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A new algorithm predicting the end of growth at five evergreen conifer forests based on nighttime temperature and the enhanced vegetation index

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ABSTRACT

Accurate estimation of vegetation phenology (the start/end of growing season, SOS/EOS) is important to understand the feedbacks of vegetation to meteorological circumstances. Because the evergreen forests have limited change in greenness, there are relatively less study to predict evergreen conifer forests phenology, especially for EOS in autumn. Using 11-year (2000–2010) records of MODIS normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI), together with gross primary production (GPP) and temperature data at five evergreen conifer forests flux sites in Canada, we comprehensively evaluated the performances of several variables in modeling flux-derived EOS. Results showed that neither NDVI nor EVI can be used to predict EOS as they had no significant correlation with ground observations. In comparison, temperature had a better predictive strength for EOS, and R^2 between EOS and mean temperature (T_{mean}), the maximum temperature (T_{max}, daytime temperature) and the minimum temperature (T_{min}, nighttime temperature) were 0.45 (RMSE = 5.1 days), 0.32 (RMSE = 5.7 days) and 0.58 (RMSE = 4.6 days), respectively. These results suggest an unreported role of nighttime temperature in regulating EOS of evergreen forests, in comparison with previous study showing leaf-out in spring by daytime temperature. Furthermore, we demonstrated that it may be because nighttime temperature has a higher relationship with soil temperature (T_s) ($R^2 = 0.67$, $p < 0.05$). We then developed a new model combining T_{min} and EVI, which improved EOS modeling greatly both for these five flux sites and also for data collected at nine PhenoCam sites. Our results imply that the accuracy of current remote sensing VI estimated EOS should be used cautiously. In particular, we revealed the usefulness of nighttime temperature in modeling EOS of evergreen forests, which may be of potential importance for future ecosystem models.

1. Introduction

Substantial studies suggest that climate warming will probably increase vegetation growth in northern terrestrial ecosystems, especially forest ecosystems, which have great influence on carbon sequestration (Buitenwerf et al., 2015; de Moura et al., 2017; Nemani et al., 2003; Wolkovich et al., 2012). Plant phenology is widely used as an independent measure and powerful indicator of how ecosystems are responding to climate change (Fu et al., 2015; Gonsamo et al., 2012; Richardson et al., 2010; Wu et al., 2017). The definition of phenology (the start of growing season and the end of growing season, SOS and EOS) by the International Biological Program (IBP) (Helmut, 1974), suggests that phenology is affected by numerous factors (e.g. temperature, precipitation, photoperiods, etc.) (Peng et al., 2017a; Richardson et al., 2013; Singh et al., 2017; Tylewicz et al., 2018; Yang et al., 2015). Previous study demonstrates that temperature is an important input for phenological models (Schwartz, 2003). Therefore, quantify the influence of meteorological variables, especially temperature, on phenology has become an urgently needed task for improving our understanding between plant productivity and climate change.

Recent studies have reported many predictive methods in detecting phenology (SOS/EOS), and those methods can be mainly divided into two categories: dynamic threshold and derivative method (Hmimina et al., 2013; Melaas et al., 2013; Running et al., 2004; Schimel et al., 2015; Schwartz, 2003; Zhang et al., 2003). Forests are the most

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Table 1
Study site locations along with Fluxnet site IDs, years of data analyzed and references.

Site-ID	Site-name	Latitude	Longitude	Elevation (m)	Data range	Reference
CA-OBS	Saskatchewan Western Boreal, Mature Black Spruce	53.99	−105.12	629	2000–2010	Barr et al. (2004)
CA-OJP	Saskatchewan Western Boreal, Mature Jack Pine	53.92	−104.69	579	2000–2010	Coursolle et al. (2006)
CA-CA1	British Columbia 1949 Douglas-fir stand	49.87	−125.33	300	2001–2009	Jassal et al. (2009)
CA-CA2	British Columbia Clearcut Douglas-fir stand (harvested winter 1999/2000)	49.87	−125.29	300	2001–2009	Jassal et al. (2009)
CA-MAN	Manitoba Northern Old Black Spruce	55.88	−98.48	259	2000–2008	Dunn et al. (2007)

important ecosystems in terrestrial carbon budget, and many studies have reported phenology modeling of deciduous forests (Pan et al., 2011; Peng et al., 2017b). For example, Gill et al. (2015) use meta-analysis to compare temperature, photoperiod and precipitation on autumn senescence, and demonstrate that temperature is the strongest predictor of date of senescence, and high-latitude sites are more sensitive to photoperiod. Fu et al. (2015) verified that global warming reduces chilling for dormancy release, resulting in a slowdown in advance of tree spring phenology. Tanja et al. (2003) showed that spring mean temperature (T_{mean}) is a main factor contributing to the recovery of evergreen boreal forest. Though T_{mean} has the potential in explaining phenology, the explanation is rather limited in several regions. Piao et al. (2015) suggested the maximum daytime temperature (T_{max}) rather than T_{mean} or the minimum nighttime temperature (T_{min}) triggered SOS of northern ecosystems. Other studies suggest that T_{min} has a higher correlation with several vegetation variables (e.g. net primary production, NPP, etc.) and is more sensitive to ecosystem productivity in spring (Alward et al., 1999). Further evidence shows that T_{min} have a closer relationship with rice grain yield than T_{max} or T_{mean} (Peng et al., 2004).

Evergreen forests have limited seasonal dynamics of greenness and the drivers of their phenology are more complex than deciduous forests (Hmimina et al., 2013). This may partly explains that there are fewer studies on estimating the phenology of evergreen forest than for deciduous forest (Melaas et al., 2013). This problem becomes even more severe for detecting the autumn senescence since this period sustains a much longer and slower change of canopy greenness compared to that of spring phenology (White et al., 2014; Wu et al., 2014). To this end, Liu et al. (2016b) produced a new model combining vegetation index and coefficient of land surface temperature variation in estimating evergreen conifer forest EOS, which improved the estimation accuracy.

Drivers controlling on the end of the growth season remain largely unknown (Gill et al., 2015; Keenan and Richardson, 2015; Liu et al., 2016a). Considering these, we comprehensively investigated the usefulness of remote sensing and temperature based phenology in this study. For remote sensing phenology, we used both the NDVI/EVI and the phenology from the logistic function processed EVI time series to present the prediction performance only by vegetation index. For temperatures, we used three variables, including the autumn mean temperature, the maximum temperature (i.e., daytime temperature) and the minimum temperature (i.e., nighttime temperature) to further compare prediction performances of temperature variables and the combination of temperature and vegetation index on EOS. The overall objectives are (1) to analyze the potential of preseason VI as an indicator of EOS, (2) to compare the predictive strength of daytime, nighttime and mean temperatures for the estimation of EOS, (3) to develop a new algorithm for modeling EOS combining remote sensing and meteorological observations, and (4) validate our new model both at nine independent PhenoCam sites and compare with the algorithm reported in Liu et al. (2016b).

2. Materials and methods

2.1. Flux sites

We selected five boreal flux sites in Canada composed of evergreen conifer trees (e.g. fir, black spruce tree, et al.), and latitudes of these flux sites ranged from 49.87°N to 55.88°N with relatively long data records (i.e., more than 8 years duration of observations). Five evergreen conifer forests sites were the Saskatchewan Western Boreal Mature Black Spruce (CA-OBS), Saskatchewan Western Boreal Mature Jack Pine (CA-OJP), British Columbia 1999/2000 Clearcut Douglas-fir stand (CA-CA2), British Columbia 1949 Douglas-fir stand (CA-CA1) and Manitoba Northern Old Black Spruce (CA-MAN). The climate of these sites can be divided into two categories that were subarctic climate and marine coast climate, and CA-OBS, CA-OJP and CA-MAN belong to subarctic climate (e.g. severe winter, no dry season and cool summer) while the other two sites belong to marine coast climate (e.g. mild with no dry season, warm summer). Detailed descriptions of flux sites are provided in Table 1.

Half-hourly CO_2 fluxes and meteorological data were collected for the five sites from http://ameriflux.lbl.gov/. The data includes temperature (T), gross primary production (GPP) and soil temperature (T_s), and the daily data were integrated based on the gap-filled and friction velocity half-hourly readings (Urbanski et al., 2015). The data were gap-filled using the Artificial Neural Network (ANN) (Papale and Valentini, 2003) or the Marginal Distribution Sampling (MDS) method for the missing data (Reichstein et al., 2005). We used the same data preprocessing method in our analysis to eliminate the impact of the pretreatments on the later comparison.

PhenoCam network data provide a time series of vegetation phenological observations for diverse ecosystems of North America and Europe from 2000 to 2015 (https://daac.ornl.gov/VEGETATION/guides/PhenoCam-V1.html). The phenology data were derived from conventional visible-wavelength automated and networked digital camera at each site to monitor plant phenology. The data products can be used for validation and development of phenological models to better understand relationships between canopy phenology and ecosystem processes (Keenan et al., 2014; Sonnentag et al., 2012). We selected nine sites that are dominated by the evergreen conifer forests for our analysis. Detailed descriptions of PhenoCam sites are given in Table 2.

2.2. Observed EOS

A Savilzky-Golay filter, using polynomial regression and weights, was adopted to derive smoothed curves for daily GPP observations, and smoothed values of daily GPP were used to calculate the onset and offset of photosynthesis, which were referred to as observed SOS and EOS (Wu et al., 2013). The start and the end of growing season were defined as the first and the last days when the smoothed daily GPP reached 10% of the seasonal maximum daily GPP, respectively (Wu et al., 2012) (Fig. 1). This method allows variations of maximum GPP values and suitable for different spatial and temporal variations compared to a fixed GPP threshold (Wu et al., 2013).

2.3. Modeled EOS

2.3.1. EOS based on NDVI and EVI

We used autumn mean NDVI and EVI (September to October) of the flux site as indicators of EOS. Both NDVI and EVI were extracted from MOD13Q1 products (16-day temporal resolution and 250 m spatial