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1 **Running head: Phenology, photography and physiology.**

2

3 **Title: Tracking forest phenology and seasonal physiology using digital repeat photography:**  
4 **a critical assessment**

5

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25

26 **Abstract**

27

28 Digital repeat photography is becoming widely used for near surface remote sensing of  
 29 vegetation. Canopy greenness, which has been used extensively for phenological applications,  
 30 can be readily quantified from camera images. Important questions remain, however, as to  
 31 whether the observed changes in canopy greenness are directly related to changes in leaf-level  
 32 traits, changes in canopy structure, or some combination thereof.

33

34 We investigated relationships between canopy greenness and various metrics of canopy structure  
 35 and function, using five years (2008-2012) of automated digital imagery, ground observations of  
 36 phenological transitions, leaf area index (LAI) measurements, and eddy-covariance estimates of  
 37 gross ecosystem photosynthesis from the Harvard Forest, a temperate deciduous forest in the  
 38 northeastern USA. Additionally, we sampled canopy sunlit leaves on a weekly basis throughout  
 39 the growing season of 2011. We measured physiological and morphological traits including leaf  
 40 size, mass (wet/dry), nitrogen content, chlorophyll fluorescence, and spectral reflectance, and  
 41 characterized individual leaf color with flatbed scanner imagery.

42

43 Our results show that observed spring and autumn phenological transition dates are well captured  
 44 by information extracted from digital repeat photography. However, spring development of both  
 45 LAI and the measured physiological and morphological traits are shown to lag behind spring  
 46 increases in canopy greenness, which rises very quickly to its maximum value before leaves are  
 47 even half their final size. Based on the hypothesis that changes in canopy greenness represent the  
 48 aggregate effect of changes in both leaf-level properties (specifically, leaf color) and changes in

49 canopy structure (specifically, LAI), we developed a two end-member mixing model. With just a  
 50 single free parameter, the model was able to reproduce the observed seasonal trajectory of  
 51 canopy greenness. This analysis shows that canopy greenness is relatively insensitive to changes  
 52 in LAI at high LAI levels, which we further demonstrate by assessing the impact of an ice-storm  
 53 on both LAI and canopy greenness.

54 Our study provides new insights into the mechanisms driving seasonal changes in canopy  
 55 greenness retrieved from digital camera imagery. The nonlinear relationship between canopy  
 56 greenness and canopy LAI has important implications both for phenological research  
 57 applications and for assessing responses of vegetation to disturbances.

58  
 59 **Keywords:** near surface remote sensing, digital repeat photography, deciduous forest phenology,  
 60 carbon cycling, green chromatic coordinate, PhenoCam, MODIS, ice-storm, greendown

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 62  
 63

64 **Introduction**

65

66 Photosynthesis by terrestrial vegetation represents the primary means by which carbon dioxide  
 67 (CO<sub>2</sub>) is removed from the atmosphere. Vegetation structure and function typically varies  
 68 seasonally, controlled in part by the onset and rate of leaf growth and senescence (Lieth 1974).  
 69 Such phenological cycles respond directly to climate, serving as indicators of the potential  
 70 impacts of climate change (Solomon et al. 2007), and generate feedbacks to the climate system  
 71 (Peñuelas et al. 2009, Richardson et al. 2013a). It is therefore important to develop systems  
 72 capable of monitoring phenology and the physiological state and function of terrestrial  
 73 vegetation.

74

75 Phenology has been an area of active interest for centuries. Observer based records primarily  
 76 focused on the timing of bud-burst and flowering, and are now used to quantify long-term  
 77 responses of these events to climate change (Aono and Kazui 2008, Thompson and Clark 2008).  
 78 In recent decades, ground based techniques (e.g. Smolander and Stenberg 1996, Barr et al. 2004)  
 79 have been developed that allow seasonal changes in canopy leaf area to be tracked using site-  
 80 specific observations made at discrete time intervals. The development of satellite remote  
 81 sensing not only allows phenological dates to be estimated on a global scale (e.g. Zhang et al.  
 82 2006), but also supports studies examining large-scale temporal changes in vegetation indices  
 83 (e.g. Xu et al. 2013). Such global land surface phenology approaches, however, are limited by  
 84 the coarse temporal and spatial scale of remote sensing data sets, and by the lack of adequate  
 85 ground validation data (White et al. 2009, Hufkens et al. 2012a).

86

87 Automated near surface remote sensing techniques have recently been developed as a bridge  
 88 between ground-based manual observations and satellite remote sensing products (Richardson et  
 89 al. 2013b). To accomplish this, imaging sensors or radiometric instruments are mounted above  
 90 the canopy to record optical properties of canopy reflectance at a high temporal resolution. Off-  
 91 the-shelf digital cameras are being increasingly used in this manner as an inexpensive, automated  
 92 means by which to quantify temporal changes in canopy optical properties (e.g., Sonnentag et al.  
 93 2012). In particular, separate extraction of brightness levels for red, green and blue (RGB) color  
 94 channels from camera images allows indices to be calculated that describe changes in ‘canopy  
 95 greenness’ over time.

96  
 97 The expanding digital image archive (e.g., the PhenoCam network, <http://phenocam.sr.unh.edu/>)  
 98 has been widely used to study temporal changes in vegetation canopies. Phenophase transition  
 99 dates of leaf emergence and senescence derived from repeat digital imagery have been shown to  
 100 parallel the phenology signal inferred from above- and below-canopy radiometric instruments  
 101 (Richardson et al. 2007). Technical issues of camera choice and calibration have been examined,  
 102 along with issues of scene illumination (Sonnentag et al. 2012). Phenological transition dates  
 103 derived from camera imagery have been used to explain temporal changes in surface-atmosphere  
 104 CO<sub>2</sub> exchange (Ahrends et al. 2008, 2009, Richardson et al. 2009), improve the parameterization  
 105 of phenology models (Migliavacca et al. 2011), and have been compared with satellite-based  
 106 land surface phenology products (Hufkens et al. 2012a). Encouraged by their demonstrated  
 107 effectiveness for canopy monitoring, automated digital cameras have become an integral part of  
 108 continental-scale monitoring networks (e.g. the Integrated Carbon Observation System, and the  
 109 National Ecological Observatory Network).

110

111 Although seasonal cycles in canopy coloration are evident from digital repeat photography  
 112 (Sonntag et al. 2012), open questions remain as to how the information extracted from digital  
 113 images corresponds to the seasonal development of canopy structure and function. Changes in  
 114 foliage related to phenology and ontogeny, (i.e. developmental stage or age) occur in various  
 115 aspects of leaf physiology (e.g. leaf color and pigmentation, leaf mass per unit area, water and  
 116 nutrient content, photosynthetic capacity, etc.) over the course of the growing season (Ma et al.  
 117 2011, McKown et al. 2012). Although canopy greenness is commonly assumed to be a surrogate  
 118 for canopy structure and function, the validity of such assumptions remains untested. For  
 119 example, in time series of deciduous forest canopy greenness, a pronounced “spike” often marks  
 120 the end of the rapid phase of spring green-up, preceding a gradual decline in greenness over the  
 121 course of the summer. Although related to phenology, the mechanisms – physiological,  
 122 morphological, or structural – directly responsible for the seasonal dynamics in canopy  
 123 greenness have yet to be identified.

124

125 In the present study, we explore relationships among seasonal changes in canopy greenness,  
 126 measured using digital repeat photography, seasonal changes in canopy structure, and the  
 127 physiological and morphological traits of individual leaves. Specifically, we assess the  
 128 relationship between camera-derived canopy greenness and measurements of both canopy- and  
 129 leaf-level traits for five years (2008-2012) at Harvard Forest, a temperate deciduous forest in the  
 130 northeastern US. We first assess seasonal cycles and interannual variability of camera-derived  
 131 greenness (and the related phenological transitions) using ground observations of phenology, leaf  
 132 area index, and eddy-covariance CO<sub>2</sub> flux measurements. We then use physiological and

133 morphological measurements on individual leaves to understand the mechanisms driving the  
134 seasonality of canopy greenness. Our goal is to identify when, and under what circumstances,  
135 information derived from digital repeat photography can be used to draw inferences about  
136 seasonal changes in leaf- and canopy-level traits related to structure and function.

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140 **Materials and Methods**

141

142 ***Study site***

143 The study was conducted at the Harvard Forest Environmental Measurement Site (EMS,  
 144 42.5378°N, 72.1715°W), located in central Massachusetts, U.S. The site is a temperate forest  
 145 dominated by hardwoods including: red oak (*Quercus rubra*, 36% basal area) and red maple  
 146 (*Acer rubrum*, 22% basal area), with other hardwoods such as yellow birch (*Betula*  
 147 *alleghaniensis*) also present. The site has annual mean precipitation of 110 cm, distributed fairly  
 148 evenly throughout the year, and a mean annual temperature of 7.1 °C.

149

150 ***Digital camera settings, image acquisition and analysis***

151 Canopy images were collected using an automated and networked digital camera (StarDot  
 152 Netcam SC 1.3 MP) mounted on top of a tower 30 m above the surface, with an oblique viewing  
 153 angle (20° from horizontal) across the canopy. Minimally compressed JPEG images from the  
 154 digital camera were taken at regular intervals (every 30 min between 04:00 and 21:30 local  
 155 time), transferred via file transfer protocol (FTP) and stored on the server of the PhenoCam  
 156 network (<http://phenocam.sr.unh.edu>). Automatic white balancing was turned off on the camera  
 157 unit to minimize day-to-day variability (Richardson et al., 2007; Richardson et al., 2009).  
 158 Aperture size was fixed but the exposure time was adjusted in response to changing light levels.  
 159 Canopy greenness was quantified using the green chromatic coordinate ( $G_{cc}$ ), which uses red ( $R$ ),  
 160 green ( $G$ ) and blue ( $B$ ) digital numbers to calculate the ratio of green within the image  
 161 ( $G_{cc}=G/(R+G+B)$ ).  $G_{cc}$  was calculated using the PhenoCam Image Processor V1.0 (available for  
 162 download: <http://phenocam.sr.unh.edu/webcam/tools/>). This software tool allows a region of

163 interest within the camera field of view to be specified and calculates  $G_{cc}$  based on the method  
164 described by Sonnentag et al. (2012). Phenophase transition dates for spring bud-burst,  
165 maximum greenness, and leaf senescence were estimated using two different approaches: A  
166 curve fitting method (Elmore et al., 2012), and a simple threshold crossing approach. For the  
167 threshold crossing approach, spring and fall transition dates were identified as the point at which  
168 the three-day running mean crossed a threshold value. We used 33% of the annual amplitude as  
169 the threshold for both spring and autumn transition points. For the curve-fitting approach  
170 (Elmore et al. 2012), transition dates were extracted from curve fits by numerically calculating  
171 the dates of extrema in the curvature change rate, following the approach used in the MODIS  
172 phenology product (Zhang et al. 2003). Uncertainty in the extracted transition dates was  
173 estimated using 1000 Monte Carlo samples based on the covariance matrix of parameter  
174 estimates. Five years (2008-2012) of continuous camera imagery were used.

### 176 *Canopy structure*

177 Leaf area index (LAI) measurements (Li-Cor LAI-2000) were made weekly during the growing  
178 season for 5 years (2008-2012) at 40 plots, established in 1993 using a stratified-random position  
179 along eight 500 m transects, running SW and NW from the EMS tower along the dominant wind  
180 directions (Barford et al. 2001).

181

182

183 Ground observations of spring and autumn phenology (bud break, leaf development, leaf  
 184 coloration and leaf fall) for the dominant tree species (red oak, n=4 individuals) were made from  
 185 2008 to 2012 at three- to-seven day intervals (Richardson and O’Keefe 2009). These  
 186 observations were used to identify the dates of bud-burst, proportional leaf size, and leaf  
 187 senescence at 50%, 75% and 95% of maximum.

188  
 189 Top-of-canopy broadband Normalized Difference Vegetation Index (NDVI) estimates were  
 190 made based on measurements of reflected radiation at 400–700 and 305–2800 nm, following  
 191 Jenkins et al. (2007). Specifically, upwelling and downwelling PAR and solar radiation were  
 192 measured at 30-minute intervals using upward and downward pointing Kipp and Zonen CMP 3  
 193 thermopile pyranometers and LI-COR (LI190SB-L) quantum radiation sensors on a walk-up  
 194 tower located adjacent to the EMS tower.

195  
 196 To estimate LAI from the radiation measurements, gap fraction ( $P$ ) was first calculated as  $P =$   
 197  $Q_t/Q_o$ , where  $Q_o$  is incident solar photosynthetic photon flux density (PPFD) measured above  
 198 the canopy and  $Q_t$  is the PPFD measured below the canopy. Measurements of  $P$  were used when  
 199 the solar zenith angle was closest to  $57^\circ$  and LAI was calculated for each sample ( $LAI = -$   
 200  $\log(P)/K$  where  $K = G(57)/\cos(57)$ ). Measurements at 57 degrees were used because at this  
 201 point, all leaf inclination distribution functions ( $G$ ) converge to 0.5. Daily LAI was then  
 202 estimated by averaging the two LAI values per day in order to consider foliar clumping effects  
 203 (Ryu et al., 2010), and smoothed with a spline function.

204

205 Satellite based daily canopy reflectance for the period 2000-2011 was measured using the  
 206 Moderate Resolution Imaging Spectroradiometer (MODIS) on the Terra satellite (MOD09GA).  
 207 Reflectance data were screened for clouds (including cirrus and cloud shadows), high viewing  
 208 zenith angle ( $>60^\circ$ ) and low retrieval quality using standard MODIS Quality Assurance data  
 209 layers (Vermote et al. 2011). The screened daily reflectance data was then used to calculate the  
 210 Normalized Difference Vegetation Index and the Enhanced Vegetation Index (NDVI, EVI;  
 211 Huete et al. 2002).

212  
 213 Leaf inclination angles of red oak were estimated at monthly intervals in 2011 using the leveled-  
 214 digital camera approach proposed and evaluated by Ryu et al. (2010) and Pisek et al. (2011),  
 215 respectively. In brief, leveled digital images were taken with a Pentax K100D digital single-lens  
 216 reflex camera along vertical tree profiles at 2 m height intervals (Pisek et al. 2013). Leaf  
 217 inclination angles were estimated using the public domain image processing software ImageJ  
 218 (<http://rsbweb.nih.gov/ij/>) as outlined in Pisek et al. (2013).

219  
 220 Gross canopy daily ecosystem photosynthesis (GEP) was estimated for 4 years (2008-2011)  
 221 using eddy-covariance measurements of net ecosystem  $\text{CO}_2$  exchange (Urbanski et al. 2007;  
 222 Keenan et al., 2012). GEP was calculated on an hourly basis as the difference between ecosystem  
 223 respiration and net ecosystem carbon uptake, and integrated to daily sums.

224

225 ***Leaf physiological and morphological traits***

226 Leaf samples were collected from upper-level canopy leaves of three dominant red oak (*Quercus*  
 227 *rubra*) trees surrounding a walk-up tower adjacent to the EMS instrument tower for the entire

228 2011 growing season. Each sample consisted of five, non-damaged sunlit leaves collected from  
 229 one branch of each tree. Samples were collected every 3-4 days for the first month following  
 230 bud-burst, then once per week until leaf abscission in mid-November. All measurements were  
 231 made directly after sampling, following a period of dark-adaptation (30 minutes) (Richardson  
 232 and Berlyn 2002).

233  
 234 Spectral measurements of leaf reflectance and transmittance were made using an ASD FieldSpec  
 235 3 portable spectrometer (Analytical Spectral Devices Inc., Boulder, CO, USA). The spectrometer  
 236 was connected to a 5 cm, three-port integrating sphere and a 10 W hemispheric collimated light  
 237 source. The sphere had an 8° near-normal incidence port, meaning that reflectance measurements  
 238 included spectral and diffuse components. The manufacturer's RS3 software (Analytical Spectral  
 239 Devices Inc.) was used to control the spectrometer. The spectral range measured was 350–2500  
 240 nm at 1nm increments. Each recorded spectral measurement consisted of 50 individual scans. A  
 241 white Spectralon reference standard was taken for calibration for each leaf measured. Raw  
 242 spectral data was processed using ViewSpecPro (Analytical Spectral Devices Inc.). Spectral  
 243 measurements were made from day-of-year 157. Spectral indices (ChINDI:  $[R750-$   
 244  $R705]/[R750+R705]$ , Gitelson et al. (2006, 2009); PRI:  $[R531-R570]/[R531+R570]$ , Gamon et  
 245 al. (1992, 1997); NDVI:  $[R750-R675]/[R750+R675]$ , Gamon et al. 1997, Gamon and Surfus  
 246 (1999); MTCI (Meris Terrestrial Chlorophyll Index),  $[R753.75-R708.75]/[R708.75+R681.25]$ ,  
 247 Dash and Curran, 2004) were calculated from the leaf level reflectance for each measurement.

248  
 249 Chlorophyll fluorescence measurements were made using a hand-held fluorometer (Opti-  
 250 sciences, OS-30p). Five readings were taken randomly across each dark-adapted leaf to calculate

251 the average measurement for the leaf. Measurements were given as the ratio of variable  
 252 fluorescence to maximum fluorescence ( $F_v/F_m$ ).

253  
 254 To measure “broadband” reflectance in the red, green and blue wavelengths, each leaf was  
 255 scanned using a flat-bed scanner (Epson 3170). A paint sample strip, consisting of varying  
 256 shades of green progressing from light to dark, was included in each scan as a reference standard.  
 257 The scanned images were analyzed to extract leaf area and leaf color (red, green and blue digital  
 258 numbers) (Matlab code available on request).

259  
 260 Leaf fresh weight was measured the day of collection, after which leaves were placed in manila  
 261 coin envelopes in an oven at 60°C for 3-5 days to dry before measuring their dry weight. Leaf  
 262 fresh and dry weight, in combination with leaf size, were used to calculate leaf mass per unit area  
 263 (LMA) and leaf water content.

264  
 265 At the end of the growing season, the leaf samples were grouped by week for carbon and  
 266 nitrogen analysis. The dried leaves were ground using a mortar and pestle, pouring a small  
 267 amount of liquid nitrogen over the sample. The mortar and pestle was cleaned using ethanol  
 268 between samples to prevent cross-sample contamination. A 3-5  $\mu\text{g}$  sample from the ground  
 269 leaves was then microbalanced. The sample was then put in a capsule in preparation for nitrogen  
 270 and carbon analysis. Carbon ( $C$ ) and nitrogen ( $N$ ) content were measured by flash-  
 271 combustion/oxidation using a Thermo Finnigan Flash EA 1112 elemental analyzer (0.06%  $C$  and  
 272 0.01%  $N$  detection limits. We express  $C$ ,  $N$  data in terms of concentration (% , g (100 g dry  
 273 matter)<sup>-1</sup>) and content per unit leaf area (g  $N$  cm<sup>-2</sup>).

274

275 ***Linear mixing model***

276 Linear mixing models are useful tools for summarizing changes in observations caused by  
 277 differences in the proportional contribution of so-called “end-members” (Adams et al. 1995). For  
 278 this analysis we used a mixing model with two end members, to test the hypothesis that seasonal  
 279 changes in camera-derived greenness could be explained by a combination of canopy LAI  
 280 (controlling the relative contribution of leaf vs. background) and seasonal changes in leaf color.  
 281 Because the contribution of both these end members is proportional to the leaf area within the  
 282 camera field of view, both were modified by a scaling factor dependent on LAI. More formally,  
 283 our model is expressed as:

284 
$$G_{cc}(t) = (1 - F_t)G_{cc}^B + F_t G_{cc}^L(t) \quad (1)$$

285 where  $G_{cc}(t)$  is the camera derived green chromatic coordinate at time  $t$ ,  $G_{cc}^B$  is the mean  
 286 background (winter) camera derived green chromatic coordinate,  $G_{cc}^L(t)$  is the scanner derived  
 287 green chromatic coordinate of individual leaves, and  $F_t$  is the fraction of the camera field of view  
 288 that contains green leaves. Following Beer’s law,  $F_t$  is a nonlinear function of LAI and can be  
 289 estimated as  $F_t = 1 - \exp(-kLAI(t))$ , where  $k$  is an optimized parameter to account for clumping  
 290 and the oblique viewing angle of the camera.  $k$  is therefore the only free parameter in the model,  
 291 and is optimized by minimizing the root mean square error between the model predictions and  
 292 the observed camera  $G_{cc}$  values.

293

294 **Results**

295

296 *Phenology of greenness, leaf area index and gross primary productivity*

297 The characteristic seasonal cycle of camera-derived  $G_{cc}$  (e.g., Sonnentag et al. 2012) was  
 298 observed each year (Fig. 1). Typical characteristics of this cycle include a steep rise and clear  
 299 peak in spring, followed by a continuous decline over summer and a steep decline during autumn  
 300 to a constant minimum in winter. Spring LAI followed the steep rise in spring  $G_{cc}$ , although LAI  
 301 consistently lagged  $G_{cc}$  (Fig. 1). In contrast to the spring peak and subsequent summer decline of  
 302  $G_{cc}$ , LAI continued to increase after peak  $G_{cc}$ , and did not decline until autumn. On average,  
 303 declines in autumn LAI lagged declines in autumn  $G_{cc}$ , reflecting changing leaf color before  
 304 actual leaf abscission.

305

306 An ice-storm in December 2008 significantly damaged the canopy at Harvard forest and lead to a  
 307 22% reduction in mid-summer LAI in 2009 compared to 2008 (Fig. 1). Mid-summer  $G_{cc}$  was  
 308 relatively unaffected by this large decline in LAI, suggesting that  $G_{cc}$  is insensitive to changes in  
 309 leaf area at high LAI levels. Mean mid-summer LAI increased steadily each year from 2009  
 310 through 2012, and had almost recovered to pre-ice-storm levels within four years.

311

312 Daily GEP was highly correlated with both LAI ( $R^2=0.79$ ,  $p<0.01$ ) and  $G_{cc}$  ( $R^2=0.76$ ,  $p<0.01$ ).

313 As with LAI, increases in spring GEP lagged increases in  $G_{cc}$ . The timing and rate of increase in  
 314 spring GEP matched the rate of increase in spring LAI in all years except 2008 (Fig. 1). A late  
 315 summer decline in GEP was evident in most years, which did not closely match either  $G_{cc}$  or  
 316 LAI. In contrast to previous suggestions that Hue is more correlated to GEP and LAI than  $G_{cc}$



317 (Mizunuma et al. 2013), we found no positive correlation between Hue and GEP ( $R=-0.2$ ,  
 318  $p=0.03$ ) or LAI ( $R=-0.3$ ,  $p<0.01$ ) at our site. Indeed the seasonal cycle of Hue is critically  
 319 dependent on the color balance of the camera (Fig. S1), and is thus unlikely to be suitable for  
 320 multi-site applications.

321

322 ***Phenological transitions***

323 Spring bud-burst and autumn coloration dates obtained from the camera images were positively  
 324 correlated with the ground observation. Spring bud-burst dates from ground observations varied  
 325 by two weeks over the five years (2008-2012), with the earliest bud-burst on day 116, and the  
 326 latest on day 128. Bud-burst dates extracted using a greendown sigmoid model (Elmore et al.  
 327 2012) correlated well ( $R^2=0.66$ ,  $p<0.1$ ) with interannual variability in observed bud-burst dates,  
 328 with a mean bias of 3.5 days (Fig. 2a). However, dates extracted from the sigmoid model  
 329 exhibited lower variance than the field observations. The Elmore model performed poorly at  
 330 predicting late springs (Fig. 2a), giving a slope between observed and predicted that differed  
 331 significantly from 1.0. A spring bud-burst  $G_{cc}$  threshold of 0.38 (15% of the mean amplitude;  
 332 Fig. 2a), identified dates that were more highly correlated to the field observations ( $R^2=0.95$ ,  
 333  $p<0.01$ ) than those from the greendown model, suggesting that the sigmoid model approach  
 334 could potentially be improved. Peak  $G_{cc}$ , estimated by curve fitting, corresponded to the  
 335 previously-mentioned spike in greenness that immediately follows the rapid spring green-up. The  
 336 timing of peak  $G_{cc}$  corresponded most closely to 50% leaf size, with leaves not reaching their  
 337 maximum size until 2-3 weeks later (Fig. 2b). Autumn dates of maximum coloration were  
 338 particularly well captured by the greendown sigmoid model ( $R^2=0.84$ ,  $p<0.1$ , Fig. 2c).

339

340 ***Phenology of leaf-level traits***

341 The measured physiological and morphological leaf traits showed marked seasonal dynamics. In  
 342 particular, chlorophyll fluorescence  $F_v/F_m$ , area and mass, nitrogen, carbon and water content,  
 343 took roughly 35 days from bud-burst to reach their maximum values (Fig. 3). This phenology of  
 344 leaf-level traits was not captured by broadband NDVI, camera  $G_{cc}$ , or the MODIS EVI and  
 345 NDVI products (Fig. 3). Each of these metrics reached their maximum about two weeks after  
 346 bud-burst, about two weeks before the end of spring leaf elongation. Chlorophyll indices (MTCI,  
 347 ChlNDI) calculated from leaf-level spectral reflectance indicate that leaf chlorophyll content  
 348 increased throughout most of the summer, with declines becoming apparent around day-of-year  
 349 (DOY) 240. In contrast, PRI from the leaf level spectra was relatively constant throughout the  
 350 season, declining only at the start of leaf coloration in the autumn (Fig. 3). Leaf angle, previously  
 351 hypothesized to be a potential cause of changes in canopy greenness (Sonntag et al. 2012), was  
 352 relatively constant throughout the year in our data. It should be noted that leaf angle  
 353 measurements directly after bud-burst were not made.

355 ***Linking phenology of leaf color, canopy structure, and camera  $G_{cc}$***

356 Sampled leaves were scanned on a flatbed scanner and leaf color information (red, green and  
 357 blue digital numbers) was extracted from the resulting images. Early season leaves were bright  
 358 yellowish-green, leading to high values of scanner derived  $G_{cc}$  (Fig. 4). Green and red declined  
 359 sharply throughout spring (and to a lesser extent through summer) until autumn, when red  
 360 increased as leaves changed color before senescing. The blue component of leaves gradually  
 361 increased throughout the season. The net effect was a steady decline in leaf level  $G_{cc}$  throughout

362 summer, with a sharp decline in autumn (Fig. 4), which paralleled patterns observed in the  
 363 camera-derived  $G_{cc}$ .

364  
 365 To test whether seasonal changes in camera  $G_{cc}$  could be explained by a combination of observed  
 366 dormant season canopy color, leaf area index and leaf color we used the linear mixing model  
 367 defined by Eq. (1). The model, with one free parameter, accurately reproduced the seasonal cycle  
 368 of camera  $G_{cc}$  ( $R^2=0.98$ ,  $p<0.001$ ), including the dynamics of the spring peak green (Fig. 5). This  
 369 shows that camera derived canopy greenness is a combination of leaf color and background  
 370 color, with the proportional contribution of each being linearly related to gap fraction. Gap  
 371 fraction is a non-linear function of leaf area, compounded by the oblique (rather than nadir) view  
 372 angle of the camera.

373  
 374 ***Scaling from the leaf to the landscape***

375 We used daily MODIS red, green, blue and near-infrared surface reflectance to calculate daily  
 376 MODIS  $G_{cc}$ , EVI and NDVI for the study area. The MODIS  $G_{cc}$  closely matched seasonal  
 377 dynamics of EVI, showing the same characteristic decline through the summer, while MODIS  
 378 NDVI remained relatively invariant during summer months (Fig. 6a). Peak-green (curve-fit  
 379 estimate) from the camera-derived  $G_{cc}$  corresponded to the time at which the MODIS derived  
 380 indices reached 50% of their amplitude (Fig. 6a). The sharp inflection point apparent in the  
 381 autumn NDVI signal suggests it may be a better-constrained metric for estimating autumn  
 382 phenology than EVI or  $G_{cc}$ .

383

384 **Discussion**

385

386 We used five years of concurrent digital repeat photography, biometric measurements, and eddy-  
 387 covariance estimates of gross daily ecosystem photosynthesis to assess the relationship between  
 388 information extracted from digital repeat photography, canopy structure, and leaf -level  
 389 physiological and morphological traits. The results show that camera-derived canopy greenness  
 390 can effectively identify inter-annual variability in spring bud-burst and autumn senescence. That  
 391 said, the rate of increase in spring canopy greenness and the date at which peak green is reached  
 392 was not a linear function of LAI. On average, peak green occurred two weeks before maximum  
 393 LAI, and spring dynamics in physiological and morphological leaf traits (e.g. maximum leaf  
 394 area, chlorophyll fluorescence, leaf mass, nitrogen and carbon content), all lagged the timing of  
 395 spring peak green from the camera.

396

397 Previous studies have hypothesized that the well defined “spring peak” in canopy greenness  
 398 observed at Harvard Forest (and other deciduous-dominated forest sites) is related to changes in  
 399 leaf-level traits (e.g. pigmentation and LMA), changes in canopy structure (i.e. leaf size, shape,  
 400 orientation), or some combination thereof (e.g. Sonnentag et al. 2012). We show that the spring  
 401 peak in canopy greenness, as derived from camera  $G_{cc}$ , does not correspond to abrupt changes in  
 402 any single leaf- or canopy-level trait. Rather, our modeling demonstrates that seasonality of  
 403 canopy greenness, including the timing and shape of the spring peak, is driven by simultaneous  
 404 changes in both leaf color *and* canopy structure (i.e. seasonality of leaf area index and gap-  
 405 fraction). The oblique viewing angle of the camera leads to a higher effective LAI within the  
 406 camera field of view (i.e., the camera sees more layers of leaves than it would if images were

407 taken looking straight down). For spring, this implies a faster increase in canopy greenness than  
 408 actual increases in LAI. The oblique viewing angle of the camera thus facilitates identification of  
 409 spring bud-burst dates by enhancing the rate of increase in spring  $G_{cc}$ . On the other hand, the  
 410 oblique viewing angle leads to saturation of  $G_{cc}$  at relatively low LAI. During summer, declines  
 411 in greenness are shown to be linearly related to leaf ontogeny and aging (Jenkins et al. 2007),  
 412 and related changes in leaf structure and pigmentation, which together influence leaf color. The  
 413 combined changes demonstrate a strong non-linear relationship between canopy greenness,  
 414 canopy structure, and leaf physiology. This also suggests that while it is feasible to back-  
 415 calculate the seasonality of canopy LAI from a seasonal trajectory of canopy greenness,  
 416 knowledge of the concurrent changes in the color of individual leaves is needed to do this  
 417 accurately.

418  
 419 Previous studies (e.g. Hufkens et al. 2012b) indicate that digital camera imagery can be used to  
 420 detect the impact of disturbances on vegetation. Our results show that  $G_{cc}$  was insensitive to  
 421 substantial interannual changes in maximum leaf area index, which were primarily caused by  
 422 damage from a winter ice-storm. Other studies have reported similar difficulty in detecting  
 423 events that induce defoliation (Mizunuma et al. 2013). Our analysis resolves this apparent  
 424 contradiction in the literature. We show that camera-derived greenness is a saturating, non-linear  
 425 function that is driven by developmental changes in leaf color and the affect of leaf area index on  
 426 the mixing of leaf color with background color showing through gaps in the canopy. Thus, in  
 427 order for a disturbance to be detectable, it must either cause a change in leaf color or sufficient  
 428 defoliation to create gaps in the canopy. In our study, for example,  $G_{cc}$  was relatively insensitive  
 429 to additional increases in leaf area above  $LAI \approx 2.5$ .

430

431 Based on this result we can identify two classes of disturbance: those that induce leaf color  
 432 change and canopy gaps (detectable) and those that lower canopy leaf area index but do not  
 433 create additional gaps within the camera field of view (non-detectable for non-catastrophic levels  
 434 of leaf loss). For example, the ice-storm in the winter of 2008 that led to a 22% reduction in  
 435 maximum LAI was not detectable in camera-derived greenness, as no changes in leaf coloration  
 436 were induced and a reduction in LAI of 22% was not sufficient to increase the proportion of gaps  
 437 in the camera field of view. In contrast, the disturbance event examined by Hufkens et al.  
 438 (2012b) induced leaf coloration before leaf abscission, thus generating a detectable signal in  
 439 camera derived greenness. It should be noted, however, that even if leaf coloration is induced, it  
 440 is possible that a significant proportion of leaves will fall while still green, producing an  
 441 undetectable change in leaf area index. Further, when damaged leaves fall from the canopy,  
 442 greenness can increase as previously covered green leaves become visible to the camera. Recent  
 443 studies have attributed the recovery of greenness post-disturbance to increased leaf area index  
 444 due to leaf re-flushing (e.g. Hufkens et al. 2012b). Studies using digital repeat photography to  
 445 characterize the effects of disturbance therefore likely underestimate the true magnitude of the  
 446 impact of disturbances in closed canopies.

447

448 Multiple models exist for extracting phenological information from time series of remotely  
 449 sensed vegetation indices. Simple thresholds are commonly used (e.g. Richardson et al. 2007),  
 450 along with curve-fitting techniques such as logistic fits (e.g., Zhang et al. 2003) and more  
 451 complex sigmoidal models (Elmore et al. 2012), among others (e.g., White et al. 2009). The  
 452 efficacy of any modeling approach will affect the quality of extracted phenological transition

453 dates, yet few studies have assessed how any given approach affects the results obtained (but see,  
 454 White et al. 2009, Garrity et al. 2010, Cong et al. 2013). In this analysis we show that a fixed  
 455 threshold based approach, is more effective for identifying spring bud-burst dates than a  
 456 greendown sigmoid model. While appropriate threshold values depend on camera settings  
 457 (Sonntag et al. 2012), the ecosystem or site in question, and may be sensitive to long-term  
 458 sensor degradation (Ide and Oguma 2010), our results indicate that using a threshold crossing  
 459 approach to phenological date estimation can be more accurate than curve-fitting approaches. A  
 460 detailed comparison of different curve-fitting methods, in combination with simple threshold-  
 461 based approaches, is needed.

462  
 463 Because autumn phenophase transition dates are much less well defined than spring counterparts,  
 464 they have been studied far less. Error estimates of autumn dates extracted from digital images  
 465 using the green-down sigmoid curve-fit approach were typically three times higher than those  
 466 extracted for spring as shown by the vertical error bars in Fig. 2. Despite this larger uncertainty,  
 467 camera-derived autumn dates corresponded closely to ground-based observations of autumn  
 468 transitions. The more pronounced inflection in MODIS NDVI time series compared to MODIS  
 469 EVI and MODIS  $G_{cc}$  suggests that the NDVI may be a better indicator of autumn transition  
 470 points than these other metrics.

471  
 472 Our results show that automated digital cameras can be very effective for detecting the start and  
 473 end of the growing season, with phenological transition dates derived from canopy imagery  
 474 corresponding well to direct human observations. However, our results also highlight many  
 475 factors that affect the interpretation of changes in canopy greenness during the growing season.

476 To maximize the utility of this relatively inexpensive instrument, several developments could be  
477 explored to resolve within-growing-season issues. The use of standard automated digital cameras  
478 in combination with high-quality filters provides an opportunity to isolate different parts of the  
479 leaf reflectance spectrum. This could enable camera-based vegetation indices to be calculated  
480 that are more closely linked to canopy physiology. For instance, near-infrared enabled cameras  
481 could provide an opportunity to calculate various broadband (albedo, NDVI) reflectance indices  
482 (Steltzer and Welker 2006, Higgins et al. 2011), or a pair of narrow-band filters ( $530\pm 5$  and  
483  $570\pm 5$  nm) could be used to measure PRI. Combining such cost-effective advances in camera  
484 technology with other near-surface remote sensing techniques (e.g. photodiodes (Garrity et al.  
485 2010), light-emitting diodes (Ryu et al. 2010a), spectroradiometers, and commercially available  
486 broadband and narrowband radiometric sensors), have significant potential to advance the field  
487 of near surface remote sensing with automated digital cameras.

488

489



490 **Conclusion**

491

492 The use of automated digital cameras for monitoring vegetation status is becoming widespread.  
 493 Digital repeat photography has been used to characterize the development of leaf area (Garrity et  
 494 al. 2011), correlated to canopy CO<sub>2</sub> fluxes (e.g., Richardson et al. 2007, 2009, Ahrends et al.  
 495 2009, Migliavacca et al. 2011) and compared to satellite based phenology metrics (Hufkens et al.  
 496 2012a). The approach has become central to phenological networks around the world  
 497 (Richardson et al. 2007, Wingate et al. 2008). Despite the widespread application of automated  
 498 digital cameras for phenological research, there has yet to be a critical assessment of the  
 499 relationship between color indices extracted from digital repeat photography, leaf physiology,  
 500 and canopy structure.

501

502 Here we use five years of ground observations of phenology, and detailed measurements of  
 503 canopy structure and leaf physiology, in combination with satellite remote sensing, to show that  
 504 observed phenological transitions of bud-burst and leaf senescence can be well characterized by  
 505 digital repeat photography. However, the development of canopy leaf area, and key  
 506 physiological and morphological leaf traits, lags behind camera-derived green-up in spring. Our  
 507 mixing model analysis shows that the seasonal cycle of canopy greenness is driven by the  
 508 combined effects of changes in canopy structure (i.e. seasonality of leaf area index) as well as  
 509 changes in the color of individual leaves (i.e., ontogeny and associated changes in pigmentation).  
 510 We discuss implications for the interpretation of seasonal changes in canopy greenness, and the  
 511 use of camera-derived canopy greenness to quantify disturbance impacts. Characterizing the

512 relationship between camera greenness, leaf physiology and canopy structure across a variety of  
 513 ecosystems will be a valuable focus of future work.

514

515

516

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694 A comparison of seasonal changes in Gcc vs seasonal changes in Hue

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**Figure 1.** Observations of leaf area index (green), eddy-covariance derived daily gross primary photosynthesis (GPP, blue), and camera derived green chromatic coordinate ( $G_{cc}$ , black), for five years at Harvard forest, MA, USA. All values are normalized relative to the mean annual maximum and minimum values. An ice storm in December of 2008 is indicated, which caused severe structural damage to the forest.

**Figure 2.** Camera derived phenophase transitions (bud-burst, peak green, end of fall) compared with ground observations of bud-burst, leaf size and leaf fall color at 50, 75 and 95% of their maximum annual value. All phenophase transitions are derived using a ‘greendown’ sigmoid curve fit to the camera  $G_{cc}$  data, with the exception of spring bud-burst dates extracted using a simple  $G_{cc}$  threshold of 0.38, shown in panel 1.

**Figure 3.** Measurements of leaf fluorescence ( $F_v/F_m$ ), spectral indices (PRI, MTCL, ChlNDI), leaf area, mass per area (LMA), water content (LWC), % carbon (C), and % nitrogen (N), MODIS EVI and NDVI, broadband NDVI (BB NDVI), mean leaf angle, and plant area index derived from fPAR (stars) and LAI-2000 (circles). Dashed vertical lines represent ground observations of 50% bud-burst, 95% leaf size, 50% leaf color and 50% leaf fall. The solid vertical line marks the date of camera-derived peak green. Note that end of autumn near-zero values of  $F_v/F_m$  are not shown.

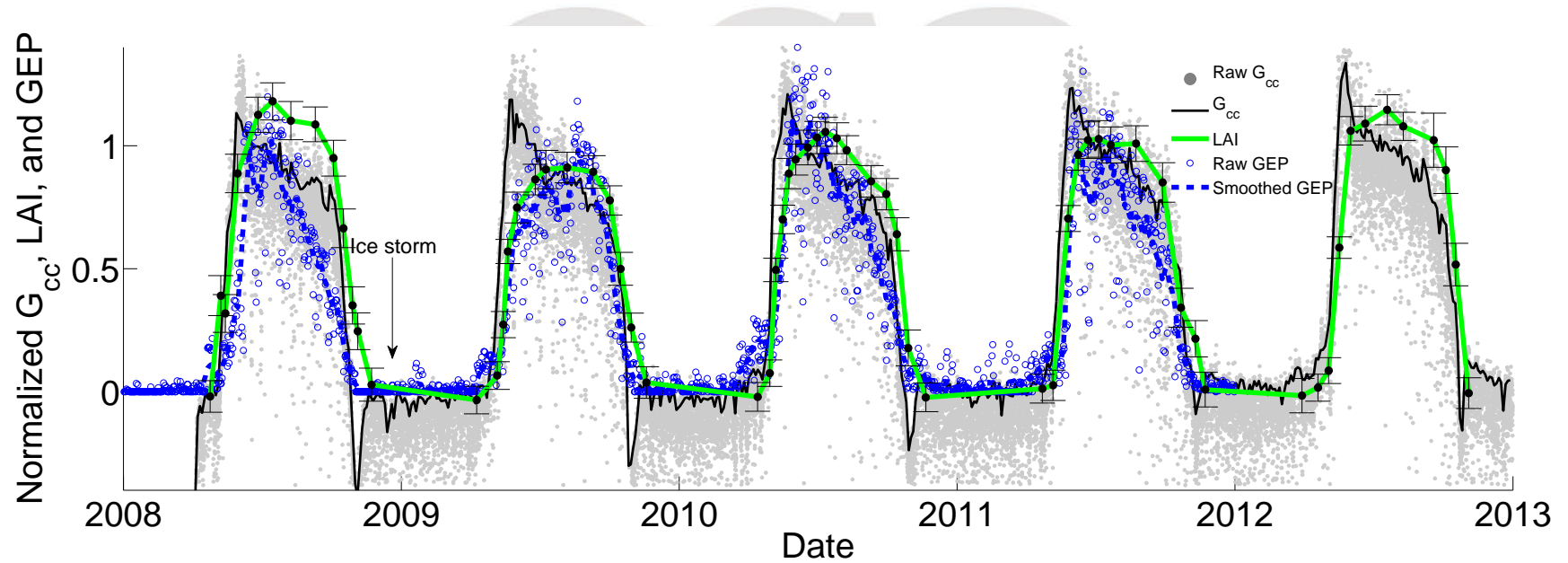
**Figure 4.** Red, Green and Blue digital numbers extracted from scanned Red Oak leaves during the growing season of 2011. Reference colors were included in each image (colored dashed lines). The extracted digital numbers were used to calculate the green chromatic coordinate for

each image (black dashed line). Actual leaf colors for each sample date are given as reference (filled circles).

**Figure 5.** Camera  $G_{cc}$  (observed, diamond) and estimated  $G_{cc}$  estimated using a linear mixing model of leaf area, gap fraction, and leaf color (closed circles). The inset shows the contribution of the two end-members.  $m1$ : the contribution of background color extinction ( $m1=(1-Ft) G_{cc}^B$ , Eq. 1);  $m2$ : the combined contribution of leaf area and color ( $m2=FtG_{cc}L(t)$ , Eq. 1)

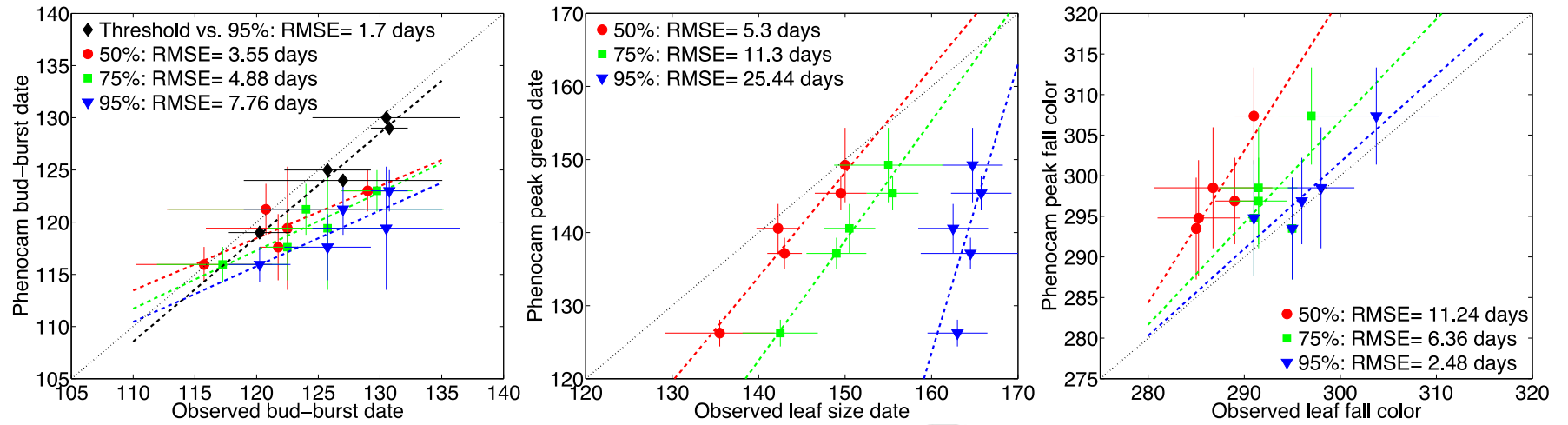
**Figure 6. (a)** Mean daily red, green and blue and near-infrared (NIR) MODIS reflectance, for the period 2001-2011, for the pixel centered on the EMS flux tower of the Harvard forest (MA, USA), and the derived MODIS  $G_{cc}$ , EVI and NDVI. **(b)** Mean daily red, green and blue Phenocam digital numbers for the period 2008-2012 at the Harvard forest (MA, USA), and the derived Phenocam  $G_{cc}$ . Vertical dashed line indicates the mean peak  $G_{cc}$  over all years.

Figure 1.



Preprint

Figure 2



preprint

Figure 3

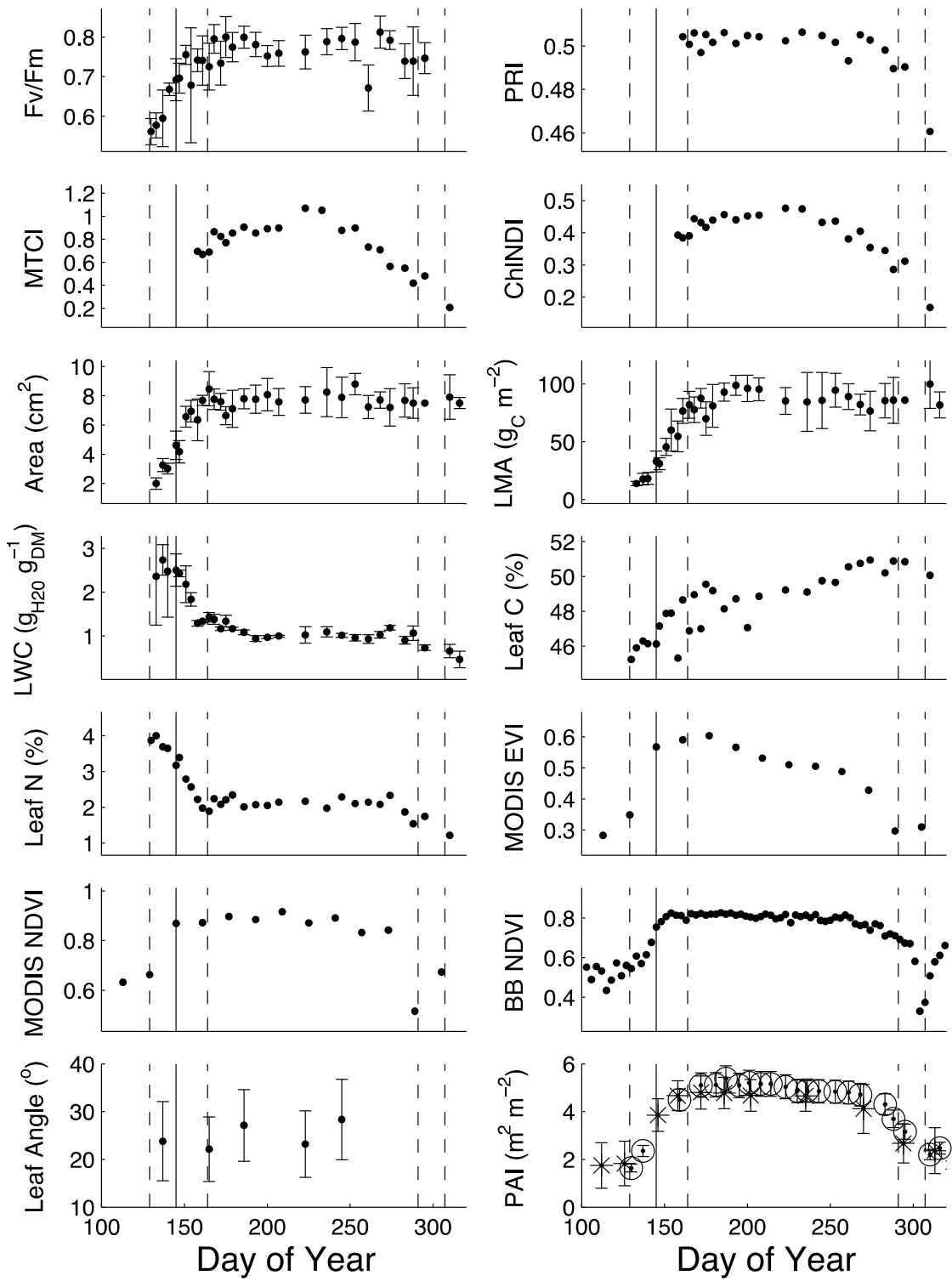
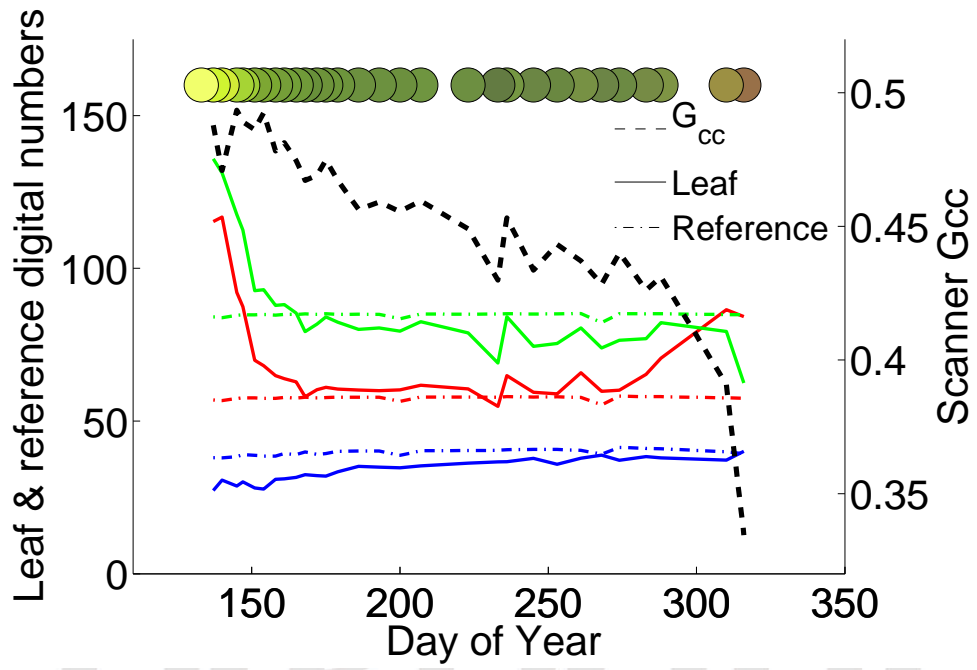




Figure 4



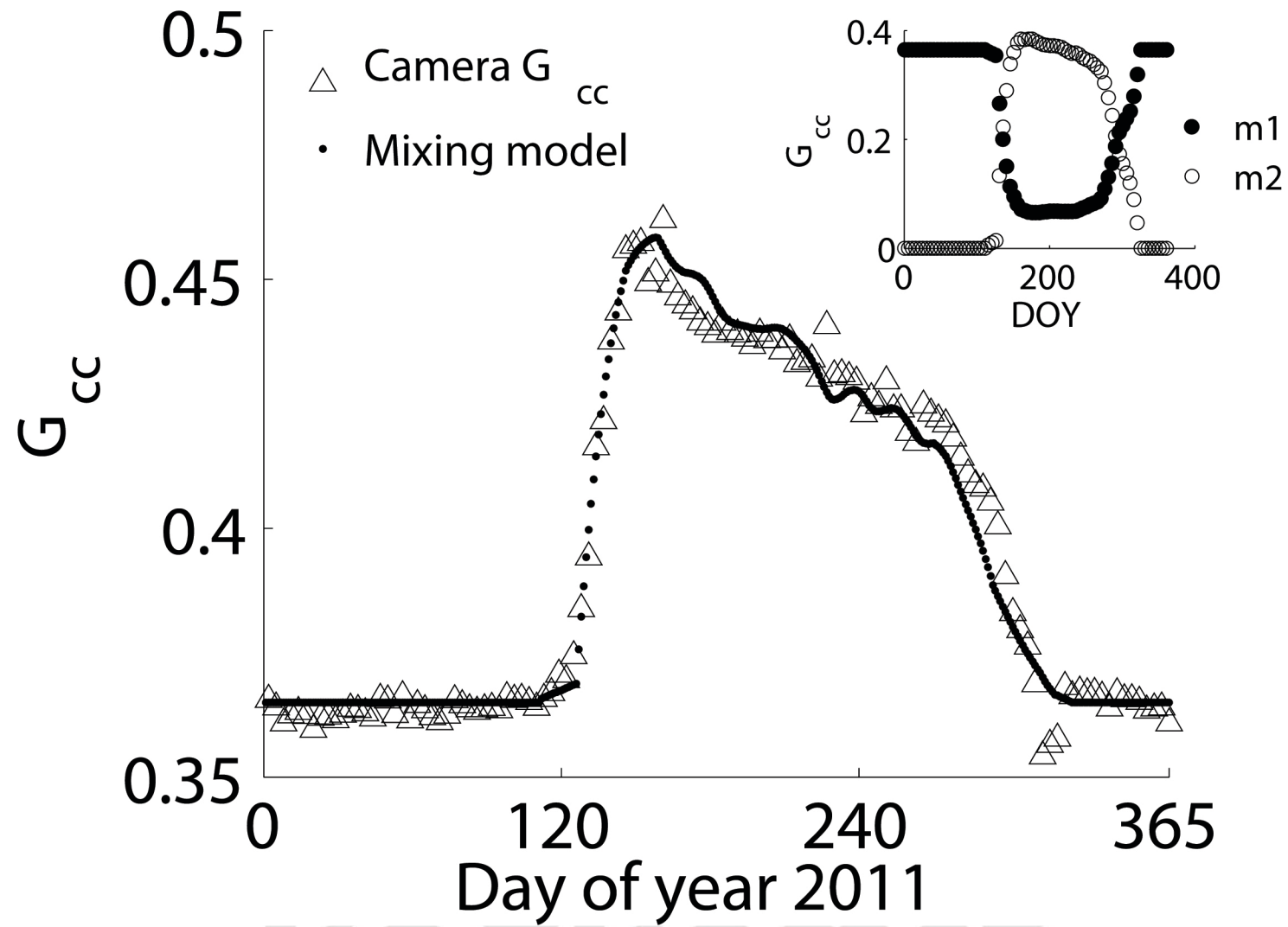


Figure 6

