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Change point estimation of deciduous forest land surface phenology

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ABSTRACT

Dramatic phenological shifts and ecosystem responses of deciduous forests to global climate change have been reported around the world. Land Surface Phenology (LSP) derived from satellite imagery is useful to estimate the phenological responses of vegetation to climate variability and inform terrestrial ecosystem models at landscape to global scales. However, there is a large (and unquantified) uncertainty in estimated phenological dates due to the relatively coarse temporal resolution of typical data and methodological limitations. To assess responses of phenology and related ecological function and services, it is essential to decrease the temporal uncertainty of estimated phenological processes. In this study, we developed a new LSP estimation method using linear change point models to determine four phenological transitions using twice-daily Moderate Resolution Imaging Spectroradiometer (MODIS) Enhanced Vegetation Index (EVI) from 2000 to 2015. We evaluated the approach using long-term phenological ground observations and compare performance of four LSP estimations generated from two data sources (i.e. 8-day and twice daily EVI time series) and two methods (i.e. double logistic and change point estimation). We found that the LSP generated from change point estimation with twice daily EVI time series had the highest accuracy (i.e. lower Root Mean Square Error (RMSE), mean bias, and Mean Absolute Error (MAE)) for both spring and fall phenology evaluated by Harvard Forest phenology observations and a large citizen science database of phenological observations from the National Phenology Network. For example, change point estimation reduced the estimation error for fall senescence date from over 40 days in the standard MODIS phenology product (version 005) to 11.5–24 days of RMSE, −2.6 to −5.8 days of mean bias, and 7.9–20.1 days of MAE. The change point methodology also enables calculation of additional metrics to describe the biophysical process of vegetation, including rates of greenup, green-down, and senescence, EVI values at each phenological transition, and the estimation uncertainties for each transition date. Our LSP estimations will improve more comprehensive investigations of landscape phenology of deciduous forest and the associated ecosystem processes at regional to global scales.

1. Introduction

Dramatic ecosystem responses to global climate change including phenological shifts of plant and animals have been reported around the world. Satellite derived Land Surface Phenology (LSP) provides a powerful tool to detect phenological responses of vegetation to climate variability and change from regional to global scales (Xie et al., 2015a, 2015b; Liu et al., 2017a). Phenological shifts detected in LSP over past decades suggest advanced spring greenup phenology and delayed autumn senescence and dormancy in temperate regions (Jeong et al., 2011; Liu et al., 2017). Spatiotemporal shifts in LSP of forest communities reflect responses and adaptation strategies to environmental changes (Gu et al., 2008), which are critically associated with animal activities (Hufkens et al., 2012; Ellwood et al., 2015), community composition (Tylianakis et al., 2008), biodiversity dynamics (Miller-Rushing et al., 2010), ecosystem processes (e.g. carbon and nitrogen cycling) (Norby et al., 2003; Niinemets, 2010; Jentsch et al., 2011; Richardson et al., 2013; Tang et al., 2016), and impact the multi-billion dollar fall foliage ecotourism industry (Spencer and Holecek, 2007; Rustad et al., 2012). In addition, satellite-derived vegetation phenology provides important parameters to inform Terrestrial Ecosystem Models (TEMs) to estimate global ecosystem processes (e.g. carbon cycling) (Wang et al., 2010; Jeong et al., 2012; Delpierre et al., 2016). Phenology of deciduous forests are more sensitive to climate change with more frequent extreme weather events than many biomes, and phenological shifts bring more substantial impacts on ecosystem function and services due to their large carbon pools and fluxes, and long recovery time to carbon stocks (Reichstein et al., 2013; Frank et al.,

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2015). Understanding how forest phenology responds to climate variability is essential to assess impacts and risks in forest ecosystems, and to support adaptation and management strategies by policy makers.

Different methods have been used to estimate LSP from Vegetation Index time series (de Beurs and Henebry, 2010; Misra et al., 2016). The commonly used methods include setting fixed thresholds or ratios of the amplitude between maximum and minimum values to identify onset and end of growing season (White et al., 1997; Wu et al., 2017), and fitting logistic curves (e.g. simple logistic, double logistic, and piecewise logistic methods) to calculate change of curvature to identify four phenological transitions (i.e. greenup, maturity, senescence, and dormancy) (Zhang et al., 2003; Liu et al., 2016). The MODIS phenology product (MCD12Q2 version 005) (Zhang et al., 2006) was developed to provide global LSP with these four phenological transitions dates. The product determined phenology using 8-day Enhanced Vegetation Index (EVI) time series and piecewise logistic curve fitting method, which has been applied in ecological research and informed TEMs (Wang et al., 2010; Keenan et al., 2014; Xia et al., 2015). Other remote sensing products representing land surface vegetation phenology (e.g. MODIS NDVI and LAI products) were also used in many land surface models and earth system models to estimate terrestrial carbon dynamics (MacBean et al., 2015; Bloom et al., 2016; Exbrayat et al., 2019).

However, there are problems with current methods to estimate LSP based on the satellite vegetation index products. For example, compared to in situ observations, estimation of greenup or start of growing season date for deciduous broadleaf forests from satellite imagery have root mean square errors (RMSE) of 5–16 days (Balzarolo et al., 2016; Liu et al., 2017b; Peng et al., 2017). However, fall phenology, including senescence and dormancy (the indicator of end of growing season) have not been thoroughly evaluated and still have a relatively large uncertainty compared with ground observations. For example, higher estimation deviations from ground observations were always found for satellite-derived fall phenology than those in spring (Wu et al., 2017; Zhang et al., 2017). Extracting the onset timing of fall senescence is still a challenge because it is difficult to define the start of decline in vegetation greenness from the gradual change in early fall (Gallinat et al., 2015; Xie et al., 2018), associated with declining solar illumination in the fall (Hutchison and Matt, 1977). This is in contrast to the greenup event defined by a quick response of plant bud break and leafing out in a short time period in early spring. Lack of accurate estimation on fall senescence of plant community may lead to biased assessment of community and ecosystem processes (Richardson et al., 2012; Exbrayat et al., 2019), since onset of plant fall senescence is an important indicator of the start point in the processes of chlorophyll degradation (Delpierre et al., 2016) and nutrient resorption (Estiarte and Peñuelas, 2015; Gallinat et al., 2015) affecting carbon budget and nitrogen cycling estimated from the TEMs and dynamic global vegetation models (DGVMs) (Medvigy et al., 2009; Wang et al., 2010; Jeong and Medvigy, 2014). Large biases and errors in the representation of phenology in terrestrial biosphere models were found for deciduous forests, which reduced the accuracy of carbon dynamics estimations and the feedbacks of terrestrial vegetation to the climate system (Richardson et al., 2012). The other problem in estimating LSP is a large or unquantified uncertainty of the inferred dates (Tang et al., 2016). The reasons for this problem probably include the relatively coarse temporal resolution combined with methodological limitations (de Beurs and Henebry, 2010; Helman, 2018). Most existing studies used 8-day or 16-day satellite imagery with smoothing and gap-filling techniques that may not accurately capture any abrupt changes in vegetative activity in the fall. Limitations of estimation methods for start and end of season (SOS and EOS) from satellite imagery (Wu et al., 2017) may also add to the large uncertainty in LSP product. In addition, most current LSP product do not quantify the uncertainty of the estimated dates or error structures (de Beurs and Henebry, 2010), which limits the possibility of generating more accurate assessment of ecological information derived from satellite imagery by removing low quality data with high uncertainties, and in turn affects the reliability of our understanding in ecological processes with the application of LSP products.

To assess responses of phenology and related ecological processes at regional to global scales, it is essential to narrow the estimation error and uncertainty of estimated phenological transitions from satellite imagery. To achieve this goal, we apply an innovative approach: change point estimation based on MODIS vegetation index time series with twice-daily temporal resolution. We expected the data source with a finer temporal resolution would increase our capability to capture the change of EVI from the seasonal change patterns with higher temporal resolution. We also expected our new method to provide more accurate and biologically relevant estimations with quantified uncertainties. We compare four LSP estimates generated from two methods (the standard piecewise logistic fitting method (Zhang et al., 2003) and our change point estimation method) and two datasets (8-day and twice daily MODIS EVI). We evaluate the estimation accuracy of four LSP estimates with long term ground-based phenology observation. We then use the LSP estimation with the best performance in capturing ground-based phenology to examine the spatial patterns of phenological transitions of deciduous forest in the central and eastern US from 2000 to 2015.

2. Materials and methods

2.1. MODIS data processing

Our study area includes all deciduous forests in the central and eastern United States (25–49°N, −99 to −65°E). We calculated the percentage of deciduous forest cover in each 500 m MODIS grid cell using the 30 m National Land Cover Database (NLCD2011) (Homer et al., 2015). Grid cells with deciduous forest cover lower than 75% were removed from the domain to reduce errors from mixed land cover types resulting in 1.2 M pixels across the central and eastern US. We randomly selected 2% (20,000 pixels) as a testing sample across the central and eastern deciduous forest biome for this study.

In order to evaluate different temporal resolutions, we used data between 2000 and 2015 from two MODIS products: 8-day surface reflectance data at 500 m spatial resolution (MCD43A4, Version 005), which are the data used for MODIS phenology product (MCD12Q2 Version 005), and twice-daily surface reflectance data from TERRA and AQUA (MOD09GA and MYD09GA, Version 006). We filtered the MOD/MYD09 data to retain only observations with the highest quality for each spectral band (no cloud, fire, snow, or salt pan, as well as low level of aerosol and cirrus clouds) based on quality information provided from the data quality layer. The Enhanced Vegetation Index (EVI) was calculated for each time step from two time series data (8-day and twice daily) using equation from Huete et al., 2002 (see Supplementary materials).

2.2. Estimation of land surface phenology

We used linear change point estimation to identify four phenological transitions from the filtered EVI time series with high-quality data. The method can estimate linear models for time series data which have one or more segmented relationships in the linear predictors. The algorithm is an iterative procedure that efficiently estimates multiple breakpoints and slopes along with standard errors based on starting values as breakpoints parameters (Muggeo, 2003). Specifically, we used the R package 'segmented' (Muggeo, 2008) to estimate four change points connected by linear segments in the EVI time series through each growing season for each pixel (see one example pixel in Fig. 1). First, we estimated four phenological transitions using double logistic fitting method (Zhang et al., 2003) based on twice daily EVI time series, and set them as starting values for the change point estimation. Second, we ran 'segmented' function with 100 iterations and 300 bootstrap samples to estimate the dates of four change points in each growing season along with associated parameters including intercepts, slopes, and

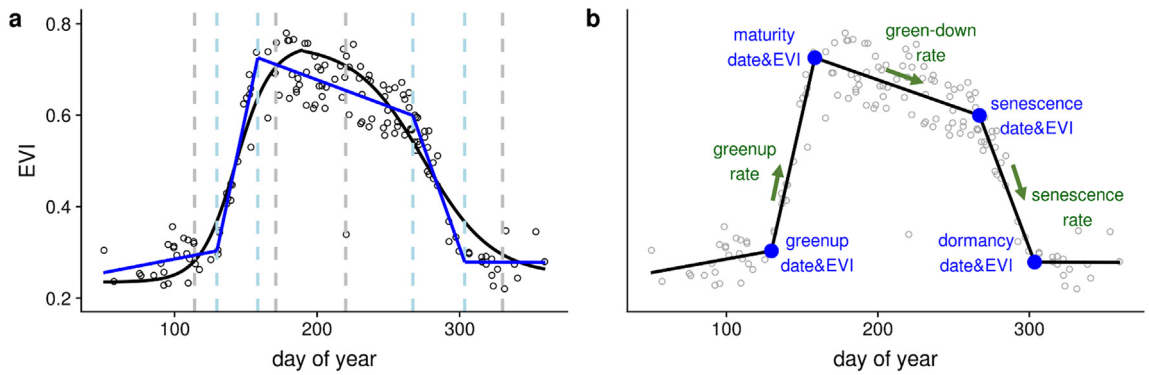

Fig. 1. Demonstrations of LSP estimated from twice daily EVI time series data of an example MODIS pixel at Harvard Forest in MA, USA. a. Two methods (solid black: piecewise logistic fitting, and solid blue: change point estimation) were used. Vertical dashed lines indicate estimated four phenological transitions (greenup, maturity, senescence, and dormancy dates) for each method (grey: piecewise logistic fitting, and light blue: change point estimation). b. Multiple LSP metrics estimated using change point estimation method including four phenological transition dates, the EVI value on each transition date, and green-up, green-down, and senescence rates. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

standard error for every parameter. Iteration and bootstrap settings were determined based on our testing on segmentation function for convergence of estimation and processing time across a range of sample pixels. The bootstrap samples were used in a bootstrap restarting algorithm to make the algorithm less sensitive to starting values (i.e. breakpoint priori parameters estimated using logistic fitting method) (Muggeo, 2008). Thirteen months of twice-daily EVI observations from January in the current year to January in the following year were used to provide more winter time data to better fit the dormant winter season change pattern at the end of the growing season. Since EVI data before January were often limited due to snow cover in the northern area, and the senescence to dormancy of vegetation was a gradual process, adding one-month data provides more EVI observations to better identify the fourth change point, dormancy date. We set four as the number of change points that should be identified by our method, since it matches the general seasonal pattern of EVI in temperate deciduous forests. The estimated timing of four change points (i.e. breakpoints) between the five fitted segments represents the four phenological transitions dates: greenup, maturity, senescence and dormancy. The change point estimation method detects the general patterns of EVI time series within an entire growing season to locate the timing of four breakpoints (Muggeo, 2003). We expect five fitted linear segments to capture the change points of EVIs for five different vegetation growth/development phases, including the dormant stage in late winter before bud break (low EVI values with relatively small variation), leaf expansion phase from bud break in early spring to full expansion in early summer (increasing EVI values), leaf maturity phase during summer (high EVI values with a slight decreasing trend), leaf senescence phase initiated by the onset of leaf coloration in fall (decreasing EVI values), and the dormant phase with no deciduous leaves in winter (low EVI values with relatively small variation). Thus, four phenological transitions determined by the change points indicate the critical transition timing of these vegetation development phases in the growing season. For each estimated date, the model provides a standard error as a quantification of estimation uncertainty. Change point estimation also quantifies additional attributes of the full seasonal change process. The estimated slope for each fitted line captures the rate of seasonal change of EVIs during each time period. At each phenological transition dates of each pixel, the EVI value on that date is also identified (Fig. 1b).

To test if change point estimation improves estimation accuracy in detecting phenological transitions, we compared this method to the standard piecewise logistic model (Zhang et al., 2003, 2009; Pouliot et al., 2011; Zhu et al., 2012; Liu et al., 2016) (see one example pixel in Fig. 1a).

2.3. Evaluation using ground-based phenology observations

We used two datasets of ground phenology observations to evaluate and compare the accuracy of the four LSP estimations. One ground observation dataset is from Harvard Forest long-term phenology observation (1993–2014) at forested area in central Massachusetts, USA (42°32′N and 72°11′W) (O'Keefe, 2000). The percentage of bud break in spring, leaf coloration and leaf drop in autumn at weekly intervals were recorded for permanently tagged tree individuals of representative woody plant species in the field by the observer, John O'Keefe, since 1990. Observations on bud break, leaf coloration and leaf drop of 12 dominant deciduous tree species during 2000 and 2014 were used (Table S1). Logistic curves were used to fit the observed percentage values in spring and autumn for each individual tree in each year to determine phenological dates (Fig. S1), because the change pattern of observed percentage values in phenology data fit well with a logistic curve with asymptotic and flat patterns at the beginning and end of observation time series for each phenophase. Onset and end dates of bud break, leaf coloration and leaf drop for each individual tree were identified by the dates with minimum changes in curvature of fitted logistic curves, indicating the beginning and end stages of each phenophase.

We also used phenological observations from the USA National Phenology Network (NPN) at multiple sites across the deciduous forest area in the central and eastern US from 2009 to 2015 to evaluate LSP estimated across a large spatial area. NPN is a citizen scientist network that allows citizen scientists to track phenology of plants and animals at selected sites and upload records through Nature's Notebook, an online phenology monitoring program, by following standardized observation protocols. In this study, we selected 26 deciduous tree species with observations from 119 sites from the NPN (Fig. 2, Table S2) based on their relatively large distributions in the study area representing local plant communities and the availability of phenological observations in the NPN dataset. According to the observation protocols from NPN, phenophase status (e.g. the presence or absence of leaves) was evaluated and monitored in each observation for each plant individual during a series of repeated observations over the course of a season (Denny et al., 2014). The phenophases used for this study included breaking leaf buds, leaves, colored leaves and falling leaves. Individual Phenometrics data were downloaded through Phenology Observation Portal online from NPN based on specified locations, species and phenophases. This Individual Phenometrics data type included estimates of the dates of phenophase onsets and ends (i.e. first and last dates of phenophase status monitoring records) for individual plants species at selected sites during 2009 and 2015 based on the observations. Thus, from NPN data, we used the first date when leaf bud break or the first

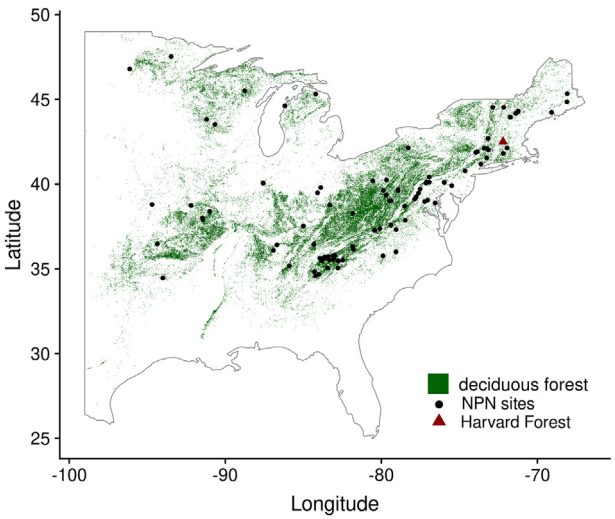

Fig. 2. Map of ground phenology observation sites in the central and eastern US. Green area indicates MODIS pixels with deciduous forest cover higher than 75%. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

leaf was observed as the onset date of bud break that is comparable to greenup date of LSP in spring. We used the first date when one or more leaves were observed to turn to late season colors in autumn as the onset date of leaf coloration that is comparable to senescence date of LSP, and the last date when one or more leaves have fallen was observed in autumn for each individual tree as end date of leaf drop that is comparable to dormancy date of LSP.

2.4. Evaluation of four LSP estimations

We evaluated the predictive accuracy across the two temporal resolutions (8-day and twice daily) and two phenological transition estimation methods (piecewise logistic and change point estimation) with the two ground-based observation datasets. We directly used the standard MODIS phenology product (MCD12Q2 version 005) as one estimation (log_8d, rf Fig. 1a), which uses the 8-day EVI time series with piecewise logistic fitting method (Zhang et al., 2003). The other three LSP estimations we calculated included the 8-day EVI time series with change point estimation (cp_8d, rf Fig. 1a), the twice daily EVI time series with piecewise logistic fitting method (log_d2, rf Fig. 1b) and change point estimation (cp_d2, rf Fig. 1b).

For both Harvard Forest and NPN phenology observations, we calculated mean values for each phenological date of all trees and species located in each MODIS pixel to compare with estimated LSP from MODIS EVI time series. For spring phenology, we compared the onset date of bud break to greenup date. For fall phenology, we compared the onset date of leaf coloration to senescence date, and compared the end date of leaf drop to dormancy date. To measure the performances of four LSP estimations, we calculated four evaluation metrics: Root Mean Square Error (RMSE), bias, Mean Absolute Error (MAE) and Pearson's correlation coefficient (r). Smaller absolute RMSE, bias values, and MAE, and larger Person's r values indicated higher estimation accuracy of LSP that better captured ground observed phenological dates of trees.

2.5. Application to LSP of deciduous forest

The LSP estimation with the best performance in evaluations was applied to our 20,000 randomly sampled pixels from the deciduous forest biome in the central and eastern US to estimate four phenological transitions (greenup, maturity, senescence and dormancy) from 2000 to 2015. Spatial variation of four phenological transitions, estimation uncertainty and other phenological metrics were examined.

3. Results

3.1. Evaluation of estimation accuracy for four LSP estimations

Overall, the change point model with twice daily EVI time series (cp_d2) resulted in the highest estimation accuracy of leaf phenology of deciduous forests, especially for autumn senescence dates, and MODIS phenology product had a better correlation in spring phenology. While RMSE, bias, and MAE values measure the differences between field observation and remote sensing product of phenology (i.e. accuracy), the Pearson's r values measure correlation and precision of LSP estimations. Compared to MODIS phenology product (MCD12Q2 version 005, log_8d in this study), cp_d2 reduced RMSE, bias, and MAE values for senescence date dramatically (Table 1). Specifically, cp_d2 had the smallest RMSE, bias, and MAE values among the 4 LSP estimations for greenup and senescence dates from both Harvard Forest and National Phenology Network sites, indicating the highest estimation accuracy in greenup and senescence dates (Table 1). For both greenup and senescence dates, we found that LSP estimations tended to make earlier

Table 1
Summary of RMSE, bias, MAE and Pearson's r between estimated phenological transition dates from remote sensing data sources and ground-based phenological dates at Harvard Forest (HF) and National Phenology Network (NPN). log_8d: 8-day EVI with piecewise logistic fitting method; cp_8d: 8-day EVI with change point estimation method; log_d2: twice daily EVI with piecewise logistic fitting method; cp_d2: twice daily EVI with change point estimation method. Numbers with bold fonts indicate the best performance (i.e. smallest RMSE, bias or MAE and highest Pearson's r values) of LSP estimation in comparisons.

Phenophase	LSP estimation	RMSE		bias		MAE		Pearson's r	
		HF	NPN	HF	NPN	HF	NPN	HF	NPN
Greenup ~ Bud break onset date	log_8d	10.9	28.0	−8.7	−14.8	9.0	23.0	0.74**	0.24
	cp_8d	11.3	26.7	−10.4	−11.9	10.4	21.2	**0.80*****	0.05
	log_d2	13.0	29.1	−12.1	−17.6	12.1	24.5	0.66**	0.16
	cp_d2	**4.4**	**24.1**	**1.3**	**−3.9**	**3.2**	**17.4**	0.68**	0.06
Senescence ~ Leaf coloration onset date	log_8d	50.8	70.1	−48.5	−62.4	48.5	63.0	**0.49**	−0.11
	cp_8d	21.9	51.7	−14.7	−32.4	15.6	40.4	−0.20	−0.16
	log_d2	49.0	58.6	−48.7	−53.8	48.7	53.8	0.38	0.06
	cp_d2	**11.5**	**24.0**	**−2.6**	**−5.8**	**7.9**	**20.1**	0.28	0.04
Dormancy ~ Leaf drop end date	log_8d	10.3	**21.9**	9.5	8.7	9.5	**17.1**	0.55*	0.04
	cp_8d	**7.4**	25.3	**4.0**	**2.0**	**5.2**	17.4	**0.70****	0.12
	log_d2	30.1	36.9	29.8	29.9	29.8	31.4	0.69**	0.11
	cp_d2	12.1	24.3	9.3	7.4	10.1	17.6	0.61*	−0.11

* Indicates significance level of $p < 0.05$.
** Indicates significance level of $p < 0.01$.
*** Indicates significance level of $p < 0.001$.

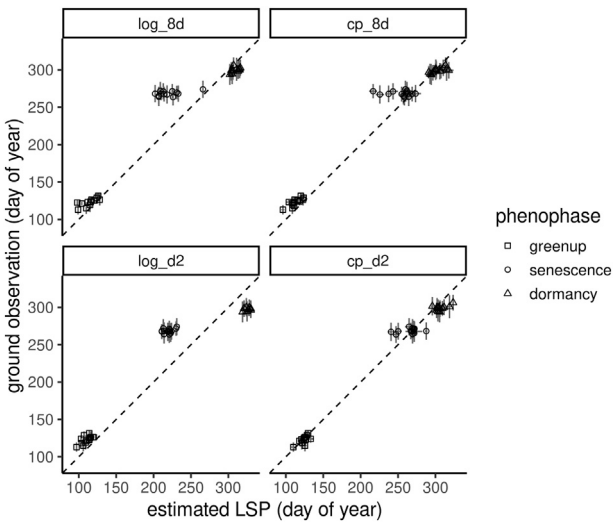

Fig. 3. Comparison of three phenological transitions between four LSP estimations evaluated in this study with ground phenology observations at Harvard Forest from 2000 to 2014. Dark grey error bars indicate phenological variations among species and trees of ground observations and estimation uncertainty in LSP estimations using change point estimation. log_8d: 8-day EVI with piecewise logistic fitting method; cp_8d: 8-day EVI with change point estimation method; log_d2: twice daily EVI with piecewise logistic fitting method; cp_d2: twice daily EVI with change point estimation method. Dashed lines are 1:1 lines.

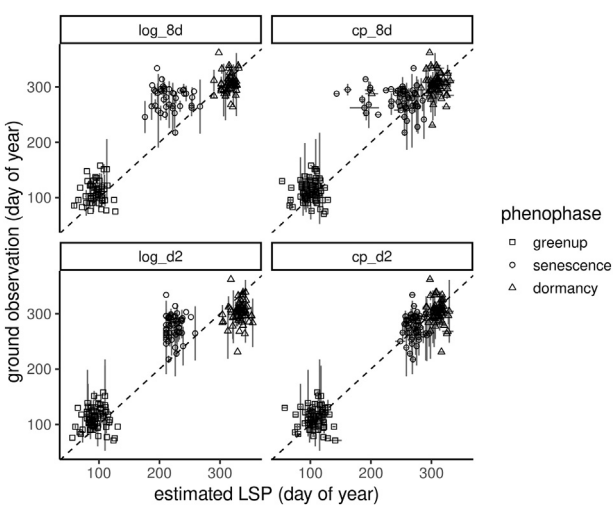

Fig. 4. Comparison of three phenological transitions between estimated four LSP estimations and ground phenology observations from National Phenology Network (2009–2015). Dark grey error bars indicate phenological variations among species and trees of ground observations and estimation uncertainty in LSP estimations using change point estimation. log_8d: 8-day EVI with piecewise logistic fitting method; cp_8d: 8-day EVI with change point estimation method; log_d2: twice daily EVI with piecewise logistic fitting method; cp_d2: twice daily EVI with change point estimation method. Dashed lines are 1:1 lines.

estimations than ground observation except cp_d2 (Figs. 3 and 4). The smaller RMSE, bias, and MAE values for greenup dates compared to senescence dates from all 4 LSP estimations indicated better performance in identifying the onset of spring phenology than the onset of fall phenology (Table 1). For the 119 sites from the NPN, the results are similar to Harvard Forest, though the phenological variations were much larger across the sites, species and individuals, as shown as more scattered plots with larger deviations from the mean dates (Fig. 4). Due to lack of community composition information and sub-pixel effects, the calculated phenological dates from ground observations may not fully represent the complete community in each pixel, which brings more uncertainties in comparisons between the datasets at two spatial scales. Therefore, we did not consider the small Pearson's r values from NPN phenology data as an important evaluation factor in our study. However, the Pearson's r values from the Harvard Forest data were highest for the 8-day change point (cp_8d) LSP estimation for greenup date, and MODIS phenology product (log_8d) had the highest Pearson's r value for senescence date, suggesting a better correlation to field observations. But all four estimations showed non-significant correlations with field observations indicating the challenge in estimation onset of senescence from remote sensing imagery. For dormancy dates, the LSP from change point estimation of 8-day EVI time series (cp_8d) had the smallest RMSE, bias, and MAE values and the highest Person's r value, indicating the highest estimation accuracy in dormancy date of cp_8d (Table 1). We found that all four LSP estimations tended to estimate later dormancy dates than observed phenology in the field (Figs. 3 and 4).

3.2. Spatial patterns of LSP of deciduous forests in the central and eastern US

Four phenological transition dates were estimated by change point estimation on twice daily EVI time series for our sampled 20,000 deciduous forest pixels at the central and eastern US during 2000 and 2015. The spatial patterns of mean and standard deviation of four dates in the central and eastern US are shown as Fig. 5. The pattern reflects the phenological variations from south to north driven by daylength and thermal conditions along with latitude and landscape in the central and eastern US. Overall, mean dates of greenup and maturity in spring in 16 years (2000–2015) ranged from February 20th to June 3rd (i.e. 51 to 154 day of year) and from April 14th to July 20th (i.e. 104 to 201 day of year) across the region, respectively (Fig. 5a–b). Mean dates of senescence and dormancy in fall in 16 years ranged from July 24th to November 5th (i.e. 205 to 309 day of year) and from September 11th to December 20th (i.e. 254 to 354 day of year) across the region, respectively (Fig. 5c–d). The standard deviation of the four phenological transition dates during 16 years quantifies the year-to-year variation (Fig. 5e–h). Our estimations suggested that fall phenology had larger inter-annual variations than spring phenology. The standard deviations of greenup and maturity dates in spring during 16 years were 9.5 and 9.4 days on average for 20,000 pixels, respectively. The standard deviations of senescence and dormancy dates in fall during 16 years were 17.8 and 11.9 days on average for 20,000 pixels, respectively.

Estimation uncertainty was quantified by standard error generated from change point estimation model for each estimated date at pixel level. From our sampled 20,000 pixels, estimation uncertainty of spring phenology was about 2.7 days, smaller than that of fall phenology, which was about 4.5 days (Fig. 6).

3.3. Multiple phenological metrics derived from change point estimation method

Other than four phenological transition dates and their estimation uncertainty, change point estimation method also provides the EVI value on each date and rates of EVI change in three growth phases. We noticed that the EVI value on each phenological transition date had inter-annual and spatial variations (Fig. 7). On average, EVI values on four phenological transition dates of deciduous forests at western areas, such as ecoregions of mixed wood shield, western areas of mixed wood plains and Ozark, Ouachita-Appalachian forests, were smaller than those of deciduous forests in other ecoregions in our study area (Fig. 7a–d). While the inter-annual fluctuations of EVI values represented by standard deviations did not show strong spatial variations, EVI values on senescence dates had a higher inter-annual variation than those on other three dates (Fig. 7e–h). Moreover, the EVI pattern in

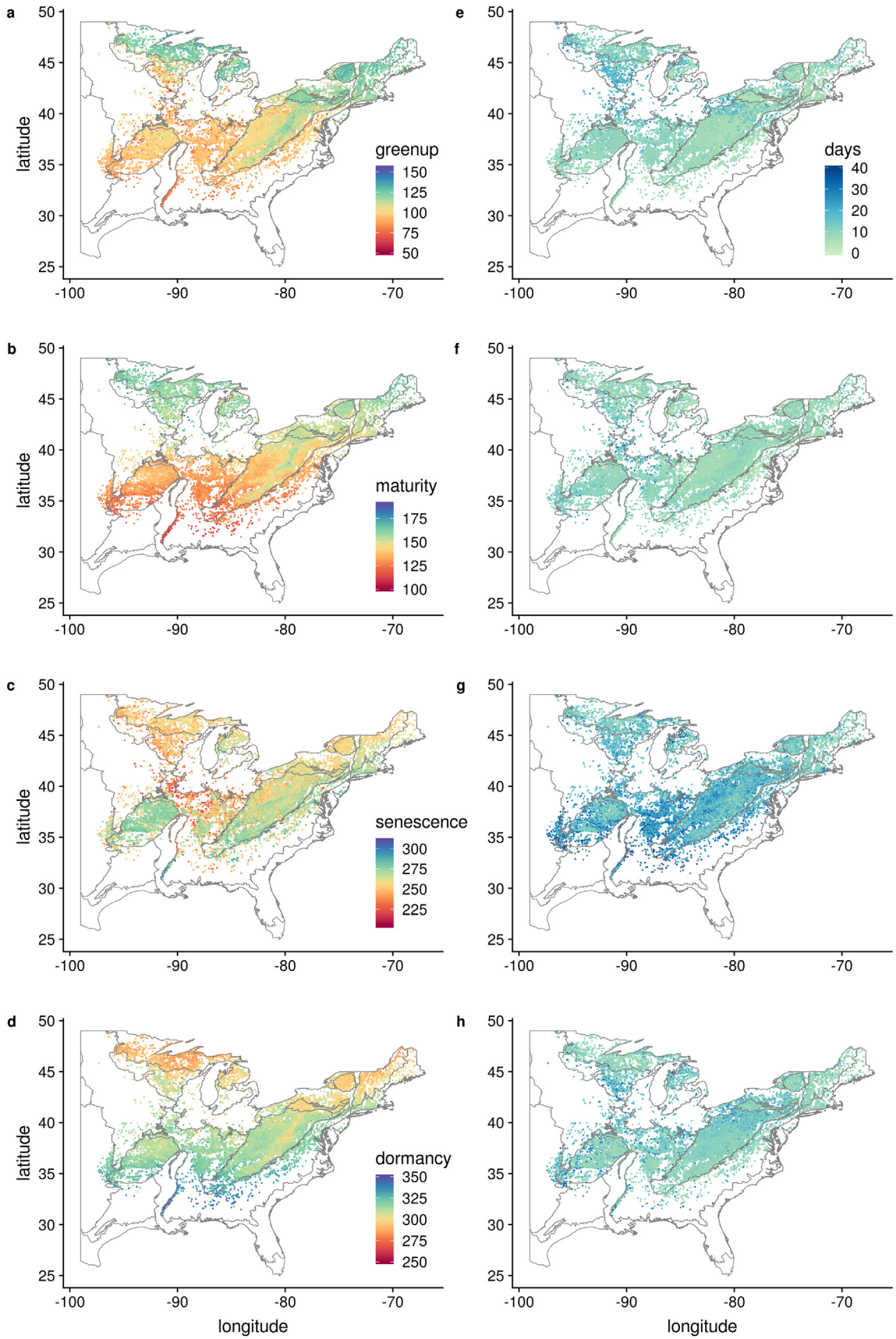

Fig. 5. Mean dates (a–d, unit: day of year) and standard deviations (e–h, unit: day) of four phenological transition dates between 2000 and 2015 of 20,000 deciduous forest pixels in the central and eastern US using change point estimation with twice daily EVI time series. Grey lines are US country boundary and ecoregions at level II.

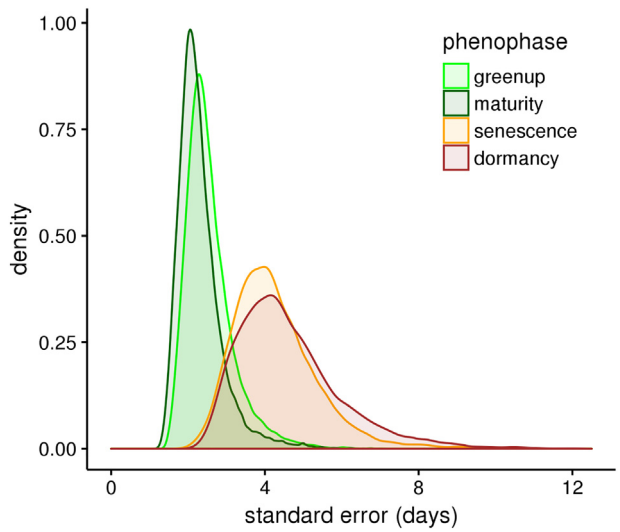

Fig. 6. Standard error of estimation of four phenological transition dates for sampled 20,000 deciduous forest pixels at the central and eastern US.

each growth phase (quantified by greenup rate in spring, green-down rate in summer, and senescence rate in fall) also had inter-annual and spatial variations (Fig. 8). The general spatial variations of the three rates were not large over 16 years on average, but both greenup and senescence rates of deciduous forests at northern areas and relatively high altitudinal areas (e.g. Appalachian forests) were higher than those of deciduous forests at other areas on average during 2000 and 2015 (Fig. 8a and b). Green-down rates of deciduous forests at Ouachita-Appalachian forests were higher than other areas (Fig. 8b). The standard deviations during 16 years of three rates were small (about 0.006) at most of our study area (Fig. 8d–f). Estimation uncertainty (standard error) was also provided for each rate. All of these phenological metrics do not aim to define forest growing cycle in a fine temporal scale (e.g. daily growth), but to provide quantifications of seasonal and inter-annual patterns in growth that reflect biological responses to environmental changes. Thus, these metrics can provide multi-dimensional description and understanding of forest phenological responses (Buitenwerf et al., 2015).

4. Discussion

This study develops a new LSP estimation methodology that overcomes one major challenge of remote sensing phenology in quantifying and reducing LSP uncertainty (de Beurs and Henebry, 2010; Helman, 2018). Evaluation using ground-based phenological dates suggested that our method improves estimation accuracy compared to existing methods. The estimation errors between LSP and ground-based leaf phenology were largely reduced by up to 50 days using our new method and data source (i.e. change point estimation method and twice daily EVI time series), especially for the fall senescence date. Our LSP estimations provide new insights in quantifying and reducing vegetation phenology estimation uncertainty from remote sensing imagery. The improvement in LSP estimation accuracy will largely help better quantify spatio-temporal phenology variation and the responses to global climate change (Jeong et al., 2011; Melaas et al., 2016), and will significantly contribute to understanding interactions between biological communities and environmental changes (Richardson et al., 2010, 2013). The quantitative uncertainty and reduced biases in remote sensing phenology products can promote the accurate assessment of biological responses to global climate change over time and space as well as help forecast the future responses for adaptation and mitigation strategy planning (Jeong and Medvigy, 2014; Liu et al., 2017b).

4.1. Improvement from change point estimation

Smaller RMSE and bias values suggested change point estimation improved LSP estimation accuracy compared to the logistic fitting methods. The piecewise logistic fitting method estimates four phenological transitions in two groups (spring and fall groups) (Zhang et al., 2003). In each group, two phenological transitions are determined by the dates with the minimum change of curvature along the fitted logistic curve. In contrast, change point estimation method determines four phenological transitions one by one following the change patterns of EVI time series through the whole year. Compared to logistic method which determines phenological transitions in separate seasons (spring and fall), the change point estimation approach locates transition points with the context of prior and current seasons, thus these transition points may be more relevant to biological transitions as life cycle events that determine different tree growth phases in the growing season. Another advantage of change point estimation method is that this method fits the change patterns for the whole year time series and accounts for the slight decrease of EVI during summer months driven by decreasing photosynthetic activity (Richardson et al., 2010). The logistic fitting method does not fit the summer decrease separately from the fall decrease pattern in EVI time series and thus estimates too early senescence date from a left skewed logistic curve (Fig. 1a) than the true phenological transition. By fitting the decreasing trend of EVI during summer time (Klosterman et al., 2014), change point estimation largely reduced the error metrics for fall senescence date from 50.8–70.1 days to 11.5–24 days of RMSE, from −48.5 to −62.4 days to only −2.6 to −5.8 days of mean bias, and 48.5–63.0 days from to 7.9–20.1 days of MAE (Table 1). We also noticed that our LSP estimation had smaller correlations with field observations than MODIS phenology product. This suggested MODIS phenology product may perform better in capturing inter-annual variations than our estimations, which might be due to data quality of twice-daily EVI time series. Future research can examine how more data preprocessing procedures can reduce the effects or any other high-quality data can be applied to our method to further improve the estimation.

Other than the four phenological transitions, change point estimation also quantifies the estimation uncertainty for each date (i.e. standard error in Fig. 6), which is not provided by existing LSP estimation methods (de Beurs and Henebry, 2010). The parameter uncertainty is a measure of how well the linear segmentation characterizes the underlying data. We found a statistically positive relationship between the uncertainty of the estimated dates and the difference between estimated greenup, senescence and dormancy dates and the ground-based observed dates from Harvard Forest ($p = 0.098$) and National Phenology Network ($p < 0.001$) (Fig. 9). The pixels with very high uncertainties may indicate problems in determining dates with high confidence. By tracking the time series data of those pixels, it may help us understand the error structures and reasons of errors in locating the change points, such as large data gaps in time series. Change point estimation also quantifies more metrics (e.g. EVI values on transition dates and greenup, green-down and senescence rates) to fully describe the seasonal change process and may provide a comprehensive understanding in biological responses to environmental changes from multiple dimensions (Figs. 7–8). For example, while longer growing seasons driven by phenological shifts may indicate higher carbon sequestration, lower photosynthetic activity due to environmental stress that reduces carbon sink are possible. This type of shift cannot be detected by shifts in phenological dates alone, but can be represented by EVI metrics (Buitenwerf et al., 2015). This is because EVI is highly related to the spatiotemporal variation of fraction of photosynthetically active radiation absorbed by the land surface (fPAR) and gross primary productivity (GPP) (Baghdadi and Zribi, 2016). Studies on the duration between phenophases have shown the effects from environmental changes on plant development processes through the growing season (Vitasse et al., 2009; Archetti et al., 2013). However, the rates of

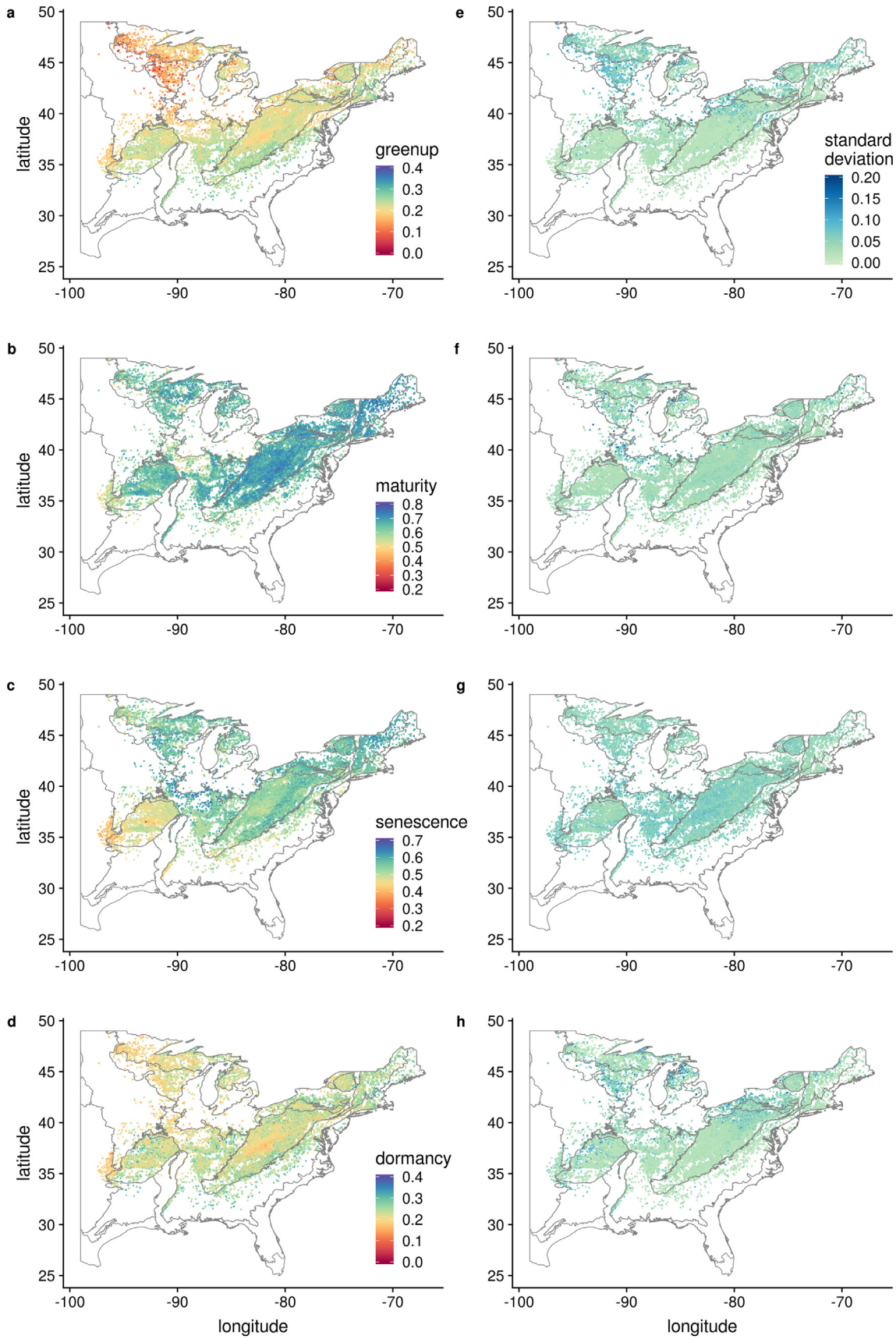

Fig. 7. Mean EVI values (a–d) and standard deviations (e–h) at four estimated phenological transition dates during 2000 and 2015 of 20,000 deciduous forest pixels in the central and eastern US using change point estimation with twice daily EVI time series. Grey lines are US country boundary and ecoregions at level II.

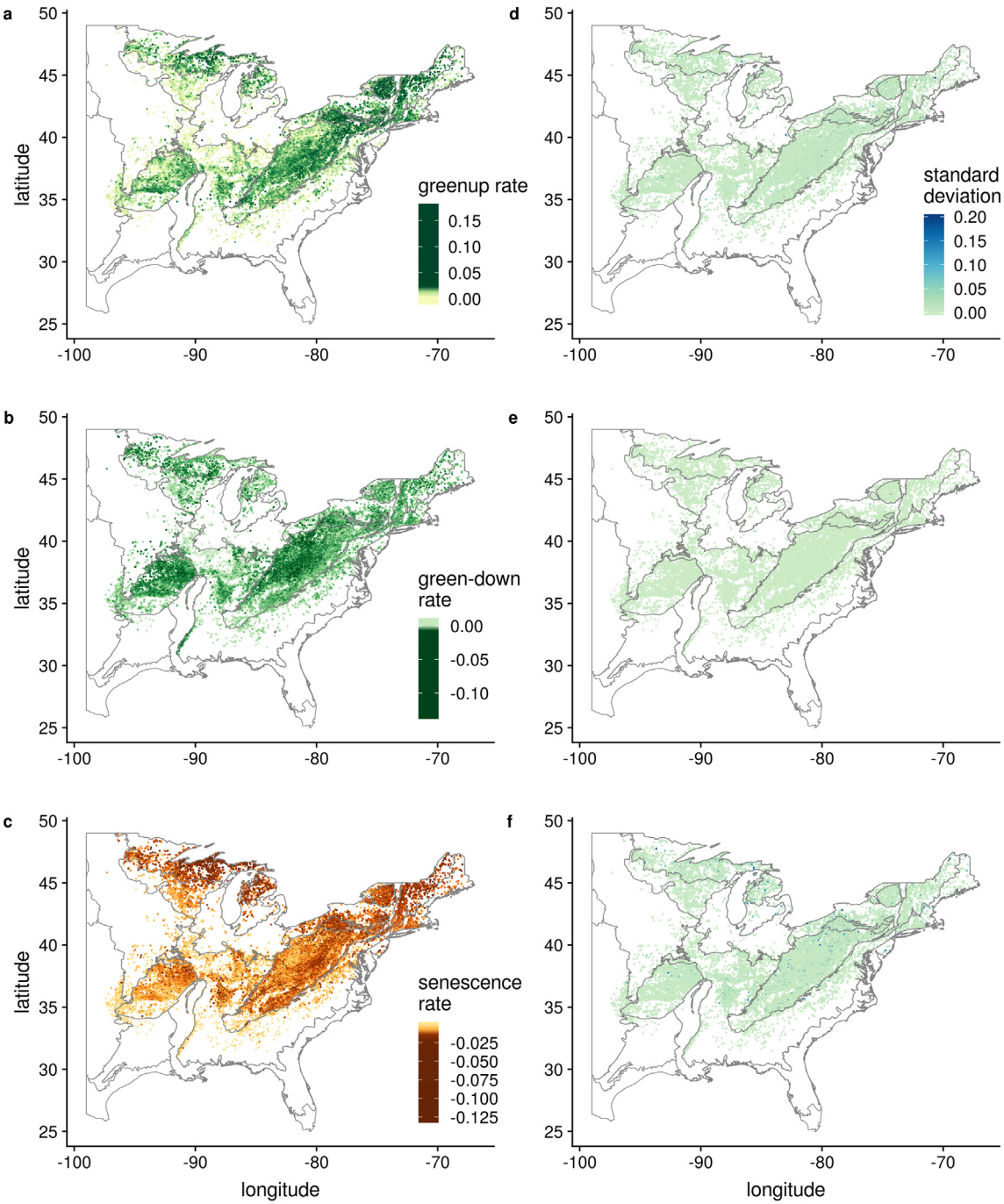

Fig. 8. Mean EVI change rates (a: greenup rate, b: green-down rate, and c: senescence rate) and standard deviations (d–f) during 2000 and 2015 of 20,000 deciduous forest pixels in the central and eastern US using change point estimation with twice daily EVI time series. Grey lines are US country boundary and ecoregions at level II.

greenness changes are rarely quantified or analyzed, which may carry more meaningful information of biological processes and responses than the length of duration between phenophases, such as plant productivity (Pettorelli et al., 2007), responses to climatic conditions (Park et al., 2015), and impacts on associated animal species (Tveraa et al., 2013). While most studies focused on the responses of phenological dates or growing season length to environmental changes (de Beurs and Henebry, 2010; Rodriguez-Galiano et al., 2016; Visser, 2016), it is still understudied how abiotic environmental changes affect variations of forest greenup rates in spring, green-down rates in summer or senescence rates in fall within forest communities (Fig. 8). Therefore, our change point estimation that quantifies multiple metrics of EVI values at transition dates and the rates of greenness changes can offer a more comprehensive and informative product to improve our understanding in the seasonal change pattern and the responses to environmental changes at community and landscape regional scales.

4.2. LSP evaluation by field observation

The evaluation metrics suggested lower performance of all LSP estimations for the NPN dataset compared with the Harvard Forest phenology data (Table 1). This is likely because the species we used in each NPN site might not adequately represent the relative abundance of species in the local deciduous forest community. Species observed at

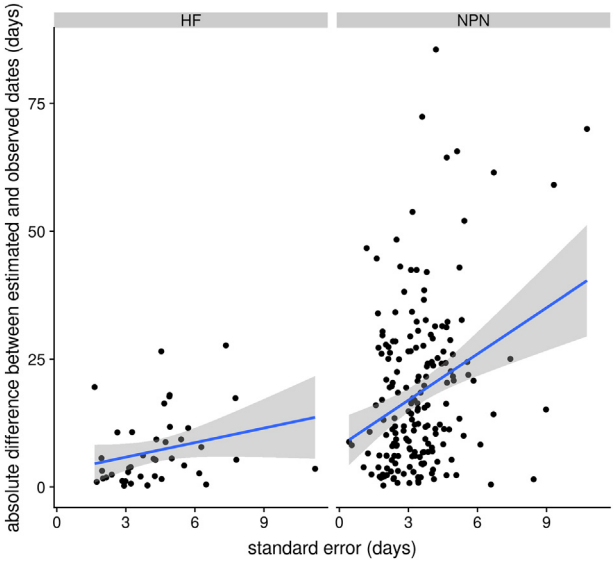

Fig. 9. The relationship between estimation uncertainty of change point estimation and estimation quality evaluated by ground observations. X axis is estimation uncertainty, quantified by standard error of estimated four phenological transition dates. Y axis shows estimation quality, quantified by the absolute difference between estimated and observed dates for Harvard Forest (HF) and National Phenology Network (NPN). Straight grey line is a fitted linear regression line. Light grey area indicates the 95% confidence level interval for predictions.

the Harvard Forest (a Long Term Ecological Research site) were selected that represent the local forest community in order to generate consistent long-term phenology observations at this particular forest ecosystem (O'Keefe, 2000). However, species observed from NPN sites were selected according to the Nature's Notebook's list of plant species with ecological and economic importance or the interests of citizen scientists, which is not directly associated to representation of local plant communities. In the evaluations, we used mean values from ground-based phenological dates among all individuals and species because we do not have information of species composition for each observation site to calculate weighted mean values. Satellite and field observations of phenology are collected at two different spatial scales: LSP is dominated by the phenology of abundant species in each location, while ground observation can be any individual or species in the area. Deviations from the two observations sources will be larger in locations where the ground-observed phenology does not represent dominant species phenology. Another explanation for the relatively poor validation with the NPN data is observation error. Citizen scientists follow the same protocol of NPN, however, observation errors may be brought by different observers with different knowledge and experiences in identifying plant species and phenophases, though general phenological patterns are apparent in the NPN dataset over large spatial areas (such as the domain of this study).

Compared to previous studies on evaluations of phenology derived from MODIS satellite imagery using Harvard Forest phenology observations (Zhang et al., 2006), our LSP estimation is more accurate for both spring and fall phenological transitions. But the evaluation also suggested our LSP estimation did not have consistently higher Pearson's r values than those from estimations using piecewise logistic method (i.e. log_8d and log_d2 in Figs. 3 and 4). However, LSPs using change point estimation on 8-day EVI time series had the highest Pearson's r values for both greenup (r = 0.8) and dormancy (r = 0.7) dates. The reason could be relatively larger fluctuation of EVI in the twice daily time series at early spring and from early summer to early fall than the 8-day EVI time series, which may add uncertainty in fitting linear lines to locate the true transitions over the twice daily time series (Fig. S2). This also may be the reason of poor performance of piecewise logistic fitting method on twice daily EVI time series (log_d2 in Figs. 3 and 4). The fluctuation of EVI time series during early spring and from early summer to fall may bring biased background values in fitting logistic curves leading to biased phenology estimations (Fig. S2c). On the contrary, change point estimation on 8-day EVI time series (cp_8d in Figs. 3 and 4) performed best in capturing inter-annual variation for both greenup (r = 0.8) and dormancy (r = 0.7) dates and increasing dormancy date estimation accuracy. But this method did not improve greenup date estimation accuracy, which may be driven by the relatively coarse temporal resolution of 8-day EVI time series that could not capture the greenup event happened quickly within 8-day intervals in spring (Fig. S2b).

4.3. Implications of improved estimation on LSP

Our results suggested change point estimation on twice daily EVI time series improved estimation on LSP of deciduous forests by narrowing RMSE by 4–6 days for greenup and 39–46 days for senescence dates. The LSP estimation will not only allow us to assess the timing of ecosystem transitions more accurately, but also facilitate our understanding of the community and ecosystem processes corresponding to global climate change. First, we can more accurately assess temporal and spatial phenological changes including long-term trends of spring and fall phenological date changes, and greenup and senescence rate changes, using our LSP estimation generated from long-term remote sensing observations across community and ecosystem scales. The temporal and spatial phenological changes and long-term trends can inform us how biological communities responded to past environmental changes, especially during the decades with anthropogenic global climatic change. Second, more accurate estimation of LSP will improve phenological modeling development, especially for fall phenology, as its complex biological response mechanism is still barely known though it is ecologically and evolutionarily important (Gallinat et al., 2015). The timing of fall senescence onset reflects when plants begin reducing photosynthesis by degrading chlorophyll and reallocating nitrogen and other resources from leaves to other structures in plants (Estiarte and Peñuelas, 2015), which can be affected by short photoperiod, low temperature and environmental stresses (e.g. heat and drought) (Estrella and Menzel, 2006; Xie et al., 2015b). Thus, improved phenological modeling based on more accurate LSP products will help understand the response mechanism of forest fall senescence and will increase our capability in measuring and assessing global climate change impacts on biogeochemistry cycles (e.g. carbon and nitrogen cycles) (Arora and Boer, 2005). In addition, our LSP estimation can be applied in terrestrial ecosystem models (TEMs) (Medvigy et al., 2009; Wang et al., 2010) as community level phenology input to identify specific phenological phases in plant growth to calculate Net Primary Productivity (NPP) allocation. Based on more accurate leaf senescence date estimation from our estimated LSP, we can reduce the bias in NPP estimation, as the onset of leaf senescence is an important parameter in determining the cessation of leaf carbon allocation in the ecosystem models (Richardson et al., 2012; Wu et al., 2013; Delpierre et al., 2016). Compared to the early senescence dates estimated from MCD12Q2 version 005 MODIS phenology product, our estimation may lead to a longer growing season and a higher leaf carbon allocation of deciduous forest. Moreover, with more biologically related estimates of growth processes and more accurate LSP estimations, our estimation will have further applications in understanding the seasonal change pattern and associated environmental conditions. For example, the estimated change rate of EVI during summer time (i.e. green-down rate in Fig. 1b) and EVI values on each phenological transition date may improve the understanding in the decoupled remotely sensed greenness and productivity of deciduous forest during dry summer under strong drought conditions (Melaas et al., 2016). Both greenup and senescence rates will provide more information in understanding how deciduous forests

respond to environmental changes as a process in spring and fall, in addition to only as a life cycle event, which will be helpful while continuing to develop mechanism-based phenological models.

Like any remote sensing product, our LSP estimation developed with change point estimation on twice daily EVI time series can be limited by data quality of the underlying vegetation index time series. Although we included only high quality data to generate the LSP, data gaps due to missing or low-quality data caused by cloud, snow and other conditions over a relatively long period, especially in the transition phases, increases the estimation uncertainty. Change point analysis may fail when the time series fails in providing change patterns that support the assigned number of breakpoints (e.g. four in our study) or convergence was not reached in all iterations and bootstraps. This happened to < 2% of our data, which was mostly due to large data gaps in cloudy or snowy seasons. In addition, unlike the double logistic method, our approach also estimates the standard error of the estimated dates, which will be higher in cases with more missing data or noise. We noticed that greenup date may occur early (e.g. in February or earlier) in the southern area of our study region, which lead to a relatively short linear segment at the beginning of the year (e.g. < 30 days), as we set the fitted time series to begin on January 1st. This did not prevent identifying the greenup date, as the change pattern of EVI values was abrupt in spring and typically can be accurately captured by change point estimation method. If this approach is used in an area where the greenup date occurs earlier (or otherwise does not align well with the calendar year), the beginning and end dates of fitted time series can be easily modified. Compared to logistic curve fitting method, the change point estimation method is more computationally intensive. The current study is based on a stratified sample of 20,000 deciduous forest pixels from the central and eastern US instead of the full 1.2 million pixels in our study region. Though the current study does not include an estimate for the entire domain, the results suggest that the change point estimation method of LSP extraction from MODIS imagery can result in higher estimation accuracy and more phenological metrics compared to the traditional logistic curve fitting method and the most commonly used MODIS phenology product. Our method is not limited to only four change points, since the number of change points in the time series can be inferred from the data or be assigned a priori to better fit the underlying ecological dynamics. For example, in ecosystems with two growing seasons, the number of change points should be increased. Although this study focused on the use of change point models to extract phenological information for deciduous forest communities with only one growing season in a year, application of change point estimation method to other biomes or vegetation types with more than one growing season in a year can be developed and evaluated in future research. Change point analysis has been used to detect climate change impacts on temporal trends of phenology and terrestrial carbon dynamics (Cleland et al., 2007; Horion et al., 2013; Buermann et al., 2016), but to our knowledge, this method is rarely used in phenological transitions detection, which might be due to limited data with a fine temporal resolution (e.g. daily). In contrast, Bayesian multiple change point analysis was used to determine phenological transitions from daily captured digital photos from time-lapse camera on forest canopies (Henneken et al., 2013), which showed the advantages in phenological dates determination with quantitative error based on fine temporal resolution time series data. While additional remote sensing observations of higher quality and finer resolution become available, change point analysis can be widely applied to improve LSP estimation. For example, daily MODIS spectral reflectance data is now available from MCD43A4 version 006 product, which may have a higher data quality than MOD/MCD09GA product with Nadir Bidirectional Reflectance Distribution Function (BRDF)-Adjusted Reflectance (NBAR). This product is used to produce a new MODIS phenology product (MCD12Q2 version 006) based on 2-band EVI time series using an updated estimation method (Friedl et al., 2019) that is not evaluated in this study. In addition, modified versions of the logistic model with other satellite data sources (e.g. Landsat and the Advanced Very High Resolution Radiometer (AVHRR)) also suggest better performance in phenological transition estimation (Elmore et al., 2012; Melaas et al., 2013; Zhang et al., 2017). In future research, more comparisons with these modified methods can be conducted to examine how change point estimation will be applied to daily time series and how it will affect the estimation performance.

5. Conclusions

In this study, we developed an improved method to identify land surface phenology transitions with change point estimation using twice-daily satellite imagery. The evaluations suggested that our change point estimation method had a better performance in capturing in-situ phenological observations than the standard piecewise logistic method, especially for the autumn senescence date. Our method also provided quantifications of estimation uncertainty and more phenological metrics to describe the biological process of deciduous forests during the whole growing season. The evaluation suggested that estimated senescence dates from MODIS phenology product were too early (> 40 days) compared to the onset date of leaf coloration in ground observations, while our proposed LSP estimation narrows the error metrics, RMSE to 11.5–24 days, mean bias to −2.6 to −5.8 days, and MAE to 7.9–20.1 days. With the largely improved estimation accuracy in phenology of deciduous forest community derived from satellite imagery at the regional scale, assessment on phenological shifts and responses to climate variation will be improved, as well as the impacts on the associated community and ecosystem processes.

CRediT authorship contribution statement

Yingying Xie: Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing - original draft, Visualization. **Adam M. Wilson:** Conceptualization, Resources, Data curation, Writing - review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rse.2020.111698.

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