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Remotely sensed phenological heterogeneity of restored wetlands: linking vegetation structure and function

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Abstract

Seasonal phenological dynamics of vegetation hold important clues on ecosystem performance towards management goals, like carbon uptake, and thus should be considered in projections of their targeted services. However, in wetlands spatio-temporal heterogeneity due to mixing of open water, soil, green and dead vegetation makes it difficult to generalize ecosystem functioning across different regions. Remote sensing observations can provide spatially-explicit, cost-effective phenology indicators; however, little is known about their capacity to indicate the links between wetland ecosystem structure and function. Here we assessed this potential by comparing one-year Enhanced Vegetation Index (EVI) from satellite products at high (5m; RapidEye) and low (30m; Landsat) spatial resolutions with eddy covariance time series of net carbon exchange, field digital camera (phenocam) greenness and water temperature among three floristically similar restored wetlands in California, USA. Phenological timing differed by wetland site: depending on satellite, the range in site-median start of greening was up to 28 days, end of greening – up to 73 days, start of senescence – up to 79 days, and end of senescence – up to 10 days. Key transition dates from satellite inputs agreed with seasonal changes in net carbon exchange, phenocam greenness and water temperatures, suggesting that phenological contrasts could result in part from site differences in vegetation configuration and litter affecting the exposure of canopy, soil and water to sunlight and thus sub-canopy microclimate and ecosystem
functioning. Yet, the agreement between satellite inputs was non-systematic, with the greatest disparities at the more heterogeneous, less vegetated site.

Phenological model fitting uncertainty increased with greater spatial resolution, highlighting the tradeoff between the accuracy of representing vegetation and the complexity of local seasonal variation. These findings highlight the sensitivity of satellite-derived phenology to structural and functional heterogeneity of ecosystems and call for more rigorous spatially-explicit analyses to inform assessments of restoration and management outcomes.

**Keywords:** phenology; wetland; eddy covariance; heterogeneity; flux footprint; remote sensing
1. Introduction

Remote sensing datasets, as they improve in temporal frequency, spatial coverage and resolution, are increasingly used to model and upscale ecosystem functions such as primary productivity and greenhouse gas fluxes (Csillik et al., 2019; Knox et al., 2017; Wolf et al., 2016). Vegetation phenology, or variation in plant cycles following seasonal and inter-annual environmental dynamics, can modulate these functions in space and time (Keenan et al., 2014, 2012; Ma et al., 2017; Ryu et al., 2010), which can be manifested in the changes in spectral indicators of plant greenness (Gu et al., 2003; Melaas et al., 2018; Richardson et al., 2018; Vogelmann et al., 2016). Remotely sensed phenological indicators have provided important insights on ecosystem sensitivity to climatic fluctuations (Friedl et al., 2014; Hufkens et al., 2012), disturbance (Kennedy et al., 2010; Sulla-Menashe et al., 2014) and land cover/use shifts (Zhang et al., 2015; Zhang and Weng, 2016; Zhu, 2017), among other factors. However, phenological patterns may be also sensitive to less well understood local effects of vegetation structure on solar energy transfer and microclimate, which may produce heterogeneity in ecosystem functioning, particularly in areas with complex environmental and floristic gradients (Huesca et al., 2015; Richardson et al., 2012; Tóth, 2018; Vrieling et al., 2018). To accurately model biogeochemical processes and ecosystem services across scales, it is critical to better understand the relationships between remotely sensed phenological complexity and on-the-
ground ecosystem properties contributing to their dynamics and management responses.

Restored wetlands present a particularly interesting and important case study to examine the phenological complexity and its implications for ecosystem functions targeted by management. Restoration has been globally expanding as a strategy to mitigate wetland losses and re-create their critical services such as carbon sequestration, ecological habitats, hydrological functions and coastal flood protection (Deverel et al., 2017; Hemes et al., 2019; Klemas, 2013; Miller and Fujii, 2010; Villa and Bernal, 2018). However, as any ecological perturbation, restoration may lead to substantial spatio-temporal variability in ecosystem structure and function, particularly early in the recovery (Chamberlain et al., 2018; Chapple and Dronova, 2017; Dronova and Taddeo, 2016; Eichelmann et al., 2018; Suding, 2011; Zhao et al., 2016). Restored systems with varying degree of spatial heterogeneity thus offer a prime setting to study the impact of phenological complexity on ecosystem functions. Leveraging remote sensing to assess restoration outcomes in a spatially-explicit manner is critical to expand the scope of monitoring efforts in heterogeneous, isolated, large, or sensitive sites and to assess the progress towards targets or detect early signals of undesirable shifts (Eichelmann et al., 2018; Hemes et al., 2019; Matthes et al., 2014; McNicol et al., 2017; Taddeo and Dronova, 2019, 2018).

The relationship between vegetation structure and ecosystem function during post-restoration recovery has been documented by several recent
studies in deciduous herbaceous marshes showing that change in the relative coverage by plants versus open water affects surface energy balance, evapotranspiration and water temperatures (Detto et al., 2006; Eichelmann et al., 2018; Goulden et al., 2007; Hill and Payton, 2000; Rejšková et al., 2012; Smesrud et al., 2014). In the absence of periodic flushing, marshes dominated by reeds may also accumulate large amounts of dead matter (litter) which affects canopy transfer of solar radiation and thereby plant density, leaf area, aboveground productivity (Dronova and Taddeo, 2016; Rocha et al., 2008; Rocha and Goulden, 2009; Schile et al., 2013) and evapotranspiration (Eichelmann et al., 2018; Goulden et al., 2007). Dense litter may substantially reduce sub-canopy soil and water temperatures (Eichelmann et al., 2018; Goulden et al., 2007), affecting seasonality of plant and microbial metabolism and thus the phenological timing of plant establishment and growth (Flanagan et al., 2015; O’Connell et al., 2019). Varying presence of litter and open water to vegetation coverage can be expected to produce heterogeneity in the timing of phenological transitions and ecosystem productivity even among floristically and hydrologically similar wetlands.

Spatially explicit indicators of vegetation phenology derived from remote sensing data could thus represent such structure-function feedbacks (Butterfield and Malmstroem, 2009), as suggested by the previously reported correlations between greenness and ecosystem function (Knox et al., 2017; Ryu et al., 2010; Toomey et al., 2015) and the sensitivity of such correlations
to canopy structure and its effects on photosynthetic efficiency of plants (Dronova et al., 2011; Dronova and Taddeo, 2016; LaRue et al., 2018; Rocha et al., 2008; Smith et al., 2002). Phenologically informed indicators of ecosystem function are also desirable for up-scaling local management outcomes to broader regions of decision making (Byrd et al., 2014; Knox et al., 2017; Richardson et al., 2012), at which assessment of 3-dimensional (3-D) vegetation structure (e.g., with light detection and ranging (lidar) systems) remains extremely costly. Fulfilling this potential requires a better understanding of how the choice of a remote sensing product may affect phenological interpretation depending on its spatial resolution and temporal frequency, as well as landscape configuration of the target ecosystems themselves. Historically popular imagery with 30+m spatial resolution has limited sensitivity to spatial structure of complex systems such as wetlands; yet the multi-decadal archives of such datasets provide nonparallel records of the long-term site dynamics (Bolton et al., 2020; Melaas et al., 2016, 2013; Woodcock et al., 2020). In turn, emerging products offering both high spatial resolution (≤10m) and high temporal frequency (<7days) can make spatially explicit phenological assessments more informative (Vrieling et al. 2018); however, it is not yet well understood to what extent the increase in spatial detail might complicate phenological estimation or differ in outcomes relative to the coarser-resolution inputs. Filling this gap becomes critical for developing new image products from sensors that differ in spatial resolution
and temporal frequency but might be used interchangeably to assess ecosystem performance (Bolton et al., 2020; Claverie et al., 2018).

In response to these needs, our study comparatively assessed phenological characteristics in a set of restored freshwater wetlands in California’s Sacramento-San Joaquin Delta, USA (Figure 1) using one-year imagery from two satellite products at high (5m) and moderate (30m) spatial resolutions. To better understand the local sensitivity of phenology to the feedbacks between structure and function, we also leveraged the time series of net carbon exchange, water temperature, and digital photograph (phenocam) greenness from the AmeriFlux eddy covariance stations. Our objectives were to assess 1) whether satellite-based phenological indicators of the greening and senescence timing differed among wetland sites with varying configuration of vegetation patches; 2) to what extent phenological metrics were sensitive to seasonal variation in ecosystem productivity represented by the nearly continuous field-measured indicator of carbon dioxide (CO$_2$) sequestration and phenocam spectral greenness, and 3) to what extent remote sensing-based estimates of phenological timing agreed between two satellite products with different spatial resolution. We expected that wetlands with larger and more contiguous patches would reach seasonal peaks of greenness and net CO$_2$ uptake later than wetlands with lower and more fragmented vegetation coverage, due to greater likelihood of accumulating litter which may restrict solar energy transfer and sub-canopy water temperatures. Using our results, we further discuss the potential of
cost-effective satellite-derived phenological metrics to elucidate canopy structure-function relationships in assessments of restoration outcomes in heterogeneous ecosystems with limited site access and key future research needs.

2. Methods

2.1. Study area and wetland sites

This study was conducted in the Sacramento-San Joaquin Delta, California, USA (hereafter the Delta), a region with Mediterranean climate characterized by wet, cool winters and dry, hot summers which allow for extensive cloud-free periods during the main growing season (March-October). This region is currently undergoing extensive wetland restoration efforts aimed at reversing land subsidence and re-establishing wildlife habitat, recreational opportunities and other benefits (Bekaert et al., 2019; Deverel, 2015; Deverel et al., 2010; Knox et al., 2015; Schaffer-Smith et al., 2018; Sharma et al., 2016). Of particular interest is the potential of restored wetlands to promote carbon sequestration and reduce emissions of greenhouse gases (Hemes et al., 2019; Knox et al., 2017; Matthes et al., 2014; Miller and Fujii, 2010; Oikawa et al., 2017), a goal shared across a broader domain of emergent freshwater marshes (Chu et al., 2014; Franz et al., 2016; Minke et al., 2016; Stefanik and Mitsch, 2012; Strachan et al., 2015). Quantifying and projecting wetland ecosystem functioning at the regional scale requires a deeper understanding of the role of spatio-temporal
complexity in wetland performance towards their management targets (Chu et al., 2015; Matthes et al., 2014; McNicol et al., 2017).

Our study focused on three wetland sites (Table 1) in the western part of the Delta (Figure 1) that had been established in 1997 (West Pond, or WP, AmeriFlux code US-Tw1), 2010 (Mayberry Farms, or MB, code US-Myb) and 2014 (East End, or EE, code US-Tw4). Currently all of them function as managed freshwater marshes excluded from tidal impacts, dominated by cattails (*Typha* spp.) and tule (*Schoenoplectus acutus*) reeds. The sites differ in size and initial design (Table 1); the oldest one was initially engineered as a fully graded unit, half-planted with tule (Miller and Fujii, 2010), while the other two sites were created with greater bathymetric complexity but no specific design for emergent wetland vegetation (Dronova and Taddeo, 2016; Hemes et al., 2018; Knox et al., 2017). All these sites provide publicly available AmeriFlux (https://ameriflux.lbl.gov) eddy covariance measurements of the greenhouse gas carbon dioxide (CO$_2$), methane (CH$_4$) and water vapor (H$_2$O) fluxes, as well as fixed-view above-canopy digital photographs (phenocam data) and several ecosystem parameters, including water temperature, administered by the UC Berkeley Biometeorology Lab. Eddy covariance technique involves high temporal frequency measurements of atmospheric concentrations of the abovementioned gases (using field-mounted open-path gas analyzers) together with the three-dimensional wind speed and several other environmental drivers (Baldocchi et al., 1988; Hemes et al., 2019). These measurements can be converted to greenhouse
gas and carbon budgets for a given time frame of interest (e.g., daily) and compared with phenological indicators derived from remote sensing images (Gonsamo et al., 2013; Knox et al., 2017). Within each wetland site, phenocam and water temperature data were collected at one location associated with the eddy covariance flux station.

These wetlands provide a useful setting for comparing phenological patterns because, despite their geographic proximity and similarities in vegetation and hydrology, they markedly differ in their landscape surface configuration (Eichelmann et al., 2018) due to varying size and geometry of plant patches and vegetation structure (Table 1). The oldest wetland (19 years in 2016, WP) is nearly fully vegetated, and near the peak season of 2016 had the tallest canopy among the three sites (Table 1). In contrast, the MB wetland (6-year old in 2016) is a mosaic of open water and smaller, more geometrically complex vegetated patches (Figure 1) covering ~64% of the whole site (Table 1). Plant canopies at MB had litter layers on average of similar height as in WP, but shorter live vegetation and lower green leaf area (Table 1). Finally, the youngest site (EE, 2 years in 2016) had the highest green leaf area and shortest litter layer among the three wetlands (Table 1). However, percent vegetation cover and mean patch size of EE were greater than those of MB (Table 1), likely because this wetland experienced a rapid colonization by Typha spp. in its first post-restoration summer and developed relatively large patches that had persisted since.
2.2. **Remote sensing data**

We used two satellite remote sensing datasets for the year 2016 with high frequency of cloud-free dates (Table A1, Appendix): 1) Landsat-8 Operational Land Imager (OLI) Tier I surface reflectance product at 30m spatial resolution, publicly available via the U.S. Geological Survey archive and Google Earth Engine (Gorelick et al., 2017) catalog (16 dates), and 2) RapidEye imagery at 5m spatial resolution provided by the Planet Labs Education and Research Program (21 dates). The latter program by Planet Labs Inc. allows researchers and educators to apply for non-commercial, limited cost-free access to the RapidEye archive and Planetscope imagery for various landscape analysis applications. In this study RapidEye data provided a unique opportunity to assess wetland phenology at high spatial resolution and temporal frequency and compare this inference with traditionally popular 30-m Landsat data (e.g., Melaas et al., 2016, 2013; Mo et al., 2015). Another reason for comparing these products was the length of their missions’ archives, covering substantial portions of the post-restoration history of these sites (with Landsat 30-m data going back to mid-1980s and RapidEye imagery – to 2009), which could facilitate longer-term multi-year phenological analyses in the future.

All Landsat images in this study were from the same tile which corresponded to path/row 44/34 in this satellite’s World Reference System 2 and covered all three study sites. In turn, RapidEye data were selected so that all three wetland sites were captured by the same dates. We then
converted each image individually from the at-sensor radiance to ground surface reflectance using imagery metadata and 6S algorithm (Kotchenova and Vermote, 2007), as surface reflectance product was not available from the provider for 2016. Satellite images were clipped to the spatial extents of the biometeorological flux footprints of each AmeriFlux eddy covariance tower averaged for the year 2016, which resulted in 30, 81 and 30 Landsat pixels and 928, 2234 and 784 RapidEye pixels for West Pond, Mayberry Farms and East End, respectively (Supplementary Table S1). Flux footprints represent areas of the landscape from which 90% of the flux originates, and were generated using an analytical two-dimensional footprint model (Detto et al., 2006; Hsieh et al., 2000; Knox et al., 2017). Each satellite image was then converted into Enhanced Vegetation Index (EVI (1); Huete et al. 2002) as a proxy of greenness:

\[
EVI = \frac{2.5 \times (NIR - \delta)}{NIR + 6 \times \delta - 7.5 \times \delta + 1}, (1)
\]

where Blue, Red and NIR indicate spectral reflectance in the blue (0.450-0.515 \(\mu\)m for Landsat and 0.440-0.510 \(\mu\)m for RapidEye), red (0.630-0.680 \(\mu\)m for Landsat and 0.630-0.685 \(\mu\)m for RapidEye) and near-infrared (0.845-0.885 \(\mu\)m for Landsat and 0.760-0.850 \(\mu\)m for RapidEye) electromagnetic regions, respectively. EVI was selected due to its wide use in phenological remote sensing studies (Klosterman et al., 2014; Melaas et al., 2018, 2016, 2013; Toomey et al., 2015), as it can circumvent important limitations of other popular indices, particularly the tendency to saturate in closed
canopies (Huete et al., 2002). Furthermore, in an earlier study focusing on two of our wetland sites, Landsat-based EVI showed stronger correlations with gross primary productivity than a set of other satellite-derived indices (Knox et al., 2017). Spectral indices and subsequent phenological metrics (Table 2) were estimated in Matlab software version R2018b (MathWorks Inc.).

To identify pixels most likely to represent vegetation phenology, we applied a spatial form of principal components analysis transformation (Machado-Machado et al., 2011) to each image time series using all the pixels within the flux footprints at the three sites. This transformation produces a series of outcomes, or principal components (PCs) representing common types of seasonal EVI trajectories in order of decreasing prevalence (as indicated by variance explained by each PC), with the maximum possible number of components equal to the number of pixels in a single-date image within the flux footprint. As the dominant plant species of our wetland sites were deciduous perennials, we focused on the “deciduous” trajectory with an early-season increase in greenness during the greening phase and subsequent decline in greenness during the senescence phase. For both Landsat and RapidEye inputs, such a trajectory was captured by the first two PCs which together accounted for 90.3% and 82% variation in each dataset, respectively (Supplementary Figure S1). In contrast, the trajectories captured by PCs 3 and 4 (Supplementary Figure S1) showed strongest
correlations with pixels from non-vegetated portions of roads and berms within the footprints. Pixels whose trajectories showed a linear correlation of 0.7 or greater with either of the first two PCs were selected for subsequent phenological metric estimation. Among these, pixels with trajectories similar to PC1 were the overwhelming majority, occupying 70-100% of the flux footprints (Supplementary Table S1).

2.3. Phenological metric estimation and comparison among wetland sites

Next, we estimated a set of phenological parameters for individual pixel seasonal trajectories by fitting the non-symmetrical double-logistic curves (Bauer et al., 2017; Head et al., 2004) to each satellite’s EVI time series and interpolating EVI to a daily step:

\[
EVI(t) = P_1 + \frac{P_2}{1+e^{P_4(t-4)}} + \frac{P_2}{1+e^{P_5(t-6-\tau)}}
\]

where the parameters \(P_1, P_2, \ldots, P_6\) determine the shape and asymmetry in the fitted double-logistic curve function (Bauer et al., 2017), while \(t\) indicates the consecutive day of year (DOY). The double-logistic function (2) was then fit using Matlab \textit{lsqcurvefit} function, and the updated parameter values were used to interpolate EVI to a daily step (details are given in Supplementary Material, section B). Goodness of fit was assessed using root mean square error (RMSE) as a measure of deviation in the fitted model curve from the empirical data in a pixel series.
Statistical distributions of RMSE contained outliers exceeding the value of 0.05, which corresponded largely to roads, berms and open water that were not representative of wetland vegetation, but also in some cases – vegetated areas with complex EVI trajectories where (2) was not sufficiently applicable despite their similarity with PC1 or PC2. Several corrective measures were applied to avoid immediately excluding such pixels from phenological estimation (discussed in Supplementary Material section B, Table S2 and Figure S3). These measures ranged from simpler steps, such as re-fitting (2) after removing the observation with the largest residual, to more complex measures, such as using a Fourier function as an alternative harmonic regression model, or a combination of multiple strategies (Supplementary Material section B, Table S2 and Figure S3). Such re-assessments were more common with RapidEye data, especially at the MB site where 69% RapidEye pixels retained after masking were fitted with the double-logistic model, in contrast to 86-100% pixels for other site/sensor combinations (Supplementary Table S3). Pixels where none of the strategies improved model fitting were excluded from the analyses (Supplementary Material section B).

Next, curvatures in the daily-interpolated EVI series were used to estimate five metrics of phenological timing (Table 2; Supplementary Figure S2; Supplementary Table S4): start and end of greening (SOG and EOG, respectively) and senescence (SOS and EOS) and the duration (DUR) of the growing season (Table 2; Supplementary Figure S2). For pixels fitted with
double-logistic model (1), these estimates were typically based on the local
minima and maxima of the 3\textsuperscript{rd} derivative in the interpolated EVI series,
indicating changes in the rate of greenness dynamics at the onsets and end
times of greening and senescence (Gonsamo et al., 2013; Misra et al., 2016;
Tan et al., 2011). Depending on a site, such cases corresponded to 91-100%
fitted pixels with Landsat data and 52-77% pixels with RapidEye inputs
(Supplementary Table S3). In special cases where curvatures at the
beginning or end of the season were insufficiently captured by the data
series or an alternative fitting model was used (Supplementary Material
section B, Tables S2 and S4), local minima or maxima of the 2\textsuperscript{nd} derivative
were admitted as the next closest approximation of phenological change
(Tan et al., 2011). Maximum greenness (MAXG, Table 2) was estimated from
the original pixel EVI values rather than predicted values, so that it could be
later compared with model RMSE. We expected that such a comparison
would help differentiate cases when modeling uncertainty resulted from
lower vegetation coverage and higher background exposure within a pixel
(Dronova and Taddeo, 2016) versus a disagreement between the
hypothetical fitted model and the spectral trajectory of pixels with high
vegetation coverage, and hence higher maximum greenness.

Importantly, the potential (dis)agreement of phenological metrics
between different satellite products may depend on multiple characteristics
of the product characteristics, including pixel size, specific timing of image
acquisitions and instrument characteristics, among others. Therefore, to
better understand the implications of varying spatial resolution on phenological estimation and differences between Landsat and RapidEye inputs, we additionally aggregated RapidEye data to a 30m pixel size matching Landsat’s resolution and evaluated the same phenological metrics for 30m RapidEye-based pixels. We then compared median values and statistical distributions of all phenological metrics within flux footprints among the wetland sites and among the satellite inputs using non-parametric Mood’s median test (Mood, 1950) and Kruskal-Wallis distribution test (Kruskal and Wallis, 1952), respectively.

2.4. Relationships among satellite-based phenological transitions and field-measured ecosystem properties

To assess the potential relationships between the indicators of satellite-detected phenology and ecosystem function, footprint-level mean and median values of the four phenological timing metrics representing start and end of greening and senescence phases (SOG, EOG, SOS and EOS) were compared with 2016 time series of two field-based ecosystem variables: spectral greenness indicator derived from midday digital photographs taken by in situ phenocams (green chromatic coordinate, or GCC (Woebbecke et al., 1995) and daily gap-filled net ecosystem exchange for CO₂ (NEE; negative values indicate net ecosystem uptake (Chapin et al., 2006); gC-CO₂m⁻²d⁻¹) from the flux towers. We subsequently fit the double-logistic model (2) to each site’s GCC and NEE time series to estimate the days of year associated with their key seasonal transitions (curvatures). We then
regressed the days of the key transitions for GCC and NEE against the start and end dates of greening and senescence estimated from the satellite-based EVI and compared the slopes and intercepts of the regressions with the 1:1 model (slope=1 and intercept=0) and between models using Landsat versus RapidEye-based metrics. We acknowledge that such relationships between EVI-based metrics and GCC should be interpreted with caution due to the view angle differences between oblique phenocam images and satellite data (Bolton et al., 2020; Vrieling et al., 2018). However, as field datasets provide independent, high temporal frequency series with large number of observations, they are useful for verifying the general agreement between satellite-derived metrics and ground-based ecosystem transitions. Finally, we compared satellite-measured EVI with water temperatures summarized as daily averages for the image dates of each time series (Table A1, Appendix) using field measurements from one location at each site, at 10-cm depth at MB and EE and 8-cm depth at WP. Water temperatures were used here to represent potential effects of vegetation and canopy structure on solar radiation transfer, and thus canopy microclimate (Eichelmann et al., 2018; Rocha et al., 2008; Schile et al., 2013). We further examined whether three wetland sites differed in the magnitude of their daily mean water temperature during the growing season and in the slopes of EVI-water temperature regressions for the dates of satellite image acquisitions.

3. Results

3.1. Site and sensor differences in phenological timing
Estimated phenological transition dates differed among wetland sites (Figure 2a-d), with several notable features. First, WP, the site with the highest vegetation and litter coverage (Table 1) showed pronounced delays in greening compared to other wetlands (Figure 2a,b); however, specific nature of these contrasts varied by satellite input. For Landsat, the median start of greening (Figure 2a, Table A2, Appendix) was relatively synchronous across the sites, with a 3-day difference between WP and MB (p>0.1), a 7-day difference between WP and EE (p>0.1) and an 9-day earlier onset at EE compared to MB (p=0.003). However, the median end of greening (Figure 2b, Table A2, Appendix) at MB was substantially earlier than at both WP (~73 days, p<0.001) and EE (~66 days, p<0.001), while the latter two sites showed similar timing (p>0.1). In contrast, for RapidEye 5m inputs, both median values and distributions of the start (Figure 2a) and the end (Figure 2b) of greening were significantly different across all site pairs (p<0.001, Table A2, Appendix), but all of these median transition date estimates similarly indicated greater (by 12-28 days) delay in greening at WP compared to the other two sites. For RapidEye data aggregated to 30m pixel size, however, only SOG was significantly different between all site pairs, but not EOG (Table A2, Appendix).

These differences were also reflected in the spatial distribution of greening dates, where the two most recently established sites, MB and EE, showed a greater proportion of pixels with relatively earlier start and end of greening compared to WP (Figures 3a-c for RapidEye-based start of greening
and Figure 3d-f for the end of greening). At the same time, however, the agreement in greening transition dates between two satellite products was not systematic among the sites (Figure 2a,b), showing the greatest disparity for the more heterogeneous MB wetland where Landsat-based median end of greening was 64 days earlier than RapidEye’s at 5m resolution (Figure 2b).

The timing of senescence also contrasted among the sites and satellite inputs. For Landsat, both the start and the end of senescence were not significantly different for any site pair (all p-values >0.1, Table A2, Appendix). For RapidEye 5m input, however, all differences were significant (p<0.001), except the start of senescence between WP and EE (p>0.1, Table A2, Appendix). Two most vegetated sites WP and EE, again, showed the most substantial delay in the start of senescence compared to MB (78 and 79 days, respectively, Figure 2c). In contrast, the RapidEye-based end of senescence for 5m inputs differed among the sites by only 2-7 days, comparable to 3-10 days for Landsat (Figure 2d). For RapidEye pixels aggregated to 30m, only SOS significantly differed between MB and the other two sites, while no site pairs significantly differed in EOS (Table A2, Appendix).

Spatial variability in senescence dates also differed among three wetlands, showing a more pronounced heterogeneity in the MB footprint (Figure 3h and 3k) but also greater prevalence of late start and end of senescence values at WP (Figure 3g and 3j) and EE (Figure 3i,l). Greater
overall variability of transition dates within the footprint of the more complex MB wetland (Figures 3b,e,h,k) also highlighted the contrasts in phenology between main vegetation patches and pixels representing water channels and water-vegetation edges (visible as the interfaces between darker water and lighter vegetation in reference images in Figure 3q). Water channel and edge pixels were often characterized by later greening and earlier senescence, which could result from differences in ecosystem elements and vegetation contributing to greenness dynamics and contrasts in physical environment (i.e., open water versus emergent patches).

Median duration of the growing season (Figure 2e) was similar for all site pairs for Landsat estimates (p>0.1), but for RapidEye it was significantly longer at EE and MB compared to WP (by 28 and 27 days, respectively, p<0.001 for each, Table A2, Appendix). After aggregating RapidEye pixels to 30m, all site pairs significantly differed in duration metric. Spatial variation in per-pixel duration estimates (Figures 3m-o) suggested that the latter differences resulted from presence of pixels with relatively early onset of greening and relatively late senescence in both younger sites, which could be areas where wetland vegetation was not obstructed by litter early in the season. In contrast, most of the pixels at the oldest WP site (RapidEye example in Figure 3m) corresponded to litter-laden patch interiors with a relatively shorter growing season.
Finally, seasonal maximum of EVI significantly differed across the three sites and their individual pairs regardless of the sensor (all p-values <0.05), with the oldest WP site being the greenest, followed by the youngest EE as the second greenest (Figure 2f). These patterns were largely consistent among the two satellite datasets, although RapidEye-based estimates of maximum greenness exhibited longer tails of high values in their distributions compared to Landsat-based ones (Figure 2f). These tails were likely due to the greater chance of capturing smaller clumps of green vegetation cover with 5m pixels compared to 30m ones. For RapidEye aggregated to 30m, maximum greenness significantly differed only between MB and each of the other sites (Table A2, Appendix).

Among the satellite inputs, the lowest agreement in metric estimates occurred at the most heterogeneous MB site where all except maximum greenness significantly differed between Landsat and both RapidEye inputs (Table A2, Appendix). For EE and WP, site-median differences between Landsat and 5-m RapidEye metrics were within 1-14 days for SOG and EOG (Figure 2a,b) and within 0-19 days for SOS, EOS and duration (Figure 2c,d,f). In contrast, for MB, input differences were most pronounced for the curvatures near peak growing season, showing a 64 day earlier EOG and 72-day later SOS with Landsat (Figures 2b and 2c, respectively). Differences in median SOG, EOS and DUR at MB were within 17-20 days, comparable to the other two sites. However, most phenological metrics did not significantly differ between Landsat and 30-m aggregated RapidEye except MAXG for WP
Similarly, only three metrics significantly differed between the original and aggregated RapidEye inputs: SOG and DUR for MB and MAXG for WP (Table A2, Appendix), indicating no substantial effect of RapidEye scaling on phenological estimation in more vegetated sites.

3.2. Curve-fitting error and sensitivity to spatial resolution of remote sensing data

The median RMSE of the fitted phenological curve models did not significantly differ among three wetlands for Landsat data (p=0.074; Figure A1, Appendix). For RapidEye 5m input, median RMSE did not differ between WP and MB (p>0.1) but was significantly lower at EE than at each of the other two sites (p<0.001). When compared among the satellite inputs, median RMSE was significantly (p<0.001) higher for the original 5m RapidEye estimates compared to Landsat’s and for the aggregated RapidEye input for each site (Figure A1, Appendix). The proportion of pixels where transition dates could be estimated using only 3rd derivative extrema of the double-logistic model alone was also lower for RapidEye (52-77%; Supplementary Table S3) compared to 91-100% for Landsat (Supplementary Table S3).

Spatial distribution of RMSE within the flux footprints (Figure 4a,c,e,g,i,k) indicated presence of local hotspots of higher fitting error that were also more evident at higher spatial resolution of RapidEye (Figure 4a,e,i). Comparing these local clusters of high RMSE to footprint aerial images (Figure 3p-r) revealed that they were more common at the different types of
wetland vegetation edges: near roads and berms, visible in the WP footprint (Figures 4a and 3p) and upper left portion of the MB footprint (Figures 4e and 3q), and near the vegetation-water interfaces in the lower left and central parts of the EE footprint (Figures 4i and 3r) and parts of the MB footprint (Figures 4e and 3q). Notably also, areas of higher RMSE often corresponded to areas with higher maximum greenness (Figure 4b,f and j for RapidEye and Figure 4d,h and l for Landsat). In fact, per-pixel RMSE significantly and positively correlated with maximum EVI for nearly all site-sensor combinations with p-value<0.001 and R^2 ranging between 0.32 and 0.66 (except for Landsat metrics at MB, p>0.1). In contrast, image regions with lower RMSE (Figures 4b,f and j) often coincided with larger, contiguous patches of wetland vegetation (Figures 3p-r).

3.3. Agreement between satellite-based phenological metrics and field variables

Both phenocam greenness (GCC) and net carbon exchange (NEE) followed a seasonal trajectory similar to the double-logistic model of satellite-based greenness for vegetation (Figures 5a and 5b, respectively). Both GCC and NEE increased in magnitude during the first half of the year, stayed close to their mid-year asymptotic values for a certain period of time and subsequently reversed in late fall. However, specific shapes and timing of these trajectories varied by site. The oldest site (WP) showed a later onset of GCC greenness (~DOY 98) compared to MB and EE (~DOYs 69 and 51,
respectively); however, the end of greening for GCC was similar between two more vegetated sites (DOYs 160 and 167 for EE and WP, respectively) than for MB (DOY 117). The latter site also had lower maximum GCC and lower magnitude of NEE (Figures 5a and 5b), which could be partially attributed to field-detected increases in water salinity during 2015-2016 that may have reduced the productivity and increased plant stress (Chamberlain et al., 2019). The dynamics of NEE indicated an earlier onset for MB around DOY 68 compared to 85 and 99 at EE and WP, respectively, followed by an earlier saturation near DOY 125, compared to 137 for EE and even more delayed (192) for WP (Figure 5b). There were also notable site differences during the senescence phase: for GCC, senescence at MB started approximately 102 and 140 days earlier than for EE and WP, respectively, though ended at a similar time close to DOY 318. For NEE, the senescence phases were delayed at WP and EE compared to MB by 17 and 19 days, respectively, at the onset of senescence and by 31 and 45 days, respectively, at the end (Figure 5b).

Field-measured water-temperature (Figure 5c) showed a strong seasonal change pattern for all sites, but differed in the rates of increase and maximum values (Figure 5c). It was consistently the lowest at WP during the main part of the growing season and similarly delayed in its seasonal increase compared to the other two sites, as could be expected with a taller canopy and presence of a litter layer affecting solar radiation transfer through the canopy and canopy microclimate (Eichelmann et al., 2018; Schile et al., 2013). In contrast, water temperature at MB site with greater...
surface complexity and smaller vegetated patches was consistently the highest among three wetlands, also showing an earlier seasonal increase (Figure 5c).

Satellite-estimated transition dates for greenness and senescence strongly aligned with the DOYs of the key seasonal transitions (all \( p < 0.001 \)) from the field-measured phenocam greenness and NEE (Figure 6a,b). For models comparing satellite and field GCC transition dates (Figure 5a), regression slopes were not significantly different from 1, nor did they differ between two satellite inputs (both \( p > 0.1 \), Table 3) despite the degree of mismatch between satellite and phenocam fields of view (Knox et al., 2017).

However, for NEE transitions (Figure 5b) the slopes of regression with Landsat and RapidEye’s median DOYs were significantly greater than 1 (\( p = 0.005 \) and \( p = 0.009 \), respectively, Table 3). These patterns indicated the tendency of satellite-based transitions to occur slightly ahead of the corresponding changes in NEE early in the season, and slightly after NEE changes late in the season (Figures 5b and 6b).

Finally, water temperature for the dates of satellite image acquisitions significantly and positively correlated with EVI of the corresponding remote sensing series (Figure 7a,b). The slopes of these relationships did not differ between satellite inputs for any of the sites (\( p > 0.1 \) for all slope...
comparisons). However, for both Landsat (Figure 7a) and RapidEye (Figure 7b), the slope of EVI-water temperature relationship for WP was significantly steeper than for either MB (p=0.006 and p=0.001 for Landsat and RapidEye, respectively) or EE (p=0.026 and p=0.023 for Landsat and RapidEye, respectively), and did not differ between the latter (p>0.1 for each). In turn, water temperatures corresponding to the dates of estimated SOG and EOG for each satellite series significantly differed (p<0.001) between three sites. These temperatures, however, were all lower for WP, indicating cooler sub-canopy conditions at the onset and the end of greening.

4. Discussion

4.1. Spatial phenological heterogeneity as the indicator of restoration outcomes

As ecological restoration efforts continue expanding, the need to understand how their novel outcomes contribute to ecosystem management and conservation becomes ever more urgent (Matthews et al., 2009; Mitsch et al., 2013; Villa and Bernal, 2018). Our analysis of satellite-based phenological metrics across three restored wetlands in California’s Delta region corroborates the unique potential of remote sensing to help develop this understanding via repeated cost-effective observations. Our findings also highlight the need for more spatially explicit phenological analyses, for two important reasons. First, the timing of phenological transitions appears to vary substantially among wetland sites with similar geographic setting,
vegetation and hydrology but contrasting surface composition and canopy structure. This limits the representativeness of aggregated single-site data and calls for individual, spatially explicit site-level observations which are becoming increasingly feasible (Csillik et al., 2019; Gorelick et al., 2017; Tóth, 2018; Woodcock et al., 2020). Second, we find that the agreement in phenological indicators between satellite inputs of different spatial resolution may also vary among wetlands with different amount and configuration of vegetation cover. Such differences in spatial heterogeneity and phenology may further contribute to the functional contrasts among sites, as suggested by the agreement between satellite-detected EVI transition dates and the timing of in situ measured phenocam greenness and CO₂ exchange (Figure 5).

From the remote sensor’s perspective, two main factors likely contributed to heterogeneity of phenological metrics and challenges in their estimation: wetland surface and plant composition (Vriel et al., 2018) and the effects of non-photosynthetic plant matter on canopy structure, radiative transfer and microclimate (Dronova and Taddeo, 2016; Farrer and Goldberg, 2009; Rocha et al., 2008; Schile et al., 2013). Despite relatively low diversity of the emergent vascular plants in these wetlands, some non-dominant species could have distinct seasonality and form local patches large enough to influence pixel-level EVI dynamics. For example, portions of the flux footprints near roads and berms included grasses, herbs and sometimes woody species, while some of the open-water areas had floating aquatic
vegetation. Both types of such locations (i.e., berms and open water areas; Figure 3p-r) differed in phenological timing from the reed-dominated wetland patches, particularly for the start of greening (Figure 3a-c) and duration (Figure 3m-o).

In turn, the 3-D complexity of plant canopies and presence of dead biomass (Dronova and Taddeo, 2016; Rocha et al., 2008; Rocha and Goulden, 2009; Tóth, 2018) likely contributed to the wide range of start and end dates of phenological phases observed even within the larger wetland vegetation patches (Figure 3p-r). Although full understanding of such effects is difficult without spatially explicit information on canopy structure, the following evidence suggests the importance of both horizontal and vertical configuration of vegetation in these patterns. First, as expected, phenological differences among wetland sites closely resonated with differences in their spatial heterogeneity and configuration. Greater greening delays within the oldest and the youngest wetlands, WP and EE (Figure 2a,b), were consistent with their greater plant coverage, patch size, canopy height and canopy-to-litter height proportion (Table 1). In contrast, less contiguous plant coverage together with smaller patch size and greater shape index at MB site (Figure 3r, Table 1) would imply a greater availability of fine-scale edge spaces both at the perimeters and inside the patches, where green vegetation may have greater access to light and become visible to remote sensors earlier compared to larger, contiguous patches of the other two sites (Dronova and Taddeo, 2016).
Second, the general agreement in the timing of remotely sensed phenological metrics and site-measured ecosystem processes indicates that phenological variability was not merely an optical artifact of litter obscuring green vegetation from the sensors’ view, but rather the outcome of more complex feedbacks among canopy structure, microclimate and plant function (Eichelmann et al., 2018; Hemes et al., 2018). Regardless of the input satellite product, delays in greening were accompanied by delays in seasonal enhancement of CO$_2$ uptake (Figures 5a,b and 6b) and phenocam greenness, which had been earlier shown to positively correlate with gross primary productivity at MB and WP (Knox et al., 2017). Presence of litter likely mediated these relationships via reduced solar energy to young short vegetation early in the season, and via its broader effects on sub-canopy microclimate and evapotranspiration (Eichelmann et al., 2018; Goulden et al., 2007; Hemes et al., 2018; Rejšková et al., 2012). Although here we cannot directly validate such causal effects due to the lack of spatially explicit data on site-level litter distribution, microclimatic contrasts among three wetlands throughout the study period were consistent with this assertion. In particular, lower water temperatures and their smaller change change in unit greenness (Figure 7a,b) at WP and EE with larger litter-laden vegetation patches could contribute to their stronger greenness delay (Figures 2b and 5c) compared to MB due to potential inhibition of plant and microbial metabolism early in the season.
Some of the deviations from a 1:1 agreement between satellite-derived phenological transition dates and those estimated from GCC and NEE series (Figure 6a,b) could also result from the differences in ecosystem sampling between satellite and ground instruments. A recent continental-scale analysis of ecosystem phenology combining Landsat-8 and Sentinel-2 imagery (Bolton et al., 2020) has noted stronger disagreements between satellite and phenocam estimates in more heterogeneous systems as well as landscapes with sparser vegetation cover. Applying this evidence to restored deciduous marshes may suggest that, similar to our findings, the agreement among different remote sensing systems should vary both with the degree of surface complexity at a given post-restoration stage, and possibly even with season, due to differences in plant density and canopy structure. These considerations, again, point to the difficulties in generalizing ecosystem cycles among heterogeneous areas (Eichelmann et al., 2018; Goulden et al., 2007; Larsen and Harvey, 2011; Rocha et al., 2008; Schile et al., 2013) and underscore the need for more spatially explicit phenological analyses at the site level, which are not feasible with oblique single-location phenocam images alone (Bolton et al., 2020; Vrieling et al., 2018).

4.2. The implications of spatial resolution and frequency of remote sensing data

Our findings also show that heterogeneity of vegetation in relation to spatial resolution of a remote sensing product is a critical consideration in selecting the input data for phenological analyses. Smaller pixels enable
more accurate representation of vegetation patch structure and floristic
components as a potential contributor to site-level ecosystem function
(Eichelmann et al., 2018; Matthes et al., 2014; McNicol et al., 2017). For
example, stronger agreement between RapidEye-based phenological
transitions with those of field GCC and NEE (Figure 6) compared to Landsat-
based ones could be in part due to better separation of vegetation and water
and thus lower likelihood of mixed-cover pixels where water may attenuate
vegetation signals (Kearney et al., 2009). As a result, 5m RapidEye pixels
retained after masking would be expected to more closely resemble green
vegetation as seen by oblique-looking phenocams than 30m Landsat pixels
with a greater chance of including background water signals (Dronova and
Taddeo 2016). In terms of spatial representation of the footprints, the cost of
“losing” a pixel due to noise and inconsistency with the phenological model
is obviously higher with coarser-resolution Landsat data, since there are
fewer overall pixels and each covers a larger area than a RapidEye’s pixel, as
was especially evident at the EE site (Supplementary Tables S1 and S3).
However, in this study benefits of the high-resolution dataset also came at
the cost of somewhat higher model fitting error (Figures A1 (Appendix) and
4) and greater diversity of pixel-level trajectories that were not always easy
to accommodate by the standard mathematical functions (Supplementary
Material section B, Tables S2 and S4). These challenges likely contributed to
greater model RMSE with 5m RapidEye inputs (Appendix Figure A1) and to
the positive association between RMSE and maximum EVI, also more evident
with RapidEye data (Figure 4). These patterns likely reflected the potential of smaller pixels to capture more nuanced and localized seasonal variation in canopy reflectance spectra, affecting seasonal change in EVI. For example, duration and consistency of the phenological phases with higher greenness could be affected by various events and processes such as flowering, disturbance, mortality, or changes in green leaf orientation (e.g., Bolton et al., 2020; Ryu et al., 2010; Sonnentag et al., 2011), making per-pixel EVI trajectories more complex than in a hypothetical model (Figure S2, Supplementary Material).

Together, these results highlight an important tradeoff between two aspects of phenological complexity in heterogeneous systems: coarser spatial resolution increases the chance of mixed pixels where phenological trajectory may be complicated by the seasonality of both vegetated and non-vegetated components, while higher resolution may accentuate local phenological and spectral variability even for exclusively vegetated pixels, posing challenges to traditional curve-fitting approaches. Smoothing the satellite-derived EVI time series using moving time windows might also be impractical if there are substantial gaps between image acquisition dates, as this might reduce the accuracy of estimated transitions. Optimizing the choice of remote sensing products thus should weigh the relative importance of spatial accuracy in representing landscape elements (e.g., patches) versus the ratio of temporal noise relative to phenologically relevant signal, both of which may increase with smaller pixel size. These findings also highlight the
shortcomings of phenological estimation approaches developed in “upland” terrestrial ecosystems within complex wetland environments and call for more rigorous wetland-specific assessments which have been scarce to date (Mo et al., 2015; Vrieling et al., 2018).

Finally, the agreement in the estimated timing of greening and senescence between satellite inputs may also depend on their image acquisition dates (Bolton et al., 2020; Melaas et al., 2016, 2013; Vrieling et al., 2018). For our single-year study this issue was not a major concern, as indicated by relatively high temporal frequency of both datasets (Table A1, Appendix) and the general agreement of the satellite-derived DOYs of greening and senescence with the phenology of field-based phenocam GCC greenness (Figure 6a). However, disparities in phenological metrics between Landsat and both original and aggregated RapidEye inputs for the most heterogeneous MB site (Table A2, Appendix) suggest that phenological analyses might be more sensitive to both sensor-specific spatial resolution and image timing in landscapes with greater complexity and phenological variability (Tóth, 2018; Vrieling et al., 2018). In general, less frequent image series can be more strongly impacted by cloudy conditions leading to prolonged gaps between usable dates. From this perspective, greater frequencies of RapidEye and other new platforms such as Sentinel-2 (Bolton et al., 2020; Claverie et al., 2018; Vrieling et al., 2018) become an obvious advantage over Landsat’s 8-16 day intervals between acquisitions even during cloud-free seasons. These considerations also argue for a wider
adoption of cost-effective, high temporal frequency phenological validation and gap-filling strategies, such as in situ phenocam systems (Knox et al., 2017; Richardson et al., 2018; Sonnentag et al., 2012) and unmanned vehicles (Tóth, 2018).

4.3. Future research needs

Collectively, our findings suggest that phenological indicators derived from high- and moderate-resolution passive remote sensing images can be sensitive to spatio-temporal heterogeneity of ecosystems and the potential links between vegetation structure and function targeted by restoration and management (Matthes et al., 2014; McNicol et al., 2017). However, a more in-depth interpretation of such couplings ultimately requires spatially explicit information on 3-D canopy structure which could be characterized using multi-angular spectral reflectance (Hilker et al., 2011) and/or active remote sensing such as lidar (LaRue et al., 2018). At present, lidar data are not systematically acquired in our study area, and high cost of such data collection over large regions generally limits their use in ecosystem monitoring (Taddeo and Dronova, 2019). However, where available, active remote sensing data could facilitate more in-depth studies of the role of canopy structure in phenological variability. Employing such instruments on the unmanned platforms (Bekaert et al., 2019; Sharma et al., 2016; Tóth, 2018) could be especially useful in complex systems to develop such an understanding in a cost-effective and spatially explicit way.

Future research should also more closely investigate the role of site-
specific environmental conditions in phenological contrasts among wetlands with similar vegetation and hydrology. In addition to patch configuration and 3-D structure, phenological patterns could be also associated with less well known variation in wetland soil and water column characteristics (Chamberlain et al., 2018; Franz et al., 2016; Minke et al., 2016; Smesrud et al., 2014; Strachan et al., 2015). In particular, the correspondence of greater phenological delay with high maximum greenness (Figure 2) in the sites with higher LAI, canopy height (Table 1) and NEE (Figure 5b) presents an interesting paradox to examine in the future. One of the possible reasons for this association could be the effects of site-specific soil properties, salinity and litter on nutrient status (Chamberlain et al., 2018; Farrer and Goldberg, 2009; Tóth, 2018), potentially affecting spectral reflectance via both the amount and chemistry of green foliage (Byrd et al., 2014). For instance, salinization of wetland soils at the MB site during the California drought of 2011-2017 reduced its annual gross ecosystem productivity compared to WP, consistent with our observed contrasts in maximum greenness between these sites (Chamberlain et al., 2018). Similarly, a study of phenological variability in freshwater Phragmites stands at Lake Balaton, Hungary (Tóth, 2018) reported a stronger sensitivity of phenological variation to sediment texture and chemical properties than to air and water temperature. Alternatively, greater litter accumulation could be hypothesized to enhance site quality (Lenssen et al., 1999) and protect the reed seedlings in patch interior from wind and water-related disturbance (Zhang and Wang, 2016),
which, again, could be tested more explicitly via experimental studies. Finally, to better understand the implications of the coupled structure-function relationships for restoration outcomes, future studies should investigate the inter-annual variability in wetland phenology using longer-term satellite product archives, such as Landsat’s, at least in areas with sufficiently cloud-free time series. Such multi-year assessments could elucidate the potential cycles in spectral contributions of litter (Anderson et al., 2016; Rocha et al., 2008) and the role of these cycles in stability and resilience of the ecosystem functions in response to climatic anomalies (Rocha and Goulden, 2010) or pest outbreaks. Increasing availability of higher-resolution remote sensing datasets capable of characterizing ecosystem heterogeneity and phenological dynamics (e.g., Sentinel-2, Planet Lab products) expands this critical new frontier for more continuous monitoring of ecosystem function (Bolton et al., 2020; Claverie et al., 2018; Matthes et al., 2014; Vrieling et al., 2018). Ultimately, the knowledge derived from comprehensive analyses of richer remote sensing series would also support the upscaling of ecosystem function and associated ecological benefits from local sites to regional scales and similar efforts in other locations.

5. Conclusions

Remote sensing products are increasingly used to characterize phenological transitions of ecosystems and their functional dynamics; however, the sensitivity of such assessments to local vegetation structure
and scale of remote sensing data is still not universally understood. This gap is especially evident in spatially heterogeneous systems such as wetlands, where remotely sensed vegetation indicators may depend on local mixing of plants and non-vegetated surfaces and the complexity of canopy structure at a given image resolution, which might further vary in the course of ecological restoration or succession. Understanding the implications of heterogeneity on remotely sensed phenological indicators thus becomes critical for interpreting links between plant structure and function and their sensitivity to management and restoration treatments.

Our study of three restored wetlands in California, USA finds that even under similar floristic composition and geographic setting, wetlands may differ in remotely sensed phenological characteristics in accordance with their contrasts in vegetation coverage and structure. Such differences are especially evident in variable length and timing of the greening phase which can be more delayed in areas with larger vegetation patches and greater accumulation of canopy litter. The consistency between site-level remotely sensed phenological metrics and field-based changes in eddy covariance NEE for CO$_2$ as well as phenocam greenness suggests that such delays may reflect the local effects of litter on canopy radiative transfer, water temperatures and microclimate. A more in-depth investigation of this assertion would benefit from incorporating spatially explicit information on local canopy structure, e.g., from lidar instruments.
We also show that both the local spatial variability in phenological metrics and the disagreement in their estimation between two satellite inputs tended to be higher in wetlands with more heterogeneous surface configuration. We also find that the uncertainty in fitting standard phenological models pixel-level greenness series increased with greater spatial resolution, likely due to greater sensitivity of smaller pixels to local-scale variation in phenological patterns within vegetation patches. Such tradeoffs between the benefits of higher spatial resolution and the analysis uncertainty raise an important question on which spatial and temporal scales most effectively represent the links between vegetation structure and function, particularly in complex systems such as restored wetlands. With the increasing interest in multi-sensor data integration efforts and higher-resolution phenological products, this question highlights an important research need to inform future remote sensing uses in monitoring, modeling and up-scaling of ecosystem function and restoration outcomes.

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Figure 1. Study area in the Sacramento-San Joaquin Delta, California, USA. Background image: aerial photo from the National Agriculture Imagery Program (NAIP) for California.

Figure 2. Statistical distributions of the main phenological metrics estimated from Landsat (darker fill), RapidEye at the original 5m spatial resolution (moderately dark fill) and RapidEye aggregated to 30m spatial resolution (lightest fill) image inputs within biometeorological footprints of East End (EE), Mayberry Farms (MB) and West Pond (WP) wetland sites: a) start of greening (SOG), b) end of greening (EOG), c) start of senescence (SOS), d) end of senescence (EOS), e) duration of the season (DUR) and f) maximum greenness (MAXG).

Figure 3. Spatial distributions of phenological metrics computed from 5m RapidEye Enhanced Vegetation Index (EVI) within biometeorological flux footprints of three wetland sites: a-c) start of greening (SOG), d-f) end of greening (EOG), g-i) start of senescence (SOS), j-l) end of senescence (EOS), m-o) duration of the growing season (DUR), and p-r) reference high-resolution aerial imagery. Vertical arrangements represent the 19-year old West Pond (WP) wetland (a,d,g,j,m,p), the 6-year old Mayberry Farms (MB) wetland (b,e,h,k,n,q) and the 2-year old East End (EE) wetland (c,f,i,l,o,r).

Figure 4. Spatial distributions of phenological curve fitting error (left panels) from models fitted to 30m Landsat and 5m RapidEye input series and
maximum greenness (right panels) at three wetland sites: a-b) West Pond, RapidEye; c-d) West Pond, Landsat; e-f) Mayberry Farms, RapidEye; g-h) Mayberry Farms, Landsat; i-j) East End, RapidEye, and k-l) East End, Landsat.

**Figure 5.** Seasonal trajectories of field-measured a) eddy covariance net ecosystem exchange (NEE, gC-CO$_2$ m$^{-2}$ d$^{-1}$; negative sign indicates net ecosystem uptake), b) phenocam green chromatic coordinate (GCC) spectral index, and c) water temperature measured at 10cm for Mayberry Farms (MB) and East End (EE) sites and at 8cm for West Pond (WP). All variables are plotted as 5-day moving window averages.

**Figure 6.** The agreement between site-median satellite-based days of year (DOYs) representing start and end transitions of the Enhanced Vegetation Index (EVI) trajectories from 30m Landsat imagery and 5m RapidEye imagery and the corresponding transitions in the trajectories of phenocam-based green chromatic coordinate (GCC) spectral index (a) and net ecosystem exchange (NEE) for CO$_2$ measured by eddy covariance stations (b). Equations represent the fitted linear regression models where $y$ denotes site median transition dates estimated from satellite-based EVI series, and $x$ denotes the transition dates from the time series of a respective field-measured metric.

**Figure 7.** The associations between satellite EVI and average daily water temperature on the corresponding image dates for a) Landsat at 30m spatial resolution, and b) RapidEye at 5m spatial resolution. Equations represent the
fitted linear regression models where \( y \) denotes EVI and \( x \) denotes water temperature of a given site.
Figures

Figure 1
Figure 5

a. Day of year (2016)

Phenocam Green Chromatic Coordinate (red-xG C).

Day of year (2016)

b. Day of year (2016)

Net Ecosystem CO₂ Exchange (g-CO₂ m⁻² d⁻¹).

c. Day of year (2016)

Daily mean water temperature (deg. C).

EE, MB, WP.
Figure 6

The figure shows two graphs comparing the schedule DOY for phenocam-based GCC spectral index and field-measured Net Ecosystem Exchange.

**Graph a:**
- Landsat $R^2 = 0.83$
- $y = 19.2 + 0.97x$
- RapidEye $R^2 = 0.95$
- $y = 16.04 + 0.95x$

**Graph b:**
- Landsat $R^2 = 0.95$
- $y = 28.10 + 1.19x$
- RapidEye $R^2 = 0.94$
- $y = 13.95 + 1.09x$

Legend:
- West Pond, Landsat
- West Pond, RapidEye
- Mayberry Farms, Landsat
- Mayberry Farms, RapidEye
- East End, Landsat
- East End, RapidEye
- 1:1 reference line
Figure 7

a. 
Water temperature, deg.C

y = 0.04 + 0.026x
R² = 0.61

y = 0.05 + 0.006x
R² = 0.82

West Pond
△ Mayberry Farms
□ East End

b. 

Water temperature, deg.C

y = 0.01 + 0.014x
R² = 0.84

y = 0.03 + 0.01x
R² = 0.63

R² = 0.71
R² = 0.82
R² = 0.84
R² = 0.65
R² = 0.63

y = -0.04 + 0.026x
R² = 0.61

y = 0.05 + 0.006x
R² = 0.82

y = -0.01 + 0.014x
R² = 0.84

y = 0.03 + 0.01x
R² = 0.63
Tables

Table 1. Landscape metrics of vegetation distribution and field measurements of canopy structure, by wetland site. All metrics except patch density and percentage values show means of the plot or site measurements with standard deviation in parentheses.

<table>
<thead>
<tr>
<th>Metric type</th>
<th>Metric</th>
<th>West Pond (WP), est. 1997</th>
<th>Mayberry Farms (MB), est. 2010</th>
<th>East End (EE), est. 2014</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spatial extent</td>
<td>Whole wetland area, km²</td>
<td>0.032</td>
<td>1.242</td>
<td>2.995</td>
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<td></td>
<td>Flux footprint area (90th percentile), km²</td>
<td>0.022</td>
<td>0.054</td>
<td>0.018</td>
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<td>Landscape metrics based on aerial images*</td>
<td>Percent vegetated cover (whole site)</td>
<td>99.7%</td>
<td>64.4%</td>
<td>82.2%</td>
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<td></td>
<td>Percent vegetated (flux tower footprint; 90th percentile)</td>
<td>74.0%</td>
<td>55.7%</td>
<td>83.2%</td>
</tr>
<tr>
<td></td>
<td>Patch density (number of patches/100 ha)</td>
<td>19.29</td>
<td>81.56</td>
<td>42.70</td>
</tr>
<tr>
<td></td>
<td>Mean Patch Area of vegetated patches, km²</td>
<td>0.05 (0)</td>
<td>0.01 (0.09)</td>
<td>0.02 (0.28)</td>
</tr>
<tr>
<td></td>
<td>Mean Shape Index of vegetated patches</td>
<td>1.42 (0)</td>
<td>1.58 (1.55)</td>
<td>1.48 (1.50)</td>
</tr>
<tr>
<td>Field measurements (summer 2016)‡</td>
<td>Green one-sided leaf area index, m²/m²</td>
<td>3.1 (1.7)</td>
<td>1.9 (2.3)</td>
<td>3.8 (2.2)</td>
</tr>
<tr>
<td></td>
<td>Canopy height, cm</td>
<td>335.5 (29.1)</td>
<td>223.7 (27.6)</td>
<td>282.4 (29.1)</td>
</tr>
<tr>
<td></td>
<td>Litter height, cm</td>
<td>211.4 (39.4)</td>
<td>211.6 (41.5)</td>
<td>161.8 (16.4)</td>
</tr>
<tr>
<td></td>
<td>Litter volume (m³ per 0.09m² plot)</td>
<td>0.134 (0.05)</td>
<td>0.100 (0.04)</td>
<td>0.022 (0.02)</td>
</tr>
<tr>
<td></td>
<td>Percent dead vegetation in plot cover</td>
<td>58.9%</td>
<td>51.7%</td>
<td>54.2%</td>
</tr>
<tr>
<td></td>
<td>Water depth, cm</td>
<td>19.6 (11.3)</td>
<td>37.9 (14.8)</td>
<td>66.3 (17.6)</td>
</tr>
</tbody>
</table>
Landscape metrics are based on vegetation patches delineated from 1-m spatial resolution aerial imagery publicly available from USDA’s National Agriculture Inventory Program (NAIP) for the summer 2016.

Field sampling was conducted between August 2 and 8, 2016 within 0.3m×0.3m sampling plots (24 plots in West Pond, 36 plots in Mayberry Farms, and 20 plots in East End). Litter height corresponds to the height of standing litter, approximated to the nearest 0.05m. Litter volume is based on visually estimated percent litter cover class (0-25%, 25-50%, 50-75%, >75%) summed across the 0.2-m increments along the vertical dimension of the canopy above each 0.3m×0.3m plot. Percent dead vegetation is a visual estimation of the percentage of the sampling plot covered by dead vegetation versus green plants or other surfaces (open water, bare soil).
Table 2. Key phenological metrics and ecosystem variables used in this study.

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Explanation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wetland site names</td>
<td></td>
<td></td>
</tr>
<tr>
<td>WP</td>
<td>West Pond</td>
<td>The oldest study site (restored in 1997)</td>
</tr>
<tr>
<td>MB</td>
<td>Mayberry Farms</td>
<td>The intermediate-aged site (restored in 2010)</td>
</tr>
<tr>
<td>EE</td>
<td>East End</td>
<td>The youngest study site (restored in 2014)</td>
</tr>
<tr>
<td>Spectral vegetation indices</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EVI</td>
<td>Enhanced Vegetation Index</td>
<td>Huete et al. 2002</td>
</tr>
<tr>
<td>GCC</td>
<td>Green Chromatic Coordinate Index</td>
<td>Woebbecke et al. 1995</td>
</tr>
<tr>
<td>Phenological metrics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DOY</td>
<td>Day of year</td>
<td>Consecutive day of year starting from Jan 1, 2016. In cases where growing season and its mathematical analysis extended beyond December 31, 2016, DOY values exceeded 365 according to the additional dates.</td>
</tr>
<tr>
<td>SOG</td>
<td>Start of greening</td>
<td>DOY representing the first major curvature point in the phenological curve indicating the onset of spring increase.</td>
</tr>
<tr>
<td>EOG</td>
<td>End of greening</td>
<td>DOY representing the second major curvature point in the phenological curve indicating the slowdown in spring EVI increase approaching maximum greenness.</td>
</tr>
<tr>
<td>SOS</td>
<td>Start of senescence</td>
<td>DOY representing the third major curvature point in the phenological curve indicating the onset of EVI decline (senescence).</td>
</tr>
<tr>
<td>EOS</td>
<td>End of senescence</td>
<td>DOY representing the last major curvature point in the phenological curve indicating the end of the fall spectral index decline.</td>
</tr>
<tr>
<td>DUR</td>
<td>Duration of the growing season</td>
<td>The difference between DOYs corresponding to EOS and SOG.</td>
</tr>
<tr>
<td>MAXG</td>
<td>Maximum greenness</td>
<td>Maximum value of the seasonal EVI.</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root mean square error</td>
<td>Standard deviation of residuals in the phenological curve model.</td>
</tr>
</tbody>
</table>
indicating the deviation of satellite-measured greenness values from the modeled trajectory.

<table>
<thead>
<tr>
<th>Ecosystem variables</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>NEE</td>
<td>Net ecosystem exchange (for CO₂)</td>
</tr>
<tr>
<td>LAI</td>
<td>Leaf area index</td>
</tr>
</tbody>
</table>

Net exchange of CO₂ carbon between the wetland ecosystem and the atmosphere based on eddy covariance CO₂ flux data. One-sided green canopy leaf area per unit ground area.
Table 3. Slope and intercept comparisons between regressions with DOYs for phenological transition dates derived from satellite inputs or seasonal trajectories of field-measured Green Chromatic Coordinate greenness (GCC) and net ecosystem exchange for CO₂ (NEE).

<table>
<thead>
<tr>
<th>Response variable</th>
<th>Predictor variable 1</th>
<th>Compared to model</th>
<th>P-value, slope comparison</th>
<th>P-value, intercept comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transition DOY for GCC</td>
<td>Site-median DOYs of key stages (Landsat)</td>
<td>Slope=1, intercept=0</td>
<td>0.226</td>
<td>0.549</td>
</tr>
<tr>
<td>Transition DOY for GCC</td>
<td>Site-median DOYs of key stages (RapidEye)</td>
<td>Slope=1, intercept=0</td>
<td>0.186</td>
<td>0.926</td>
</tr>
<tr>
<td>Transition DOY for NEE</td>
<td>Site-median DOYs of key stages (Landsat)</td>
<td>Slope=1, intercept=0</td>
<td>0.004</td>
<td>0.031</td>
</tr>
<tr>
<td>Transition DOY for NEE</td>
<td>Site-median DOYs of key stages (RapidEye)</td>
<td>Slope=1, intercept=0</td>
<td>0.005</td>
<td>0.053</td>
</tr>
<tr>
<td>Transition DOY for NEE</td>
<td>Site-median DOYs of key stages (RapidEye)</td>
<td>With site-median DOYs of key stages from RapidEye</td>
<td>0.983</td>
<td>0.883</td>
</tr>
<tr>
<td>Transition DOY for GCC</td>
<td>Site-median DOYs of key stages (Landsat)</td>
<td>With site-median DOYs of key stages from RapidEye</td>
<td>0.663</td>
<td>0.635</td>
</tr>
</tbody>
</table>
Figure A1. Root mean square error (RMSE) of per-pixel phenological model fitting for three different satellite data inputs (Landsat at 30m spatial resolution, RapidEye at the original 5m spatial resolution and RapidEye aggregated to 30m spatial resolution) averaged for the CO\textsubscript{2} flux footprints of wetland sites West Pond (WP), Mayberry (MB) and East End (EE). Upper error bars show standard deviations of RMSE for each respective group.

Table A1. Satellite products and dates used in phenological metric estimation (DOY stands for consecutive day of year starting from January 1, 2016).

<table>
<thead>
<tr>
<th>Month</th>
<th>Year</th>
<th>Date: Landsat-8 Surface Reflectance Tier 1 (DOY)</th>
<th>Date: RapidEye Geocorrected At-sensor Radiance (DOY)</th>
</tr>
</thead>
<tbody>
<tr>
<td>February</td>
<td>2016</td>
<td>4 (35)</td>
<td>15 (46)</td>
</tr>
<tr>
<td>March</td>
<td>2016</td>
<td>23 (83)</td>
<td>17 (77)</td>
</tr>
</tbody>
</table>
### Table A2. Mood’s test results for pairwise comparisons of phenological metrics between site and sensor pairs. Values represent test chi-square statistic estimated using Matlab mediantest function by Keine (2020).

#### Site pair comparisons for a given satellite input

<table>
<thead>
<tr>
<th>Metric</th>
<th>Landsat (30m)</th>
<th>RapidEye (5m)</th>
<th>Aggregated RapidEye (30m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOG</td>
<td>1.71</td>
<td>2.67</td>
<td><strong>13.12</strong></td>
</tr>
<tr>
<td>EOG</td>
<td><strong>24.38</strong></td>
<td>2.67</td>
<td><strong>23.63</strong></td>
</tr>
<tr>
<td>SOS</td>
<td>1.02</td>
<td>2.30</td>
<td>1.16</td>
</tr>
<tr>
<td>EOS</td>
<td>2.57</td>
<td>0.03</td>
<td>0.20</td>
</tr>
<tr>
<td>DUR</td>
<td>1.34</td>
<td>2.30</td>
<td>0.10</td>
</tr>
<tr>
<td>MAXG</td>
<td><strong>50.00</strong></td>
<td><strong>17.53</strong></td>
<td><strong>18.52</strong></td>
</tr>
</tbody>
</table>

#### Satellite input comparisons for a given site

<table>
<thead>
<tr>
<th>Metric</th>
<th>Landsat (30m) &amp; original RapidEye data (5m)</th>
<th>Landsat &amp; aggregated RapidEye data (30m)</th>
<th>Original (5m) &amp; aggregated (30m) RapidEye data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WP</td>
<td>MB</td>
<td>EE</td>
</tr>
<tr>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
</tr>
<tr>
<td>SOG</td>
<td>7.85*</td>
<td>13.32*</td>
<td>0.09</td>
</tr>
<tr>
<td>EOG</td>
<td>0.39</td>
<td>23.59*</td>
<td>6.13*</td>
</tr>
<tr>
<td>SOS</td>
<td>15.62*</td>
<td>25.42*</td>
<td>5.44*</td>
</tr>
<tr>
<td>EOS</td>
<td>0.92</td>
<td>16.66*</td>
<td>1.94</td>
</tr>
<tr>
<td>DUR</td>
<td>0.06</td>
<td>8.07*</td>
<td>0.34</td>
</tr>
<tr>
<td>MAXG</td>
<td>11.38*</td>
<td>1.52</td>
<td>5.96*</td>
</tr>
</tbody>
</table>

* p-value <0.05
Supplementary Material

A. Selecting pixels for phenological estimation within the biogeochemical footprints

Figure S1. Seasonal trajectories of the first four principal components (together explaining >90% variation in the data) derived from Landsat (left) and RapidEye 2016 Enhanced Vegetation Index (EVI) time series of the pixels inside the biometeorological flux footprints combined among the three wetland study sites.

Note that PC1 trajectory here is the most consistent with the deciduous vegetation where the greenness values are expected to be low at the beginning of the year, then increase until the seasonal maximum is reached and then decrease again at the end of the growing season. PC2 represents a similar pattern; however, it is somewhat shifted in time. The early-season increase in the trajectory is delayed compared to PC1, while the end-of-season decrease continues into the winter time frame as suggested by the initial decrease in the trajectory during the days 0-100 as a spillover from the previous year.
Table S1. Selection of pixels for phenological curve fitting based on the similarity to deciduous trajectory within the biogeochemical flux footprints of three wetland sites represented by the first and second principal components (PC1 and PC2, respectively) of the greenness series from each satellite product. Here “in mask” denotes pixels included in the subsequent phenological analyses.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Landsat</th>
<th></th>
<th>RapidEye</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>West</td>
<td>Mayberry Farms</td>
<td>East</td>
<td>West</td>
</tr>
<tr>
<td>Total pixel count</td>
<td>33</td>
<td>81</td>
<td>30</td>
<td>928</td>
</tr>
<tr>
<td>Pixels with ≥0.7 correlation to PC1</td>
<td>33</td>
<td>68</td>
<td>21</td>
<td>799</td>
</tr>
<tr>
<td>Pixels with ≥0.7 correlation to PC2</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>18</td>
</tr>
</tbody>
</table>

| Pixels with ≥0.7 correlation to PC1 or PC2 as % total | 100%   | 84%   | 80%   | 88%   | 86%   | 96%   |

B. Phenological parameter estimation

1. Double-logistic model for seasonal greenness

As a proxy of vegetation greenness, we used the Enhanced Vegetation Index (EVI) which has been widely used in terrestrial phenological analyses and sometimes preferred over other popular indicators due to greater sensitivity to vegetation signals in closed canopy setting (Huete et al., 2002; Melaas et al., 2016, 2013):

\[
EVI = \frac{2.5 \cdot |NIR - \hat{\lambda}|}{NIR + 6 \cdot \hat{\lambda} - 7.5 \cdot \hat{\lambda}^2 + 1}, \tag{1}
\]

Fitting a curve to per-pixel phenological series of EVI is an important step in the analyses because it allows interpolating greenness (spectral vegetation index) values from discrete observations of available image dates to a daily time step. While a variety of algorithms and functions have been proposed for such interpolations, studies focusing on vegetation with deciduous seasonality have often considered sigmoid logistic functions consistent with the non-linear dynamics of greenness proxies (Figure S2), i.e., more rapid
changes during the early season green-up and late season senescence and low variation during the low greenness (i.e., before the start of greening and after the end of senescence) and high greenness (between end of greening and start of senescence) phases (Gonsamo et al., 2013; Klosterman et al., 2014; Misra et al., 2016; Son et al., 2016; Tan et al., 2011; Toomey et al., 2015; Xu et al., 2014).

Figure S2: Deciduous phenological trajectory represented by a double-logistic function.

A double-logistic function (Bauer et al., 2017; Head et al., 2004) captures both increase (green-up) and decrease (senescence) phases by a single equation with different parameter sets for each phase to the Enhanced Vegetation Index (EVI) series:

\[
EVI(t) = P_1 + \frac{P_2}{1 + e^{P_3(t - P_4)}} + \frac{P_2}{1 + e^{P_3(t - P_6 - t)}}
\]

where the parameters \(P_1, P_2, \ldots, P_6\) determine the shape and asymmetry in the fitted double-logistic curve (Bauer et al., 2017) and \(t\) indicates the day of year (DOY).

Fitting the function in (2) as a regression model to the input series of EVI involves finding a set of parameter values \(P_1, P_2, \ldots, P_6\) which minimize the “cost function”, i.e. a measure of error as the distance between the original and fitted values. By the nature of model (2), its cost function may have more than one local minimum in the multi-dimensional space of its
parameters, which may complicate the search for their best fitting set. To help achieve the global, rather than local, minimum corresponding to the least predictive error, it is important to constrain the search space by providing the initial guess on the parameters $P_1, P_2, \ldots, P_6$. As such a guess would be specific to both the shape and the extrema of the individual per-pixel trajectories, a fixed set of numbers might not be applicable to all the pixels in the sample, especially in landscapes with high local variation in greenness. To automate such initial parameter guessing in this study, we estimated the starting values of $P_3, P_4, P_5$ and $P_6$ using the extrema in the first derivative of a first-order Fourier function fitted to the original pixel EVI series. The starting values of $P_1$ and $P_2$ were approximated by the minimum and the difference between maximum and minimum, respectively, of the original EVI series for each pixel.

2. Extracting phenological metrics for the timing of greening and senescence

Following the fitting of the double-logistic function, curvatures in the pixel daily interpolated EVI series were used to estimate the start and end dates of greening and senescence phases and the duration of the growing season (Figure S2). Such key transitions can be approximated by the local minima and maxima in the curve derivatives; however, specific choices of the latter vary among studies. Tan and colleagues (2011) provide a detailed analysis and interpretation of such curvatures, indicating that the 3rd derivative’s extrema approximate more closely the timing of changes in the actual curvature of greenness, while the 2nd derivative’s extrema represent the timing when the majority of a pixel changes in greenness. The latter study preferred 3rd derivative as the primary indicator of the greening and senescence transitions, more consistent with how they might be detected in ground-scale phenological observations (Tan et al., 2011). Another study focusing on a rural landscape with broadleaf forest areas in Germany (Misra et al., 2016) also recommended the 3rd derivative over 2nd as the former more effectively captured inter-annual phenological variability and contributions from the forest understory species. A well-defined double-logistic curve typically has three prominent peaks and two troughs in the 2nd derivative and three peaks and three troughs in the 3rd derivative (Figure S3).
Figure S3. An interpolated double-logistic curve fitted to the raw greenness series (left panel) with its second (middle panel) and third (right panel) derivatives.

3. Special cases and challenges in double-logistic fitting

Many previous phenological studies have focused on “upland” terrestrial ecosystems and used moderate to coarse spatial resolution imagery, where seasonal change in aboveground vegetation biomass, cover and health are often the main contributors to variation in spectral indicators, consistent with generalized models such as (2). However, in wetland environments, phenological dynamics may show high local heterogeneity due to inundation effects on plant reflectance spectra, zoning of plant communities along elevation gradients, local disturbance and other factors (Kearney et al., 2009; Knox et al., 2017; Mo et al., 2015). For hydrologically managed wetlands such as in our study area, we expected that spatial variability in the amount and height of litter, dominant species and disturbance such as pest outbreaks could be especially important contributors to the local timing of green-up and senescence and the specific shape and magnitude of seasonal EVI trajectories (Eichelmann et al., 2018; Knox et al., 2017; Rocha et al., 2008).

Indeed, initial efforts to fit double-logistic function (2) to per-pixel EVI series of our wetland sites revealed that some of the pixel trajectories were difficult to accommodate by this model, as summarized in Table S2. Such cases were diagnosed using model root mean square error (RMSE)>0.05 and number of peaks and troughs in both 2nd and 3rd derivatives inconsistent with the double-logistic model (Figure S3), or both (Figure S4). To avoid excluding such pixels entirely from the analysis, considering our primary focus on analyzing phenological heterogeneity, we adopted a set of corrective strategies (Table S2), sometimes applying more than one of them to a given pixel (Figure S4).
### Table S2. Examples of the common challenges in fitting double-logistic function to EVI series.

<table>
<thead>
<tr>
<th>Challenge</th>
<th>Example of EVI series</th>
<th>Potential strategies*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short-term spike in greenness at the beginning or the end of the peak greenness phase, deviating from the main region of high EVI values but consistent with the overall timing of the higher greenness phase</td>
<td><img src="image1.png" alt="Graph" /></td>
<td>Remove the observation with the largest residual and re-fit the model.</td>
</tr>
<tr>
<td>Insufficient curvature at the very onset of greening and the very end of senescence</td>
<td><img src="image2.png" alt="Graph" /></td>
<td>To facilitate the fitting, extend the time series by replicating the minimum EVI at 16 days at each end of the series, assuming that the values do not change substantially during the lowest greenness phase.**</td>
</tr>
<tr>
<td>Insufficient representation of double-logistic curvature at some stages of greening and/or senescence, leading to fewer than expected extrema in the 3rd derivative function</td>
<td><img src="image3.png" alt="Graph" /></td>
<td>Consider 2nd derivative extrema as the next closest approximation for a given indicator of the greening and/or senescence timing.</td>
</tr>
<tr>
<td>Complex variation of EVI values near the peak of the growing season which, however, remains constrained within a certain range of high greenness values</td>
<td><img src="image4.png" alt="Graph" /></td>
<td>If the 3rd derivative has 3 maxima and 3 minima, use these extrema as in double-logistic model which may still fit reasonably well to such a series. In case of a more complex trajectory implied by high model RMSE &gt;0.05, use the 2nd order Fourier fitting function and its derivative extrema.</td>
</tr>
<tr>
<td>Complex trajectory with high variation of EVI values at the peak growing season without a well-defined plateau of high greenness values</td>
<td><img src="image1.png" alt="Graph" /></td>
<td>Use the 2\textsuperscript{nd} order Fourier function and its 2\textsuperscript{nd} and 3\textsuperscript{rd} derivative extrema instead of the double-logistic model; to facilitate the fitting, artificially extend the time series replicating the minimum EVI at 16 days at each end of the series.</td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Greenness trajectory represents a single peak instead of a plateau</td>
<td><img src="image2.png" alt="Graph" /></td>
<td>If the 3\textsuperscript{rd} derivative has 3 maxima and 3 minima while the 2\textsuperscript{nd} derivative has 2 maxima and 1 minimum, the case is consistent with the double-logistic model, and the 3\textsuperscript{rd} derivative’s extrema can be used for transition dates. If there is insufficient early- or late-season curvature, consider 2rd derivative extrema or, with high model RMSE &gt;0.05, use the 2\textsuperscript{nd} order Fourier function and its derivative extrema.</td>
</tr>
<tr>
<td>Substantial noise despite the evidence of the overall seasonal increase and decrease in greenness</td>
<td><img src="image3.png" alt="Graph" /></td>
<td>If none of the corrective measures achieve a satisfactory level of error, exclude the pixel from the analysis.</td>
</tr>
</tbody>
</table>

*Potential strategies presented here are not necessarily mutually exclusive and more than one strategy may be sometimes used for a particular special case pixel.*

**This measure was based on the assumption that late December and January would be the periods of the lowest greenness for the respective pixels, which would be also consistent with the general trajectory of phenocam greenness for each wetland site.*
In some cases, pixel trajectories could not be reasonably approximated by a double-logistic model due to the nature of signal variation. Such were, for instance, cases when the main increase in greenness was accompanied by smaller-magnitude fluctuations during the “low” greenness periods, or when the peak-season greenness values exhibited more complex variation not consistent with either a plateau or a single peak (Table S2). For such pixels, RMSE could remain high or the number of meaningful extrema in 2nd and 3rd derivative could be insufficient even after implementing the initial corrective measures (Figure S4). The second-order Fourier function was considered as an alternative “harmonic regression” model (Brooks et al., 2012; Wallace et al., 2013; Wilson et al., 2018) because it allows representing the expected periodicity of deciduous vegetation greenness while also accommodating some degree of complexity in the main EVI trajectory:

\[ EVI(t) = a_0 + \sum_{i=1}^{n} a_i \cos(iwt) + b_i \sin(iwt) \]  

where \( t \) is the time (day of year), \( a_0 \) is a constant (intercept) related to \( i=0 \), \( w \) is the fundamental frequency of the signal, \( n \) is the number of harmonics in the series (here \( n=2 \) for the second-order function). We then similarly used the extrema of 3rd and, where necessary, 2nd derivatives of the fitted Fourier curve to estimate the days of the key transitions. Overall, such cases were relatively uncommon, representing 0-14% pixels in most sites (Table S3), except for RapidEye pixels at one of our wetlands, the Mayberry Farms site,

**Figure S4.** A flowchart diagram representing major steps in curve-fitting.
where they constituted ~31% of the sample (Table S3) and occurred both within water and within vegetated areas.

If for a given pixel none of the corrective measures sufficiently improved the fit, that pixel was excluded from the analysis completely. Such excluded pixels ultimately constituted for Landsat and RapidEye inputs, respectively, 3% and 1% of the originally selected pixels at West Pond, 12% & 8% of the selected pixels at East End and 4% of pixels with both input products at Mayberry Farms (Table S3). Visual examination showed that these cases often corresponded to open-water areas where EVI trajectories could be influenced by algae, changes in water chemistry and physical disturbance affecting spectral values, such as wind-induced ripples. A more detailed list of special cases and rules considered in assigning curvatures of the 2nd and 3rd curve derivatives as key transition dates is provided in Table S4 below.

**Table S3.** Differences in model fitting to pixels from two satellite input sources within the wetland site flux footprints.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Landsat</th>
<th></th>
<th>RapidEye</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>West Pond</td>
<td>Mayberry Farms</td>
<td>East End</td>
<td>West Pond</td>
</tr>
<tr>
<td>Pixels with fitted curves (% of in-mask pixels)</td>
<td>32</td>
<td>65</td>
<td>21</td>
<td>807</td>
</tr>
<tr>
<td>% of in-mask pixels</td>
<td><strong>97%</strong></td>
<td><strong>96%</strong></td>
<td><strong>88%</strong></td>
<td><strong>99%</strong></td>
</tr>
<tr>
<td>Pixels with double-logistic fitting</td>
<td>31</td>
<td>65</td>
<td>18</td>
<td>775</td>
</tr>
<tr>
<td>% all fitted</td>
<td><strong>97%</strong></td>
<td><strong>100%</strong></td>
<td><strong>86%</strong></td>
<td><strong>96%</strong></td>
</tr>
<tr>
<td>Pixels with 2nd order Fourier fitting</td>
<td>1</td>
<td>0</td>
<td>3</td>
<td>31</td>
</tr>
<tr>
<td>% all fitted</td>
<td><strong>3%</strong></td>
<td><strong>0%</strong></td>
<td><strong>14%</strong></td>
<td><strong>4%</strong></td>
</tr>
<tr>
<td>Pixels with double-logistic model where transitions were estimated with only 3rd derivative extrema</td>
<td>30</td>
<td>59</td>
<td>18</td>
<td>598</td>
</tr>
<tr>
<td>% all fitted</td>
<td><strong>97%</strong></td>
<td><strong>91%</strong></td>
<td><strong>100%</strong></td>
<td><strong>77%</strong></td>
</tr>
</tbody>
</table>
Table S4. Rules and special cases for approximating phenological transition dates using the timing of the curvatures of the 2\textsuperscript{nd} and 3\textsuperscript{rd} derivatives of the fitted functions. Cases where second or third derivatives had less than 2 peaks were excluded from estimation. The terms such as “first”, “last”, “penultimate” and “earliest” below refer to the timing, i.e., day of year associated with a given curvature.

<table>
<thead>
<tr>
<th>Number (#) of curvature points (peaks &amp; troughs) in the 2\textsuperscript{nd} &amp; 3\textsuperscript{rd} derivatives of the fitted curve</th>
<th>Phenological transition dates inferred from the timing of the curvatures in the 2\textsuperscript{nd} and/or 3\textsuperscript{rd} derivatives</th>
<th>Special cases, if any</th>
</tr>
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<tbody>
<tr>
<td>( \geq 3 )</td>
<td>2</td>
<td>3</td>
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<td>( \geq 3 )</td>
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<tbody>
<tr>
<td>4</td>
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<td>3</td>
<td>3</td>
<td>First peak of 3\textsuperscript{rd}</td>
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<td></td>
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<td></td>
<td></td>
<td>Penultimate trough of 2\textsuperscript{nd}</td>
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<td></td>
<td>Penultimate trough of 3\textsuperscript{rd}</td>
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<td>Last trough of 3\textsuperscript{rd}</td>
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**Fourier function:**

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<td>3</td>
<td>First peak of 3\textsuperscript{rd}</td>
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<td>Penultimate peak of 3\textsuperscript{rd}</td>
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<td></td>
<td>Penultimate trough of 3\textsuperscript{rd}</td>
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<td></td>
<td></td>
<td></td>
<td>Last trough of 3\textsuperscript{rd}</td>
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<td></td>
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<td></td>
<td>If estimated EOG&gt;SOS, use the last peak of 2\textsuperscript{nd} for SOS</td>
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<td>2</td>
<td>First peak of 2\textsuperscript{nd}</td>
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<td>First trough of 2\textsuperscript{nd}</td>
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<td>Penultimate peak of 3\textsuperscript{rd}</td>
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<td></td>
<td>Later of the last peaks of 2\textsuperscript{nd} &amp; 3\textsuperscript{rd}</td>
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<tr>
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<td>Earliest of the first peak of 2\textsuperscript{nd} &amp; first trough of 3\textsuperscript{rd}</td>
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<td>First peak of 3\textsuperscript{rd}</td>
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<td></td>
<td>Same as EOG (single-peak trajectory)</td>
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<td></td>
<td>Later of the last peaks of 2\textsuperscript{nd} &amp; 3\textsuperscript{rd}</td>
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<td></td>
<td>Special case if predicted EVI at the first peak of 3\textsuperscript{rd} is greater than EVI at the last troughs of both 2\textsuperscript{nd} &amp; 3\textsuperscript{rd} derivatives. Additionally, for EOG &amp; SOS use last trough of 3\textsuperscript{rd} if the absolute difference in EVI between first peak of 3\textsuperscript{rd} &amp; last trough of 3\textsuperscript{rd} is &lt;0.1</td>
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<td>Earliest of the first peak of 2\textsuperscript{nd} &amp; first trough of 3\textsuperscript{rd}</td>
<td>First trough of 3\textsuperscript{rd}</td>
<td>Same as EOG (single-peak trajectory)</td>
<td>Later of the last peaks of 2\textsuperscript{nd} &amp; 3\textsuperscript{rd}</td>
<td>Special case if predicted EVI at the last trough of 3\textsuperscript{rd} &gt;EVI at the last trough of 2\textsuperscript{nd}</td>
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<td>Earliest of the first peak of 2\textsuperscript{nd}</td>
<td>First trough of 2\textsuperscript{nd}</td>
<td>Same as EOG (single-peak trajectory)</td>
<td>Later of the last peaks of 2\textsuperscript{nd} &amp; 3\textsuperscript{rd}</td>
<td>Special case if predicted EVI at the last trough of 3\textsuperscript{rd} &lt;EVI at the last trough of 2\textsuperscript{nd}</td>
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<td>First peak of 2(^{nd}) &amp; first trough of 3(^{rd})</td>
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<td>First peak of 3(^{rd})</td>
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<td>Earlier of the first peaks of 2(^{nd}) &amp; 3(^{rd})</td>
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<td>Earlier of the first peak of 3(^{rd}) &amp; first trough of 2(^{nd})</td>
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<td>2nd &amp; 3rd derivatives</td>
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<tr>
<td>First peak of 2nd</td>
<td>First trough of 3rd</td>
<td>Same as EOG</td>
<td>Later of the last peaks of 2nd &amp; 3rd</td>
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<tr>
<td>Special case if predicted EVI at the last trough of 3rd &gt;EVI at the last trough of 2nd</td>
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<tr>
<td>First peak of 2nd</td>
<td>First trough of 2nd</td>
<td>Same as EOG</td>
<td>Later of the last peaks of 2nd &amp; 3rd</td>
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<tr>
<td>Special case if predicted EVI at the last trough of 3rd &lt;EVI at the last trough of 2nd</td>
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<tr>
<td>First peak of 2nd</td>
<td>Second peak of 3rd</td>
<td>Second peak of 3rd</td>
<td>Last peak of 3rd</td>
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<tr>
<td>Additional cases considered if model RMSE &lt;0.05</td>
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<tr>
<td>Earlier of the first peak of 3rd &amp; first trough of 2nd</td>
<td>Trough of the 3rd (one value)</td>
<td>Last trough of the 2nd</td>
<td>Last peak of the 2nd</td>
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<tr>
<td>Earlier of the first peak of 2nd &amp; first trough of 3rd</td>
<td>Earlier of the two values with the highest predicted EVI within the set including first peak of 3rd, first trough of 2nd, last trough of 3rd &amp; last trough of 2nd</td>
<td>Later of the two latest values with the highest predicted EVI within the set including first peak of 3rd, first trough of 2nd, last trough of 3rd &amp; last trough of 2nd</td>
<td>Last peak of the 3rd</td>
<td></td>
</tr>
<tr>
<td>Estimation of EOG and SOS requires a special adjustment because their correspondence to peaks vs troughs depended on the (as)symmetry of the overall fitted curve which could vary depending on a pixel's time series</td>
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4. References for Supplementary Material


