

# Using Time Series Segmentation for Deriving Vegetation Phenology Indices from MODIS NDVI Data

Varun Chandola\*, Dafeng Hui†, Lianhong Gu‡, Budhendra Bhaduri\* and Ranga Raju Vatsavai\*

\*Geographic Information Science & Technology

Oak Ridge National Laboratory

Oak Ridge, TN 37831-6017

Email: chandolav,vatsavairr,bhaduribl@ornl.gov

†Department of Biological Sciences

Tennessee State University

Nashville, TN 37209

Email: dhui@tnstate.edu

‡Environmental Sciences Division

Oak Ridge National Laboratory

Oak Ridge, TN 37831-6017

Email: lianhong-gu@ornl.gov

**Abstract**—Characterizing vegetation phenology is a highly significant problem, due to its importance in regulating ecosystem carbon cycling, interacting with climate changes, and decision-making of croplands managements. While ground based sensors, such as the AmeriFlux sensors, can provide measurements at high temporal resolution (every hour) and can be used to accurately calculate vegetation phenology indices, they are limited to only a few sites. Remote sensing data, such as the Normalized Difference Vegetation Index (NDVI), collected using the MODerate Resolution Imaging Spectroradiometer (MODIS), can provide global coverage, though at a much coarser temporal resolution (16 days). In this study we use data mining based time series segmentation methods to derive phenology indices from NDVI data, and compare it with the phenology indices derived from the AmeriFlux data using a widely used model fitting approach. Results show a significant correlation (as high as 0.60) between the indices derived from these two different data sources. This study demonstrates that data driven methods can be effectively employed to provide realistic estimates of vegetation phenology indices using periodic time series data and has the potential to be used at large spatial scales and for long-term remote sensing data.

**Keywords**-vegetation phenology; time series; segmentation

## I. INTRODUCTION

Vegetation (or plant) phenology is the study of the timing of seasonal cycles of vegetation activity, such as onset of greening in the spring, timing of the maximum of the growing season, leaf senescence, vegetation dormancy, and the total length of growing season [1], [2]. Many such events are *recurring plant life cycle states* that are initiated by environmental factors and are sensitive to climatic variation and change [3], [4]. Thus, phenological studies can be used to evaluate the effects of climate change. Vegetation phenological stages of crops are also important indicators in

agricultural production, management, planning and decision-making [2], [5]. In addition, vegetation phenology is important for predicting ecosystem carbon, nitrogen, and water fluxes [6], [7], as the seasonal and interannual variation of phenology have been linked to net primary production estimation, crop yields, and water supply [8], [9]. Variability in growing season length is likely to have a direct impact on the ecosystem carbon and water balances [9], [10]. Characterization of vegetation phenology at site, regional, and national scales has been recognized as important for many scientific and practical applications [2]. Accurate assessment of phenological events, therefore, becomes increasingly vital for investigating vegetation-climate interactions, quantifying ecosystem fluxes and croplands managements [11].

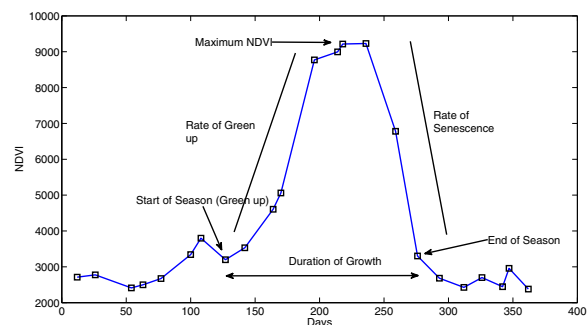


Figure 1. Phenological Characteristics from NDVI Time Series for a Cropland Site (Bondville, USA, 2006)

Vegetation phenology can be assessed using different approaches at scales from small plots to large spatial

scales. Field phenology measurements can be conducted using methods such as manual observations, digital camera automatic recording [12], and plant area index measurements using LAI-2000 Plant Canopy Analyzer [13], and ecological modeling [14]. The data obtained from ground sensors which are a part of the *AmeriFlux* network<sup>1</sup> have been used to study vegetation phenology. But such methods are constrained to limited spatial extents and to limited ecosystems. At large spatial scales, remotely sensed data such as these from the Advanced Very High Resolution Radiometer (AVHRR) and the MODerate resolution Imaging Spectroradiometer (MODIS) sensors are commonly used [15]. MODIS vegetation products such as Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) have been proved to be effective for quantifying vegetation greenness, canopy carbon and water fluxes [16], [17] and monitoring the phenological changes of vegetation across large spatial scales and over long time periods [18]–[20]. Figure I shows some of the phenological characteristics in an annual NDVI time series. Particularly, the vegetation products generated from MODIS onboard Terra and Aqua offer an unprecedented opportunity for researchers to develop long-term records of vegetation phenology at spatial scales as small as 250 m [21].

Recent efforts in phenology studies have been focused on developing new techniques or improving methods for estimating specific dates of vegetation transitions with improved satellite data e.g., MODIS-NDVI, EVI [15], [21], [22]. Most of these methods analyze the vegetation time series (NDVI, EVI) for each spatial location and can be grouped into the following four broad categories [22]: *threshold based* [23], *derivatives based* [24], *smoothing functions based* [25], [26], and *model fitting based* [27]–[29]. These methods have been developed for a particular vegetation type or specific geographical areas, and thus are not globally applicable. Data mining based methods, which do not rely on vegetation specific and geographical assumptions, can provide such globally applicable methods. While several data mining based methods have been applied to remote sensing data for tasks such as crop classification [30], [31] and change detection [32]–[34], there has not been significant application of data mining methods for identification of phenological characteristics from remote sensing data.

In the paper we investigate how data mining based methods can be used to extract phenology characteristics from remote sensing data. We pose the problem of phenology identification from remote sensing data, as a time series segmentation problem. Several data mining based time series segmentation methods have been proposed in literature which identify homogenous segments in a given time series. We investigated two such methods, *bottom up segmentation* [35] and *piecewise linear regression* [36], [37].

These time series segmentation based methods have the potential to detect key phenological indices such as the onset of vegetation green-up, end of plant growth, and length of growing seasons for a range of ecosystems and vegetation types. We applied this method to 43 AmeriFlux sites and derived phenological indices using the MODIS NDVI data. To validate the methods, we also derived field phenology using a model fitting method [29] based on *Net Ecosystem Exchange* (NEE) data measured by the eddy covariance sensors at the AmeriFlux sites. One frequently mentioned pitfall for satellite derived phenology study is the lack of comparable ground-based phenology measurements. Since the NEE data measured ecosystem carbon flux of whole ecosystem with footprints similar to a pixel of MODIS NDVI measurement, these phenological indices were more comparable. The major objectives of this study were 1) to derive vegetation phenological indices using time series segmentation based methods at selected AmeriFlux sites using MODIS NDVI data; and 2) to compare the phenological indices with field estimations from NEE data. We focused on identifying the green-up or start of season (SOS) index, though same methodology can be applied for other phenology indices.

## II. RELATED WORK

Existing methods that analyze remote sensing data (specifically, NDVI time series) for identifying SOS and other phenological indices can be broadly grouped into four categories [22], viz., *threshold based*, *derivatives based*, *smoothing functions based*, and *model fitting based*. Threshold based methods apply a pre-specified threshold on the NDVI values and determine the day when the NDVI value crosses the threshold to estimate SOS [23]. While such methods are simple to apply, their performance is highly reliant on specifying an optimal threshold, which is a challenging task, especially since the NDVI time series are often noisy. Derivatives based methods [24] generally accept the maximal increase in NDVI as the SOS. Such methods cannot handle the noise in the time series, and hence often find it challenging to differentiate between actual change in the NDVI and the change induced by the noisy data. The smoothing function based methods account for the noise by smoothing the time series data using methods such as moving average [26] and fourier analysis [25]. The drawback of such methods are that they tend to smooth out the presence of interesting disturbances in the data. Model fitting based methods fit multiple mathematical models to the time series such as logistic models [29], Gaussian local functions [27], and quadratic models [28]. A key limitation of using mathematical models is that they entail estimation of multiple parameters (sometimes more than 4), which is challenging with limited annual observations in NDVI data.

Time series segmentation has been a widely researched problem in statistics and data mining community. Methods

<sup>1</sup><http://public.ornl.gov/ameriflux/index.html>

for time series segmentation can be broadly classified into four categories, viz., *linear model based*, *polynomial model based*, *signal processing based*, and *non-parametric* methods. Linear model based methods identify segments in a given time series, such that each segment can be explained using a linear model, such as a linear regression model [36], [37]. Polynomial model based methods employ non-linear models for each segment [38]. Signal processing based methods employ methods such as wavelets [39] and fourier transforms [40] to approximate the given time series in terms of a set of functions, where each function corresponds to a segment. Non-parametric methods have been developed in the data mining community. The objective of such methods is to greedily obtain a segmentation of the given time series which optimizes an objective criterion [32], [35]. In this paper, we investigate two such time series segmentation method [35] for identifying SOS from NDVI time series.

### III. PROBLEM STATEMENT

The problem studied in this paper is to identify phenology characteristics from a given annual NDVI time series (See Figure I). Typically, following indices are retrieved:

- 1) Onset of vegetation green-up or start of the season (SOS).
- 2) End of plant growth or end of the seasons (EOS).
- 3) Timing of the maximum of the growing season.
- 4) Length of the growing season.

In this paper we will focus on the SOS index only. Based on the estimates of the SOS, the second problem studied in this paper is to identify annual trends in the SOS for each spatial location.

### IV. METHODS FOR PHENOLOGY IDENTIFICATION

In this section, we briefly describe the methods that we have applied for identifying the phenology characteristics from observational time series. The first method is a model fitting based technique which was developed for ground sensor observations collected from AmeriFlux sites [29]. The second method is a mining based time series segmentation algorithm applied to the problem of phenology identification.

#### A. Model Fitting Based Phenology Identification

The *double logistic curve fitting* method [29] fits a composite growth function to the plant canopy photosynthesis observations, obtained from the AmeriFlux sensors. The composite growth function can be written as:

$$A(t) = y_0 + \frac{a_1}{\left[1 + \exp\left(-\frac{t-t_{01}}{b_1}\right)\right]^{c_1}} + \frac{a_2}{\left[1 + \exp\left(-\frac{t-t_{02}}{b_2}\right)\right]^{c_2}} \quad (1)$$

where  $A(t)$  is the observation on day  $t$ , and  $(y_0, a_1, a_2, b_1, b_2, c_1, c_2, t_{01}, t_{02})$  are the model parameters

to be estimated from the given data. Based on the model parameters, the SOS can be estimated as:

$$SOS = t_{PRD} - A_p \frac{t_{PRD}}{k_{PRR}} \quad (2)$$

where,  $t_{PRD}$  or the peak recession day is computed as:

$$t_{PRD} \approx t_{01} + b_1 \ln c_1 \quad (3)$$

and,  $k_{PRR}$  or the peak recovery rate is the growth rate of  $A(t)$  ( $= \frac{dA(t)}{dt}$ ) on the peak recession day, i.e.,  $k_{PRR} = k(t_{PRD})$ . Other phenological indices, such as EOS, can also be estimated in a similar fashion [29].

#### B. Time Series Segmentation Based Phenology Identification

The time series segmentation based methods “break” the given time series into  $k$  segments, such that each segment is homogenous based on an objective function. The most widely used objective function is linear, i.e., the task is to break the time series into  $k$  straight lines. While most methods do not assume that  $k$  is known, for the purpose of phenology identification,  $k$  is fixed at 5 (See Figure I). This relaxation also makes the problem computationally more tractable. It should be noted that the objective of the segmentation algorithms is to find the segmentation with lowest reconstruction error and are not specifically designed to extract the phenological features. In this paper we are exploring the hypothesis that such methods, though not directly utilizing any phenology related information, are still applicable to the task of phenology identification.

1) *Piecewise Linear Regression*: The first segmentation method entails fitting multiple straight lines using linear regression [37]. The objective function to evaluate a potential segment is to compute the residual error of the fitted linear regression model. The brute force segmentation method finds all possible segmentations of the time series and then evaluates each candidate segmentation using the sum of the residual errors for each segment. The segmentation with the lowest total residual error is chosen as the final segmentation. But the same segmentation can be achieved using a faster *dynamic programming* based implementation [41] which computes the segmentation for a time series of length  $t$  using the optimal segmentation obtained for  $t - k$  ( $k = 1, 2, \dots$ ) length prefixes of the time series.

2) *Bottom Up Segmentation*: Keogh et al [35] describe the heuristic based bottom up segmentation algorithm. The algorithm starts with the finest possible segmentation of the original time series of length  $t$ , i.e., with  $t/2$  segments. Next, the algorithm computes the cost of merging every adjacent pair of segments and iteratively merges the lowest cost pair. This process is repeated until only  $k$  segments are left. The cost of merging can be computed in multiple ways, using methods such as linear interpolation or linear regression. In this paper we explore bottom up segmentation used with linear interpolation.

## V. EXPERIMENTAL RESULTS

We present results comparing the SOS index estimated by the segmentation based methods (See Section IV-B) using the MODIS NDVI data to the index estimated by the model fitting method (See Section IV-A) using the AmeriFlux data across several AmeriFlux sites.

### A. Data

1) *AmeriFlux Data*: The analysis on AmeriFlux data was based on gross canopy photosynthetic rates (GPP) which were derived from NEE. Compared to NEE, using GPP to derive phenology indices avoids some short-term influences of soil temperature and moisture influences on ecosystem respiration, and provides more stable estimation of phenology indices [29]. To compare the phenology indices derived from MODIS data and NEE measurements at AmeriFlux sites, we selected sites with at least three years of flux measurements after 2002. 43 sites were selected, including 7 deciduous forests, 8 coniferous forests, 5 grasslands, and 9 croplands. Totally, we obtained 131 annual cycles for these 43 sites where both AmeriFlux and MODIS data was available. Level 4 GPP data for the chosen sites was downloaded at the AmeriFlux website<sup>2</sup>. While original data was available at half hour time intervals, we chose the daily maximum value to construct daily time series for each site. The gaps in the level 4 GPP data are filled using two methods, *Artificial Neural Network* (ANN) based [42] and *Marginal Distribution Sampling* (MDS) based [43]. We experimented with both types of data and found that the phenology indices derived were very similar. Thus, only the MDS gap-filled data were used in the phenology analysis.

2) *MODIS Data*: For each of the 43 selected AmeriFlux sites, we downloaded MODIS NDVI time series from 2002 onwards. Annual MODIS NDVI time series (See Figure 1 consists of 23 observations (one observation every 16 days). Each observation is accompanied with a reliability code; observations with non-zero reliability code were treated as missing. Missing values were imputed using a *Gaussian process* based time series forecasting method [34]. The NDVI time series were smoothed using the *Savitzky Golay* time series filter [44] available in MATLAB.

### B. Comparison of Results Using MODIS NDVI and AmeriFlux GPP Data

We compare the model fitting based SOS estimates using the method proposed by Gu et al. [29] (referred to as MF) on AmeriFlux data with the estimates using the bottom up segmentation (BU) and piecewise linear regression (LR) methods on MODIS data. For comparison, we also applied the MF method on MODIS data. Note that when estimating SOS for MODIS data using the MF method, only 59 annual cycles (26 AmeriFlux sites) yielded estimates, while for

Method	Correlation	$p$ -value	Average Abs. Difference
BU	0.51	0.00	23.43
LR	<b>0.65</b>	0.00	22.16
MF	0.40	0.04	32.64

Table I  
COMPARISON BETWEEN ESTIMATES USING DIFFERENT METHODS ON MODIS DATA AND ESTIMATES USING MF METHOD ON AMERIFLUX DATA

other 72 cycles the number of observations in annual NDVI data was not sufficient for estimating the model parameters. Figure 2 show the scatter plots for the three different comparisons, each data point corresponds to the averaged SOS estimates across multiple years for a single site. For each plot, we also show the linear fit and the  $R^2$  values for the fitted data. Comparison between the estimates using three methods on MODIS data and the MF estimates using AmeriFlux data (correlation and average absolute difference) are shown in Table I.

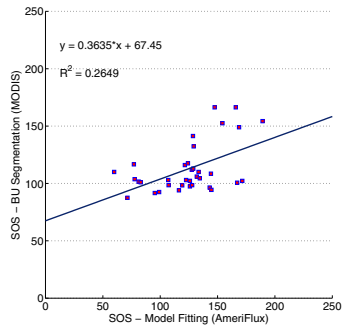
Results in Figure 2 and Table I indicate that for MODIS NDVI data, the time series segmentation based methods are significantly better than the model fitting based method in terms of agreement with the estimates obtained from the AmeriFlux data. The correlation between the estimates using the piecewise linear regression based method (LR) on MODIS data and the estimates using the model fitting based method (MF) on the AmeriFlux data is the highest (0.65) while the correlation between the estimates using the MF method on AmeriFlux and MODIS data is the lowest (0.40). Additionally, a shortcoming of the MF method is that it fails to estimate the model parameters for most of the MODIS time series. The average absolute difference from the MF estimates using AmeriFlux data for BU method is 23 and for LR method is 22, which is reasonable given the fact that NDVI observations are 16 day composites.

## VI. CONCLUSIONS

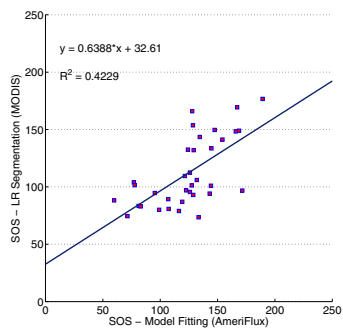
The prime objective of this study was to evaluate data mining based time series segmentation methods to determine key phenological indices of terrestrial ecosystems based on satellite remote sensing products. Our results demonstrated that the two methods evaluated in this paper were able to detect the start of the growing season for a range of ecosystems and at different locations. The detection methods were also quite robust and able to deal with a variety of situations including missing values due to clouds, possible outliers, and did not require ancillary information and expert knowledge.

One classic criticism of remote sensing phenology studies is the validation of satellite data derived phenology, as the field-based phenological observations are usually sparse and do not cover the full climate range. Validation is also complicated by the fact that the satellite derived

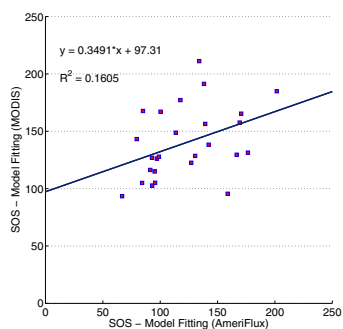
<sup>2</sup><http://public.ornl.gov/ameriflux/fairuse.cfm>



(a) MF (AmeriFlux) vs. BU (MODIS)



(b) MF (AmeriFlux) vs. LR (MODIS)



(c) MF (AmeriFlux) vs. MF (MODIS)

Figure 2. Comparison of SOS estimates using different methods on AmeriFlux GPP and MODIS NDVI data.

phenological indices are not compatible with traditional field phenological indices. Direct comparisons of remote sensing phenology with field observations are mostly problematic because 1) field observations are measured for relatively smaller areas (from 1 to 100  $m^2$ ) compared to the remote sensing observations which correspond to coarser spatial resolution ( $> 250m^2$ ), 2) geo-location uncertainties, and 3) limited temporal sampling for remote sensing observations. Flux based phenology provides a general measurement of the photosynthetic activity of the whole vegetation cover. In this study, we derived field phenological indices based on eddy covariance measurements which have footprints similar to

the scale of MODIS NDVI which had a high resolution of 250 m. Since the MODIS NDVI data were retrieved at pixels where the eddy flux towers were centered, the phenological indices derived from these two data sources were more comparable. Indeed, our results demonstrate that there is a good correspondence of the phenological indices between the satellite approach and the eddy flux method, with a correlation of 0.65 between the time series segmentation based approach using satellite data and the traditional model fitting based approach using the eddy covariance data.

This study demonstrated that the data mining based time series segmentation methods can be applied to remote sensing satellite data such as MODIS NDVI to derive the vegetation phenology. Satellite phenology allows monitoring of terrestrial vegetation on a global scale and provides an integrative view at the landscape level [45]. Any requirement to document vegetation phenology over large areas will have to rely on remote sensing, even though these observations may only be indirectly related to the events [46]. As more satellite data is being collected, long-term vegetation phenology at different spatial scales can be derived from these measurements.

#### REFERENCES

- [1] M. A. White *et al.*, "A global framework for monitoring phenological responses to climate change," *Geophysical Research Letters*, v. 32, 2005.
- [2] G. Upadhyay *et al.*, "Derivation of crop phenological parameters using multi-date SPOT-VGT-NDVI data: A case study for punjab," *Journal of the Indian Society of Remote Sensing*, v. 36, no. 1, pp. 37–50, 2008.
- [3] F.-W. Badeck *et al.*, "Responses of spring phenology to climate change," *New Phytologist*, v. 162, no. 2, pp. 295–309, 2004.
- [4] E. Graham *et al.*, "Public internet-connected cameras used as a cross-continental ground-based plant phenology monitoring system," *Global Change Biology*, 2010.
- [5] J. Xin *et al.*, "Mapping crop key phenological stages in the north china plain using noaa time series images," *International Journal of Applied Earth Observation and Geoinformation*, v. 4, no. 2, pp. 109 – 117, 2002.
- [6] D. D. Baldocchi *et al.*, "Predicting the onset of net carbon uptake by deciduous forests with soil temperature and climate data: a synthesis of fluxnet data," *International Journal of Biometeorology*, v. 49, pp. 377–387, 2005.
- [7] A. D. Richardson *et al.*, "Influence of spring phenology on seasonal and annual carbon balance in two contrasting new england forests," *Tree Physiol*, v. 29, no. 3, pp. 321–331, 2009.
- [8] J. D. Aber *et al.*, "Predicting the effects of climate change on water yield and forest production in the Northeastern United States," *Climate Research*, v. 5, no. 207-222, 1995.
- [9] J. P. Jenkins *et al.*, "Detecting and predicting spatial and interannual patterns of temperate forest springtime phenology in the eastern U.S." *Geophysical Research Letters*, v. 29, no. 2201, 2002.

- [10] T. A. Black *et al.*, “Impact of spring temperature on carbon sequestration by a boreal aspen forest,” *The Role of Boreal Forests and Forestry in the Global Carbon Budget*, 2000.
- [11] M. Li *et al.*, “Investigating phenological changes using MODIS vegetation indices in deciduous broadleaf forest over continental u.s. during 2000-2008,” *Ecological Informatics*, 2010.
- [12] A. Richardson *et al.*, “Use of digital webcam images to track spring green-up in a deciduous broadleaf forest,” *Oecologia*, v. 152, pp. 323–334, 2007.
- [13] G. Deblonde *et al.*, “Measuring leaf area index with the Li-Cor LAI-2000 in pine stands,” *Ecology*, v. 75, no. 5, pp. 1507–1511, 1994.
- [14] M. Boschetti *et al.*, “Agro-ecological modelling for monitoring rice productions: contribution of field experiment and multi-temporal eo data,” in *Remote Sensing for Agriculture, Ecosystems, and Hydrology VII*, M. Owe and G. D’Urso, Eds., v. 5976, 2005.
- [15] M. White *et al.*, “Intercomparison, interpretation, and assessment of spring phenology in North America estimated from remote sensing for 1982-2006,” *Global Change Biology*, v. 20, no. 10, pp. 2335–2359, 2009.
- [16] X. Xiao *et al.*, “Modeling gross primary production of an evergreen needleleaf forest using MODIS and climate data,” *Ecological Applications*, v. 15, no. 3, pp. 954–969, 2005.
- [17] ———, “Mapping paddy rice agriculture in south and southeast asia using multi-temporal MODIS images,” *Remote Sensing of Environment*, v. 100, no. 1, pp. 95 – 113, 2006.
- [18] T. Sakamoto *et al.*, “A crop phenology detection method using time-series MODIS data,” *Remote Sensing of Environment*, v. 96, no. 3-4, pp. 366 – 374, 2005.
- [19] X. Zhang *et al.*, “Global vegetation phenology from moderate resolution imaging spectroradiometer (MODIS): Evaluation of global patterns and comparison with in situ measurements,” *Journal of Geophysical Research*, v. 111, 2006.
- [20] H. Yan *et al.*, “Modeling gross primary productivity for winter wheat-maize double cropping system using MODIS time series and CO<sub>2</sub> eddy flux tower data,” *Agriculture, Ecosystems and Environment*, v. 129, no. 4, pp. 391 – 400, 2009.
- [21] D. E. Ahl *et al.*, “Monitoring spring canopy phenology of a deciduous broadleaf forest using MODIS,” *Remote Sensing of Environment*, v. 104, no. 1, pp. 88 – 95, 2006.
- [22] K. M. Beurs and G. M. Henebry, “Spatio-temporal statistical methods for modeling land surface phenology,” in *Phenological Research*, I. L. Hudson and M. R. Keatley, Eds. Springer Netherlands, 2010, pp. 177–208.
- [23] M. A. White *et al.*, “A continental phenology model for monitoring vegetation responses to interannual climatic variability,” *Global Biogeochemical Cycles*, v. 11, pp. 217–234, 1997.
- [24] H. Balzter *et al.*, “Coupling of vegetation growing season anomalies and fire activity with hemispheric and regional-scale climate patterns in central and east siberia,” *Journal of Climate*, v. 20, no. 15, pp. 3713–3729, 2007.
- [25] A. Moody and D. M. Johnson, “Land-surface phenologies from avhrr using the discrete fourier transform,” *Remote Sensing of Environment*, v. 75, no. 3, pp. 305 – 323, 2001.
- [26] S. Archibald and R. Scholes, “Leaf green-up in a semi-arid african savanna - separating tree and grass responses to environmental cues,” *Journal of Vegetation Science*, v. 18, no. 4, pp. 583–594, 2007.
- [27] P. Jonsson and L. Eklundh, “Seasonality extraction by function fitting to time-series of satellite sensor data,” *Geoscience and Remote Sensing, IEEE Transactions on*, v. 40, no. 8, pp. 1824 – 1832, aug 2002.
- [28] K. M. Beurs and G. M. Henebry, “A statistical framework for the analysis of long image time series,” *International Journal of Remote Sensing*, v. 26, no. 8, pp. 1551–1573, 2005.
- [29] L. Gu *et al.*, “Characterizing the seasonal dynamics of plant community photosynthesis across a range of vegetation types,” in *Phenology of Ecosystem Processes*, A. Noormets, Ed. Springer New York, 2009, pp. 35–58.
- [30] B. Bradley and J. Mustard, “Comparison of phenology trends by land cover class : a case study in the great basin, USA,” *Global Change Biology*, v. 14, no. 2, pp. 334–346, 2008.
- [31] G. Jun *et al.*, “Spatially adaptive classification and active learning of multispectral data with gaussian processes,” in *ICDMW ’09*, 2009, pp. 597–603.
- [32] S. Boriah *et al.*, “Land cover change detection: a case study,” in *Proceeding of the 14th KDD*, 2008, pp. 857–865.
- [33] R. R. Vatsavai, “Phenological event detection from multitemporal image data,” in *SensorKDD ’09: Proceedings of the Third International Workshop on Knowledge Discovery from Sensor Data*. New York, NY, USA: ACM, 2009, pp. 49–55.
- [34] V. Chandola and R. R. Vatsavai, “Scalable time series change detection for biomass monitoring using gaussian process,” in *Proceeding of the NASA Conference on Intelligent Data Understanding*, 2010.
- [35] E. Keogh *et al.*, “An online algorithm for segmenting time series,” in *ICDM 2001: Proceedings of the first IEEE International Conference on Data Mining*, 2001, pp. 289–296.
- [36] D. M. Hawkins, “Point estimation of the parameters of piecewise regression models,” *Applied Statistics*, v. 25, no. 1, pp. 51–57, 1976.
- [37] J. Liu *et al.*, “On segmented multivariate regression,” *Statistica Sinica*, v. 7, pp. 497–526, 1997.
- [38] V. Guralnik and J. Srivastava, “Event detection from time series data,” in *KDD ’99*, 1999, pp. 33–42.
- [39] M. Sharifzadeh *et al.*, “Change detection in time series data using wavelet footprints,” *Advances in Spatial and Temporal Databases*, pp. 127–144, 2005.

- [40] T. Ogden and E. Parzen, "Change-point approach to data analytic wavelet thresholding," *Statistics and Computing*, v. 6, no. 2, pp. 93–99, 1996.
- [41] D. M. Hawkins, "Fitting multiple change-point models to data," *Computational Statistics & Data Analysis*, v. 37, no. 3, pp. 323–341, 2001.
- [42] D. Papale and A. Valentini, "A new assessment of European forests carbon exchanges by eddy fluxes and artificial neural network spatialization," *Global Change Biology*, v. 9, pp. 525–535, 2003.
- [43] M. Reichstein *et al.*, "On the separation of net ecosystem exchange into assimilation and ecosystem respiration: review and improved algorithm," *Global Change Biology*, v. 11, no. 9, pp. 1424–1439, 2005.
- [44] A. Savitzky and M. J. E. Golay, "Smoothing and differentiation of data by simplified least squares procedures," *Analytical Chemistry*, v. 36, pp. 1627–1639, 1964.
- [45] S. Studer *et al.*, "A comparative study of satellite and ground-based phenology," *International Journal of Biometeorology*, v. 51, pp. 405–414, 2007.
- [46] J. Verbesselt *et al.*, "Detecting trend and seasonal changes in satellite image time series," *Remote Sensing of Environment*, v. 114, no. 1, pp. 106 – 115, 2010.