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Modeling spatiotemporal variations in leaf coloring date of three tree species across China

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ABSTRACT

Autumn phenology can regulate climate-biosphere interactions and net primary production within the ecosystem. However, studies modeling spatiotemporal variations in leaf coloring date (LCD) remain limited, especially for species-specific phenology on a continental scale. Aiming to simulate spatiotemporal variations in LCD in three widespread tree species (*Ulmus pumila*, *Fraxinus chinensis,* and *Robinia pseudoacacia*) across China, we used phenological observation records acquired from the China Phenology Observation Network (CPON) during 1963–2010 to establish and compare three LCD models (multiple regression (MA), temperature-photoperiod (TP), spring-influenced autumn (SIA)). Subsequently, we simulated the mean LCD of the three species using the most effective model and examined the effect of geographical factors (i.e., latitude, longitude, and altitude) on LCD through multiple regression analysis. Empirical Orthogonal Function (EOF) analysis was applied to identifying the most extensive and influential spatial modes of LCD variability and how they changed with time. The results showed that: (1) The LCD of *F. chinensis* was fitted better with the statistical model using monthly temperature as the independent variables (MR model). The LCD of *F. chinensis* was delayed by a temperature rise in August and September, but advanced by a temperature rise in May and June. The LCD of *U. pumila* and *R. pseudoacacia* was fitted better with the TP and SIA models, in which the photoperiod determined the date when the cold temperature started to accumulate. (2) The simulated mean LCD of *U. pumila*, *F. chinensis,* and *R. pseudoacacia* was October 6, October 16 and October 22, respectively. Latitude, longitude, and altitude had a significant influence on mean LCD of the three tree species. With increasing latitude and altitude, the LCD of all three species became earlier. However, the impact of longitude on the mean LCD varied among species. (3) For all the three species, the first EOF mode presented a consistent pattern of LCD variability across space, suggesting that an earlier or later LCD occurred simultaneously in the whole China. Meanwhile, the second EOF mode exhibited contrary signals of LCD variability in the north and south for *F. chinensis* and *R. pseudoacacia*. Over the past 50 years, the LCD of all the three species has delayed. The delaying trend revealed by the first EOF mode was 1.25 ($p < 0.01$), 0.21 ($p < 0.01$), and 0.53 days/decade (not significant) for *U. pumila*, *F. chinensis* and *R. pseudoacacia*, respectively. These results provide the basis for a better understanding of the phenology process in autumn and how it responds to climate change.

1. Introduction

Phenological changes have dramatic effects on carbon balance, nutrient cycles, biodiversity and net primary production in ecosystems (Cleland et al., 2007; Ge et al., 2014b), and control many feedbacks of the climate system (Ge et al., 2014a; Richardson et al., 2013). Several studies have concluded that autumn phenology might have a greater effect than spring phenology on the extension of growing season length (Garonna et al., 2014; Liu et al., 2016b) and changes in net ecosystem productivity (Wu et al., 2013). Thus, a comprehensive understanding of spatiotemporal patterns of autumn phenology could help understand structure and function of the ecosystem in autumn and to predict future ecosystem dynamics.

Phenological models play a critical role in quantifying climate-biosphere interactions (Visser, 2016; Xin, 2016). Through phenological models and meteorological data, the phenophases and their spatiotemporal patterns could be simulated accurately (Aono and Omoto, 1990; Bluemel and Chmielewski, 2012; Chuine, 2000). Compared with

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spring phenological models, models regarding autumn phenology remain limited, mainly due to lack of knowledge about the phenology process and its mechanism (Olsson and Jonsson, 2015). Many external environmental factors, such as temperature, drought, ozone, nutrient deficiency, and pathogen infection, may have considerable influences on the autumn phenology process (Lim et al., 2007), and the influences may differ across species and ecosystems (Gill et al., 2015). Therefore, existing autumn phenology models based either on observations of individual trees or remote sensing have different parametric equations (Jeong and Medvigy, 2014).

The existed autumn phenological models are mostly set up according to several main influencing factors. A great number of studies put forward that temperature is the most important factor impacting autumn phenology (Chen and Xu, 2012; Ge et al., 2015; Menzel, 2003), because cold temperature may lead to water freezing in leaves and force deciduous trees to shed their leaves to prevent damage (Jeong and Medvigy, 2014). However, the start date of leaf coloring is determined by a specific threshold of minimum temperature (Estrella and Menzel, 2006) or accumulated cold temperature (Yu et al., 2016) according to different hypotheses. Photoperiod is another factor influencing autumn phenology (Fracheboud et al., 2009), especially in regions at high latitudes (Gill et al., 2015; Way and Montgomery, 2015), which can affect the formation of leaf abscission meristems and the ability of plants to tolerate low temperature (Korner and Basler, 2010). Moreover, precipitation may improve soil moisture content and change the photosynthetic efficiency by affecting the plant carboxylation reaction, and further lead to shifts in autumn phenology (Zu and Yang, 2016). Recently, spring phenology has been found to exert a significant influence on the timing of autumn phenology (Fu et al., 2014; Liu et al., 2016a), and is considered in a recent phenological model (Keenan and Richardson, 2015).

To date, many autumn phenological models are developed on the basis of few data from limited sites (Jeong et al., 2013). Thus, the established models may have great errors when simulating phenology in broad geographical regions (Basler, 2016; Delpierre et al., 2009). Several studies have made systematic comparisons among various autumn phenology models in Europe (Olsson and Jonsson, 2015) and America (Jeong and Medvigy, 2014), and have found that temperature and photoperiod can explain the variation in autumn phenology for most species, but that the parameters may vary greatly among species. However, no previous study has focused on the species-specific autumn phenology model up to date in China.

In order to compensate the above shortage and fill this knowledge gap, this study used three phenology models for simulating leaf coloring date (LCD) of three cosmopolite tree species (*Ulmus pumila*, *Fraxinus chinensis*, and *Robinia pseudoacacia*) across a large part of China. Based on the optimal model, we simulated the LCD variations in the three species over the past 50 years and analyzed their spatiotemporal patterns through empirical orthogonal function (EOF) analysis. The overall aim of the study was to explore the spatiotemporal pattern of autumn phenological change in typical species in China and try to discuss the mechanism of autumn phenology process in response to climate change.

2. Materials and methods

2.1. Data source

The three plant species (*U. pumila*, *F. chinensis,* and *R. pseudoacacia*), selected for study all have strong tolerance to severe environments, such as drought conditions and alkaline or saline soils (Solla et al., 2005; Wu et al., 1994). These species are widespread and can reflect the autumn phenological changes over large regions in China. Data on the distribution of *U. pumila* and *F. chinensis* (Fig. 1) were obtained from the Atlas of Woody Plants in China (Fang et al., 2009). The distribution of *R. pseudoacacia* in China was determined according to the Flora of China (Wu et al., 1994) and Chinese Virtual Herbarium (CVH, www.cvh.ac.cn).

The LCD data of the three species were obtained from China Phenological Observation Network (CPON) (Table A.1–A.3), which were mainly observed at sites located in eastern China (Fig. 1). The LCD for an individual tree was defined as the date when 99% of its leaves had visibly changed color. The phenological observations were interrupted during several periods (Fig. 2), so the average number of records per year was 8.6, 8.2, and 9.7 for *U. pumila*, *F. chinensis,* and *R. pseudoacacia*, respectively.

The meteorological data were downloaded from the China meteorological data service center (http://data.cma.cn/). For fitting the phenology model, we used daily air temperature data obtained near CPON sites from 1963 to 2010. For LCD simulation, we utilized a gridded dataset of daily surface air temperature at 0.5° × 0.5° resolution during 1961–2012. This dataset was generated by interpolating the data from 2472 meteorological stations using ANUSPLIN software and thin plate spline method.

2.2. Methods

2.2.1. Model calibration and validation

Three autumn models were applied to simulate the LCD. The first one was a multiple regression (MR) model. Estrella and Menzel (2006) found that LCD was delayed by a temperature rise in August and September but advanced by a temperature rise in May and June. Based on this empirical relationship, the MR model was built as a multiple linear regression function between autumn phenophase and monthly temperature:

$$P_l = aT_5 + bT_6 + cT_7 + dT_8 + eT_9 + \varepsilon \tag{1}$$

where a, b, c, d, and e are model parameters, T_5, T_6, T_7, T_8, and T_9 are the mean temperature in May, June, July, August, and September, respectively, and ε is a constant term.

The second model was a process-based model based on temperature and photoperiod (TP model), which defines a coloring state $CDD(d)$ for each day to depict the progress of leaf coloring (Delpierre et al., 2009). In the TP model, $CDD(d)$ is determined by accumulated cold temperatures and regulated by daily photoperiod [Eq. (3)]. For some species, the photoperiod not only decides the date when cold temperatures begin to accumulate [Eq. (2)], but also influences the cold degree sum effect [Eq. (4)]. The combined effect of temperature and photoperiod is shown as:

$$iCDD(d) = =\begin{cases} 0 & \mathrm{P(d)} \geq P_{start} \\ \mathrm{CDD(d-1)+CDD(d)} & \mathrm{P(d)} < P_{start} \end{cases} \tag{2}$$

$$CDD(d) = \begin{cases} 0 & \mathrm{T(d)} \geq T_b,\ \mathrm{P(d)} < P_{start} \\ [T_b - T(d)]^x \times f\,[P(d)]^y & \mathrm{T(d)} < T_b,\ \mathrm{P(d)} < P_{start} \end{cases} \tag{3}$$

$$f\,[P(d)] = \frac{P(d)}{P_{start}} \tag{4}$$

where i$CDD(d)$ represents the accumulated coloring state. The cold temperatures below a limit T_b are accumulated when the day length becomes shorter than P_{start}. $P(d)$ and $T(d)$ represent the daily day length and mean temperature, respectively. $f[P(d)]$ is a function of $P(d)$, which suggests that photoperiods shorter than the P_{start} threshold may weaken the cold-degree effect. Two exponent indices x and y (take any of 0, 1, 2) are used to measure the possible effects of temperature and day length. The day length $P(d)$ depends on the day of the year (DOY) and latitude (L) (Forsythe et al., 1995).

The appearance of LCD (d) is recognized when $iCDD$ achieves a threshold Y_{crit}, given by:

$$iCDD(d) \geq Y_{crit} \tag{5}$$

The third autumn model was a spring-influenced autumn (SIA)