

A Qualitative Characterization of Spring Vegetation Phenology Using MODIS
Imagery for the Piedmont of North Carolina from 2000 to 2007

By

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Abstract

Recent studies have shown vegetation phenology around the world is being altered by increased variability in temperatures associated with a warming climate. The onset of spring and the duration of the growing season in many eastern states has been pushed forward an average of 2-5 days and lengthened by as much as 10-15 days respectively, as a response to climatic forcing. Analyzing phenological changes to forest dynamics is aided by the use of satellite imagery with high temporal and spatial resolution to accurately estimate the timing of recurrent events associated with the flush of green vegetation at the beginning of spring in deciduous forests. This study used daily MODIS images at 250m processed to Normalized Difference in Vegetation Index (NDVI) for the spring greenup from 2000-2003 and 2007. Of the 792 available images, 20 sites along the Piedmont, coastal plain, and mountains of North Carolina were filtered (a lowpass Savitsky-Golay convolution filter) to remove atmospheric noise, and used to estimate relevant phenological parameters. Onset of spring, length of growing season, rate of green-up, as well as maximum green-up, were identified using a segmented regression technique. Over the study period, the Piedmont sites exhibited high variability in dates of onset among sites (± 5 days) and negatively between years (± 6 days), with concurrent variability in growing season length. Furthermore, using the NDVI response in regressions of climate variables at the AmeriFLUX site in Duke Forest from 2001-2003, showed growing degree-days since last freeze and mean soil temperature as most significantly in agreement with phenological change. Future studies should focus on acquiring daily satellite imagery to monitor the changes and variability seen among sites and years with careful attention given to severe weather anomalies. Creating maps of relevant climatic variables may provide a more accurate means of predicting phenology and determining the influence of site-specific environmental variables.

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TABLE OF CONTENTS

<i>Abstract</i>	<i>i</i>
<i>Acknowledgements</i>	<i>ii</i>
<i>Introduction</i>	<i>2</i>
<i>Research Questions</i>	<i>10</i>
<i>Methods</i>	<i>12</i>
<i>MODIS Imagery Characteristics</i>	<i>12</i>
<i>Thresholding and Lowpass Filtering</i>	<i>14</i>
<i>Segmentation Analysis</i>	<i>15</i>
<i>Linear Regressions with AmeriFLUX Climate Data</i>	<i>15</i>
<i>Results</i>	<i>16</i>
<i>Image Processing</i>	<i>16</i>
<i>Estimates of Spring Phenology</i>	<i>17</i>
<i>Climate Regressions with NDVI</i>	<i>19</i>
<i>Discussion</i>	<i>21</i>
<i>Management Implications</i>	<i>26</i>
<i>Conclusions</i>	<i>28</i>
<i>Literature Cited</i>	<i>30</i>
TABLES & FIGURES	1

TABLES & FIGURES

<i>Table 1: Site Characterizations.....</i>	<i>1</i>
<i>Figure 1: Map of Study Site Locations.....</i>	<i>2</i>
<i>Figure 2: Map of Site Characterizations according to NLCD 2001.....</i>	<i>3</i>
<i>Figure 3: Distribution of Raw NDVI Values.....</i>	<i>4</i>
<i>Figure 4: Expected distribution of NDVI Values.....</i>	<i>5</i>
<i>Table 2: Image Processing Information.....</i>	<i>6</i>
<i>Figure 5: Thresholding and Lowpass Filtering.....</i>	<i>7</i>
<i>Figure 6: Savtisky-Golay Convolution.....</i>	<i>8</i>
<i>Figure 7: Example of Segmentation Plot.....</i>	<i>9</i>
<i>Figure 8: Site 2 Phenology from 2000-2007.....</i>	<i>10</i>
<i>Figure 9: Site 14 Phenology from 2000-2007.....</i>	<i>11</i>
<i>Figures 10-14: Dates of Onset for Piedmont Sites by year.....</i>	<i>12-16</i>
<i>Figures 15-19: Dates of NDVI Maximum for Piedmont Sites by year.....</i>	<i>17-21</i>
<i>Figures 20-24: Map of Mean Onset Difference for Piedmont Sites by year.....</i>	<i>22-26</i>
<i>Figures 25-29: Map of Mean NDVI Max. Difference for Piedmont Sites by year..</i>	<i>27-31</i>
<i>Figure 30: Map of Onset Standard Deviation for Piedmont Sites – All years.....</i>	<i>32</i>
<i>Figure 31: Map of NDVI Max. Standard Deviation for Piedmont Sites – All years.....</i>	<i>33</i>
<i>Table 3: Dates of Onset, NDVI Max. & Days in Greenup for all sites.....</i>	<i>34</i>
<i>Table 4: AmeriFLUX Climatic Variables w/ Pearson’s R with NDVI.....</i>	<i>35</i>
<i>Figure 32: Best Correlates in AmeriFLUX 2001 Climate Variables.....</i>	<i>36</i>
<i>Figure 33: Best Correlates in AmeriFLUX 2002 Climate Variables.....</i>	<i>37</i>
<i>Figure 34: Best Correlates in AmeriFLUX 2003 Climate Variables.....</i>	<i>38</i>
<i>Table 5: Climatic Regression Predictor Estimates for 2001-2003.....</i>	<i>39</i>
<i>Figure 35: Conditional Plots of Residual NDVI with gDDSLF given SoilT25cm.....</i>	<i>40</i>
<i>Figure 36: Conditional Plots of Residual NDVI with SoilT25cm given gDDSLF.....</i>	<i>41</i>
<i>Figure 37: Pairs Plots of 2001 AmeriFLUX Climate Regression Variables.....</i>	<i>42</i>
<i>Figure 38: Pairs Plots of 2002 AmeriFLUX Climate Regression Variables.....</i>	<i>43</i>
<i>Figure 39: Pairs Plots of 2003 AmeriFLUX Climate Regression Variables.....</i>	<i>44</i>

Introduction

The recent focus on global climate change has driven many scientists and policymakers to address how climate alterations may affect the worldwide distribution of natural resources and agricultural products. The potential for biotic shifts, accompanied by the responses of vegetation dynamics due to known climate interactions have redirected many studies to move towards interpreting large-scale historical changes and the timing of recurring biological events. A rapidly developing approach relies on a combination of ground observations and satellite imagery to describe and quantify temporal variability in vegetation phenology and link this response to climatic variability. Many approaches have focused on regional or biome phenology, relating changes in biophysical factors with the seasonal flux proxies like Net Primary Productivity (NPP), Leaf Area Indices (LAI), and fraction of Photosynthetically Active Radiation (fPAR) (White, 2006). Often these studies assume that predictive models are an adequate substitute for the lack of real-time or time-series information on the ground. However, it has been found that depending on the location of the study, confounding factors like proximity to urban areas, land conversion, temporal resolution, and understory effects can introduce considerable variability that can drastically alter real-time phenology monitoring protocols (White, 2006; Reed et al., 1994). Using ancillary data like the National Land Cover Dataset (MRLC, 2001), and higher quality sensors with large spatial coverage and high temporal resolution can markedly increase the accuracy and relevance of such models in land-use planning and forest management.

Phenology or the study of recurrent or seasonal timing of biological events in nature, encapsulates a broad seasonal association with events like the blooming of flowers and trees, and recurrent animal/bird migration, among others. Phenology is concerned with the relationship between weather events and the response of organisms to predictable patterns of climatic perturbations. For example, deciduous forests follow a predictable pattern of bud burst, flowering, and leaf-senescence in response to seasonal temperature, precipitation, and sometimes photoperiod (Hunter & Lechowicz, 1992). The latter, being a response to the earth's geometric configuration, and the former two, being directly driven by climatic forcing (Lechowicz, 2001). Consequently, within natural climatic variability some phenological events like flowering can be predicted within 2-5 days of onset (Lechowicz, 1995). Furthermore, functional organization of species-specific evolutionary adaptation favors the offset of phenology within similar species to capitalize on resource limitations and predators-avoidance effects throughout the year (Lechowicz, 1984). For example, leaf longevity in deciduous tree species can be measured in months, while evergreen species hold leaves over-winter and often for years. The distinction in over-winter leaf habit, along with spring-summer overlapping of leaf production are driven by well-defined functional and ecological considerations that can be seen in single species (Reich et al. 1997).

As a result of differences among many species, the analysis of phenology relative to community composition and changing climate is complex, however, some generalizable trends exist. Within a natural range of climatic variability, where postulated dominant drivers like temperature and precipitation are concerned, species phenological response

can track changing realities given known climate forces. However, as climate shifts, we can expect that a species phenological response may also shift to accommodate timing of biological processes, competition, and trophic interactions in several other possible ways (Harrington et al, 1999). Some paleoecological evidence suggests that species may migrate and colonize new landscapes to accommodate well-adapted climatic regimes, as is the case with latitudinal variation in plant communities pre- and post- glaciation in northern temperate forests (Potter and Brooks, 1998). Alternatively, species may not migrate at all, but adapt to a changing climate if climatic shifts are within a certain degree of tolerable variation that allow a species to persist. Or lastly, species neither migrate nor adapt to changing climatic conditions and become less dominant or extinct locally; it is however, difficult to predict what effect species response would have on community and ecosystem response (Lechowicz, 2001).

This tight coupling of phenology, species distribution, and climate allows scientists to study trends in phenology that serve as natural indicators of climate change, and where suitable records exist, we can estimate the degree to which climatic trends have influenced the natural dispersal of species (Harrington et al, 1999). Global climatic trends indicating an increase in temperature on the earth's surface have been tied to changes in various phenological events. Modeling (White et al, 1999), ground data (Menzel and Fabian, 1999) and satellite observations (Myeni et al. 1997) support a recent increase in 8-10 days in the mid-latitude forest growing season resulting from earlier onset of spring and the later onset of winter. This has also been linked to potential changes in the migration and egg laying of birds (Sparks and Carey, 1995), insects

(Parmesan et al 1999), and other, flowering plant species (Fitter et al, 1995; Sparks and Carey, 1995; Bradley et al., 1995). Studies discussing the widespread impact to many species, communities, or ecosystems are lacking, and no evidence at this time suggests disruption to species migration or extinction, however, it is postulated that alterations to phenology can lead to biotic reorganization in global ecosystems (Lechowicz, 1995).

With the advent of daily satellite imagery at resolutions that allow for simultaneous ground surveys, some of these issues have been explored through vegetation phenology studies that rely on a variety of indices to quantify green-up in different areas of the world. Imaging sensors like the Advanced Very High Resolution Radiometer (AVHRR) and the Moderate Resolution Imaging Spectroradiometer (MODIS) can be used to create indices that enhance vegetation spectral signatures from onset of the growing season, to peak greenness, and final senescence. By collecting and analyzing a time-series of these indices, we can quantify the ecological rates of change and correlate them where large-scale terrestrial vegetation dynamics and climate system interactions (Schwartz, 1999; White et al., 1997; Zhang , 2004; Zhang et al. 2006). However, using strictly a remote sensing approach does have its limitations. Some studies suggest the weak correlation between ground observations and satellite signals to be caused by qualitative differences in each method (van Leeuwen and Orr, 2006). Where vegetation indices measure the absorption of different light spectra by photosynthetically active tissues, the signal is compromised by sometimes overwhelming temporal, spatial, and atmospheric effects (Myeni et al. 1998; Badeck et al. 2004), whereas, incorporating ground observations can mitigate such limitations. Other studies suggest that temporal compositing of satellite

data to reduce atmospheric and cloud effects, compromises the estimation of spring phenology parameters by the upper limit of the temporal resolution achieved, and potential influences of understory vegetation to the received signal (Ahl et al, 2006). These issues along with existing spatial and temporal resolution, and a limited historical archive of satellite imagery comprise the largest impediments to developing more precise estimates. Conversely, a strictly field-based approach contains uncertainty associated with observer bias, scaling sampled forest stands to regional responses, and errors associated with the equipment used in measuring phenological change.

The satellite-based vegetation index approach relies on radiometrically/atmospherically corrected and enhanced imagery to monitor temporal shifts in the ratio of absorbed near infrared (NIR) to visible red (R) radiation (1). Where high tissue absorption in the visible red wavelengths and high reflectance in the NIR wavelengths, reflect the amount of useable radiation for photosynthetic activity in the sensed vegetation. In one such index, White et al. (2005) used the Normalized Difference in Vegetation Index (NDVI; Rouse et al., 1974) to normalize the NIR/R ratio and to find globally distinct regions where vegetation acts in similar ways temporally and spectrally. These clusters were used to derive phenoregions, that can develop and sight monitoring programs that represent heterogeneous land cover, and different biophysical climate regimes. Furthermore, NDVI has been used extensively in creating estimates of potential land cover to be used in the development of global biophysical databases and the current iterations of global climate models (Loveland & Belward, 1997).

(1)

$$\text{NDVI} = (\rho_{\text{NIR}} - \rho_{\text{VR}}) / (\rho_{\text{NIR}} + \rho_{\text{VR}})$$

ρ = the unitless reflectance value of the Bands Brightness Value

Several pitfalls to this index are that NDVI values become saturated at high canopy brightness values, and slope/ratio-based indices tend to be nonlinear in nature, and additive noise effects like atmospheric path radiances increases actual NDVI values.

Another effort, the Enhanced Vegetation Index (EVI, Huete, 1988), modifies the NDVI by correcting for the biomass brightness problem by minimizing aerosol influences (caused by the blue visible wavelengths) and mitigating soil background affects (2).

However, limitations spatially and temporally make this a more difficult index to generate.

(2)

$$\text{EVI} = G ((\rho_{\text{NIR}} - \rho_{\text{VR}}) / (\rho_{\text{NIR}} + C_1 \times \rho_{\text{VR}} - C_2 \times \rho_{\text{Blue}} + L))$$

ρ = the unitless reflectance value of the Bands Brightness Value

G = Gain Factor = 2.5

L = Differential NIR and VR nonlinear canopy adjustment = 1

C1 = Coefficient of Aerosol resistance term (Uses blue band aerosol influences in the red band) = 6

C2 = Coefficient of Aerosol resistance term (Uses blue band aerosol influences in the red band) = 7.5

(Huete, Justice, & Liu, 1994; Huete, Liu, Batchily, & van Leeuwen, 1997).

Increased user access to timely satellite imagery has allowed scientists and conservation professionals to become visually familiar with ecosystem changes that occur simultaneously around the earth. Satellites like MODIS, offer a variety of products that

can be used when describing temporal changes within and between spatial extents.

Another benefit of MODIS stems from its Aqua and Terra phase instrumentation that aids in correcting surface reflectance deviations from atmospheric scattering. This allows for standardized comparisons among temporally different satellite images. Real-time correction allows the user greater utility in analysis of the products. MODIS delivers free, daily imagery products in many forms including NDVI and EVI surface reflectance grids. This decreases the time from download to analyses and onboard instrument calibration standardizes instrument precision.

Most of the MODIS NDVI/EVI products are developed through Bidirectional Reflectance Distribution Function (BRDF) and Constrained-view angle-maximum value compositing (CV-MVC) which processes image quality (cloud cover, forest fires, atmospheric disturbance, etc.) by compositing Vegetation Indices (VI) values from pixels in multiple daily (8, 16, 32 day) composites. Then the function chooses the pixel, with the highest VI value within the given timeframe that has the 'closest to nadir' view in the composite window (Huete et al., 2002). Spatial and temporal discontinuities are minimized however, the temporal window does not reflect the inherent variability from day-to-day, so transition dates can only be estimated from the minimum size of the temporal window. Additionally, the BRDF method uses the off nadir values from a series of at least five pixels to interpolate the probable nadir VI value (Huete et al., 2002).

Analyzing a time-series of these vegetation indices can be used to provide an estimate of transition dates that describes seasonal vegetation response. These transition dates are (1)

green-up, the date of onset of photosynthetic activity; (2) maturity, the date at which plant green leaf area is maximum; (3) senescence, the date at which photosynthetic activity and green leaf area begin to rapidly decrease; (4) dormancy, the date at which physiological activity decreases to a near-zero state. (Brugger et al. 2003). These dates of change are estimated from non-linear responses of the satellite signal, where spectral cues are indicative of vegetation dynamics. By complimenting the vegetation indices with spatially interpolated climatic datasets, one can investigate the significance and correlation among variables to identify natural drivers of phenology. For example, the onset of greenup has a very strong response to temperature change and is crucial for accurately assessing the start and length of the growing season (White et al., 1997; Cayen et al., 2001; Chuine & Beaubien, 2001; Fitzjarrald et al., 2001; Schwartz & Crawford, 2001). Brugger et al (2003) found that in American beech (*Fagus silvatica*) temperature is the main determinant in budburst, and leaf coloring is driven by a combination of temperature, photoperiod, and precipitation (Menzel, 2002). Once a firm grasp of the onset is established for a baseline comparison among years, the duration of the growing season can be established. For example, in northern latitude phenoregions, the timing of snow cover patterns often signals the beginning of the growing season. Some areas that are dominated by high precipitation variability show a strong association to phenology (White, 2004). In areas of the Southeast, phenology has been empirically associated with photoperiod, temperature, and precipitation (Taylor, 1974). The physiological reason for this arises from a hormone response within the plant that is a result of the summation of heat/cool triggering growth. Heating units influence the thermodynamic properties of the plant soil system. Other potential predictors of onset are: soil moisture, soil temperature,

ambient temperature and relative humidity. Because of the changes in potential predictors as the growing season progresses a synoptic regression model can be developed to determine the contribution of driving variables to growing season persistence (Schwartz, 2003). Scientists typically agree, however, that chilling during the autumn and winter; period of warming in the late winter and spring; and photoperiod are staples of a complete phenological model (Jackson et al., 2001).

Research Questions: The primary literature addresses the benefits of using remotely sensed data to quantify temporal and seasonal changes in the process of greenup in the eastern U.S. The existing studies, however, are sparse in determining the extent to which climatic variables play a role in the timing, duration, and intensity of vegetation phenological events over regional scales. Discerning the correlations between climatic variables and temporal changes in vegetation using remotely sensed imagery can greatly add to our existing knowledge of the drivers behind phenological change. This study describes the temporal and spatial events that lead to final leafing-out in a context of the Normalized Difference Vegetation Index (NDVI) by using a sample of daily MODIS Terra images from February through July for 2000-2003 and 2007. These time-series data serve as the response of vegetation to phenology across approximately 20 study sites across North Carolina. The vast majority of the sites are located within the Piedmont in rural and urban areas with the goal of discerning transition dates across distinct land cover types and to determine any generalizable trends over time of the onset of spring. The remaining sites are located in the mountains and coastal plain and are included to examine the effect of spatial distribution of sites on spring phenology. Then, I use

climatic data sets of temperature, humidity, precipitation, and soil temperature to derive and model the compositional determinants behind the NDVI satellite response to vegetation using a response-transformed linear model.

Objective 1: Create a five-year time-series of daily MODIS NDVI images to qualitatively describe the temporal changes associated with green-up across 20 sites in North Carolina.

Objective 2: Develop a suitable method to reduce the noise associated with clouds and atmospheric effects while preserving the temporal resolution of the dataset. Characterize the temporal response of NDVI during spring green-up, annual NDVI maximum, the annual phenological variability, for 20 sites during 2000-2003 & 2007.

Objective 3: Examine correlations between daily NDVI response and detailed climate variables such as; growing degree-days, days since last frost, soil temperature, soil moisture, precipitation, and vapor pressure deficit collected at the Duke Forest AmeriFLUX site.

Methods

I developed the phenological dataset using (MODIS) imagery onboard NASA's Terra spacecraft. Terra's orbit around the Earth is timed so that it passes from north to south across the equator in the morning, and it views the entire Earth's surface every 1 to 2 days, acquiring data in 36 spectral bands. From MODIS's Daily L2G Surface Reflectance 250m MOD09GQ product (Version 005) (USGS, 2007), the first two bands of surface reflectance, the visible red (R, with bandwidth of 620-670 nm), and the near-infrared (NIR, with bandwidth of 841-876 nm), were extracted to create NDVI. Images were acquired for the period of February-July for the years 2000-2003 & 2007. These years were chosen because at the time of download, and they were the only years that had been updated to version 005 processing, which was completed by May 2008. This new NDVI dataset, allowed for a higher temporal resolution (almost daily) and an improved maximum spatial resolution (250m) to estimate phenological parameters than existing MODIS NDVI products (Table 2). An EVI product, not considered in this study, would be limited to 500-meter spatial resolution (the resolution of the necessary MODIS blue band), which we considered too coarse for the highly fragmented Piedmont of North Carolina. All images come atmospherically corrected to Level 1, Top of Atmosphere Reflectance, to alleviate cloud and aerosol thickness influence (Vermote et al., 1997). Data compression is contained within HDF-EOS format as 16-bit signed integer in the Horizontal 5 Vertical 11 tile.

In order to systemically remove noisy daily images used for the analysis, NDVI images were created, followed by thresholding and lowpass filtering techniques for all of the available images and then later sampled individually to evaluate for quality. Data

processing was conducted in ERDAS Imagine Version 9.1 (Leica Geosystems, 2007). First, images were imported and converted from Sinusoidal WGS84 to UTM Zone 17N WGS 94 and clipped to a boundary polygon of North Carolina. Next, using the Modeler in Imagine, NDVI grids were produced to determine daily NDVI response values for the spring green-up in North Carolina. In order to sample the images at predefined site locations the images were then imported into Arc GIS 9.2 (ESRI, 2007) and sampled at 20 site locations using Hawth's tools "Intersect point" tool to sample each raster and create a table that depicted the site identification and associated NDVI value as a normalized ratio between -1 and 1 (Figure 1). All sites were chosen *a priori* within a 510-m buffer of deciduous forest area based on the 2001 National Land Cover Dataset (NLCD)(Figure 2; Table 1). This buffer was designed to accommodate a potential horizontal error of 0.5 MODIS pixels due to pixel misregistration .

After sampling each NDVI image for the years described above, the data were extracted to a database and most of the analyses were performed in R (R Development Core Team, 2007). An extensive amount of noise was reduced before the processed NDVI signal could be used to quantify the parameter estimates according to phenological events (Figure 4). Unprocessed data obscured the typical sigmoid curve that is associated with the spring deciduous response (Figure 3-4). A lower and upper threshold were applied to the samples in order to remove any confounding noise to the signal based on aerosol, atmospheric, or cloud effects that would compromise parameter estimation. Several smoothing techniques were applied in order to determine which was the best approach at processing the signal for later fit to a piece-wise model. Among those tested was the

Savitsky-Golay convolution (Savitsky and Golay, 1964)(Figure 6). This is a lowpass technique to fit a local polynomial regression on a distribution of points. It determines a smoothed value for each point while still maintaining minima, maxima, and width. Other smoothing filters, such as, a moving average tends to lose this information. Another lowpass filter used was the piece-wise logistic function that fit a nonlinear curve based on localized sampling of changes in slope, stepped progressively through the time-series (Cleveland, 1981)(Figure 5).

After the data were smoothed a segmented linear model was applied to estimate the date of onset, the rate of change in greenness post-onset, and the point at which the NDVI signal reach a consistent maximum (Figure 7). The segmented model is a modification on a linear regression, which estimates a broken-line relationship composed of slope parameters and the break points where the linear relation changes. Where the prevalence of sample values increases dramatically a break point is fixed and afterward a new slope is calculated (Muggeo, 2003). After estimating the phenological parameters described above, the relationships among and within samples could be further established.

From the parameters associated with the onset of greenness with the study years, I wanted to identify the climatic and environmental drivers associated with the resultant NDVI response. From the sampled sites, I focused on one in very close proximity to the AmeriFlux site located in the Blackwood Division of Duke Forest. I chose this site because climatic variables and other ecosystem measurements are recorded on a daily basis that include soil and air factors that are likely inherent to spring phenology. From

2001-2003, I examined correlations between these *in situ* ecosystem measurements and satellite-derived measurements of spring phenology over time (Table 4). The data were imported into R, and the NDVI response was transformed to a linear relationship that could be directly compared to the climatic variables through linear regression. Because of the nonlinear nature of the NDVI response, adapting a regression model based on climatic variables was difficult given an unwieldy logistic assumption. In order to create a response that could be linearly regressed on the predictor variables, I had to first transform the response to a linear form.

$$NDVI(t) = \frac{1}{1 + e^{-\beta_0 + \beta_1 x_t}}$$

$$Z_i = \ln \frac{NDVI}{1 - NDVI}$$

$$Z_i = \beta_0 + \beta_1 x_1 + \beta_2 y_2 + \dots \dots \dots \beta_n k_n + \varepsilon_i$$

In this regression form, the slope coefficients correspond with the significant predictors of the response. In order to determine a likely model to correlate with the NDVI response, I used all available climate variables.

Results

Image Processing

From the large volume of images and the sampling design across North Carolina, systematic filtering of sample NDVI estimates from site-specific criteria were used to maintain the maximum number of daily samples per site. The initial number of images acquired from the Land Processes Data Archive and Acquisition Center (LPDAAC) totaled to 792 (Table 2). Thresholding by lower and upper bounds of NDVI estimates for individual sites allowed me to determine local limits to include estimates based on values of temporally proximal values and weekly maximums to determine degraded images from cloud cover, atmospheric effects, or view angle. Low variability in interannual NDVI estimates required year-dependent thresholding of individual sites (Figure 4). After testing several lowpass filter techniques, I used the Savitsky-Golay convolution (Figure 5-6). The Savitsky-Golay convolution preserved most of the features of the original data while retaining the variability that is indicative of daily satellite imagery. Alternative approaches such as the locally weighted polynomial (LOWESS) achieved a smoothed curve of the predicted signal, however, individual point estimates were unwieldy and too generalized to reflect a modest amount of variability in the satellite imagery. After further processing using the Savitsky-Golay convolution filter, the number of available sample images was further reduced to approximately 379 or 48% of the total (Table 2). Over the potential green-up period and the whole sampling period, the mean sampling interval held constant over the 4 years at around 2-3 days. Sampling intervals where many consecutive images were missing were uncommon, however, there were occasions throughout the sampling periods that missing estimates spanned larger ranges from 7-26 days that could compromise estimates of the onset of spring. The

distribution of sampling intervals across the sampling period remained relatively constant, except for the skew attributed to large intervals later on in the season.

Estimates of Spring Phenology

From the segmented piece-wise regression for phenology performed in R, I was able to estimate slope coefficient values and regression breakpoints for 20 sites across the Piedmont of NC (Figure 7-9 Ex.; Table 3). Assuming a rapid change in NDVI indicates a pronounced phenological change for these forested stands, spring phenology can be estimated from five segmentation parameters. One, the initial slope of winter NDVI leading up to first estimate of onset, which for the purpose of this analysis we can assume as zero. Two, the Julian day estimate of spring onset, estimated as the point in the regression when the local slope goes above the maximum difference in the slopes preceding and after, this estimate was calculated as the breakpoint. Three, the local slope after the onset breakpoint that estimates the rate of change associated with the data. Four, the breakpoint of NDVI maximum immediately after the slope reaches its maximum and before the slope returned to assumed zero. Five, the slope associated with summer greenness of consistently high NDVI, where point estimates show a narrow range of variability (Figure 7). For ease of use in the result and discussion, I focused on dates of onset, day of NDVI Maximum, and the difference of the preceding two estimates (Table 3).

Dates of Onset

For 2000, across the piedmont, the mean Julian day of onset was 88 ± 4 days (Figure 10). For 2001, the mean Julian day of onset decreases to 81 ± 7 days with a total increase in variation (Figure 11). Year 2002 holds very closely to the estimates obtained for 2001,

with similar variation and mean onset date of 88 ± 6 days (Figure 12). Furthermore, the mean Julian day of onset from 2003 to 2007 decreases from a high in previous years to days 79 ± 7 and 80 ± 6 days (Figure 13-14) with a total of approximately 1.1 days/year from 2000-2007. Most of the study years exhibited high variability in date of onset among sites (Figure 21-24; 30). Across three sites in the mountains and on the coastal plain, the date of onset holds relatively constant day 109 ± 8 days and day 76 ± 11 days, respectively (Table 3).

NDVI Saturation

The mean Julian date of NDVI maximum or the signal closest to saturation, changes on average 1.75 Julian days from 2000 to 2007. The mean date of NDVI maximum across the piedmont sites in 2000 was Julian day 119 ± 6 with a steady increase from 2001-2003 (125 ± 8 ; 128 ± 11 ; 127 ± 9) (Figures 15-18 & 25-28). The maximum decreased slightly by 2007 to day 123 ± 4 , however, a mean yearly increase of 0.25 days/year was observed over the entire sampling period (Figures 19, 29 & 31). Similar to the dates of onset, the dates of NDVI Maximum varied little from 2000-2007 from day 145 ± 6 days in the mountains, and day 120 ± 9 days on the coastal plain.

Greenup Length

Finally, taking a look at the mean differences of onset and NDVI maximum is a good indication of the rate at which greenup is occurring across North Carolina for the period sampled. The mean length of greenup shows a low in 2000 at 30 ± 9 days and increases steadily in 2001 (44 ± 14 days), 2002 (40 ± 14 days) to higher values in 2003 (48 ± 12 days) and 2007 (45 ± 8 days). The length of greenup increased from 2000-2007 at a mean rate of about 1.5 days/year with a mean total increase from 2000-2007 of 7 days. The estimates of greenup length are buffered by the increased variability in the estimates, so

the data are inconclusive as to existing trends. Again, estimates of greenup length in the mountains and coastal plain depicted a less significant trend across the sampling period (Table 3).

Slope of Greenup

The values associated with the slope of greenup obtained from the segmented model show a slight decrease in the rate of change across the sampled period. In 2000, the slope was its highest at 0.0180 ± 0.00297 . However, the slope decreases quickly in 2001 (0.0082 ± 0.00212) and 2002 (0.0100 ± 0.0048). There was a slight rebound in 2003 (0.0119 ± 0.0183), however the slope decreased again in 2007 (0.0074 ± 0.00183).

Climatic Regressions

This collection of variables were highly correlated with each other (Table 4), so by using the top three variables that captured the most variability in the data, we used their contribution to the strengths of the model as the most likely contributors to the NDVI response (Figure 32-34). In each of the model years, cumulative heat units, such as, growing degree days since last freeze, and soil characteristics, such as, mean soil temperature were the most significant predictors in determining the NDVI response (Table 5). Mean air temperature had a meaningful contribution to predicting the response in 2001, however, its contribution to overall R^2 was inconsistent over the study period (Table 5). Mean soil moisture captured the highest amount of variability in 2002 (0.65) and 2003 (0.28), but again, its contribution in other years was not significant. By using individual predictors to explain NDVI response, it is easier to remove variables like mean soil moisture and mean air temperature as being highly variable estimates that may not be

consistently good predictors of phenology. In all three years, growing degree-days since last freeze captured a significant proportion of the variability (0.527, 0.515, 0.338) in the model, and it likely has very close ties with mean soil temperature. Mean soil temperature was most likely the next best predictor of the NDVI response for all three years (0.765, 0.59, 0.309).

Initial time-series analyses showed, given low values of soil temperature and growing degree days since last freeze, a conditional plot of the predicted residuals from the NDVI response and Julian day can be explained by either predictor variables. However, as growing degree day since last freeze and mean soil temperature increase less and less of the variability in the residuals can be explained by these two variables, suggesting the influence of other explanatory variables not discussed by this study (Figure 36-37).

Discussion

My results showed that, though we only have a partial concept of daily spring phenology on the piedmont: (1) Daily processing of MODIS images to NDVI provides a much more appropriate sampling interval to estimate the phenological parameters than 16-day NDVI composites. (2) The Savitsky-Golay convolution filter provides an adequate means of signal processing for pixel-based phenological analyses. (3) Estimates of phenological parameters from segmented regression analyses provide a consistent method for identifying key spring phenology dates. (4) The effects of climate on spring phenology show a strong correlation with mean soil temperature and growing degree days since last freeze, however, describing the remaining variability is a matter for future studies.

Daily satellite imagery at a resolution that fits to daily phenology of individual patches is an incredibly fortunate occurrence. Aerosol and cloud frequency tend to increase at the same time that spring phenology is occurring, which limits the number of available images to analyze. Of the remaining images, some are still subject to low frequency noise that can be the result of haze or view angle differences. Temporal compositing and directional reflectance algorithms tend to limit this noise, however, they also tend to limit the number of available images to only the best over a longer time interval. In most cases, the selection of maximum NDVI values for a particular window are adequate when general trends in phenology are sought, however, precision and accuracy are compromised at the upper end of the sampling interval. Using lowpass filters, like the Savitsky-Golay convolution, approximates of the NDVI signal, but accounts temporally proximate variation in the response from view angle and cloud effects to present more

information throughout the sampling period. Unfiltered images would be the best examples of tying the satellite signal to actual vegetation dynamics, however, noise would still be a presiding impediment to this. In my opinion, by taking a lowpass filter approach, the user can both trace meaningful changes in both the sky conditions and phenological dynamics. Given the number of available images acquired and the number of NDVI rasters created for these analyses, it seems that there could be a use for cloudy images in spring phenology trend identification that was not addressed by this study. The creation of such a large dataset lends itself well to further analyses into forest dynamics, phenology, and land-cover change.

Given the number of available images, the Savitsky-Golay convolution was a good approximation of the distribution of actual sampled NDVI values. Variability in the distribution of data points was retained and consistent estimates from the segmented regression model provided further confidence in the smoothing technique.

However, it is evident that the determination of breakpoints is influenced by the available image interval. For example, the fewer samples there are over a longer period, the greater the probability that a breakpoint would be misplaced. The high temporal resolution of images prevented this from occurring, however, I am making the assumption that I am able to see the dates of greenup at an accuracy close to the mean sampling interval. Which in most of this analysis was between 2-3 days. Furthermore, my methods were designed to limit the influence of individual points in the time-series, and be based on the overall distribution of the time-series.

The segmentation analysis following the Savitsky-Golay filter was successful in describing the general trends associated with the onset and rate of change in spring as represented by 4 discrete dates: Julian date of Spring Onset, Rate of Change to NDVI maximum, Julian date of NDVI maximum, and the difference between the two breakpoint dates. However, the parameter estimates may be slightly biased according to a known vernal equinox shift that was not corrected for in this study (Sagarin, 2001). The high variability in dates of onset and NDVI maximum observed between sites is a matter for further study. Based on a cursory look at the climatic variables used in the AmeriFLUX regressions, all more or less do a good job at predicting the NDVI response, however, the remaining variability may be picked up from other site-specific environmental variables like; slope, aspect, cover type, and species composition that were not discussed in this study. Furthermore, the variability observed between years at the dates of onset and NDVI maximum asked the question is this beyond the level of natural variability, where a trend might exist? Or, what kinds of severe weather events happened within the study period that may have an impact on the following year's phenology?

Across all of the Piedmont sites there was no obvious distinction between urban and rural proximity to land cover. However, sites did show high variability between sites, between years, and ecoregions. From the data, spring onset across most sites occurred earlier than the other study years. It appeared the mean date of onset from latest to earliest year follows the order of; 2000, 2002, 2001, 2003 and 2007. Given the limited span of time in the dataset, concrete conclusions are hard to justify, however, for the selected years the

dates of onset is moving slightly earlier on average 1.1 days per year. Given the lack of historical records in North Carolina of the dates of spring onset, it is hard to determine if this is outside the natural range of variability. However, there has been recent evidence of earlier spring onset in other studies (Schwartz, 1994; Myneni et al. 1997; Zhang et al 2003). Furthermore, an image of severe weather events or climatic anomalies can potentially be observed in the exceedingly high variability in the phenology in 2003 (Figure 23). In study years preceding and following 2003, I did not observe such a high level of variability in dates of onset and NDVI maximum. One postulated reason this may have occurred could have been from delayed or erratic timing of budburst due to the worst drought in North Carolina's history in 2002 and/or a severe ice storm that occurred in December of 2002. This is a matter for further study, and this dataset may lend valuable insights into such events.

After conducting a regression analysis on the MODIS-NDVI response and climatic data from the AmeriFLUX site for 2001-2003, it is evident that hardwood spring phenology dynamics are most strongly correlated to changes in mean soil temperature and growing degree days since last freeze. In all three of the years studied, these two variables were both highly correlated with the NDVI response and were significant predictors of the response. The other variables studied on the dataset were all highly correlated, both with the response and among predictors; however, mean soil temperature and growing degree days since last freeze were the most significant predictors of the changes to NDVI. As discussed above, the inter-annual variability associated with these data appear to be increasing, as a consequence, the onset and duration of spring greenup are occurring

earlier and taking longer to reach a maximum. If continued monitoring of phenology is a priority, many of the climatic variables used in this study can conceivably be used as biophysical proxies of the NDVI response. In terms of the acquisition of the relevant data, I would recommend that effort be driven towards collecting cumulative heating units like, growing degree days, as being the most beneficial. Using existing national weather stations this data can be collected on a daily basis and potentially interpolated over the landscape to provide maps of variables to compliment the change in NDVI.

The decreasing influence of each of the predictors from 2001-2003 suggests that change in response may be due to more than just mean soil temperature and day since last freeze. It is hard to tell by limited number of variables measured, which is the presiding predictor, but based on initial time-series analysis the amount of residual variation tends to increase throughout spring, and is not captured fully by cumulative heating units or soil characteristics (Figure 35-36). Judging by hormonal signals released by root systems to trigger the production of leaves and plant growth, mean soil temperature as impacted by the days since last freeze may serve to act as a minimum requirement for onset to occur, considering its low variability compared with potentially wide fluctuations in air temperature. While mean soil temperature may be a sub-surface influence, days since last freeze can act as above ground inhibitors of bud hardiness and subsequent shoot development (Waring, 1967). Also, the increased variability in daily temperatures has an overall lengthening effect on the accumulation of heating degree units, seen as significant in other phenological models, and the differences between onset and NDVI maximum in this study (Jackson et al, 2001). These processes may serve to explain the change in

NDVI in the early parts of spring; however, the question remains for future studies to determine site variability, yearly variability, and the variability remaining in the residuals after potential predictors are accounted for.

Management Implications

Increasingly, realities associated with the global security of agriculture, biodiversity, and forest ecosystems are addressing the global implications of change measured by satellite imagery. Vegetation phenology is just one of the global processes that can be measured by such imagery to better monitor the extent and impacts of changing climate. By understanding the climatic cues associated with changes to forest structure, the timing of biological events can be anticipated to benefit human uses like the regrowth of forests and agricultural. Furthermore, not understanding how phenology is changing has broad impacts to food security in developing regions of the world. For farmers throughout the world, sowing a field too early before the onset of anticipated rains can have drastic results to the yield of their crop. Furthermore, for insects and pollinators that time their yearly growth cycle to the flowering of plants and trees, the offset of spring by several days has the potential to effect of the success of the next years survival. From this study, we can see that at least in the southeastern U.S., the dates of spring onset and the duration to NDVI maximum are becoming highly variable under constraints imposed by an increased variability in climate. The effects among sites and between years are a matter for further study, however, it appears air temperatures with a high amount of variability are effecting the overall heat accumulation and posing an increased risk of frost that can potentially threaten effective bud growth. With such a limited time-series it is hard to

determine if the range of variability seen here is beyond the natural range. Further monitoring and consistent updating of MODIS images should help to support this.

Conclusion

This analysis provided an effective means of exploring the parameters and trends associated with vegetation phenology from 2000-2007, where changing climate may be having an influence on forest phenology. After processing the available images to NDVI a detailed dataset was created to trace the variability in greenup throughout the spring. After employing a Savitsky-Golay filter to reduce the noise associated with the data. A segmented model was used to estimate phenological parameters like date of onset, rate of spring greenup, duration of spring greenup, and date of NDVI maximum. From 20 sites located across North Carolina, the largest variability in parameter estimates is located on the piedmont. On average, the date of onset has been pushed forward 1.1 days/year over the study period and lengthened 1.75 days/year. Uncertainty associated with the available data, lack of baseline information, shifting vernal equinox bias, and parameter estimation precludes me from extrapolating beyond the sampling period. When the NDVI values were compared with climatic variables the analysis showed that growing degree-days since last freeze and mean soil temperature were significant predictors of phenology from 2001-2003. Looking at the phenological response, as the dates of onset are changing the days since last freeze and the variability in air temperature increased to have coincident effects on soil temperature. Overall this increased variability in air temperatures and increase in potential freezing episodes can have broad impacts to forest growth and agriculture. Further monitoring should continue to use daily MODIS imagery to follow changes in NDVI, as well as, using data from existing weather stations to interpolate surfaces of potential predictors. Future study should address other site-specific environmental factors that are causing variability in the timing of phenological

parameters. As well as, determine the relative contribution that severe weather events and climatic anomalies have on local phenology between years. By continuing with such monitoring, we may be able to determine if the natural range of phenological variability is being altered, and what potential impacts this may have on biotic communities.

Literature Cited

- Ahl, D.E., S.T. Gower, S.N. Burrows, N.V. Shabanov, R.B. Myneni, Y. Knyazikhin. (2006). Monitoring spring canopy phenology of a deciduous broadleaf forest using MODIS. *Remote Sensing of the Environment* 104:88-95.
- Badeck, F-W., A. Bondeau, K. Böttcher, D. Doktor, W. Lucht, J. Schaber, S. Sitch (2004) Responses of spring phenology to climate change. *New Phytologist* 162 (2), 295–309.
- Baldocchi, D. 2006. Geographic distribution of plants and phenology. University of California, Berkeley.
- Bradley, N.L., A.C. Leopold, J. Ross & W. Huffaker. (1999) Phenological changes reflect climate change in Wisconsin. *Proceeding of the National Academy of Sciences, USA*, 96:9701-9704.
- Brugger, R., M. Dobberin & N. Krauchi. (2003). Phenological Variation in Forest Trees. *In Phenology: An Integrative Environmental Science*. Pp. 255-267 Kluwer Academic Publishers.
- Cayan, D.R., Kammerdiener, S.A., Dettinger, M.D. et al. (2001). Changes in the onset of spring in the western United States. *Bulletin of the American Meteorological Society*, 82:399-415.
- Chuine, I., Beaubien, E. (2001). Phenology is a major determinant of tree species range. *Ecology Letters*. 4:500-510.
- Cleveland, W.S. (1981). LOWESS: A program for smoothing scatterplots by robust locally weighted regression, *The American Statistician*. 35:54.
- Didan, K. & A. Huete. (2004). Analysis of the global vegetation dynamic metrics using MODIS vegetation index and land cover products. *IEEE*.
- Duchemin B, Goubier J, Courrier G.(1999). Monitoring phenological key stages and cycle duration of temperate deciduous forest ecosystems with NOAA/AVHRR data. *Remote Sensing of Environment*, 67, 68–82.
- ESRI. (2007). Arc Map Version 9.2. Redlands CA.
- Fitter, A.H., R.S.R. Fitter, I.T.B. Harris & M.H. Williamson. (1995). Relationships between first flowering date and temperature in the flora of a locality in central England. *Functional Ecology*, 149:55-60.
- Fitzjarrald, D.R., Avededo, O.C., Moore, K.E. (2001). Climatic consequences of Leaf presence in the eastern United States, *Journal of Climate*. 14:598-614.
- Harrington, R.I. Woiwood and T. Sparks. (1999). Climate Change and trophic interactions. *Trends in Ecology and Evolution*, 14:146-150.
- Huete, A.R. (1988). Adjusting vegetation indices for soil influences. *International Agrophysics*. 4:367-376.
- Huete, A., Justice, C., & Liu, H. (1994). Development of vegetation and soil indices for MODIS-EOS. *Remote Sensing of Environment*, 49, 224– 234.
- Huete, A. R., Liu, H. Q., Batchily, K., & van Leeuwen, W. J. D. (1997). A comparison of vegetation indices over a global set of TM images for EOS-MODIS. *Remote Sensing of Environment*, 59, 440–451.
- Huete, A., K. Didan, T. Miura, E.P Rodriguez, X. Gao, & L.G. Ferreira. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of the Environment*. 83:195-213.

- Huete, A & K. Didan. (2004). MODIS seasonal and inter-annual responses of semiarid ecosystems to drought in the southwest USA. *IEEE*.
- Hunter, A.F. & M.J. Lechowicz. (1992). Predicting the timing of budburst in temperate trees. *Journal of Applied Ecology*, 29: 597-604.
- Jackson, R.B., Lechowicz, M.J., Li, X. & Mooney, H.A. (2001). Phenology, growth and allocation in global terrestrial productivity. In: *Terrestrial Global Productivity*. Eds. Roy et al. Academic Press. Pp 61-82
- Loveland, T.R. & A.S. Belward. (1997). The IGBP-DIS global 1km land cover data set, DISCover from 1-km AVHRR data *International Journal of Remote Sensing*, 21:1303-1330.
- Lechowicz, M.J. (1984). Why do temperate trees leaf out at different times? Adaptation and ecology of forest communities. *American Naturalist*, 124:821-842
- Lechowicz, M.J. (1995). Seasonality of flowering and fruiting in temperate forest trees. *Canadian Journal of Botany*, 73:175-183.
- Lechowicz, M.J. (2001). Phenology, *In The Encyclopedia of Global Environmental Change*, Vol. 2. The Earth System: biological and ecological dimensions of global environmental change. Wiley, London,
- Leica Geosystems Geospatial Imaging, LLC. (2006) ERDAS: Imagine, v. 9.1. Worldwide Headquarters Norcross, GA 30092 USA.
- Lloyd, D. 1990. A phenological classification of terrestrial vegetation cover using shortwave vegetation index imagery. *International Journal of Remote Sensing*, 11, 2269–2279.
- Muggeo, V.M.R. (2003). Estimating regression models with unknown break-points. *Statistics in Medicine*. 22:3055-3071.
- Menzel, A. & P. Fabian. (1999). Growing season extended in Europe. *Nature*, 397: 659.
- Menzel, A. 2002. Phenology: Its importance to the global climate change community. *Climate Change*. 54:379-385.
- Myneni, R.B., C.D., Keeling, C.J. Tucker, G. Asrar, & R.R. Nemani. 1997. Increased plant growth in the northern high latitudes from 1981 to 1991. *Nature*, 386:698-701.
- Myneni, R.B., C.J. Tucker, G. Asrar & C.D. Keeling. (1998). Interannual variations in satellite-sensed vegetation index data from 1981-1991. *Journal of Geophysical Research*. 103:6145-6160.
- Moulin, S, L. Kergoat, N. Viovy, et al. 1997. Global-scale assessment of vegetation phenology using NOAA/AVHRR satellite measurements. *Journal of Climate*, 10, 1154–1170.
- Multi-Resolution Land Characteristics Consortium (MRLC). (2001) National Land Cover Dataset: 2001. Environmental Protection Agency. URL: <http://www.epa.gov/mrlc/>.
- Parmesan, C., N. Ryrholm, C. Stefanescu, J.K. Hill, C.D. Thomas, H. Descimon, B. Huntley, L. Kalla, J. Kullberg, T. Tammaru, W.J. Tennent, J.E. Thomas, M. Warren. (1999). Poleward shifts in geographical ranges of butterfly species associated with regional warming. *Nature*, 399: 579-583.
- Potter, C.S. & V. Brooks. (1998). Global analysis of empirical relations between annual climate and seasonality of NDVI. *International Journal of Remote Sensing*, 19:2921-2948.
- R Development Core Team (2007). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

- ISBN 3-900051-07-0, URL <http://www.R-project.org>.
- Reed, B.C., J.F. Brown, D. VanderZee, T.L. Loveland, J.W. Merchant, D.O. Ohlen, 1994. Measuring phenological variability from satellite imagery. Journal of Vegetation Science 5: 703-714.
- Reed, B.C., M. White, and J.F. Brown, 2003. Remote Sensing Phenology. Chapter 5 in Phenology: An Integrative Environmental Science, Kluwer Publishing, pp. 365-382.
- Reich, P.B. M.B., Walters, & D.S. Ellsworth. (1997). From tropics to tundra: Global convergence in plant functioning. Proceeding of the National Academy of Sciences of the USA, 94: 13730-13735.
- Rouse, J.W., Haas, R.H., Schell, J.A., Deering, D.W., Harlan, J.C. (1974). Monitoring the vernal advancement of retrogradation of natural vegetation, NASA/GSFC, Type III, Final Report, Greenbelt, MD, 371 pp.
- Sagarin, R. (2001). False estimates of the advance of spring. Nature 414:600.
- Savitsky, A. & M.J.E. Golay (1964). Smoothing and Differentiation of Data by Simplified Least Squares Procedures. Analytical Chemistry. 36:1627-1639.
- Schwartz, M.D. (1994). Monitoring global change with phenology: the case of the spring green wave. International Journal of Biometeorology. 38:18-22.
- Schwartz, M.D. (1998). Green-wave phenology. Nature. 394:839-840.
- Schwartz, M.D. & B.C. Reed. (1999). Surface phenology and satellite sensor-derived onset of greenness: an initial comparison. International Journal of Remote Sensing, 20(17):3451-3457.
- Schwartz, M.D., & T.M. Crawford. (2001). Detecting energy-balance modifications at the onset of spring. Physical Geography. 21:394-409.
- Schwartz, M.D., B.C. Reed, & M.A. White. 2002. Assessing satellite-derived start-of-season measures in the conterminous USA. Int. J. Climat. 22:1793-1805.
- Schwartz, M.D. 2003. Phenoclimatic Measures: Assessment of the Onset of Spring. . *In* Phenology: An Integrative Environmental Science. Pp. 255-267 Kluwer Academic Publishers.
- Sparks, T.H., & P.D. Carey. (1995). The responses of species to climate over two centuries: and analysis of the Marsham phenological record, 1736-1947. Journal of Ecology, 83:321-329.
- Taylor, F.G. (1974). Phenodynamics of production in a mesic deciduous forest. *In*: Phenology and Seasonality Modeling. Pp. 237-254. Ed. By H. Leith. Springer-Verlag, NY, NY, USA. 437 pp.
- United States Geological Survey. (2007). Land Processes Distributed Active Archive Center. MODIS Imagery Surface Reflectance Daily L2G Global 250m Vers. 005. Earth Resources Observation and Science Center (EROS) Sioux Falls, SD URL: <http://LPDAAC.usgs.gov>.
- Van Leeuwen, W.J.D., B.J. Orr, S.E. Marsh, & S.M. Herrman. (2006). Multi-sensor NDVI data continuity: Uncertainties and implications for vegetations monitoring applications Remote Sensing of the Environment, 100(1);67-81.
- Vermote, E.F., El Saleous, N.Z., Justice, C.O., Kaufman, Y.J., Privette, J., Remer, L., et al. (1997) Atmospheric correction of visible to middle infrared EOS-MODIS data over land surface, background, operational algorithm and validation, Journal of Geophysical Research, 102(14), 17131-17141.

- White, M.A., P.E. Thornton, S.W. Running. 1997. A continental phenology model for monitoring vegetation responses to interannual climatic variability. Global Biogeochemical Cycles, 11:217-234.
- White, M.A., F. Hoffman, W.W. Hargrove, and R.R. Nemani. 2005. A global framework for monitoring phenological responses to climate change. Geophysical Research Letters, 32:L0475, doi:10.1029/2004GL021961.
- White, M.A. & R.R. Nemani 2006. Real-time monitoring and short-term forecasting of Land surface phenology. Remote Sensing of the Environment. 104:43-49.
- Zhang, X., M.A. Friedl, C.B. Schaaf. et al. 2003. Monitoring vegetation phenology using MODIS. Remote Sensing of Environment, 84, 471–475.
- Zhang, X., Friedl, M.A., Schaaf, C.B., & Strahler, A.H. (2004). Climate controls on vegetation phenological patterns in northern mid- and high latitudes inferred from MODIS data. Global Change Biology, 10, 1-13.
- Zhang, X., M.A. Friedl, and C.B. Schaaf. 2006, Global vegetation phenology from Moderate Resolution Imaging Spectroradiometer (MODIS): Evaluation of global patterns and comparison with in situ measurements, J. Geophys. Res., 111, G04017, doi:10.1029/2006JG000217.

