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A snow-free vegetation index for improved monitoring of vegetation spring green-up date in deciduous ecosystems





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ABSTRACT

Vegetative spring green-up date (GUD), an indicator of plants' sensitivity to climate change, exerts an important influence on biogeochemical cycles. Conventionally, large-scale monitoring of spring phenology is primarily detected by satellite-based vegetation indices (VIs), e.g. the Normalized Difference Vegetation Index (NDVI). However, these indices have long been criticized, as the derived GUD can be biased by snowmelt. To minimize the snowmelt effect in monitoring spring phenology, we developed a new index, Normalized Difference Phenology Index (NDPI), which is a 3-band VI, designed to best contrast vegetation from the background (i.e. soil and snow in this study) as well as to minimize the difference among the backgrounds. We examined the rigorousness of NDPI in three ways. First, we conducted mathematical simulations to show that NDPI is mathematically robust and performs superior to NDVI for differentiating vegetation from the background, theoretically justifying NDPI for spring phenology monitoring. Second, we applied NDPI using MODIS land surface reflectance products to real vegetative ecosystems of three in-situ PhenoCam sites. Our results show that, despite large snow cover in the winter and snowmelt process in the spring, the temporal trajectories of NDPI closely track the vegetation green-up events. Finally, we applied NDPI to 11 eddy-covariance tower sites, spanning large gradients in latitude and vegetation types in deciduous ecosystems, using the same MODIS products. Our results suggest that the GUD derived by using NDPI is consistent with daily gross primary production (GPP) derived GUD, with R (Spearman's correlation) = 0.93, Bias = 2.90 days, and RMSE (the root mean square error) = 7.75 days, which outcompetes the snow removed NDVI approach, with R = 0.90, Bias = 7.34 days, and RMSE = 10.91 days. We concluded that our newly-developed NDPI is robust to snowmelt effect and is a reliable approach for monitoring spring green-up in deciduous ecosystems.

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1. Introduction

Vegetative spring green-up date (GUD) is a sensitive indicator of temperate and boreal ecosystems responding to global climate change (Wolkovich et al., 2012; Fu et al., 2016; Menzel and Fabian, 1999; Parmesan and Yohe, 2003; Wang et al., 2016). A number of studies have reported that the start of spring is occurring earlier in the recent decades in temperate and boreal ecosystems in the Northern Hemisphere (e.g. Buitenwerf et al., 2015; Myneni et al., 1997; Zhou et al., 2001). This shift in phenology exerts an important influence on large-

* Corresponding author. E-mail address: chenjin@bnu.edu.cn (J. Chen). scale biogeochemical cycles (Richardson et al., 2010; Xia et al., 2015). For example, Richardson et al. (2009) showed that earlier spring onset resulted in higher annual gross primary productivity (GPP) at two forest sites in the United States. However, a reliable approach for monitoring spring phenology in these ecosystems is still lacking.

For decades, satellite remote sensing has offered an attractive tool for large-scale motoring of vegetative status (Buitenwerf et al., 2015; Wang et al., 2015). The most widely used remote sensing product is the Normalized Difference Vegetation Index (NDVI). It uses two reflectance spectral bands and ratios them to provide an estimate of canopy greenness, a composite property of both leaf-level (leaf intercellular structure and biochemical compostion) and canopy-level (canopy leaf area and structure) properties. In general, NDVI is a good indicator of plant growth status (Pettorelli et al., 2005), and is thus widely used for phenology monitoring.

However, satellite-derived NDVI can be affected by two natural processes of snowmelt and vegetative growth in spring, as these two processes can both increase NDVI value. As a result, the derived vegetation phenology (e.g. GUD) using the NDVI approach can be contaminated by the snowmelt (Delbart et al., 2005; Shabanov et al., 2002). This snowmelt effect, without fair justifications, can even lead to the misinterpretation of climate impact on vegetative phenology. For example, Zhang et al. (2013) found that GUD in the Tibetan Plateau advanced continuously from 1982 to 2011 by using three long-term NDVI time series. However, more recent studies (e.g. Shen et al., 2013; Wang et al., 2013) argued that the detected spring phenological trend in the Tibetan Plateau might be due to the artifact caused by declining snow cover. Therefore, it urgently calls for a new, more accurate approach for monitoring spring vegetation phenology, which is robust to the snowmelt effect (White et al., 2005).

To minimize the snowmelt artifact on NDVI-detected GUD, a number of methods have been proposed in the past decades. However, a mathematically rigorous and generalized method is still lacking. An important prerequisite for most previous approaches is the prior knowledge of temporal changes of snow cover. This prior knowledge can either be empirically determined (Beck et al., 2006; Karlsen et al., 2014), or rely on auxiliary data (Cao et al., 2015; Wang et al., 2015) which limits the general applicability of these approaches.

Several other vegetation indices (VIs) to account for the snowmelt effect have also been proposed and examined, but all these VIs are subject to various issues limiting their effectiveness. For example, some remote sensing scientists advocated the use of the Normalized Difference Infrared Index (NDII) (also referred to as the Normalized Difference Water Index (NDWI)) which includes the spectral band (shortwave-infrared) sensitive to foliar water content, for vegetative phenology monitoring (e.g. Delbart et al., 2005; Delbart et al., 2006; Dunn and de Beurs, 2011). This is because NDII increases with vegetation growth but decreases with snowmelt, and thus it is promising in being able to decouple snowmelt from vegetation growth. However, the NDII approach is disadvantageous for those regions where snowmelt and the start of vegetative growth occur at the same period (Gonsamo et al., 2012). In some burned areas, NDII is also found to be not sensitive to vegetation growth (Peckham et al., 2008). Phenology Index (PI), a composite VI of NDVI and NDII, was proposed as an alternative approach to overcome the drawback of using NDII alone (Gonsamo et al., 2012). The issue of using PI is that it is not sensitive to vegetation growth when the vegetation is sparse. More recently, (Thompson et al., 2015) characterized the vegetation phenology by constructing a phase-spaces using both NDVI and NDII. Days of the year (DOYs) for a pixel are classified as one of two types, i.e. snow-free phase and snow-covered phase, and the GUD is defined as the date when the pixel entered and remained in the snow-free phase for no <10 days without returning to the snow-covered phase. This method, however, is somewhat complex and would fail to estimate a consistent phenological time series for the areas where snow cover occasionally happens in between years (e.g. the site CN-Hab in this study).

In this study, we aim to develop a new VI that is resistant to snowmelt and can more accurately monitor spring phenology for snow covered regions. The newly developed VI is the Normalized Difference Phenology Index (NDPI), which is a 3-band VI, using the spectral signal from red, near-infrared (NIR) and shortwave-infrared (SWIR) bands respectively (as used in NDVI and NDII). To evaluate the robustness and performance of the new index in detecting GUD, we firstly performed mathematical simulations and then applied NDPI to real vegetative ecosystems using MODIS land surface reflectance products, validated by using observations from three in-situ PhenoCam sites, and 11 eddy-covariance (EC) flux sites. We show that NDPI is robust to snowmelt and can indicate the GUD in spring better than other VIs (e.g. NDVI) in snow covered regions, especially in deciduous ecosystems.

2. Methodology and data

2.1. Definition of vegetation indices (VIs)

2.1.1. Normalized Difference Vegetation Index (NDVI)

NDVI is calculated from the red (ρ_{red}) and near-infrared (NIR, ρ_{NIR}) band reflectance as follows (Asrar et al., 1984):

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \tag{1}$$

The red band is located in the strong chlorophyll absorption region (about 600–700 nm), and the NIR band is located in the high reflectance plateau which is related to the leaf internal structure (about 700–1100 nm). NDVI is correlated with the leaf area index (LAI) and the absorption of photosynthetically active radiation by the canopy (Asrar et al., 1984).

2.1.2. Normalized Difference Infrared Index (NDII)

NDII (NDWI) has a similar definition to that of NDVI but replaces ρ_{red} with the shortwave-infrared radiation (SWIR, about 1300–2700 nm) reflectance (ρ_{SWIR} , Hardisky et al., 1983):

$$NDII = \frac{\rho_{NIR} - \rho_{SWIR}}{\rho_{NIR} + \rho_{SWIR}}$$
(2)

A large absorption by leaf water is observed in the SWIR bandwidth and thus this index reflects the effect of leaf water content (Fensholt and Sandholt, 2003). The exact wavelength of SWIR varies slightly depending on researchers. For instance, the wavelength of SWIR was defined as 1240 nm in Gao (1996), and 1580–1750 nm in Xiao et al. (2002). Despite the difference in the SWIR wavelength used, they accomplish similar things with each other.

2.1.3. Phenology Index (PI)

Gonsamo et al. (2012) proposed the PI which is a complex combination of NDVI and NDII:

$$PI = \begin{cases} 0, & if \ NDVI \ or \ NDII < 0 \\ & NDVI^2 - NDII^2 \\ & 0, if \ PI < 0 \end{cases}$$
(3)

Pl was designed to improve the capability of monitoring vegetation phenology by removing the wetness and brightness effects from greenness of land surface, especially the confounding effect of the snow (Gonsamo et al., 2012). The authors constrained the variance of Pl caused by snow dynamics by assigning zero to Pl for some conditions.

2.1.4. Normalized Difference Phenology Index (NDPI)

We proposed a new index, NDPI, motived by Gonsamo et al. (2012). NDPI directly employs the red, NIR and SWIR bandwidths. The most desirable property of NDPI is to be free of the snowmelt effect but is sensitive to initial vegetation growth during the spring green-up period. To achieve this goal, we firstly examined spectral reflectance curves of typical main components of the land surface (Fig. 1). The reflectance of both soil and snow varies monotonically from red to SWIR wavelengths (increasing for soil; decreasing for snow). For vegetation, however, the reflectance of NIR bandwidth is high while the reflectance of the red and SWIR bandwidth are low. To make use of this unique feature, we first define a new red-SWIR reflectance (ρ_{red}^{SWIR}) as the weighted sum of the red and SWIR reflectance in order to minimize the difference between soil and snow that are the main components of the land surface in the non-growing season:

$$\rho_{red}^{SWIR} = \alpha \times \rho_{red} + (1 - \alpha) \times \rho_{SWIR}$$
(4)

where α is a weighting coefficient which must be determined, and it is

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