



Multi-criteria evaluation of the suitability of growth functions for modeling remotely sensed phenology



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ABSTRACT

Reliable information related to vegetation phenology is required to improve understanding of land–atmosphere coupling and the biosphere's response and feedbacks to climate change. The logistic function is commonly used to model bounded growth and decay and extract phenological information from remotely sensed vegetation indices. However, several other growth functions can also model bounded growth and decay and may have more desirable properties than the logistic function for capturing deciduous forest phenology. We employed three complimentary criteria and evaluated the suitability of the Gompertz, logistic, mirror-Gompertz, and Richards functions to reliably capture remotely sensed phenology of deciduous forests. Our analyses showed that although all the four growth functions fit remotely sensed data equally well, their ability to capture rapidly changing phenology early in spring and late in fall differs significantly. Using 10 years of field measurements from two deciduous forest sites in the northeastern United States, we showed that dynamics in the fraction of absorbed photosynthetically active radiation (FAPAR) phenology is asymmetric in both spring and fall. It develops more rapidly early in spring and decays more rapidly late in fall. A flexible function that can capture these asymmetric dynamics is likely to capture the phenological development and the transition dates better. Comparison with field measurements of start-of-season (SOS), end-of-season (EOS), and growing period length (GPL) confirmed this. Mean differences between modeled and observed GPL was 13.5 and 18.5 days for the Richards and logistic function, respectively, at Harvard Forest and 2.6 and 7.1 days, respectively at Hubbard Brook Forest. Our analyses also showed that FAPAR and normalized difference vegetation index have a strong linear relationship in spring, but correlate poorly in fall. Our results suggest that a flexible function like Richards is likely to be more reliable for modeling phenology and retrieving information of transitions events from remotely sensed NDVI.

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1. Introduction

Vegetation phenology exerts important controls on biophysical and biochemical exchanges between the land surface and the atmosphere (Sellers and Hall, 1992). Phenology also regulates primary productivity in forests and agricultural systems (Angert et al., 2005; Buermann et al., 2007), and is recognized as a simple yet powerful integrator of the biosphere's response to climate change (Menzel, 2000; Chuine et al., 2004). High quality information about the timing of phenological transition events, especially the start-of-season (SOS), the end-of-season (EOS), and the photosynthetically

active growing period length (GPL), is thus required to estimate seasonal and interannual variations in ecosystem productivity and to improve our understanding of dynamic interactions between the atmosphere and biosphere. At the large spatial scales, remotely sensed data from sensors such as the Advanced Very High Resolution Radiometer (AVHRR), the Moderate Resolution Imaging Spectroradiometer (MODIS), and the Satellite Pour l'Observation de la Terre (SPOT) are the only source of repeated and consistent observations of phenology (Reed et al., 1994). As a consequence, remotely sensed estimates of phenology are now widely viewed to be an important source of information for studying ecosystem dynamics in response to climate variability and change (Hufkens et al., 2012).

The seasonal pattern of variation in terrestrial ecosystems observed from remote sensing is often referred to as land surface phenology, and a number of remote sensing algorithms have been

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developed to model seasonal dynamics and extract information on phenological transition events (Olsson and Eklundh, 1994; Moulin et al., 1997; Moody and Johnson, 2001; Beck et al., 2006; Fisher et al., 2006; Hermance et al., 2007). However, because ground truth data are rare and are generally not collected using sample designs or at spatial scales commensurate with requirements validating results from remote sensing, the relative merits of different algorithms are poorly understood (Liang and Schwartz, 2009). Indirect measures of phenology related to river stage and discharge, snow melt, and climate have been used for validation (e.g. White et al., 2009), but it is not clear if the uncertainty in these data sets is significantly less than the uncertainty associated with estimates obtained from remote sensing. Further, recent studies have found that phenological information obtained by different algorithms do not correlate well with one another (White et al., 2009; Schwartz and Hanes, 2010).

Most remote sensing algorithms, either implicitly or explicitly, assume that pixel-scale phenology follows a well-defined seasonal trajectory. As a result, both parametric and non-parametric models have been used to capture this trajectory (see Hermance et al., 2007, for a succinct summary). They also assume that phenological transition events occur at specific points in the modeled trajectory that satisfy well-defined criteria or conditions (de Beurs and Henebry, 2004). While these two assumptions form the core of nearly every algorithm, their justification has not been rigorously considered. Many land surface phenology algorithms use piecewise or double logistic functions to model seasonal dynamics in remotely sensed vegetation indices (Jönsson and Eklundh, 2002; Ahl et al., 2006; Soudani et al., 2008; Beck et al., 2006; Hird and McDermid, 2009; Atkinson et al., 2012). This approach is also widely used to model field observations of plant phenology (Richardson et al., 2006). The logistic function is favored because it readily models bounded growth, enabling easy and rapid determination of phenological transition events. Bounded irreversible growth can, however, be modeled by many different growth functions including the Gompertz, mirror-Gompertz, Bertalanffy, Weibull, Richards, and expolinear functions (Gompertz, 1825; Richards, 1959; Morris and Silk, 1992; Katsanevakis, 2006; Buchwald, 2007). Although, all of these growth functions model bounded growth and decay, they differ significantly from one another in representing underlying dynamics as the variable of interest progresses from the lower asymptote to the upper asymptote, and vice versa. It is therefore likely that these differences affect the ability of these functions to model land surface phenology, and by extension, to capture phenological transition events. To date, however, no comprehensive assessment of this issue has been performed and it has been widely assumed that logistic function is the most suitable (Fisher et al., 2006).

In this study we assessed the comparative suitability of four bounded growth functions to model land surface phenology in temperate deciduous forests in the northeastern United States. We evaluated the logistic, Gompertz, and Richards functions for modeling spring phenology, and the logistic, mirror-Gompertz and Richards functions for modeling fall phenology. Given the limited availability of field data for validating phenological transition dates estimated from remote sensing, we employ three independent but complimentary criteria to perform this assessment. First, we compared rates of phenological change predicted by each growth function to observed rates of phenological change based on high temporal resolution field measurements of the fraction of absorbed photosynthetically active radiation (FAPAR) collected at two field sites in New England. Second, we analyzed how well each model fits MODIS normalized difference vegetation index (NDVI) data from “pure” deciduous forest pixels. Finally, we compared estimates of SOS, EOS and GPL retrieved by each of the growth functions with corresponding estimates obtained from long-term

Table 1

Form of four growth functions, whose suitability to model and retrieve phenological information from remotely sensed normalized difference vegetation index (NDVI) is examined in the study. In the equations below, t is time, $C(t)$ the remotely sensed canopy state at time t , C_{\max} is the upper asymptote, C_{\min} the lower asymptote, k is the growth rate, $t(m)$ is the time at inflection point, and S is a shape parameter. The equations below show the form employed for spring growth, when $C(t)$ progresses from C_{\min} to C_{\max} .

Function	Form
Logistic	$C(t) = C_{\min} + \frac{C_{\max} - C_{\min}}{1 + \text{Exp}^{-k(t - t(m))}}$
Gompertz	$C(t) = (C_{\max} - C_{\min}) * \text{Exp}^{-\text{Exp}^{-k(t - t(m))}}$
Mirror-Gompertz	$C(t) = (1 - (C_{\max} - C_{\min})) * \text{Exp}^{-\text{Exp}^{-k(t - t(m))}}$
Richards	$C(t) = C_{\min} + \frac{C_{\max} - C_{\min}}{\left[1 + S * \text{Exp}^{-k(t - t(m))}\right]^{1/S}}$

visual observations of canopy development and senescence collected at field sites. Because high quality field data to test the accuracy of phenological information derived from sensors such as MODIS is relatively rare and labor intensive, this multi-criteria approach provides a complementary basis to conventional field-based studies for assessing the comparative suitability of different growth functions for modeling land surface phenology. In addition, as part of this analysis, we also examine the relationship between 8-day MODIS NDVI and daily measurements of FAPAR during the periods when canopies are rapidly growing or senescing.

2. Growth functions and land surface phenology

We compared the suitability of four growth functions to track forest canopy phenology in this study. The form of each of the four growth functions is presented in Table 1 and is determined by four common parameters: an upper and lower asymptote (C_{\max} and C_{\min} , respectively), a growth rate (k), and an inflection point ($t(m)$). The amplitude of each growth function is the difference between C_{\max} and C_{\min} . We denote time with t and the state of canopy greenness at time t by $C(t)$. In the spring, the start of canopy development was defined as the time when $C(t)$ reaches 5% of the growth function's amplitude. Similarly, the time of full canopy development was defined to occur when $C(t)$ reaches 95% of the amplitude. In the fall, we used the same thresholds to define the start of senescence and end of the growing season. We used the 5th and 95th percentiles because they cover a realistic range of values for phenological development, and because growth functions yield unrealistically slow dynamics near their asymptotes.

We use $R(t)$ to define the rate of change in $C(t)$. To simplify comparisons with field data, we discretize $R(t)$ for each function for five equal time periods (identified as T1, T2, T3, T4 and T5) in both the growth and senescence periods. The percentage of total change realized in each time interval T1–T5 is denoted by G1, G2, G3, G4 and G5. Fig. 1 shows examples of $C(t)$ and $R(t)$ for each of the four growth functions along with corresponding values of G1–G5. The exact values of G1–G5 depend on the values of the asymptotes and the parameters used in each case, but the broad pattern is consistent within the range of parameter values meaningful to model canopy development and senescence. As Fig. 1 shows, each of the four growth functions exhibits a characteristic pattern in the rate of change, $R(t)$, which uniquely identifies the form of phenological change predicted by each function during the spring growth and fall senescence periods.

The logistic function describes a process where $R(t)$ is symmetrical around its inflection point, which occurs when $C(t)$ has covered half the distance between C_{\min} and C_{\max} (Fig. 1a). The growth rate is maximum in the third interval (G3, Fig. 1b). From a phenological perspective the logistic function describes a canopy

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