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Authors

Dronova, Iryna
Taddeo, Sophie
Hemes, Kyle S
et al.

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1 **Remotely sensed phenological heterogeneity of restored wetlands:**

2 **linking vegetation structure and function**

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4 Iryna Dronova[1,2]*, Sophie Taddeo[2,3], Kyle S. Hemes[1,4], Sara H. Knox[5], Alex

5 Valach[1], Patricia Y. Oikawa[6], Kuno Kasak[1,7], Dennis D. Baldocchi[1]

6

7 [1]Division of Ecosystem Science, Department of Environmental Science, Policy

8 and Management, College of Natural Resources, University of California

9 Berkeley, Berkeley CA 94720-3114

10 [2]Department of Landscape Architecture and Environmental Planning, College

11 of Environmental Design, University of California Berkeley, Berkeley CA

12 94720-2000

13 [3]Plant Science and Conservation, Chicago Botanic Garden, Glencoe, IL 60022,

14 USA

15 [4]Stanford Woods Institute for the Environment, Stanford University, Stanford,

16 CA 94305, USA

17 [5]Department of Geography, The University of British Columbia, Vancouver

18 BC, Canada, V6T 1Z2

19 [6]Department of Earth and Environmental Sciences, California State

20 University, East Bay,

21 Hayward, CA 94542

22 [7]Department of Geography, University of Tartu, Vanemuise 46, 50410, Tartu,

23 Estonia

24

25   *corresponding author, email: idronova@berkeley.edu

26

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

50   functioning. Yet, the agreement between satellite inputs was non-systematic,

51   with the greatest disparities at the more heterogeneous, less vegetated site.

52   Phenological model fitting uncertainty increased with greater spatial

53   resolution, highlighting the tradeoff between the accuracy of representing

54   vegetation and the complexity of local seasonal variation. These findings

55   highlight the sensitivity of satellite-derived phenology to structural and

56   functional heterogeneity of ecosystems and call for more rigorous spatially-

57   explicit analyses to inform assessments of restoration and management

58   outcomes.

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62   **Keywords:** phenology; wetland; eddy covariance; heterogeneity; flux

63   footprint; remote sensing

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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-

89 ground ecosystem properties contributing to their dynamics and

90 management responses.

91   Restored wetlands present a particularly interesting and important case

92 study to examine the phenological complexity and its implications for

93 ecosystem functions targeted by management. Restoration has been

94 globally expanding as a strategy to mitigate wetland losses and re-create

95 their critical services such as carbon sequestration, ecological habitats,

96 hydrological functions and coastal flood protection (Deverel et al., 2017;

97 Hemes et al., 2019; Klemas, 2013; Miller and Fujii, 2010; Villa and Bernal,

98 2018). However, as any ecological perturbation, restoration may lead to

99 substantial spatio-temporal variability in ecosystem structure and function,

100 particularly early in the recovery (Chamberlain et al., 2018; Chapple and

101 Dronova, 2017; Dronova and Taddeo, 2016; Eichelmann et al., 2018; Suding,

102 2011; Zhao et al., 2016). Restored systems with varying degree of spatial

103 heterogeneity thus offer a prime setting to study the impact of phenological

104 complexity on ecosystem functions. Leveraging remote sensing to assess

105 restoration outcomes in a spatially-explicit manner is critical to expand the

106 scope of monitoring efforts in heterogeneous, isolated, large, or sensitive

107 sites and to assess the progress towards targets or detect early signals of

108 undesirable shifts (Eichelmann et al., 2018; Hemes et al., 2019; Matthes et

109 al., 2014; McNicol et al., 2017; Taddeo and Dronova, 2019, 2018).

110   The relationship between vegetation structure and ecosystem function

111 during post-restoration recovery has been documented by several recent

112   studies in deciduous herbaceous marshes showing that change in the

113   relative coverage by plants versus open water affects surface energy

114   balance, evapotranspiration and water temperatures (Detto et al., 2006;

115   Eichelmann et al., 2018; Goulden et al., 2007; Hill and Payton, 2000;

116   Rejšková et al., 2012; Smesrud et al., 2014). In the absence of periodic

117   flushing, marshes dominated by reeds may also accumulate large amounts

118   of dead matter (litter) which affects canopy transfer of solar radiation and

119   thereby plant density, leaf area, aboveground productivity (Dronova and

120   Taddeo, 2016; Rocha et al., 2008; Rocha and Goulden, 2009; Schile et al.,

121   2013) and evapotranspiration (Eichelmann et al., 2018; Goulden et al.,

122   2007). Dense litter may substantially reduce sub-canopy soil and water

123   temperatures (Eichelmann et al., 2018; Goulden et al., 2007), affecting

124   seasonality of plant and microbial metabolism and thus the phenological

125   timing of plant establishment and growth (Flanagan et al., 2015; O'Connell et

126   al., 2019). Varying presence of litter and open water to vegetation coverage

127   can be expected to produce heterogeneity in the timing of phenological

128   transitions and ecosystem productivity even among floristically and

129   hydrologically similar wetlands.

130   Spatially explicit indicators of vegetation phenology derived from remote

131   sensing data could thus represent such structure-function feedbacks

132   (Butterfield and Malmstroem, 2009), as suggested by the previously reported

133   correlations between greenness and ecosystem function (Knox et al., 2017;

134   Ryu et al., 2010; Toomey et al., 2015) and the sensitivity of such correlations

135   to canopy structure and its effects on photosynthetic efficiency of plants

136   (Dronova et al., 2011; Dronova and Taddeo, 2016; LaRue et al., 2018; Rocha

137   et al., 2008; Smith et al., 2002). Phenologically informed indicators of

138   ecosystem function are also desirable for up-scaling local management

139   outcomes to broader regions of decision making (Byrd et al., 2014; Knox et

140   al., 2017; Richardson et al., 2012), at which assessment of 3-dimensional (3-

141   D) vegetation structure (e.g., with light detection and ranging (lidar)

142   systems) remains extremely costly. Fulfilling this potential requires a better

143   understanding of how the choice of a remote sensing product may affect

144   phenological interpretation depending on its spatial resolution and temporal

145   frequency, as well as landscape configuration of the target ecosystems

146   themselves. Historically popular imagery with 30+m spatial resolution has

147   limited sensitivity to spatial structure of complex systems such as wetlands;

148   yet the multi-decadal archives of such datasets provide nonparallel records

149   of the long-term site dynamics (Bolton et al., 2020; Melaas et al., 2016,

150   2013; Woodcock et al., 2020). In turn, emerging products offering both high

151   spatial resolution (≤10m) and high temporal frequency (<7days) can make

152   spatially explicit phenological assessments more informative (Vrieling et al.

153   2018); however, it is not yet well understood to what extent the increase in

154   spatial detail might complicate phenological estimation or differ in outcomes

155   relative to the coarser-resolution inputs. Filling this gap becomes critical for

156   developing new image products from sensors that differ in spatial resolution

157   and temporal frequency but might be used interchangeably to assess

158   ecosystem performance (Bolton et al., 2020; Claverie et al., 2018).

159   In response to these needs, our study comparatively assessed

160   phenological characteristics in a set of restored freshwater wetlands in

161   California's Sacramento-San Joaquin Delta, USA (Figure 1) using one-year

162   imagery from two satellite products at high (5m) and moderate (30m) spatial

163   resolutions. To better understand the local sensitivity of phenology to the

164   feedbacks between structure and function, we also leveraged the time series

165   of net carbon exchange, water temperature, and digital photograph

166   (phenocam) greenness from the AmeriFlux eddy covariance stations. Our

167   objectives were to assess 1) whether satellite-based phenological indicators

168   of the greening and senescence timing differed among wetland sites with

169   varying configuration of vegetation patches; 2) to what extent phenological

170   metrics were sensitive to seasonal variation in ecosystem productivity

171   represented by the nearly continuous field-measured indicator of carbon

172   dioxide (CO_2) sequestration and phenocam spectral greenness, and 3) to

173   what extent remote sensing-based estimates of phenological timing agreed

174   between two satellite products with different spatial resolution. We expected

175   that wetlands with larger and more contiguous patches would reach seasonal

176   peaks of greenness and net CO_2 uptake later than wetlands with lower and

177   more fragmented vegetation coverage, due to greater likelihood of

178   accumulating litter which may restrict solar energy transfer and sub-canopy

179   water temperatures. Using our results, we further discuss the potential of

180 cost-effective satellite-derived phenological metrics to elucidate canopy

181 structure-function relationships in assessments of restoration outcomes in

182 heterogeneous ecosystems with limited site access and key future research

183 needs.

184 FIGURE 1 ABOUT HERE

185 **2. Methods**

186 **2.1.   Study area and wetland sites**

187 This study was conducted in the Sacramento-San Joaquin Delta,

188 California, USA (hereafter the Delta), a region with Mediterranean climate

189 characterized by wet, cool winters and dry, hot summers which allow for

190 extensive cloud-free periods during the main growing season (March-

191 October). This region is currently undergoing extensive wetland restoration

192 efforts aimed at reversing land subsidence and re-establishing wildlife

193 habitat, recreational opportunities and other benefits (Bekaert et al., 2019;

194 Deverel, 2015; Deverel et al., 2010; Knox et al., 2015; Schaffer-Smith et al.,

195 2018; Sharma et al., 2016). Of particular interest is the potential of restored

196 wetlands to promote carbon sequestration and reduce emissions of

197 greenhouse gases (Hemes et al., 2019; Knox et al., 2017; Matthes et al.,

198 2014; Miller and Fujii, 2010; Oikawa et al., 2017), a goal shared across a

199 broader domain of emergent freshwater marshes (Chu et al., 2014; Franz et

200 al., 2016; Minke et al., 2016; Stefanik and Mitsch, 2012; Strachan et al.,

201 2015). Quantifying and projecting wetland ecosystem functioning at the

202 regional scale requires a deeper understanding of the role of spatio-temporal

203 complexity in wetland performance towards their management targets (Chu

204 et al., 2015; Matthes et al., 2014; McNicol et al., 2017).

205   Our study focused on three wetland sites (Table 1) in the western part of

206 the Delta (Figure 1) that had been established in 1997 (West Pond, or WP,

207 AmeriFlux code US-Tw1), 2010 (Mayberry Farms, or MB, code US-Myb) and

208 2014 (East End, or EE, code US-Tw4). Currently all of them function as

209 managed freshwater marshes excluded from tidal impacts, dominated by

210 cattails (*Typha* spp.) and tule (*Schoenoplectus acutus*) reeds. The sites differ

211 in size and initial design (Table 1); the oldest one was initially engineered as

212 a fully graded unit, half-planted with tule (Miller and Fujii, 2010), while the

213 other two sites were created with greater bathymetric complexity but no

214 specific design for emergent wetland vegetation (Dronova and Taddeo,

215 2016; Hemes et al., 2018; Knox et al., 2017). All these sites provide publicly

216 available AmeriFlux (https://ameriflux.lbl.gov) eddy covariance

217 measurements of the greenhouse gas carbon dioxide (CO_2), methane (CH_4)

218 and water vapor (H_2O) fluxes, as well as fixed-view above-canopy digital

219 photographs (phenocam data) and several ecosystem parameters, including

220 water temperature, administered by the UC Berkeley Biometeorology Lab.

221 Eddy covariance technique involves high temporal frequency measurements

222 of atmospheric concentrations of the abovementioned gases (using field-

223 mounted open-path gas analyzers) together with the three-dimensional wind

224 speed and several other environmental drivers (Baldocchi et al., 1988;

225 Hemes et al., 2019). These measurements can be converted to greenhouse

226 gas and carbon budgets for a given time frame of interest (e.g., daily) and

227 compared with phenological indicators derived from remote sensing images

228 (Gonsamo et al., 2013; Knox et al., 2017). Within each wetland site,

229 phenocam and water temperature data were collected at one location

230 associated with the eddy covariance flux station.

231   These wetlands provide a useful setting for comparing phenological

232 patterns because, despite their geographic proximity and similarities in

233 vegetation and hydrology, they markedly differ in their landscape surface

234 configuration (Eichelmann et al., 2018) due to varying size and geometry of

235 plant patches and vegetation structure (Table 1). The oldest wetland (19

236 years in 2016, WP) is nearly fully vegetated, and near the peak season of

237 2016 had the tallest canopy among the three sites (Table 1). In contrast, the

238 MB wetland (6-year old in 2016) is a mosaic of open water and smaller, more

239 geometrically complex vegetated patches (Figure 1) covering ~64% of the

240 whole site (Table 1). Plant canopies at MB had litter layers on average of

241 similar height as in WP, but shorter live vegetation and lower green leaf area

242 (Table 1). Finally, the youngest site (EE, 2 years in 2016) had the highest

243 green leaf area and shortest litter layer among the three wetlands (Table 1).

244 However, percent vegetation cover and mean patch size of EE were greater

245 than those of MB (Table 1), likely because this wetland experienced a rapid

246 colonization by *Typha* spp. in its first post-restoration summer and developed

247 relatively large patches that had persisted since.

248   TABLE 1 ABOUT HERE

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

272 converted each image individually from the at-sensor radiance to ground

273 surface reflectance using imagery metadata and 6S algorithm (Kotchenova

274 and Vermote, 2007), as surface reflectance product was not available from

275 the provider for 2016. Satellite images were clipped to the spatial extents of

276 the biometeorological flux footprints of each AmeriFlux eddy covariance

277 tower averaged for the year 2016, which resulted in 30, 81 and 30 Landsat

278 pixels and 928, 2234 and 784 RapidEye pixels for West Pond, Mayberry

279 Farms and East End, respectively (Supplementary Table S1). Flux footprints

280 represent areas of the landscape from which 90% of the flux originates, and

281 were generated using an analytical two-dimensional footprint model (Detto

282 et al., 2006; Hsieh et al., 2000; Knox et al., 2017). Each satellite image was

283 then converted into Enhanced Vegetation Index (EVI (1); Huete et al. 2002)

284 as a proxy of greenness:

285 $$EVI = \frac{2.5*(NIR - ¿)}{(NIR + 6*¿ - 7.5*¿ + 1)}, (1)$$

286 where *Blue*, *Red* and *NIR* indicate spectral reflectance in the blue (0.450-

287 0.515 µm for Landsat and 0.440-0.510 µm for RapidEye), red (0.630-0.680

288 µm for Landsat and 0.630-0.685 µm for RapidEye) and near-infrared (0.845-

289 0.885 µm for Landsat and 0.760-0.850 µm for RapidEye) electromagnetic

290 regions, respectively. EVI was selected due to its wide use in phenological

291 remote sensing studies (Klosterman et al., 2014; Melaas et al., 2018, 2016,

292 2013; Toomey et al., 2015), as it can circumvent important limitations of

293 other popular indices, particularly the tendency to saturate in closed

294 canopies (Huete et al., 2002). Furthermore, in an earlier study focusing on

295 two of our wetland sites, Landsat-based EVI showed stronger correlations

296 with gross primary productivity than a set of other satellite-derived indices

297 (Knox et al., 2017). Spectral indices and subsequent phenological metrics

298 (Table 2) were estimated in Matlab software version R2018b (MathWorks

299 Inc.).

300   FIGURE 2 ABOUT HERE

301   To identify pixels most likely to represent vegetation phenology, we

302 applied a spatial form of principal components analysis transformation

303 (Machado-Machado et al., 2011) to each image time series using all the

304 pixels within the flux footprints at the three sites. This transformation

305 produces a series of outcomes, or principal components (PCs) representing

306 common types of seasonal EVI trajectories in order of decreasing prevalence

307 (as indicated by variance explained by each PC), with the maximum possible

308 number of components equal to the number of pixels in a single-date image

309 within the flux footprint. As the dominant plant species of our wetland sites

310 were deciduous perennials, we focused on the "deciduous" trajectory with an

311 early-season increase in greenness during the greening phase and

312 subsequent decline in greenness during the senescence phase. For both

313 Landsat and RapidEye inputs, such a trajectory was captured by the first two

314 PCs which together accounted for 90.3% and 82% variation in each dataset,

315 respectively (Supplementary Figure S1). In contrast, the trajectories

316 captured by PCs 3 and 4 (Supplementary Figure S1) showed strongest

317 correlations with pixels from non-vegetated portions of roads and berms

318 within the footprints. Pixels whose trajectories showed a linear correlation of

319 0.7 or greater with either of the first two PCs were selected for subsequent

320 phenological metric estimation. Among these, pixels with trajectories similar

321 to PC1 were the overwhelming majority, occupying 70-100% of the flux

322 footprints (Supplementary Table S1).

323 **2.3.   Phenological metric estimation and comparison among**

324 **wetland sites**

325 Next, we estimated a set of phenological parameters for individual pixel

326 seasonal trajectories by fitting the non-symmetrical double-logistic curves

327 (Bauer et al., 2017; Head et al., 2004) to each satellite's EVI time series and

328 interpolating EVI to a daily step:

329 $$EVI(t) = P_1 + \frac{P_2}{1 + e^{P_3(P_{¿¿}4 - t)} + \frac{P_2}{1 + e^{P_5(P_{¿¿}6 - t)}, (2)¿}}¿$$

330 where the parameters P_1, P_2,..., P_6 determine the shape and asymmetry in

331 the fitted double-logistic curve function (Bauer et al., 2017), while t indicates

332 the consecutive day of year (DOY). The double-logistic function (2) was then

333 fit using Matlab *lsqcurvefit* function, and the updated parameter values were

334 used to interpolate EVI to a daily step (details are given in Supplementary

335 Material, section B). Goodness of fit was assessed using root mean square

336 error (RMSE) as a measure of deviation in the fitted model curve from the

337 empirical data in a pixel series.

338　　　　Statistical distributions of RMSE contained outliers exceeding the value

339　of 0.05, which corresponded largely to roads, berms and open water that

340　were not representative of wetland vegetation, but also in some cases –

341　vegetated areas with complex EVI trajectories where (2) was not sufficiently

342　applicable despite their similarity with PC1 or PC2. Several corrective

343　measures were applied to avoid immediately excluding such pixels from

344　phenological estimation (discussed in Supplementary Material section B,

345　Table S2 and Figure S3). These measures ranged from simpler steps, such as

346　re-fitting (2) after removing the observation with the largest residual, to

347　more complex measures, such as using a Fourier function as an alternative

348　harmonic regression model, or a combination of multiple strategies

349　(Supplementary Material section B, Table S2 and Figure S3). Such re-

350　assessments were more common with RapidEye data, especially at the MB

351　site where 69% RapidEye pixels retained after masking were fitted with the

352　double-logistic model, in contrast to 86-100% pixels for other site/sensor

353　combinations (Supplementary Table S3). Pixels where none of the strategies

354　improved model fitting were excluded from the analyses (Supplementary

355　Material section B).

356　　　　Next, curvatures in the daily-interpolated EVI series were used to

357　estimate five metrics of phenological timing (Table 2; Supplementary Figure

358　S2; Supplementary Table S4): start and end of greening (SOG and EOG,

359　respectively) and senescence (SOS and EOS) and the duration (DUR) of the

360　growing season (Table 2; Supplementary Figure S2). For pixels fitted with

361 double-logistic model (1), these estimates were typically based on the local

362 minima and maxima of the 3rd derivative in the interpolated EVI series,

363 indicating changes in the rate of greenness dynamics at the onsets and end

364 times of greening and senescence (Gonsamo et al., 2013; Misra et al., 2016;

365 Tan et al., 2011). Depending on a site, such cases corresponded to 91-100%

366 fitted pixels with Landsat data and 52-77% pixels with RapidEye inputs

367 (Supplementary Table S3). In special cases where curvatures at the

368 beginning or end of the season were insufficiently captured by the data

369 series or an alternative fitting model was used (Supplementary Material

370 section B, Tables S2 and S4), local minima or maxima of the 2nd derivative

371 were admitted as the next closest approximation of phenological change

372 (Tan et al., 2011). Maximum greenness (MAXG, Table 2) was estimated from

373 the original pixel EVI values rather than predicted values, so that it could be

374 later compared with model RMSE. We expected that such a comparison

375 would help differentiate cases when modeling uncertainty resulted from

376 lower vegetation coverage and higher background exposure within a pixel

377 (Dronova and Taddeo, 2016) versus a disagreement between the

378 hypothetical fitted model and the spectral trajectory of pixels with high

379 vegetation coverage, and hence higher maximum greenness.

380   Importantly, the potential (dis)agreement of phenological metrics

381 between different satellite products may depend on multiple characteristics

382 of the product characteristics, including pixel size, specific timing of image

383 acquisitions and instrument characteristics, among others. Therefore, to

384 better understand the implications of varying spatial resolution on

385 phenological estimation and differences between Landsat and RapidEye

386 inputs, we additionally aggregated RapidEye data to a 30m pixel size

387 matching Landsat's resolution and evaluated the same phenological metrics

388 for 30m RapidEye-based pixels. We then compared median values and

389 statistical distributions of all phenological metrics within flux footprints

390 among the wetland sites and among the satellite inputs using non-

391 parametric Mood's median test (Mood, 1950) and Kruskal-Wallis distribution

392 test (Kruskal and Wallis, 1952), respectively.

393 **2.4.   Relationships among satellite-based phenological**

394 **transitions and field-measured ecosystem properties**

395 To assess the potential relationships between the indicators of satellite-

396 detected phenology and ecosystem function, footprint-level mean and

397 median values of the four phenological timing metrics representing start and

398 end of greening and senescence phases (SOG, EOG, SOS and EOS) were

399 compared with 2016 time series of two field-based ecosystem variables:

400 spectral greenness indicator derived from midday digital photographs taken

401 by in situ phenocams (green chromatic coordinate, or GCC (Woebbecke et

402 al., 1995) and daily gap-filled net ecosystem exchange for CO_2 (NEE;

403 negative values indicate net ecosystem uptake (Chapin et al., 2006); gC-

404 $CO_2 m^{-2} d^{-1}$) from the flux towers. We subsequently fit the double-logistic

405 model (2) to each site's GCC and NEE time series to estimate the days of

406 year associated with their key seasonal transitions (curvatures). We then

407 regressed the days of the key transitions for GCC and NEE against the start

408 and end dates of greening and senescence estimated from the satellite-

409 based EVI and compared the slopes and intercepts of the regressions with

410 the 1:1 model (slope=1 and intercept=0) and between models using Landsat

411 versus RapidEye-based metrics. We acknowledge that such relationships

412 between EVI-based metrics and GCC should be interpreted with caution due

413 to the view angle differences between oblique phenocam images and

414 satellite data (Bolton et al., 2020; Vrieling et al., 2018). However, as field

415 datasets provide independent, high temporal frequency series with large

416 number of observations, they are useful for verifying the general agreement

417 between satellite-derived metrics and ground-based ecosystem transitions.

418   Finally, we compared satellite-measured EVI with water temperatures

419 summarized as daily averages for the image dates of each time series (Table

420 A1, Appendix) using field measurements from one location at each site, at

421 10-cm depth at MB and EE and 8-cm depth at WP. Water temperatures were

422 used here to represent potential effects of vegetation and canopy structure

423 on solar radiation transfer, and thus canopy microclimate (Eichelmann et al.,

424 2018; Rocha et al., 2008; Schile et al., 2013). We further examined whether

425 three wetland sites differed in the magnitude of their daily mean water

426 temperature during the growing season and in the slopes of EVI-water

427 temperature regressions for the dates of satellite image acquisitions.

428 **3. Results**

429   **3.1.   Site and sensor differences in phenological timing**

430   Estimated phenological transition dates differed among wetland sites

431   (Figure 2a-d), with several notable features. First, WP, the site with the

432   highest vegetation and litter coverage (Table 1) showed pronounced delays

433   in greening compared to other wetlands (Figure 2a,b); however, specific

434   nature of these contrasts varied by satellite input. For Landsat, the median

435   start of greening (Figure 2a, Table A2, Appendix) was relatively synchronous

436   across the sites, with a 3-day difference between WP and MB (p>0.1), a 7-

437   day difference between WP and EE (p>0.1) and an 9-day earlier onset at EE

438   compared to MB (p=0.003). However, the median end of greening (Figure

439   2b, Table A2, Appendix) at MB was substantially earlier than at both WP (~73

440   days, p<0.001) and EE (~66 days, p<0.001), while the latter two sites

441   showed similar timing (p>0.1). In contrast, for RapidEye 5m inputs, both

442   median values and distributions of the start (Figure 2a) and the end (Figure

443   2b) of greening were significantly different across all site pairs (p<0.001,

444   Table A2, Appendix), but all of these median transition date estimates

445   similarly indicated greater (by 12-28 days) delay in greening at WP

446   compared to the other two sites. For RapidEye data aggregated to 30m pixel

447   size, however, only SOG was significantly different between all site pairs, but

448   not EOG (Table A2, Appendix).

449   These differences were also reflected in the spatial distribution of

450   greening dates, where the two most recently established sites, MB and EE,

451   showed a greater proportion of pixels with relatively earlier start and end of

452   greening compared to WP (Figures 3a-c for RapidEye-based start of greening

453 and Figure 3d-f for the end of greening). At the same time, however, the

454 agreement in greening transition dates between two satellite products was

455 not systematic among the sites (Figure 2a,b), showing the greatest disparity

456 for the more heterogeneous MB wetland where Landsat-based median end of

457 greening was 64 days earlier than RapidEye's at 5m resolution (Figure 2b).

458   FIGURE 2 ABOUT HERE

459   The timing of senescence also contrasted among the sites and satellite

460 inputs. For Landsat, both the start and the end of senescence were not

461 significantly different for any site pair (all p-values >0.1, Table A2,

462 Appendix). For RapidEye 5m input, however, all differences were significant

463 (p<0.001), except the start of senescence between WP and EE (p>0.1, Table

464 A2, Appendix). Two most vegetated sites WP and EE, again, showed the most

465 substantial delay in the start of senescence compared to MB (78 and 79

466 days, respectively, Figure 2c). In contrast, the RapidEye-based end of

467 senescence for 5m inputs differed among the sites by only 2-7 days,

468 comparable to 3-10 days for Landsat (Figure 2d). For RapidEye pixels

469 aggregated to 30m, only SOS significantly differed between MB and the

470 other two sites, while no site pairs significantly differed in EOS (Table A2,

471 Appendix).

472   Spatial variability in senescence dates also differed among three

473 wetlands, showing a more pronounced heterogeneity in the MB footprint

474 (Figure 3h and 3k) but also greater prevalence of late start and end of

475 senescence values at WP (Figure 3g and 3j) and EE (Figure 3i,l). Greater

476 overall variability of transition dates within the footprint of the more complex

477 MB wetland (Figures 3b,e,h,k) also highlighted the contrasts in phenology

478 between main vegetation patches and pixels representing water channels

479 and water-vegetation edges (visible as the interfaces between darker water

480 and lighter vegetation in reference images in Figure 3q). Water channel and

481 edge pixels were often characterized by later greening and earlier

482 senescence, which could result from differences in ecosystem elements and

483 vegetation contributing to greenness dynamics and contrasts in physical

484 environment (i.e., open water versus emergent patches).

485   FIGURE 3 ABOUT HERE

486   Median duration of the growing season (Figure 2e) was similar for all site

487 pairs for Landsat estimates (p>0.1), but for RapidEye it was significantly

488 longer at EE and MB compared to WP (by 28 and 27 days, respectively,

489 p<0.001 for each, Table A2, Appendix). After aggregating RapidEye pixels to

490 30m, all site pairs significantly differed in duration metric. Spatial variation in

491 per-pixel duration estimates (Figures 3m-o) suggested that the latter

492 differences resulted from presence of pixels with relatively early onset of

493 greening and relatively late senescence in both younger sites, which could

494 be areas where wetland vegetation was not obstructed by litter early in the

495 season. In contrast, most of the pixels at the oldest WP site (RapidEye

496 example in Figure 3m) corresponded to litter-laden patch interiors with a

497 relatively shorter growing season.

498   Finally, seasonal maximum of EVI significantly differed across the three

499   sites and their individual pairs regardless of the sensor (all p-values <0.05),

500   with the oldest WP site being the greenest, followed by the youngest EE as

501   the second greenest (Figure 2f). These patterns were largely consistent

502   among the two satellite datasets, although RapidEye-based estimates of

503   maximum greenness exhibited longer tails of high values in their

504   distributions compared to Landsat-based ones (Figure 2f). These tails were

505   likely due to the greater chance of capturing smaller clumps of green

506   vegetation cover with 5m pixels compared to 30m ones. For RapidEye

507   aggregated to 30m, maximum greenness significantly differed only between

508   MB and each of the other sites (Table A2, Appendix).

509   Among the satellite inputs, the lowest agreement in metric estimates

510   occurred at the most heterogeneous MB site where all except maximum

511   greenness significantly differed between Landsat and both RapidEye inputs

512   (Table A2, Appendix). For EE and WP, site-median differences between

513   Landsat and 5-m RapidEye metrics were within 1-14 days for SOG and EOG

514   (Figure 2a,b) and within 0-19 days for SOS, EOS and duration (Figure 2c,d,f).

515   In contrast, for MB, input differences were most pronounced for the

516   curvatures near peak growing season, showing a 64 day earlier EOG and 72-

517   day later SOS with Landsat (Figures 2b and 2c, respectively). Differences in

518   median SOG, EOS and DUR at MB were within 17-20 days, comparable to the

519   other two sites. However, most phenological metrics did not significantly

520   differ between Landsat and 30-m aggregated RapidEye except MAXG for WP

521 (Table A2, Appendix). Similarly, only three metrics significantly differed

522 between the original and aggregated RapidEye inputs: SOG and DUR for MB

523 and MAXG for WP (Table A2, Appendix), indicating no substantial effect of

524 RapidEye scaling on phenological estimation in more vegetated sites.

525 **3.2.** **Curve-fitting error and sensitivity to spatial resolution of**

526 **remote sensing data**

527 The median RMSE of the fitted phenological curve models did not

528 significantly differ among three wetlands for Landsat data (p=0.074; Figure

529 A1, Appendix). For RapidEye 5m input, median RMSE did not differ between

530 WP and MB (p>0.1) but was significantly lower at EE than at each of the

531 other two sites (p<0.001). When compared among the satellite inputs,

532 median RMSE was significantly (p<0.001) higher for the original 5m

533 RapidEye estimates compared to Landsat's and for the aggregated RapidEye

534 input for each site (Figure A1, Appendix). The proportion of pixels where

535 transition dates could be estimated using only 3rd derivative extrema of the

536 double-logistic model alone was also lower for RapidEye (52-77%;

537 Supplementary Table S3) compared to 91-100% for Landsat (Supplementary

538 Table S3).

539 Spatial distribution of RMSE within the flux footprints (Figure 4a,c,e,g,i,k)

540 indicated presence of local hotspots of higher fitting error that were also

541 more evident at higher spatial resolution of RapidEye (Figure 4a,e,i).

542 Comparing these local clusters of high RMSE to footprint aerial images

543 (Figure 3p-r) revealed that they were more common at the different types of

544   wetland vegetation edges: near roads and berms, visible in the WP footprint

545   (Figures 4a and 3p) and upper left portion of the MB footprint (Figures 4e and

546   3q), and near the vegetation-water interfaces in the lower left and central

547   parts of the EE footprint (Figures 4i and 3r) and parts of the MB footprint

548   (Figures 4e and 3q). Notably also, areas of higher RMSE often corresponded

549   to areas with higher maximum greenness (Figure 4b,f and j for RapidEye and

550   Figure 4d,h and l for Landsat). In fact, per-pixel RMSE significantly and

551   positively correlated with maximum EVI for nearly all site-sensor

552   combinations with p-value<0.001 and R^2 ranging between 0.32 and 0.66

553   (except for Landsat metrics at MB, p>0.1). In contrast, image regions with

554   lower RMSE (Figures 4b,f and j) often coincided with larger, contiguous

555   patches of wetland vegetation (Figures 3p-r).

556   FIGURE 4 ABOUT HERE

557   **3.3.   Agreement between satellite-based phenological metrics**

558   **and field variables**

559   Both phenocam greenness (GCC) and net carbon exchange (NEE) followed

560   a seasonal trajectory similar to the double-logistic model of satellite-based

561   greenness for vegetation (Figures 5a and 5b, respectively). Both GCC and

562   NEE increased in magnitude during the first half of the year, stayed close to

563   their mid-year asymptotic values for a certain period of time and

564   subsequently reversed in late fall. However, specific shapes and timing of

565   these trajectories varied by site. The oldest site (WP) showed a later onset of

566   GCC greenness (~DOY 98) compared to MB and EE (~DOYs 69 and 51,

567 respectively); however, the end of greening for GCC was similar between two

568 more vegetated sites (DOYs 160 and 167 for EE and WP, respectively) than

569 for MB (DOY 117). The latter site also had lower maximum GCC and lower

570 magnitude of NEE (Figures 5a and 5b), which could be partially attributed to

571 field-detected increases in water salinity during 2015-2016 that may have

572 reduced the productivity and increased plant stress (Chamberlain et al.,

573 2019). The dynamics of NEE indicated an earlier onset for MB around DOY 68

574 compared to 85 and 99 at EE and WP, respectively, followed by an earlier

575 saturation near DOY 125, compared to 137 for EE and even more delayed

576 (192) for WP (Figure 5b). There were also notable site differences during the

577 senescence phase: for GCC, senescence at MB started approximately 102

578 and 140 days earlier than for EE and WP, respectively, though ended at a

579 similar time close to DOY 318. For NEE, the senescence phases were delayed

580 at WP and EE compared to MB by 17 and 19 days, respectively, at the onset

581 of senescence and by 31 and 45 days, respectively, at the end (Figure 5b).

582   Field-measured water-temperature (Figure 5c) showed a strong seasonal

583 change pattern for all sites, but differed in the rates of increase and

584 maximum values (Figure 5c). It was consistently the lowest at WP during the

585 main part of the growing season and similarly delayed in its seasonal

586 increase compared to the other two sites, as could be expected with a taller

587 canopy and presence of a litter layer affecting solar radiation transfer

588 through the canopy and canopy microclimate (Eichelmann et al., 2018;

589 Schile et al., 2013). In contrast, water temperature at MB site with greater

590 surface complexity and smaller vegetated patches was consistently the

591 highest among three wetlands, also showing an earlier seasonal increase

592 (Figure 5c).

593   FIGURE 5 ABOUT HERE

594   Satellite-estimated transition dates for greenness and senescence

595 strongly aligned with the DOYs of the key seasonal transitions (all p<0.001)

596 from the field-measured phenocam greenness and NEE (Figure 6a,b). For

597 models comparing satellite and field GCC transition dates (Figure 5a),

598 regression slopes were not significantly different from 1, nor did they differ

599 between two satellite inputs (both p>0.1, Table 3) despite the degree of

600 mismatch between satellite and phenocam fields of view (Knox et al., 2017).

601 However, for NEE transitions (Figure 5b) the slopes of regression with

602 Landsat and RapidEye's median DOYs were significantly greater than 1

603 (p=0.005 and p=0.009, respectively, Table 3). These patterns indicated the

604 tendency of satellite-based transitions to occur slightly ahead of the

605 corresponding changes in NEE early in the season, and slightly after NEE

606 changes late in the season (Figures 5b and 6b).

607   FIGURE 6 ABOUT HERE

608   TABLE 3 ABOUT HERE

609   Finally, water temperature for the dates of satellite image acquisitions

610 significantly and positively correlated with EVI of the corresponding remote

611 sensing series (Figure 7a,b). The slopes of these relationships did not differ

612 between satellite inputs for any of the sites (p>0.1 for all slope

613 comparisons). However, for both Landsat (Figure 7a) and RapidEye (Figure

614 7b), the slope of EVI-water temperature relationship for WP was significantly

615 steeper than for either MB (p=0.006 and p=0.001 for Landsat and RapidEye,

616 respectively) or EE (p=0.026 and p=0.023 for Landsat and RapidEye,

617 respectively), and did not differ between the latter (p>0.1 for each). In turn,

618 water temperatures corresponding to the dates of estimated SOG and EOG

619 for each satellite series significantly differed (p<0.001) between three sites.

620 These temperatures, however, were all lower for WP, indicating cooler sub-

621 canopy conditions at the onset and the end of greening.

622 FIGURE 7 ABOUT HERE

623 **4. Discussion**

624 **4.1.   Spatial phenological heterogeneity as the indicator of**

625 **restoration outcomes**

626 As ecological restoration efforts continue expanding, the need to

627 understand how their novel outcomes contribute to ecosystem management

628 and conservation becomes ever more urgent (Matthews et al., 2009; Mitsch

629 et al., 2013; Villa and Bernal, 2018). Our analysis of satellite-based

630 phenological metrics across three restored wetlands in California's Delta

631 region corroborates the unique potential of remote sensing to help develop

632 this understanding via repeated cost-effective observations. Our findings

633 also highlight the need for more spatially explicit phenological analyses, for

634 two important reasons. First, the timing of phenological transitions appears

635 to vary substantially among wetland sites with similar geographic setting,

636 vegetation and hydrology but contrasting surface composition and canopy

637 structure. This limits the representativeness of aggregated single-site data

638 and calls for individual, spatially explicit site-level observations which are

639 becoming increasingly feasible (Csillik et al., 2019; Gorelick et al., 2017;

640 Tóth, 2018; Woodcock et al., 2020). Second, we find that the agreement in

641 phenological indicators between satellite inputs of different spatial resolution

642 may also vary among wetlands with different amount and configuration of

643 vegetation cover. Such differences in spatial heterogeneity and phenology

644 may further contribute to the functional contrasts among sites, as suggested

645 by the agreement between satellite-detected EVI transition dates and the

646 timing of in situ measured phenocam greenness and CO_2 exchange (Figure

647 5).

648   From the remote sensor's perspective, two main factors likely contributed

649 to heterogeneity of phenological metrics and challenges in their estimation:

650 wetland surface and plant composition (Vrieling et al., 2018) and the effects

651 of non-photosynthetic plant matter on canopy structure, radiative transfer

652 and microclimate (Dronova and Taddeo, 2016; Farrer and Goldberg, 2009;

653 Rocha et al., 2008; Schile et al., 2013). Despite relatively low diversity of the

654 emergent vascular plants in these wetlands, some non-dominant species

655 could have distinct seasonality and form local patches large enough to

656 influence pixel-level EVI dynamics. For example, portions of the flux

657 footprints near roads and berms included grasses, herbs and sometimes

658 woody species, while some of the open-water areas had floating aquatic

659 vegetation. Both types of such locations (i.e., berms and open water areas;

660 Figure 3p-r) differed in phenological timing from the reed-dominated wetland

661 patches, particularly for the start of greening (Figure 3a-c) and duration

662 (Figure 3m-o).

663   In turn, the 3-D complexity of plant canopies and presence of dead

664 biomass (Dronova and Taddeo, 2016; Rocha et al., 2008; Rocha and

665 Goulden, 2009; Tóth, 2018) likely contributed to the wide range of start and

666 end dates of phenological phases observed even within the larger wetland

667 vegetation patches (Figure 3p-r). Although full understanding of such effects

668 is difficult without spatially explicit information on canopy structure, the

669 following evidence suggests the importance of both horizontal and vertical

670 configuration of vegetation in these patterns. First, as expected,

671 phenological differences among wetland sites closely resonated with

672 differences in their spatial heterogeneity and configuration. Greater greening

673 delays within the oldest and the youngest wetlands, WP and EE (Figure 2a,b),

674 were consistent with their greater plant coverage, patch size, canopy height

675 and canopy-to-litter height proportion (Table 1). In contrast, less contiguous

676 plant coverage together with smaller patch size and greater shape index at

677 MB site (Figure 3r, Table 1) would imply a greater availability of fine-scale

678 edge spaces both at the perimeters and inside the patches, where green

679 vegetation may have greater access to light and become visible to remote

680 sensors earlier compared to larger, contiguous patches of the other two sites

681 (Dronova and Taddeo, 2016).

682   Second, the general agreement in the timing of remotely sensed

683   phenological metrics and site-measured ecosystem processes indicates that

684   phenological variability was not merely an optical artifact of litter obscuring

685   green vegetation from the sensors' view, but rather the outcome of more

686   complex feedbacks among canopy structure, microclimate and plant function

687   (Eichelmann et al., 2018; Hemes et al., 2018). Regardless of the input

688   satellite product, delays in greening were accompanied by delays in seasonal

689   enhancement of CO_2 uptake (Figures 5a,b and 6b) and phenocam greenness,

690   which had been earlier shown to positively correlate with gross primary

691   productivity at MB and WP (Knox et al., 2017). Presence of litter likely

692   mediated these relationships via reduced solar energy to young short

693   vegetation early in the season, and via its broader effects on sub-canopy

694   microclimate and evapotranspiration (Eichelmann et al., 2018; Goulden et

695   al., 2007; Hemes et al., 2018; Rejšková et al., 2012). Although here we

696   cannot directly validate such causal effects due to the lack of spatially

697   explicit data on site-level litter distribution, microclimatic contrasts among

698   three wetlands throughout the study period were consistent with this

699   assertion. In particular, lower water temperatures and their smaller change

700   change in unit greenness (Figure 7a,b) at WP and EE with larger litter-laden

701   vegetation patches could contribute to their stronger greenness delay

702   (Figures 2b and 5c) compared to MB due to potential inhibition of plant and

703   microbial metabolism early in the season.

704   Some of the deviations from a 1:1 agreement between satellite-derived

705   phenological transition dates and those estimated from GCC and NEE series

706   (Figure 6a,b) could also result from the differences in ecosystem sampling

707   between satellite and ground instruments. A recent continental-scale

708   analysis of ecosystem phenology combining Landsat-8 and Sentinel-2

709   imagery (Bolton et al., 2020) has noted stronger disagreements between

710   satellite and phenocam estimates in more heterogeneous systems as well as

711   landscapes with sparser vegetation cover. Applying this evidence to restored

712   deciduous marshes may suggest that, similar to our findings, the agreement

713   among different remote sensing systems should vary both with the degree of

714   surface complexity at a given post-restoration stage, and possibly even with

715   season, due to differences in plant density and canopy structure. These

716   considerations, again, point to the difficulties in generalizing ecosystem

717   cycles among heterogeneous areas (Eichelmann et al., 2018; Goulden et al.,

718   2007; Larsen and Harvey, 2011; Rocha et al., 2008; Schile et al., 2013) and

719   underscore the need for more spatially explicit phenological analyses at the

720   site level, which are not feasible with oblique single-location phenocam

721   images alone (Bolton et al., 2020; Vrieling et al., 2018).

722   **4.2.   The implications of spatial resolution and frequency of**

723   **remote sensing data**

724   Our findings also show that heterogeneity of vegetation in relation to

725   spatial resolution of a remote sensing product is a critical consideration in

726   selecting the input data for phenological analyses. Smaller pixels enable

727 more accurate representation of vegetation patch structure and floristic

728 components as a potential contributor to site-level ecosystem function

729 (Eichelmann et al., 2018; Matthes et al., 2014; McNicol et al., 2017). For

730 example, stronger agreement between RapidEye-based phenological

731 transitions with those of field GCC and NEE (Figure 6) compared to Landsat-

732 based ones could be in part due to better separation of vegetation and water

733 and thus lower likelihood of mixed-cover pixels where water may attenuate

734 vegetation signals (Kearney et al., 2009). As a result, 5m RapidEye pixels

735 retained after masking would be expected to more closely resemble green

736 vegetation as seen by oblique-looking phenocams than 30m Landsat pixels

737 with a greater chance of including background water signals (Dronova and

738 Taddeo 2016). In terms of spatial representation of the footprints, the cost of

739 "losing" a pixel due to noise and inconsistency with the phenological model

740 is obviously higher with coarser-resolution Landsat data, since there are

741 fewer overall pixels and each covers a larger area than a RapidEye's pixel, as

742 was especially evident at the EE site (Supplementary Tables S1 and S3).

743   However, in this study benefits of the high-resolution dataset also came at

744 the cost of somewhat higher model fitting error (Figures A1 (Appendix) and

745 4) and greater diversity of pixel-level trajectories that were not always easy

746 to accommodate by the standard mathematical functions (Supplementary

747 Material section B, Tables S2 and S4). These challenges likely contributed to

748 greater model RMSE with 5m RapidEye inputs (Appendix Figure A1) and to

749 the positive association between RMSE and maximum EVI, also more evident

750   with RapidEye data (Figure 4). These patterns likely reflected the potential of

751   smaller pixels to capture more nuanced and localized seasonal variation in

752   canopy reflectance spectra, affecting seasonal change in EVI. For example,

753   duration and consistency of the phenological phases with higher greenness

754   could be affected by various events and processes such as flowering,

755   disturbance, mortality, or changes in green leaf orientation (e.g., Bolton et

756   al., 2020; Ryu et al., 2010; Sonnentag et al., 2011), making per-pixel EVI

757   trajectories more complex than in a hypothetical model (Figure S2,

758   Supplementary Material).

759   Together, these results highlight an important tradeoff between two

760   aspects of phenological complexity in heterogeneous systems: coarser

761   spatial resolution increases the chance of mixed pixels where phenological

762   trajectory may be complicated by the seasonality of both vegetated and non-

763   vegetated components, while higher resolution may accentuate local

764   phenological and spectral variability even for exclusively vegetated pixels,

765   posing challenges to traditional curve-fitting approaches. Smoothing the

766   satellite-derived EVI time series using moving time windows might also be

767   impractical if there are substantial gaps between image acquisition dates, as

768   this might reduce the accuracy of estimated transitions. Optimizing the

769   choice of remote sensing products thus should weigh the relative importance

770   of spatial accuracy in representing landscape elements (e.g., patches) versus

771   the ratio of temporal noise relative to phenologically relevant signal, both of

772   which may increase with smaller pixel size. These findings also highlight the

773 shortcomings of phenological estimation approaches developed in "upland"

774 terrestrial ecosystems within complex wetland environments and call for

775 more rigorous wetland-specific assessments which have been scarce to date

776 (Mo et al., 2015; Vrieling et al., 2018).

777   Finally, the agreement in the estimated timing of greening and

778 senescence between satellite inputs may also depend on their image

779 acquisition dates (Bolton et al., 2020; Melaas et al., 2016, 2013; Vrieling et

780 al., 2018). For our single-year study this issue was not a major concern, as

781 indicated by relatively high temporal frequency of both datasets (Table A1,

782 Appendix) and the general agreement of the satellite-derived DOYs of

783 greening and senescence with the phenology of field-based phenocam GCC

784 greenness (Figure 6a). However, disparities in phenological metrics between

785 Landsat and both original and aggregated RapidEye inputs for the most

786 heterogeneous MB site (Table A2, Appendix) suggest that phenological

787 analyses might be more sensitive to both sensor-specific spatial resolution

788 and image timing in landscapes with greater complexity and phenological

789 variability (Tóth, 2018; Vrieling et al., 2018). In general, less frequent image

790 series can be more strongly impacted by cloudy conditions leading to

791 prolonged gaps between usable dates. From this perspective, greater

792 frequencies of RapidEye and other new platforms such as Sentinel-2 (Bolton

793 et al., 2020; Claverie et al., 2018; Vrieling et al., 2018) become an obvious

794 advantage over Landsat's 8-16 day intervals between acquisitions even

795 during cloud-free seasons. These considerations also argue for a wider

796   adoption of cost-effective, high temporal frequency phenological validation

797   and gap-filling strategies, such as in situ phenocam systems (Knox et al.,

798   2017; Richardson et al., 2018; Sonnentag et al., 2012) and unmanned

799   vehicles (Tóth, 2018).

800   **4.3.   Future research needs**

801   Collectively, our findings suggest that phenological indicators derived

802   from high- and moderate-resolution passive remote sensing images can be

803   sensitive to spatio-temporal heterogeneity of ecosystems and the potential

804   links between vegetation structure and function targeted by restoration and

805   management (Matthes et al., 2014; McNicol et al., 2017). However, a more

806   in-depth interpretation of such couplings ultimately requires spatially explicit

807   information on 3-D canopy structure which could be characterized using

808   multi-angular spectral reflectance (Hilker et al., 2011) and/or active remote

809   sensing such as lidar (LaRue et al., 2018). At present, lidar data are not

810   systematically acquired in our study area, and high cost of such data

811   collection over large regions generally limits their use in ecosystem

812   monitoring (Taddeo and Dronova, 2019). However, where available, active

813   remote sensing data could facilitate more in-depth studies of the role of

814   canopy structure in phenological variability. Employing such instruments on

815   the unmanned platforms (Bekaert et al., 2019; Sharma et al., 2016; Tóth,

816   2018) could be especially useful in complex systems to develop such an

817   understanding in a cost-effective and spatially explicit way.

818   Future research should also more closely investigate the role of site-

819 specific environmental conditions in phenological contrasts among wetlands

820 with similar vegetation and hydrology. In addition to patch configuration and

821 3-D structure, phenological patterns could be also associated with less well

822 known variation in wetland soil and water column characteristics

823 (Chamberlain et al., 2018; Franz et al., 2016; Minke et al., 2016; Smesrud et

824 al., 2014; Strachan et al., 2015). In particular, the correspondence of greater

825 phenological delay with high maximum greenness (Figure 2) in the sites with

826 higher LAI, canopy height (Table 1) and NEE (Figure 5b) presents an

827 interesting paradox to examine in the future. One of the possible reasons for

828 this association could be the effects of site-specific soil properties, salinity

829 and litter on nutrient status (Chamberlain et al., 2018; Farrer and Goldberg,

830 2009; Tóth, 2018), potentially affecting spectral reflectance via both the

831 amount and chemistry of green foliage (Byrd et al., 2014). For instance,

832 salinization of wetland soils at the MB site during the California drought of

833 2011-2017 reduced its annual gross ecosystem productivity compared to

834 WP, consistent with our observed contrasts in maximum greenness between

835 these sites (Chamberlain et al., 2018). Similarly, a study of phenological

836 variability in freshwater *Phragmites* stands at Lake Balaton, Hungary (Tóth,

837 2018) reported a stronger sensitivity of phenological variation to sediment

838 texture and chemical properties than to air and water temperature.

839 Alternatively, greater litter accumulation could be hypothesized to enhance

840 site quality (Lenssen et al., 1999) and protect the reed seedlings in patch

841 interior from wind and water-related disturbance (Zhang and Wang, 2016),

842 which, again, could be tested more explicitly via experimental studies.

843   Finally, to better understand the implications of the coupled structure-

844 function relationships for restoration outcomes, future studies should

845 investigate the inter-annual variability in wetland phenology using longer-

846 term satellite product archives, such as Landsat's, at least in areas with

847 sufficiently cloud-free time series. Such multi-year assessments could

848 elucidate the potential cycles in spectral contributions of litter (Anderson et

849 al., 2016; Rocha et al., 2008) and the role of these cycles in stability and

850 resilience of the ecosystem functions in response to climatic anomalies

851 (Rocha and Goulden, 2010) or pest outbreaks. Increasing availability of

852 higher-resolution remote sensing datasets capable of characterizing

853 ecosystem heterogeneity and phenological dynamics (e.g., Sentinel-2, Planet

854 Lab products) expands this critical new frontier for more continuous

855 monitoring of ecosystem function (Bolton et al., 2020; Claverie et al., 2018;

856 Matthes et al., 2014; Vrieling et al., 2018). Ultimately, the knowledge derived

857 from comprehensive analyses of richer remote sensing series would also

858 support the upscaling of ecosystem function and associated ecological

859 benefits from local sites to regional scales and similar efforts in other

860 locations.

861 **5. Conclusions**

862   Remote sensing products are increasingly used to characterize

863 phenological transitions of ecosystems and their functional dynamics;

864 however, the sensitivity of such assessments to local vegetation structure

865 and scale of remote sensing data is still not universally understood. This gap

866 is especially evident in spatially heterogeneous systems such as wetlands,

867 where remotely sensed vegetation indicators may depend on local mixing of

868 plants and non-vegetated surfaces and the complexity of canopy structure at

869 a given image resolution, which might further vary in the course of ecological

870 restoration or succession. Understanding the implications of heterogeneity

871 on remotely sensed phenological indicators thus becomes critical for

872 interpreting links between plant structure and function and their sensitivity

873 to management and restoration treatments.

874   Our study of three restored wetlands in California, USA finds that even

875 under similar floristic composition and geographic setting, wetlands may

876 differ in remotely sensed phenological characteristics in accordance with

877 their contrasts in vegetation coverage and structure. Such differences are

878 especially evident in variable length and timing of the greening phase which

879 can be more delayed in areas with larger vegetation patches and greater

880 accumulation of canopy litter. The consistency between site-level remotely

881 sensed phenological metrics and field-based changes in eddy covariance

882 NEE for CO_2 as well as phenocam greenness suggests that such delays may

883 reflect the local effects of litter on canopy radiative transfer, water

884 temperatures and microclimate. A more in-depth investigation of this

885 assertion would benefit from incorporating spatially explicit information on

886 local canopy structure, e.g., from lidar instruments.

887   We also show that both the local spatial variability in phenological metrics

888   and the disagreement in their estimation between two satellite inputs tended

889   to be higher in wetlands with more heterogeneous surface configuration. We

890   also find that the uncertainty in fitting standard phenological models pixel-

891   level greenness series increased with greater spatial resolution, likely due to

892   greater sensitivity of smaller pixels to local-scale variation in phenological

893   patterns within vegetation patches. Such tradeoffs between the benefits of

894   higher spatial resolution and the analysis uncertainty raise an important

895   question on which spatial and temporal scales most effectively represent the

896   links between vegetation structure and function, particularly in complex

897   systems such as restored wetlands. With the increasing interest in multi-

898   sensor data integration efforts and higher-resolution phenological products,

899   this question highlights an important research need to inform future remote

900   sensing uses in monitoring, modeling and up-scaling of ecosystem function

901   and restoration outcomes.

902   **Acknowledgements**

References

915   Anderson, F.E., Bergamaschi, B., Sturtevant, C., Knox, S., Hastings, L.,
916   Windham-Myers, L., Detto, M., Hestir, E.L., Drexler, J., Miller, R.L.,
917   Matthes, J.H., Verfaillie, J., Baldocchi, D., Snyder, R.L., Fujii, R., 2016.
918   Variation of energy and carbon fluxes from a restored temperate
919   freshwater wetland and implications for carbon market verification
920   protocols: Variability in Wetland Fluxes. J. Geophys. Res.
921   Biogeosciences 121, 777–795. https://doi.org/10.1002/2015JG003083
922   Baldocchi, D., Hicks, B., Meyers, T., 1988. Measuring biosphere-atmosphere
923   exchanges of biologically related gases with micrometeorological
924   methods. Ecology 69, 1331–1340. https://doi.org/10.2307/1941631
925   Bauer, L.G.M., Hametner, B., Mayer, C.C., Wassertheurer, S., 2017.
926   Mathematical Wave Fitting Models for the Quantification of the Diurnal
927   Profile and Variability of Pulse Wave Analysis Parameters. SNE Simul.
928   Notes Eur. 27, 153–160. https://doi.org/10.11128/sne.27.tn.10386
929   Bekaert, D.P.S., Jones, C.E., An, K., Huang, M.-H., 2019. Exploiting UAVSAR
930   for a comprehensive analysis of subsidence in the Sacramento Delta.
931   Remote Sens. Environ. 220, 124–134.
932   https://doi.org/10.1016/j.rse.2018.10.023
933   Bolton, D.K., Gray, J.M., Melaas, E.K., Moon, M., Eklundh, L., Friedl, M.A.,
934   2020. Continental-scale land surface phenology from harmonized
935   Landsat 8 and Sentinel-2 imagery. Remote Sensing of Environment
936   240, 111685. https://doi.org/10.1016/j.rse.2020.111685
937   Butterfield, H.S., Malmstroem, C.M., 2009. The effects of phenology on
938   indirect measures of aboveground biomass in annual grasses. Int. J.
939   Remote Sens. 30, 3133–3146.
940   https://doi.org/10.1080/01431160802558774
941   Byrd, K.B., O'Connell, J.L., Di Tommaso, S., Kelly, M., 2014. Evaluation of
942   sensor types and environmental controls on mapping biomass of
943   coastal marsh emergent vegetation. Remote Sens. Environ. 149, 166–
944   180. https://doi.org/10.1016/j.rse.2014.04.003
945   Chamberlain, S.D., Anthony, T.L., Silver, W.L., Eichelmann, E., Hemes, K.S.,
946   Oikawa, P.Y., Sturtevant, C., Szutu, D.J., Verfaillie, J.G., Baldocchi, D.D.,
947   2018. Soil properties and sediment accretion modulate methane fluxes
948   from restored wetlands. Glob. Change Biol. 24, 4107–4121.
949   https://doi.org/10.1111/gcb.14124

950   Chamberlain, S.D., Hemes, K.S., Eichelmann, E., Szutu, D.J., Verfaillie, J.G.,
951   Baldocchi, D.D., 2019. Effect of Drought-Induced Salinization on
952   Wetland Methane Emissions, Gross Ecosystem Productivity, and Their
953   Interactions. Ecosystems. https://doi.org/10.1007/s10021-019-00430-5
954   Chapin, F.S., Woodwell, G.M., Randerson, J.T., Rastetter, E.B., Lovett, G.M.,
955   Baldocchi, D.D., Clark, D.A., Harmon, M.E., Schimel, D.S., Valentini, R.,
956   Wirth, C., Aber, J.D., Cole, J.J., Goulden, M.L., Harden, J.W., Heimann,
957   M., Howarth, R.W., Matson, P.A., McGuire, A.D., Melillo, J.M., Mooney,
958   H.A., Neff, J.C., Houghton, R.A., Pace, M.L., Ryan, M.G., Running, S.W.,
959   Sala, O.E., Schlesinger, W.H., Schulze, E.-D., 2006. Reconciling Carbon-
960   cycle Concepts, Terminology, and Methods. Ecosystems 9, 1041–1050.
961   https://doi.org/10.1007/s10021-005-0105-7
962   Chapple, D., Dronova, I., 2017. Vegetation Development in a Tidal Marsh
963   Restoration Project during a Historic Drought: A Remote Sensing
964   Approach. Front. Mar. Sci. 4. https://doi.org/10.3389/fmars.2017.00243
965   Chu, H., Chen, J., Gottgens, J.F., Ouyang, Z., John, R., Czajkowski, K., Becker,
966   R., 2014. Net ecosystem methane and carbon dioxide exchanges in a
967   Lake Erie coastal marsh and a nearby cropland: CH4 and CO2 fluxes in
968   a freshwater marsh. J. Geophys. Res. Biogeosciences 119, 722–740.
969   https://doi.org/10.1002/2013JG002520
970   Chu, H., Gottgens, J.F., Chen, J., Sun, G., Desai, A.R., Ouyang, Z., Shao, C.,
971   Czajkowski, K., 2015. Climatic variability, hydrologic anomaly, and
972   methane emission can turn productive freshwater marshes into net
973   carbon sources. Glob. Change Biol. 21, 1165–1181.
974   https://doi.org/10.1111/gcb.12760
975   Claverie, M., Ju, J., Masek, J.G., Dungan, J.L., Vermote, E.F., Roger, J.-C.,
976   Skakun, S.V., Justice, C., 2018. The Harmonized Landsat and Sentinel-2
977   surface reflectance data set. Remote Sens. Environ. 219, 145–161.
978   https://doi.org/10.1016/j.rse.2018.09.002
979   Csillik, O., Kumar, P., Mascaro, J., O'Shea, T., Asner, G.P., 2019. Monitoring
980   tropical forest carbon stocks and emissions using Planet satellite data.
981   Sci. Rep. 9, 17831. https://doi.org/10.1038/s41598-019-54386-6
982   Detto, M., Montaldo, N., Albertson, J.D., Mancini, M., Katul, G., 2006. Soil
983   moisture and vegetation controls on evapotranspiration in a
984   heterogeneous Mediterranean ecosystem on Sardinia, Italy:
985   EVAPOTRANSPIRATION IN MEDITERRANEAN ECOSYSTEM. Water
986   Resour. Res. 42. https://doi.org/10.1029/2005WR004693
987   Deverel, S., 2015. Evolution of Arability and Land Use, Sacramento-San
988   Joaquin Delta, California. San Franc. Estuary Watershed Sci. 13, 1–34.
989   Deverel, S., Leighton, D., HydroFocus, Inc., Lucero, C., HydroFocus, Inc.,
990   Ingrum, T., HydroFocus, Inc., 2017. Simulation of Subsidence Mitigation
991   Effects on Island Drain Flow, Seepage, and Organic Carbon Loads on
992   Subsided Islands Sacramento–San Joaquin Delta. San Franc. Estuary
993   Watershed Sci. 15. https://doi.org/10.15447/sfews.2017v15iss4art2
994   Deverel, S.J., Leighton, D.A., Hydrofocus, Inc., 2010. Historic, Recent, and
995   Future Subsidence, Sacramento-San Joaquin Delta, California, USA. San

996   Franc. Estuary Watershed Sci. 8.
997   https://doi.org/10.15447/sfews.2010v8iss2art1
998 Dronova, I., Bergen, K.M., Ellsworth, D.S., 2011. Forest Canopy Properties
999   and Variation in Aboveground Net Primary Production over Upper Great
1000   Lakes Landscapes. Ecosystems 14, 865–879.
1001   https://doi.org/10.1007/s10021-011-9451-9
1002 Dronova, I., Taddeo, S., 2016. Canopy Leaf Area Index in Non-Forested
1003   Marshes of the California Delta. Wetlands 36, 705–716. https://doi.org/
1004   10.1007/s13157-016-0780-5
1005 Eichelmann, E., Hemes, K.S., Knox, S.H., Oikawa, P.Y., Chamberlain, S.D.,
1006   Sturtevant, C., Verfaillie, J., Baldocchi, D.D., 2018. The effect of land
1007   cover type and structure on evapotranspiration from agricultural and
1008   wetland sites in the Sacramento–San Joaquin River Delta, California.
1009   Agric. For. Meteorol. 256–257, 179–195.
1010   https://doi.org/10.1016/j.agrformet.2018.03.007
1011 Farrer, E.C., Goldberg, D.E., 2009. Litter drives ecosystem and plant
1012   community changes in cattail invasion. Ecol. Appl. 19, 398–412. https://
1013   doi.org/10.1890/08-0485.1
1014 Flanagan, N.E., Richardson, C.J., Ho, M., 2015. Connecting differential
1015   responses of native and invasive riparian plants to climate change and
1016   environmental alteration. Ecol. Appl. 25, 753–767.
1017   https://doi.org/10.1890/14-0767.1
1018 Franz, D., Koebsch, F., Larmanou, E., Augustin, J., Sachs, T., 2016. High net
1019   CO$_2$ and CH$_4$ release at
1020   a eutrophic shallow lake on a formerly drained fen. Biogeosciences 13,
1021   3051–3070. https://doi.org/10.5194/bg-13-3051-2016
1022 Friedl, M.A., Gray, J.M., Melaas, E.K., Richardson, A.D., Hufkens, K., Keenan,
1023   T.F., Bailey, A., O'Keefe, J., 2014. A tale of two springs: using recent
1024   climate anomalies to characterize the sensitivity of temperate forest
1025   phenology to climate change. Environ. Res. Lett. 9, 054006.
1026   https://doi.org/10.1088/1748-9326/9/5/054006
1027 Gonsamo, A., Chen, J.M., D'Odorico, P., 2013. Deriving land surface
1028   phenology indicators from CO2 eddy covariance measurements. Ecol.
1029   Indic. 29, 203–207. https://doi.org/10.1016/j.ecolind.2012.12.026
1030 Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R.,
1031   2017. Google Earth Engine: Planetary-scale geospatial analysis for
1032   everyone. Remote Sens. Environ. 202, 18–27.
1033   https://doi.org/10.1016/j.rse.2017.06.031
1034 Goulden, M.L., Litvak, M., Miller, S.D., 2007. Factors that control Typha marsh
1035   evapotranspiration. Aquat. Bot. 86, 97–106.
1036   https://doi.org/10.1016/j.aquabot.2006.09.005
1037 Gu, L., Post, W.M., Baldocchi, D., Andy Black, T., Verma, S.B., Vesala, T.,
1038   Wofsy, S.C., 2003. Phenology of Vegetation Photosynthesis, in:
1039   Schwartz, M.D. (Ed.), Phenology: An Integrative Environmental Science.
1040   Springer Netherlands, Dordrecht, pp. 467–485.
1041   https://doi.org/10.1007/978-94-007-0632-3_29

1042 Head, G.A., Lukoshkova, E.V., Mayorov, D.N., van den Buuse, M., 2004. Non-
1043   symmetrical double-logistic analysis of 24-h blood pressure recordings
1044   in normotensive and hypertensive rats: J. Hypertens. 22, 2075–2085.
1045   https://doi.org/10.1097/00004872-200411000-00008
1046 Hemes, K.S., Chamberlain, S.D., Eichelmann, E., Anthony, T., Valach, A.,
1047   Kasak, K., Szutu, D., Verfaillie, J., Silver, W.L., Baldocchi, D.D., 2019.
1048   Assessing the carbon and climate benefit of restoring degraded
1049   agricultural peat soils to managed wetlands. Agric. For. Meteorol. 268,
1050   202–214. https://doi.org/10.1016/j.agrformet.2019.01.017
1051 Hemes, K.S., Eichelmann, E., Chamberlain, S.D., Knox, S.H., Oikawa, P.Y.,
1052   Sturtevant, C., Verfaillie, J., Szutu, D., Baldocchi, D.D., 2018. A Unique
1053   Combination of Aerodynamic and Surface Properties Contribute to
1054   Surface Cooling in Restored Wetlands of the Sacramento-San Joaquin
1055   Delta, California. J. Geophys. Res. Biogeosciences 123, 2072–2090.
1056   https://doi.org/10.1029/2018JG004494
1057 Hilker, T., Gitelson, A., Coops, N.C., Hall, F.G., Black, T.A., 2011. Tracking
1058   plant physiological properties from multi-angular tower-based remote
1059   sensing. Oecologia 165, 865–876. https://doi.org/10.1007/s00442-010-
1060   1901-0
1061 Hill, D.T., Payton, J.D., 2000. Effect of plant fill ratio on water temperature in
1062   constructed wetlands1This work was supported by the Alabama
1063   Agricultural Experiment Station (AAES) under Regional Research
1064   Project S-275 and by the USDA-NRCS under Cooperative Agreement
1065   No. 68-4104-2-18. It is designated as Journal Series No. 2-985925 by
1066   the AAES.1. Bioresour. Technol. 71, 283–289.
1067   https://doi.org/10.1016/S0960-8524(99)90071-8
1068 Hsieh, C.-I., Katul, G., Chi, T., 2000. An approximate analytical model for
1069   footprint estimation of scalar fluxes in thermally stratified atmospheric
1070   flows. Adv. Water Resour. 23, 765–772. https://doi.org/10.1016/S0309-
1071   1708(99)00042-1
1072 Huesca, M., Merino-de-Miguel, S., Eklundh, L., Litago, J., Cicuendez, V.,
1073   Rodriguez-Rastrero, M., Ustin, S.L., Palacios-Orueta, A., 2015.
1074   Ecosystem functional assessment based on the "optical type" concept
1075   and self-similarity patterns: An application using MODIS-NDVI time
1076   series autocorrelation. Int. J. Appl. Earth Obs. Geoinformation 43, 132–
1077   148. https://doi.org/10.1016/j.jag.2015.04.008
1078 Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., Ferreira, L.G., 2002.
1079   Overview of the radiometric and biophysical performance of the MODIS
1080   vegetation indices. Remote Sens. Environ. 83, 195–213. https://doi.org/
1081   10.1016/S0034-4257(02)00096-2
1082 Hufkens, K., Friedl, M., Sonnentag, O., Braswell, B.H., Milliman, T.,
1083   Richardson, A.D., 2012. Linking near-surface and satellite remote
1084   sensing measurements of deciduous broadleaf forest phenology.
1085   Remote Sens. Environ. 117, 307–321.
1086   https://doi.org/10.1016/j.rse.2011.10.006

Keine, C., 2020. Moods Median Test (https://github.com/ChristianKeine/Moods-Mediantest), GitHub. Retrieved August 16, 2020.

Kearney, M.S., Stutzer, D., Turpie, K., Stevenson, J.C., 2009. The Effects of Tidal Inundation on the Reflectance Characteristics of Coastal Marsh Vegetation. J. Coast. Res. 25, 1177–1186. https://doi.org/10.2112/08-1080.1

Keenan, T.F., Baker, I., Barr, A., Ciais, P., Davis, K., Dietze, M., Dragoni, D., Gough, C.M., Grant, R., Hollinger, D., Hufkens, K., Poulter, B., McCaughey, H., Raczka, B., Ryu, Y., Schaefer, K., Tian, H., Verbeeck, H., Zhao, M., Richardson, A.D., 2012. Terrestrial biosphere model performance for inter-annual variability of land-atmosphere CO2 exchange. Glob. Change Biol. 18, 1971–1987. https://doi.org/10.1111/j.1365-2486.2012.02678.x

Keenan, T.F., Darby, B., Felts, E., Sonnentag, O., Friedl, M.A., Hufkens, K., O'Keefe, J., Klosterman, S., Munger, J.W., Toomey, M., Richardson, A.D., 2014. Tracking forest phenology and seasonal physiology using digital repeat photography: a critical assessment. Ecol. Appl. 24, 1478–1489.

Kennedy, R.E., Yang, Z., Cohen, W.B., 2010. Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr - Temporal segmentation algorithms. Remote Sens. Environ. 114, 2897–2910. https://doi.org/10.1016/j.rse.2010.07.008

Klemas, V., 2013. Using Remote Sensing to Select and Monitor Wetland Restoration Sites: An Overview. J. Coast. Res. 29, 958–970.

Klosterman, S.T., Hufkens, K., Gray, J.M., Melaas, E., Sonnentag, O., Lavine, I., Mitchell, L., Norman, R., Friedl, M.A., Richardson, A.D., 2014. Evaluating remote sensing of deciduous forest phenology at multiple spatial scales using PhenoCam imagery. Biogeosciences 11, 4305–4320. https://doi.org/10.5194/bg-11-4305-2014

Knox, S.H., Dronova, I., Sturtevant, C., Oikawa, P.Y., Matthes, J.H., Verfaillie, J., Baldocchi, D., 2017. Using digital camera and Landsat imagery with eddy covariance data to model gross primary production in restored wetlands. Agric. For. Meteorol. 237, 233–245. https://doi.org/10.1016/j.agrformet.2017.02.020

Knox, S.H., Sturtevant, C., Matthes, J.H., Koteen, L., Verfaillie, J., Baldocchi, D., 2015. Agricultural peatland restoration: effects of land-use change on greenhouse gas (CO2 and CH4) fluxes in the Sacramento-San Joaquin Delta. Glob. Change Biol. 21, 750–765. https://doi.org/10.1111/gcb.12745

Kotchenova, S.Y., Vermote, E.F., 2007. Validation of a vector version of the 6S radiative transfer code for atmospheric correction of satellite data Part II Homogeneous Lambertian and anisotropic surfaces. Appl. Opt. 46, 4455. https://doi.org/10.1364/AO.46.004455

Kruskal, W.H., Wallis, W.A., 1952. Use of Ranks in One-Criterion Variance Analysis. Journal of the American Statistical Association 47, 583–621. https://doi.org/10.1080/01621459.1952.10483441

Larsen, L.G., Harvey, J.W., 2011. Modeling of hydroecological feedbacks predicts distinct classes of landscape pattern, process, and restoration potential in shallow aquatic ecosystems. Geomorphology 126, 279–296. https://doi.org/10.1016/j.geomorph.2010.03.015

LaRue, E.A., Atkins, J.W., Dahlin, K., Fahey, R., Fei, S., Gough, C., Hardiman, B.S., 2018. Linking Landsat to terrestrial LiDAR: Vegetation metrics of forest greenness are correlated with canopy structural complexity. Int. J. Appl. Earth Obs. Geoinformation 73, 420–427. https://doi.org/10.1016/j.jag.2018.07.001

Lenssen, J.P.M., Menting, F.B.J., van der Putten, W.H., Blom, C.W.P.M., 1999. Effects of sediment type and water level on biomass production of wetland plant species. Aquat. Bot. 64, 151–165. https://doi.org/10.1016/S0304-3770(99)00012-1

Ma, S., Osuna, J.L., Verfaillie, J., Baldocchi, D.D., 2017. Photosynthetic responses to temperature across leaf–canopy–ecosystem scales: a 15-year study in a Californian oak-grass savanna. Photosynth. Res. 132, 277–291. https://doi.org/10.1007/s11120-017-0388-5

Machado-Machado, E.A., Neeti, N., Eastman, J.R., Chen, H., 2011. Implications of space-time orientation for Principal Components Analysis of Earth observation image time series. Earth Sci. Inform. 4, 117–124. https://doi.org/10.1007/s12145-011-0082-7

Matthes, J.H., Sturtevant, C., Verfaillie, J., Knox, S., Baldocchi, D., 2014. Parsing the variability in CH4 flux at a spatially heterogeneous wetland: Integrating multiple eddy covariance towers with high-resolution flux footprint analysis. J. Geophys. Res.-Biogeosciences 119, 1322–1339. https://doi.org/10.1002/2014JG002642

Matthews, J.W., Spyreas, G., Endress, A.G., 2009. Trajectories of vegetation-based indicators used to assess wetland restoration progress. Ecol. Appl. 19, 2093–2107. https://doi.org/10.1890/08-1371.1

McNicol, G., Sturtevant, C.S., Knox, S.H., Dronova, I., Baldocchi, D.D., Silver, W.L., 2017. Effects of seasonality, transport pathway, and spatial structure on greenhouse gas fluxes in a restored wetland. Glob. Change Biol. 23, 2768–2782. https://doi.org/10.1111/gcb.13580

Melaas, E.K., Friedl, M.A., Richardson, A.D., 2016. Multiscale modeling of spring phenology across Deciduous Forests in the Eastern United States. Glob. Change Biol. 22, 792–805. https://doi.org/10.1111/gcb.13122

Melaas, E.K., Friedl, M.A., Zhu, Z., 2013. Detecting interannual variation in deciduous broadleaf forest phenology using Landsat TM/ETM plus data. Remote Sens. Environ. 132, 176–185. https://doi.org/10.1016/j.rse.2013.01.011

Melaas, E.K., Sulla-Menashe, D., Friedl, M.A., 2018. Multidecadal Changes and Interannual Variation in Springtime Phenology of North American Temperate and Boreal Deciduous Forests. Geophys. Res. Lett. 45, 2679–2687. https://doi.org/10.1002/2017GL076933

Miller, R.L., Fujii, R., 2010. Plant community, primary productivity, and environmental conditions following wetland re-establishment in the Sacramento-San Joaquin Delta, California. Wetl. Ecol. Manag. 18, 1–16. https://doi.org/10.1007/s11273-009-9143-9

Minke, M., Augustin, J., Burlo, A., Yarmashuk, T., Chuvashova, H., Thiele, A., Freibauer, A., Tikhonov, V., Hoffmann, M., 2016. Water level, vegetation composition, and plant productivity explaingreenhouse gas fluxes in temperate cutover fens after inundation. Biogeosciences 13, 3945–3970. https://doi.org/10.5194/bg-13-3945-2016

Misra, G., Buras, A., Menzel, A., 2016. Effects of Different Methods on the Comparison between Land Surface and Ground Phenology—A Methodological Case Study from South-Western Germany. Remote Sens. 8, 753. https://doi.org/10.3390/rs8090753

Mitsch, W.J., Bernal, B., Nahlik, A.M., Mander, U., Zhang, L., Anderson, C.J., Jorgensen, S.E., Brix, H., 2013. Wetlands, carbon, and climate change. Landsc. Ecol. 28, 583–597. https://doi.org/10.1007/s10980-012-9758-8

Mo, Y., Momen, B., Kearney, M.S., 2015. Quantifying moderate resolution remote sensing phenology of Louisiana coastal marshes. Ecol. Model. 312, 191–199. https://doi.org/10.1016/j.ecolmodel.2015.05.022

Mood. A.M., 1950. Introduction to the Theory of Statistics. New York: McGraw-Hill.

O'Connell, J.L., Alber, M., Pennings, S.C., 2019. Microspatial Differences in Soil Temperature Cause Phenology Change on Par with Long-Term Climate Warming in Salt Marshes. Ecosystems. https://doi.org/10.1007/s10021-019-00418-1

Oikawa, P.Y., Jenerette, G.D., Knox, S.H., Sturtevant, C., Verfaillie, J., Dronova, I., Poindexter, C.M., Eichelmann, E., Baldocchi, D.D., 2017. Evaluation of a hierarchy of models reveals importance of substrate limitation for predicting carbon dioxide and methane exchange in restored wetlands: Model for Wetland Greenhouse Gas Fluxes. J. Geophys. Res. Biogeosciences 122, 145–167. https://doi.org/10.1002/2016JG003438

Rejšková, A., Čížková, H., Brom, J., Pokorný, J., 2012. Transpiration, evapotranspiration and energy fluxes in a temperate wetland dominated by Phalaris arundinacea under hot summer conditions. Ecohydrology 5, 19–27. https://doi.org/10.1002/eco.184

Richardson, A.D., Anderson, R.S., Arain, M.A., Barr, A.G., Bohrer, G., Chen, G., Chen, J.M., Ciais, P., Davis, K.J., Desai, A.R., Dietze, M.C., Dragoni, D., Garrity, S.R., Gough, C.M., Grant, R., Hollinger, D.Y., Margolis, H.A., McCaughey, H., Migliavacca, M., Monson, R.K., Munger, J.W., Poulter, B., Raczka, B.M., Ricciuto, D.M., Sahoo, A.K., Schaefer, K., Tian, H., Vargas, R., Verbeeck, H., Xiao, J., Xue, Y., 2012. Terrestrial biosphere models need better representation of vegetation phenology: results from the North American Carbon Program Site Synthesis. Glob. Change Biol. 18, 566–584. https://doi.org/10.1111/j.1365-2486.2011.02562.x

Richardson, A.D., Hufkens, K., Milliman, T., Aubrecht, D.M., Chen, M., Gray, J.M., Johnston, M.R., Keenan, T.F., Klosterman, S.T., Kosmala, M., Melaas, E.K., Friedl, M.A., Frolking, S., 2018. Tracking vegetation phenology across diverse North American biomes using PhenoCam imagery. Sci. Data 5, 180028. https://doi.org/10.1038/sdata.2018.28

Rocha, A.V., Goulden, M.L., 2010. Drought legacies influence the long-term carbon balance of a freshwater marsh. J. Geophys. Res. 115, G00H02. https://doi.org/10.1029/2009JG001215

Rocha, A.V., Goulden, M.L., 2009. Why is marsh productivity so high? New insights from eddy covariance and biomass measurements in a Typha marsh. Agric. For. Meteorol. 149, 159–168. https://doi.org/10.1016/j.agrformet.2008.07.010

Rocha, A.V., Potts, D.L., Goulden, M.L., 2008. Standing litter as a driver of interannual CO(2) exchange variability in a freshwater marsh. J. Geophys. Res.-Biogeosciences 113, G04020. https://doi.org/10.1029/2008JG000713

Ryu, Y., Baldocchi, D.D., Verfaillie, J., Ma, S., Falk, M., Ruiz-Mercado, I., Hehn, T., Sonnentag, O., 2010. Testing the performance of a novel spectral reflectance sensor, built with light emitting diodes (LEDs), to monitor ecosystem metabolism, structure and function. Agric. For. Meteorol. 150, 1597–1606. https://doi.org/10.1016/j.agrformet.2010.08.009

Schaffer-Smith, D., Swenson, J.J., Reiter, M.E., Isola, J.E., 2018. Quantifying shorebird habitat in managed wetlands by modeling shallow water depth dynamics. Ecol. Appl. 28, 1534–1545. https://doi.org/10.1002/eap.1732

Schile, L.M., Byrd, K.B., Windham-Myers, L., Kelly, M., 2013. Accounting for non-photosynthetic vegetation in remote-sensing-based estimates of carbon flux in wetlands. Remote Sens. Lett. 4, 542–551. https://doi.org/10.1080/2150704X.2013.766372

Sharma, P., Jones, C.E., Dudas, J., Bawden, G.W., Deverel, S., 2016. Monitoring of subsidence with UAVSAR on Sherman Island in California's Sacramento–San Joaquin Delta. Remote Sens. Environ. 181, 218–236. https://doi.org/10.1016/j.rse.2016.04.012

Smesrud, J.K., Boyd, M.S., Cuenca, R.H., Eisner, S.L., 2014. A mechanistic energy balance model for predicting water temperature in surface flow wetlands. Ecol. Eng. 67, 11–24. https://doi.org/10.1016/j.ecoleng.2014.03.006

Smith, M.L., Ollinger, S.V., Martin, M.E., Aber, J.D., Hallett, R.A., Goodale, C.L., 2002. Direct estimation of aboveground forest productivity through hyperspectral remote sensing of canopy nitrogen. Ecol. Appl. 12, 1286–1302.

Sonnentag, O., Detto, M., Vargas, R., Ryu, Y., Runkle, B.R.K., Kelly, M., Baldocchi, D.D., 2011. Tracking the structural and functional development of a perennial pepperweed (Lepidium latifolium L.) infestation using a multi-year archive of webcam imagery and eddy

1268   covariance measurements. Agric. For. Meteorol. 151, 916–926. https://
1269   doi.org/10.1016/j.agrformet.2011.02.011
1270 Sonnentag, O., Hufkens, K., Teshera-Sterne, C., Young, A.M., Friedl, M.,
1271   Braswell, B.H., Milliman, T., O'Keefe, J., Richardson, A.D., 2012. Digital
1272   repeat photography for phenological research in forest ecosystems.
1273   Agric. For. Meteorol. 152, 159–177.
1274   https://doi.org/10.1016/j.agrformet.2011.09.009
1275 Stefanik, K.C., Mitsch, W.J., 2012. Structural and functional vegetation
1276   development in created and restored wetland mitigation banks of
1277   different ages. Ecol. Eng. 39, 104–112.
1278   https://doi.org/10.1016/j.ecoleng.2011.11.016
1279 Strachan, I.B., Nugent, K.A., Crombie, S., Bonneville, M.-C., 2015. Carbon
1280   dioxide and methane exchange at a cool-temperate freshwater marsh.
1281   Environ. Res. Lett. 10, 065006. https://doi.org/10.1088/1748-
1282   9326/10/6/065006
1283 Suding, K.N., 2011. Toward an Era of Restoration in Ecology: Successes,
1284   Failures, and Opportunities Ahead, in: Futuyma, D.J., Shaffer, H.B.,
1285   Simberloff, D. (Eds.), Annual Review of Ecology, Evolution, and
1286   Systematics, Vol 42. pp. 465–487.
1287 Sulla-Menashe, D., Kennedy, R.E., Yang, Z., Braaten, J., Krankina, O.N., Friedl,
1288   M.A., 2014. Detecting forest disturbance in the Pacific Northwest from
1289   MODIS time series using temporal segmentation. Remote Sens.
1290   Environ. 151, 114–123. https://doi.org/10.1016/j.rse.2013.07.042
1291 Taddeo, S., Dronova, I., 2019. Geospatial Tools for the Large-Scale
1292   Monitoring of Wetlands in the San Francisco Estuary: Opportunities and
1293   Challenges. San Franc. Estuary Watershed Sci. 17.
1294   https://doi.org/10.15447/sfews.2019v17iss2art2
1295 Taddeo, S., Dronova, I., 2018. Indicators of vegetation development in
1296   restored wetlands. Ecol. Indic. 94, 454–467.
1297   https://doi.org/10.1016/j.ecolind.2018.07.010
1298 Tan, B., Morisette, J.T., Wolfe, R.E., Gao, F., Ederer, G.A., Nightingale, J.,
1299   Pedelty, J.A., 2011. An Enhanced TIMESAT Algorithm for Estimating
1300   Vegetation Phenology Metrics From MODIS Data. IEEE J. Sel. Top. Appl.
1301   Earth Obs. Remote Sens. 4, 361–371.
1302   https://doi.org/10.1109/JSTARS.2010.2075916
1303 Toomey, M., Friedl, M.A., Frolking, S., Hufkens, K., Klosterman, S., Sonnentag,
1304   O., Baldocchi, D.D., Bernacchi, C.J., Biraud, S.C., Bohrer, G., Brzostek,
1305   E., Burns, S.P., Coursolle, C., Hollinger, D.Y., Margolis, H.A.,
1306   McCaughey, H., Monson, R.K., Munger, J.W., Pallardy, S., Phillips, R.P.,
1307   Torn, M.S., Wharton, S., Zeri, M., Richardson, A.D., 2015. Greenness
1308   indices from digital cameras predict the timing and seasonal dynamics
1309   of canopy-scale photosynthesis. Ecol. Appl. 25, 99–115. https://doi.org/
1310   10.1890/14-0005.1
1311 Tóth, V.R., 2018. Monitoring Spatial Variability and Temporal Dynamics of
1312   Phragmites Using Unmanned Aerial Vehicles. Frontiers in Plant Science
1313   9. https://doi.org/10.3389/fpls.2018.00728

1314   Villa, J.A., Bernal, B., 2018. Carbon sequestration in wetlands, from science to
1315   practice: An overview of the biogeochemical process, measurement
1316   methods, and policy framework. Ecol. Eng. 114, 115–128.
1317   https://doi.org/10.1016/j.ecoleng.2017.06.037
1318   Vogelmann, J.E., Gallant, A.L., Shi, H., Zhu, Z., 2016. Perspectives on
1319   monitoring gradual change across the continuity of Landsat sensors
1320   using time-series data. Remote Sens. Environ. 185, 258–270.
1321   https://doi.org/10.1016/j.rse.2016.02.06
1322   Vrieling, A., Meroni, M., Darvishzadeh, R., Skidmore, A.K., Wang, T., Zurita-
1323   Milla, R., Oosterbeek, K., O'Connor, B., Paganini, M., 2018. Vegetation
1324   phenology from Sentinel-2 and field cameras for a Dutch barrier island.
1325   Remote Sensing of Environment 215, 517–529. https://doi.org/10.1016/
1326   j.rse.2018.03.014
1327   Woebbecke, D., Meyer, G., Vonbargen, K., Mortensen, D., 1995. Color
1328   indexes for weed identification under various soil, residue, and lighting
1329   conditions. Trans. Asae 38, 259–269.
1330   Wolf, S., Keenan, T.F., Fisher, J.B., Baldocchi, D.D., Desai, A.R., Richardson,
1331   A.D., Scott, R.L., Law, B.E., Litvak, M.E., Brunsell, N.A., Peters, W., van
1332   der Laan-Luijkx, I.T., 2016. Warm spring reduced carbon cycle impact
1333   of the 2012 US summer drought. Proc. Natl. Acad. Sci. 113, 5880–5885.
1334   https://doi.org/10.1073/pnas.1519620113
1335   Woodcock, C.E., Loveland, T.R., Herold, M., Bauer, M.E., 2020. Transitioning
1336   from change detection to monitoring with remote sensing: A paradigm
1337   shift. Remote Sens. Environ. 238, 111558.
1338   https://doi.org/10.1016/j.rse.2019.111558
1339   Zhang, G., Xiao, X., Dong, J., Kou, W., Jin, C., Qin, Y., Zhou, Y., Wang, J.,
1340   Menarguez, M.A., Biradar, C., 2015. Mapping paddy rice planting areas
1341   through time series analysis of MODIS land surface temperature and
1342   vegetation index data. ISPRS J. Photogramm. Remote Sens. 106, 157–
1343   171. https://doi.org/10.1016/j.isprsjprs.2015.05.011
1344   Zhang, L., Wang, B., 2016. Intraspecific interactions shift from competitive to
1345   facilitative across a low to high disturbance gradient in a salt marsh.
1346   Plant Ecol. 217, 959–967. https://doi.org/10.1007/s11258-016-0621-x
1347   Zhang, L., Weng, Q., 2016. Annual dynamics of impervious surface in the
1348   Pearl River Delta, China, from 1988 to 2013, using time series Landsat
1349   imagery. ISPRS J. Photogramm. Remote Sens. 113, 86–96.
1350   https://doi.org/10.1016/j.isprsjprs.2016.01.003
1351   Zhao, Q., Bai, J., Huang, L., Gu, B., Lu, Q., Gao, Z., 2016. A review of
1352   methodologies and success indicators for coastal wetland restoration.
1353   Ecol. Indic. 60, 442–452. https://doi.org/10.1016/j.ecolind.2015.07.003
1354   Zhu, Z., 2017. Change detection using landsat time series: A review of
1355   frequencies, preprocessing, algorithms, and applications. ISPRS J.
1356   Photogramm. Remote Sens. 130, 370–384.
1357   https://doi.org/10.1016/j.isprsjprs.2017.06.013
1358

1381   maximum greenness (right panels) at three wetland sites: a-b) West Pond,

1382   RapidEye; c-d) West Pond, Landsat; e-f) Mayberry Farms, RapidEye; g-h)

1383   Mayberry Farms, Landsat; i-j) East End, RapidEye, and k-l) East End, Landsat.

1384   **Figure 5.** Seasonal trajectories of field-measured a) eddy covariance net

1385   ecosystem exchange (NEE, $gC\text{-}CO_2 m^{-2} d^{-1}$; negative sign indicates net

1386   ecosystem uptake), b) phenocam green chromatic coordinate (GCC) spectral

1387   index, and c) water temperature measured at 10cm for Mayberry Farms (MB)

1388   and East End (EE) sites and at 8cm for West Pond (WP). All variables are

1389   plotted as 5-day moving window averages.

1390   **Figure 6.** The agreement between site-median satellite-based days of year

1391   (DOYs) representing start and end transitions of the Enhanced Vegetation

1392   Index (EVI) trajectories from 30m Landsat imagery and 5m RapidEye

1393   imagery and the corresponding transitions in the trajectories of phenocam-

1394   based green chromatic coordinate (GCC) spectral index (a) and net

1395   ecosystem exchange (NEE) for CO_2 measured by eddy covariance stations

1396   (b). Equations represent the fitted linear regression models where y denotes

1397   site median transition dates estimated from satellite-based EVI series, and x

1398   denotes the transition dates from the time series of a respective field-

1399   measured metric.

1400   **Figure 7.** The associations between satellite EVI and average daily water

1401   temperature on the corresponding image dates for a) Landsat at 30m spatial

1402   resolution, and b) RapidEye at 5m spatial resolution. Equations represent the

1403   fitted linear regression models where y denotes EVI and x denotes water

1404   temperature of a given site.

1405

1406 **Figures**

1407

1408 Figure 1

1409

1410   Figure 2

1411

1412   Figure 3

West Pond (since 1997)   Mayberry Farms (since 2010)   East End (since 2014)

1413
1414

1415   Figure 4

Model RMSE   **Maximum EVI**

West Pond (since 1997)

RMSE: <0.02, 0.02 - 0.03, 0.03 - 0.04, 0.04 - 0.05, >0.05

Maximum EVI: <0.2, 0.2 - 0.3, 0.3 - 0.4, 0.4 - 0.5, >0.5

Mayberry Farms (since 2010)
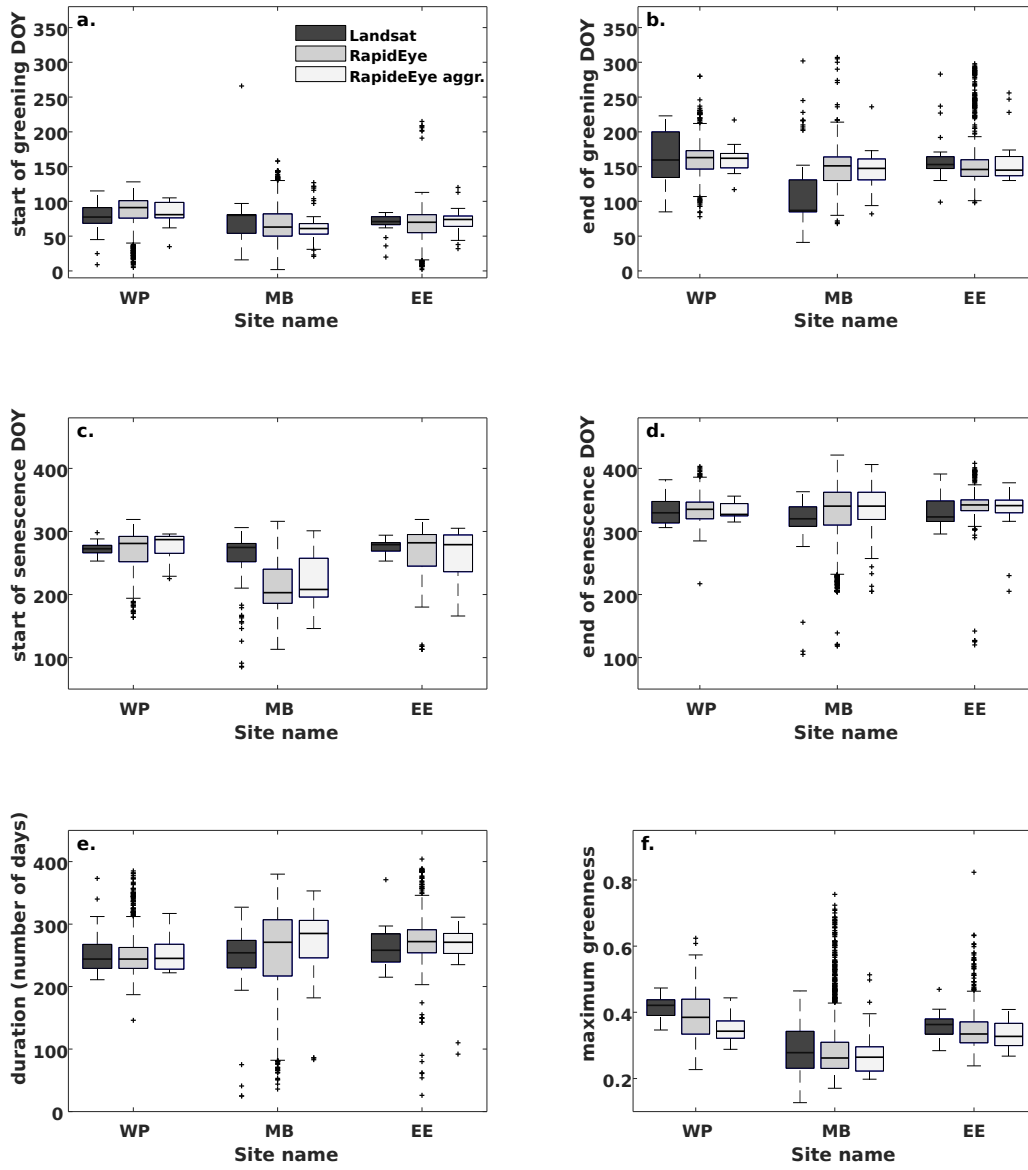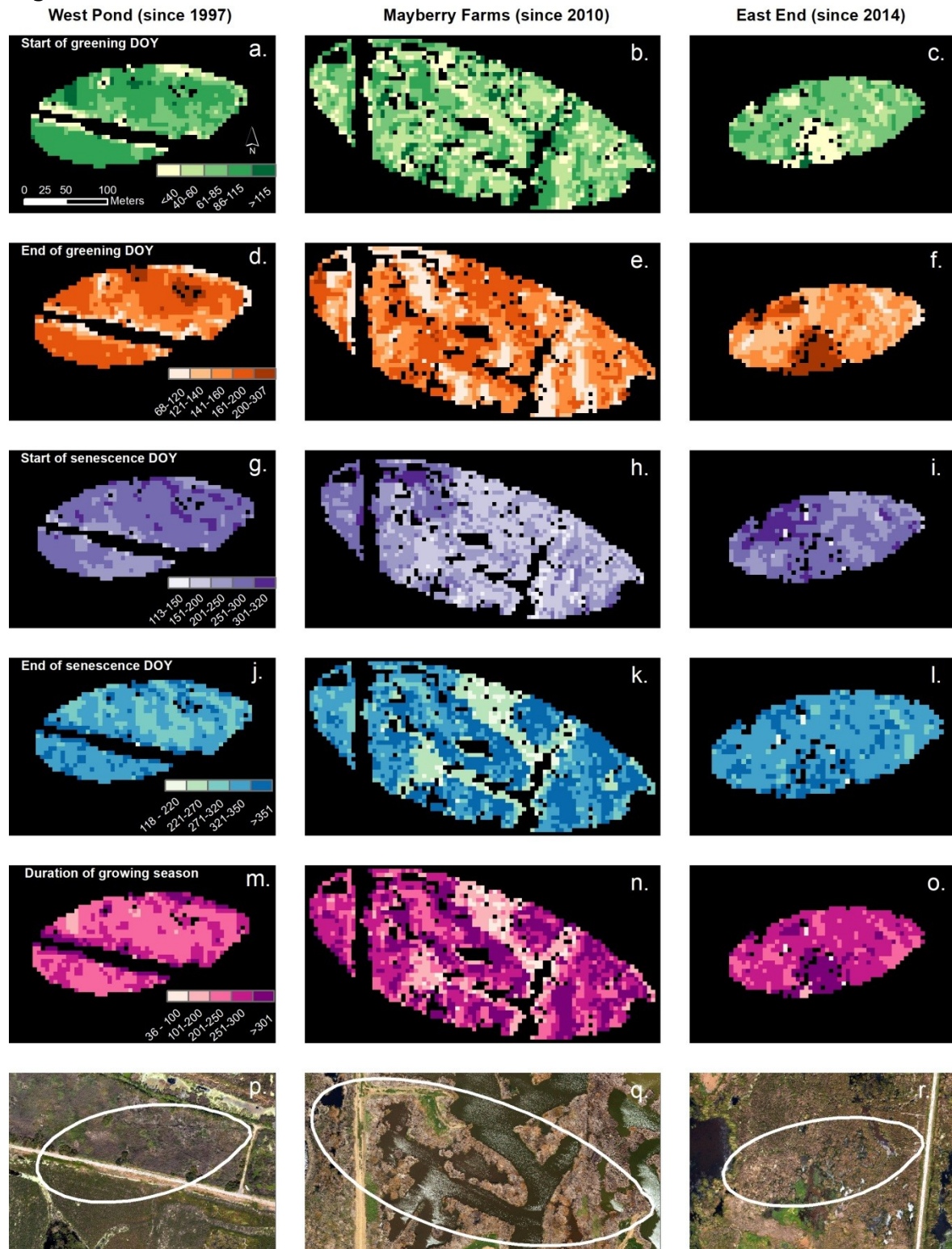
East End (since 2014)
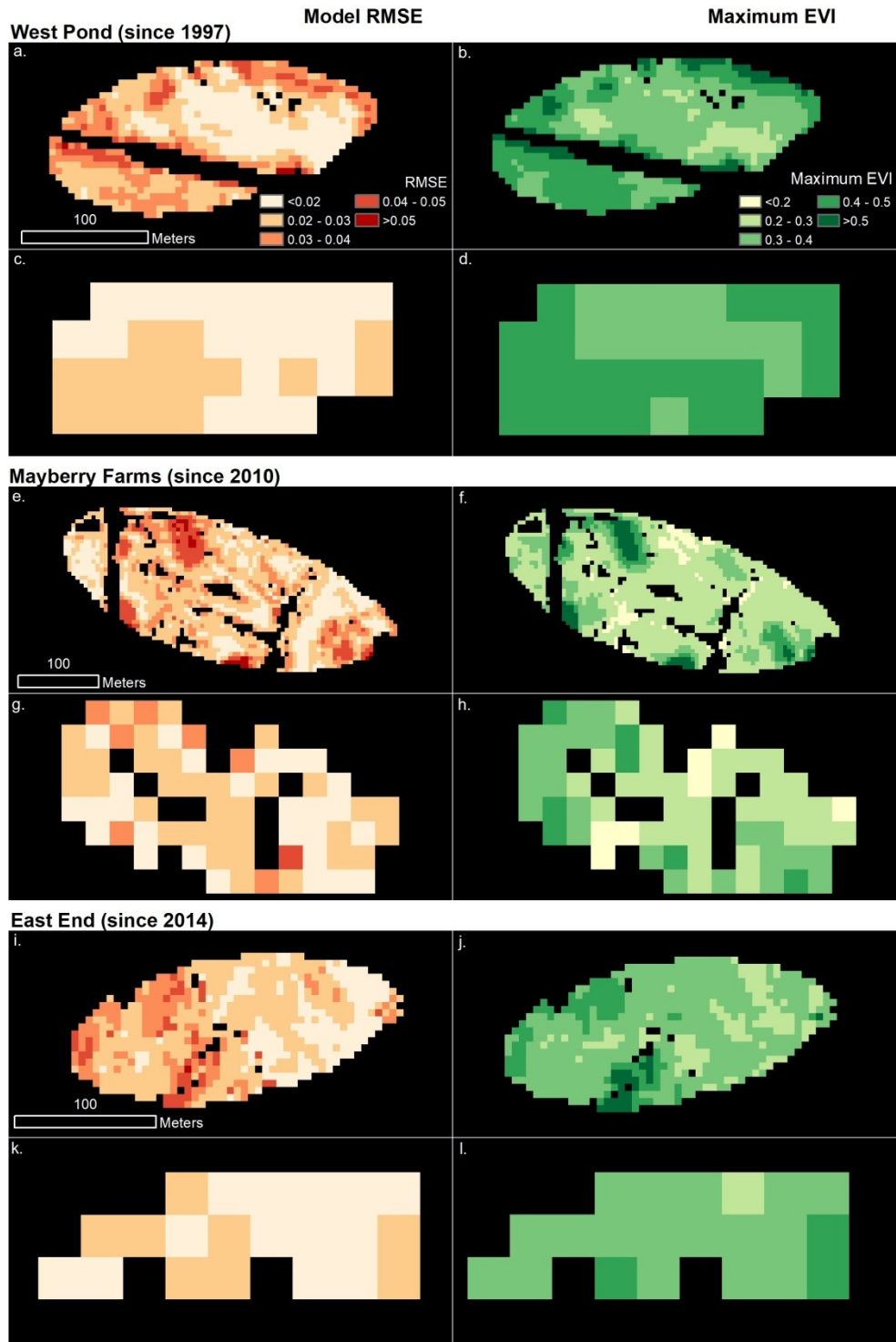
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1418 Figure 5

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1422   Figure 6

a.
Landsat R^2=0.83
y=19.2+0.97x

RapidEye R^2=0.95
y=16.04+0.95x

- ● West Pond, Landsat
- ⊙ West Pond, RapidEye
- ▲ Mayberry Farms, Landsat
- △ Mayberry Farms, RapidEye
- ■ East End, Landsat
- □ East End, RapidEye
- ⋯ 1:1 reference line

Site-median schedule DOY for satellite-based EVI

Schedule DOY for phenocam-based GCC spectral index

b.
Landsat R^2=0.95
y=-28.10+1.19x

RapidEye R^2=0.94
y=-13.95+1.09x

Schedule DOY for field-measured Net Ecosystem Exchange

1423
1424

1425   Figure 7

1426
1427

1428 **Tables**

1429 **Table 1**. Landscape metrics of vegetation distribution and field

1430 measurements of canopy structure, by wetland site. All metrics except patch

1431 density and percentage values show means of the plot or site measurements

1432 with standard deviation in parentheses.

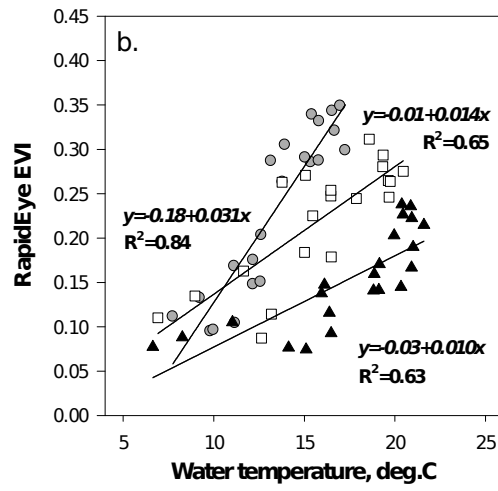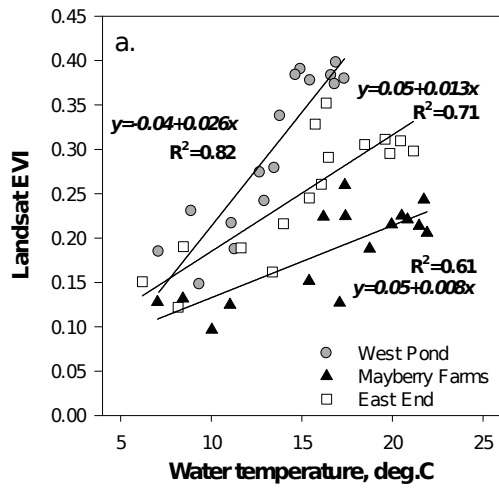| Metric type	Metric	Site		
		West Pond (WP), est. 1997	**Mayberry Farms (MB), est. 2010**	**East End (EE), est. 2014**
Spatial extent	Whole wetland area, km^2	0.032	1.242	2.995
	Flux footprint area (90th percentile), km^2	0.022	0.054	0.018
Landscape metrics based on aerial images*	Percent vegetated cover (whole site)	99.7%	64.4%	82.2%
	Percent vegetated (flux tower footprint; 90th percentile)	74.0%	55.7%	83.2%
	Patch density (number of patches/ 100 ha)	19.29	81.56	42.70
	Mean Patch Area of vegetated patches, km^2	0.05 (0)	0.01 (0.09)	0.02 (0.28)
	Mean Shape Index of vegetated patches	1.42 (0)	1.58 (1.55)	1.48 (1.50)
Field measurements (summer 2016) ‡	Green one-sided leaf area index, $m^2 m^{-2}$	3.1 (1.7)	1.9 (2.3)	3.8 (2.2)
	Canopy height, cm	335.5 (29.1)	223.7 (27.6)	282.4 (29.1)
	Litter height, cm	211.4 (39. 4)	211.6 (41.5)	161.8 (16.4)
	Litter volume (m^3 per 0.09m^2 plot)	0.134 (0.05)	0.100 (0.04)	0.022 (0.02)
	Percent dead vegetation in plot cover	58.9%	51.7%	54.2%
	Water depth, cm	19.6 (11.3)	37.9 (14.8)	66.3 (17.6)

1433   * Landscape metrics are based on vegetation patches delineated from 1-m spatial resolution

1434   aerial imagery publicly available from USDA's National Agriculture Inventory Program (NAIP)

1435   for the summer 2016.

1436   ‡Field sampling was conducted between August 2 and 8, 2016 within 0.3m×0.3m sampling

1437   plots (24 plots in West Pond, 36 plots in Mayberry Farms, and 20 plots in East End). Litter

1438   height corresponds to the height of standing litter, approximated to the nearest 0.05m.

1439   Litter volume is based on visually estimated percent litter cover class (0-25%, 25-50%, 50-

1440   75%, >75%) summed across the 0.2-m increments along the vertical dimension of the

1441   canopy above each 0.3m×0.3m plot. Percent dead vegetation is a visual estimation of the

1442   percentage of the sampling plot covered by dead vegetation versus green plants or other

1443   surfaces (open water, bare soil).

1444 **Table 2.** Key phenological metrics and ecosystem variables used in this
1445 study.

Abbreviation	Explanation	Definition
Wetland site names		
WP	West Pond	The oldest study site (restored in 1997)
MB	Mayberry Farms	The intermediate-aged site (restored in 2010)
EE	East End	The youngest study site (restored in 2014)
Spectral vegetation indices		
EVI	Enhanced Vegetation Index	Huete et al. 2002
GCC	Green Chromatic Coordinate Index	Woebbecke et al. 1995
Phenological metrics		
DOY	Day of year	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.
SOG	Start of greening	DOY representing the first major curvature point in the phenological curve indicating the onset of spring increase.
EOG	End of greening	DOY representing the second major curvature point in the phenological curve indicating the slowdown in spring EVI increase approaching maximum greenness.
SOS	Start of senescence	DOY representing the third major curvature point in the phenological curve indicating the onset of EVI decline (senescence).
EOS	End of senescence	DOY representing the last major curvature point in the phenological curve indicating the end of the fall spectral index decline.
DUR	Duration of the growing season	The difference between DOYs corresponding to EOS and SOG.
MAXG	Maximum greenness	Maximum value of the seasonal EVI.
RMSE	Root mean square error	Standard deviation of residuals in the phenological curve model

		indicating the deviation of satellite-measured greenness values from the modeled trajectory.
Ecosystem variables		
NEE	Net ecosystem exchange (for CO_2)	Net exchange of CO_2 carbon between the wetland ecosystem and the atmosphere based on eddy covariance CO_2 flux data.
LAI	Leaf area index	One-sided green canopy leaf area per unit ground area.

1446

1447 **Table 3.** Slope and intercept comparisons between regressions with DOYs

1448 for phenological transition dates derived from satellite inputs or seasonal

1449 trajectories of field-measured Green Chromatic Coordinate greenness (GCC)

1450 and net ecosystem exchange for CO_2 (NEE).

1451

Response variable	Predictor variable 1	Compared to model	P-value, slope comparison	P-value, intercept comparison
Transition DOY for GCC	Site-median DOYs of key stages (Landsat)	Slope=1, intercept=0	0.226	0.549
Transition DOY for GCC	Site-median DOYs of key stages (RapidEye)	Slope=1, intercept=0	0.186	0.926
Transition DOY for NEE	Site-median DOYs of key stages (Landsat)	Slope=1, intercept=0	0.004	0.031
Transition DOY for NEE	Site-median DOYs of key stages (RapidEye)	Slope=1, intercept=0	0.005	0.053
Transition DOY for NEE	Site-median DOYs of key stages (Landsat)	With site-median DOYs of key stages from RapidEye	0.983	0.883
Transition DOY for GCC	Site-median DOYs of key stages (Landsat)	With site-median DOYs of key stages from RapidEye	0.663	0.635

1452
1453

1454 **Appendix**

1455

1456 Figure A1. Root mean square error (RMSE) of per-pixel phenological model

1457 fitting for three different satellite data inputs (Landsat at 30m spatial

1458 resolution, RapidEye at the original 5m spatial resolution and RapidEye

1459 aggregated to 30m spatial resolution) averaged for the CO_2 flux footprints of

1460 wetland sites West Pond (WP), Mayberry (MB) and East End (EE). Upper error

1461 bars show standard deviations of RMSE for each respective group.
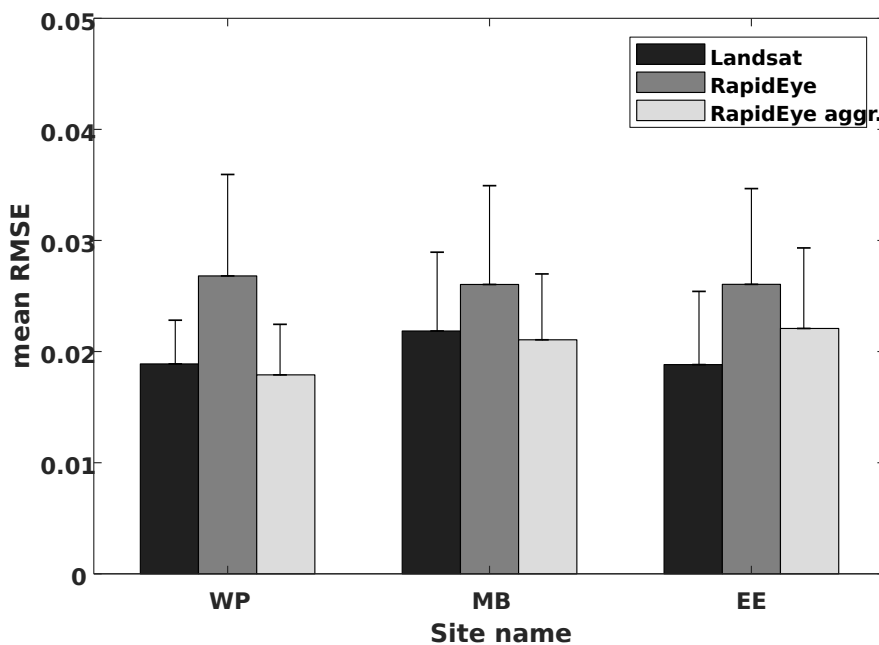
1462

1463 Table A1. Satellite products and dates used in phenological metric estimation

1464 (DOY stands for consecutive day of year starting from January 1, 2016).

1465

Month	Year	Date: Landsat-8 Surface Reflectance Tier 1 (DOY)	Date: RapidEye Geocorrected At-sensor Radiance (DOY)
February	2016	4 (35)	15 (46) 22(53)
March	2016	23 (83)	17 (77)

April	2016	24 (115)	17 (108) 20 (111)
May	2016	10 (131) 26 (147)	1 (122) 26 (147)
June	2016	11 (163) 27 (179)	1 (153) 20 (172) 22 (174)
July	2016	13 (195) 29 (211)	16 (198) 23 (205)
August	2016	14 (227)	2 (215)
September	2016	23 (267)	7 (251) 24 (268)
October	2016	1 (275)	18 (292) 20 (294)
November	2016	2 (307) 18 (323)	8 (313) 18 (323)
December	2016	4 (339)	3 (338) 26 (361)
January	2017	5 (371 since Jan 1, 2016)	

1466

1467 Table A2. Mood's test results for pairwise comparisons of phenological
1468 metrics between site and sensor pairs. Values represent test chi-square
1469 statistic estimated using Matlab mediantest function by Keine (2020).

	Site pair comparisons for a given satellite input								
Metric	Landsat (30m)			RapidEye (5m)			Aggregated RapidEye (30m)		
	WP&MB	WP&EE	MB&EE	WP&MB	WP&EE	MB&EE	WP&MB	WP&EE	MB&EE
SOG	1.71	2.67	**13.12***	**438.15***	**281.69***	**37.82***	**15.08***	**3.94***	**11.03***
EOG	**24.38***	2.67	**23.63***	**112.72***	**167.99***	**23.39***	2.06	2.95	0.23
SOS	1.02	2.30	1.16	**856.81***	0.23	**738.61***	**22.39***	1.17	**14.93***
EOS	2.57	0.03	0.20	**12.26***	**37.97***	**4.26***	1.72	1.43	0.23
DUR	1.34	2.30	0.10	**145.18***	**249.35***	0.57	**5.82***	**4.36***	**4.03***
MAXG	**50.00***	**17.53***	**18.52***	**882.24***	**169.47***	**695.58***	**21.74***	1.17	**23.89***
Metric	*Satellite input comparisons for a given site*								
	Landsat (30m) & original RapidEye data (5m)			Landsat & aggregated RapidEye data (30m)			Original (5m) & aggregated (30m) RapidEye data		

	WP	MB	EE	WP	MB	EE	WP	MB	EE
SOG	**7.85***	**13.32***	0.09	2.58	**23.94***	1.97	0.37	**4.57***	2.88
EOG	0.39	**23.59***	**6.13***	0.16	**29.48***	3.67	0.04	0.39	0.08
SOS	**15.62***	**25.42***	**5.44***	2.58	**29.52***	0.73	0.73	2.58	0.59
EOS	0.92	**16.66***	1.94	0.35	**8.40***	3.81	1.30	0.01	0.47
DUR	0.06	**8.07***	0.34	0.16	**8.40***	0.57	0.10	**4.80***	0.00
MAXG	**11.38***	1.52	**5.96***	**15.06***	0.20	2.67	**7.27***	0.02	0.69

1470 * p-value <0.05

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1472

1473

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.

Landsat

RapidEye

1492
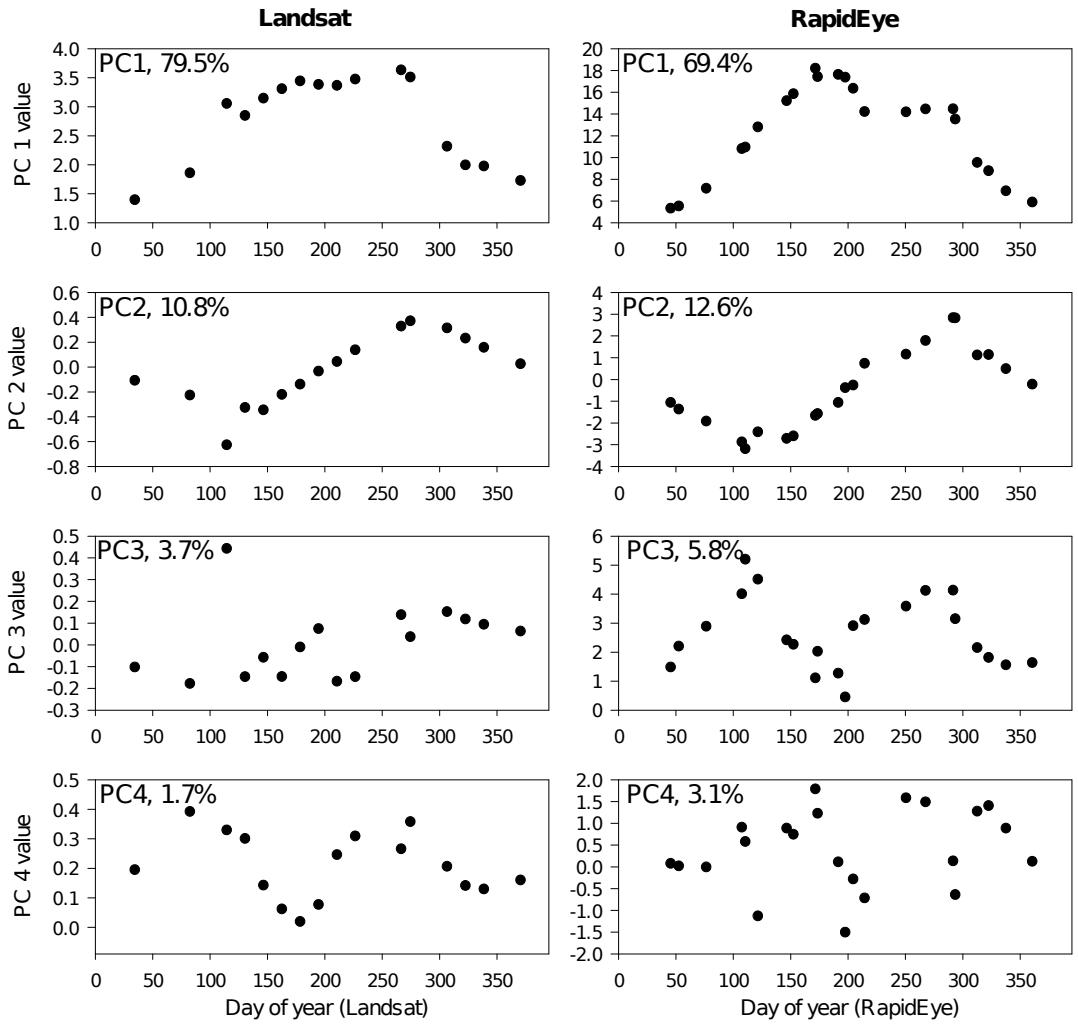
1493 **Table S1.** Selection of pixels for phenological curve fitting based on the
1494 similarity to deciduous trajectory within the biogeochemical flux footprints of
1495 three wetland sites represented by the first and second principal
1496 components (PC1 and PC2, respectively) of the greenness series from each
1497 satellite product. Here "in mask" denotes pixels included in the subsequent
1498 phenological analyses.

Metric	Landsat			RapidEye		
	West Pond	Mayberry Farms	East End	West Pond	Mayberry Farms	East End
Total pixel count	33	81	30	928	2234	784
Pixels with ≥0.7 correlation to PC1	33	68	21	799	1924	664
Pixels with ≥0.7 correlation to PC2	0	0	3	18	0	87
Pixels with ≥0.7 correlation to PC1 or PC 2 as %total	**100%**	**84%**	**80%**	**88%**	**86%**	**96%**

1499

1500 **B. Phenological parameter estimation**

1501

1502 **1. Double-logistic model for seasonal greenness**

1503 As a proxy of vegetation greenness, we used the Enhanced Vegetation Index
1504 (EVI) which has been widely used in terrestrial phenological analyses and
1505 sometimes preferred over other popular indicators due to greater sensitivity
1506 to vegetation signals in closed canopy setting (Huete et al., 2002; Melaas et
1507 al., 2016, 2013):

1508 $$EVI = \frac{2.5 * (NIR - ¿)}{(NIR + 6 * ¿ - 7.5 * ¿ + 1)}, (1)$$

1509 Fitting a curve to per-pixel phenological series of EVI is an important step in
1510 the analyses because it allows interpolating greenness (spectral vegetation
1511 index) values from discrete observations of available image dates to a daily
1512 time step. While a variety of algorithms and functions have been proposed
1513 for such interpolations, studies focusing on vegetation with deciduous
1514 seasonality have often considered sigmoid logistic functions consistent with
1515 the non-linear dynamics of greenness proxies (Figure S2), i.e., more rapid

1516 changes during the early season green-up and late season senescence and
1517 low variation during the low greenness (i.e., before the start of greening and
1518 after the end of senescence) and high greenness (between end of greening
1519 and start of senescence) phases (Gonsamo et al., 2013; Klosterman et al.,
1520 2014; Misra et al., 2016; Son et al., 2016; Tan et al., 2011; Toomey et al.,
1521 2015; Xu et al., 2014).
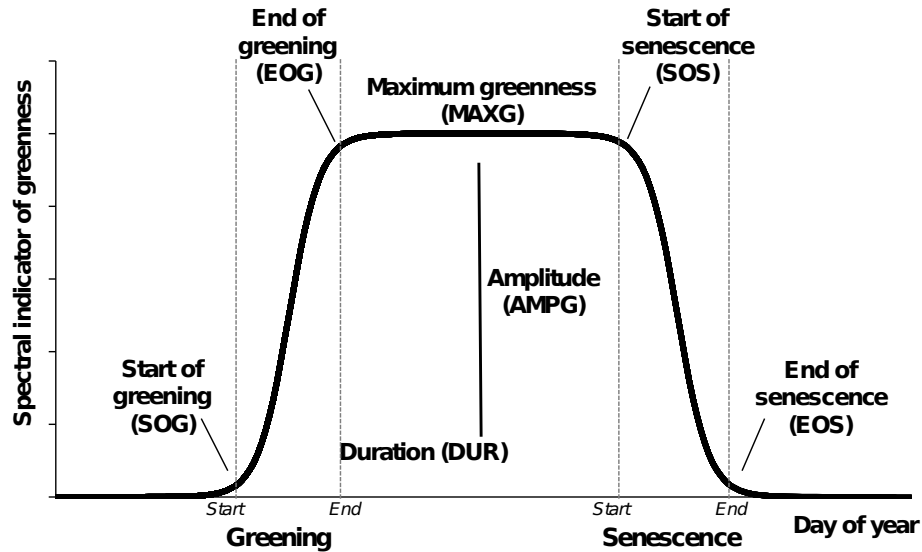
1522
1523 **Figure S2:** Deciduous phenological trajectory represented by a double-
1524 logistic function.
1525
1526 A double-logistic function (Bauer et al., 2017; Head et al., 2004) captures
1527 both increase (green-up) and decrease (senescence) phases by a single
1528 equation with different parameter sets for each phase to the Enhanced
1529 Vegetation Index (EVI) series:

1530
$$EVI(t) = P_1 + \frac{P_2}{1 + e^{P_3(P¿¿4-t)} + \dfrac{P_2}{1 + e^{P_5(P¿¿6-t)}}}, (2)¿$$

1531 where the parameters P_1, P_2,..., P_6 determine the shape and asymmetry in
1532 the fitted double-logistic curve (Bauer et al., 2017) and t indicates the day of
1533 year (DOY).
1534
1535 Fitting the function in (2) as a regression model to the input series of EVI
1536 involves finding a set of parameter values P_1, P_2,..., P_6 which minimize the
1537 "cost function", i.e. a measure of error as the distance between the original
1538 and fitted values. By the nature of model (2), its cost function may have
1539 more than one local minimum in the multi-dimensional space of its

1540 parameters, which may complicate the search for their best fitting set. To
1541 help achieve the global, rather than local, minimum corresponding to the
1542 least predictive error, it is important to constrain the search space by
1543 providing the initial guess on the parameters P_1, P_2,…, P_6. As such a guess
1544 would be specific to both the shape and the extrema of the individual per-
1545 pixel trajectories, a fixed set of numbers might not be applicable to all the
1546 pixels in the sample, especially in landscapes with high local variation in
1547 greenness. To automate such initial parameter guessing in this study, we
1548 estimated the starting values of P_3, P_4, P_5 and P_6 using the extrema in the first
1549 derivative of a first-order Fourier function fitted to the original pixel EVI
1550 series. The starting values of P_1 and P_2 were approximated by the minimum
1551 and the difference between maximum and minimum, respectively, of the
1552 original EVI series for each pixel.
1553
1554
1555 **2. Extracting phenological metrics for the timing of greening and**
1556   **senescence**

1557 Following the fitting of the double-logistic function, curvatures in the pixel
1558 daily interpolated EVI series were used to estimate the start and end dates of
1559 greening and senescence phases and the duration of the growing season
1560 (Figure S2). Such key transitions can be approximated by the local minima
1561 and maxima in the curve derivatives; however, specific choices of the latter
1562 vary among studies. Tan and colleagues (2011) provide a detailed analysis
1563 and interpretation of such curvatures, indicating that the 3rd derivative's
1564 extrema approximate more closely the timing of changes in the actual
1565 curvature of greenness, while the 2nd derivative's extrema represent the
1566 timing when the majority of a pixel changes in greenness. The latter study
1567 preferred 3rd derivative as the primary indicator of the greening and
1568 senescence transitions, more consistent with how they might be detected in
1569 ground-scale phenological observations (Tan et al., 2011). Another study
1570 focusing on a rural landscape with broadleaf forest areas in Germany (Misra
1571 et al., 2016) also recommended the 3rd derivative over 2nd as the former
1572 more effectively captured inter-annual phenological variability and
1573 contributions from the forest understory species. A well-defined double-
1574 logistic curve typically has three prominent peaks and two troughs in the 2nd
1575 derivative and three peaks and three troughs in the 3rd derivative (Figure
1576 S3).
1577
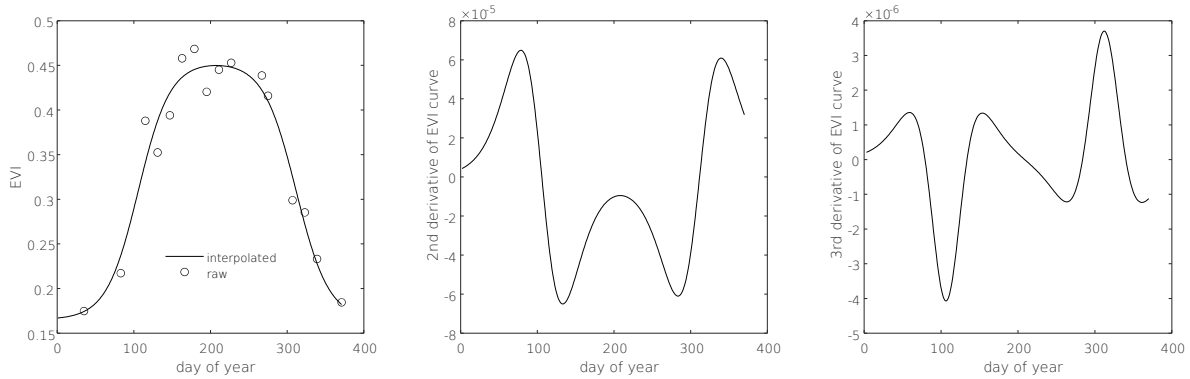
1578

1579 **Figure S3.** An interpolated double-logistic curve fitted to the raw greenness
1580 series (left panel) with its second (middle panel) and third (right panel)
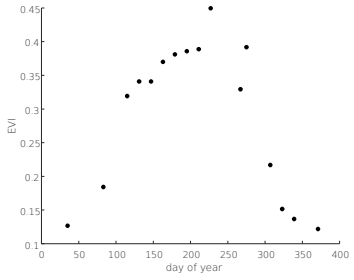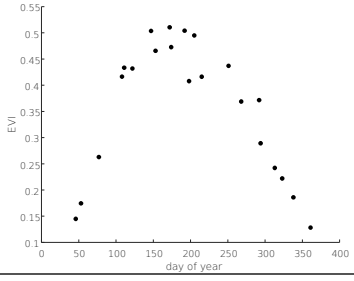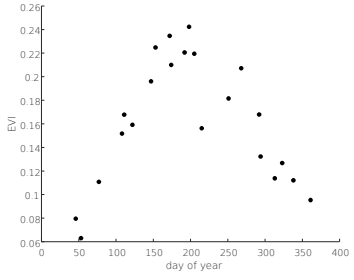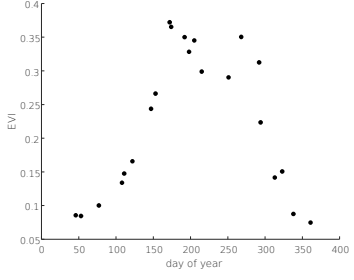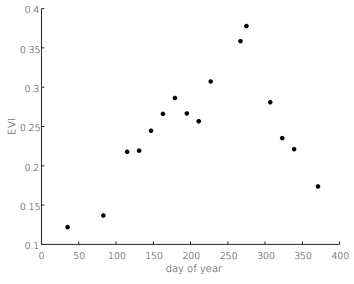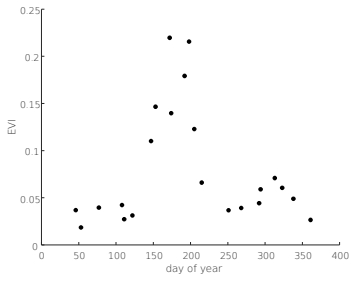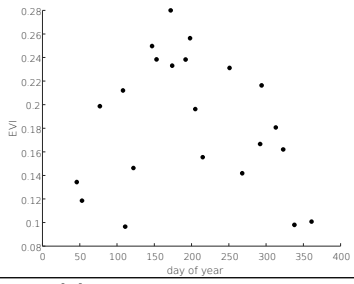1581 derivatives.

1582

1583 **3. Special cases and challenges in double-logistic fitting**

1584 Many previous phenological studies have focused on "upland" terrestrial
1585 ecosystems and used moderate to coarse spatial resolution imagery, where
1586 seasonal change in aboveground vegetation biomass, cover and health are
1587 often the main contributors to variation in spectral indicators, consistent with
1588 generalized models such as (2). However, in wetland environments,
1589 phenological dynamics may show high local heterogeneity due to inundation
1590 effects on plant reflectance spectra, zoning of plant communities along
1591 elevation gradients, local disturbance and other factors (Kearney et al.,
1592 2009; Knox et al., 2017; Mo et al., 2015). For hydrologically managed
1593 wetlands such as in our study area, we expected that spatial variability in the
1594 amount and height of litter, dominant species and disturbance such as pest
1595 outbreaks could be especially important contributors to the local timing of
1596 green-up and senescence and the specific shape and magnitude of seasonal
1597 EVI trajectories (Eichelmann et al., 2018; Knox et al., 2017; Rocha et al.,
1598 2008).
1599 Indeed, initial efforts to fit double-logistic function (2) to per-pixel EVI series
1600 of our wetland sites revealed that some of the pixel trajectories were difficult
1601 to accommodate by this model, as summarized in Table S2. Such cases were
1602 diagnosed using model root mean square error (RMSE)>0.05 and number of
1603 peaks and troughs in both 2nd and 3rd derivatives inconsistent with the
1604 double-logistic model (Figure S3), or both (Figure S4). To avoid excluding
1605 such pixels entirely from the analysis, considering our primary focus on
1606 analyzing phenological heterogeneity, we adopted a set of corrective
1607 strategies (Table S2), sometimes applying more than one of them to a given
1608 pixel (Figure S4).

1609 **Table S2.** Examples of the common challenges in fitting double-logistic
1610 function to EVI series.

Challenge	Example of EVI series	Potential strategies*
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		Remove the observation with the largest residual and re-fit the model.
Insufficient curvature at the very onset of greening and the very end of senescence		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.**
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		Consider 2nd derivative extrema as the next closest approximation for a given indicator of the greening and/or senescence timing.
Complex variation of EVI values near the peak of the growing season which, however, remains constrained within a certain range of high greenness values		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 >0.05, use the 2nd order Fourier fitting function and its derivative extrema.

Complex trajectory with high variation of EVI values at the peak growing season without a well-defined plateau of high greenness values		Use the 2nd order Fourier function and its 2nd and 3rd 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.
Greenness trajectory represents a single peak instead of a plateau		If the 3rd derivative has 3 maxima and 3 minima while the 2nd derivative has 2 maxima and 1 minimum, the case is consistent with the double-logistic model, and the 3rd 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 >0.05, use the 2nd order Fourier function and its derivative extrema.
Substantial noise despite the evidence of the overall seasonal increase and decrease in greenness		If none of the corrective measures achieve a satisfactory level of error, exclude the pixel from the analysis.

1611   *Potential strategies presented here are not necessarily mutually exclusive and
1612   more than one strategy may be sometimes used for a particular special case pixel.

1613   **This measure was based on the assumption that late December and January
1614   would be the periods of the lowest greenness for the respective pixels, which would
1615   be also consistent with the general trajectory of phenocam greenness for each
1616   wetland site.

RMSE≤0.05 **Initial double-logistic model fitting & RMSE estimation** RMSE>0.05

RMSE≤0.05 Extend time series by adding a minimum greenness at the beginning & end; re-fit RMSE>0.05

consistent Examine if 2nd & 3rd derivative extrema are consistent with the double-logistic model not consistent

RMSE≤0.05 Remove the largest-residual observation & re-fit the model RMSE>0.05

sufficient Check if the number of extrema is sufficient to include 2nd derivative extrema; extend series again if not not sufficient

Fit 2nd order Fourier model instead of double-logistic RMSE>0.05 or insufficient extrema in 2nd & 3rd derivatives

RMSE≤0.05

RMSE≤0.05 Extend the time series & re-fit 2nd order Fourier model

RMSE>0.05 or insufficient extrema in 2nd & 3rd derivatives

Use 3rd derivative extrema as proxies for main transition dates

Use extrema in the 3rd & 2nd derivatives of the double-logistic function as proxies for main transition dates

Use extrema in the 3rd & 2nd derivatives of the 2nd order Fourier fit as proxies for main transition dates

Exclude the pixel from further analysis

Figure S4. A flowchart diagram representing major steps in curve-fitting.

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:

$$EVI(t)=a_0+\sum_{i=1}^{n} a_i\cos(iwt)+b_i\sin(iwt) \quad (3)$$

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,

1642 where they constituted ~31% of the sample (Table S3) and occurred both
1643 within water and within vegetated areas.
1644
1645 If for a given pixel none of the corrective measures sufficiently improved the
1646 fit, that pixel was excluded from the analysis completely. Such excluded
1647 pixels ultimately constituted for Landsat and RapidEye inputs, respectively,
1648 3% and 1% of the originally selected pixels at West Pond, 12% & 8% of the
1649 selected pixels at East End and 4% of pixels with both input products at
1650 Mayberry Farms (Table S3). Visual examination showed that these cases
1651 often corresponded to open-water areas where EVI trajectories could be
1652 influenced by algae, changes in water chemistry and physical disturbance
1653 affecting spectral values, such as wind-induced ripples. A more detailed list
1654 of special cases and rules considered in assigning curvatures of the 2nd and
1655 3rd curve derivatives as key transition dates is provided in Table S4 below.
1656
1657 **Table S3**. Differences in model fitting to pixels from two satellite input
1658 sources within the wetland site flux footprints.

Metric	Landsat			RapidEye		
	West Pond	Mayberry Farms	East End	West Pond	Mayberry Farms	East End
Pixels with fitted curves (%of in-mask pixels)	32	65	21	807	1850	692
%of in-mask pixels	**97%**	**96%**	**88%**	**99%**	**96%**	**92%**
Pixels with double-logistic fitting	31	65	18	775	1277	612
%all fitted	97%	100%	86%	96%	69%	88%
Pixels with 2nd order Fourier fitting	1	0	3	31	573	80
%all fitted	3%	0%	14%	4%	31%	12%
Pixels with double-logistic model where transitions were estimated with only 3rd derivative extrema	30	59	18	598	659	416
%all fitted	97%	91%	100%	77%	52%	68%

1659

1660

1661 **Table S4.** Rules and special cases for approximating phenological transition dates using the timing of the
1662 curvatures of the 2nd and 3rd derivatives of the fitted functions. Cases where second or third derivatives
1663 had less than 2 peaks were excluded from estimation. The terms such as "first", "last", "penultimate" and
1664 "earliest" below refer to the timing, i.e., day of year associated with a given curvature.

Number (#) of curvature points (peaks & troughs) in the 2nd & 3rd derivatives of the fitted curve				Phenological transition dates inferred from the timing of the curvatures in the 2nd and/or 3rd derivatives				Special cases, if any
2nd, #peaks	2nd, #troughs	3rd, #peaks	3rd, #troughs	SOG	EOG	SOS	EOS	
Double-logistic curve function								
≥3	2	3	3	First peak of 3rd	Penultimate peak of 3rd	Penultimate trough of 3rd	Last trough of 3rd	If estimated EOG>SOS, use SOS as last trough of 3rd and EOS as the last peak of the 2nd
≥3	2	3	2	First peak of 3rd	Penultimate peak of 3rd	Last trough of 3rd	Last peak of 2nd	
≥3	3	3	3	First peak of 3rd	Penultimate peak of 3rd	Last trough of 3rd	Last peak of 2nd	
≥3	3	3	2	First peak of 3rd	Penultimate peak of 3rd	Last trough of 3rd	Last peak of 2nd	
≥3	2	2	3	First peak of 2nd	First peak of 3rd	Penultimate trough of 3rd	Last trough of 3rd	
≥3	2	2	2	First peak of 3rd	Last peak of 3rd	Last trough of 3rd	Later of the last peaks of 2nd & 3rd	
≥3	3	4	3	First peak of 3rd	Second peak of 3rd	Penultimate trough of 3rd	Last trough of 3rd	
≥3	3	3	4	First peak of 3rd	Penultimate peak of 3rd	Penultimate trough of 3rd	Last trough of 3rd	
≥3	2	4	3	First peak of 3rd	Second peak of 3rd	Penultimate trough of 3rd	Later of the last troughs of 2nd & 3rd	
3	1	2	3	First trough of 3rd	First peak of 3rd	Penultimate trough of	Last trough of 3rd	

						3rd		
3	1	3	2	First peak of 3rd	Penultimate peak of 3rd	Penultimate peak of 2nd	Last peak of 2nd	
2	2	3	3	First peak of 3rd	Penultimate peak of 3rd	Penultimate trough of 3rd	Last trough of 3rd	If penultimate peak of 3rd is later than penultimate trough of 3rd, use SOS as penultimate peak of 3rd and EOS as the last peak of 2nd
2	2	3	2	First peak of 3rd	Penultimate peak of 3rd	Last trough of 3rd	Last peak of 3rd	If estimated EOG>SOS, approximate both EOG & SOS as the first trough of 3rd
2	2	2	3	Earlier of the first peak of 3rd & the first trough of 2nd	Last trough of 2nd	Last peak of 3rd	Last trough of 3rd	
2	3	3	3	First peak of 2nd	Penultimate trough of 2nd	Last trough of 3rd	Last peak of 3rd	
2	3	2	2	First peak of 2nd	Penultimate trough of 2nd	Penultimate trough of 2nd	Last trough of 3rd	
2	3	3	2	First peak of 2nd	Penultimate trough of 2nd	Penultimate trough of 2nd	Last trough of 3rd	
2	3	2	3	First peak of 3rd	Penultimate trough of 2nd	Penultimate trough of 3rd	Last trough of 3rd	
2	1	3	3	First peak of 3rd	Penultimate peak of 3rd	Penultimate trough of 3rd	Last trough of 3rd	
2	1	3	2	First peak of 3rd	Penultimate peak of 3rd	Later of the penultimate peak of 3rd & last trough of 3rd	Last peak of 2nd	

2	2	3	4	First peak of 3rd	Penultimate peak of 3rd	Penultimate trough of 3rd	Last trough of 3rd	
4	3	3	3	First peak of 3rd	Penultimate trough of 2nd	Penultimate trough of 3rd	Last trough of 3rd	
Fourier function:								
3	2	3	3	First peak of 3rd	Penultimate peak of 3rd	Penultimate trough of 3rd	Last trough of 3rd	If estimated EOG>SOS, use the last peak of 2nd for SOS
3	2	3	2	First peak of 2nd	First trough of 2nd	Penultimate peak of 3rd	Later of the last peaks of 2nd & 3rd	
3	2	2	2	Earliest of the first peak of 2nd & first trough of 3rd	First peak of 3rd	Same as EOG (single-peak trajectory)	Later of the last peaks of 2nd & 3rd	Special case if predicted EVI at the first peak of 3rd is greater than EVI at the last troughs of both 2nd & 3rd derivatives. Additionally, for EOG & SOS use last trough of 3rd if the absolute difference in EVI between first peak of 3rd & last trough of 3rd is <0.1, and use the last trough of 2nd if the absolute difference in EVI between the first peak of 3rd & last trough of 2nd <0.1
				Earliest of the first peak of 2nd & first trough of 3rd	First trough of 3rd	Same as EOG (single-peak trajectory)	Later of the last peaks of 2nd & 3rd	Special case if predicted EVI at the last trough of 3rd >EVI at the last trough of 2nd
				Earliest of the first peak of 2nd	First trough of 2nd	Same as EOG (single-	Later of the last peaks of 2nd & 3rd	Special case if predicted EVI at the last trough of 3rd <EVI at the last

				& first trough of 3rd		peak trajectory)	trough of 2nd	
3	2	2	3	First peak of 2nd	First peak of 3rd	Penultimate trough of 3rd	Last peak of 2nd	
3	3	3	2	First peak of 3rd	Penultimate peak of 3rd	Penultimate peak of 3rd	Last peak of 3rd	
3	3	4	3	First peak of 3rd	Second peak of 3rd	Penultimate trough of 3rd	Last trough of 3rd	
3	3	3	3	Earlier of the first peaks of 2nd & 3rd	Penultimate trough of 2nd	Penultimate peak of 3rd	Last peak of 3rd	
2	2	2	3	Earlier of the first peak of 3rd & first trough of 2nd	Last trough of 2nd	Last trough of 2nd	Last trough of 3rd	
2	2	3	3	First peak of 3rd	Second peak of 3rd	Second peak of 3rd	Last peak of 2nd	
2	2	3	2	First peak of 2nd	First trough of 2nd	Penultimate peak of 3rd	Last peak of 3rd	
2	3	2	3	First peak of 2nd	Second trough of 2nd	Second trough of 2nd	Last peak of 2nd	
2	3	3	3	First peak of 3rd	Second trough of 2nd	Second trough of 2nd	Later of the last peak of 3rd & the last trough of 2nd	
2	3	3	2	First peak of 2nd	Second trough of 2nd	Second trough of 2nd	Last trough of 3rd	
2	3	2	2	First peak of 2nd	First peak of 3rd	Same as EOG	Later of the last peaks of 2nd & 3rd	Special case if predicted EVI at the first peak of 3rd is greater than EVI at the last troughs of both

								2nd & 3rd derivatives
2	3	2	2	First peak of 2nd	First trough of 3rd	Same as EOG	Later of the last peaks of 2nd & 3rd	Special case if predicted EVI at the last trough of 3rd >EVI at the last trough of 2nd
2	3	2	2	First peak of 2nd	First trough of 2nd	Same as EOG	Later of the last peaks of 2nd & 3rd	Special case if predicted EVI at the last trough of 3rd <EVI at the last trough of 2nd
2	1	3	2	First peak of 2nd	Second peak of 3rd	Second peak of 3rd	Last peak of 3rd	
Additional cases considered if model RMSE <0.05								
2	2	2	1	Earlier of the first peak of 3rd & first trough of 2nd	Trough of the 3rd (one value)	Last trough of the 2nd	Last peak of the 2nd	
2	2	2	2	Earlier of the first peak of 2nd & first trough of 3rd	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 & last trough of 2nd	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 & last trough of 2nd	Last peak of the 3rd	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

1665
1666

4. References for Supplementary Material

Bauer, L.G.M., Hametner, B., Mayer, C.C., Wassertheurer, S., 2017. Mathematical Wave Fitting Models for the Quantification of the Diurnal Profile and Variability of Pulse Wave Analysis Parameters. SNE Simulation Notes Europe 27, 153–160. https://doi.org/10.11128/sne.27.tn.10386

Brooks, E.B., Thomas, V.A., Wynne, R.H., Coulston, J.W., 2012. Fitting the Multitemporal Curve: A Fourier Series Approach to the Missing Data Problem in Remote Sensing Analysis. IEEE Transactions on Geoscience and Remote Sensing 50, 3340–3353. https://doi.org/10.1109/TGRS.2012.2183137

Eichelmann, E., Hemes, K.S., Knox, S.H., Oikawa, P.Y., Chamberlain, S.D., Sturtevant, C., Verfaillie, J., Baldocchi, D.D., 2018. The effect of land cover type and structure on evapotranspiration from agricultural and wetland sites in the Sacramento–San Joaquin River Delta, California. Agricultural and Forest Meteorology 256–257, 179–195. https://doi.org/10.1016/j.agrformet.2018.03.007

Gonsamo, A., Chen, J.M., D'Odorico, P., 2013. Deriving land surface phenology indicators from CO_2 eddy covariance measurements. Ecological Indicators 29, 203–207. https://doi.org/10.1016/j.ecolind.2012.12.026

Head, G.A., Lukoshkova, E.V., Mayorov, D.N., van den Buuse, M., 2004. Non-symmetrical double-logistic analysis of 24-h blood pressure recordings in normotensive and hypertensive rats: Journal of Hypertension 22, 2075–2085. https://doi.org/10.1097/00004872-200411000-00008

Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., Ferreira, L.G., 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment 83, 195–213. https://doi.org/10.1016/S0034-4257(02)00096-2

Kearney, M.S., Stutzer, D., Turpie, K., Stevenson, J.C., 2009. The Effects of Tidal Inundation on the Reflectance Characteristics of Coastal Marsh Vegetation. Journal of Coastal Research 25, 1177–1186. https://doi.org/10.2112/08-1080.1

Klosterman, S.T., Hufkens, K., Gray, J.M., Melaas, E., Sonnentag, O., Lavine, I., Mitchell, L., Norman, R., Friedl, M.A., Richardson, A.D., 2014. Evaluating remote sensing of deciduous forest phenology at multiple spatial scales using PhenoCam imagery. Biogeosciences 11, 4305–4320. https://doi.org/10.5194/bg-11-4305-2014

Knox, S.H., Dronova, I., Sturtevant, C., Oikawa, P.Y., Matthes, J.H., Verfaillie, J., Baldocchi, D., 2017. Using digital camera and Landsat imagery with eddy covariance data to model gross primary production in restored wetlands. Agricultural and Forest Meteorology 237, 233–245. https://doi.org/10.1016/j.agrformet.2017.02.020

Melaas, E.K., Friedl, M.A., Zhu, Z., 2013. Detecting interannual variation in deciduous broadleaf forest phenology using Landsat TM/ETM plus data.

1712   Remote Sensing of Environment 132, 176–185. https://doi.org/10.1016/
1713   j.rse.2013.01.011
1714 Melaas, E.K., Sulla-Menashe, D., Gray, J.M., Black, T.A., Morin, T.H.,
1715   Richardson, A.D., Friedl, M.A., 2016. Multisite analysis of land surface
1716   phenology in North American temperate and boreal deciduous forests
1717   from Landsat. Remote Sensing of Environment 186, 452–464.
1718   https://doi.org/10.1016/j.rse.2016.09.014
1719 Misra, G., Buras, A., Menzel, A., 2016. Effects of Different Methods on the
1720   Comparison between Land Surface and Ground Phenology—A
1721   Methodological Case Study from South-Western Germany. Remote
1722   Sensing 8, 753. https://doi.org/10.3390/rs8090753
1723 Mo, Y., Momen, B., Kearney, M.S., 2015. Quantifying moderate resolution
1724   remote sensing phenology of Louisiana coastal marshes. Ecological
1725   Modelling 312, 191–199.
1726   https://doi.org/10.1016/j.ecolmodel.2015.05.022
1727 Rocha, A.V., Potts, D.L., Goulden, M.L., 2008. Standing litter as a driver of
1728   interannual CO(2) exchange variability in a freshwater marsh. Journal
1729   of Geophysical Research-Biogeosciences 113, G04020.
1730   https://doi.org/10.1029/2008JG000713
1731 Son, N.-T., Chen, C.-F., Chang, L.-Y., Chen, C.-R., Sobue, S.-I., Minh, V.-Q.,
1732   Chiang, S.-H., Nguyen, L.-D., Lin, Y.-W., 2016. A logistic-based method
1733   for rice monitoring from multitemporal MODIS-Landsat fusion data.
1734   European Journal of Remote Sensing 49, 39–56.
1735   https://doi.org/10.5721/EuJRS20164903
1736 Tan, B., Morisette, J.T., Wolfe, R.E., Gao, F., Ederer, G.A., Nightingale, J.,
1737   Pedelty, J.A., 2011. An Enhanced TIMESAT Algorithm for Estimating
1738   Vegetation Phenology Metrics From MODIS Data. IEEE J. Sel. Top. Appl.
1739   Earth Observations Remote Sensing 4, 361–371.
1740   https://doi.org/10.1109/JSTARS.2010.2075916
1741 Toomey, M., Friedl, M.A., Frolking, S., Hufkens, K., Klosterman, S., Sonnentag,
1742   O., Baldocchi, D.D., Bernacchi, C.J., Biraud, S.C., Bohrer, G., Brzostek,
1743   E., Burns, S.P., Coursolle, C., Hollinger, D.Y., Margolis, H.A.,
1744   McCaughey, H., Monson, R.K., Munger, J.W., Pallardy, S., Phillips, R.P.,
1745   Torn, M.S., Wharton, S., Zeri, M., Richardson, A.D., 2015. Greenness
1746   indices from digital cameras predict the timing and seasonal dynamics
1747   of canopy-scale photosynthesis. Ecological Applications 25, 99–115.
1748   https://doi.org/10.1890/14-0005.1
1749 Wallace, C.S.A., Villarreal, M.L., van Riper III, C., 2013. Influence of monsoon-
1750   related riparian phenology on yellow-billed cuckoo habitat selection in
1751   Arizona. Journal of Biogeography 40, 2094–2107.
1752   https://doi.org/10.1111/jbi.12167
1753 Wilson, B.T., Knight, J.F., McRoberts, R.E., 2018. Harmonic regression of
1754   Landsat time series for modeling attributes from national forest
1755   inventory data. ISPRS Journal of Photogrammetry and Remote Sensing
1756   137, 29–46. https://doi.org/10.1016/j.isprsjprs.2018.01.006

1757   Xu, H., Twine, T., Yang, X., 2014. Evaluating Remotely Sensed Phenological
1758   Metrics in a Dynamic Ecosystem Model. Remote Sensing 6, 4660–4686.
1759   https://doi.org/10.3390/rs6064660
1760
1761