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1 **A comparison of ground-based methods for**
2 **obtaining large-scale, high resolution data on the**
3 **spring leaf phenology of temperate tree species**

4

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13

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17

18 **Abstract**

19 Phenological variation in spring leafing between and within species can determine plant
20 responses to warmer winter and spring temperatures in the short term. Methods are
21 needed for monitoring canopy development that can be replicated on a large-scale,
22 while retaining fine-scale resolution at the level of individual trees. Citizen science has
23 potential to provide this, but a range of approaches exist in terms of the phenophase
24 recorded (e.g., budburst or leaf expansion), how the phenophase is characterised (first
25 events or intensity monitoring), and the portion of tree crown assessed and observation
26 frequency. A comparison of spring budburst and leaf expansion of four tree species
27 (*Fraxinus excelsior*, *Fagus sylvatica*, *Quercus robur* and *Acer pseudoplatanus*) was
28 monitored in one woodland using (1) counts of expanded leaves on three crown
29 sections, (2) percentage estimates of expanded leaves across the whole crown, and (3)
30 a greenness index from photography. Logistic growth models were applied to make
31 comparisons. First-event dates were found to be misleading due to high variation in leaf
32 development rates within and between species. Percentage estimates and counts
33 produced similar estimates of leaf expansion timing and rate. The greenness index
34 produced similar estimates of timing, but not rate, and was compromised by
35 practicalities of photographing individual crowns in closed canopy woodland. Citizen
36 scientists could collect data across the period of spring leafing, with visual counts and/or
37 estimates made every 3–4 days, subject to tests of reliability in pilot citizen science
38 studies.

39 **1. Introduction**

40 Changes in leaf phenology of temperate trees are one of the best studied and most
41 recognisable impacts of climate change, with evidence of earlier leafing with warmer
42 spring temperatures over the last 50–60 years (Menzel and Fabian 1999; Menzel et al.
43 2006; Polgar and Primack 2011; Fu et al. 2015; Melaas et al. 2018). Phenological data
44 at the ecosystem level are now often obtained from remote-sensing, capturing
45 phenological trends at regional and global scales, but at coarse temporal and spatial
46 resolutions (Buitenwerf et al. 2015; Crabbe et al. 2016; Hamunyela et al. 2013; Wang et
47 al. 2016; White et al. 2014; Wu and Liu 2013). By contrast, ground-based observations
48 gather species and site-specific information, but tend to lack geographic coverage and
49 vary considerably in their approaches to characterising phenology (Denny et al. 2014).

50 While many studies have focussed on identifying large-scale phenological patterns, few
51 have investigated how changes in phenology affect local-level forest ecosystem
52 dynamics (Cole and Sheldon 2017). Leaf phenology is fundamental to tree growth,
53 fitness and survival (Chuine 2010; Vitasse et al. 2009b), and timing of canopy
54 development has widespread implications for competition dynamics and trophic
55 interactions (Cole and Sheldon 2017; Roberts et al. 2015; Thackeray et al. 2010).
56 Therefore, understanding subtle changes in timing and order of leaf expansion in a
57 forest ecosystem is important.

58 Since forests are highly heterogeneous, there is a need for widespread monitoring of
59 forests at high spatial and temporal resolution. Phenology at the local level varies
60 according to species composition and genetic diversity (Basler 2016; Cleland et al.
61 2007; Polgar and Primack 2011). Environmental factors such as topography (Fisher et
62 al. 2006) and soils (Arend et al. 2016; Lapenis et al. 2017) can vary markedly over small
63 spatial gradients, and influence phenology at scales missed by remote-sensing.

64 Therefore, harmonised methods that enable large-scale data collection on the
65 phenology of individual trees are needed to understand impacts on ecosystem
66 dynamics and biodiversity.

67 Monitoring methods that detect subtle changes in the sequence of leaf expansion
68 among different tree species will be important for predicting future changes in forest
69 composition. For example, Roberts et al. (2015) predicted a shift away from
70 phenological complementarity, increasing competition for light and soil moisture, and

71 driving changes in forest composition over time. Monitoring methods also need to detect
72 within-species variability. Variation within species occurs between populations as a
73 result of genetic adaptation to environmental conditions, particularly in relation to
74 latitude and altitude (Chmura and Rozkowski 2002; Vitasse et al. 2009b). Delpierre et
75 al. (2017) found that within-population genetic and phenotypic variability in budburst
76 dates for oak and beech were more important than local environmental factors though
77 this is likely to vary according to the heterogeneity of the forest site. Marked differences
78 between neighbouring individuals of the same species demonstrate the need for high
79 levels of replication of individual trees within and between sites. The extent of genetic
80 and/or phenotypic variation within a species population could determine its persistence
81 in a forest ecosystem. It could also determine the survival of insect species with
82 synchronised life-cycles, and in turn the species that depend on them for food (Cole and
83 Sheldon 2017).

84 At present the approaches used in observational studies to characterise leaf phenology
85 vary considerably. Key historic phenological records are based on first event dates
86 (Primack and Miller-Rushing 2012; Sparks and Carey 1995) and many subsequent
87 studies have characterised tree leaf phenology based on first budburst or first leaf
88 expansion (Collinson and Sparks 2008; Menzel and Fabian 1999; Polgar et al. 2014;
89 Roberts et al. 2015; Schaber and Badeck 2005; Fu et al. 2015). A number of
90 international and national phenology monitoring programmes use first event metrics
91 (Chmielewski No date; Project Budburst 2017; Nature's Calendar 2017; NatureWatch
92 Canada 2017) as they need less survey effort (Miller-Rushing et al. 2008). Although
93 some studies have shown correlations between different phenophases in tree leafing
94 (e.g., Vander Mijnsbrugge and Janssens 2019), there is some evidence that relying on
95 budburst dates alone to represent leafing phenology could lead to the misrepresentation
96 of leaf development as a whole (Richardson and O'Keefe 2009).

97 As an alternative to recording first budburst or first leaf expansion dates, some studies
98 have recorded multiple dates to identify transitions between phenophase growth stages,
99 using standardised scales such as the BBCH system (Finn et al. 2007) or bespoke
100 indices (Capdevielle-Vargas et al. 2015; Cole and Sheldon 2017; Richardson et al.
101 2006; Vitasse et al. 2009a). Recently the USA National Phenology Network (USA-NPN)
102 introduced status and intensity monitoring into their citizen science programme (Denny
103 et al. 2014; Elmendorf et al. 2016). Observers are encouraged to record both the

104 phenophase growth stage and the intensity, for example by estimating the percentage
105 budburst or leaf expansion, in order to track the entire progress of canopy development
106 for individual trees. The advantage of collecting time-series for individual trees is it
107 enables the rate of canopy development to be established, and peak leaf development
108 timing to be identified. However, as observations increase in complexity, data quality
109 challenges arise. Lower levels of accuracy have been reported when citizen scientists
110 have to identify emerging leaves, as opposed to expanding leaves, as the former is
111 harder to identify, particularly when the canopy is very high (Fuccillo et al. 2015).
112 Subjectivity associated with visual estimates can also be a problem leading to between-
113 observer bias (Morrison 2016), particularly where a large and variable canopy is being
114 considered, and can be affected by training and experience (Bison et al. 2019; Feldman
115 et al. 2018).

116 Observations should be made frequently enough to detect subtle variation in leaf
117 expansion timing between and within species. Observational studies have monitored
118 trees every other day (Wesolowski and Rowinski 2006), 2–3 times per week
119 (Capdevielle-Vargas et al. 2015; Cole and Sheldon 2017), once a week (Delpierre et al.
120 2017; Richardson et al. 2006) and every 10 days (Vitasse et al. 2009a). Remote-
121 sensing tends to obtain data sets with an 8–16 day resolution due to loss of images
122 from cloud cover and atmospheric interference (Hamunyela et al. 2013; Ahl et al. 2006).
123 It would be useful to determine how estimates of the same phenological process are
124 affected by observations at different temporal grains, *i.e.*, every two days, four days *etc.*

125 Near-surface remote sensing techniques have emerged that provide high spatial and
126 temporal resolution data on phenology of individual trees (Jeong et al, 2013; Keenan et
127 al. 2014). Digital cameras or Normalised Difference Vegetation Index (NDVI) sensors
128 that track canopy greening can be positioned just above the canopy, and capture data
129 at multiple intervals per day. These methods detect green signals that indicate leaf
130 emergence and development with high accuracy (Inoue et al. 2014; Soudani et al.
131 2012). They are not affected by cloud conditions as is satellite imagery (Polgar and
132 Primack 2011), but may be affected by understorey greening (Inoue et al. 2014).
133 Sideways-facing cameras, as used in the Phenocams network in the USA (Richardson
134 et al. 2007) and the Phenological Eyes Network in Japan (Inoue et al. 2014), are less
135 influenced by the understorey, though image quality can be affected by light conditions
136 (Mizunuma et al. 2012). With both types of imagery it is possible, though sometimes

137 difficult, to isolate trees so that time-series of individual tree canopy development can be
138 derived (Inoue et al. 2014; Polgar and Primack 2011). Despite the lower cost associated
139 with these techniques, in comparison to manually operated techniques such as
140 hemispherical photography (Richardson et al. 2007; Soudani et al. 2012), the cost and
141 logistics of installing equipment still limit this approach to a relatively small number of
142 sites.

143 Given the recent rise in citizen science and phenology monitoring, citizen scientists
144 could repeatedly photograph tree crowns and branches at fine spatial and temporal
145 resolutions, avoiding time-consuming visual estimates with potential for between-
146 observer bias. However, the practicalities of photographing individual tree crowns and
147 branches from the ground within a forest requires testing, along with the derivation of
148 phenological metrics from the photographic sequences.

149 In this study, we aim to test three different approaches to monitor the progress of spring
150 canopy leafing in four species of tree in an English woodland: (1) counts of expanded
151 leaves on three crown sections, (2) percentage estimates of expanded leaves across
152 the whole crown, and (3) a greenness index from photography. We used these
153 observations to determine key parameters of the time-series data, including first
154 budburst, 50% completion estimates, and 95% leafing completion. We consider the
155 potential use of these methods by citizen scientists in monitoring programmes
156 associated with climate change.

157 2. Materials and methods

158 2.1. Study site and data collection

159 The study took place in Widey Woods, an 8 ha broadleaved woodland in Plymouth,
160 England (50°24 N, 7°7 W), during spring 2015. The four tree species included were
161 European ash (*Fraxinus excelsior*), European beech (*Fagus sylvatica*), pedunculate oak
162 (*Quercus robur*) and sycamore (*Acer pseudoplatanus*). These were selected as they
163 were dominant in the canopy of the study site, and are widespread across European
164 temperate forests. Ten mature trees from each species were haphazardly selected for
165 inclusion and GPS-marked for ease of relocation. Trees were selected within the
166 diameter at breast height (DBH) size of 20–60 cm. Average DBH was 35 cm (± 10 cm)
167 and average height was 18 m (± 4 cm).

168 The same observer visited trees each week from the middle of February 2015 to look
169 for signs of imminent budburst, indicated by swelling. Checks began three weeks prior
170 to earliest reported budburst for target species (Elmendorf et al. 2016), based on
171 budburst records from the previous year for south-west England (Nature's Calendar
172 2017). Bud-swelling was evident from the last week in March, so trees were visited
173 every other day from then onwards, until all trees had attained full leaf expansion (2
174 June).

175 First budburst was recorded as the day of year (DOY) when green leaves were first
176 visible emerging between bud scales at any location on the tree. First leaf expansion
177 was recorded as the DOY when the first leaf with characteristic shape for its species
178 was visible on the tree. From the date of first leaf expansion, two different methods of
179 visual estimation were used to monitor canopy development. First, the extent of leaf
180 expansion across the whole crown was estimated as a percentage of buds with
181 expanded leaves. Estimates were made in increments of 5% between 5–100%, but
182 allowed for smaller increments between 1–5% so that early activity could be captured.
183 Secondly, counts were made of expanded leaves in three sections of the crown. These
184 sections were established prior to first budburst, and reference photographs were taken
185 to ensure the same areas were assessed on each visit. In each section, a count was
186 made of the number of buds out of 50 that had at least one fully expanded leaf present,
187 giving a total count out of 150 buds. Binoculars with x10 magnification were used to aid
188 observations, and a clicker counter used to reduce risk of counting errors.

189 For each tree, data were converted along a proportional scale from 0 to 1, with 0
190 representing the crown prior to leaf expansion, and 1 representing the crown with full
191 leaf expansion. For count data, this was achieved using equation (1):

$$a = (x - crown_{MIN}) / (crown_{MAX} - crown_{MIN}) \quad (1)$$

194 Here, a represents the leaf expansion proportion for a given DOY, x is the number of
195 leaves out of 150 buds that were expanded on that DOY, $crown_{MIN}$ represents the
196 number of leaves expanded at the start of the time series (*i.e.*, 0), and $crown_{MAX}$
197 represents the number of buds with at least one fully expanded leaf at the end of the
198 time series. As the canopy estimate data were in percent increments, these were simply
199 divided by 100 to convert them to proportions.

200 In addition to visual observations, photographs were taken to estimate leaf development
201 on a subset of eight of the surveyed trees (four ash, two beech, one oak and one
202 sycamore). The same crown sections that were used for counts were photographed,
203 with the photographer standing at a fixed distance from the tree. Photographs were
204 taken using a Panasonic Lumix DMC-TZ35 16.1 MP camera. The camera was
205 handheld, and automatic exposure settings were used. It is important to note that while
206 photos were taken of the same tree sections that counts were conducted on, they
207 captured a larger area of the branch than the 50 buds assessed using the count
208 method. Furthermore, the size of branch area captured in a photo was not standardised
209 across the photographs, as the method was supposed to be rapid and easily used by
210 citizen scientists conducting a walk around a site. Photographing stopped once the
211 count data indicated all buds had expanded leaves.

212 Images were stored as JPEGs (4608 x 3456) and analysed using the open access
213 software ImageJ (Rueden 2016). The Region of Interest (ROI) manager was used to
214 ensure the area contained in the image for each tree section was consistent for each
215 date, accounting for small discrepancies in the original field of view. To estimate crown
216 greening, red, green and blue colour channels were separated and analysed
217 independently. The analysis was done using the multi-measure tool in the ROI manager
218 to derive mean digital numbers (DN) representing intensity for each colour channel. The
219 Greenness Index for each image was calculated using equation (2), after Richardson et
220 al. (2007).

221
$$\text{Greenness Index (\%)} = \frac{\text{Green DN}}{\text{Red DN} + \text{Green DN} + \text{Blue DN}}$$

222 (2)

223 Greenness Index values were then standardised on a proportional scale using equation
 224 (1), to provide a time-series of crown greening from 0 (no leaves) to 1 (maximum green
 225 signal). In this case, a in equation (1) is the Greenness Index proportion on a given
 226 DOY, x is the absolute Greenness Index value on that DOY, $crown_{MIN}$ is the minimum
 227 Greenness Index value (*i.e.*, from the first photo in the series where the crown section
 228 had no budburst), and $crown_{MAX}$ represents the highest Greenness Index value in the
 229 photo series. Proportions were averaged across the three crown sections to obtain a
 230 single time series of crown greening for each photographed tree.

231 **2.2. Deriving phenological metrics from time-series data**

232 A range of phenological metrics were derived to characterise the phenology of each
 233 individual tree. In addition to first budburst DOY and first leaf expansion DOY obtained
 234 from visual observation of the whole crown, full leafing was determined as the DOY
 235 when it was first observed that expanded leaves exceeded 95% (hereafter referred to
 236 as completion DOY). We then fitted each time series, obtained from both observational
 237 and photographic methods, using a logistic growth model to identify when expanded
 238 leaves/crown greening reached the half maximum (hereafter referred to as 50% DOY)
 239 and to characterise the rate of the process. For observational methods, time to 50%
 240 expanded leaves was then calculated as the number of days from first budburst to 50%
 241 DOY.

242 Logistic growth models have been widely used to characterise landscape and forest-
 243 level phenology from remote sensing data (Calders et al. 2015; Richardson et al. 2007;
 244 Zhang et al. 2003). Logistic growth uses non-linear regression to fit a sigmoidal curve,
 245 equation (3):

246
$$y = \frac{\theta_1}{1 + \exp [-(\theta_2 + \theta_3 x)]}$$

247 (3)

248 where y is the response variable (proportion of expanded leaves/greening), x is the
 249 predictor variable (DOY), and θ_1 , θ_2 and θ_3 are the model fitting parameters (Fox and
 250 Weisberg 2011). θ_1 is the upper asymptote. As the data were based on proportions, θ_1

251 was fixed at 1, as this was the maximum possible value. Two parameters are derived
252 from the model: the rate parameter (θ_3) and the half-maximum (ψ). The rate parameter
253 is based on the steepness of the curve at its mid-point and represented the proportional
254 increase per day. The half-maximum is a measure of timing, and represented the DOY
255 when expanded leaves/greening reached 50%, calculated as $\psi = \theta_2/\theta_3$, and hereafter
256 referred to as 50% DOY. Standard error and statistical significance of model parameter
257 estimates were assessed to provide a measure of confidence in the model fits for
258 individual trees. All logistic models were fitted using the car package and nls function in
259 R (Fox and Weisberg 2011).

260 Finally, we generated time-series to explore the effect of interval time between sampling
261 days (temporal grain) on 50% DOY and rate values from count and percentage estimate
262 data. The original data was collected every other day (two-day temporal grain), so
263 temporal grains of four-days and six-days were simulated by removing data for different
264 DOYs. Regardless of when leaf expansion began for each tree, the start date for
265 different temporal grains was held constant at DOY 107 for all time-series (which was
266 the DOY when leaf expansion was first observed across the monitored trees), as in
267 practise individual trees at a site would be monitored on the same days. Where the
268 DOY for $crown_{MAX}$ was removed as a result of altering the temporal grain, we inserted
269 the maximum value on the next DOY when data collection would have been carried out.
270 We then re-ran the logistic growth model for each tree.

271 **2.3. Statistical analyses**

272 Linear regression was used to explore relatedness between first budburst DOY, first leaf
273 expansion DOY, 50% DOY and completion DOY, based on observational methods
274 (count and percentage estimates). To explore whether these different metrics (and
275 methods) identified different phenological patterns between species, separate one-way
276 analysis of variance (ANOVA) tests were carried out for each metric and method,
277 followed by pairwise comparisons of species using Tukey Honestly Significant
278 Difference (HSD) tests. One-way ANOVA and Tukey HSD tests were also used to
279 identify whether the time to leaf expansion (*i.e.*, from first budburst to 50% DOY)
280 differed between species.

281 Linear regression was then used to explore relatedness between 50% DOY and rate
282 metrics from counts, percentage estimates and photographs. Where relationships were

283 identified, paired t-tests were conducted to assess whether the methods produced
284 different absolute values of 50% DOY and rate for individual trees. Finally, linear
285 regression and paired t-tests were used to compare 50% DOY and rate metrics derived
286 from the 2-day temporal grain, with those derived from 4-day and 6-day temporal grains.
287 All statistical analyses were carried out in R 3.3 (R Core Team, 2016).

288

289 **3. Results**

290 **3.1. Comparison of phenological patterns from first event dates vs. time-series** 291 **data**

292 Species were different in terms of first budburst dates (Supplementary Material Table 1;
293 Fig. 1), with pairwise comparisons showing that ash budburst was significantly later than
294 oak ($p = 0.003$) and sycamore ($p = 0.045$), but the other species were not different (p
295 > 0.05). There were significant differences between species in terms of first leaf
296 expansion and 50% DOY, and ash did not differ from other species ($p > 0.05$).

297 According to first leaf expansion dates, beech and oak were significantly different ($p =$
298 0.027) as were sycamore and oak ($p = 0.015$), with oak leaf expansion beginning later
299 than the other two species. However, using the 50% DOY only oak and sycamore were
300 different, with oak leafing later than sycamore ($p = 0.036$). Using the completion DOY
301 metric, differences between species were only significant based on visual estimates of
302 percentage expanded leaves across the whole crown, with oak significantly later than
303 sycamore ($p = 0.046$), but the other species did not differ ($p > 0.05$).

304 As well as identifying differences between species, it is clear that there is considerable
305 variation within species (Fig. 1 and Fig. 2). Ash is the most variable in terms of first
306 budburst dates, with a 30-day difference in budburst timing from the earliest to the latest
307 individual (Fig. 1). Other species showed lower intra-species variation in budburst timing
308 (16–19 days). Both oak and ash were highly variable in terms of first leaf expansion
309 (varying by 22–28 days respectively). However, oaks were much more consistent in
310 terms of expanded leaves 50% DOY and completion DOY. Ash remained highly
311 variable throughout the whole process of leaf development, with ash trees being both
312 the earliest and latest to achieve full leaf expansion. Beech were fairly consistent in their
313 first budburst and leaf expansion dates, though variability increased as time progressed.

314 Sycamore were consistent in first budburst and completion of leaf expansion, but varied
315 considerably at the start of leaf expansion and in their 50% DOY.

316 There was a significant difference between oak and all three other species, in the time
317 taken from first budburst to 50% DOY (Fig. 1), with oak taking significantly longer to
318 achieve leaf expansion than the other three species. However, no significant differences
319 were found between species in the time taken from first leaf expansion to 50% DOY,
320 indicated by the similar rates of leaf expansion. The relationship between all metrics of
321 leaf expansion timing, including first leaf expansion dates, were strongly related (all $R^2 >$
322 0.80 , $p < 0.001$). The relationship between first budburst dates and leaf expansion
323 appears curved, and was poorly explained by a linear model (Fig. 3; $R^2 = 0.40$, $p <$
324 0.001 based on counts, $R^2 = 0.42$, $p < 0.001$ based on percentage estimates). This
325 indicates that trees with later budburst tended to expand leaves more rapidly than trees
326 with earlier budburst.

327 **3.2. Comparison of methods for obtaining time-series data**

328 All time series data from count and percentage estimate methods could be fit to the
329 logistic model, obtaining model parameters with low standard error and high
330 significance, indicating good fits (Supplementary Material Tables 2 and 3). Count and
331 percentage estimate methods were highly related in terms of the 50% DOY values
332 derived from the logistic model fits ($R^2 = 0.97$, $p < 0.001$) and produced statistically
333 similar values for individual trees (Table 1). Both methods identified very similar
334 phenological patterns across species based on 50% DOY and completion DOY (Fig. 1).
335 They also identified similar rates of leaf expansion between species, though the count
336 method showed higher variability of leaf expansion rate for beech and sycamore (Fig.
337 1). However, estimates of leaf expansion rate from the two methods were statistically
338 similar (Table 1).

339 Logistic models for the remaining eight time-series of Greenness Index values for whole
340 crowns produced good fits with significant parameter estimates and low standard error
341 (Supplementary Material: Table 4). Statistical comparisons between counts and
342 photographs showed that 50% DOY values were related (Fig. 4, $R^2 = 0.76$, $p < 0.001$),
343 and pairs of values were not statistically different (paired t-test: $t_{19} = 0.10$, $p = 0.923$).
344 However, there was no relationship between the rate parameters from the two methods
345 ($R^2 = 0.01$, $p = 0.696$).

346 After removing every other observation from the time-series to simulate a four-day
347 temporal grain, logistic models could be fitted to all forty time-series based on
348 percentage estimate data, and to thirty-seven time-series based on count data
349 (Supplementary Material: Tables 5 and 6). The three time-series that could not be fitted
350 with the logistic model (one from beech and two from oak) had only three data points
351 remaining after removal of every other observation, since leaf expansion occurred very
352 rapidly in those individuals. Using the 4-day temporal grain, 50% DOY and rate values
353 were highly similar to values obtained from the 2-day temporal grain, for both
354 percentage estimate and count data (Table 1). A six-day temporal grain was tested, but
355 ten logistic models based on count data failed to run due to there being only three data
356 points remaining (Supplementary Material: Table 7). Using estimate data, the six-day
357 temporal grain still produced model fits for all but one time-series, but two further time-
358 series had non-significant parameter estimates (Supplementary Material: Table 8).

359 **4. Discussion**

360 The order in which species reached first budburst did not reflect the order in which they
361 reached 50% or full leaf expansion. Oak was a particularly notable case in this study,
362 taking on average twice as long to reach 50% leaf expansion after first budburst,
363 compared to the other species. This appears to be due to a longer delay from first
364 budburst to first leaf expansion, rather than a slower rate of leaf expansion, as there
365 was no difference in leaf expansion rate between species. There was also intra-species
366 variation in the time taken from first budburst to 50% DOY. The curved relationship
367 between first budburst dates and 50% DOY was noticeable for all species, indicating a
368 tendency for individuals with later budburst to leaf more rapidly than conspecific
369 individuals with earlier budburst, as has been observed elsewhere (Cole and Sheldon
370 2017). Interestingly, the curvature is most pronounced in oak, which is the species that
371 bursts bud earliest.

372 Given that first budburst dates were a poor predictor of leaf expansion timing, we
373 suggest that caution be exercised when interpreting first budburst dates, as they do not
374 fully characterise the trajectory of canopy development, or necessarily signal the order
375 in which tree canopies mature. While first leaf expansion dates show more similar
376 patterns to 50% DOY, they still identify a different ordering of phenology between
377 species, and show different patterns of intra-species variation. In order to predict
378 impacts of changing phenology on ecosystem processes and function, it is important to

379 capture the entire process of individual tree canopy development. Later stages of leaf
380 expansion correspond more closely to remote sensing indices, so would better validate
381 satellite data (Elmore et al. 2016; White et al. 2014). In addition, finer-scale detection of
382 variation in leaf development timing between and within species will help to identify
383 environmental cues and improve predictive models for biosphere-climate modelling
384 (Richardson et al. 2012). In this study, there were no significant differences between
385 species in terms of leaf expansion rate, but there was substantial intra-species variation.
386 The majority of phenology studies focus on timing metrics, and the rate of a process is
387 often ignored (Brown et al. 2017), missing important information on within-species
388 variability. The degree of variation in leaf expansion rate within a species could have
389 important implications for fitness and resilience in a population. For example, two trees
390 sharing similar 50% DOYs could have very different leaf emergence timings, making
391 one individual more vulnerable to spring frosts and herbivory damage, but potentially
392 able to take better advantage of milder conditions if they occurred. In a variable spring
393 environment, a range of different phenological responses within a population is a likely
394 outcome, since each different response would have some selective advantages and
395 disadvantages, depending on specific conditions at any one time, with no single
396 response displacing all others. The balance between these responses is also likely to
397 be modified by climate change. The opportunity to see this population-level plasticity is
398 one reason why time-series data are preferable to event monitoring data.

399 Considerable intraspecific variation was also observed in leaf expansion timing, in
400 agreement with other studies that have monitored multiple individuals of a species at a
401 single site (Capdevielle-Vargas et al. 2015; Cole and Sheldon 2017; Delpierre et al.
402 2017). The level of intraspecific variation differed between phenophases, further
403 highlighting that snapshot assessments of tree phenology can be misleading.
404 Interestingly, in this study there was no significant difference in leaf expansion timing
405 between ash and sycamore, though ash is typically considered a late-leafing species
406 while sycamore an early-leafing species (Morecroft et al. 2008; Roberts et al. 2015;
407 Sparks and Carey 1995). The high variability among the ash trees in this study, if
408 typical, could increase this species' resilience to climate change. The fact that such
409 variability exists within species, confirms the value of methods that facilitate high levels
410 of within-site and within-species replication. While ten individuals is the recommended
411 minimum sample size by the USA-NPN (Denny et al. 2014), we recommend that larger

412 sample sizes be used initially where possible (Elmendorf et al. 2016) until suitable
413 minimum sample sizes for target species have been proposed based on their inherent
414 variability.

415 Even when the interval between observations was extended, the model still provided
416 very similar estimates of 50% DOY and rate. Our results suggest that for the relatively
417 short time series of individual trees, observations at 3–4 day intervals are sufficient to
418 describe phenological patterns in our study region. Less frequent observations could
419 limit the reliability of the phenological model, especially in warmer years where budburst
420 and leaf emergence could be more condensed.

421 We found that observing three relatively small sections of a tree gives comparable
422 results to whole tree crown estimates. This is promising, as three sections can be
423 assessed relatively quickly, and though more time consuming than a single estimate of
424 a tree crown, observer bias may be reduced by the increase in objectivity (Galloway et
425 al. 2006; Vittoz et al. 2010). However, the trees included in this study were relatively
426 small trees. The comparability between crown sections and whole crowns could
427 decrease as crown size increases, as a smaller proportion of the total crown is
428 assessed—though large trees pose problems for phenology monitoring generally, both
429 in terms of viewing buds in order to make counts, and in terms of making accurate
430 estimates (Fuccillo et al. 2015; Vittoz and Guisan 2007). Trials of count and estimate
431 methods are needed with citizen scientists, to determine levels of error associated with
432 both approaches, and the extent to which this varies with crown size, height and
433 species.

434 Ground-based photography offers potential to supplement data collection on individual
435 tree phenology, though several issues need to be considered. Firstly, in a forest
436 situation, the position from which photographs are taken must be carefully chosen. We
437 had to exclude many of our trees because of the influence of background foliage,
438 despite efforts to choose branch sections that would be unimpeded by surrounding
439 vegetation. Given the potential difficulty in selecting appropriate regions to photograph,
440 the use of fixed camera mounts (University of New Hampshire 2017; Smith and Ramsay
441 2018) might be necessary if this method was to be used with citizen scientists. This
442 would also ensure photos were taken of the same branch sections, and would allow
443 different surveyors to take images.

444 However, image processing costs must be carefully considered before use in a large
445 citizen science project, since the effort involved could be high. A crowd-sourcing
446 approach, where citizen scientists classify and analyse images online, has already been
447 used to validate plant phenology data from webcam images (Kosmala et al. 2016) and
448 to classify images of crown health in tropical rainforests (Zooniverse No date). Another
449 option is to take advantage of the rapidly developing technology in smartphone apps.
450 Tichý (2016) developed an app for calculating canopy cover (*i.e.*, the vertical projection
451 of the tree canopy onto the ground surface) from canopy photos taken with a
452 smartphone or tablet. Image analysis algorithms are able to detect and eliminate poor
453 quality images (*e.g.*, those with lens flare), and select appropriate thresholds for
454 separating canopy and sky pixels (Glatthorn and Beckschäfer 2014). An app for
455 estimating chlorophyll content of individual leaves can be used as a cost-effective
456 alternative to professional chlorophyll meters (Vesali et al. 2015), and carries out an
457 analysis similar to our greenness method. Such an approach could be extended to
458 assess greenness indices for plant canopies, using automatic algorithms to correct for
459 lighting variation (Brown et al. 2016), allowing citizen scientists to track the green-up of
460 the canopy in spring.

461 The greenness index data was comparable to visual observations in terms of 50% DOY
462 but not rate. Previous studies using fixed cameras on canopy towers, found greenness
463 to be closely related to leaf expansion, though in one study greenness identified earlier
464 50% DOY than visual observations (Mizunuma et al. 2011). Greenness is a function of
465 both leaf expansion and pigment changes, so while related, leaf expansion and
466 greenness are different (Keenan et al. 2014). This must be borne in mind when
467 interpreting data from different methods. Greenness indices are an additional gauge of
468 leaf development, and should be seen as complementary to leaf expansion data, rather
469 than a substitute for it.

470 **5. Conclusions**

471 Citizen science phenology monitoring has the potential to replicate high resolution data,
472 to describe tree leaf phenology in relation to a range of environmental and genetic
473 factors. However, time-series data to track the development of individual tree crowns is
474 necessary. Reliance on first event dates can mislead on the order of leaf development
475 among species, and does not provide a rate of leaf development. Fixed mount
476 photography from the ground could be used to supplement data on canopy greening

477 currently collected through projects such as Phenocams. Low-cost digital cameras and
478 smartphone cameras are becoming increasingly advanced, which could enhance
479 prospects for obtaining reliable data on canopy greening. Nevertheless, visual
480 observations remain the most viable option for widespread data collection on individual
481 tree phenology at present. Further research is needed to assess volunteer accuracy
482 using counts and percentage estimates of expanded leaves, along with further
483 refinement of photographic approaches.

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717 **Table**

Method comparison	Metric	Relationship between methods (regression)		Difference in absolute values between methods (paired t-test)		
		R^2	p	df	t	p
Counts vs Whole crown percentage estimates	50% DOY	0.97	<0.001	39	0.083	0.935
	Completion of LE	0.96	<0.001	39	2.811	0.008
	Rate of LE	0.55	<0.001	39	0.609	0.546
4-day v 2-day temporal grain (Counts)	50% DOY	0.99	<0.001	36	1.320	0.195
	Rate of LE	0.88	<0.001	36	-0.921	0.363
2-day v 4-day observation frequency (Whole crown percentage estimates)	50% DOY	0.99	<0.001	39	0.073	0.942
	Rate of LE	0.89	<0.001	39	-1.787	0.082

718

719 Table 1: Comparison of methods for deriving time-series data on tree leaf development. The relationship between methods is
720 explored with regressions: whether the first variable can be used as a predictor for the second variable. The proportion of variation
721 explained (R^2) and statistical significance (p) is shown. Where significant relationships existed, paired t -tests were carried out to
722 assess whether the two methods produced different absolute values (significant p -values in bold).

723

724 **Figures**

725 **Fig. 1.** Comparison of phenological patterns for four tree species, derived from different
726 metrics and methods: first budburst dates; first leaf expansion dates; 50% DOY (from
727 percentage estimates); 50% DOY (from counts); time from first budburst to 50% DOY
728 (from percentage estimates); time from first budburst to 50% DOY (from counts); leaf
729 expansion rate (as percentage estimates per day); leaf expansion rate (as number of
730 leaves per day); completion DOY (from percentage estimates); completion DOY (from
731 counts). On the box and whisker plots, the horizontal black line shows the median, the
732 red line is the mean, the box represents values within the 25–75% quartiles, and the
733 whiskers show the 10% and 90% percentiles. In each panel, species sharing the same
734 letter above the x-axis were not statistically different.

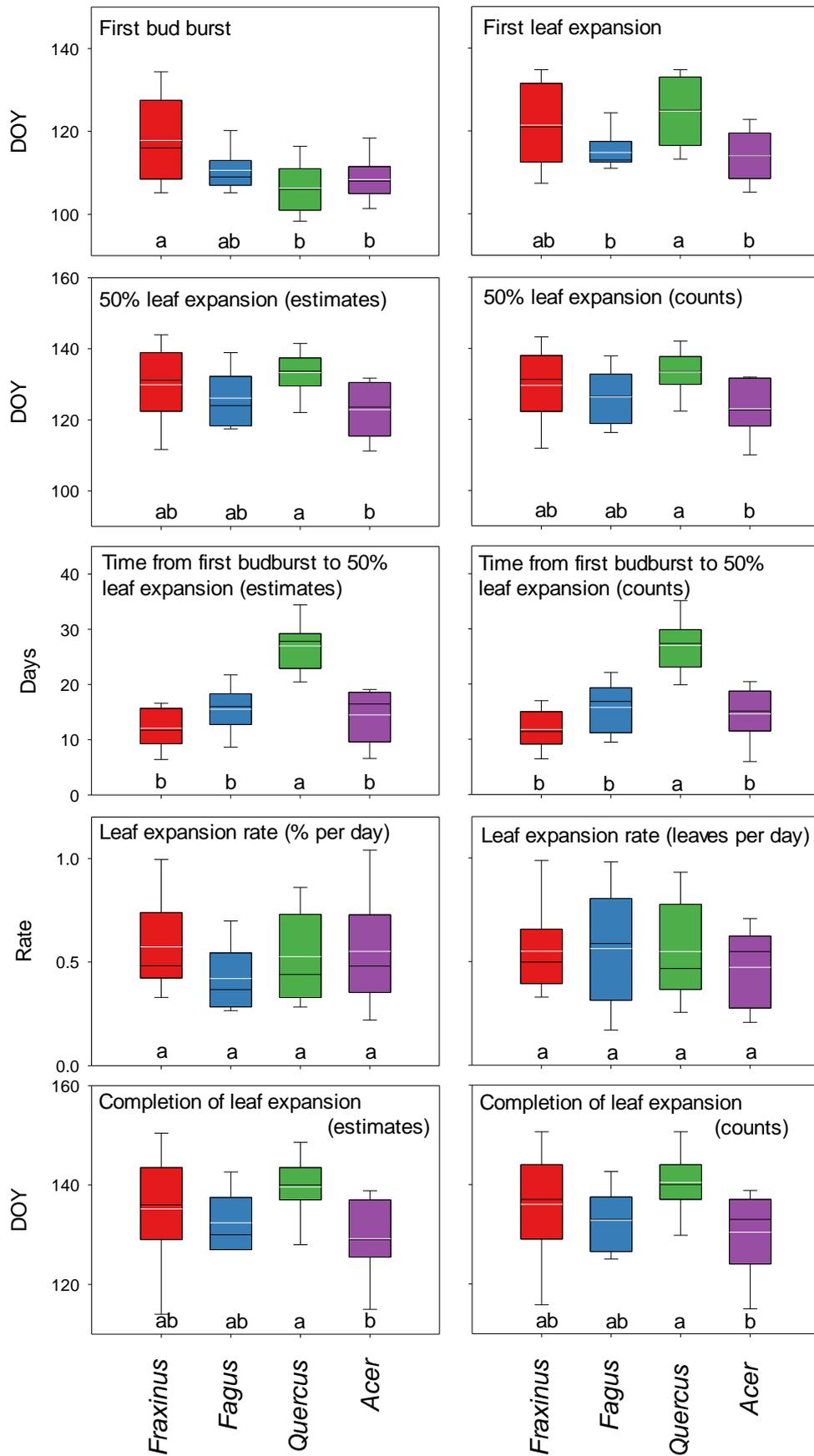
735 **Fig. 2.** Logistic growth models showing model fits for 10 individual trees in each species
736 category, based on count data.

737 **Fig. 3.** Relationship between first budburst dates and 50% DOY for the four tree
738 species; a = 50% DOY from percentage estimate data; b = 50% DOY from count data.
739 For each species, a second-order polynomial fit ($R^2 = 0.64\text{--}0.93$, $p > 0.05$) shows a
740 curved relationship.

741 **Fig. 4.** Comparison of 50% DOY values from visual counts of leaf expansion on tree
742 sections and 50% DOY values from photo-derived greenness index on tree sections.
743 Data are from counts and photos of eight different trees (each a combined value from
744 three different sections of the canopy). The line of best fit is shown.

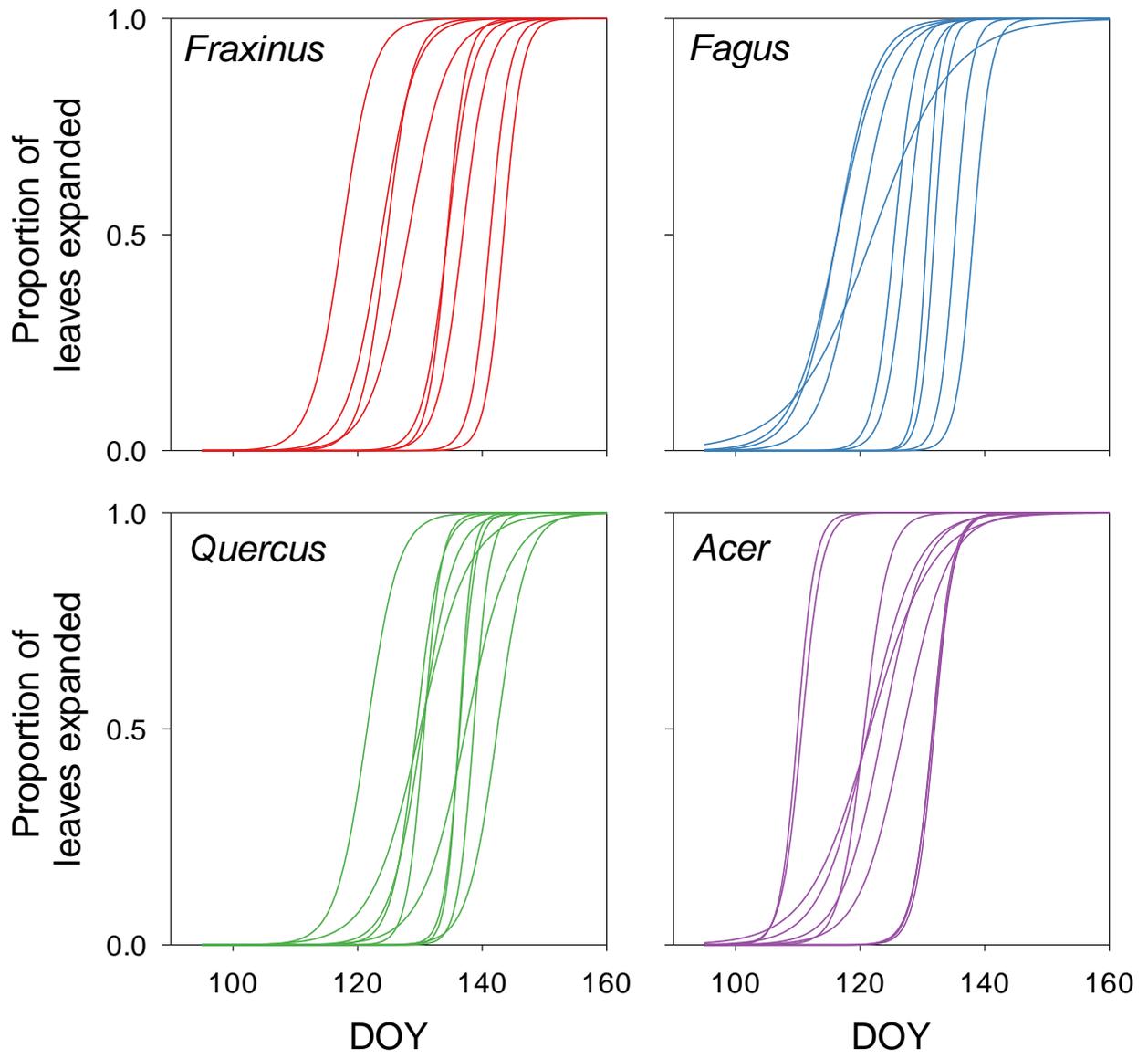
745

746 Fig. 1

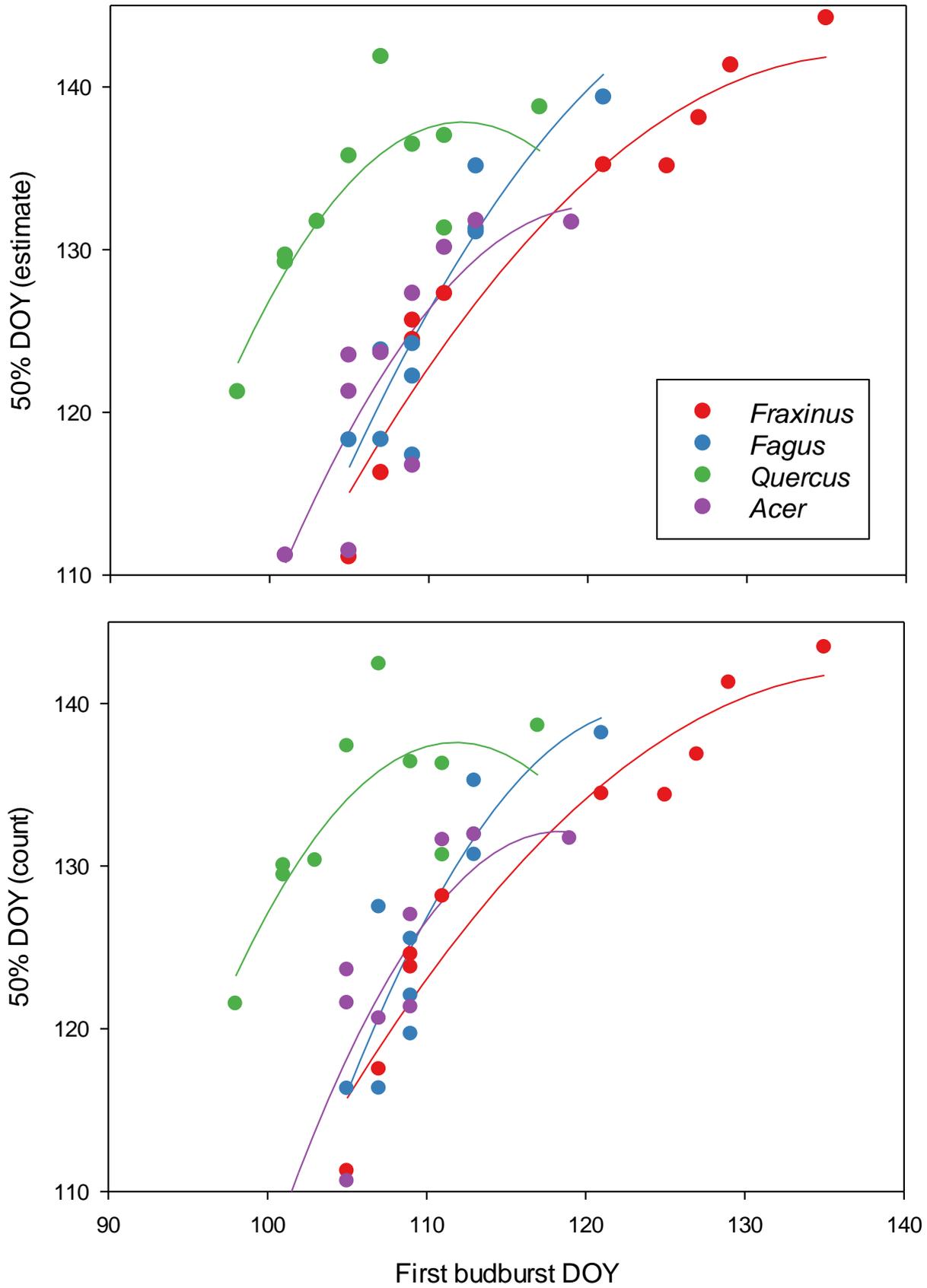


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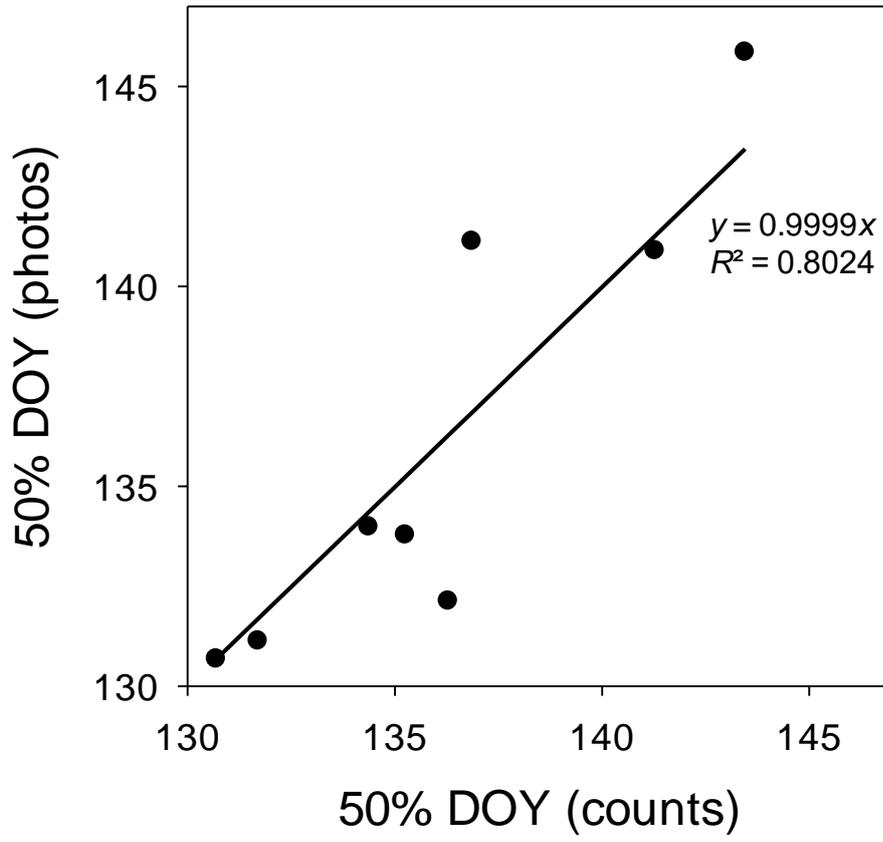
752 Fig. 3



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756 Fig. 4



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