because we were interested in the model's ability to identify the correct year-to-year ordering of onset dates.

2.6. Comparison to Ground Observation

[12] We compared satellite observed onset dates to ground measured phenological data at the Hubbard Brook Experimental Forest in New Hampshire, USA [*Martin*, 1993] in order to ascertain what level of actual leaf development correlated to the 0.45 NDVI threshold. In this data, weekly developmental observations were recorded each spring for the dominant forest species, using an integer scale (phenologic stage) ranging from 0 (no foliage) to 4 (full canopy). For 1989–93, the years coincident with available NDVI, we compared the ground based phenological data to NDVI-based onset dates of the 0.5° grid cell containing Hubbard Brook. For each phenologic stage in the ground data set, we averaged observations of all species types. Using phenophase thresholds of 0.1 to 1.5, we extracted a single onset day for each year from the ground data and compared them with the NDVI-based onsets.

3. Results

[13] Mean GDD sum at phenologic onset generally increases from north to south across the domain (Figure 2a), predicted onset day decreases from north to south (Figure 2b). The required temperature accumulation ranges from an average of 100°C-days in the north to 1000°C-days in the south. Onset predictions range from

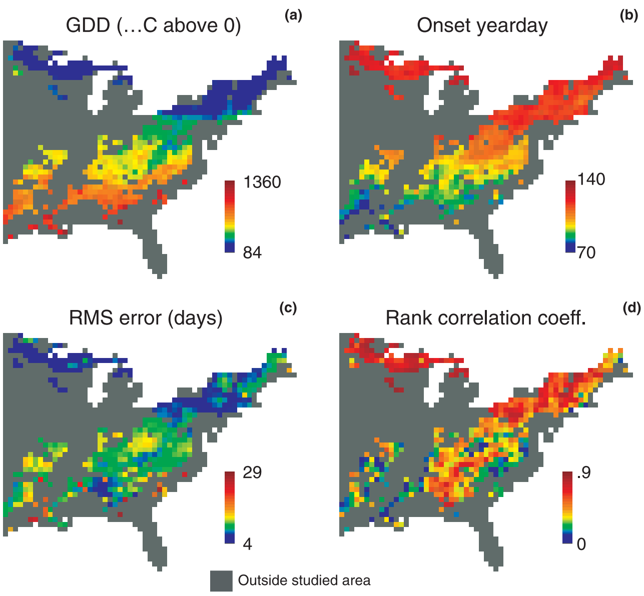

Figure 2. (a) 12-year mean GDD sum (accumulated temperature at the NDVI observed onset day). (b) Modeled spring phenological onset day using the calculated mean GDD sum and mean temperature. (c) RMS error between the 12 satellite observed onset days and the cross validation predicted onset days. (d) Rank correlation quantifies the relative ordering of the 12 cross validation predicted onset values with respect to the 12 satellite observed values. High rank correlation in the north indicates that interannual variation in the seasonal NDVI vegetation signal can be perceptible above the interannual noise in the data.

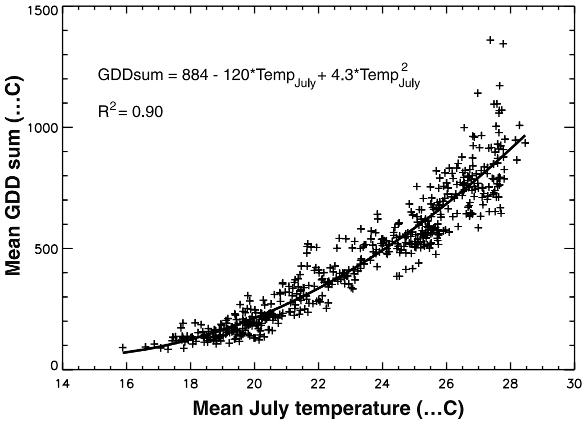

Figure 3. Spatially generalized form of the phenology prediction algorithm using mean July temperature.

approximately yearday 85 (Mar. 25) in the southern class to yearday 125 (May 5) in the north. This relationship was further generalized by regressing mean GDD sum against simple climatological variables. A regression against average July temperature (Figure 3) provided the best fit.

[14] In general, the ability of the model to predict each year's satellite observed onset decreases from north to south (Table 1, Figure 2c) owing, in part, to NDVI signal noise in the beginning of the year. Similarly, rank correlation, was highest in the northern vegetation class (Table 1, Figure 2d), reflecting the best ordering of onset predictions to observations over the 12 year period.

[15] It is not clear why year-to-year variability in GDD sum and NDVI threshold crossing are strongly coupled only in the northern forests. We ruled out snow effects because of the lateness of the estimated onset dates. Southern phenology may be driven more strongly by other environmental factors, or may be influenced by a higher degree of sub-0.5° heterogeneity.

3.1. Ground Validation

[16] Using a range of phenophase thresholds at Hubbard Brook, we found that a low threshold of 0.3 phenologic stage units yielded both the strongest R^2 and rank correlation with respect to the remote sensing, (Figure 4) suggesting that NDVI must be sensitive to the early stages of vegetation onset.

4. Discussion

[17] Diagnostic analysis of AVHRR-NDVI and temperature time series data resulted in a simple model of vegetation seasonality. In contrast to earlier research on modeling phenology [*White et al.*, 1999, 1997] we expanded the spatial and temporal extent of the remote sensing data used to calibrate the phenology model and explore its application on interannual time scales. We also applied a constant NDVI threshold without transforming the data because all temperate forest pixels had a sufficiently high maximum NDVI to reach a common threshold in the spring. Moreover, we found that noise in the NDVI signal, particularly during the winter was amplified when NDVI was scaled. We chose the 0.45 threshold because it is higher than the extreme wintertime values and it roughly corresponds to the steepest ascent of the NDVI curve, but our results were not sensitive to its value from 0.4 to 0.6. If other land cover types were included, it might become necessary to prescribe different thresholds. Because the spatial variability in the remote sensing is large in comparison to temporal variability, *Botta et al.*, [2000] computed an average of all years for their analysis of spatial patterns. Since our primary interest was searching for year-to-year structure in NDVI, we kept all available years of AVHRR as independent data.

[18] The observed phenologic threshold at Hubbard Brook corresponding to the NDVI calculated onset is relatively low (0.3 in a 0–4 range), indicating that, for this pixel, satellite observations show substantial greening before bud break occurs in the dominant tree species. Vegetation diversity within the 0.5° pixel may be partially responsible for this. Snow melt and early growth of understory vegetation at the site would increase pixel NDVI and require a moderately high NDVI threshold to indicate initial growth of the canopy. Also, Hubbard Brook is located at a high elevation relative to the rest of the pixel. Temperature gradients cause vegetation growth to begin earlier at low elevations, so the 0.5° cell will already be greening up by the time onset of leaf development in the canopy trees at the Hubbard Brook site occurs.

[19] The existence of non-vegetation effects in AVHRR derived NDVI has been documented [*Los et al.*, 2000; *Gutman*, 1999; *Cihlar et al.*, 1998] but is difficult to address. Furthermore, interannual NDVI has rarely been evaluated with independent observations [*Hagen et al.*, in press], except for ENSO studies in the tropics [*Asner et al.*, 2000; *Myneni et al.*, 1996] in which a significant atmospheric contribution to the expected between precipitation-

Table 1. Model Statistics by Forest Vegetation Class (± Standard Deviation)

	Number of pixels	RMS error (days)	Rank correlation
Cool temperate mixed	141	6.91 ± 1.88	0.62 ± 0.14
Temperate decidious	185	9.42 ± 2.45	0.41 ± 0.20
Warm temperate/subtropical mixed	204	10.71 ± 3.74	0.31 ± 0.19
Whole domain	*530*	*9.25 ± 3.27*	*0.43 ± 0.22*

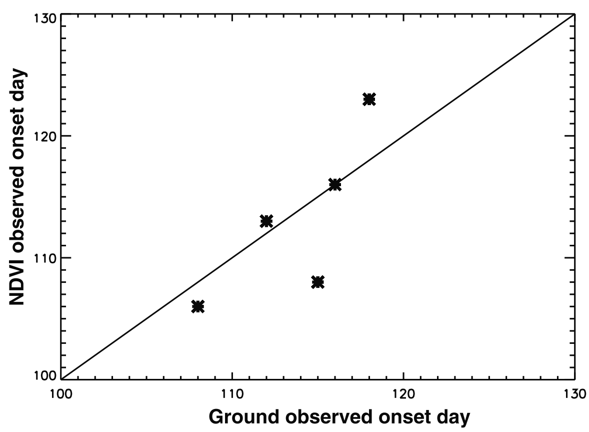

Figure 4. Satellite observed onset dates show a moderate R^2 correlation of 0.62 and a near perfect rank correlation of 0.9 with respect to the ground measured values.

NDVI relationship cannot be ruled out because of water vapor variability. However, our analysis reveals a structure in the interannual NDVI signal that provides a representation of year-to-year changes in seasonality, particularly in the northern portion of the domain where NDVI seasonality is most pronounced. While we do not assume that NDVI is directly representative of canopy conditions, we do assume that correlations between NDVI threshold crossing dates and GDD sum must be mediated by a vegetation response. Drawing conclusions about actual long-term trends in NDVI and, by corollary, vegetation activity from the existing satellite record is tenuous [*Fitzjarrald et al.*, 2001; *Schwartz*, 1998] and we show only the emergence of a weak interannual signal. While the new generation of remote sensing instruments (eg. MODIS, VGT) will provide an improved means of detecting spatial and temporal variability in vegetation characteristics like phenology, AVHRR data currently provides the longest global vegetation time series.

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