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Modeling grassland spring onset across the Western United States using climate variables and MODIS-derived phenology metrics

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ABSTRACT

Vegetation phenology strongly controls photosynthetic activity and ecosystem function and is essential for monitoring the response of vegetation to climate change and variability. Terrestrial ecosystem models require robust phenology models to understand and simulate the relationship between ecosystems and a changing climate. While current phenology models are able to capture inter-annual variation in the timing of vegetation spring onset, their spatiotemporal performances are not well understood. Using green-up dates derived from MODIS, we test 9 phenological models that predict the timing of grassland spring onset via commonly available climatological variables. Model evaluation using satellite observations suggests that Modified Growing-Degree Day (MGDD) models and Accumulated Growing Season Index (AGSI) models achieve reasonable accuracy (RMSE < 20 days) after model calibration. Inclusion of a photoperiod trigger and varied critical forcing thresholds in the temperature-based phenology model improves model applicability at a regional scale. In addition, we observe that AGSI models outperform MGDD models by capturing inter-annual phenology variation in large semi-arid areas, likely due to the explicit consideration of water availability. Further validation based on flux tower sites shows good agreement between the modeled timing of spring onset and references derived from satellite observations and in-situ measurements. Our results confirm recent studies and indicate that there is a need to calibrate current phenology models to predict grassland spring onsets accurately across space and time. We demonstrate the feasibility of combining satellite observations and climatic datasets to develop and refine phenology models for characterizing the spatiotemporal patterns of grassland green-up variations.

1. Introduction

Vegetation phenology, characterizing the recurring and periodic cycles of vegetation green-up and senescence, is highly sensitive to climate change and variability (Cleland, Chuine, Menzel, Mooney, & Schwartz, 2007; Koerner & Basler, 2010; Piao, Fang, Zhou, Ciais, & Zhu, 2006; Richardson et al., 2013). Environmental drivers, such as temperature, photoperiod, water and nutrient availability, regulate the timing of the spring onset of natural vegetation (Friedl et al., 2014; Piao et al., 2011; Yu, Price, Ellis, & Shi, 2003). Numerous studies using in-situ measurements and satellite observations have documented decadal shifts in vegetation phenology under a changing climate at both regional and global scales (Broich et al., 2014; Julien & Sobrino, 2009; Wu & Liu, 2013; Yang, Mustard, Tang, & Xu, 2012). The shifts of key phenophases, such as spring onset and autumn senescence, control vegetation photosynthetic activities (Churkina, Schimel, Braswell, & Xiao, 2005; Richardson et al., 2010) and have profound impacts on global carbon and water cycles in both field measurements and model simulations (Dragoni et al., 2011; Jeong, Medvigy, Shevliakova, & Malyshev, 2012; Piao, Friedlingstein, Ciais, Viovy, & Demarty, 2007). Robust climate-driven models of vegetation phenology are therefore critical for projecting climate change scenarios (Cramer et al., 2001; Levis & Bonan, 2004).

Modeling springtime vegetation phenology via climate variables has received extensive attention in recent publications, and a variety of climate-driven phenological models have been proposed and tested using in-situ measurements (Cesaraccio, Spano, Snyder, & Duce, 2004; Melaas, Richardson, et al., 2013; Richardson, Bailey, Denny, Martin, & O'Keefe, 2006; Yang et al., 2012). Based on species-level observations of tree budburst, it is generally considered that temperature is the main driver for spring onsets of temperate forests (Bale et al., 2002; Chuine, Cour, & Rousseau, 1999; Hanninen & Kramer, 2007; Kaduk & Los, 2011; Wu, Gonsamo, Gough, Chen, & Xu, 2014). The temperature-based phenology models have been widely employed as sub-models in terrestrial biosphere models (Cramer et al., 2001; Kucharik et al., 2006). Most of these phenology models are empirical, with prescribed

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values of parameters (Yang et al., 2012). However, recent studies have argued that the current model schemes do not capture the spatiotemporal variation of vegetation phenology metrics derived from satellite observations (Fisher, Richardson, & Mustard, 2007), particularly for grasslands. The responses of grasslands to local climates are more complicated than that of the forest biome. While grasses in moist environments are sensitive to temperature variation, the spring onset of dry grasslands is limited by soil water availability (Choler, Sea, Briggs, Raupach, & Leuning, 2010; De Michele, Vezzoli, Pavlopoulos, & Scholes, 2008; Liu, Tian, Hu, Hu, & Sivapalan, 2013) and often initiated by precipitation events (Ji & Peters, 2004; Lotsch, Friedl, Anderson, & Tucker, 2003; Shen, Tang, Chen, Zhu, & Zheng, 2011). Given that grassland is a key component in terrestrial biomes, it is important to further develop and refine the climate-driven phenological models for grasslands.

Though modeling grassland green-up is a research frontier in phenological studies, model development is constrained by the lack of long-term records of grass phenology from ground observations (White et al., 2009), possibly because the phenomenon of grass green-up is challenging to define with respect to tree budburst or leaf expansion (i.e., based on the percentage of leaves at their full sizes). Observations from digital cameras (Coops et al., 2012; Nijland et al., 2014) and measurements from flux towers (Melaas, Richardson, et al., 2013) provide alternative ways to infer and define the timing of vegetation green-up for specific sites, but robust model development and evaluation require sufficient site-year data. In addition to model validation using in-situ observations, there is a need for improved understanding of the spatiotemporal performance of phenology models over large geographic regions with appropriate datasets.

Satellite remote sensing provides abundant time-series observations of land surfaces for regional and global phenological studies. Vegetation indices derived from satellite observations have been shown to have close relationships with vegetation chlorophyll abundance and photosynthetic activity (Huete et al., 2002; Myneni, Hall, Sellers, & Marshak, 1995) and have proven suitable to derive key phenophases such as spring green-up and autumn browning (Fisher & Mustard, 2007; Zhang et al., 2003). Commonly used approaches that derive vegetation spring onset from satellite observations include those based on: 1) predefined thresholds of spectral vegetation indices (White, Thornton, & Running, 1997); 2) when time series of vegetation indices reach certain ratios of the seasonal amplitude (Jönsson & Eklundh, 2004), 3) the rate of increase in vegetation indices during the early growing seasons (Piao et al., 2011), and 4) higher-order derivatives of the time series of vegetation indices (Tan et al., 2011). Though the definition of spring onset varies across studies, satellite-derived spring onsets have shown good agreement with digital camera observations (Hufkens et al., 2012) and time series of CO_2 fluxes measured at tower sites (Bottcher et al., 2014).

Long-term observations from AVHRR dating back to the early 1980s have been used to quantify changes in phenology at regional and global scales (Heumann, Seaquist, Eklundh, & Jönsson, 2007; Tateishi & Ebata, 2004; White et al., 2009). However, due to sensor degradation and data quality issues, recent studies based on the AVHRR datasets have led to conflicting results concerning the trend and magnitude of phenological shifts in specific regions, such as the Tibetan Plateau (Piao et al., 2011; Wu & Liu, 2013; Zhang, Zhang, Dong, & Xiao, 2013). The coarse resolution of the AVHRR dataset also hinders validation using ground observations (Wang et al., 2011). Data from MODIS sensors with an improved signal-to-noise ratio and moderate spatial resolution have been used routinely to provide high-quality datasets (Justice et al., 2002). The product of MODIS Land Cover Dynamics (MCD12Q2) has been examined and validated in several recent studies (Ganguly, Friedl, Tan, Zhang, & Verma, 2010; Zhang et al., 2003). A relatively new time series of MCD12Q2 dataset is now available, which offers opportunities to refine and evaluate phenological models at a large scale.

The objectives of this study are to 1) use phenology metrics derived from MODIS for model refinement and validation, 2) propose a new method to characterize the spatiotemporal patterns of regional phenology variations, and 3) use flux measurements at tower sites to validate both MODIS-derived green-up dates and spring phenology models.

2. Materials and methods

2.1. Study area and data preprocessing

We performed our analysis for the Western United States (25° to 49° N, −125° to −95° W), where reliable daily climate data are available (Fig. 1). Climatic zones range from temperate in the North to tropical in the South. Temperature generally decreases with latitude and varies as a function of topography. Annual precipitation ranges widely across large areas and shows an east–west gradient. The study area includes over 95% of the grasslands in the United States and has a variety of grass species mixed with shrubs or local species of short vegetation.

To match the spatial resolution of the climate data, we preprocessed remotely sensed data from standard MODIS products and scaled up the timing of grassland green-up from MODIS resolution to a 0.125° × 0.125° resolution. Ten-year (2001–2010) data of vegetation green-up dates were extracted from the first layer of MCD12Q2 product (Ganguly et al., 2010). The timing of vegetation green-up in MCD12Q2 was derived based on the changing rates in the time series of Enhanced Vegetation Index (see for example in Fig. 2A). Because we only attempted to model springtime green-up (from Jan 1st to July 1st), areas such as California, where grass green-up begins in November and December, were not included in our analysis. The MODIS Land Cover Type product (MCD12Q1) was used to screen non-grass pixels (Friedl et al., 2002; Friedl et al., 2010). To reduce the influences of land-cover and land-use changes, we only processed pixels that were mapped as grasslands consistently in both 2001 and 2010. Apparent anomalies of grassland green-up dates within each 0.125° grid cell were excluded based on the criteria of mean ± 3 standard deviation (Roy, Jin, Lewis, & Justice, 2005). To minimize the effect of elevation on vegetation phenology, we obtained digital elevation maps from NOAA's Global Land One-km Base Elevation (GLOBE) project (Hastings & Dunbar, 1998) and excluded MODIS pixels that have an elevation exceeding mean ± 100 m of each 0.125° grid cell (Peng et al., 2014). The timing of grassland green-up for each 0.125° grid cell was then determined as the median value for all qualified MODIS observations within the corresponding grid cell. However, if the standard deviation of within-pixel grassland green-up was greater than 30 days, we excluded those grid cells for further analysis because grasses respond diversely to local climates. Because remotely sensed data contain inherent noise (Xin, Olofsson, Zhu, Tan, & Woodcock, 2013), the above processes were applied to ensure that MCD12Q2-derived grassland phenology data were of high quality for model calibration and evaluation.

Daily climate data, including photoperiod, temperature, and vapor pressure deficit, were used as forcing drivers in phenology models. To test model robustness, we processed two observational climate datasets that have been widely used in scientific research: 1) the Maurer02v2 datasets (Maurer, Wood, Adam, Lettenmaier, & Nijssen, 2002) originally developed in coordination with NASA's National Land Data Assimilation System (NLDAS) project (Maurer, personal communication; http://hydro.engr.scu.edu/files/gridded_obs/daily/ncfiles_2010/), and 2) the Daymet datasets (Thornton et al., 2012) distributed by the Oak Ridge National Laboratory (ORNL) Distributed Active Archive Center (http://daymet.ornl.gov/). To analyze the influences of soil moisture, we obtained hourly NLDAS NOAH model data achieved by NASA Goddard Earth Sciences Data and Information Services Center (ftp://hydro1.sci.gsfc.nasa.gov/). Hourly root zone (0 to 1 m for grass) soil moisture content derived from the NOAH model were averaged to daily mean values. All climate and soil moisture datasets from 2000 to 2010 were processed to daily data at a 0.125° × 0.125° resolution under the Geographic