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The mixed pixel effect in land surface phenology: A simulation study

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ABSTRACT

Because of the limited spatiotemporal resolutions in vegetation index (VI) products, land surface phenology (LSP) results may not well capture ground-based phenological changes. This is likely the result of the mixed pixel effect: (1) a pixel in VI products may contain an unknown composition of vegetation species or land cover types; and (2) these species differ in their sensitivity to climatic variations. The mixed pixel effect has induced inconsistent findings in LSP with in situ observations of spring phenology. To this end, this study has designed a series of simulation experiments to initiate the methodological exploration of how the green-up date (GUD) of a mixed pixel could be altered by the endmember GUDs and different non-GUD variables, including the endmember composition, minimum and maximum normalized difference vegetation index (NDVI), and the length of the growth period. The study has also compared the sensitivity of two generally adopted GUD identification methods, the relative threshold method and the curvature method (also known as the inflection-point method). The simulations with two endmembers show that even if there is no change in the endmember GUDs, the GUD of the mixed pixel could be substantially altered by the changes in non-GUD variables. In addition, the study has also developed a simulation toolkit for the GUD identification with cases of three or more endmembers. The results of the study provide insights into effective strategies for analyzing spring phenology using VI products: the mixed pixel effect can be alleviated by selecting pixels that are relatively stable in the land cover or species composition. This simulation study calls for in situ phenological observations to validate the LSP, such as conducting climate-controlled experiments on few mixed species at a small spatial scale. The paper also argues for the necessity of isolating GUD trends caused by non-phenological changes in the study of spring phenology.

1. Introduction

Land surface phenology (LSP) studies the seasonality of vegetated land surfaces by remotely sensed imageries (White et al., 2009). LSP viewed as a long-term, globally-sensed landscape feature is able to overcome the limited spatiotemporal coverage inherent in plot-based, in-situ observations (e.g., human observations, canopy cameras, flux towers) of the ecosystem. As a result, LSP serves an effective role in complementing measurements at places not covered by onsite observation stations (Reed et al., 1994; Zhao and Schwartz, 2003). It provides corroborating evidence for validating ecological responses to historical climate change scenarios (Badeck et al., 2004).

Using vegetation indices (VIs), notably the normalized difference vegetation index (NDVI) and the enhanced vegetation index (EVI), LSP studies can derive phenological metrics as indications of ecosystem dynamics (Zhang et al., 2003). The green-up date (GUD; also known as the start-of-season [SOS]), as an important phenological metric, characterizes the onset of measurable photosynthetic activities or the timing of spring arrivals. Despite the proliferating applications of the GUD as a synoptic variable in research on climate change (Brown et al., 2012; Shen et al., 2014; Stöckli and Vidale, 2004), arguments arose about the reliability of the LSP in replicating ground-based phenological events and testing the climatic sensitivity of vegetation (White et al., 2009), such as the arguable advance of the GUD in the Tibetan Plateau as a response to climate change (Shen et al., 2013; Zhang et al., 2013).

In addition to atmospheric interference (e.g., clouds, aerosols) and algorithmic corrections that contaminate or modify the true spectral information (Ahl et al., 2006), two important geographic uncertainties may obfuscate the identification of the GUD because of the coarse spatiotemporal resolutions in VI products (e.g., GIMMS, MODIS, SPOT VGT). The first source of uncertainty pertains to the temporal mismatch of remotely sensed data with ground observations. For example, the moderate resolution imaging spectroradiometer (MODIS) VI products

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cannot completely match the ground dates, because the vegetation growth between the green-up and the maturity is a dynamic and rapid process (e.g., using an 8- or 16-day MODIS products to detect a 10–12 day growth period; Ahl et al., 2006). The second source of uncertainty is the mixed pixel effect, also known as the point vs. pixel problem (Reed et al., 1994; White et al., 2009). The mixed pixel effect arises because that (1) a pixel in VI products may contain an unknown composition of vegetation species or land cover types (both can be regarded as endmembers in spectral mixture models) and that (2) these species differ in their sensitivity to climatic variations in terms of the GUDs (Badeck et al., 2004; Duchemin et al., 1999; Schwartz and Reed, 1999; Zhang et al., 2017). In addition, the greenness of understory phenology further complicates the detecting of overstory signal (Ahl et al., 2006; Tremblay and Larocque, 2001). As the pixel-based GUD trend can be induced by the change of a single variable or a combination of variables (e.g., species compositions, species GUDs) encapsulated in a mixed pixel, it is far from clear about the precise mechanism that dictates the phenological outcome. Alternative solutions were employed to alleviate the effect, such as comparing the phenological detections between images of different resolutions (Zhang et al., 2017), except few cases where mixed species were examined separately (Badeck et al., 2004; Duchemin et al., 1999).

Although the mixed pixel effect in the LSP has received increasing attention, it is unclear as to what extent the effect is actually shaping the surface reflectance and eventually contributing to the observed GUD shift. Under the context of climate change, the interannual dynamics of the LSP is not necessarily the result of shifted phenological patterns but could be partially attributed to the alteration of the land cover, such as the introduction of a new species or the expansion of agricultural lands (Helman, 2017). To this end, this paper has explored how the GUD of a mixed pixel could be mechanistically altered by both the endmember GUDs and different non-GUD variables in an annual development cycle.

2. Method

2.1. Simulation of annual NDVI temporal profile

The annual NDVI dynamics representing the growth or senescence period of a plant species *m* in a development cycle can be described by a logistic model, as shown in Eq. (1) (Ratkowsky, 1983; Zhang et al., 2003).

$$\mathrm{NDVI_m}(t) = \frac{c}{1 + e^{a+bt}} + d \tag{1}$$

where t is the day of the year (DOY), a and b are parameters associated with the timing and change rate ($b < 0$ for the growth period and $b > 0$ for the senescence period) of the NDVI trajectory, c is the amplitude of the trajectory, and d is the minimum NDVI value ($\mathrm{NDVI_{min}}$). In this respect, the value of $c + d$ yields the maximum NDVI value ($\mathrm{NDVI_{max}}$) at the timing of full maturity.

We started the analysis with a simulated mixed pixel composed of two endmembers: endmember A belongs to a deciduous forest and endmember B belongs to a cropland. The annual NDVI profiles of these two endmembers were derived from the MODIS VI products (16-day MVC 250-m MOD13Q1, Collection 6; Huete et al., 2002) based on the 16-year (2001–16) temporal profiles of endmembers in two selected land parcels in Northeast China. The process of the data collection is included in the Supplementary Data. The averaged NDVI profiles of the two endmembers are shown in Fig. 1a. The GUDs of the endmembers were identified at the inflection point of the logistic curve when the rate of change in curvature reached the first local maximum (Zhang et al., 2003). We then generated a mixed pixel based on specific compositions of the two endmembers. The NDVI value of the mixed pixel ($\mathrm{NDVI_{mix}}$) was generated as a linear combination of the NDVI values of endmembers weighted by their contribution factors (Adams et al., 1986), as shown in Eq. (2) and Fig. 1b.

$$\mathrm{NDVI_{mix}} = \sum_{m=1}^{M} f_m \mathrm{NDVI_m} \quad \text{s. t.} \quad \sum_{m=1}^{M} f_m = 1 \tag{2}$$

where $\mathrm{NDVI_m}$ denotes the NDVI value of endmember m (composed of vegetation and soil background), f_m denotes the contribution factor of endmember m in the mixed pixel, and M is the number of endmembers in the mixed pixel (M = 2 in this study).

The original NDVI values of the endmembers were extracted from a MODIS pixel, in which both vegetation and soil background signals were included. The independent contribution of soil to a mixed pixel thus cannot be considered in Eq. (2). Moreover, as the NDVI is an integrated signal dictated by both the green vegetation fraction (GVF) and the leaf area index (LAI; Gao et al., 2000), f_m was used to represent the bilateral contributions from both the GVF and the LAI rather than the vegetation fraction per se. More importantly, although the linear spectral mixture model was strictly valid for the original reflectance values, existing studies demonstrated that this linear mixture model would introduce only minor and negligible errors when replacing the reflectance by the non-linearly transitioned NDVI (Aman et al., 1992; Kerdiles and Grondona, 1995). This evidence ensured an acceptable level of accuracy for deriving the aggregate NDVI of the simulated mixed pixel. Based on Eq. (2), the annual $\mathrm{NDVI_{mix}}$ temporal profiles with different f_m were generated (Fig. 1b).

2.2. Detection of GUD_{mix}

In this pilot study, we employed two widely adopted methods for detecting the spring phenology in terms of the $\mathrm{GUD_{mix}}$: (1) the relative threshold method (Jönsson and Eklundh, 2004; White et al., 1997; Yu et al., 2010) and (2) the curvature method (also called the inflection-point method; Zhang et al., 2003; Zhang and Goldberg, 2011), which was used to produce the MODIS phenological product (MCD12Q2; Zhang et al., 2006). These two methods were compared and tested for their sensitivity to the mixed pixel effect. In the relative threshold method, the GUD of the mixed pixel ($\mathrm{GUD_{mix}}$) was identified as the day when the $\mathrm{NDVI_{mix}}$ reached a specific percentage (i.e., 10%) of its annual amplitude (White et al., 1997). For the curvature method, the sigmoid-shaped logistic function was fitted to the $\mathrm{NDVI_{mix}}$ data, followed by the identification of the $\mathrm{GUD_{mix}}$ as the day when the rate of change in the $\mathrm{NDVI_{mix}}$ curvature reached its first local maximum (Fig. 1c).

2.3. Simulation experiments

The rationale of the simulation approach was to evaluate the sensitivity of the $\mathrm{GUD_{mix}}$ to four non-GUD variables (f_m, $\mathrm{NDVI_{max}}$, $\mathrm{NDVI_{min}}$, and the growth period between the GUD and the maturity date) and the endmember GUDs under different scenarios (Table 1 and Fig. 2). Each test variable was simulated 20 times (corresponding to twenty years of phenological changes) by adjusting the variable at an equal increment (e.g., in Fig. 2b, the $\mathrm{NDVI_{max}}$ of endmember A decreases from 0.9 to 0.7 at an increment of 0.01, where only five key variables were used for better visualization). The rationale of choosing the range of the test was based on the statistics of the variable in the 16-year MODIS VI product (see the Supplementary Data for details).

3. Results

Scenario I changes the f_a from 0.3 to 0.7 (and thus f_b from 0.7 to 0.3) at an increment of 0.02. With the two original NDVI temporal profiles unchanged, increasing the f_a (the early GUD endmember) considerably advances the $\mathrm{GUD_{mix}}$, as shown in Fig. 3. In the other respect, increasing the f_b (the late GUD endmember) delays the $\mathrm{GUD_{mix}}$ to a considerable extent (not visualized in the article). This scenario