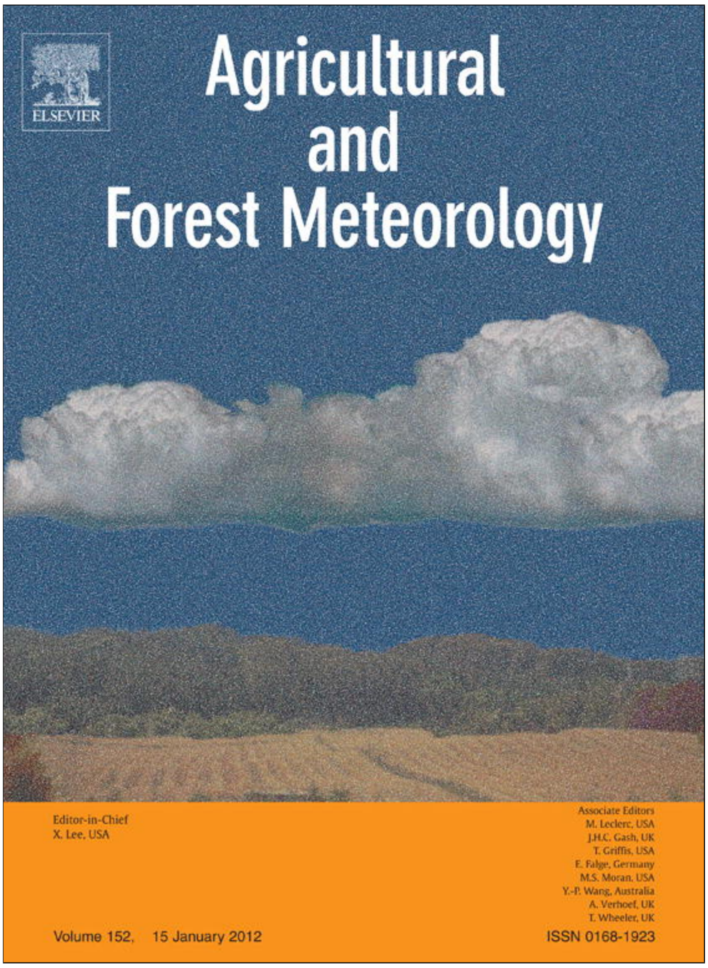
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Predicting deciduous forest carbon uptake phenology by upscaling FLUXNET measurements using remote sensing data

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A B S T R A C T

Terrestrial ecosystems are highly sensitive to climatic changes in early and late growing seasons. Land surface phenology (LSP), the study of the timing of recurring seasonal pattern of variation in vegetated land surfaces observed from synoptic sensors, has thus received much attention due to its role as a surrogate in detecting the impact of climate change. Although several studies have been conducted on the growing season LSP, studies on the net carbon uptake phenology (CUP) defined as the detrended zero-crossing timing of net ecosystem productivity from a source to a sink in spring and *vice versa* in autumn, have been scarce. Here we present a CUP determination approach using the commonly available remote sensing data in four selected temperate and boreal deciduous forest CO_2 flux tower sites. We test a hypothesis that the mean monthly surface temperature and LSP derived from remote sensing observations explain the CUP both in spring and autumn seasons. Our approach predicts the observed CUP in spring and autumn within 8 day mean errors, equivalent to the temporal resolution of the 8-day composite remote sensing dataset used in this study for the four flux tower sites. The results from this study will have a large implication for global change studies with increasing amount of valuable remote sensing data to be used for monitoring CUP beyond the footprints of CO_2 flux towers.

1. Introduction

The carbon balance of terrestrial ecosystems is highly sensitive to climatic changes in early and late growing seasons (Bergeron et al., 2007; Piao et al., 2007, 2008; Wu et al., 2012a,b). Changes in land surface phenology (LSP) events have the potential to broadly impact terrestrial ecosystems and human societies, by altering the timing of, for example, global carbon, water, and nitrogen cycles, interspecific interactions both among plants and between plants and insects, crop production, frost damage, pollination seasons, and spreading diseases (Cook et al., 2010; de Beurs et al., 2009; de Beurs and Henebry, 2010; Menzel and Fabian, 1999; Menzel et al., 2006; Penuelas and Filella, 2001; Schwartz, 1998; Schwartz and Reiter, 2000; White et al., 1999, 2009). While the seasonal patterns of vegetated land surface variability are related to biological phenomena, LSP is distinct from traditional definition of plant phenology, which is the study of the timing of recurring biological events, the causes of their timing with regard to biotic and abiotic forces, and the interrelation among phases of the same or different species (Lieth, 1974). Therefore, after de Beurs and Henebry (2004), we define LSP as the study of the timing of recurring seasonal pattern of variation in vegetated land surfaces observed from synoptic sensors. Due to the increasing availability of synoptic multi-temporal optical satellite data, LSP has emerged as an important focus for ecological and global change researches (Bradley et al., 2011; Cleland et al., 2007; de Beurs and Henebry, 2004; Lokupitiya et al., 2009; Menzel, 2002; Nakaji et al., 2011; Park et al., 2012; Post and Inouye, 2008; Shen et al., 2011; Siebert and Ewert, 2012; Sonnentag et al., 2012). Remote sensing based LSP estimate provides aggregated spatiotemporal information at moderate to coarse spatial resolutions, which relate to the timing of vegetation growth, senescence, dormancy, and associated surface phenomena at seasonal and interannual scales. Spring and autumn temperatures over northern latitudes have risen by about 1.1 °C and 0.8 °C, respectively, over the two decades before the year 2000 (Mitchell and Jones, 2005) with a simultaneous greening trend characterized by a longer growing season and greater photosynthetic activity (Myneni et al., 1997; Zhou et al., 2001). These observations have led to speculation that spring and autumn warming could enhance carbon sequestration and extend the period of the net carbon uptake in the future (Churkina et al., 2005).

Despite significant recent efforts to characterize, understand, and model the spatiotemporal variation of LSP (Hudson and Keatley, 2010; White et al., 2009), the carbon uptake phenology (CUP) has scarcely been studied due to a limited number and a poor

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spatial representativeness of the CO_2 eddy covariance tower sites. The globally distributed network of eddy covariance stations sample only a small subset of the Earth's biomes, disturbance regimes, and land management systems (Churkina et al., 2005). In addition to this, the eddy covariance techniques are currently limited to relatively flat terrains. Thus, studying the CUP over large heterogeneous areas remains challenging. Remote sensing provides spatially comprehensive measures of land surface properties with high temporal frequencies to study LSP from reflected, backscattered and emitted radiation measurements, whereas CO_2 eddy covariance measurements allow determination of CUP from ecosystem CO_2 fluxes. The CUP is controlled by the growing season LSP, but is not identical because growth will typically commence and terminate some time before and after the net ecosystem productivity (NEP) changes sign in spring and autumn, respectively (Fig. 1). CUP is defined as the detrended zero-crossing timing of NEP from a source to a sink in spring and *vice versa* in autumn. CUP is characterized by two phenologically distinct days of a given year; *i.e.*, start of carbon uptake (SCU) and end of carbon uptake (ECU) days. SCU is the upward zero-crossing day of the detrended NEP from a source to a sink in spring whereas ECU is the downward zero-crossing day of NEP from a sink to a source in autumn. Eddy covariance tower measurements give both gross primary productivity (GPP) and NEP:

$$\mathrm{GPP} = \mathrm{NEP} + R \tag{1}$$

where R is the ecosystem respiration (Baldocchi, 2003). GPP is related with remote sensing measures of photosynthetic biomass optical thickness often expressed as vegetation index (*e.g.*, Gitelson et al., 2008). Recent studies have attempted to relate remote sensing and ground based photographic LSP estimates with that of the GPP based LSP estimates (Gonsamo et al., submitted for publication; Migliavacca et al., 2011; Richardson et al., 2010; Xiao et al., 2009). However, only a number of limited attempts have been made to estimate CUP dates from, for example, using the LSP dates (Churkina et al., 2005), remote sensing radiation and vegetation products (Garrity et al., 2011), and soil and air temperature proxies (Baldocchi et al., 2005). These studies have shown that differences in the seasonal pattern of assimilatory and respiratory processes are responsible for divergences in CUP among ecosystems. However, the asynchronicity of photosynthesis and respiration, due to their sensitivity to different environmental drivers, makes CUP difficult to predict based on a single factor related to either photosynthesis or respiration. All of the previous studies (Baldocchi et al., 2005; Churkina et al., 2005), have provided precedents to explore the potential of remote sensing data for estimating CUP dates beyond the footprints of flux towers. The LSP is determined by the start (SOS) and end (EOS) of growing season days in response to various environmental factors, such as precipitation, light, nutrient, temperature, disturbances, pests and diseases, and other biotic forces (*e.g.*, Larcher, 1995; Rathcke and Lacey, 1985; Schwartz, 2003; Wheelwright, 1985; van Schaik et al., 1993). CUP dates occur within LSP dates in temperate and boreal forests in a given calendar year. The difference between SCU and SOS, called spring interval, usually lasts less than a month whereas the autumn interval, *i.e.*, the difference between EOS and ECU lasts up to 4 months in boreal forests (Wu et al., 2012a). While the LSP dates (SOS and EOS) can be retrieved from synoptic sensors such as remote sensing and GPP measurements (Migliavacca et al., 2011; Richardson et al., 2010, 2012; White et al., 2009; Wu et al., 2012a; Xiao et al., 2009), the main environmental factor controling the CUP dates (SCU and ECU) in temparate and boreal forest is temprature (*e.g.*, Piao et al., 2008; Suni et al., 2003; Tanja et al., 2003; Wu et al., 2012a). Piao et al. (2008) has shown that there is no significant correlation between CUP dates and precipitation anomalies in temperate and boreal ecosystems. Thus, we hypothesize that, temperature is the main factor for the transition of SOS to SCU in spring, and ECU to EOS in autumn.

Both LSP and temperature can be retrieved using satellite remote sensing observations. Therefore, in this study, we test the potential of remotely sensed temperature and phenology index (PI) for determining the CUP over temperature limited temperate and boreal forests. Our main goal is to develop a simple CUP estimation method that can incorporate photosynthesis and respiration based on commonly available spatiotemporal datasets such as remote sensing and gridded meteorological observations. The results from this study will have a significant implication for global change studies with increasing amount of valuable remote sensing and eddy covariance measurements being integrated for comprehensive analysis of environmental controls on ecosystem productivity. We do not intend for this study to be considered a comprehensive analysis of CUP across the global flux networks sites. The selected four temperate and boreal flux sites consist long term CO_2 flux and meteorology measurements over phenologically distinct mature forests sites.

2. Materials and methods

We restrict this study to FLUXNET networks from Canadian Carbon Program (CCP: http://www.fluxnet-canada.ca) and AmeriFlux

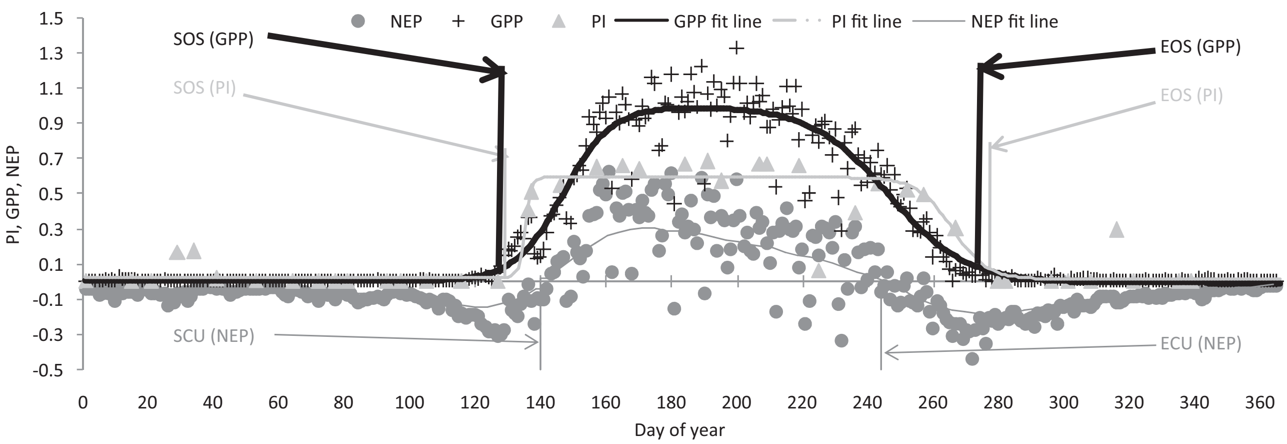

Fig. 1. A schematic of curve fitting mechanism for the phenology index (PI), gross primary productivity (GPP), and net ecosystem productivity (NEP) time series for the Saskatchewan Old Aspen flux tower site for year 2007. PI data points which fall further from the fit line are subsequently assigned less weight in the phenological fit. Both the PI and GPP were fitted using a double logistic function. The exact start (SOS) and end of season (EOS) are shown as estimated from PI and GPP for year 2007 indicated by vertical lines. Whereas, start (SCU) and end of carbon uptake (ECU) are estimated from NEP.

Table 1
List of the CO_2 eddy covariance tower sites used in this analysis, years of the flux measurements, overstorey *genera*, their location, mean annual air temperature (T_a) and references describing site characteristics and measurements.

Site	*Genera*	Location	Years	T_a (°C)	References for data and site
Old Aspen, Saskatchewan (CA OA)	*Populus*	53.63N/106.20W	1997–2010	0.4	Barr et al. (2004), Black et al. (2000)
Harvard Forest, Massachusetts (US HA1)	*Quercus/Acer*	42.54N/72.17W	1992–2008	7.4	Urbanski et al. (2007)
University of Michigan Biological Station, Michigan (US UMB)	*Populus*	45.56N/84.71W	1999–2008	5.5	Gough et al. (2008)
Morgan Monroe, Indiana (US MMS)	*Quercus/Acer*	39.32N/86.41W	1999–2008	11.8	Schmid et al. (2000)

(http://public.ornl.gov/ameriflux/dataproducts.shtml) mature forest study sites whose trees have broad leaves and deciduous habits, with long term (minimum of 10 years) CO_2 flux measurements. The key *genera* at the sites used in this analysis include *Populus* (aspen), *Acer* (maple), and *Quercus* (oak), although other deciduous and needleleaf trees are present in all of the sites. Most of these forest sites are closed canopies; their leaf area indices ranged between 2 and 5, with average tree age ranging between 60 and 110. The mean annual precipitation ranged between 470 and 1120 mm. The selected long term records of four broadleaf forest sites represent diversity in regions, age structure, climate, and species composition of typical old growth deciduous vegetation across North America (Table 1). Characteristics of the sites used in this analysis, and primary references describing additional site details are summarized in Table 1.

For CCP sites, a standard procedure was used to estimate the daily NEP and GPP from gap-filled half-hourly measurements (Barr et al., 2004). Empirical regressions of night-time net ecosystem exchange to temperature and daytime GPP to photosynthetically active radiation (PAR) were used to estimate GPP to fill gaps as discussed in Barr et al. (2004). For the AmeriFlux sites, level-4 daily products were used which contain gap-filled and friction velocity, u_* filtered records of carbon fluxes with flags regarding the quality of the original and gap-filled data. The half-hourly datasets were gap-filled using the Marginal Distribution Sampling (MDS) method (Reichstein et al., 2005). Although different gap-filling methods were used among CCP and AmeriFlux datasets, the reliability of the daily NEP and GPP time series for phenology studies are guaranteed given the annual multiple site comparisons of most methods tended to cluster on similar results to within 10% of each other (Desai et al., 2008; Moffat et al., 2007; Papale et al., 2006). Monthly mean air temperature (T_a) was also collected from sensors located above the forest canopy at each flux tower site.

Two distinct procedures were used each to retrieve the CUP and the LSP days from NEP and GPP measurements, respectively (Fig. 1). A negative exponential model using polynomial regression and weights computed from the Gaussian density function was used to derive the smoothed curves for daily NEP observations. Then the two CUP days, *i.e.*, start of carbon uptake (SCU) and end of carbon uptake (ECU) from the zero-crossing of detrended NEP time series are determined as illustrated in Fig. 1. For the LSP determination from daily GPP, we used the seven parameter double logistic function:

$$y(t) = \alpha_1 + \frac{\alpha_2}{1 + e^{-\partial_1(t-\beta_1)}} - \frac{\alpha_3}{1 + e^{-\partial_2(t-\beta_2)}} \quad (2)$$

where $y(t)$ is the observed GPP at day of year (DOY) t, α_1 is the background GPP. $\alpha_2 - \alpha_1$ is the difference between the background and the amplitude of spring and early summer plateau, and $\alpha_3 - \alpha_1$ is the difference between the background and the amplitude of late summer plateau and autumn both in GPP units. ∂_1 and ∂_2 are the transition in slope coefficients, and β_1 and β_2 are the midpoints in DOY of these transitions for green-up and senescence/abscission, respectively. The two slope midpoint DOYs (β_1 and β_2) are good indicators of SOS and EOS from satellite measurement of normalized difference vegetation index (NDVI) (*e.g.*, Fisher and Mustard, 2007). However, for GPP, SOS is the DOY at the start of the slope of ascending curve and EOS is the end of descending curve since GPP follows strictly that of land surface photosynthesis (Fig. 1). Therefore, the LSP from GPP can be estimated from Eq. (2) parameters as the start of slope in spring (SOS = $\beta_1 - 4.562/(2\partial_1)$), and the end of slope in autumn (EOS = $\beta_2 + 4.562/(2\partial_2)$). Given the DOYs of the midpoint slope of spring greenup (β_1) and autumn browndown (β_2), the spring plateau (α_2) and ranges ($\alpha_2 - \alpha_1$), the autumn plateau (α_3) and ranges ($\alpha_3 - \alpha_1$), and the average slopes of the spring ($\alpha_2\partial_1/4.562$) and the autumn ($\alpha_3\partial_2/4.562$) linear transition lines, we can mathematically estimate the minima and maxima of the third derivatives by applying triangle identities. The SOS and EOS are the dates defined by the intersect of the tangent at the steepest part of the curves and of the tangents at the asymptotic starts and asymptotic ends of the curves, respectively corresponding to the roots of the third derivative of the fitted curve.

We used the remote sensing data from the MODIS Terra satellite measurements. The 8-day composite reflectances from three spectral bands, namely red (620–670 nm), near infrared (NIR: 841–875 nm), and shortwave infrared (SWIR: 1628–1652 nm) were extracted for each 500 m flux tower pixel from MODIS surface reflectance product (MOD09A1). In the production of MOD09A1, atmospheric corrections for gases, thin cirrus clouds and aerosols are implemented (Vermote and Vermeulen, 1999). We have extracted the reflectances and the exact acquisition date for a single pixel of each flux tower site for dates spanning from 1 January 2001 to 31 December 2010 from the DAAC database of Oak Ridge National Laboratory (http://daac.ornl.gov/MODIS/). We have used the newly developed phenology index (PI) (Gonsamo et al., submitted for publication) derived from the commonly used vegetation indices for phenology studies: normalized difference vegetation index (NDVI = (NIR − red)/(NIR + red)) (*e.g.*, White et al., 2009), and normalized difference infrared index (NDII = (NIR − SWIR)/(NIR + SWIR)) (Delbart et al., 2005). PI is calculated as follow:

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

PI combines the merits of NDVI and NDII by taking the difference of squared greenness and wetness to remove the soil and snow cover dynamics from key vegetation LSP cycles. PI was validated and found to be better estimator of SOS and EOS compared to the sole use of NDVI or NDII (Gonsamo et al., submitted for publication). Eq. (2) was used to derive the SOS and EOS from PI following the same procedure described above for GPP (Fig. 1). We have developed a simple weighting scheme, which gives a weight of half for the sum-of-squared-error for the local value of PI if they are less than half or more than twice of the median value of the moving window average of three points in the iterative curve-fitting process.

The mean monthly day time land surface temperature (T_s) was also extracted from the Version5 MODIS Terra 8-day Land Surface Temperature & Emissivity (MOD11A2) product at 1 km spatial resolution. The day time orbit of Terra around the Earth passes from north to south across the equator at about 10:30 a.m. local solar time. The MODIS T_s is derived from two thermal infrared bands, *i.e.*, band 31 (10.78–11.28 μm) and band 32 (11.77–12.27 μm) using the split-window algorithm which corrects for atmospheric effects (Vancutsem et al., 2010). We have used three sets of 8-day products to estimate the monthly average value. The missing values due to poor quality input data were filled with the average value of the two nearest measurements in time. MODIS T_s is one of the MODIS's land science team products which is underexploited for climatic and environmental studies due to several definition and conceptual ambiguities for the meaning of T_s (Jin and Dickinson, 2010; Shreve, 2010). Unlike the *in situ* measured thermodynamic T_a at CO_2 flux tower height, the MODIS T_s is defined by radiation emitted by land surface at the instantaneous view time.

One of the first steps of predicting the CUP using the remote sensing data is to search for proxy flux tower explanatory measurements which can also be measured using satellite observations. To do this, we first start with measured CO_2 flux and meteorology data. The SOS and EOS derived from GPP together with the monthly T_a measured using the *in situ* sensors were used as explanatory variables to estimate both SCU and ECU. Next is to predict the CUP using the remote sensing SOS, EOS and T_s based on the sensitivity analysis of the *in situ* measurements. The predictive performance of the least-squares linear regression model (CUP = f (LSP, T, β) where T is mean monthly temperature and β is regression coefficient) was evaluated using coefficient of determination (R^2), root mean square error (RMSE), and leave-one-out cross-validation approach (Shao, 1993).

3. Results

3.1. Carbon uptake phenology prediction from in situ CO_2 flux and meteorology data

Table 2 presents the CUP predictive performances based on LSP dates and mean monthly T_a explanatory variables obtained from the CO_2 flux and meteorology observations, respectively. We have used the GPP SOS, T_a values in February, March, April and May, the combination of GPP SOS with May T_a, and the combination of GPP SOS with April T_a and May T_a to predict the SCU (Table 2). Among the four monthly T_a values, May T_a explains the SCU variance ranging from 0.36% to 83.37%. May T_a explains the most followed by SOS and April T_a. There are distinctive discrepancies among the flux tower sites regarding the performances of each monthly T_a and SOS (Table 2). The combination of SOS with April T_a and May T_a explains the most variance to predict SCU. Accordingly, we have selected the combination of SOS, April T_a and May T_a for subsequent SCU prediction using the remote sensing data. Similarly, we have also evaluated the monthly T_a ranging from June to October in addition to GPP EOS to predict the ECU. August T_a and September T_a were found to be the best explanatory variables next to EOS to predict the ECU (Table 2). For ECU prediction, we have selected the combination of EOS, August T_a and September T_a for subsequent prediction using the remote sensing data. Generally speaking, May T_a is the best temperature predictor variable for SCU whereas September T_a is for ECU. SOS and EOS also perform comparably with May T_a and September T_a for predicting SCU and ECU, respectively. Model predictions of both SCU and ECU performed poorly at Harvard Forest (US HA1) and for SCU at Morgan Monroe (US MMS) (Table 2).

Fig. 2 presents the scatter plots of the predicted CUP from the *in situ* measurements and observed CUP following a linear regression (Fig. 2a) and leave-one-out cross-validation (Fig. 2b) approach based on the best performing explanatory variables, whereas the interannual variability is presented in Fig. 2c. All *in situ* results presented in Fig. 2 are for years after 2001 for subsequent comparisons with remote sensing results. For both predicted SCU and ECU, the root mean square errors (RMSEs) were fewer than 8 days (Fig. 2). All of the predictive performances shown in Fig. 2 are statistically significant ($p < 0.05$, two-tailed). The predicted SCU, ECU, and the carbon uptake period (ECU–SCU) capture all of the interannual variability of the observed values in three of the four flux tower sites (Fig. 2c). The US HA1 flux tower site has shown poor performance for interannual variability for two years of SCU and one year of ECU predictions (Fig. 2c). 2005, the year where the observed SCU comes approximately 1 month later than the preceding and the subsequent years have shown less agreement with the predicted SCU. This year has relatively low NEP and GPP due to the drought. Compared to the poor performances of all of the explanatory variables presented in Table 1 for US HA1 site, the interannual variability of the predicted CUP captures the observed dates very well (Fig. 2c).

3.2. Carbon uptake phenology prediction from satellite remote sensing data

Table 3 presents the predicting performances of monthly T_s and LSP dates as retrieved from remote sensing data for estimating CUP dates. The monthly mean temperature, SOS, and EOS from remote sensing data have relatively comparable performances as the *in situ* observation for predicting SCU and ECU dates (Tables 2 and 3). Some of the discrepancies can be explained by varying number of data points as the MODIS satellite data can

Table 2
The predicting performances of start (SOS) and end (EOS) of land surface phenology, and monthly mean air temperatures and their combination for estimating the start (SCU) and end (ECU) of carbon uptake given in percent coefficient of determination (R^2) for each flux tower site and all available data values. The regression analyses are made for the entire flux and meteorology measurement years given in Table 1. The SOS and EOS, monthly mean air temperatures, and SCU and ECU are from the *in situ* CO_2 eddy covariance and meteorology measurements. The best performing explanatory variables are given in bold.

SCU	SOS	February	March	April	May	June	SOS, May	SOS, April, May
CA OA (n = 14)	85.8*	0.4	18.8	41.2*	83.4*	3.9	94.5*	**94.4***
US HA1 (n = 19)	20.2	0.21	1.5	0.1	29.0*	7.9	29.9	**29.1**
US UMB (n = 10)	64.9*	0.1	26.4	15.67	80.7*	15.0	83.8*	**87.6***
US MMS (n = 10)	3.0	1.3	4.0	18.3	0.4	0.4	5.5	**21.0**
All (n = 53)	56.3*	25.3*	39.5*	55.2*	69.7*	35.2*	71.3*	**72.5***
ECU	**EOS**	**June**	**July**	**August**	**September**	**October**	**EOS, September**	**EOS, August, September**
CA OA (n = 14)	50.2*	1.7	10.8	14.2	25.9	31.5*	51.8*	**52.4***
US HA1 (n = 19)	8.1	5.4	10.1	1.3	1.2	0.9	8.3	**9.8**
US UMB (n = 10)	23.8	2.0	2.1	1.1	58.1*	6.0	60.5*	**60.5***
US MMS (n = 10)	89.7*	29.3	0.6	48.6*	41.7*	3.3	90.3*	**90.4***
All (n = 53)	69.0*	42.7*	26.9*	45.6*	62.9*	6.5*	80.1*	**80.3***

* Correlation is significant at the 0.05 p-value level (2-tailed).

only be used after the year 2001. Although May temperature and SOS can almost explain the variances of SCU from both *in situ* and remote sensing observations, April temperature was added despite the fact that the addition did not result in significant improvements (Tables 2 and 3). The same is true for ECU estimation as the combination of September temperature and EOS is comparable with the combination of August temperature, September temperature and EOS for predicting ECU (Tables 2 and 3). In both cases, the additional monthly temperatures were added with the assumption that more explanatory temperature variables will make the predicting performance of the regression model more stable in extreme weather years and capture the detrended CUP dates.

Fig. 3a presents the scatter plot of the predicted CUP from remote sensing data and observed CUP following a linear regression, whereas Fig. 3b and c presents the scatter plot and the interannual variability of the observed and predicted CUP dates following the leave-one-out cross-validation approach, respectively. The RMSE of the predictions for both SCU and ECU following the linear regression and leave-one-out cross-validation is comparable with the temporal resolution of the satellite data (~8 days). This shows that the CUP can be predicted solely using the remote sensing data to the accuracy which is comparable to the 8-day composite temporal sampling resolution of satellite sensor in the four temperate and boreal deciduous forest CO_2 flux tower sites. Generally speaking, the performance of the CUP prediction using the *in situ* T_a and LSP dates (Fig. 2) resulted in comparable performance with that of solely based on remote sensing LSP dates and T_s (Fig. 3). This results show that CUP can be estimated using remote sensing observations with the same performance as the *in situ* measurements. The interannual variability of CUP dates from remote sensing data (Fig. 3c) is also comparable with that of *in situ* observations (Fig. 2c). The interannual performances illustrated in Figs. 2c and 3c therefore prove that the remote sensing based approach for CUP estimation works very well even across various sites ranging 14° of latitude with significant site characteristics' variations (Table 1). This will avoid the need for the site-by-site calibration of the regression model.

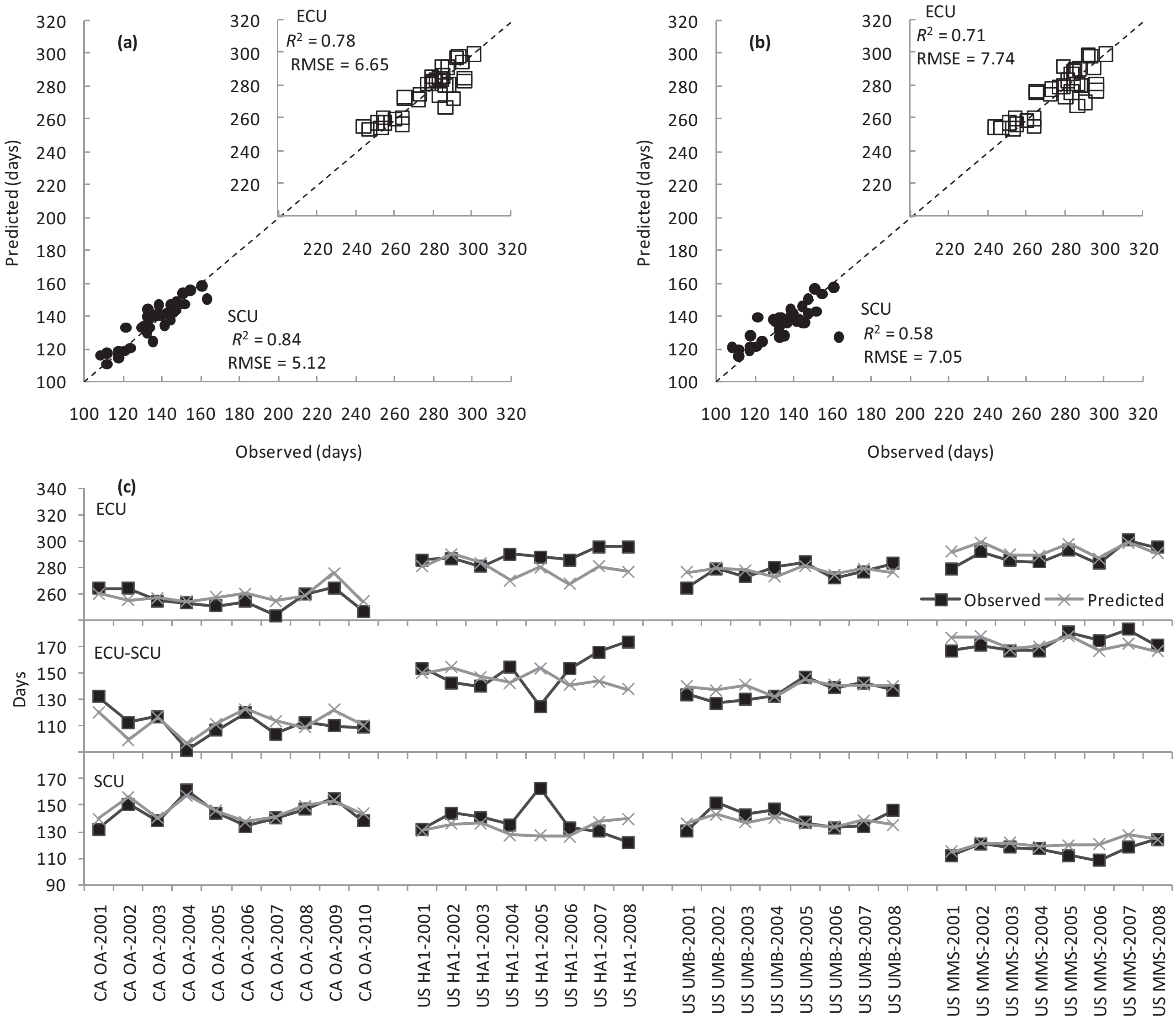

Fig. 2. Relationships between measured and estimated carbon uptake phenology (CUP) from the *in situ* measurements after year 2001. (a) Relationships between the start (SCU) and end (ECU) of carbon uptake observed and predicted based on the best performing explanatory variables given in Table 2, (b) relationships between SCU and ECU observed and predicted based on best performing explanatory variables following leave-one-out cross-validation approach, and (c) the interannual evolution of the observed SCU and ECU plotted along with the predicted values following leave-one-out cross-validation approach. (a) and (b) are plotted for all flux measurement years whereas (c) is presented only for those years where there is remote sensing data for subsequent comparison. Regression analyses were based on all site values.

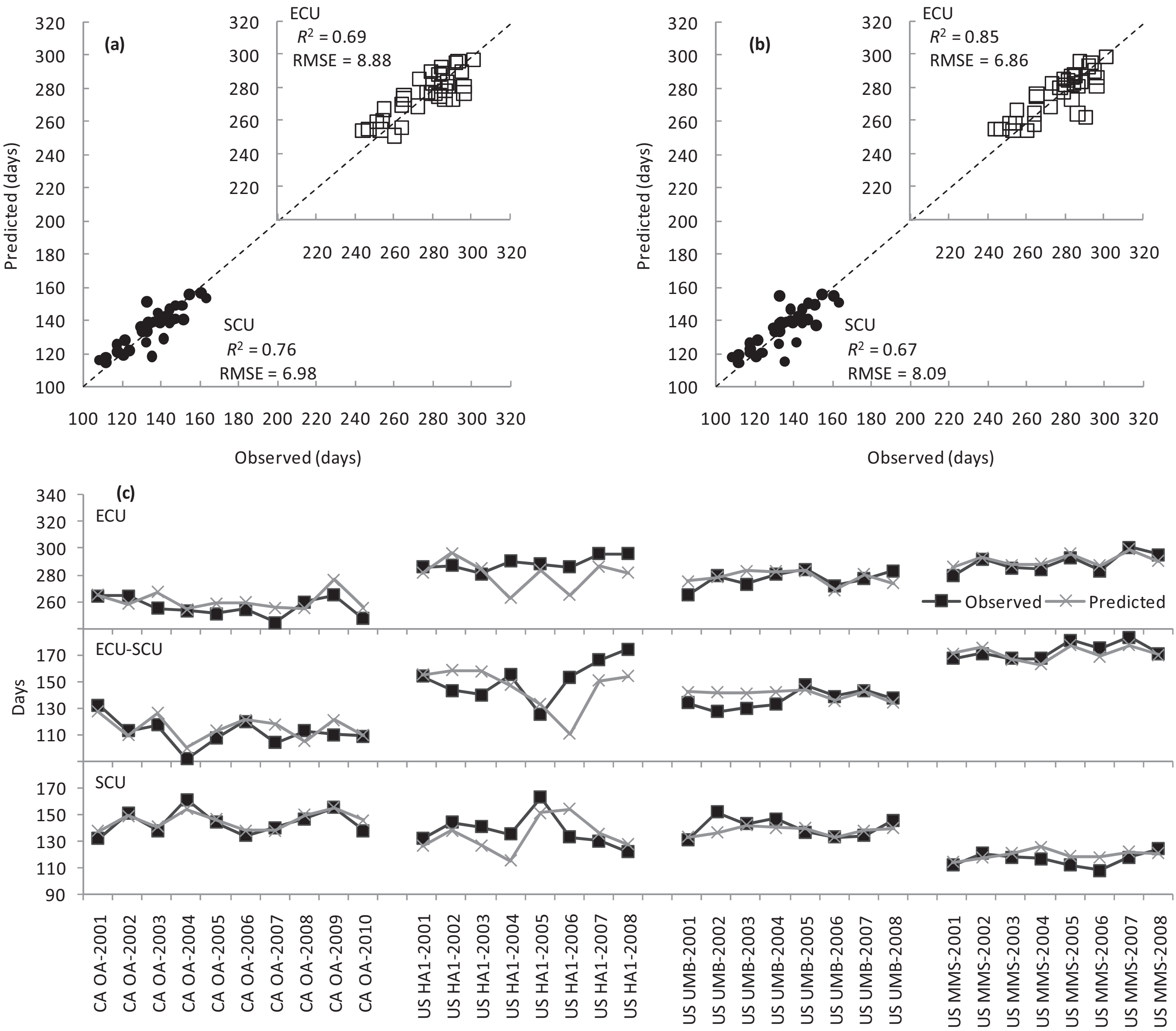

Fig. 3. Relationships of carbon uptake phenology (CUP) between estimates from the remote sensing data and measured values from the *in situ* CO_2 eddy covariance observations. (a) Relationships between the start (SCU) and end (ECU) of carbon uptake observed and predicted based on the best performing explanatory variables given in Table 2, (b) relationships between SCU and ECU observed and predicted based on best performing explanatory variables following leave-one-out cross-validation approach, and (c) the interannual evolution of the observed SCU and ECU plotted along with the predicted values following leave-one-out cross-validation approach. Regression analyses were based on all site values.

4. Potentials and challenges

Before we attempt to present detailed potentials and challenges of our working approach, it is crucial that we demonstrate whether or not predicting CUP based on LSP and monthly temperatures works across a representative sample of the study sites. Because the dependent and independent variables have sampling and measurement errors and the remote sensing data are only for limited site-years, the lack of statistical significance for some of the relationships may not hold for larger area studies. A major strength of our approach, compared with traditional phenological models based on temperature thresholds of a chilling sum, cumulative heat sums or growing degree days (GDD) approach (Richardson et al., 2012) is that our method does not rely on an arbitrary heat unit threshold that must be calibrated on a site-by-site basis. One of the remarkable works attempting to link CUP with surface variables, *i.e.*, air and soil temperatures was that of Baldocchi et al. (2005). However, their method has not been operational as the soil temperature is not easily measurable or available variable from remote sensing and meteorology networks. In our approach, both the surface temperature and LSP dates can be obtained from easily available remote sensing observations. Figs. 2 and 3 show the results obtained from the all available data regression analysis as such site-by-site calibration was not required as the traditional phenology approaches do for example with arbitrary site specific temperature threshold for GDD (Barr et al., 2004; Richardson et al., 2012; Thompson and Clark, 2006; Wu et al., 2012a,b). The results are noteworthy given the large range of age, leaf area index, latitude, temperature, and precipitation regimes in the four study sites. The poor performance of our approach at US HA1 for SCU and ECU and at US MMS for SCU estimations remains to be explained. However, even at US HA1 forest, most of the interannual variability

Table 3
The predicting performances of start (SOS) and end (EOS) of land surface phenology, and monthly mean surface temperatures and their combinations for estimating the start (SCU) and end (ECU) of carbon uptake given in percent coefficient of determination (R^2) for each flux tower site and all available data values. The SOS and EOS, and monthly mean surface temperatures were derived from remote sensing data whereas the observed SCU and ECU were from the *in situ* CO_2 eddy covariance measurements. The best performing explanatory variables are given in bold.

SCU	SOS	April	May	SOS, May	SOS, April, May
CA OA (n = 10)	84.5*	25.5	40.5*	84.8*	**92.2***
US HA1 (n = 8)	31.5	1.6	20.5	31.9	**37.2**
US UMB (n = 8)	84.5*	38.1	15.1	90.6*	**94.1***
US MMS (n = 8)	37.8	0.2	8.0	49.0	**53.3**
All (n = 34)	74.2*	40.0*	26.4*	74.3*	**75.7***
ECU	**EOS**	**August**	**September**	**EOS, September**	**EOS, August, September**
CA OA (n = 10)	39.6	24.9	23.6	41.9	**65.6**
US HA1 (n = 8)	1.8	3.4	0.6	1.7	**9.6**
US UMB (n = 8)	23.4	3.0	13.7	26.1	**33.6**
US MMS (n = 8)	89.0*	45.8	34.6	94.1*	**96.0***
All (n = 34)	63.8*	43.2*	66.2*	72.3*	**74.0***

* Correlation is significant at the 0.05 p-value level (2-tailed).

in CUP was captured both from the *in situ* and remote sensing observations (Figs. 2c and 3c). The *in situ* estimation of CUP dates from the detrended NEP time series is also challenging for US HA1 forest site since there is prolonged intermittent increase and decrease of NEP values around zero in spring and autumn seasons. Other explanation of the poor performance can come from the significant coniferous vegetation composition such as Eastern Hemlock and White Pine in Harvard Forest site which do not respond the same way as deciduous forest for interannual variability of air temperature and LSP. In that case, our method may not work well in predominantly coniferous vegetation types. This is also the case for many ecosystem process models which account for phenology only considering the deciduous vegetation types (Richardson et al., 2012). However, the feasibility of our approach for coniferous vegetation remains to be further tested in larger study areas.

Remote sensing of CUP as presented in this study has a compelling operational potential given the easily available remote sensing data. The main strength is that both of the explanatory variables, *i.e.*, LSP and surface temperature can be estimated with commonly available remote sensing and meteorological observations at regional and global scales. Results from Tables 2 and 3 show that the remote sensing surface temperature (T_s) can be used with comparable performance as the *in situ* measured air temperature (T_a) for CUP estimation. Research has shown (Richardson et al., 2012) the need for improved understanding of the environmental controls on vegetation phenology and incorporation of this knowledge into ecosystem process models. Existing ecosystem and climate models are less likely to predict future responses of phenology to climate change and therefore will misrepresent the seasonality and interannual variability of key biosphere–atmosphere feedbacks and interactions. By being able to predict CUP in addition to LSP, we can understand the environmental controls both on assimilatory and respiratory ecosystem processes. Only then we can account for the comprehensive feedbacks of biosphere and atmosphere to climate changes. Currently, even the state-of-the-art land surface schemes typically have a poor representation of vegetation phenology (Kovalskyy and Henebry, 2012; Morisette et al., 2009). The work by Garrity et al. (2011) found that no single source of vegetation and radiation products from remote sensing data which are all based on the visible and near infrared reflectances showing strong autocorrelation were able to accurately describe the CUP. Our work includes the interlaced impact of both the LSP derived from visible, near infrared and shortwave infrared reflectances, and temperature derived from thermal emissivity of land surfaces to predict CUP.

There are however challenges that should be addressed in future research. Most grasses, agricultural crops, and young forest stands are carbon sources for most part of the growing season. Therefore, irrespective of the LSP, environmental conditions, and species similarities, forest age also plays a large role on CUP. Although we can easily separate non forest vegetation from forest based on remote sensing land cover maps, forest age mapping still remains a challenge. Our approach does not separate middle aged and mature forests from young forests. However, one of the possible solutions for separating mature forest from young forest or non forest vegetations would be the use of weight either the annual GPP sum from flux tower sites or the annual integrated NDVI sum from remote sensing data. This should also be further explored.

The development of new leaves is a prerequisite for photosynthetic uptake in deciduous forest. In temperature limited temperate and boreal deciduous forests, the site turns carbon sink within the same year only after the leaf onset, while the interannual variation of the rate and timing being determined predominately by temperature (*e.g.*, Piao et al., 2008; Suni et al., 2003; Tanja et al., 2003; Wu et al., 2012a). This is not the case in most coniferous forests. It is difficult to define CUP in conifers because NEP may be positive throughout the year. In evergreen conifer forests, spring recovery of photosynthetic capacity is unrelated to changes in canopy structure such as LSP but instead requires only sufficiently mild air temperatures (Tanja et al., 2003). Even if arbitrarily chosen minimum NEP thresholds correlate well with cumulative temperature or model estimates (Suni et al., 2003), it is difficult to apply these at different sites, or justify them on a mechanistic basis. The transition from net negative to net positive NEP is more flexible in coniferous than in deciduous trees because the seasonality of coniferous species is not determined by LSP. For example, the SCU in an evergreen coniferous forest in Manitoba, Canada, preceded that at US HA1 deciduous flux tower site, USA, by a month or more even though the deciduous stand is 13° farther south than the evergreen one (Goulden et al., 1998). In this regard, the strength of our approach, as compared to the commonly used temperature sum, is that the temperature sum is irreversible by nature whereas the recovery of NEP in a coniferous forest is not. Depending on the fluctuations in air temperature, the recovery of NEP of evergreen species, can be reversed and begin again. Therefore, our approach uses monthly air temperature, two months each for spring and autumn which are reversible variables compared to a single temperature sum values to estimate the detrended CUP dates. However, the degree to how much this can be useful in coniferous forest needs to be further investigated.

5. Conclusions

This study has provided a methodology to predict CUP from easily available remote sensing observations. The CUP in contrast to LSP provides the combined responses of photosynthesis and respiration to environmental controls. The results suggest that CUP estimation is possible based on remote sensing explanatory surface variables. LSP dates combined with mean monthly air temperatures explain CUP variability by more than 70% in spring and autumn. A more comprehensive analysis, based on multi-year data from the CO_2 eddy covariance sites across the globe for various plant functional types, is planned as a future FLUXNET synthesis (http://www.fluxdata.org/) project in combination with remote sensing observations. This exercise would involve improved estimation of LSP dates such as the use of USA National Phenology Network (http://www.usanpn.org), PhenoCam networks (http://phenocam.sr.unh.edu), and other related citizen phenology networks together with gridded meteorology datasets.

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