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Modeling vegetation green-up dates across the Tibetan Plateau by including both seasonal and daily temperature and precipitation

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ABSTRACT

Shifts in vegetation phenology induced by climate change are substantially modifying various ecosystem processes, and those changes can in turn affect weather and climate systems. Realistic modeling of spring vegetation green-up is critical to improving process-based ecosystem models of the Tibetan Plateau (TP) and for better understanding of the coupling between TP terrestrial biophysical processes and the Asian monsoon system. However, no model is available for simulating the vegetation green-up date (VGD) across the entire TP. In this study, we first assessed the ability of several existing state-of-the-art phenological models to estimate VGD across the TP. We then modified the existing models by adding environmental constraints identified by partial least-squares analyses. The modified models simulated VGDs with lower estimation errors than other models (Mean absolute error: 8.2 days vs. 8.7–12.9 days; $P < 0.01$, *t*-test). Moreover, although our model captured the inter-annual variations in VGD better than any previous model, the correlation coefficient between predicted and remotely sensed VGDs was still low, especially in the western TP. This study revealed the necessity of considering multiple factors in VGD models and highlighted the challenge of developing models that will better represent phenology in future ecosystem models.

1. Introduction

Vegetation green-up date (VGD) characterizes the onset of photosynthetic activity on land and has important implications for terrestrial ecosystem processes, such as carbon and water cycling and the energy balance between the biosphere and atmosphere (Cleland et al., 2007; Forkel et al., 2015; Jeong et al., 2012; Keenan et al., 2014; Menzel and Fabian, 1999; Richardson et al., 2013; Wu et al., 2016). It is also considered to be the simplest and one of the most sensitive indicators of the response of vegetation to recent climate warming, especially at high latitudes and in high-altitude regions (Körner and Basler, 2010; Parmesan, 2006; Peñuelas et al., 2009; Vitasse et al., 2011; Walther et al., 2002; Zheng et al., 2016). The Tibetan Plateau (hereafter TP), covering an area of approximately 2.5×10^6 km^2 and with an average elevation higher than 4000 m, is the largest and highest alpine ecoregion in the world and has experienced extraordinary warming in the past four decades, during which the mean annual temperature has increased at a rate of 0.39 °C per decade (Deng et al., 2017). A growing number of studies have used ground records and satellite observations to study the temporal shifts of the VGD and the linkages of those shifts to climate on the TP (reviewed by Shen et al., 2015b). Shifts in spring vegetation phenology could induce changes in surface biophysical processes and further potentially affect the regional and eastern Asian climate (Zhang et al., 2011).

It is widely recognized that heat accumulation in the preceding period of time (preseason) is the main trigger of VGD on the cold TP (e.g., Piao et al., 2011; Shen et al., 2011). Investigators have also explored the influences on VGD of some other environmental factors, such as the winter temperature and its relationship to chilling effects (Yu et al., 2010), preseason precipitation (Shen et al., 2015a), photoperiod, and sunshine duration (Wang et al., 2015). For example, Yu et al. (2010) found that winter warming slowed the fulfillment of the chilling

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requirement and consequently delayed spring phenology across the TP from the mid-1990s to 2006. That report, however, has stimulated a broad debate about whether there is a strong winter chilling effect on the TP. Some later studies have argued that warmer winters do not postpone spring phenology on the TP (e.g., Chen et al., 2015; Cong et al., 2017; Zhang et al., 2013). Besides the winter temperature, several studies have emphasized the important impacts of preseason precipitation on spring phenology in the dry areas of the TP and have suggested including this factor in climate-driven phenology models to improve phenology simulations (Shen et al., 2011; Shen et al., 2015a).

In addition to these seasonal climate variables, some recent studies have emphasized that VGD is affected by the asymmetric impacts of daytime and nighttime temperatures (Fu et al., 2016; Hanes, 2014; Piao et al., 2015; Rossi and Isabel, 2017; Shen et al., 2016). Piao et al. (2015) have suggested that spring phenology is more strongly related with daily maximum temperature than with daily minimum temperature over northern middle and high latitudes. Fu et al. (2016), on the basis of a manipulative experiment, have further indicated that the impact of daytime temperatures on the leaf unfolding phenology of three temperate tree species is three times that of nighttime temperatures. In contrast, Shen et al. (2016) correlated VGD with daily maximum and minimum temperatures, and they found a stronger impact of minimum temperatures on the TP and hypothesized this as a low-temperature constraint. These discoveries have been crucial for understanding what temperature really drives spring phenology on the TP.

Despite this progress, however, it is still unclear how VGD across the TP is codetermined by temperature at both seasonal (winter vs. spring) and diurnal (daytime vs. nighttime) time scales and by preseason precipitation. More importantly, little is known about whether, and to what extent, including these reported environmental cues might improve phenological models and yield more realistic phenological predictions for the TP. We found that there have been few previous efforts to model VGD on the TP, and those limited efforts have been made for only a few species at several separate sites (Chen et al., 2015) that could not represent the entire TP. More accurate prediction of VGD requires the inclusion of essential mechanisms in the phenological model without overfitting model coefficients (Linkosalo et al., 2008). Previous studies have revealed correlations between environmental cues and VGDs, but there remains a gap to incorporate such correlations for an improvement of VGD predictions on the TP.

To fill knowledge gaps, we first investigated the combined effect of multiple climate variables on satellite-derived VGD (2001–2015) across the TP. We then assessed the performance of several existing state-of-the-art, climate-driven phenological models in predicting VGD. We then developed a new phenological model involving multiple environmental cues to improve VGD simulations across the entire TP.

2. Materials and methods

2.1. Retrieving VGDs using satellite observations

VGDs across the TP during 2001–2015 were estimated on the basis of a time series of normalized difference vegetation index (NDVI) values. Raw NDVI values were calculated from the nadir bidirectional reflectance distribution function (BRDF)-adjusted reflectance observed by the Moderate Resolution Imaging Spectroradiometer (MODIS) (Product No. MCD43A4; Schaaf et al., 2002). The MCD43A4 dataset has a composited 8-day and 500-m temporal-spatial resolution and was available from the website of the National Aeronautics and Space Administration (http://reverb.echo.nasa.gov/reverb). We then performed some necessary preprocessing of the generated raw time-series NDVI data to reduce noise in the time series: (1) the BRDF-albedo quality flag (Product No. MCD43A2) was used to identify winter NDVI values contaminated by the presence of snow or ice; (2) these contaminated NDVI data were replaced by median values of the uncontaminated NDVI values between the previous November and the following March of all years (Zhang et al., 2006); (3) remaining gaps in the time series were linearly interpolated, and the time series was further smoothed by a three-point median-value filter, as suggested by the official User Guide (http://www.bu.edu/lcsc/files/2012/08/MCD12Q2_UserGuide.pdf).

After preprocessing, the NDVI time-series was fitted to a logistic function. VGD was then defined as the date when the rate of change of the curvature of the fitted function reached its first local maximum (for details, see Zhang et al., 2003). This method actually captures the time of the initial rapid increase of vegetation greenness and has been widely validated and used (e.g., Ganguly et al., 2010; Zhang et al., 2006; Zhu et al., 2012). Only the pixels with obvious seasonal changes were included for analysis. These pixels were identified according to the following criteria: the annual NDVI maximum occurred between June and September; the average NDVI during July–September was larger than 0.1; and the July–September average exceeded 1.2 times the average NDVI during January–March (Cao et al., 2015; Shen et al., 2014).

2.2. Climate data

The China Meteorological Forcing Dataset was used to analyze the relationships between VGD and climate factors for each pixel. This dataset was provided by the Data Assimilation and Modeling Center for Multi-spheres, Institute of Tibetan Plateau Research, Chinese Academy of Sciences (Chen et al., 2011; Yang et al., 2010). Air temperature and precipitation data in that dataset have a spatial resolution of $0.1^{\circ} \times 0.1^{\circ}$ and a temporal resolution as short as 3 h. Air temperatures were produced by merging station meteorological observations made by the China Meteorological Administration (CMA) and the corresponding Princeton forcing data (Sheffield et al., 2006). Precipitation data were produced from CMA station observations, Tropical Rainfall Measuring Mission satellite precipitation analysis data (3B42; Huffman et al., 2007), and APHRODITE (Asian Precipitation − Highly Resolved Observational Data Integration Towards Evaluation of Water Resources) precipitation data (Yatagai et al., 2009).

2.3. Statistical analyses

We performed partial least-squares regressions (PLSRs) to evaluate the influences of multiple climate factors on inter-annual variations of the VGD. Compared with ordinary least-squares multiple regression, PLSR is more useful when the sample size is small and there is multicollinearity among the independent variables (Wold, 1995). The climatic factors in our PLSR analyses included daytime mean temperature (T_{daytime}) and daily minimum temperature ($T_{\min}$) during the preseason period, preseason accumulated precipitation (AP), and winter daily mean temperature (T_{winter}). T_{daytime} was calculated as the mean of the four temperatures recorded during successive 3-h time intervals from 8:00 AM to 8:00 PM The duration of the preseason used to calculate T_{daytime} was determined to be the period of time preceding the multiyear average VGD during which the VGD was most correlated with T_{daytime}. We constrained this length of time to be 15–90 days in increments of 15 days to suppress the potential influence of occasionally abnormal temperatures. The preseason length for $T_{\min}$ was determined in a similar way. The time interval for calculating AP extended from 1 January to the multiyear average VGD. T_{winter} was calculated as the daily mean temperature from October 1 of the previous year to January 31 of the given year.

We quantified the influence of each climate factor on the VGD on the basis of two evaluation indicators from the PLSR analyses. One was the model coefficient (MC) in the regression model. A positive or negative MC for a climate factor indicated that the climate factor was positively or negatively correlated, respectively, with VGD. The other was the variable importance on PLSR projection (VIP), which is a metric of the ability of each climate factor to explain the variance of the VGD (Yu et al., 2010). A climate factor with a VIP score greater than 1