

2020-03

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Smith, AM

<http://hdl.handle.net/10026.1/15597>

10.1007/s00484-019-01839-2

International Journal of Biometeorology

Springer Science and Business Media LLC

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

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Key words: citizen science, budburst, leaf expansion, canopy greening, climate change.

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Abstract

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

1. Introduction

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

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

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

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

Monitoring methods that detect subtle changes in the sequence of leaf expansion among different tree species will be important for predicting future changes in forest composition. For example, Roberts et al. (2015) predicted a shift away from 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

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

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

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

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

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

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

2. Materials and methods

2.1. Study site and data collection

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

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

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

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

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

(1)

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

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

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

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

(2)

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

2.2. Deriving phenological metrics from time-series data

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

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

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

(3)

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

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

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

2.3. Statistical analyses

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

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

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

3. Results

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

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

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

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

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

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

3.2. Comparison of methods for obtaining time-series data

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

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

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

4. Discussion

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

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

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

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

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

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

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

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

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

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

5. Conclusions

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

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

6. Acknowledgements

The authors would like to thank Hayley Partridge for collecting the data used in this study, and Nicola Steer for providing advice on the logistic growth model. This research did not receive a grant from funding agencies in the public, commercial, or not-for-profit sectors.

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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

Figures

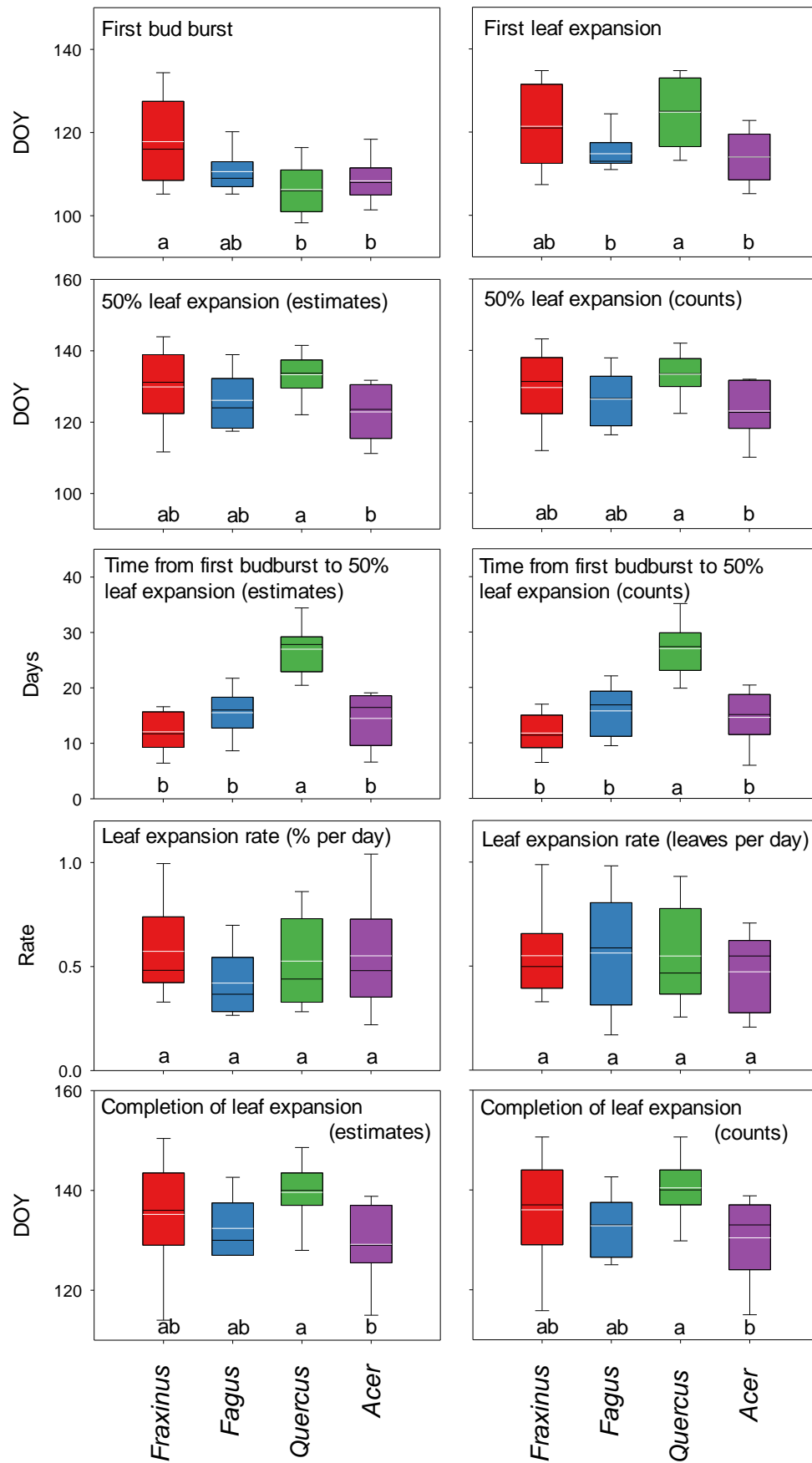
Fig. 1. Comparison of phenological patterns for four tree species, derived from different metrics and methods: first budburst dates; first leaf expansion dates; 50% DOY (from percentage estimates); 50% DOY (from counts); time from first budburst to 50% DOY (from percentage estimates); time from first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

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

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

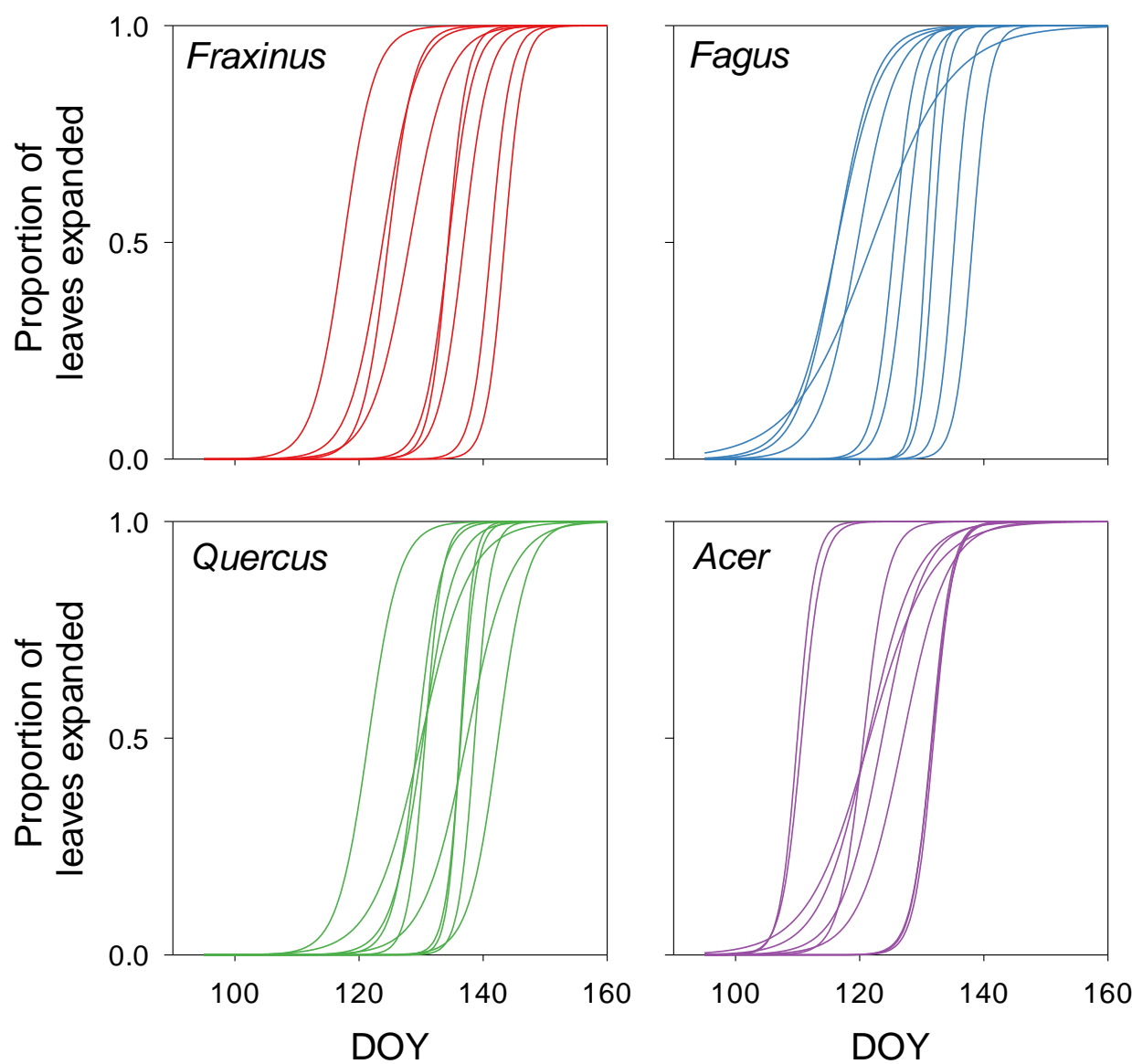
Fig. 4. Comparison of 50% DOY values from visual counts of leaf expansion on tree sections and 50% DOY values from photo-derived greenness index on tree sections. Data are from counts and photos of eight different trees (each a combined value from three different sections of the canopy). The line of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

746 Fig. 1

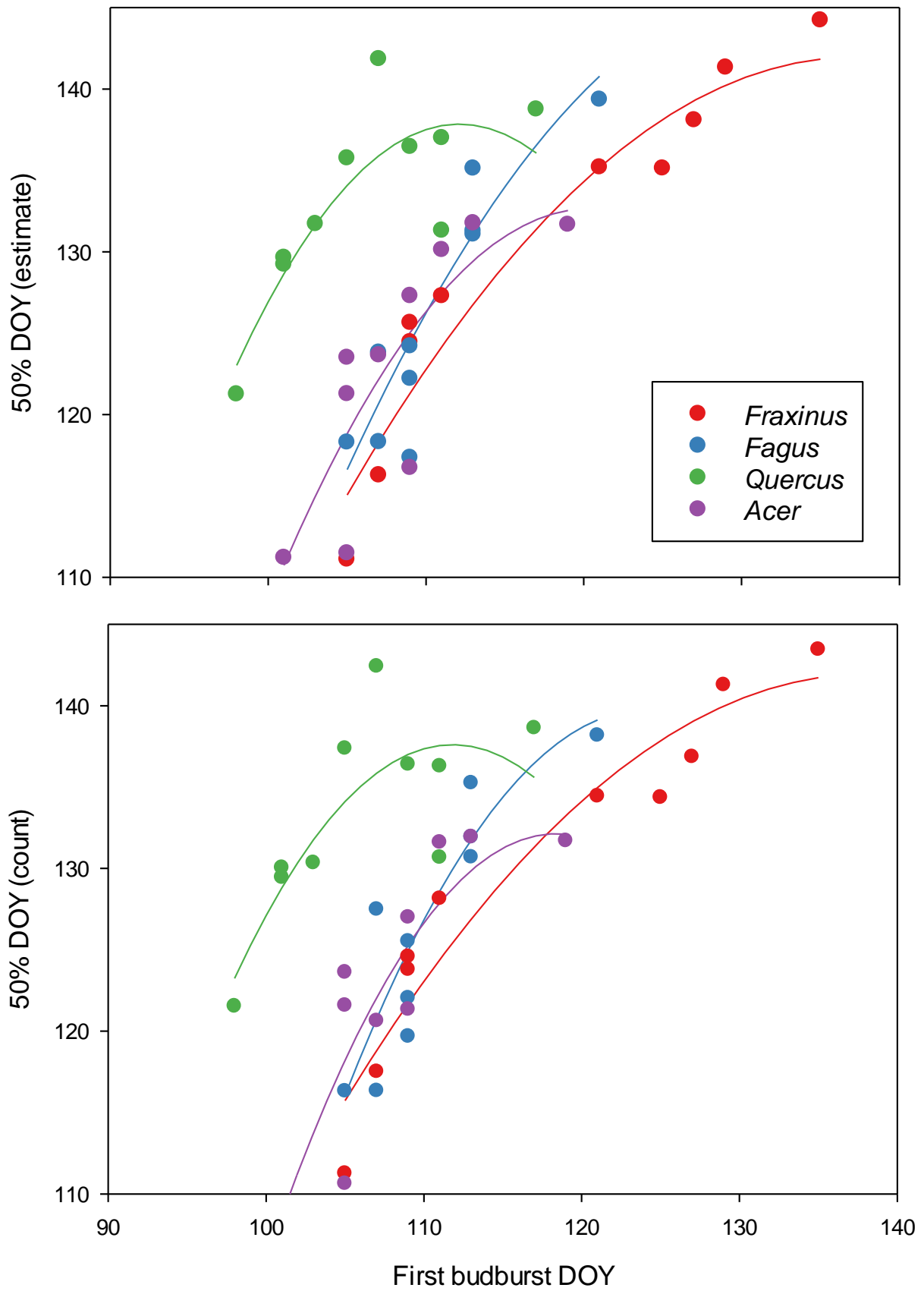


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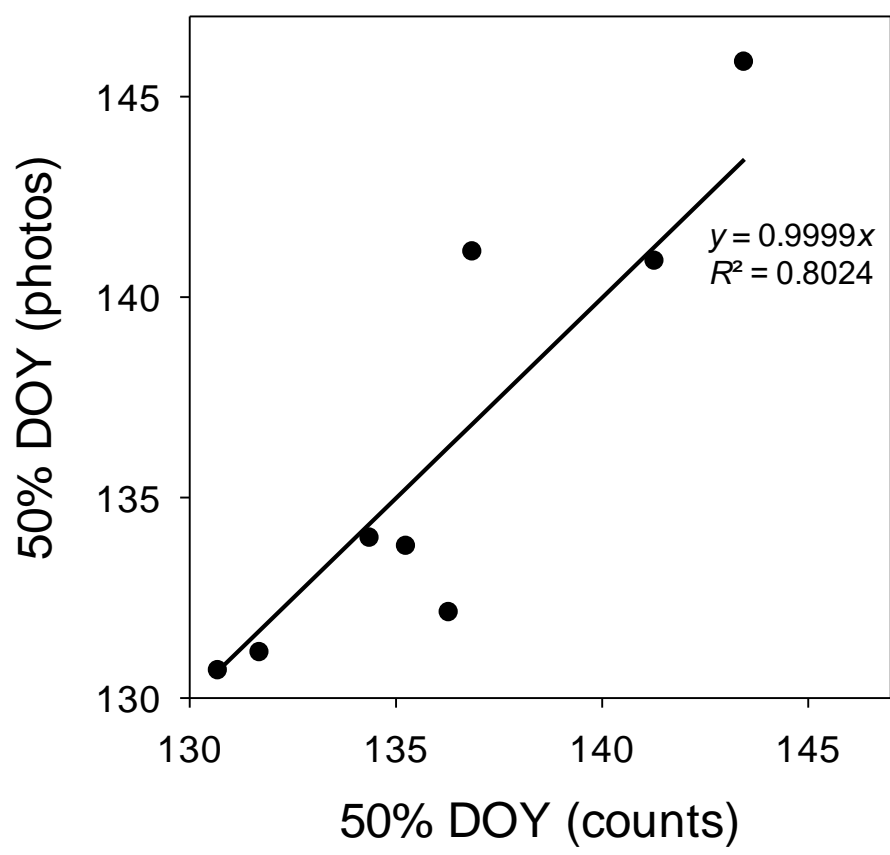


752 Fig. 3

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756 Fig. 4



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