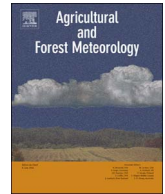




Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

Scaling up spring phenology derived from remote sensing images

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ARTICLE INFO

Keywords:

Scale effecting
Scale up
Spring phenology
Validation
Average
Percentile

ABSTRACT

Land surface phenology, especially spring phenology, has been reported as a powerful indicator of ecosystem responses to climate change. It also exerts strong control on the carbon, water and energy balances and, hence, climatic feedbacks. Researchers have produced numerous spring phenology products from various coarse-resolution remote sensing data at regional or global scales. Scaling up observations of spring phenology from plot-level (or finer resolution) to coarser resolution is important for the validation, synthesis, and evaluation of those products. The best method for scaling up is unclear although coarse resolution data can be obtained by averaging across fine-scale pixels, or selecting the start of spring phenology (SOS) date associated with the earliest 30% (or another percentile) of fine-scale pixels within a coarse-scale pixel. In this study, we tested different methods that were average and percentile approaches to aggregate SOS as measured at 250 m (SOS (250 m)) resolution to 8 km (SOS (8 km)) resolution pixels, and then to ecosystems and national scales for the continental United States. The results indicated that the average absolute difference (AAD) between SOS (250 m) and SOS (8 km) from the average approach was close to that achieved by the percentile approach. Relatively large AAD values occurred in the western and southern regions of the continental United States. The distribution of AAD was positively related to landscape heterogeneity. The percentile approach generally yielded smaller AADs than the average approach did, but these two approaches performed similarly. Across landscapes and ecosystems, the optimal percentile usually ranged from 30–45th instead of a single value. Our findings indicated that the percentile approach may be best for finer scale areas, but that the average approach is an adequate alternative for scaling up SOS in most circumstances. In addition, the detailed error distributions of scaling up spring phenology across scales are helpful to identify the appropriate method of scaling up for validating the coarse SOS products derived from remote sensing images.

1. Introduction

Phenology indicates the timing of periodic events in the life cycle of living organism (Piao et al., 2015). Land surface phenology (LSP), especially start of spring phenology (SOS), has been reported as an independent measure and powerful indicator of ecosystem responses to climate change (Linderholm, 2006; White et al., 2009; Zhang et al., 2014; Piao et al., 2015; Peng et al., 2017a,b,c). The trend of earlier spring phenology, particularly at mid- and high-latitudes in the Northern Hemisphere, have been observed and caused by the global warming (Myneni et al., 1997; Schaber and Badeck, 2005; Zhou et al., 2001). Moreover, the changes of vegetation phenology also affect

carbon, water and energy exchanges between the vegetation and the atmosphere (White et al., 2009; Delbart et al., 2015; Both et al., 2009; Picard et al., 2005; Richardson et al., 2013). Such as earlier spring phenology would advance soil water depletion and enhance mid-summer drought in some cases (White and Nemani, 2003). Therefore, accurate observation of SOS is important to understand regional-to-global carbon budget and climate change (Piao et al., 2015; Zhang et al., 2017; Peng et al., 2017a,b,c). Although the use of ground observations by volunteers, scientists, and ground-based cameras is growing (Richardson et al., 2007; Sonnentag et al., 2012; Denny et al., 2014), satellite-based remote sensing is still widely used to monitor spring phenology because of its significant advantages with respect to

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synoptic coverage and repeated temporal sampling at regional and global scales (Myneni et al., 1997; Zhang et al., 2003; White et al., 2009; Gonsamo et al., 2012; Delbart et al., 2015). Various coarse-resolution remote sensing images are available to detect spring phenology from regional to global scales. Such as the advanced very high resolution radiometer (AVHRR) captures images and has the Normalized Difference Vegetation Index (NDVI) products at spatial resolutions between 1.1–8 km. These data are the coarsest and most commonly used satellite data for measuring spring phenology (White et al., 2009; Zhang et al., 2007, 2014; de Jong et al., 2011; Julien and Sobrino, 2009; Zhou et al., 2001), because they boast the longest and densest time series available with global coverage (time series begin ~1982). Other data used for phenology detection extend back about 10–17 years, which include the medium-resolution imaging spectrometer (MERIS) data (300 m), the moderate-resolution imaging spectroradiometer (MODIS) data (250 m–0.05°), and the Systeme Probatoire d'Observation de la Terre (SPOT) vegetation data (1 km) (Zhang et al., 2003; Fisher et al., 2006; White et al., 2009; Ganguly et al., 2010; Dash et al., 2010; Guyon et al., 2011). Landsat images with spatial resolutions of 30 m have temporal resolution of ~16 days, making them an impractical source for consistent annual time series of regional-scale phenology for most parts of the planet (Zhang et al., 2017).

Validation of the satellite-derived phenology products is an important and challenging task in remote sensing, but a primary challenge is to determine an appropriate method to scale up plot-level or finer resolution observations to the coarser resolution observations from many satellites (Buermann et al., 2002; de Beurs et al., 2009; Herold et al., 2008; Weiss et al., 2007). Previous studies have generally validated coarser resolution spring phenology data by averaging finer resolution data (Delbart et al., 2015; Román et al., 2011). Recently, a percentile approach was developed, and it was found that the 30th percentile of fine-resolution (30 m) phenology data corresponded best (i.e., had the smallest errors) to coarser resolution (500 m) spring phenology data (Zhang et al., 2017). This method reflects that spring greenup is not able to be captured by coarse-resolution data until the greenup has occurred in 30% of fine-resolution pixels, which also indicates that coarse-resolution greenup dates represents mostly the relatively early greenup values at fine-resolution pixels (Zhang et al., 2017). However, to our knowledge no studies have compared the results between averaged and percentile approaches. Zhang et al. (2017) pointed out that this type of comparison is needed to verify if the 30th percentile is always the optimal percentile across various landscapes and ecosystems. In addition, studies have rarely evaluated the methods of aggregating satellite-derived spring phenology data from finer to coarser spatial resolutions (from 250 m to 8 km), especially for large regions.

In this study, we used an ecoregions map over the contiguous United States to identify ecosystems at the province and division scale. We explored the relationships between finer (250 m) and coarser (8 km) resolution images and compared the average and percentile approaches for aggregating and scaling up the start of spring phenology (SOS).

2. Methods

2.1. Data

For our base phenology data, we used MOD13Q1 vegetation index data, which are provided every 16 days at a 250 m spatial resolution as a gridded level-3 product in sinusoidal projection. We did not use finer spatial resolution images (such as 30 m Landsat images) because of the long repeat cycle of observations (~16 days for Landsat). This coarse temporal resolution makes it impractical to consistently produce annual time series for phenology detections at a regional scale for full coverage across the continental United States (Zhang et al., 2017). It is because the time gap between two valid observations could be more than one month if an observation is of low quality on a particular day because of

cloud cover or other impacts. Our MOD13Q1 data, in contrast, consisted of the best quality observations (e.g., low clouds, low view angle, high NDVI/EVI value) of daily observations, composited across 16-day increments. Thus, weather conditions had limited impacts on data. We acquired enhanced vegetation index (EVI) and the quality assessment (QA) information in 2007 and 2008 from <ftp://ladsweb.nascom.nasa.gov/allData/6/>. The MOD13Q1 Collection 6 algorithm uses pre-composited (8-day) surface reflectance data, as opposed to daily data, and uses a new robust 2-band EVI instead of a backup algorithm from soil adjusted vegetation index (SAVI) (Huete et al., 2002; Jiang et al., 2008; Didan, 2015). A cloud-free, nadir-view pixel with no residual atmospheric contamination produces the best quality pixels. Only the higher quality cloud-free data are retained for further compositing. The current surface reflectance employs a minimum blue band approach to minimize effects of aerosols and other contaminants (Huete et al., 2002; Jiang et al., 2008; Didan, 2015).

To quantify land cover type, we used the MODIS product MCD12Q1, which has a 500 m resolution and was produced using a supervised classification algorithm based on high-quality land cover training sites; training sites were developed using high-resolution imagery and ancillary data (Muchoney et al., 1999). We used the most recent version of MCD12Q1. The primary land cover scheme was provided by an International Geosphere-Biosphere Program (IGBP) land cover classification scheme (Friedl et al., 2010), which was used to calculate the indicators of landscape fragment (ILF).

For validation of our MOD13Q1-derived estimates of SOS phenology, we used MCD12Q2, which has a 500 m resolution, and is a MODIS Collection 5 product acquired from the combined TERRA and AQUA platforms. We downloaded these data from <http://e4ftl01.cr.usgs.gov>. MCD12Q2 primarily used MODIS EVI, which was computed from MODIS the nadir bidirectional reflectance distribution function (BRDF)-adjusted reflectance (NBAR). EVI was produced every 8 days using overlapping 16 day compositing windows, and there was a maximum of 46 possible EVI values for any year. Those time series underwent a gap-filling and smoothing process (Zhang et al., 2006; Ganguly et al., 2010). Phenophase transition dates were estimated by identifying local maxima and minima in the rate of change of curvature of the fitted logistic function (Zhang et al., 2003).

For ground-based observations, we used observations of first leaf of common lilac collected by the USA National Phenology Network (USA-NPN). The USA-NPN is a consortium of individuals and organizations that collect, share, and use phenology data, and aims to develop and distribute derived phenological information (Denny et al., 2014). USA-NPN lilac phenology data have been widely used in previous studies (Allstadt et al., 2015; Ault et al., 2015; Piao et al., 2015; Verger et al., 2016), and have been proven useful for providing species-specific phenological data (White et al., 2009; Kellermann et al., 2015; Glynn and Owen, 2015; Piao et al., 2015). We used lilac first leaf observations collected at 95 sites (Fig. 1) in 2007 (USA-NPN, 2015).

We quantified ecoregions of the continental United States (Fig. 1) based on data from the Forest and Rangeland Ecosystem Science Center. This data set categorized ecoregions at four levels, of which we used the three largest: (1) domains, the largest ecosystems; (2) divisions, which are differentiated based on precipitation and temperature; and (3) provinces, which are based on vegetation or other natural land covers (Bailey, 2004; Omernik and Bailey, 1997). In addition, vegetation in the same ecoregion has the similar climate and human conditions (Yang et al., 2017). In this study, we merged several closely related divisions to get six divisions as shown in Fig. 1.

2.2. SOS estimation from MODIS EVI

For MOD13Q1 data, pixels contaminated by cloud, aerosols, and other contaminants were marked as invalid and removed; the remaining EVI data in 2007 and 2008 across the continental United States were aggregated across 250 m resolution pixels within 35 × 35-pixel

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