

1 Fine-tuning mast seeding: as resources accumulate,  
2 plants become more sensitive to weather cues

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13

## 14 **Abstract**

15 Interannual variability of seed production, known as masting, has far-reaching ecological impacts  
16 including effects on forest regeneration and the population dynamics of seed consumers. It is  
17 important to understand the mechanisms driving masting to predict how plant populations  
18 and ecosystem dynamics may change into the future, and for short-term forecasting of seed  
19 production to aid management. We used long-term observations of individual flowering effort  
20 in snow tussocks (*Chionochloa pallens*) and seed production in European beech (*Fagus sylvatica*)  
21 to test how endogenous resource levels and weather variation interact in driving masting. In  
22 both species, there was an interaction between the weather cue and plant resources. If resource  
23 reserves were high, even weak temperature cues triggered relatively high reproductive effort, and  
24 depleted resources suppressed reproduction even in the presence of strong cues. Thus, resource  
25 dynamics played dual roles of both suppressant and prompter of reproduction, allowing plants to  
26 fine-tune the length of intervals between large-seeding years regardless of variable cue frequency.  
27 The strong interaction between resource reserves and weather cues has immediate application  
28 in mast forecasting models increasingly important for global afforestation efforts. Moreover, the  
29 important role of resource reserves in the plant response to weather cues will dictate the masting  
30 responses to climate change.

31 *keywords:* | flowering | mast seeding | seed production | reproduction | resource budgets |

### 32 **Declaration of interests**

34 No competing interests to declare.

## 35 **Introduction**

36 Synchronous and highly variable reproduction among years by a population of perennial plants,  
37 called mast seeding or masting, characterizes the reproduction of numerous plant species (Qiu  
38 *et al.*, 2023; Journé *et al.*, 2023). Resulting boom and bust dynamics have widespread con-  
39 sequences for food webs, nutrient cycling, plant and fungi community dynamics, and nature  
40 management (Ostfeld & Keesing, 2000; Clark *et al.*, 2019; Pearse *et al.*, 2021; Michaud *et al.*,  
41 2024). It is therefore important to understand the mechanisms driving masting patterns to help  
42 predict how plant populations and ecosystem dynamics may change into the future (Hackett-Pain  
43 & Bogdziewicz, 2021), as well as for short-term forecasting of seed production to aid man-  
44 agement decisions (Elliott & Kemp, 2016; Journé *et al.*, 2023). Both these goals are urgent:  
45 accumulating evidence indicates that masting patterns can be altered by climate change with  
46 severe consequences for seed supply (Hackett-Pain & Bogdziewicz, 2021), but the response  
47 hinges on the proximate mechanisms involved (Shibata *et al.*, 2020; LaMontagne *et al.*, 2021;  
48 Yukich-Clendon *et al.*, 2023). At the same time, ambitious afforestation plans widely planned

49 across countries (Steffen *et al.*, 2015; Richardson *et al.*, 2023) increase seed demand and require  
50 mast forecasting tools to aid efficient seed collection (Pearse *et al.*, 2021; Fargione *et al.*, 2021).  
51 Yet, while major evolutionary drivers of masting are relatively well-explored (Bogdziewicz *et al.*,  
52 2024), the proximate drivers of mast seeding, imperative for climate change biology and fore-  
53 casting, are less well crystallized. Multiple drivers play a role, including weather cues, internal  
54 resource dynamics, and underlying environmental variation (Norton & Kelly, 1988; Crone &  
55 Rapp, 2014; Pearse *et al.*, 2016; Pesendorfer *et al.*, 2021). It remains unclear how these various  
56 mechanisms apply across species and how they interact (Bogdziewicz *et al.*, 2024).

57 Two major mechanisms can increase masting variation above the baseline generated by  
58 weather variation (resource matching); weather cues and internal resource budgets (Pearse *et al.*,  
59 2016; Bogdziewicz *et al.*, 2024). Selection for high interannual variation in seed production can  
60 make plants hypersensitive to weather variation (Kelly *et al.*, 2013; Bogdziewicz *et al.*, 2020b).  
61 The relationship between seeding and weather is often exponential, with heavy reproduction  
62 resulting from high values of the weather cue (Kelly *et al.*, 2013; Fernández-Martínez *et al.*,  
63 2017; Schermer *et al.*, 2020; Smith *et al.*, 2021). Moreover, seed production requires substantial  
64 nutrient investment, which led to the formulation of resource budget models (Satake & Iwasa,  
65 2000; Crone *et al.*, 2009). Briefly, these models assume a resource threshold for reproduction so  
66 that reproduction is only initiated when sufficient internal resources accumulate. Resources are  
67 depleted by seed production, and the time required to replenish depleted resources amplifies the  
68 interannual variation in seed production (Crone & Rapp, 2014; Han & Kabeya, 2017). Finally,  
69 resource status and cues may be integrated if flowering induction by the weather cue is dependent  
70 on the resource state of the plant (Smaill *et al.*, 2011; Monks *et al.*, 2016).

71 These various drivers of masting have been recently unified by the formulation of the general  
72 model of masting, suggesting that each mechanism is potentially involved but with varying  
73 importance across species (Bogdziewicz *et al.*, 2024). For example, the model predicts that  
74 in extreme cases, masting can be driven almost solely by weather cues, but whether that is  
75 indeed the case needs to be tested (Bogdziewicz *et al.*, 2024). Clarifying these different drivers  
76 is imperative for a more accurate prediction of masting both in the long and short term. For  
77 example, where cues are dominant, the increased cueing frequency associated with climate  
78 warming will lead to more frequent reproduction, but if resource levels are also important  
79 then the mast years may also be smaller in magnitude (i.e. dampened interannual variation)  
80 (Bogdziewicz, 2022).

81 A major example of a weather cue hypothesized to generate masting without the need to  
82 invoke resource dynamics is the  $\Delta T$  differential-temperature cue, i.e. the temperature difference  
83 between the two previous summers (see Glossary) (Kelly *et al.*, 2013). The  $\Delta T$  model gave a good  
84 fit to observational seeding data, but was criticized as potentially just a proxy that captures the  
85 interaction between resource state and environmental drivers (Pearse *et al.*, 2014; Monks *et al.*,  
86 2016). Specifically, the low temperature in T2 (two years before seedfall) may veto reproduction  
87 in T1 (lack of cue), resulting in resource accumulation. Subsequent hot T1 summer (strong

88 cue) combines with accrued resources and triggers large flowering in year T0. Indeed, a model  
89 including an interaction between T1 and T2 (T1 x T2) provided a better fit to the data than the  $\Delta T$   
90 in four *Chionochloa* species, supporting that hypothesis (Monks *et al.*, 2016). Nonetheless, the  
91 issue is far from settled. Several studies compared the  $\Delta T$  fit to reproductive data with models  
92 that included  $\Delta T$  decomposed to various combinations of T1, T2, and lagged reproductive effort,  
93 with some finding support for  $\Delta T$  (Holland & James, 2014; Kon & Saito, 2015; LaMontagne  
94 *et al.*, 2021), but others failing to find support (Moreira *et al.*, 2015; Monks *et al.*, 2016).  
95 However, the majority of studies were inconclusive. Only one replaced T2 with an estimate of  
96 resource state (Monks *et al.*, 2016). Yet, as that study replaced the T2 cue with resource state,  
97 the T2 cue was no longer included (Monks *et al.*, 2016). Several studies used lagged (previous  
98 year) seed production as a resource depletion proxy (Pearse *et al.*, 2014; Holland & James,  
99 2014; Bisi *et al.*, 2016). Yet, that is an imperfect proxy as it only includes the preceding year's  
100 resource investment in seed production, foregoing information on reproductive investment in  
101 years before that. Moreover, most of these studies were conducted at the population level which  
102 includes noise created by imperfect synchronization of seed production between individuals  
103 (Koenig *et al.*, 2003; Abe *et al.*, 2016). Testing whether reproduction depends on the resource  
104 state requires supplementing (not replacing) the T2 cue with an estimate of each individual  
105 plant's resource state.

### Glossary

- **Weather cue** - weather conditions, such as warm summer, that trigger reproduction, typically by promoting heavy flowering.
- **T0, T1, T2 cues** - weather cues occurring in the same year as seedfall (T0), or lagged by one year (T1) or two years (T2) before seedfall. In the current study, the T1 and T2 cues are summer temperatures (January - February for snow tussocks, and June-July for European beech).
- **$\Delta T$  cue** - a weather cue based on a difference ( $\Delta$ ) in weather (temperature T) from one growing season to the next, here temperature difference between the two previous summers ( $\Delta T = T1 - T2$ ).
- **Resource reserves** - here, reconstructed stored resources from individual-level seed/flower production data, following the Rees *et al.* (2002) method. In short, resource reserves are estimated as negative of residuals of the linear relationship between cumulative reproductive effort and cumulative time.

106 Using resource reserves together with the T2 weather cue is important to test whether the  
107 T1+T2 model involves mechanisms unrelated to the resource state. Molecular mechanisms  
108 behind weather cues likely include gene regulatory networks that integrate various signals, such  
109 as temperature and photoperiod, allowing flowering to occur only when specific cues are received

110 (Satake & Kelly, 2021). For example, in European beech (*Fagus sylvatica*), high temperatures  
111 after the summer solstice (when the day length peaks) trigger flowering (Journé *et al.*, 2024).  
112 Crucially, both T1 and T2 summer temperature effects on seed production are seen only after  
113 the summer solstice, suggesting environmental signal integration, not resource-related effects in  
114 summer T2 (Journé *et al.*, 2024). In another example, drought and subsequent cold temperatures  
115 initiate a molecular regulation that triggers flowering in *Shorea*, and drought does not feed into  
116 the model via its effect on resource accumulation (Yeoh *et al.*, 2017; Chen *et al.*, 2018). Finally,  
117 despite the  $\Delta T$  being initially criticized for the lack of a known underlying mechanism, later  
118 studies introduced an epigenetic summer memory model (Samarth *et al.*, 2020). The T2 summer  
119 temperature initiates the activation of the floral integrator genes such as FT and SOC1. Then,  
120 elevated summer T1 temperature is required to activate these genes sufficiently to allow the plant  
121 to fully commit to the reproductive transition (Samarth *et al.*, 2020, 2021).

122 Resource availability may also regulate the flowering gene expressions modulated by en-  
123 vironmental signals. For example in *Fagus crenata* the interannual variation in flowering is  
124 associated with off-and-on cycles of expression in major flowering genes, with the expression of  
125 genes depending on nitrogen supply (Miyazaki *et al.*, 2014). Thus, our current understanding of  
126 mechanisms triggering reproduction requires the T1xT2 (or  $\Delta T$ ) model to be supplemented with  
127 the plant's resource reserves to incorporate the full suite of possible drivers. Such comprehensive  
128 testing has not been done so far.

129 Here, we used 35-year-long flowering observations in 81 alpine snow tussock plants (*Chinochloa*  
130 *pallens*) and 16-year-long seed production observations in 32 European beech (*Fagus sylvatica*)  
131 trees to test the drivers of masting in these species. In *C. pallens*, the  $\Delta T$  model fitted better than  
132 the T1+T2 model (Kelly *et al.*, 2013), but with data from a different site T1xT2 was later found  
133 to fit even better (Monks *et al.*, 2016). Transplant experiments showed that high T1 temperatures  
134 indeed trigger reproduction through activation of molecular flowering pathways (Samarth *et al.*,  
135 2022). The role of low temperatures in T2 summer is unclear, as it may represent either a veto  
136 that allows resource accumulation (Monks *et al.*, 2016), or molecular priming that modulates  
137 the plant response to summer T1 temperatures (Kelly *et al.*, 2013; Samarth *et al.*, 2020). In  
138 *F. sylvatica*, the  $\Delta T$  consistently scored lower compared to the T1 + T2 and T1 x T2 mod-  
139 els, although very few studies are available (Bogdziewicz *et al.*, 2017b; Vacchiano *et al.*, 2017;  
140 Szymkowiak *et al.*, 2024). The effects of summer T2 temperatures on seeding in European beech  
141 were long believed to represent resource priming (Piovesan & Adams, 2005; Drobyshev *et al.*,  
142 2014; Vacchiano *et al.*, 2017), but the fact that correlations between seeding and temperature  
143 appear only after the summer solstice questions that interpretation (Journé *et al.*, 2024).

144 We constructed models to specifically test these various mechanisms (summarized in Table  
145 1). By reconstructing the resource reserves of individuals, we tested whether the T2 effects are  
146 just a proxy for plant resource state or not. By including the  $\Delta T$  in the models together with  
147 estimated resource reserves, we test whether  $\Delta T$  is indeed largely independent from the resource  
148 reserves of the plant, as previously hypothesized (Kelly *et al.*, 2013; Bogdziewicz *et al.*, 2024).

**Table 1:** Summary of predictors we tested and associated hypothetical mechanisms. T1 and T2 are temperature cues (mean summer temperatures one and two years before reproduction, respectively);  $\Delta T$  is a differential-temperature cue (T1 - T2), and R is individual plant resource reserves (estimated from individual-level annual flower and seed production records, see Glossary).

Predictor	Hypothetical mechanism
T1	High temperatures promote heavy flowering through enhancing flowering genes expression
T2	Environmental signal: low temperatures promote heavy flowering through activation of the floral integrator genes that are later activated by T1 cues. Alternatively, surrogate for past seed production: negative summer temperatures decrease seed production in T1, enhancing seed production in T0
T1 x T2	The response to T1 temperature is amplified by low T2 temperature. Specific values of each year's temperatures interact, with a higher slope of T1 effect for lower T2 temperatures.
$\Delta T$	Plants measure the relative change in temperature between T2 and T1, with absolute values of T1 and T2 being unimportant
T1 + R or $\Delta T$ + R	Resource state acts as a veto, i.e. suppresses reproduction when depleted, even in the presence of cues.
T1 x R or $\Delta T$ x R	In addition to the resource state acting as veto when resources are depleted, the resource reserves acts as an amplifier of plant response to the cue, if reserves are high.

149 Finally, by including the interaction between an individual's resource reserves and weather cues,  
 150 we tested whether accumulated resources modify plant responses to the weather cue.

## 151 **Materials and Methods**

152 **Study species** Snow tussocks (*Chionochloa pallens*, Poaceae) and European beech (*Fagus syl-*  
 153 *vatica*, Fagaceae) are well-studied masting species (masting time series in Fig. S1). *Chionochloa*  
 154 *pallens* (mid-ribbed snow tussock, hereafter abbreviated to just snow tussock) is a long-lived  
 155 grass, up to 1.5 m tall, growing in the alpine zone in New Zealand. European beech (Fagaceae)  
 156 is a pan-European deciduous forest tree of high economic and ecological importance (Leuschner  
 157 & Ellenberg, 2017; Chakraborty *et al.*, 2024). Masting in both species reduces seed predation  
 158 rates, and in beech increases pollination efficiency (Kelly & Sullivan, 1997; Kelly *et al.*, 2001;  
 159 Bogdziewicz *et al.*, 2020c; Pesendorfer *et al.*, 2024). In both species, temperature cues (T1,  
 160 T2, and/or  $\Delta T$ ) and resource reserves are considered masting drivers (Piovesan & Adams, 2005;  
 161 Kelly *et al.*, 2013; Monks *et al.*, 2016; Vacchiano *et al.*, 2017), but a comprehensive test of a full  
 162 suite of drivers has not been attempted.

163 **Flowering and seed production monitoring** In snow tussocks, we monitored flowering in  
164 permanent transects at 1070 m, Mount Hutt, Canterbury, New Zealand annually between 1990  
165 and 2024. Three transects, each 20 m long, were marked with steel pegs, and all tussocks that  
166 touched the line were mapped ( $n = 81$ ). Each February, the number of inflorescences (flower  
167 stalks, abbreviated to flowers) were counted on each mapped plant (Rees *et al.*, 2002; Kelly  
168 *et al.*, 2013). During this interval, no plants died. The flower counts were censuses.

169 In European beech (*Fagus sylvatica*), we sampled seed production at 15 sites spaced across  
170 England annually between 1980 and 2023 (44 years) (Bogdziewicz *et al.*, 2023). The ground  
171 below each tree was searched for seeds for 7 minutes, and all seeds found were counted. In  
172 this study, we used the data on 32 individuals for which full records were available from 1990  
173 to 2005. After 2006, the interannual variation and synchrony of seed production in these  
174 populations declined due to warming (Bogdziewicz *et al.*, 2020c). That included the disrupted  
175 relationship between the weather cues and masting; more frequent cue occurrence appears  
176 to deplete the energy budgets of trees, resulting in weaker responses to cues (Bogdziewicz  
177 *et al.*, 2021). To exclude that confounding factor, we have used only the 16 years of the data  
178 (1990-2005), which resulted in 32 trees spaced across 12 sites.

179 **Reconstructing resource reserves** To reconstruct a plant's resource reserves from flowering  
180 and seed production data, we followed the approach developed by Rees *et al.* (2002). The  
181 method allows internal resource dynamics to be estimated from time series of reproductive  
182 effort and resource gain without directly measuring a plant's energy stores, and has been used  
183 successfully across various woody and herbaceous species (Rees *et al.*, 2002; Crone *et al.*, 2005a;  
184 Bogdziewicz *et al.*, 2018, 2019). In short, this analysis involves first fitting a linear model of  
185 cumulative reproduction (summed flower or seed count) vs cumulative years (as a surrogate  
186 of resource acquisition over time) for each species. We used linear mixed models (LMMs)  
187 implemented via the 'lme4' package (Bates *et al.*, 2015) with plant ID as random intercepts and  
188 cumulative years as a random slope. The model for European beech included also site ID as a  
189 random intercept. The random effect structure allowed fitting a unique intercept for each plant  
190 which estimates resource reserves of a plant at the beginning of the monitoring period (Rees  
191 *et al.*, 2002), while random slope allowed for different mean rates of reproduction on each plant  
192 due to variations in size or heterogeneous resource acquisition of individuals over time (Crone  
193 *et al.*, 2005b). The model takes the form:

$$\text{cumulative\_reproduction}_i \sim N\left(\beta_{1j[i]}(\text{cumulative\_year}), \sigma^2\right)$$

$$\beta_{1j} \sim N\left(\mu_{\beta_{1j}}, \sigma_{\beta_{1j}}^2\right), \text{ for plant ID } j = 1, \dots, J$$

195 Residuals for each plant from these two models (one for each species) can be used to estimate  
196 the resource reserves of that individual in each year. Basically, the regression line represents  
197 the long-term mean rate of reproduction for that plant. If the cumulative flowering gets above  
198 the regression line, the plant has been reproducing faster than the average (its expenditure is 'in  
199 overdraft'), giving a positive residual; whereas after an extended period of low flowering, the

200 cumulative flowering line falls below the regression, suggesting spending has fallen behind the  
201 mean and giving a negative residual. To reflect the inverse relationship between expenditure  
202 and resource reserves, we take the negative of these residuals, ensuring that positive residuals  
203 correspond to lower stored resources (overdraft) and negative residuals to higher stored resources  
204 (Rees *et al.*, 2002; Crone *et al.*, 2005b). Temporal dynamics of reconstructed resource reserves  
205 are presented in Fig. S1. Note that the approach we used here for the reconstruction of resource  
206 reserves makes no assumption about the limiting resource, i.e. whether that is carbon, nitrogen,  
207 or another limiting resource (Han & Kabeya, 2017). In fact, because cumulative reproduction  
208 is on the Y axis, the units of resource reserves are flower stalks for snow tussocks and seeds  
209 for European beech, including exactly the combination of carbon, nitrogen and other resources  
210 required for reproduction in that species. The OSF repository that includes the data supporting  
211 the paper also includes a a custom R code for the method application.

212 **Hypothesis testing** We constructed two sets of models for each species in which annual,  
213 plant-level flowering (snow tussocks) or seed production (European beech) was included as a  
214 response. All models included plant ID (both species), and site ID (European beech) as random  
215 intercepts. We used the Tweedie error family and logit link and for this purpose, we scaled  
216 the response values to fall between 0 and 1 at the series level. Each set then included various  
217 combinations of predictors including past summer temperatures (T1 and T2 weather cues, or  
218  $\Delta T = [T1-T2]$ ), plant resource reserves (estimated resources plant *i* has in the year before  
219 flowering *t-1*), and specific interactions. The interactions were between T1 and T2, between  
220 T1 and resource reserves, or between  $\Delta T$  and resource reserves. We have not fitted models  
221 with all possible predictor combinations; rather, we have fitted ones relevant to the hypothesized  
222 mechanisms involved. Models were ranked using the standard AIC criteria (Burnham *et al.*,  
223 2011). Collinearity between predictors was checked with VIF (< 1.3 in all models).

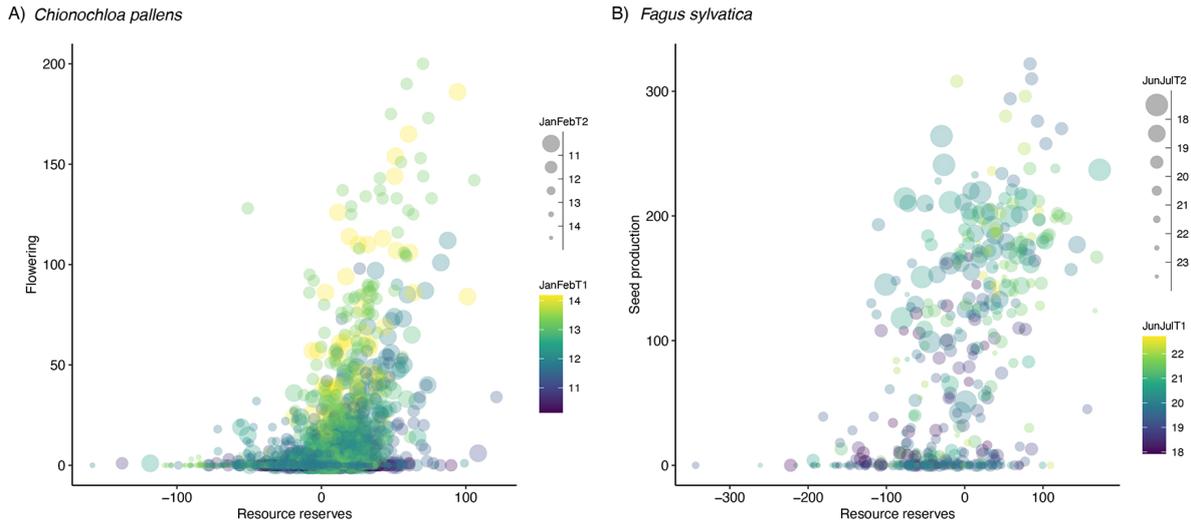
## 224 Results

225 In snow tussocks, the best-fitting model included the interaction term between reconstructed  
226 resource reserves and summer T1 temperature (Table 2). The top model also included the T1  
227 x T2 interaction. Thus, the effect of the T1 cue on reproductive effort is modified both by  
228 resource reserves and the T2 cue (Table 2). The support for such a complicated model was  
229 strong in snow tussocks (AIC weight = 0.99). In European beech, the top model also includes  
230 the interaction between resource reserves and summer T1 temperature, but the importance of the  
231 T1xT2 interaction is equivocal, with the less complicated model (T1 x Resources + T2) being  
232 similarly supported ( $\Delta AIC = 0.48$ ; Table 2). Importantly, despite the direct inclusion of resource  
233 reserves, summer T2 temperature was retained in the top model for both species, suggesting T2  
234 temperatures do not only affect masting indirectly via resource dynamics (Table 2).

235 In both species, the high reproductive effort required the alignment of both strong weather

**Table 2:** Model selection tables. Each model includes individual-level annual flowering (*C. pallens*) or seed production (*F. sylvatica*) as a response, plant ID (both species) and site ID (European beech) as random intercept, Tweedie error distribution, and logit link. T1 and T2 are summer temperatures (June and July in *F. sylvatica* and January and February in *C. pallens*), where numbers indicate lags: 1 for the previous year, and 2 for summer two years before flowering. Resources reserves, abbreviated to R in the Table, are the negative of residuals of cumulative reproduction fitted against cumulative years, see Methods.

Model	AIC	$\Delta$ AIC	weight
<b><i>Chionochloa pallens</i></b>			
T1 $\times$ R + T1 $\times$ T2	1052.1	0.0	0.995
T1 $\times$ R + T2	1064.0	11.9	0.003
T1 $\times$ T2 + R	1064.0	11.9	0.003
$\Delta$ T $\times$ R	1076.9	24.8	<0.001
$\Delta$ T + R	1098.7	46.6	<0.001
T1 + R + T2	1100.2	48.0	<0.001
T1 $\times$ T2	1139.0	86.9	<0.001
T1 + T2	1223.7	171.6	<0.001
$\Delta$ T	1232.1	180.0	<0.001
T1 $\times$ R	1521.1	469.0	<0.001
T1 + R	1603.9	551.8	<0.001
<b><i>Fagus sylvatica</i></b>			
T1 $\times$ R + T1 $\times$ T2	394.8	0.0	0.52
T1 $\times$ R + T2	394.9	0.2	0.48
$\Delta$ T $\times$ R	416.2	21.4	<0.001
T1 $\times$ T2 + R	419.9	25.1	<0.001
$\Delta$ T + R	420.5	25.7	<0.001
T1 + R + T2	422.3	27.5	<0.001
T1 $\times$ R	449.9	55.2	<0.001
T1 + R	479.0	84.3	<0.001
T1 $\times$ T2	553.0	158.3	<0.001
T1 + T2	555.0	160.3	<0.001
$\Delta$ T	557.0	162.2	<0.001

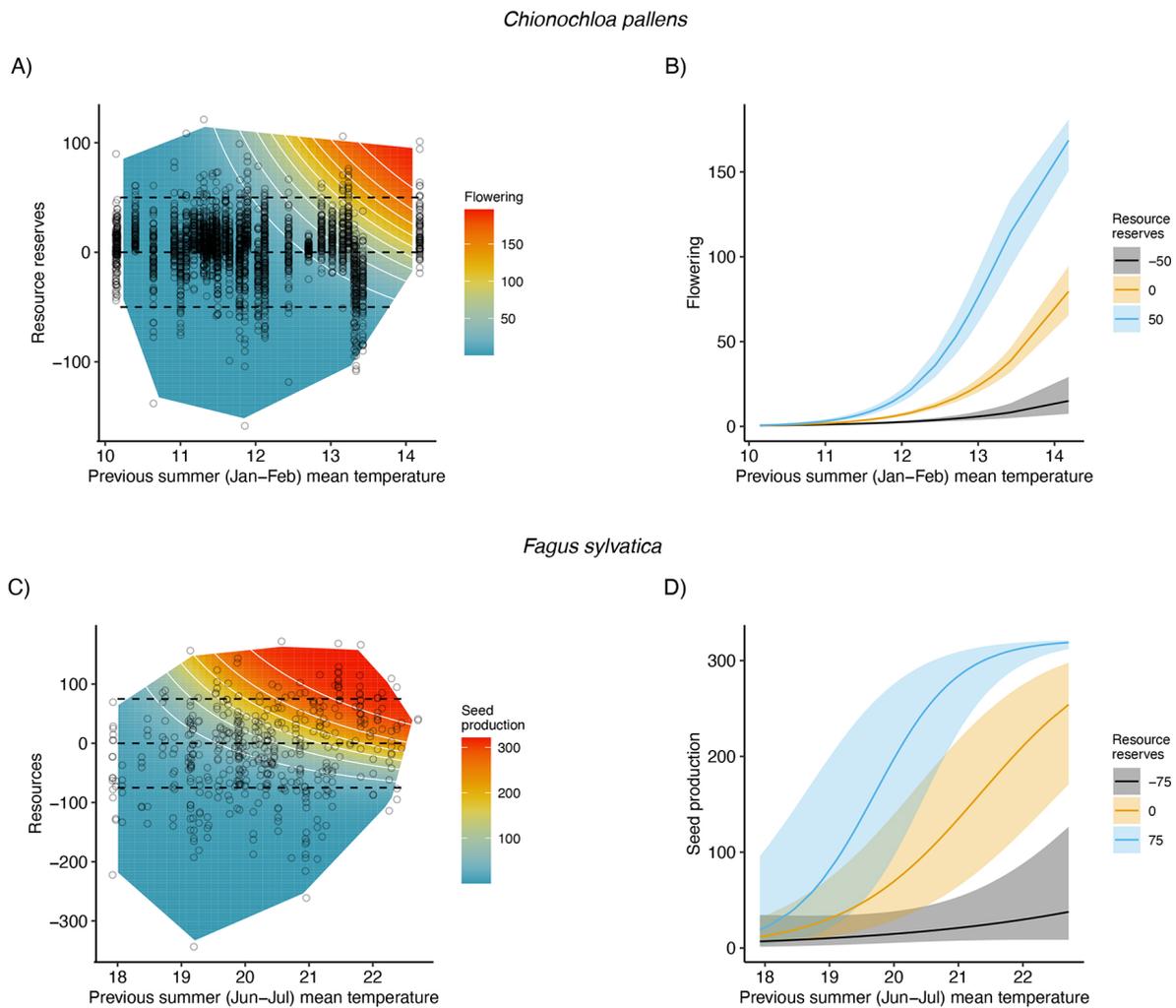


**Figure 1: Relationships between the reconstructed resource reserves and annual variation in flowering effort in *Chionochloa pallens* and seed production in *Fagus sylvatica*.** Each point is an annual flowering effort (or seed production) of an individual plant, mapped along the gradient of resource reserves (Rees *et al.*, 2002). Resource reserves are expressed as negative residuals of cumulative reproduction fitted against cumulative years, see Methods. Units of resource reserves are flowers in A and seeds in B. Point sizes and colors are scaled according to the mean summer temperatures two years and one year before flowering.

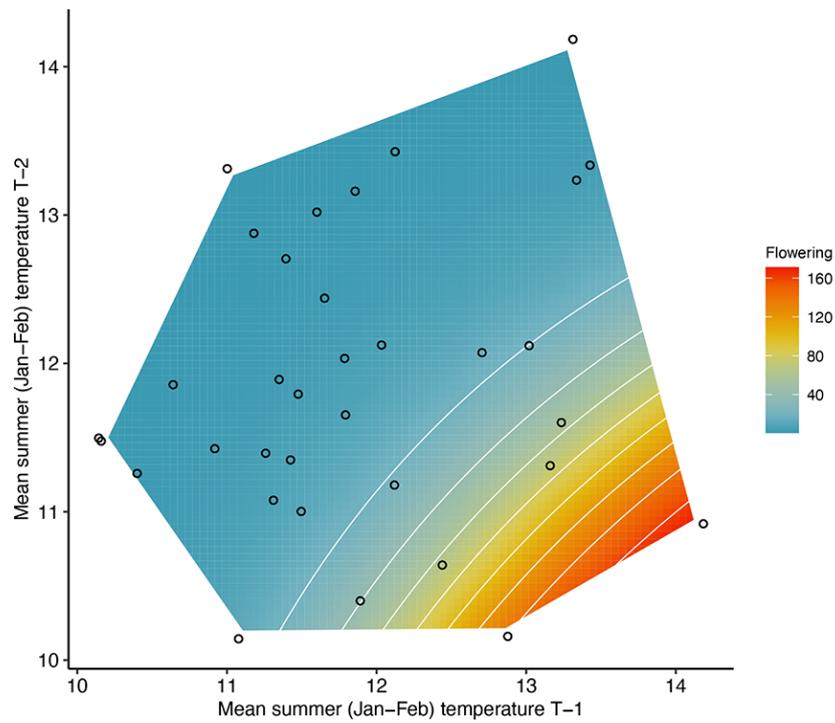
236 cues and large resource reserves (Fig. 1, 2, Table 3). The interaction between weather cues and  
 237 resource reserves was strong; if resources were depleted, even very hot summer T1 led to only  
 238 minor reproductive effort (Fig. 2). For example, in snow tussocks, estimated individual-level  
 239 reproductive effort in response to a 14 °C T1 cue was ~10 flowers if resources were depleted,  
 240 but was 17-fold larger if resource reserves were high (Fig. 2). In contrast, if reserves were  
 241 large, heavy reproduction could be initiated even if the cue was relatively weak. For example,  
 242 in European beech, individual-level seed production in response to a 21 °C T1 cue was ~110  
 243 for the average level of resource storage, but reached almost 300 if storage was high (Fig. 2).  
 244 Even a relatively cold T1 (e.g. 19 °C) resulted in relatively good seed production of ~100  
 245 seeds if resource reserves were high (Fig. 2). Finally, the T1 x T2 negative interaction in snow  
 246 tussocks resulted in heavy reproduction occurring only when a hot summer occurred after a cold  
 247 one (Table 3, Fig. 3). The modulating effect of the T2 cue on the T1 cue was similar to that  
 248 of resource reserves; if T2 summer was hot, even high T1 temperatures did not trigger heavy  
 249 reproduction (Fig. 3).

## 250 Discussion

251 Our study was inspired by the recently formulated general model of masting, which suggests  
 252 that environmental cues could drive masting without the need to invoke resource dynamics  
 253 (Bogdziewicz *et al.*, 2024). We examined two species where strong weather cues indicated that



**Figure 2: Previous summer temperatures and reconstructed resources reserves interact to determine annual variation in flowering effort in *Chionochloa pallens* and seed production in *Fagus sylvatica*.** A) and C) Surface plots show estimated individual-level flowering (*C. pallens*) or seed production (*F. sylvatica*) effort across combinations of previous summer (January-February in case of *C. pallens* and June-July in case of *F. sylvatica*) mean daily temperature (°C) and the reconstructed resource reserves, with the convex hulls (parameter space across which predictions are computed) defined by observations (black circles). Points show individual-level annual flowering or seed production. Black horizontal dashed lines at A) and C) indicate the conditional relationships plotted in B) and D), i.e., the relationship between flowering or seed production effort and summer temperature for selected levels of reconstructed resource reserves. Prediction lines and associated 95% CI at B) and D) are sections through surfaces highlighted by transects at A) and C). Resource reserves are expressed as negative residuals of cumulative reproduction fitted against cumulative years, see Methods. Estimates are derived from GLMM with Tweedie distribution and logit link that included plant ID as a random intercept. The best fitting models plotted (AIC selection Table 2) included also the negative effects of summer temperature two years before flowering or seed production (model summary Table 3).



**Figure 3:** Previous summer temperatures interact to determine annual variation in flowering effort in *Chionochloa pallens*. The surface plot shows estimated individual-level flowering effort across combinations of the previous summer (January-February) mean temperatures one and two years before flowering. The convex hull (parameter space across which predictions are computed) is defined by observations (black circles). Note that the apparently small number of points is the result of overplotting, as all individuals in each year ( $N = 81$ ) fall into the same area defined by past years' temperatures.

**Table 3:** Summary of the best-fitting generalized linear mixed model testing the effects of previous summer temperatures and resource reserves on annual variation in reproductive output in *Chionochloa pallens* and *Fagus sylvatica*. The models included individual-level annual flowering (*C. pallens*) or seed production (*F. sylvatica*) as a response and were fitted with Tweedie error distribution and logit link. T1 and T2 are mean summer temperatures a year or two years before flowering, respectively. Resources reserves (R) are reconstructed deviations from the equilibrium energy budget (see Methods).

Effect	$\beta$	SE	Z	p
<b><i>Chionochloa pallens</i> (<math>R^2 = 0.55</math>)</b>				
Intercept	-51.90	13.660	-3.80	0.001
T1	5.39	1.156	4.66	<0.001
T2	2.74	1.144	2.39	0.017
R	-0.10	0.031	-3.18	0.001
T1 $\times$ R	0.01	0.003	3.81	<0.001
T1 $\times$ T2	-0.34	0.097	-3.53	<0.001
<b><i>Fagus sylvatica</i> (<math>R^2 = 0.62</math>)</b>				
Intercept	-5.80	2.638	-2.20	0.028
T1	0.96	0.103	9.33	<0.001
T2	-0.72	0.099	-7.33	<0.001
R	-0.13	0.029	-4.64	<0.001
T1 $\times$ R	0.01	0.001	5.34	<0.001

254 resource effects might be relatively minor compared to the influence of these cues (Kelly *et al.*,  
255 2013; Vacchiano *et al.*, 2017; Journé *et al.*, 2024). Contrary to this assumption and predictions  
256 of the general model, our findings reveal that resource reserves also have a strong effect, which  
257 enables both species to fine-tune their reproductive schedules, balancing the benefits and costs  
258 of masting. This fine-tuning allows plants to optimize their reproductive timing, delaying  
259 reproduction when necessary but avoiding excessively long intervals between mast events.

260 Our findings highlight a dual function of resource reserves in its interaction with weather  
261 cues (T1) at both low and high resource levels. At low resource reserves, depleted reserves act  
262 as a 'veto' on reproduction (Isagi *et al.*, 1997; Crone *et al.*, 2009; Schermer *et al.*, 2020), not as a  
263 complete block but as a significant reduction that can largely suppress reproduction even in the  
264 presence of strong cues. This strong effect runs contrary to earlier predictions that a temperature-  
265 difference ( $\Delta T$ ) cue would render the resource veto rare and statistically hard to detect (Kelly  
266 *et al.*, 2013). The constraint on consecutive heavy reproduction due to resource depletion has  
267 important ecological consequences: it prevents large seeding events from aligning with booms  
268 in seed consumer populations after mast years, thus maintaining the starvation-satiation cycle  
269 that enhances reproductive efficiency (Zwolak *et al.*, 2022). At high resource reserves, the T1  $\times$   
270 resource interaction has been previously hypothesized (Monks *et al.*, 2016; Ascoli *et al.*, 2017),  
271 but its effects rarely directly documented. As time increases since the last major flowering  
272 episode and the plant's resource balance becomes more positive, the weather cue needed to

273 trigger heavy reproduction decreases. This beneficially affects reproduction timing by reducing  
274 the gap between large events, even when the ideal weather cue is delayed (Waller, 1979; Kelly,  
275 1994; Bogdziewicz *et al.*, 2024). These dual interactive effects enable plants to fine-tune their  
276 reproductive schedules: they are less sensitive to cues shortly after a big event but become more  
277 sensitive over time. This maintains a more constant long-term reproductive effort, preventing it  
278 from being overly influenced by unusual weather patterns, and helps plants balance the benefits  
279 and costs of masting—delaying reproduction without waiting too long.

280 While resource reserves clearly play an important role, our findings indicate that temperature  
281 two years prior to flowering (T2) acts as a distinct signal integrated into flowering regulatory  
282 networks, rather than merely serving as a surrogate for resource reserves. Our models retained  
283 both estimated resource reserves and the T2 cue, suggesting that T2 operates independently  
284 of resource reserves. We interpret these results as evidence that temperatures in T1 and T2  
285 are integral components of flowering regulatory networks, likely incorporating multiple signals  
286 such as photoperiod (Journé *et al.*, 2024) and nutrient availability (Miyazaki *et al.*, 2014).

287 The strong role of resource reserves in modulating the plant response to weather cues has  
288 important implications for masting forecasting. The statistical models used previously have  
289 not incorporated interactions, and their major shortcoming was poor performance in accurately  
290 predicting seed production in the largest mast years (Journé *et al.*, 2023). In light of the  
291 results reported here that is unsurprising, as the coefficient for the T1 cues in those models was  
292 averaged across resource conditions. However, the plant response could be orders of magnitude  
293 stronger in years when strong cues and large resource reserves align. We thus suggest that  
294 integrating interactions between surrogates of resource levels and weather cues may greatly  
295 improve the forecasting models' performance. Furthermore, our study indicates a practical  
296 approach to incorporating resource reserves into forecast models that do not require direct field  
297 measurement (Han & Kabeya, 2017), or reliance on climate proxies of resource uptake (Ascoli  
298 *et al.*, 2017). Additionally, using the approach proposed by (Rees *et al.*, 2002) does not require  
299 assumptions about the resources locally limiting masting. These are often unknown, including  
300 in our study systems, but resource reserves are estimated in units of real-world plant reproductive  
301 output (flowers or seeds).

302 The interaction between resource reserves and weather cues has significant implications for  
303 the climate change biology of mast seeding. Our findings reveal that the fine-tuning mechanism  
304 by which plants adjust their reproductive schedules is asymmetrical. At low cue frequency  
305 and high resource balance, plants can amplify their flowering response even to weaker cues,  
306 producing large seed crops. This allows masting to persist effectively under conditions with  
307 infrequent cues, such as in colder climates. In contrast, at high cue frequency, plants will  
308 be less able to adjust. Frequent cues lead to repeated depletion of resource reserves, and  
309 the interaction suppresses flowering due to low resource reserves. However, as soon as plants  
310 accumulate some resources, another cue occurs, prompting plants to flower. This results in more  
311 frequent reproduction but smaller seed crops, a phenomenon observed as masting breakdown

312 in European beech after 2005 (Bogdziewicz *et al.*, 2021; Foest *et al.*, 2024). Importantly,  
313 environmental changes not only increase cue frequency but may also impact resource dynamics  
314 through factors such as nitrogen and phosphorus deposition and CO<sub>2</sub> fertilization (LaDeau &  
315 Clark, 2006; Bogdziewicz *et al.*, 2017a; McClory *et al.*, 2024). The net effect depends on  
316 whether resource availability can keep pace with the increased cue frequency. If resources  
317 do not increase sufficiently, we predict more frequent but smaller seed crops. Conversely, if  
318 resources can match the higher cue frequency, plants may produce frequent and still large crops.

319 Finally, we highlight the challenges in identifying weather cues driving masting. Distinguish-  
320 ing between absolute and relative temperature cues is crucial; a  $\Delta T$  (year-to-year temperature  
321 difference) cue would render masting largely insensitive to gradual climate warming because  
322 increases in mean temperature have little effect on interannual variations (Kelly *et al.*, 2013).  
323 Observational data have inconsistently supported absolute versus relative temperature cues, even  
324 within the same species. In our study, absolute temperatures (T1 and T2) were better predic-  
325 tors of masting in snow tussocks and European beech than  $\Delta T$ . Previous studies have variously  
326 identified absolute T1, T1 and T2,  $\Delta T$ , or T1×T2 as significant drivers (Kelly *et al.*, 2008,  
327 2013; Monks *et al.*, 2016; Bogdziewicz *et al.*, 2020c). These discrepancies may result from  
328 differences in study sites, data durations, or models used. There is a trade-off between testing  
329 too many climate variables—risking spurious correlations—and too few, potentially missing  
330 complex drivers. Moreover, modeling studies have shown that  $\Delta T$  models can fit data well even  
331 when the true drivers are absolute temperatures combined with resource availability (Monks  
332 *et al.*, 2016), highlighting limitations of observational data (Bogdziewicz *et al.*, 2020a).

333 To unambiguously identify masting cues, we propose genetic studies and experimental  
334 manipulations. Genetic analyses can detect subtle weather events triggering reproduction (Satake  
335 *et al.*, 2021, 2022), and technological advances are reducing the required effort and cost (Satake  
336 & Kelly, 2021). Experimental manipulations, such as altering fertilizer levels, water stress,  
337 pollination, or temperature, can also provide insights (Crone & Rapp, 2014; Bogdziewicz *et al.*,  
338 2020a), though they are challenging to implement at large scales. Alternatively, observational  
339 studies during climate warming can serve as 'natural experiments' to distinguish between cues  
340 (Redmond *et al.*, 2012; Wion *et al.*, 2020; LaMontagne *et al.*, 2021). In North American conifers,  
341 masting remained unaffected by long-term warming, suggesting  $\Delta T$  is the cue (LaMontagne *et al.*,  
342 2021). In contrast, European beech experienced 'masting breakdown' under warming conditions,  
343 consistent with absolute temperature cues driving masting (Bogdziewicz *et al.*, 2020c; Foest  
344 *et al.*, 2024). This led to increased seed predation and decreased pollination efficiency, resulting  
345 in an up to 80% decline in viable seed output (Bogdziewicz *et al.*, 2023). However, natural  
346 experiments may involve modest temperature changes; for example, LaMontagne *et al.* (2021)  
347 reported a low warming rate (0.09°C per decade). An analysis across 50 European beech seed  
348 production series indicated that changes in variability are related to the rate of temperature  
349 change, suggesting slow warming may not significantly impact masting (Foest *et al.*, 2024).

350 In conclusion, our study demonstrates that masting in snow tussocks and European beech is

351 driven by the interactive effects of resource reserves and summer temperatures. This indicates  
352 that resource reserves are a key driver of masting, providing selective advantages by allowing  
353 high resource levels to act as a promoter of flowering; a weather cue still provides synchrony,  
354 but resource levels modify how big the weather cue has to be. Understanding these interactions  
355 could improve the predictive accuracy of masting forecasting tools (Journé *et al.*, 2023) and  
356 explain the reduced cue sensitivity observed with warming in European beech (Bogdziewicz  
357 *et al.*, 2021; Foest *et al.*, 2024). Determining whether plants respond to relative ( $\Delta T$ ) or absolute  
358 (T1 and T2) temperature cues is essential for understanding how climate change will affect  
359 perennial reproduction. We stress that our study is observational, and experiments are needed  
360 to draw definitive conclusions about the specific weather cues driving mast crops. Experimental  
361 approaches, such as artificial warming or transplanting plants to different climates, are needed.  
362 Future research should focus on pinpointing the molecular mechanisms that integrate T1 and  
363 T2 cues (Satake & Kelly, 2021; Satake *et al.*, 2022; Journé *et al.*, 2024), clarifying the role of  
364 relative versus absolute temperature variations (Kelly *et al.*, 2013; LaMontagne *et al.*, 2021),  
365 and determining how environmental fertilization and increasing cue frequency will influence  
366 reproductive patterns in perennial plants.

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### 373 **Author Contributions Statement**

374 DK, MB, JSz, AHP designed the study, DK and AHP collected and curated the data, JSz ran the  
375 analysis, all authors contributed to the data interpretation, MB and DK drafted the manuscript,  
376 and all authors revised and approved the text.

377

### **Data availability statement**

The data supporting the results is available at the OSF, together with a custom R code that allows application of the Rees *et al.* (2002) method: [https://osf.io/25vy6/?view\\_only=328a8d6572ba49f38811cd7e2d9735c8](https://osf.io/25vy6/?view_only=328a8d6572ba49f38811cd7e2d9735c8)

## 378 **References**

379 Abe, T., Tachiki, Y., Kon, H., Nagasaka, A., Onodera, K., Minamino, K. *et al.* (2016). Pa-  
380 rameterisation and validation of a resource budget model for masting using spatiotemporal

381 flowering data of individual trees. *Ecology Letters*, 19, 1129–1139.

382 Ascoli, D., Vacchiano, G., Turco, M., Conedera, M., Drobyshev, I., Maringer, J. *et al.* (2017).  
383 Inter-annual and decadal changes in teleconnections drive continental-scale synchronization  
384 of tree reproduction. *Nature Communications* 2017 8:1, 8, 1–9.

385 Bates, D., Mächler, M., Bolker, B.M. & Walker, S.C. (2015). Fitting linear mixed-effects models  
386 using lme4. *Journal of Statistical Software*, 67.

387 Bisi, F., von Hardenberg, J., Bertolino, S., Wauters, L.A., Imperio, S., Preatoni, D.G. *et al.*  
388 (2016). Current and future conifer seed production in the alps: testing weather factors as cues  
389 behind masting. *European Journal of Forest Research*, 135, 743–754.

390 Bogdziewicz, M. (2022). How will global change affect plant reproduction? a framework for  
391 mast seeding trends. *New Phytologist*, 234, 14–20.

392 Bogdziewicz, M., Ascoli, D., Hacket-Pain, A., Koenig, W.D., Pearse, I., Pesendorfer, M. *et al.*  
393 (2020a). From theory to experiments for testing the proximate mechanisms of mast seeding:  
394 an agenda for an experimental ecology. *Ecology Letters*, 23, 210–220.

395 Bogdziewicz, M., Crone, E., Steele, M. & Zwolak, R. (2017a). Effects of nitrogen deposition  
396 on reproduction in a masting tree: benefits of higher seed production are trumped by negative  
397 biotic interactions. *Journal of Ecology*, 105, 310–320.

398 Bogdziewicz, M., Hacket-Pain, A., Kelly, D., Thomas, P.A., Lageard, J. & Tanentzap, A.J.  
399 (2021). Climate warming causes mast seeding to break down by reducing sensitivity to  
400 weather cues. *Glob Change Biol*, 27, 1952–1961.

401 Bogdziewicz, M., Kelly, D., Ascoli, D., Caignard, T., Chianucci, F., Crone, E.E. *et al.* (2024).  
402 Evolutionary ecology of masting: mechanisms, models, and climate change. *Trends in*  
403 *Ecology Evolution*, 39, 851–862.

404 Bogdziewicz, M., Kelly, D., Tanentzap, A.J., Thomas, P., Foest, J., Lageard, J. *et al.* (2023).  
405 Reproductive collapse in european beech results from declining pollination efficiency in large  
406 trees. *Glob Change Biol*, 29, 4595–4604.

407 Bogdziewicz, M., Kelly, D., Tanentzap, A.J., Thomas, P.A., Lageard, J.G. & Hacket-Pain, A.  
408 (2020b). Climate change strengthens selection for mast seeding in european beech. *Curr Biol*,  
409 30, 3477–3483.e2.

410 Bogdziewicz, M., Kelly, D., Thomas, P.A., Lageard, J.G.A. & Hacket-Pain, A. (2020c). Climate  
411 warming disrupts mast seeding and its fitness benefits in european beech. *Nat Plants*, 6,  
412 88–94.

- 413 Bogdziewicz, M., Steele, M.A., Marino, S. & Crone, E.E. (2018). Correlated seed failure as  
414 an environmental veto to synchronize reproduction of masting plants. *New Phytologist*, 219,  
415 98–108.
- 416 Bogdziewicz, M., Szymkowiak, J., Kasprzyk, I., Grewling, , Borowski, Z., Borycka, K. *et al.*  
417 (2017b). Masting in wind-pollinated trees: System-specific roles of weather and pollination  
418 dynamics in driving seed production. *Ecology*, 98, 2615–2625.
- 419 Bogdziewicz, M., Żywiec, M., Espelta, J., Fernández-Martinez, M., Calama, R., Ledwoń, M.  
420 *et al.* (2019). Environmental veto synchronizes mast seeding in four contrasting tree species.  
421 *American Naturalist*, 194, 246–259.
- 422 Burnham, K.P., Anderson, D.R. & Huyvaert, K.P. (2011). Aic model selection and multi-  
423 model inference in behavioral ecology: Some background, observations, and comparisons.  
424 *Behavioral Ecology and Sociobiology*, 65, 23–35.
- 425 Chakraborty, D., Ciceu, A., Ballian, D., Garzón, M.B., Bolte, A., Bozic, G. *et al.* (2024).  
426 Assisted tree migration can preserve the european forest carbon sink under climate change.  
427 *Nature Climate Change*, 14, 845–852.
- 428 Chen, Y.Y., Satake, A., Sun, I.F., Kosugi, Y., Tani, M., Numata, S. *et al.* (2018). Species-specific  
429 flowering cues among general flowering shorea species at the pasoh research forest, malaysia.  
430 *J Ecol*, 106, 586–598.
- 431 Clark, J.S., Nuñez, C.L. & Tomasek, B. (2019). Foodwebs based on unreliable foundations:  
432 spatiotemporal masting merged with consumer movement, storage, and diet. *Ecological*  
433 *Monographs*, 89, e01381.
- 434 Crone, E.E., Miller, E. & Sala, A. (2009). How do plants know when other plants are flowering?  
435 resource depletion, pollen limitation and mast-seeding in a perennial wildflower. *Ecol Lett*,  
436 12, 1119–1126.
- 437 Crone, E.E., Polansky, L. & Lesica, P. (2005a). Empirical models of pollen limitation, resource  
438 acquisition, and mast seeding by a bee-pollinated wildflower. *American Naturalist*, 166,  
439 396–408.
- 440 Crone, E.E., Polansky, L. & Lesica, P. (2005b). Empirical models of pollen limitation, resource  
441 acquisition, and mast seeding by a bee-pollinated wildflower. *American Naturalist*, 166,  
442 396–408.
- 443 Crone, E.E. & Rapp, J.M. (2014). Resource depletion, pollen coupling, and the ecology of mast  
444 seeding. *Annals of the New York Academy of Sciences*, 1322, 21–34.

- 445 Drobyshev, I., Niklasson, M., Mazerolle, M.J. & Bergeron, Y. (2014). Reconstruction of a 253-  
446 year long mast record of european beech reveals its association with large scale temperature  
447 variability and no long-term trend in mast frequencies. *Agricultural and Forest Meteorology*,  
448 192-193, 9–17.
- 449 Elliott, G. & Kemp, J. (2016). Large-scale pest control in new zealand beech forests. *Ecol*  
450 *Manag Restor*, 17, 200–209.
- 451 Fargione, J., Haase, D.L., Burney, O.T., Kildisheva, O.A., Edge, G., Cook-Patton, S.C. *et al.*  
452 (2021). Challenges to the reforestation pipeline in the united states. *Frontiers in Forests and*  
453 *Global Change*, 4, 629198.
- 454 Fernández-Martínez, M., Vicca, S., Janssens, I.A., Espelta, J.M. & Peñuelas, J. (2017). The north  
455 atlantic oscillation synchronises fruit production in western european forests. *Ecography*, 40,  
456 864–874.
- 457 Foest, J.J., Bogdziewicz, M., Pesendorfer, M.B., Ascoli, D., Cutini, A., Nussbaumer, A. *et al.*  
458 (2024). Widespread breakdown in masting in european beech due to rising summer temper-  
459 atures. *Glob Change Biol*, 30, e17307.
- 460 Hacket-Pain, A. & Bogdziewicz, M. (2021). Climate change and plant reproduction: trends and  
461 drivers of mast seeding change. *Philos Trans R Soc Lond B Biol Sci*, 376, 20200379.
- 462 Han, Q. & Kabeya, D. (2017). Recent developments in understanding mast seeding in relation  
463 to dynamics of carbon and nitrogen resources in temperate trees. *Ecological Research*, 32,  
464 771–778.
- 465 Holland, E.P. & James, A. (2014). Assessing the efficacy of population-level models of mast  
466 seeding. *Theoretical Ecology 2014 8:1*, 8, 121–132.
- 467 Isagi, Y., Sugimura, K., Ssumida, A. & Ito, H. (1997). How does masting happen and synchro-  
468 nize? *Journal of Theoretical Biology*, 187, 231–239.
- 469 Journé, V., Hacket-Pain, A. & Bogdziewicz, M. (2023). Evolution of masting in plants is linked  
470 to investment in low tissue mortality. *Nat Commu*, 14, 7998.
- 471 Journé, V., Hacket-Pain, A., Oberklammer, I., Pesendorfer, M.B. & Bogdziewicz, M. (2023).  
472 Forecasting seed production in perennial plants: identifying challenges and charting a path  
473 forward. *New Phytol*, 239, 466–476.
- 474 Journé, V., Szymkowiak, J., Foest, J., Hacket-Pain, A., Kelly, D. & Bogdziewicz, M. (2024).  
475 Summer solstice orchestrates the subcontinental-scale synchrony of mast seeding. *Nat Plants*,  
476 10, 367–373.
- 477 Kelly, D. (1994). The evolutionary ecology of mast seeding. *Trends Ecol Evol*, 9, 465–470.

- 478 Kelly, D., Geldenhuis, A., James, A., Holland, E.P., Plank, M.J., Brockie, R.E. *et al.* (2013).  
479 Of mast and mean: differential-temperature cue makes mast seeding insensitive to climate  
480 change. *Ecol Lett*, 16, 90–98.
- 481 Kelly, D., Hart, D.E. & Allen, R.B. (2001). Evaluating the wind pollination benefits of mast  
482 seeding. *Ecology*, 82, 117–126.
- 483 Kelly, D. & Sullivan, J.J. (1997). Quantifying the benefits of mast seeding on predator satiation  
484 and wind pollination in chionochloa pallens (poaceae). *Oikos*, 78, 143–150.
- 485 Kelly, D., Turnbull, M.H., Pharis, R.P. & Sarfati, M.S. (2008). Mast seeding, predator satiation,  
486 and temperature cues in chionochloa (poaceae). *Population Ecology*, 50, 343–355.
- 487 Koenig, W.D., Kelly, D., Sork, V.L., Duncan, R.P., Elkinton, J.S., Peltonen, M.S. *et al.* (2003).  
488 Dissecting components of population-level variation in seed production and the evolution of  
489 masting behavior. *Oikos*, 102, 581–591.
- 490 Kon, H. & Saito, H. (2015). Test of the temperature difference model predicting masting  
491 behavior. *Canadian Journal of Forest Research*, 45, 1835–1844.
- 492 LaDeau, S.L. & Clark, J.S. (2006). Elevated co2 and tree fecundity: The role of tree size,  
493 interannual variability, and population heterogeneity. *Global Change Biology*, 12, 822–833.
- 494 LaMontagne, J.M., Redmond, M.D., Wion, A.P. & Greene, D.F. (2021). An assessment of  
495 temporal variability in mast seeding of north american pinaceae. *Philos Trans R Soc Lond B*  
496 *Biol Sci*, 376, 20200373.
- 497 Leuschner, C. & Ellenberg, H. (2017). Beech and mixed beech forests. *Ecology of Central*  
498 *European Forests: Vegetation Ecology of Central Europe*, 1, 351–441.
- 499 McClory, R., Ellis, R.H., Lukac, M., Clark, J., Mayoral, C., Hart, K.M. *et al.* (2024). Carbon diox-  
500 ide enrichment affected flower numbers transiently and increased successful post-pollination  
501 development stably but without altering final acorn production in mature pedunculate oak  
502 (*quercus robur* l.). *Journal of Forestry Research*, 35, 73.
- 503 Michaud, T.J., Pearse, I.S., Kauserud, H., Andrew, C.J. & Kennedy, P.G. (2024). Mast seeding  
504 in european beech (*fagus sylvatica* l.) is associated with reduced fungal sporocarp production  
505 and community diversity. *Ecology Letters*, 27, e14460.
- 506 Miyazaki, Y., Maruyama, Y., Chiba, Y., Kobayashi, M.J., Joseph, B., Shimizu, K.K. *et al.* (2014).  
507 Nitrogen as a key regulator of flowering in *fagus crenata*: understanding the physiological  
508 mechanism of masting by gene expression analysis. *Ecology Letters*, 17, 1299–1309.

- 509 Monks, A., Monks, J.M. & Tanentzap, A.J. (2016). Resource limitation underlying multiple  
510 masting models makes mast seeding sensitive to future climate change. *New Phytol*, 210,  
511 419–430.
- 512 Moreira, X., Abdala-Roberts, L., Linhart, Y.B. & Mooney, K.A. (2015). Effects of climate  
513 on reproductive investment in a masting species: Assessment of climatic predictors and  
514 underlying mechanisms. *Journal of Ecology*, 103, 1317–1324.
- 515 Norton, D.A. & Kelly, D. (1988). Mast seeding over 33 years by *dacrydium cupressinum* lamb.  
516 (rimu) (podocarpaceae) in new zealand: The importance of economies of scale. *Funct Ecol*,  
517 2, 399–408.
- 518 Ostfeld, R.S. & Keesing, F. (2000). Pulsed resources and community dynamics of consumers  
519 in terrestrial ecosystems. *Trends Ecol Evol*, 15, 232–237.
- 520 Pearse, I.S., Koenig, W.D. & Kelly, D. (2016). Mechanisms of mast seeding: resources, weather,  
521 cues, and selection. *New Phytol*, 212, 546–562.
- 522 Pearse, I.S., Koenig, W.D. & Knops, J.M.H. (2014). Cues versus proximate drivers: testing the  
523 mechanism behind masting behavior. *Source: Oikos*, 123, 179–184.
- 524 Pearse, I.S., Wion, A.P., Gonzalez, A.D. & Pesendorfer, M.B. (2021). Understanding mast  
525 seeding for conservation and land management. *Philos Trans R Soc Lond B Biol Sci*, 376,  
526 34657466.
- 527 Pesendorfer, M.B., Ascoli, D., Bogdziewicz, M., Hacket-Pain, A., Pearse, I.S. & Vacchiano, G.  
528 (2021). The ecology and evolution of synchronized reproduction in long-lived plants. *Philos*  
529 *Trans R Soc Lond B Biol Sci*, 376, 20200369.
- 530 Pesendorfer, M.B., Bogdziewicz, M., Oberklammer, I., Nopp-Mayr, U., Szwagrzyk, J. &  
531 Gratzner, G. (2024). Positive spatial and temporal density-dependence drive early reproductive  
532 economy-of-scale effects of masting in a european old-growth forest community. *Journal of*  
533 *Ecology*, 112, 1872–1884.
- 534 Piovesan, G. & Adams, J.M. (2005). The evolutionary ecology of masting: Does the envi-  
535 ronmental prediction hypothesis also have a role in mesic temperate forests? *Ecological*  
536 *Research*, 20, 739–743.
- 537 Qiu, T., Aravena, M.C., Ascoli, D., Bergeron, Y., Bogdziewicz, M., Boivin, T. *et al.* (2023).  
538 Masting is uncommon in trees that depend on mutualist dispersers in the context of global  
539 climate and fertility gradients. *Nat Plants*, 9, 1044–1056.
- 540 Redmond, M.D., Forcella, F. & Barger, N.N. (2012). Declines in pinyon pine cone production  
541 associated with regional warming. *Ecosphere*, 3, 120.

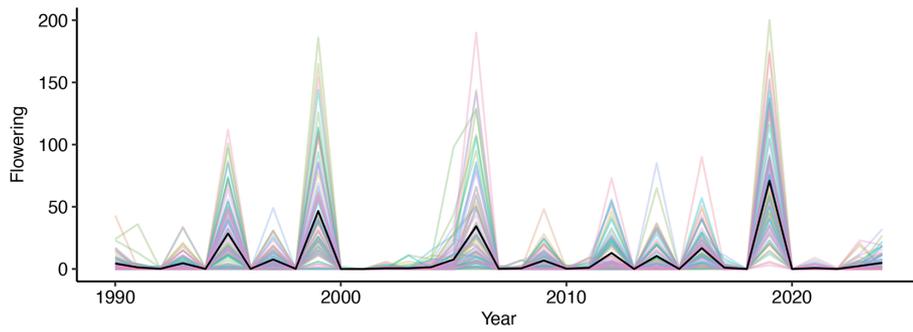
- 542 Rees, M., Kelly, D. & Bjørnstad, O.N. (2002). Snow tussocks, chaos, and the evolution of mast  
543 seeding. *Am Nat*, 160, 44–59.
- 544 Richardson, K., Steffen, W., Lucht, W., Bendtsen, J., Cornell, S.E., Donges, J.F. *et al.* (2023).  
545 Earth beyond six of nine planetary boundaries. 9, eadh2458.
- 546 Samarth, Kelly, D., Turnbull, M.H. & Jameson, P.E. (2020). Molecular control of masting: An  
547 introduction to an epigenetic summer memory. *Ann Bot*, 125, 851–858.
- 548 Samarth, Lee, R., Kelly, D., Turnbull, M.H., Macknight, R., Poole, A.M. *et al.* (2022). A novel  
549 *tfl1* gene induces flowering in the mast seeding alpine snow tussock, *chionochloa pallens*  
550 (poaceae). *Molecular Ecology*, 31, 822–838.
- 551 Samarth, Lee, R., Kelly, D., Turnbull, M.H., Macknight, R.C., Poole, A.M. *et al.* (2021).  
552 Molecular control of the floral transition in the mast seeding plant *celmisia lyallii* (asteraceae).  
553 *Mol Ecol*, 30, 1846–1863.
- 554 Satake, A. & Iwasa, Y. (2000). Pollen coupling of forest trees: Forming synchronized and  
555 periodic reproduction out of chaos. *J Theor Biol*, 203, 63–84.
- 556 Satake, A. & Kelly, D. (2021). Studying the genetic basis of masting. *Philos Trans R Soc Lond*  
557 *B Biol Sci*, 376, 20210116.
- 558 Satake, A., Nagahama, A. & Sasaki, E. (2022). A cross-scale approach to unravel the molecular  
559 basis of plant phenology in temperate and tropical climates. *New Phytologist*, 233, 2340–2353.
- 560 Satake, A., Yao, T.L., Kosugi, Y. & Chen, Y. (2021). Testing the environmental prediction  
561 hypothesis for community-wide mass flowering in south-east asia. *Biotropica*, 53, 608–618.
- 562 Schermer, E., Bel-Venner, M.C., Gaillard, J.M., Dray, S., Boulanger, V., Roncé, I.L. *et al.*  
563 (2020). Flower phenology as a disruptor of the fruiting dynamics in temperate oak species.  
564 *New Phytol*, 225, 1181–1192.
- 565 Shibata, M., Masaki, T., Yagihashi, T., Shimada, T. & Saitoh, T. (2020). Decadal changes in  
566 masting behaviour of oak trees with rising temperature. *J Ecol*, 108, 1088–1100.
- 567 Smaill, S.J., Clinton, P.W., Allen, R.B. & Davis, M.R. (2011). Climate cues and resources  
568 interact to determine seed production by a masting species. *Journal of Ecology*, 99, 870–877.
- 569 Smith, S.J., McCarthy, B.C., Hutchinson, T.F. & Snell, R.S. (2021). Both weather and resources  
570 influence masting in chestnut oak (*quercus montana* willd.) and black oak (*q. velutina* lam.).  
571 *Plant Ecology*, 222, 409–420.
- 572 Steffen, W., Richardson, K., Rockström, J., Cornell, S.E., Fetzer, I., Bennett, E.M. *et al.* (2015).  
573 Planetary boundaries: Guiding human development on a changing planet. *Science*, 347.

- 574 Szymkowiak, J., Foest, J., Hacket-Pain, A., Journé, V., Ascoli, D. & Bogdziewicz, M. (2024).  
575 Tail-dependence of masting synchrony results in continent-wide seed scarcity. *Ecology Letters*,  
576 27, e14474.
- 577 Vacchiano, G., Hacket-Pain, A., Turco, M., Motta, R., Maringer, J., Conedera, M. *et al.* (2017).  
578 Spatial patterns and broad-scale weather cues of beech mast seeding in europe. *New Phytol-*  
579 *ogist*, 215, 595–608.
- 580 Waller, D.M. (1979). Models of mast fruiting in trees. *J Theor Biol*, 80, 223–232.
- 581 Wion, A.P., Weisberg, P.J., Pearse, I.S. & Redmond, M.D. (2020). Aridity drives spatiotemporal  
582 patterns of masting across the latitudinal range of a dryland conifer. *Ecography*, 43, 569–580.
- 583 Yeoh, S.H., Satake, A., Numata, S., Ichie, T., Lee, S.L., Basherudin, N. *et al.* (2017). Unravelling  
584 proximate cues of mass flowering in the tropical forests of south-east asia from gene expression  
585 analyses. *Molecular Ecology*, 26, 5074–5085.
- 586 Yukich-Clendon, O.M.M., Carpenter, J.K., Kelly, D., Timoti, P., Burns, B.R., Boswijk, G. *et al.*  
587 (2023). Global change explains reduced seeding in a widespread new zealand tree: indigenous  
588 tūhoe knowledge informs mechanistic analysis. *Front For Glob Change*, 6, 1172326.
- 589 Zwolak, R., Celebias, P. & Bogdziewicz, M. (2022). Global patterns in the predator satiation  
590 effect of masting: A meta-analysis. *PNAS*, 119, e2105655119.

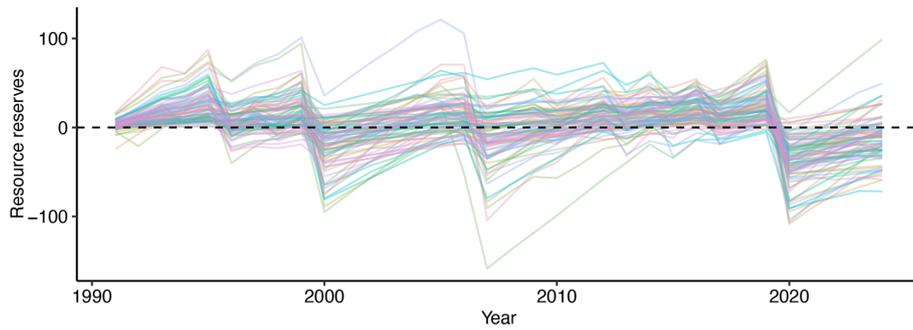
591 **Supporting Information**

592 Kelly et al. Fine-tuning mast seeding: as resources accumulate, plants become more sensitive  
593 to weather cues.

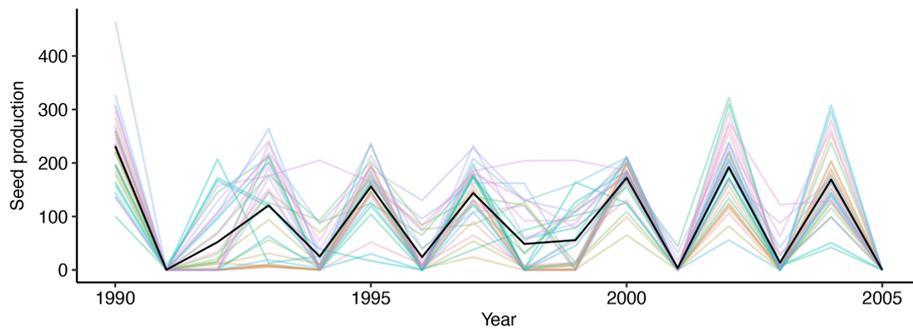
A) *Chionochloa pallens*



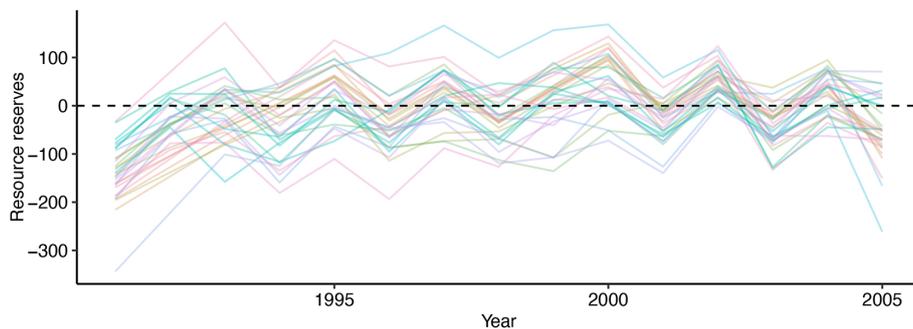
B) *Chionochloa pallens*



C) *Fagus sylvatica*

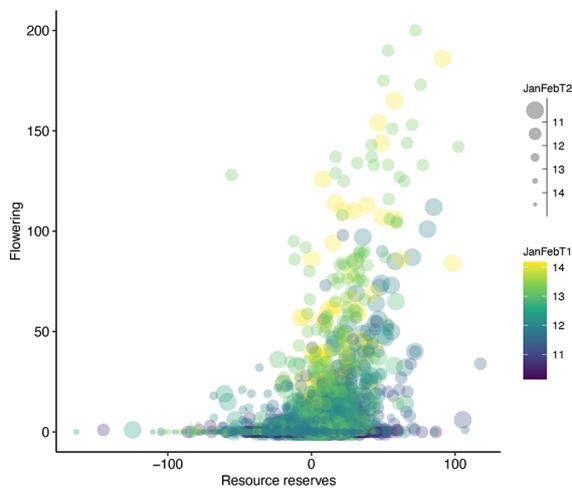


D) *Fagus sylvatica*

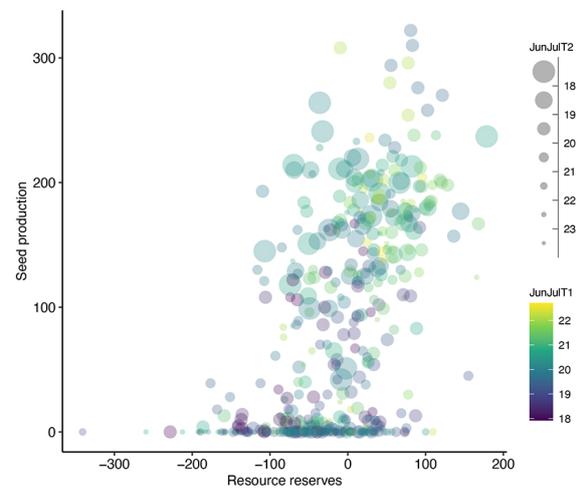


**Figure S1:** Temporal patterns of A) flowering effort and B) reconstructed resource reserves in snow tussocks (*Chionochloa pallens*), and C) seed production and D) resource reserves in European beech (*Fagus sylvatica*). Note that after large flowering efforts, resource reserves take multiple years to recover. Each color line represents an individual plant (N = 81 in tussocks, and N = 32 in beech), while the solid black lines show annual mean flowering or seed production effort across all monitored plants. Resource reserves are reconstructed following the Rees *et al.* (2002) method, and are expressed as negative residuals of cumulative reproduction fitted against cumulative years, see Methods.

A) *Chionochloa pallens*



B) *Fagus sylvatica*



**Figure S2: Relationships between the reconstructed energy reserves (estimated using annual resource gain proportional to growing-season temperatures) and annual reproductive effort.** Each point is the annual flowering effort (in *Chionochloa pallens*) or seed production (in *Fagus sylvatica*) of an individual plant, plotted against that plant's reconstructed resource reserves (annual deviations from the equilibrium energy budget) at flower initiation. Point sizes and colors are scaled according to the mean summer temperatures two years and one year prior to flowering.