

1 **Comparing two ground-based seed count methods and their effect** 2 **on masting metrics**

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13 **Abstract**

14 Masting, i.e. interannually variable and synchronized seed production, plays a crucial role in forest
15 ecosystems, influencing wildlife dynamics, pathogen prevalence, and forest regeneration. Accurately
16 capturing masting variability is important for effective forest management, conservation efforts, and
17 predicting ecosystem responses to environmental changes. The adoption of low-cost methods facilitates the
18 large-scale data acquisition needed in this time of unprecedented environmental upheaval, but it is
19 important to understand the reliability of such methods. We investigated the relationship between the timed
20 count method and the quadrat-based method for monitoring seed production in European beech (*Fagus*
21 *sylvatica*). The timed count method is fast, cost-effective, and suitable for areas with public access. These

22 characteristics make time counts a practical choice for large-scale seed monitoring. However, the method has
23 not been cross-calibrated with more traditional ground-based methods like quadrat sampling, which
24 involves exhaustive seed collection from designated plots under tree canopies. Our research reveals a
25 loglinear relationship between seed counts obtained by the two methods, and shows that the timed count is
26 an effective method of estimating seed production. We also found that seed production exhibits greater
27 dispersion in patchiness at lower levels of seed fall, which explains why the timed count method, covering a
28 larger area, captures greater variability in seed fall compared to the quadrat method in such contexts. This
29 highlights the importance of choosing an appropriate sampling strategy to accurately assess seed fall. The
30 differences between the two methods introduce variability into derived masting metrics, such as the
31 coefficient of variation and synchrony, with individual-level seed production variability metrics being more
32 affected than population-level ones. The findings underscore the importance of understanding how
33 different sampling methods can impact long-term ecological studies, particularly those focused on masting
34 behaviour.

35 **Introduction**

36 Researchers have long been counting seeds to estimate the interannual variability of seed production in a
37 population (i.e. masting), since this seed production variability has important applied and ecological
38 consequences (Ascoli et al., 2017a; Hilton and Packham, 2003; Koenig, 2021). For instance, the resource
39 pulses associated with high seeding years affect the population dynamics and behaviour of wildlife including
40 insects, rodents, larger mammals, and birds (Jones et al., 1998; Maag et al., 2024; Ostfeld and Keesing, 2000;
41 Touzot et al., 2020). Via cascading effects, masting also influences the prevalence of pathogens, including
42 Lyme disease, and haemorrhagic fever (Bregnard et al., 2021; Clement et al., 2009; Reil et al., 2016; Tersago
43 et al., 2009). Moreover, masting dictates seedling emergence, recruitment and forest regeneration (Maringer

44 et al., 2020; Zhang et al., 2022; Zwolak et al., 2016). Effective management of natural systems therefore relies
45 on our understanding of masting (Pearse et al., 2021).

46 Our grasp of the spatio-temporal variability in masting, and its effects on the ecosystem, depends on the
47 availability of extensive records of both seed quantity and quality. Increasing seed sampling across climate
48 change gradients, for instance, is particularly important as it can reveal the drivers of changes in masting and
49 help to predict the response of masting to further environmental change (Foest et al., 2024; Hackett-Pain and
50 Bogdziewicz, 2021). Moreover, unpredictable seed supply is a challenge for forest restoration and
51 afforestation projects (Kettle, 2012; Pearse et al., 2021; Whittet et al., 2016). Models which forecast masting,
52 built on seed monitoring data, can help improve the timing of seed sourcing for such projects (Journé et al.,
53 2023b; Pearse et al., 2021). Thus, there is a demand for reliable, well-understood and cost-effective seed
54 production monitoring methods.

55 The adoption of low-cost methods can improve large scale data acquisition, and support the longevity of
56 seed monitoring projects (Koenig et al., 2020, 1994b). Yet, it is important to understand the reliability of
57 such methods, and cross-calibrate them with reference methods. One easy to implement, time-effective, and
58 low-cost monitoring method which requires no infrastructure is the timed count used to monitor seed
59 production in European beech (*Fagus sylvatica*) since 1980 in the United Kingdom (Packham et al., 2008).
60 This time-efficient method is easily learned and takes only 3.5 minutes per tree. Moreover, it is suitable for
61 monitoring in areas with public access and areas where seed traps cannot be deployed. Its low cost and speed
62 facilitate the acquisition of large sample sizes – a trait especially important when seed production is variable
63 between years and individuals, as is the case for masting seeding (Koenig et al., 1994b). In contrast to another
64 well established and efficient method, namely the 30-second binocular count of fruit in the canopy (the
65 ‘Koenig method’; Koenig et al., 1994a; Touzot et al., 2018), the timed count method can be used when
66 branches are difficult to see (including in closed canopy forest), and allows for further assessment of seed
67 quality post-sampling. This is highly relevant as, for example, UK beech seeds collected with the timed count

68 can be examined to measure rates of seed predation and pollination. Such efforts have revealed that due to
69 temporal changes in masting associated with climate warming, the number of viable seeds declined by up to
70 83% over the last four decades, despite increasing total seed production (Bogdziewicz et al., 2023, 2020).
71 Crucially, the joint monitoring of seed quantity and quality uncovered a highly concerning process that
72 would have otherwise remained hidden, and opened further research avenues to mitigate the impacts of
73 decreased viable seed supply (Bogdziewicz et al., 2024). Here, we investigate how this timed count method
74 relates to a more traditional ground-plot method, which is performed by collecting all seeds from quadrats
75 placed under the tree canopy.

76 We predicted that the relationship between timed and quadrat seed counts is loglinear because a degree of
77 saturation can occur when using effort-based methods such as timed counts. That is, there are physical limits
78 to how many seeds can be collected within a certain time frame (Koenig et al., 1994a; Touzot et al., 2018).
79 Exhaustive counts within quadrats would not feature such saturation. Although logarithmic functions do
80 not include a plateau parameter for the maximum number of seeds collected with the timed count, they are
81 particularly useful to describe processes where the rate of change slows down as the quantity being measured
82 increases. In contrast to more complex nonlinear models, logarithmic transformations within the context of
83 linear models are versatile and can easily be incorporated regardless of the directionality (i.e. from timed
84 counts to quadrat counts or vice versa).

85 Another reason we anticipated nonlinearity arises from the potential impact of seed fall patchiness on seed
86 count estimates derived from the two methods. Generally, comparing estimates obtained with different
87 methods can improve insights on the properties of the system in which we obtain data. Touzot et al. (2018),
88 for instance, found evidence of predation satiation by contrasting estimates obtained with exposed ground
89 plots and seed trap nets (which offer some protection against predation). Here, we expected to observe
90 differences related to sampling area. The timed count method covers a larger sampling area than is typical for
91 an area-based count (whole or large canopy nets can be used but such nets are highly intensive; (Fleurot et

92 al., 2023; Touzot et al., 2018), and seeds are picked up from multiple locations under the crown of each
93 individual. Where the observer collects seeds from is unlikely to be random – while care is taken to sample
94 from multiple areas, the observer could be drawn to patches of seeds. In plants which produce clusters of
95 heavy fruits, the comparatively small seed shadow can feature strong aggregation (Cousens et al., 2008).
96 When seed production is patchy, the observer might sample more seeds from seed fall patches that would be
97 missed by the quadrat sampling method as this method samples only a fraction of the surface area. Possibly,
98 seed fall is patchier at lower levels of seed fall than at higher levels. At low seed fall levels only some branches
99 may produce seeds (resulting in patchiness), while at higher seed fall, more or most branches participate
100 (resulting in random to uniform seed fall). However, it is also possible that total seed fall affects the
101 dispersion of patchiness. For example, at low seed fall levels, the seed fall distribution may be uniform (in the
102 extreme: there are zero seeds, falling in zero plots) or random (i.e. there are a few seeds falling randomly from
103 across the canopy), but in some trees, a limited number of branches produce a relatively large seed crop,
104 resulting in a patchy distribution of seed fall.

105 Alongside the need to cross-calibrate seed sampling methods, it is important to investigate how the use of
106 different sampling methods translates into measures of masting variability. Long-term seed production
107 records are becoming increasingly available (Hackett-Pain et al., 2022), and seed sampling methods vary
108 among time series. This is unsurprising, as methods vary in terms of collecting effort (i.e. time), required
109 infrastructure, and their usefulness for particular species and habitats (e.g. small or large seeded species,
110 closed canopy or savanna). Masting research increasingly uses integrated datasets which combine multiple
111 methods (e.g. Ascoli et al., 2017b; Dale et al., 2021; Journé et al., 2023a; Lobry et al., 2023; Pearse et al.,
112 2020), but we have a limited understanding of the effects of such collation; seed collection methods can
113 affect seed production estimates (Koenig et al., 1994a; Touzot et al., 2018), which may translate into metrics
114 derived from such data.

115 The aim of this study was to establish the relationship between the timed count and a reference method, i.e.
116 quadrat counts. Subsequently, we aimed to test how the choice of method influences masting metrics.
117 Specifically, we examined (1) if the relationship between timed counts and area-based counts is loglinear in
118 nature, rather than linear, (2) if patchiness and the dispersion of patchiness vary as a function of total seed
119 fall, and (3) the effect of sampling method on masting metrics at the individual and population level.

120 **Methods**

121 To test how estimates of seed fall obtained with a timed count and a quadrat-based count relate to each
122 other, we collected seeds from European beech (*Fagus sylvatica*) in early October in 2022 and 2023. We
123 subsequently used this relationship between the two methods to test the effect of the collection method on
124 individual and population-level masting metrics using a dataset spanning 43 years of observation (the
125 English Beech Mast Survey dataset, EBMS; Packham et al., 2008).

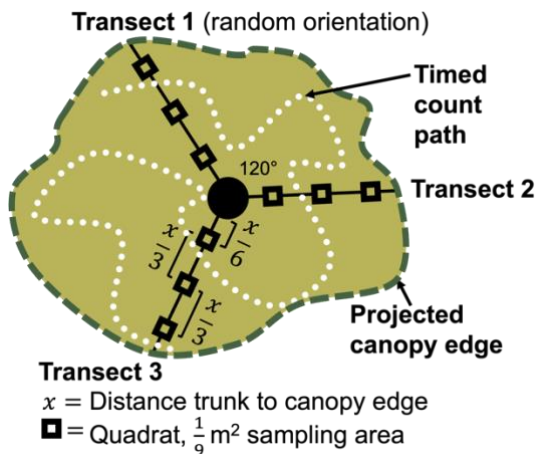
126 **Species and sites**

127 We sampled seed production under 59 beech canopies in early October of 2022 (N = 30) and 2023 (N = 29),
128 across 5 sites. The sampled individuals are part of the English Beech Mast Survey, and grow at sites near
129 Woodbury, Killerton, Buckholt, Painswick, and Portway. A detailed description of sites can be found in
130 Packham et al. (2008), and an overview of the EBMS sites can be found in Fig. S1.

131 **Sampling designs**

132 To limit interference between sampling methods, quadrats were laid out before the timed count was
133 conducted, and seeds found inside quadrats were not collected with the timed count method. Typically, the
134 quadrats covered between 0.2 – 3% of the projected crown area, so the timed count was not significantly
135 affected by the presence of the quadrats. Collected seeds were counted in the lab.

136 **Quadrat count**



137 *Figure 1: Graphical example of sampling layout under a tree canopy (dashed line). Quadrats were sampled*
138 *along three transects, and a representation of a timed count sampling path is shown in a white dotted line. The*
139 *black circle represents the tree trunk. Figure not to scale. Increasing canopy size reduces the relative sampling*
140 *area covered by the methods, particularly when using the quadrat sampling method.*

141 Under each tree, 9 quadrats (surface area: $1/9 \text{ m}^2$ each) were laid out along three transects, 120° apart (Fig.
142 1). Along each transect, three quadrats were placed at $1/6$ th, $1/2$ nd and $5/6$ th of the distance between the
143 tree trunk and the canopy edge, starting at the tree trunk. All current-year seeds were collected from each
144 quadrat by one observer, and another observer then checked that no seeds were missed.

145 **Timed count**

146 The timed count method was performed by collecting seeds under a tree for 3.5 minutes, and doubling the
147 number of collected nuts (to obtain a 7-minute count for historical reasons; doubling may theoretically
148 inflate counts, particularly during low-seeding years, but also increase the frequency of zeros. It was
149 implemented to reduce fieldwork time, ensuring the feasibility of this long-term, large-scale study). This
150 effort-based method has been used since 1980 in the EBMS (Packham et al., 2008). When performing the
151 timed count, particular attention is paid to searching as much of the below-canopy area as possible, instead

152 of sampling in a particular area. Moreover, when sampling, each seed is picked up and placed in the sample
153 bag separately.

154 **Statistical analyses**

155 Analyses were performed in R (v. 4.4.1; R Core Team, 2023). Regression models were constructed with
156 glmmTMB (v. 1.1.9; Brooks et al., 2017), unless differently indicated. Models were validated with
157 DHARMA (v. 0.4.6; Hartig and Lohse, 2022).

158 ***Comparing seed count estimates***

159 We tested the nature of the relationship between seed counts obtained with the two methods by
160 constructing two linear mixed models and comparing their fit with AICc. The input consisted of raw seed
161 count observations (X_{ij}), where each observation represented counts from a specific tree (i) in a given year (j).
162 In the first model, the dependent variable ‘Timed seed count’ was modelled as a function of ‘Quadrat seed
163 count’. In the second model, the dependent variable was considered to be a function of $\ln(1 + \text{Quadrat seed}$
164 $\text{count})$.

165 To account for non-independence, we included tree ID nested with site as random intercept. To test if
166 sampling year should be included in the model, we added year as a predictor, as well as a two-way interaction
167 term of year with the quadrat seed count. Neither additive and interaction terms were significant, thus we
168 removed the sampling year from the final model.

169 To convert timed count estimates into quadrat count estimates (i.e. seeds/m²), we constructed a third
170 model, with the natural log of $1 + \text{‘Quadrat seed count’}$ as the dependent, and ‘Timed seed count’ as the
171 independent variable. The same random intercepts were included in this model.

172 Using a linear model, we tested if seed fall is patchier at lower levels of seed production (i.e. lower tree level
173 quadrat count), and if seed fall levels affect the dispersion of patchiness. Patchiness was calculated with

174 Lloyd's index of patchiness (I_p ; Lloyd, 1967; Wade et al., 2018), using nine quadrats for each sampled
175 canopy. It is obtained as follows (Lloyd, 1967; Wade et al., 2018):

$$176 \quad I_p = \frac{m + \left(\frac{V}{m} - 1\right)}{m} = 1 + \frac{(V - m)}{m^2}$$

177 where 'm' is the mean seed count across samples (i.e. quadrats) and 'V' is the variance of seed counts. An
178 index of 1 signifies that seed fall across quadrats follows a random distribution, values below one signify
179 uniformity, and values over 1 indicate a patchy distribution.

180 *Effects on masting metrics*

181 Since calculation of masting metrics requires many years of observation, it is not possible to use the two years
182 of data we collected to calculate and compare the timed- and ground-based derived masting metrics.

183 Therefore, we used the relationship between timed seed counts and quadrat counts derived from the linear
184 mixed model described under 'Comparing seed count estimates' to convert timed seed counts to quadrat
185 seed counts. These estimated quadrat seed count and observed timed seed count series were then used to
186 investigate how individual and population-level estimates of masting metrics (specifically, CV, kCV, AR(1),
187 Psd, and S; see below) would differ between methods, using data from the EBMS (3663 annual observations;
188 15 sites with sample sizes > 3 individuals; Packham et al., 2008). Loess models were fitted with the
189 'geom_smooth' function of the ggplot2 package (v. 3.5.1) to aid visual interpretation of the relationships
190 between metrics (Wickham, 2016), and for each metric (obtained with two methods) the Spearman rank
191 correlation was calculated.

192 CV is the coefficient of variation of seed production and is the most used metric to describe masting (Kelly
193 and Sork, 2002). It is the standard deviation divided by the mean of seed production. kCV is a newly
194 proposed bounded alternative to CV (Lobry et al., 2023). The kCV can be obtained by dividing CV^2 by $1 +$
195 CV^2 , and subsequently taking the square root (Lobry et al., 2023). AR(1) captures the temporal

196 autocorrelation of seed production at lag 1 year, and can be considered as a deterministic component of year-
197 to-year variability (Bogdziewicz, 2022; Schermer et al., 2020). It was obtained with the 'Acf' function in the
198 forecast package (v. 8.23; Hyndman and Khandakar, 2008). The Psd is calculated by taking the proportion
199 of high seed years to all years, as proposed by LaMontagne and Boutin (2007) (note that we use 'high seed
200 years' rather than 'mast years' as recommended by the Bogdziewicz, et al. (2024) review on masting). High
201 seed years are the years where the standardised annual deviate of reproductive effort exceeds the absolute
202 magnitude of the largest deviate below the mean. Synchrony of seed production (S) captures the average
203 synchrony between an individual tree and conspecifics at a site at the individual level (S_i), and at the
204 population level (S_p), it describes the site-level average between-individual synchrony. Synchrony was
205 calculated at the individual level (i.e. S_i) with the average Pearson correlation between a tree's seed
206 production and the seed production of all other trees at a site. The population-level estimate of synchrony
207 (S_p) was obtained by calculating individual-level synchrony for all trees in a site, and then taking the average.
208 For all metrics other than synchrony, individual-level and population-level estimates were obtained by using
209 individual-level and population-level average seed production time series respectively.

210 When quadrat counts show a loglinear relationship with timed counts, small differences in timed counts at
211 high seed fall levels can be transformed into unrealistically large quadrat counts. Therefore, we refrained
212 from extrapolating beyond the maximum value on which the relationship between methods is based. Years
213 in individual-level time series which had seed count values larger than the largest observation in our field
214 study (i.e. 270 seeds; 4% of observations in the UK beech dataset) were excluded from the analyses
215 comparing the masting metrics from the timed-and quadrat count data. Since individual-level time series
216 were used to calculate population-level time series (i.e. by taking the average timed count per site per year),
217 these large observations were also removed prior to the calculation of population-level time series.

218 Individual-level time series were split into 10-year segments to increase sample sizes and capture more
219 variation, starting from the first year of observation. Since masting behaviour in UK beech has changed over

220 time due to climate warming, dividing long time series into shorter segments is also justified biologically
221 (Bogdziewicz et al., 2020). Any years where fewer than three individuals were sampled at a site were removed
222 from population-level time series. Individual or population time series segments comprising fewer than six
223 annual observations were excluded from the analysis. This approach resulted in 359 individual-level
224 segments (3116 annual observations), and 45 population-level segments (446 annual observations).

225 **Results**

226 We collected a total of 11,109 seeds with the quadrat seed count (average: 188.3 seeds/m², range: 12-886
227 seeds/m²). A total of 8,312 seeds were collected with the timed count (average: 140.9 seeds/individual, range:
228 12-270 seeds/individual). We found that the relationship between the two sampling methods was loglinear
229 and had a good fit across sites (Fig. 2). Additionally, collected evidence supports the prediction that seed fall
230 can be patchier at lower levels of seed production (Fig. 3). Lastly, we show that seed collection methods
231 result in variation in masting metrics, particularly for individual-level metrics (Fig. 4).

232 **Comparing seed count estimates**

233 *Nature of the relationship*

234 In both the linear and loglinear model predicting timed seed counts using quadrat counts, the quadrat seed
235 count predictor was statistically significant (linear model: 0.27 ± 0.03 SE, $z = 8.88$, $p < 0.001$; natural log
236 model: 56.63 ± 4.23 SE, $z = 13.39$, $p < 0.001$). Nonetheless, the model with a logarithmic relationship better
237 fit the data ($\Delta AICc$: -33.57; Model fit of natural log model of timed counts: marginal $R^2 = 0.74$, conditional
238 $R^2 = 0.79$), matching our predictions. Timed counts (T) can be estimated from quadrat seed counts (Q)
239 using this formula:

$$240 \quad T \approx -130.374 + 56.632 \times \ln(1 + Q)$$

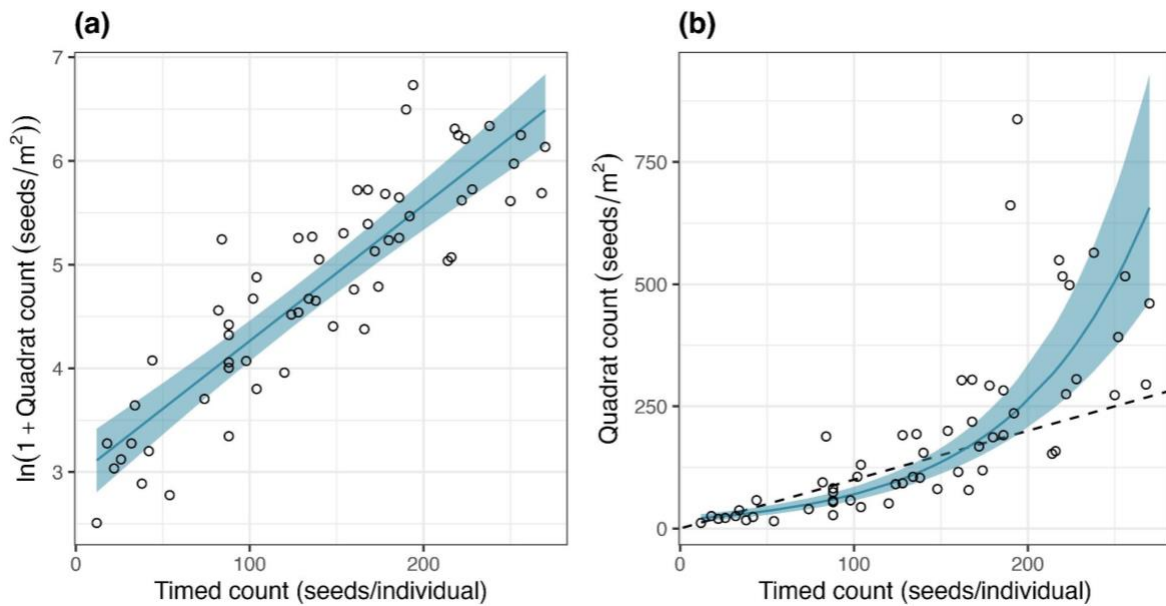
241 Similarly, the model estimating quadrat seed counts using timed counts showed a significant relationship
 242 with timed seed counts (Table 1, Fig. 2), and a good model fit (marginal $R^2 = 0.77$, conditional $R^2 = 0.78$).
 243 Estimated quadrat seed counts can be obtained from timed counts (T) as follows:

244
$$\ln(1 + Q) \approx 2.95 + 0.013 \times T$$

245 Therefore,

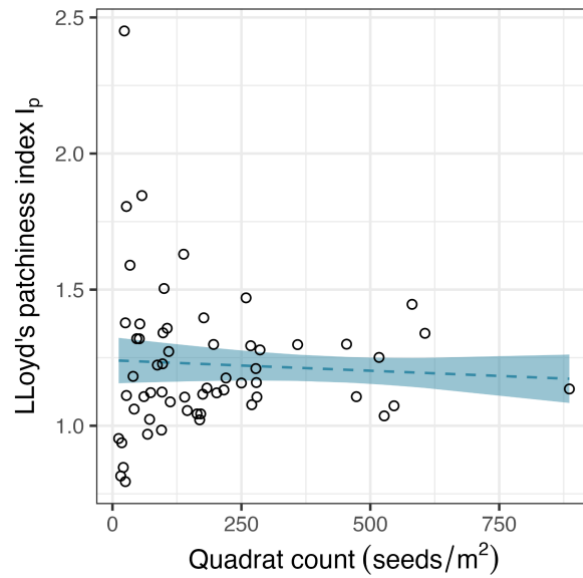
246
$$Q \approx e^{2.955 + 0.013 \times T} - 1$$

247 The minor differences between the marginal and conditional R^2 indicate that site and tree exerted little
 248 influence on the estimated quadrat seed counts. In the natural log model of timed counts, site and tree
 249 explained 2.135×10^2 and 1.857×10^{-7} of the variance respectively, and the residual variance was $9.983 \times$
 250 10^2 . In the natural log model of quadrat counts, the variance explained by site and tree were 1.012×10^2 and
 251 6.504×10^{-10} respectively, with a residual variance of 2.446×10^{-1} .



252
 253 *Figure 2: Relationship between the two ground-based sampling methods, the timed count and the quadrat*
 254 *count method. Partial residuals of tree-level observations are shown as points. (a) The relationship is shown with*
 255 *the quadrat counts on a natural logarithmic (ln) scale, and (b) with back-transformed quadrat counts. The*

256 dashed line shows the bisector. Prediction lines (blue) and shaded 95% confidence intervals were obtained with
 257 a linear mixed model.



258 Figure 3: Seed production patchiness across levels of seed production. Points show tree-level partial residuals.
 259 Most canopies show a patchy seed production of seed fall ($I_p > 1$). The blue dashed non-significant prediction
 260 line and shaded 95% confidence interval were obtained with a linear model.

261 Table 1: Summary of linear mixed model showing how logarithmic quadrat count estimates (i.e. $\ln(1 +$
 262 quadrat count)) can be obtained from timed counts.

Effect	Group	Term	Estimate	SE	z	P-value
Random	Residual	sd Observation	0.495			
Random	Site	sd (Intercept)	0.101			
Random	Tree: Site	sd (Intercept)	< 0.001			
Fixed		(Intercept)	2.955	0.166	17.752	< 0.001
Fixed		Timed count	0.013	0.001	12.352	< 0.001

N: 59, Sites: 5, Trees: 48, Marginal R^2 : 0.774, Conditional R^2 : 0.783, sd = standard deviation.

263

264 ***Patchiness of seed fall***

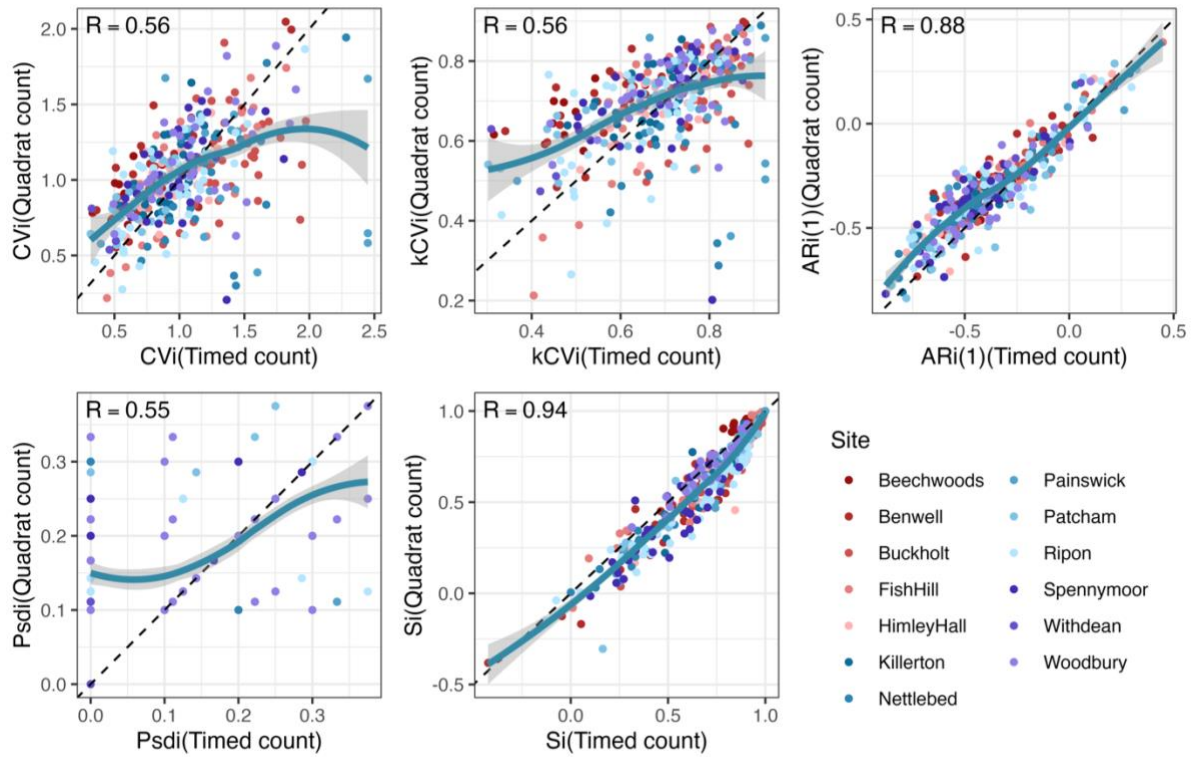
265 As is evident from Fig. 2b, the timed count detects more variation in seed production at lower levels of
266 quadrat counts. Most canopies show a patchy seed production of seed fall (i.e. Lloyd's index of patchiness
267 exceeds 1; Fig. 3, For seed fall patterns per tree, see Fig. S2). While patchiness does not decrease with seed fall
268 ($-7.65 \times 10^{-5} \pm 8.43 \times 10^{-5}$ SE, $z = -0.91$, $p = 0.36$), the decrease in the dispersion of patchiness is statistically
269 significant ($-2.07 \times 10^{-3} \pm 3.70 \times 10^{-4}$, $z = -5.59$, $p < 0.001$).

270 **Effects on masting metrics**

271 ***Individual level***

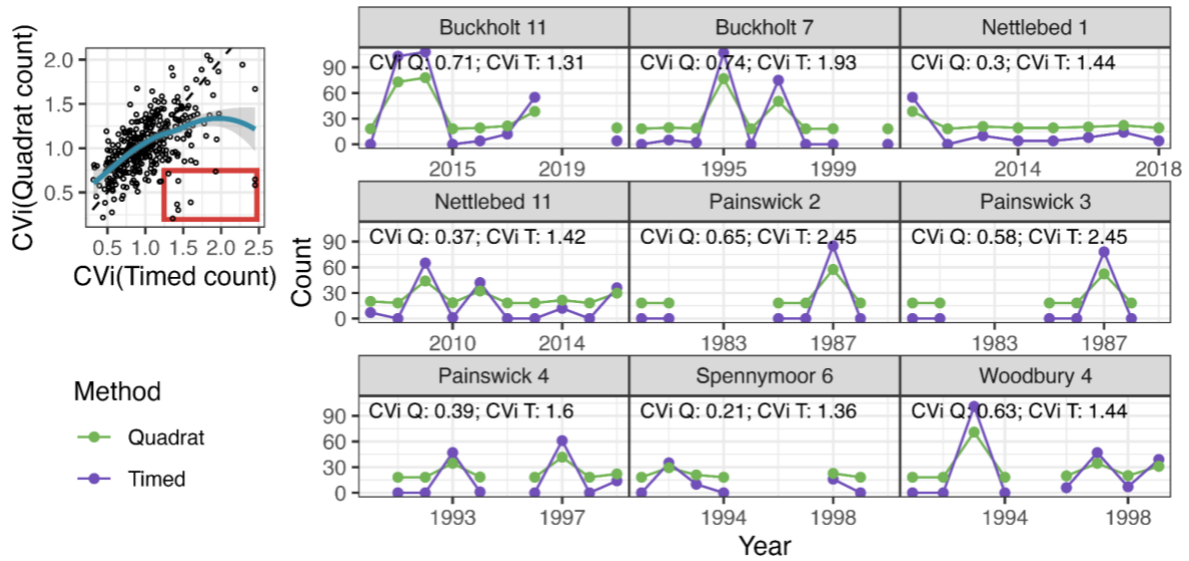
272 Not all masting metrics are similarly sensitive to the seed collection method (Fig. 4). The spearman rank
273 correlations range between 0.55 (Psd) and 0.94 (S). Moreover, loess regression lines cross the bisector,
274 indicating that for lower levels of the timed count metrics, the timed count underestimates the reference
275 metrics, and at higher levels they tend to overestimate them. However, this is less pronounced for Ari and Si
276 than for the other metrics.

277 Fig. 5 allows for a closer inspection of time series segments which differ substantially in their CVi values
278 obtained with the two methods. The lower CVi can be explained by two processes, both associated with the
279 shape of the estimated relationship between seed counts obtained via the two methods at the low levels of
280 timed counts. Firstly, the maximal timed counts in these segments are relatively low (see Fig. 2, quadrat seed
281 counts associated with timed counts ≤ 164 are below the bisector), and are therefore scaled down during the
282 conversion to quadrat counts. Secondly, the model predicts some seeds in quadrats even if timed counts are
283 zero, which decreases the number of very low-seeding years. Together, these processes decrease the
284 amplitude of variation between high and low seeding years, resulting in lower CVi. In contrast, synchrony
285 (Si) and temporal autocorrelation at lag 1 year (ARi(1)) are comparable between the two methods.



286

287 *Figure 4: Relationships between metrics (CV, kCV, AR, Psd, S) obtained with two different methods, at the*
 288 *individual level (i). CV: coefficient of variation, kCV: Kvalseth coefficient of variation, AR(1): temporal*
 289 *autocorrelation at lag 1 year, Psd: proportion of high seeding years, S: synchrony. The thin black dashed line*
 290 *represents the bisector. The thicker blue loess regression lines and 95% confidence interval are added for visual*
 291 *interpretation. Points represent time series segments, where the colour indicates the site. The spearman rank*
 292 *correlation (R) is shown in the top-left of each subplot.*

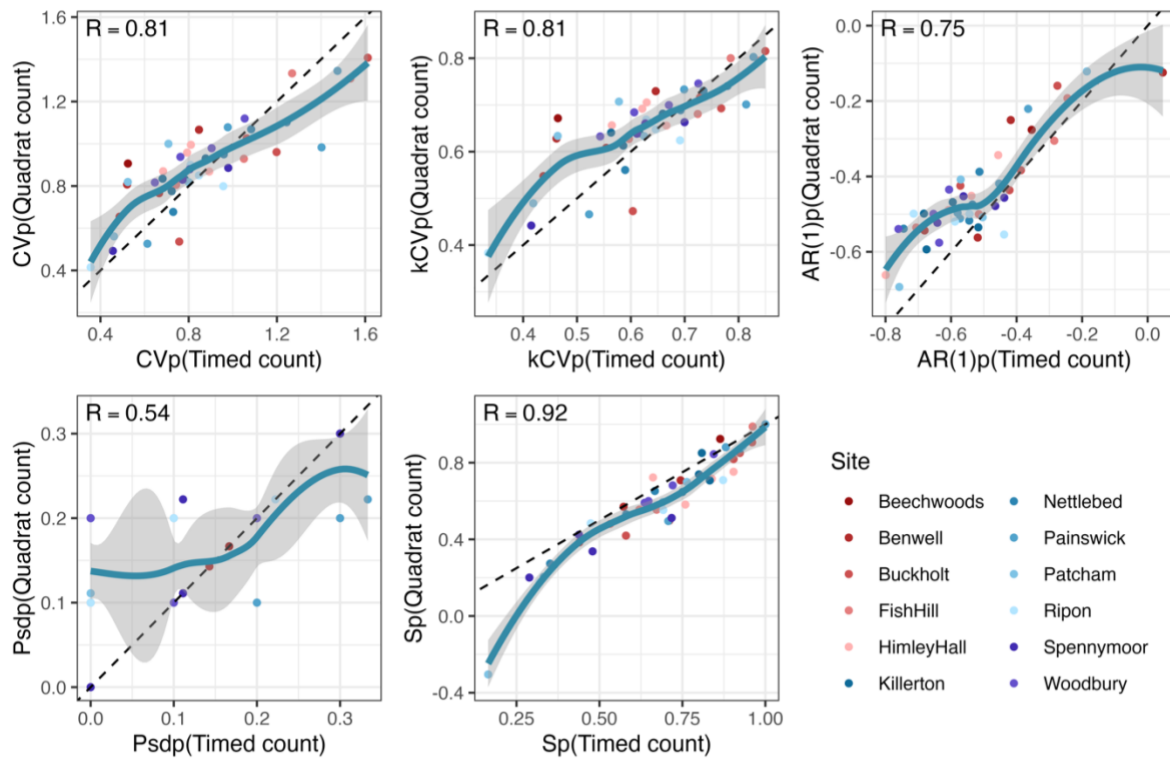


293

294 *Figure 5: Illustration of differences between level of temporal variability measured with the CVi (coefficient of*
 295 *variation at the individual level) of timed count (CVi T) and quadrat count (CVi Q) time series. Nine time*
 296 *series segments (faceted by Site and Tree ID) are plotted over time, with colour specifying the counting method.*
 297 *These time series match the points which fall within the red rectangle in the top-left plot (i.e. the first subplot of*
 298 *Fig. 4). Note that missing values either represent missing data, or measured values from the timed count that*
 299 *fell beyond the range of values to develop the conversion model.*

300 **Population level**

301 The differences between seed production variability metrics (i.e. CV_p, kCV_p) obtained with the two seed
 302 collection methods are less pronounced at the population level (Fig. 6). Spearman rank correlations range
 303 between 0.54 for P_{sd} and 0.92 for S. P_{sd} is the only metric with a relatively poor fit between metrics of the
 304 two seed collection methods at the population level.



305

306 *Figure 6: Relationships between metrics (CV, kCV, AR(1), Psdp, S) obtained with two different methods, at the*
 307 *population level (p). CV: coefficient of variation, kCV: Kvalseth coefficient of variation, AR(1): temporal*
 308 *autocorrelation at lag 1 year, Psdp: proportion of high seeding years, S: synchrony. The thin black dashed line*
 309 *represents the bisector. The thicker blue loess regression lines and 95% confidence interval are added for visual*
 310 *interpretation. Points represent time series segments, where the colour indicates the site. The spearman rank*
 311 *correlation (R) is shown in the top-left of each subplot.*

312 Discussion

313 The timed count has been used for multiple decades (Packham et al., 2008), and data obtained with this
 314 method has been used in several publications on the ecology of seed production in perennial plants
 315 (Bogdziewicz et al., 2023, 2020; Foest et al., 2024; Journé et al., 2024, 2023b). Until now, it remained
 316 unclear how this method relates to the more commonly used area-based methods. Our study showed that
 317 the relationship between seed counts obtained with the two methods is loglinear and has a good fit across

318 sites, allowing for translation between the two sampling methods. Since timed counts are considerably faster
319 than quadrat counts, those interested in measuring seed production over time more efficiently might
320 consider adopting this method. To illustrate, a single observer employing the timed count sampled around
321 six trees per hour. This estimate includes conducting the seed count, labelling and storing bags, taking notes
322 and moving between trees. To conduct the quadrat counts under the same canopies, two to three observers
323 managed to sample around nine trees per 8-hour working day (~1.13 trees per hour). This equates to over a
324 tenfold difference in sampling speed. Differences in seed counting time in the lab were also substantial; on
325 average we counted 141 seeds per tree for the timed count, and 188 per tree for the quadrat count, resulting
326 in a lab effort that was one-third greater for quadrat counts.

327 While the presented formulas can be used to translate between timed and quadrat counts, some caution is
328 warranted. Firstly, we advise recalibrating the loglinear relationship to local conditions (or, when site
329 conditions have changed substantially over time) when seeking to convert timed seed counts into quadrat
330 counts (Tattoni et al., 2021). This is because the exact relationship may differ between plant species (e.g.
331 different seed sizes resulting in different ease of sampling with timed counts, and therefore, different
332 counts), site conditions (i.e. we measured trees in mature, relatively open, limited understory stands, but
333 timed counts may be lower in more challenging sites compared to quadrat counts), and possibly observers.
334 Regardless, an important insight resulting from this work is that the timed count is broadly equivalent to log
335 converted quadrat counts, and, by extension, $\ln(\text{seeds}/\text{m}^2)$. Generally, caution is warranted when converting
336 between methods which are characterised by a loglinear relationship (and extrapolating may yield unrealistic
337 results). Namely, small changes in timed counts at high seed fall levels would be transformed into large
338 changes in quadrat count estimates. Further work is required to expand the current dataset, incorporating
339 timed seed counts > 270 seeds/7 minutes.

340 When using timed counts to predict quadrat counts, the goodness of fit (i.e. marginal $R^2 = 0.77$) is
341 comparable with another quick and easy referenced seed count method. Namely, Koenig et al. (1994a) and

342 Perry and Thill (1999), who compared the Koenig 30-second visual count method with seed traps found an
343 R^2 of 0.72 and 0.76 respectively. We could not contrast the timed count with seed traps (which are generally
344 considered to be the ‘gold standard’ as they limit post-dispersal seed predation; Perry and Thill, 1999;
345 Touzot et al., 2018), since these traps can easily be vandalised in publicly accessible stands. We therefore
346 stress that to minimise bias from post-dispersal seed predation in estimating tree seed production from either
347 quadrats or timed counts, sampling must be well-timed: too early, and few nuts will have fallen; too late, and
348 seed consumers like squirrels may have removed many (Packham et al., 2008). However, the reference
349 method we used, i.e. ground plots, have recently been compared to seed traps, and they are themselves
350 strongly related (Chianucci et al., 2021; Tattoni et al., 2021; Touzot et al., 2018).

351 Secondly, by contrasting the two methods with different strengths, we show that seed production patchiness
352 might explain why the timed method picks up more variation under low-seed production canopies than the
353 quadrat (Fig. 3). We found that most seed fall is patchy, and the dispersion of seed fall patchiness decreases
354 with increasing seed crop size. This indicates that especially at low seed crop sizes, there are at least some trees
355 with highly patchy seed fall. When seed fall is variable underneath a canopy, it is crucial to sample from
356 across the seed fall shadow (Perry and Thill, 1999). While the quadrats were placed along multiple transects,
357 their surface area was small (i.e. $1/9 \text{ m}^2$ per quadrat). The smallest canopy under which we sampled was 36
358 m^2 whereas the largest canopy was 403 m^2 . This means that the combined quadrats only captured between
359 3% and 0.2% of the seed fall area, which makes it probable that many aggregations of seeds were missed. In
360 contrast, the timed count covered substantially more ground. This likely enabled the observer to collect
361 seeds from more aggregations when present, and consequently pick up more variation in seed production at
362 low seed fall levels.

363 The observed patchiness underscores the general importance of sampling a sufficient proportion of the
364 canopy (Perry and Thill, 1999). In the field, it is customary for area-based seed collection methods to sample
365 1 m^2 to obtain an individual-level seed production estimate (e.g. Ida, 2021; Koenig et al., 1994a; Patterson et

366 al., 2023; Rodríguez-Ramírez et al., 2021). This is most likely done for practical reasons. Increasing the
367 sampling area while using seed traps or quadrats comes at the cost of increased infrastructure or time.
368 However, our findings show that it is advisable to increase this sampling area if resources permit and if
369 individual-level variation of seed production is of interest (as done in e.g. Fleurot et al., 2023). Adopting
370 methods which sample a larger area at a low cost such as the Koenig method, which samples approximately
371 13% of the canopy (Koenig et al., 1994a), or the timed count is a possible solution when resources are
372 limited. The timed count method may be preferable for beech since beech produces fruits regardless of
373 pollination. Unlike the Koenig method, which would require additional estimation on the proportion of
374 filled seeds, the timed count allows for accurate discrimination between filled and unfilled seeds. It is worth
375 noting that it is not currently known which of the two methods tested here better captures the ‘true’ value of
376 whole-plant seed supply. Further research into the small-scale spatial structure of seed fall is required to
377 establish the optimal sampling area given the observed patchiness.

378 Our findings reveal that seed sampling differences translate into variation in masting metrics, measured at
379 the individual and population level. The differences between the often-used variability metric CV tended to
380 be larger for individual-level time series than for population-level time series. Regardless, the findings
381 underpin the need to understand the underlying characteristics of the specific data collection method
382 chosen on seed counts and masting metrics. Refining our grasp on the effects of sampling methods on
383 masting metrics is becoming increasingly pressing, as large-scale research on masting ecology gains
384 momentum with the availability of large, combined datasets (e.g. Foest et al., 2024; Hackett-Pain et al., 2022;
385 Journé et al., 2024, 2023a; Szymkowiak et al., 2024). While such datasets are invaluable resources for
386 studying the wide-ranging impacts of masting on ecosystems (Pearse et al., 2021), comparisons of masting
387 metrics across datasets obtained via different seed collection methods likely contain additional variation
388 associated with the method used. Such variation may obscure ecologically relevant patterns (Mason et al.,

389 2018). In the light of our results, we advise that modelling in such studies should include sampling method
390 as a covariate, especially if individual-level masting metrics are compared.

391 While our study sheds light on how seed sampling methods impact masting metrics at both individual and
392 population levels, important challenges remain. Seed production is measured with a wide variety of other
393 methods (Hackett-Pain et al., 2022), and one gap in our understanding is how population-level estimates
394 derived from individual-level data differ from stand-based estimates. In other words, do we obtain similar
395 population-level estimates of masting if seed fall is sampled not directly under tree canopies, but
396 systematically or at randomised locations in stands (Chianucci et al., 2021)? Both methods may yield
397 different time series and metrics, as the relative individual-plant contributions to the population-level mean
398 can vary (Minor and Kobe, 2017). If population-level seed crop is calculated from individual-level seed
399 production, then each individual contributes equally to the population-level mean. In contrast, in stand-
400 based estimates, the relative contribution is affected by the fecundity of trees and the location of seed traps.
401 This could affect masting metrics, as dominant and fecund trees can show different masting patterns
402 (Szymkowiak et al., 2023), and can be responsible for a disproportionate fraction of the overall population-
403 level seed production (Minor and Kobe, 2017). It is important for the research communities interested in
404 seed production to prioritise efforts to better understand the variation associated with measurement
405 methods and mitigate for it.

406 **Recommendations**

407 In summary, we recommend using timed counts for seed production sampling due to its efficiency,
408 information on seed viability, and good fit with traditional quadrat counts through a loglinear relationship.
409 Although further research is needed to determine the optimum sampling area for whole-plant seed supply, it
410 is advised to sample areas larger than 1 m² per tree. Lastly, using sampling methods as covariates in

411 regeneration studies is crucial to account for variation between different seed collection techniques, and the
412 effects of other sampling methods on seed counts and masting metrics is necessary.

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422 **Conflict of interest statement**

423 None declared.

424 **Author contributions**

425 The study was conceptualised by JJF, MB, and AH-P, and supervised by AH-P. JJF wrote the initial draft,
426 conducted the analysis and visualisation. JJF, AH-P, TC, MH and PT collected data. All authors
427 contributed critically to the interpretation of the analysis and drafts, and gave final approval for publication.

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614

615 **Supporting information**

616 **Comparing two ground-based seed count methods and their effect on**
617 **masting metrics**

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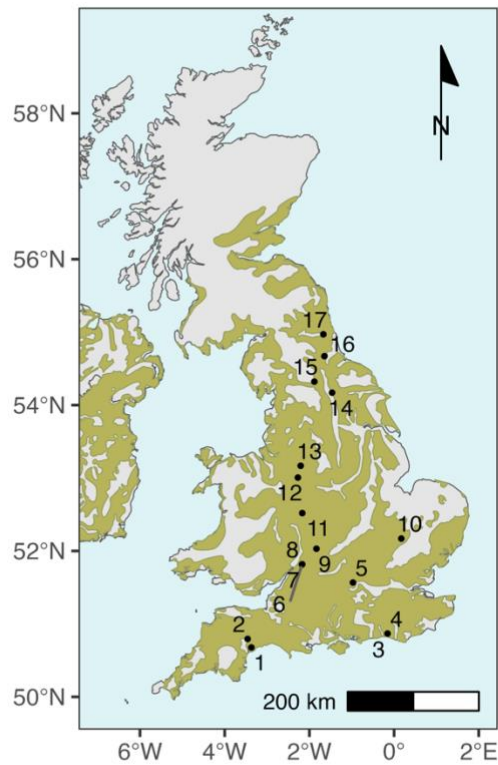
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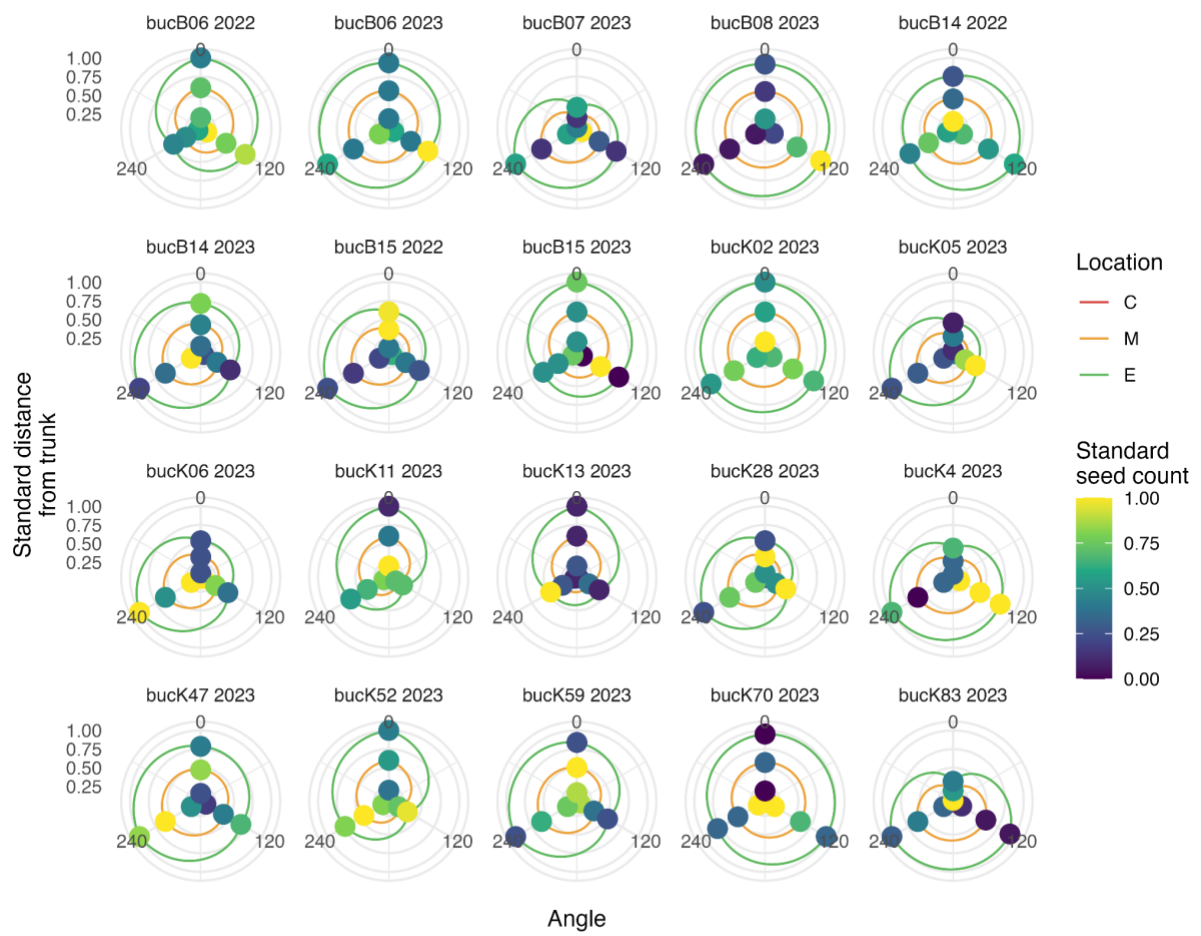
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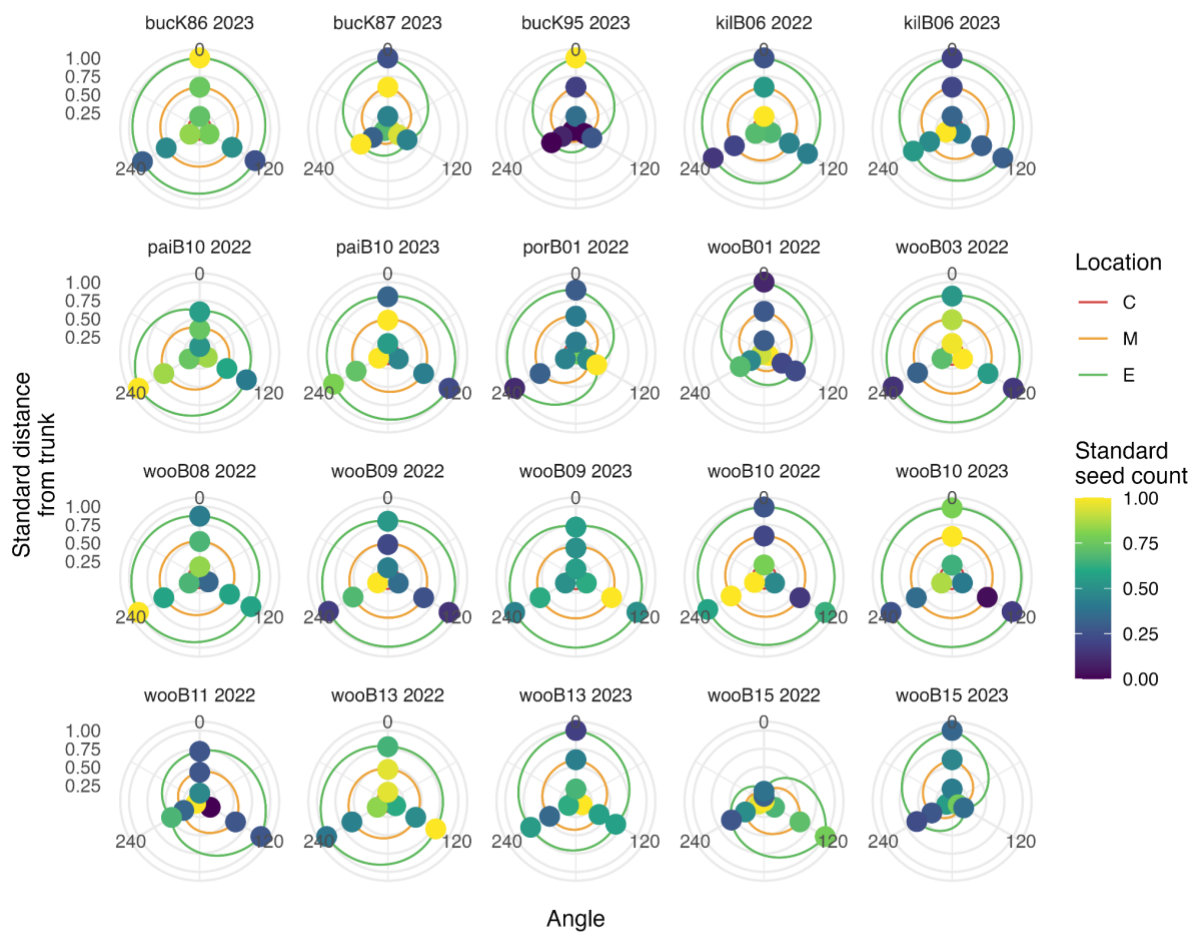


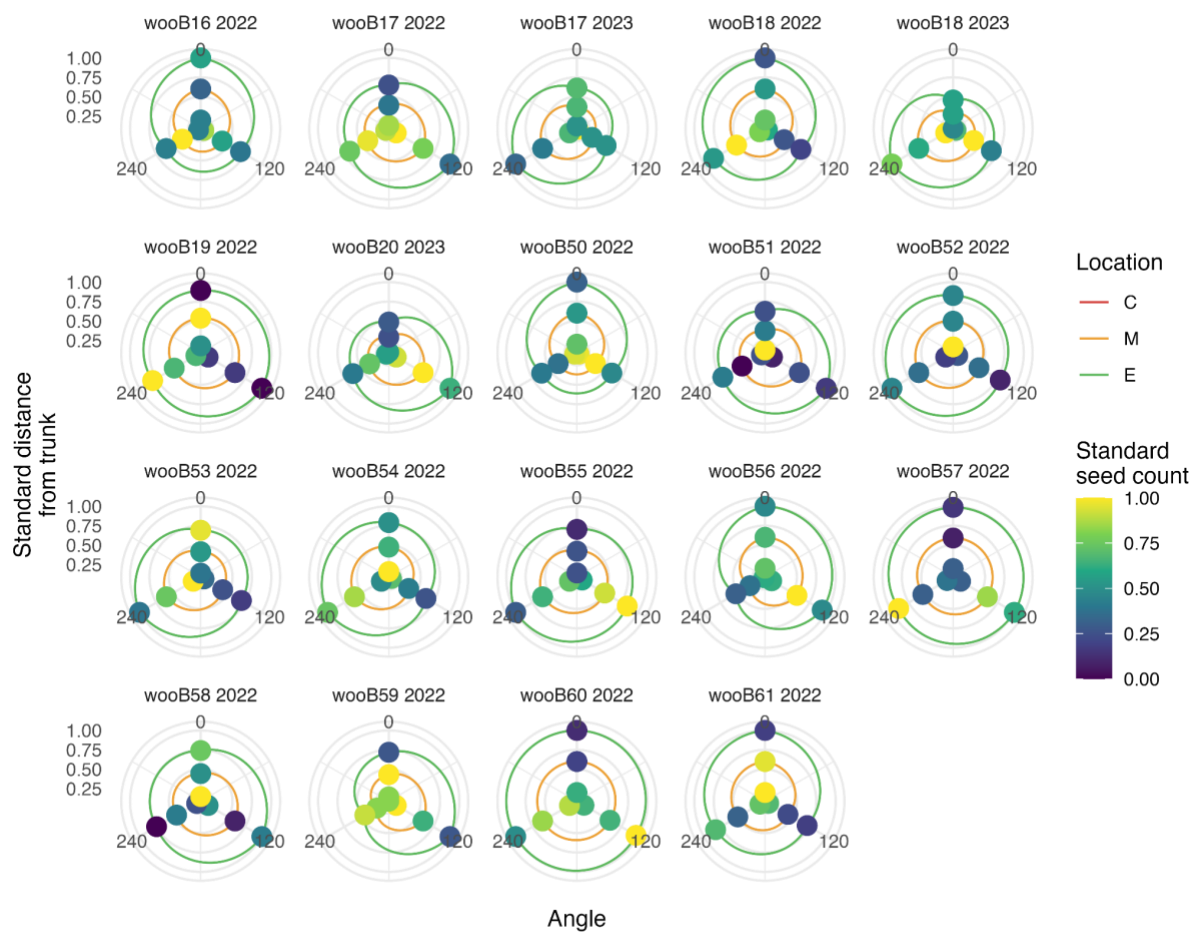
- 1 Woodbury
- 2 Killerton
- 3 Withdean
- 4 Patcham
- 5 Nettlebed
- 6 Painswick *
- 7 Portway *
- 8 Buckholt
- 9 Fish hill *
- 10 Beechwoods
- 11 Himley hall *
- 12 Keele *
- 13 Congleton
- 14 Ripon *
- 15 Gillfield
- 16 Spennymoor
- 17 Benwell

629

630 *Figure S1:* An overview of the EBMS sampling sites in the United Kingdom. An asterisk (*) was added to the
 631 site name to indicate locations where the survey was initiated after the original EBMS sites, and in some cases
 632 subsequently retired from the survey. These shorter records have not been included in prior studies using the
 633 EBMS record. Quadrat sampling was conducted in sites 1, 2, 6, 7, and 8.







636

637 *Figure S2: Seed production estimates under all tree canopies obtained with quadrat counts. Panel titles show 3-*
 638 *letter site code, the Tree ID preceded by the letter B or K, and year. Coloured points indicate standardised seed*
 639 *counts (at the tree level, using the maximum). The three sampling transects are shown, where the randomised*
 640 *orientation of the first transect is plotted at an angle of 0 degrees. The coloured lines indicate the relative*
 641 *distance from the canopy edge (i.e. Core (C), Middle (M), (Edge).*