

1 **Inferring phenotypic plasticity and population responses to climate across tree species**  
2 **ranges using forest inventory data**

3  
4 **Running title:** Understanding phenotypic variation in natural populations

5  
6 Thibaut Fréjaville<sup>1\*</sup>, Bruno Fady<sup>2</sup>, Antoine Kremer<sup>3</sup>, Alexis Ducousso<sup>3</sup>, Marta Benito Garzón<sup>1</sup>

7 <sup>1</sup> *BIOGECO (UMR 1202), INRA, Univ Bordeaux, 33615 Pessac, France*

8 <sup>2</sup> *INRA, UR629, Ecologie des Forêts Méditerranéennes (URFM), 84914 Avignon, France*

9 <sup>3</sup> *BIOGECO (UMR 1202), INRA, Univ Bordeaux, 33610 Cestas, France*

10 *\*Correspondence author. E-mail: thibaut.frejaville@gmail.com*

11  
12 **Acknowledgements**

13 This publication is part of a project that has received funding from the “Investments for the  
14 Future” program IdEx Bordeaux (ANR-10-IDEX-03-02) and the European Union’s Horizon  
15 2020 research and innovation programme under grant agreement No. 676876 (GenTree). We  
16 are very grateful to Juan Fernandez Manjarrés (CNRS-Université Paris-Sud) with whom the  
17 discussion about how to use NFI for splitting genetic and plastic effects started many years  
18 ago. We are indebted to Denis Vauthier and Franck Rei (INRA UEFM, Avignon), Fabrice  
19 Bonne, Thierry Paul and Vincent Rousselet (INRA UEFL, Nancy) and Jean Gauvin (INRA  
20 UGBFOR, Orléans) for data collection in the *Abies alba* provenance tests. We acknowledge  
21 colleagues from different European institutions for providing access and use of provenance  
22 data in *Quercus petraea*: Jon Kehlet Hansen, University of Copenhagen, for Denmark;  
23 Brigitte Musch and the staff of the French Office National des Forêts for France; Hans-  
24 Martin Rau, Jochen Kleinschmit, Josef Svolba of Niedersächsische Forstliche  
25 Versuchsanstalt, Abteilung Forstpflanzenzüchtung, Staufenberg, Escherode and Wilfried  
26 Steiner, Alwin Janssen, Nordwestdeutsche Forstliche Versuchsanstalt, Abteilung  
27 Waldgenressourcen, Hann-Münden, for Germany; Władysław Chałupka, Henryk Fober of  
28 the Instytut Dendrologii PAN, Kórnik for Poland; Steve J Lee, Alan M. Fletcher and Edward  
29 P. Cundall, Northern Research Station, for the United Kingdom.

30 **ABSTRACT**

31 **Aim:** To test whether intraspecific trait responses to climate within and among populations  
32 across species distribution ranges can be untangled using field observations, under the  
33 rationale that, in natural forest tree populations, long-term climate shapes local adaptation of  
34 populations while recent climate change drives phenotypic plasticity.

35 **Location:** Europe.

36 **Time period:** 1901-2014.

37 **Taxa:** Silver fir (*Abies alba* Mill.) and sessile oak (*Quercus petraea* (Matt.) Liebl.).

38 **Methods:** We estimated the variation of individual tree height as a function of long-term and  
39 short-term climates to tease apart provenance effects (variation among populations of  
40 different geographical origin), plasticity (within population) and their interaction, using  
41 mixed-effect models calibrated with National Forest Inventory data (*in-situ* models). To  
42 validate our approach, we tested the ability of *in-situ* models to predict independently tree  
43 height observations in common gardens where provenance and plastic effects can be  
44 measured and separated. *In-situ* model predictions of tree height variation among  
45 provenances and among planting sites were compared to observations in common gardens  
46 and to predictions from a similar model calibrated using common garden data (*ex-situ*  
47 model).

48 **Results:** In *Q. petraea*, we found high correlations between *in-situ* and *ex-situ* model  
49 predictions of provenance and plasticity effects and their interaction on tree height ( $r > 0.80$ ).  
50 We showed that the *in-situ* models significantly predicted tree height variation among  
51 provenances and sites for *Abies alba* and *Quercus petraea*. Spatial predictions of phenotypic  
52 plasticity across species distribution ranges indicate decreasing tree height in populations of  
53 warmer climates in response to recent anthropogenic climate warming.

54 **Main conclusions:** Our modelling approach using National Forest Inventory observations  
55 provides a new perspective for understanding local adaptation to climate and phenotypic  
56 plasticity across species ranges. Its application is particularly interesting for species for which  
57 common garden experiments do not exist or do not cover the entire climatic range of the  
58 species.

59 **Keywords:** *Abies alba*, common gardens, intraspecific trait variation, national forest  
60 inventory, *Quercus petraea*, tree height

61

## 62 INTRODUCTION

63 Understanding the causes of phenotypic variation across species distribution ranges is  
64 important because phenotypic traits are fundamental drivers of community assembly,  
65 ecosystem functioning, and population response to climate change (Diaz *et al.*, 2004; Shipley  
66 *et al.*, 2006; Alberto *et al.*, 2013; Kunstler *et al.*, 2016). Phenotypic variation within and  
67 among populations are the two components of intraspecific trait responses to environmental  
68 factors. Traits vary within populations according to phenotypic plasticity (i.e., the capacity of  
69 one genotype to render different phenotypes under different environments, Valladares *et al.*,  
70 2006), and among populations according to local adaptation (i.e., the fact that individuals  
71 have a better fitness in their local environment than individuals from other populations,  
72 Kawecki & Ebert, 2004) in addition to neutral and maladaptive components of genetic  
73 variation (Savolainen *et al.*, 2007; Leimu & Fischer, 2008). The spatial distribution of the  
74 amount of phenotypic variation that can be attributed to phenotypic plasticity or to local  
75 adaptation may change the response of organisms to climate change as predicted by  
76 theoretical approaches (Chevin *et al.*, 2010; Valladares *et al.*, 2014). Yet, attributing the cause  
77 of trait-climate relationships across species ranges to among and within population

78 components remains a challenge without using costly, long-term common garden  
79 experiments (Benito Garzón *et al.*, 2019).

80 Long-term spatial divergence under different climatic conditions is known to promote  
81 phenotypic differentiation of populations as a result of local adaptation to climate (Mimura &  
82 Aitken, 2010; Savolainen *et al.*, 2013; Yeaman *et al.*, 2016), which affects their current  
83 response to a particular climate (Rehfeldt *et al.*, 2002; Savolainen *et al.*, 2007; Valladares *et*  
84 *al.*, 2014). However, significantly less is known about the distribution of phenotypic  
85 plasticity and its importance for populations for coping with rapid climate change across the  
86 species range, especially in long-lived sessile organisms such as forest trees (Nicotra *et al.*,  
87 2010; Benito Garzón *et al.*, 2011; Valladares *et al.*, 2014; Duputié *et al.*, 2015).

88 Patterns of phenotypic plasticity and local adaptation of populations have long been  
89 assessed using common garden or reciprocal transplant experiments (also named ‘provenance  
90 tests’ or ‘genetic trials’), in which genotypes of known climatic origin (i.e., provenances) are  
91 growing in experimental plantations where short-term environmental conditions are  
92 controlled. In common gardens, trait differences among provenances that are related to the  
93 long-term climate of origin of the provenance are often interpreted in terms of local  
94 adaptation (e.g. Mimura & Aitken, 2010; Savolainen *et al.*, 2013; Benito Garzón *et al.*, 2019),  
95 although neutral and maladaptive components of genetic variation may also be responsible  
96 for differences among provenances (Savolainen *et al.*, 2007; Leimu & Fischer, 2008). On the  
97 other hand, plasticity is quantified by trait variation with the short-term climatic conditions at  
98 the planting sites (see Matyas, 1994; Wang *et al.*, 2006; Leites *et al.*, 2012 for forest trees).  
99 Common gardens have been established for a few economically important tree species for  
100 which only a restricted range of populations and ontogenic stages have been studied, which  
101 makes the understanding of phenotypic variation across species ranges limited (Fady *et al.*,  
102 2016).

103 On the other hand, causes of phenotypic variation are confounded in natural conditions, in  
104 addition to the effects of ontogeny and competition. National Forest Inventories (NFI)  
105 provide extensive data of phenotypic variation of forest trees in natural conditions, and hence,  
106 they have been widely used to test different ecological questions such as the effects of  
107 functional traits on competition, forest productivity and response to climate change (Kunstler  
108 *et al.*, 2016; Ratcliffe *et al.*, 2016; Ruiz-Benito *et al.*, 2017), but to date, how phenotypic  
109 traits in NFI vary as a function of differences among provenances and plasticity remains  
110 unexplored.

111 Here we show that intraspecific trait variation among provenances, species plasticity and  
112 their interaction, can be statistically estimated using the field data recorded in French NFI for  
113 two ecologically and economically important forest tree species usually managed using  
114 natural regeneration, *Abies alba* Mill. and *Quercus petraea* (Matt.) Liebl. We use tree height,  
115 an important adaptive and fitness-related trait (Savolainen *et al.*, 2007; Díaz *et al.*, 2016), to  
116 independently test our approach on field observations (NFI) and we validate our findings  
117 using common garden data. Our approach expands the space-for-time substitution analysis  
118 developed in common gardens (Matyas, 1994; Rehfeldt *et al.*, 2002; Leites *et al.*, 2012) to  
119 field observations of phenotypic trait variation, with the rationale that trees inventoried in the  
120 field have a local origin (i.e. seed sources originated within the bioclimatic region inhabited  
121 by the trees). In particular, to separate the sources of phenotypic variation in nature, we  
122 examined climatic variations that occur at two temporal and spatial scales: first, regional  
123 patterns in long-term climate (LTC) that have promoted trait variation among provenances as  
124 a result of local adaptation (Savolainen *et al.*, 2007; Mimura & Aitken, 2010; Kremer *et al.*,  
125 2012) – analysed in common gardens by growing different provenances in a same location –  
126 and, second, short-term climate (STC) that shapes plastic responses of individual trees to  
127 recent climate change (Nicotra *et al.*, 2010; Valladares *et al.*, 2014) – analysed in common

128 gardens by growing the same provenance in different locations. Our approach opens new  
129 perspectives for the understanding of phenotypic variation patterns across species distribution  
130 ranges using large field observation datasets such as forest inventories.

131

## 132 **METHODS**

133 We analysed tree height (m), a fitness-related phenotypic trait, measured both in NFI and  
134 common gardens. We selected two major European forest species with contrasted life history  
135 traits and ecological requirements: *Abies alba* Mill. (a montane evergreen needle-leaved  
136 gymnosperm) and *Quercus petraea* (Matt.) Liebl. (a temperate deciduous broadleaved  
137 angiosperm). In the NFI, these two species are traditionally managed using natural  
138 regeneration, thus adult trees are assumed to derive from the local gene pool.

139 We calibrated two independent mixed-effect models of individual tree height using NFI (*in-*  
140 *situ* model) and common garden data (*ex-situ* model), respectively. To validate our models we  
141 used two different methods (Fig. 1). The first one is a validation using common garden data:  
142 it directly compares the results of the *in-situ* model with independent tree height  
143 measurements standardized by common garden and by provenance to respectively separate  
144 the effects of the provenance and plasticity. The second one is a validation using *ex-situ*  
145 model predictions: it compares the predictions of *in situ* and *ex-situ* models regarding the  
146 relative contribution to the model of the climate of the planting site (plastic effect) and that of  
147 the climate of the origin of the provenances (provenance effect), and the interaction between  
148 both. All analyses and computations were carried out in the R software environment (R Core  
149 Team, 2013).

150

151 **Phenotypic data**

152 *National Forest Inventories (NFI)*

153 Observation data comprised ten annual campaigns of the French NFI (2005–2014;  
154 <http://inventaire-forestier.ign.fr>), which consists of a regular grid (1 km<sup>2</sup>) of temporary forest  
155 plots of 707 m<sup>2</sup> each. In this study, we focused on French NFI (Appendix S1, Fig. S1.1)  
156 because inventories of neighbouring countries do not provide age data, thereby preventing the  
157 effect of age to be accounted for in models. Nevertheless, the distribution of French NFI plots  
158 has a good representativeness of the climatic range of the two species (Fig. S2.1). In each  
159 NFI plot, we selected trees for which height (in m), diameter at breast height (dbh; in cm) and  
160 age (years) data were measured. In particular, tree age was estimated from wood increment  
161 cores collected at breast height (1.30 m) for the one or two of the largest dominant trees in the  
162 plot. To account for stand density and the local abundance of neighbouring trees on tree  
163 height variation among plots, we computed for each NFI plot the sum of the basal area of  
164 neighbouring trees larger than 7.5 cm dbh (Kunstler *et al.*, 2016). We removed plots outside  
165 the natural distribution range of the species (Fig. S1.1), identified as plantation or if there was  
166 any evidence of recent (<5 years) management, for example logging. We assumed that trees  
167 in the remaining plots originated from local provenances within the same bioclimatic region.  
168 The final dataset consisted of 5376 trees from 3614 plots for *Q. petraea*, and 1304 trees from  
169 904 plots for *A. alba*.

170

171 *Common gardens*

172 Common garden data were used to independently validate *in-situ* models (NFI calibration).  
173 They were established for breeding purposes during 1990–1996 for *Q. petraea* and 1967–  
174 1972 for *A. alba*, as follows: (i) seeds were collected from seed sources (hereafter  
175 provenances) throughout the natural distribution range of the species ( $N = 141$  for *Q. petraea*,

176  $N = 47$  for *A. alba*); (ii) the seeds were sown in a nursery; (iii) seedlings were transplanted to  
177 several sites, i.e., common gardens ( $N = 13$  for *Q. petraea*,  $N = 6$  for *A. alba*; Fig. S1.1),  
178 using a randomised block design; and (iv) measurements of tree height were made at several  
179 different years. To avoid pseudo-replication, we randomly selected a single measurement year  
180 for each tree. Neighbour basal area was assumed to be constant because plantations have a  
181 regular spacing design. Tree age at the time of height measurement was considered to be the  
182 time since sowing. A detailed description of the *Q. petraea* provenance tests is provided in a  
183 previous study (Sáenz-Romero *et al.*, 2017). A description of the *A. alba* provenances studied  
184 in common gardens is provided in Appendix S1 (Tables S1-S2).

185

#### 186 **Climate data**

187 To analyse phenotypic trait response to long-term climate and recent climate change, we used  
188 the yearly climate grids (1901–2014) at 30 arc sec resolution ( $\sim 1 \text{ km}^2$ ) of the EuMedClim  
189 dataset covering Europe and the Mediterranean Basin (Fréjaville & Benito Garzón, 2018).  
190 For the present study, the following bioclimatic variables were considered (Fig. S2.1): annual  
191 mean temperature, maximum temperature of the warmest month, minimum temperature of  
192 the coldest month, annual precipitation, precipitation of the wettest and the driest month,  
193 annual potential evapotranspiration, potential evapotranspiration of the warmest and the  
194 coldest month and water balance (precipitation minus potential evapotranspiration) of the  
195 wettest and the driest month. EuMedClim was computed following an anomaly approach  
196 using the fine 30' resolution of WorldClim climate means (version 1.4, Hijmans *et al.*, 2005)  
197 to adjust the coarse spatial  $0.5^\circ$  resolution of yearly climate data from the Climate Research  
198 Unit (version ts3.23, Harris *et al.*, 2014). EuMedClim provides inter-annual variation of  
199 bioclimatic conditions at high spatial resolution, allowing the analysis of climate at different



200 spatial and temporal scales instead of using climate means over a reference period (e.g.  
201 WorldClim).

202 To fulfil the requirements of our modelling approach based on the different climate scales  
203 at which phenotypic plasticity and local adaptation act, we split the climate data into three  
204 different sets of data: (i) long-term climate (LTC) that is the average climate value of the  
205 1901–1960 period, and represents the climate driven local adaptation in the past for  
206 provenances (for common gardens) or for a common bioclimatic origin (for NFI, assuming  
207 that that all trees have a local origin in a given bioclimatic origin – Appendix S2); (ii) short-  
208 term climate (STC) represents the plastic response of trees to recent climate and is calculated  
209 as the local climate averaged over the 10 years preceding the measurements (NFI and  
210 common garden data); iii) recent climate change (RCC), calculated by subtracting LTC from  
211 STC to avoid collinearity problems between LTC and STC in NFI.

212

### 213 **Models of intra-specific trait variability**

214 Hereafter, we refer to models calibrated using NFI data as *in-situ* models and to models  
215 calibrated using common gardens as *ex-situ* models. For a given species, the phenotypic trait  
216  $T_{ijk}$  (tree height) of the  $i^{\text{th}}$  tree individual of the  $j^{\text{th}}$  bioclimatic region (or provenance) in the  $k^{\text{th}}$   
217 plot (or common garden) was modelled as follows:

$$218 \log(T_{ijk}) = \alpha_0 + \alpha_1 LTC_j + \alpha_2 LTC_j^2 + \alpha_3 RCC_{jk} + \alpha_4 RCC_{jk}^2 + \alpha_5 LTC_j \times RCC_{jk} + \beta + \delta + \varepsilon \quad (1)$$

219 where  $LTC_j$  is the long-term climate of either the  $j^{\text{th}}$  bioclimatic region in NFI or the  $j^{\text{th}}$   
220 provenance in common gardens;  $RCC_{jk}$  is the recent climate change defined as the difference  
221 between the STC at the  $k^{\text{th}}$  site (i.e., the NFI plot or the common garden) and  $LTC_j$ . We  
222 included quadratic terms for both  $LTC_j$  and  $RCC_{jk}$  to consider non-linear shapes in height

223 responses to climate across species ranges.  $\beta$  includes ontogeny and neighbour basal area  
224 covariates and is defined as:

$$225 \beta = \alpha_6 \log(\text{age}_{ijk}) + \alpha_7 \log(\text{BAc}_{ijk}) + \alpha_6 \log(\text{age}_{ijk}) \times \text{RCC}_{jk} + \alpha_7 \log(\text{BAc}_{ijk}) \times \text{LTC}_j \quad (2)$$

226 where *age* is the tree age (in years, estimated at breast height in NFI and as the time since  
227 sowing in common gardens) and *BAc* is the sum of the basal area of neighbouring trees  
228 (assumed to be constant in common gardens).  $\delta$  gathers random effects and  $\varepsilon$  is the model  
229 error. To control for differences among sampling units in soil fertility, management (or  
230 disturbances) and environmental factors not accounted for by fixed effects, we set as random  
231 effects the plot nested within the bioclimatic region in *in-situ* models and the block nested  
232 within the site in *ex-situ* models (randomised block design). In the case of *A. alba*, the  
233 bioclimatic region random effect was not retained because it inflated p-values of LTC terms  
234 in the *in-situ* model (high redundancy). One main difference between NFI and common  
235 garden data is the age of trees (Fig. S4.1). We reduced this difference by excluding old trees  
236 (> 200 years) in NFI and saplings (< 10 years) in common gardens, and we added *age* as a  
237 covariate in the models to control for ontogeny. To control for potential differences in growth  
238 response to climate change among ontogenic stages, we added the interaction term  $\text{age}_{ijk} \times$   
239  $\text{RCC}_{jk}$  in both models. We also introduced *BAc* as covariate to control for neighbour basal  
240 area (Fig. S4.1) and the interaction term  $\text{BAc}_{ijk} \times \text{LTC}_j$  to control for potential differences in  
241 neighbour basal area effects among bioclimatic regions in *in-situ* models. A saturated model  
242 form including  $\text{BAc}_{ijk} \times \text{RCC}_{jk}$  and  $\text{age}_{ijk} \times \text{LTC}_j$  interaction terms was not retained as they  
243 were not significant and decreased model parsimony and the significance of parameters of  
244 interest. Models were fitted using the R package nlme (Pinheiro *et al.*, 2015). Coefficients of  
245 determination were used to compute the percentage of explained variance by fixed effects  
246 alone ( $R^2_{\text{marginal}}$ ) and both fixed and random effects ( $R^2_{\text{conditional}}$ ) (Nakagawa & Schielzeth,  
247 2013).

248 For each species, we selected one single explanatory bioclimatic variable to represent LTC  
 249 and RCC, the same between the two datasets (to enable comparison). The variable selection  
 250 process was as follows. First, we fitted one model per dataset for each bioclimatic variable  
 251 (Fig. S2.1) using eqns (1-2). Second, we removed models when parameter estimates for LTC  
 252 and RCC were not significant at  $P = 0.1$  or when positive quadratic relationships were fit ( $\alpha_2$   
 253  $> 0$  or  $\alpha_4 > 0$ ) to keep models with decreasing tree height towards one or both ends of the  
 254 climatic gradient. Third, competitive models were compared using the Akaike information  
 255 criterion (AIC), and the final model selection was based on the lowest AIC values for both  
 256 *in-situ* and *ex-situ* models (to enable comparison).

257

## 258 **Model predictions**

259 *Separating provenance effect, plasticity and their interaction*

260 Model coefficients were used to separate components of phenotypic variation by substituting  
 261 RCC to its climatic components ( $RCC_{jk} = STC_k - LTC_j$ ) in eqn. (1):

$$262 \log(T_{ijk}) = \alpha_0 + (\alpha_1 - \alpha_3)LTC_j + (\alpha_2 + \alpha_4 - \alpha_5)LTC_j^2 + \alpha_3STC_k + \alpha_4STC_k^2$$

$$263 + (\alpha_5 - 2\alpha_4)LTC_j \times RCC_{jk} + \beta + \delta + \varepsilon \quad (3)$$

264 This analytical decomposition enables to estimate the relative effects of the long-term and  
 265 short-term climate in the field, using RCC and LTC from eqn. (1). From eqn. (3), coefficients  
 266 associated to linear ( $\alpha_1 - \alpha_3$ ) and quadratic ( $\alpha_2 + \alpha_4 - \alpha_5$ ) variation of LTC are used to predict the  
 267 effect of the provenance, coefficients associated to linear ( $\alpha_3$ ) and quadratic ( $\alpha_4$ ) variation of  
 268 STC are used to predict phenotypic plasticity (reaction norms) and those associated to  $LTC_j \times$   
 269  $STC_k$  ( $\alpha_5 - 2\alpha_4$ ) are used to predict their interaction.

270

## 271 *Spatial predictions*

272 The *in-situ* and *ex-situ* models were used to make spatial predictions of provenance and  
273 plasticity effects, their interaction and the total component of tree height response to climate  
274 across Europe. We computed  $LTC_j$  and  $STC_k$  in each grid cell (30 arc sec resolution)  
275 respectively using the long-term (1901–1960) and the recent short-term (2001–2014)  
276 averaged values of the corresponding climatic variables to compute maps according to fitted  
277 parameters in eqn. (3). Effects of covariates were fixed for *age* (12-year-old trees), *BAC* (30  
278  $\text{m}^2 \text{ha}^{-1}$ ) and for their interaction with  $RCC_{jk}$  and  $LTC_j$  (both averaged across the species  
279 natural range), respectively, according to eqn. (2), and these constants (including the intercept  
280  $\alpha_0$ ) were added to the total variation component.

281

## 282 **Model validation**

283 To validate our approach, we used two alternative methods (Fig. 1) to test the ability of *in-*  
284 *situ* models to predict independent tree height observations in common gardens where the  
285 effects of the provenance, plasticity and their interaction can be separated.

286

## 287 *Validation using common garden data*

288 To compare the predictions of *in-situ* models with raw common garden data, we first  
289 predicted the mean height of each provenance in each site (provenance-by-site mean) from  
290 eqn. (3), as a function of the LTC of the provenance and the STC of the site for a given age  
291 and neighbour basal area. Then, we compared these predictions to observed values in  
292 common gardens. Both predicted and observed provenance-by-site means were standardized  
293 across sites and provenances to estimate provenance and plasticity effects, respectively (see

294 Appendix S3). Correlations between predicted and observed values were tested using Pearson  
295 correlation coefficients.

296

### 297 *Validation using ex-situ model predictions*

298 To compare the predictions of *in-situ* and *ex-situ* models, we predicted provenance and  
299 plasticity effects, and their interaction, as a function of LTC and STC conditions in common  
300 gardens using both *in-situ* and *ex-situ* models (see Appendix S3). From eqn. (3), the mean  
301 tree height of a provenance planted in several common gardens was predicted for a given age  
302 and neighbour basal area as a function of the LTC of the provenance (provenance effect) and  
303 the mean tree height of each provenance was predicted as a function of the STC of the site  
304 (plasticity of the provenance). Correlations between paired predictions from *in-situ* and *ex-*  
305 *situ* models of provenance and plasticity effects, their interaction and the sum of all three  
306 components of tree height (total variation) were tested using Pearson correlation coefficients.  
307 For the interaction component, correlation coefficients were computed separately for the  
308 mean plastic responses (reaction norms) of cold, core and warm provenances. We classified  
309 provenances among cold, core and warm parts of the range using the 1-33<sup>th</sup>, 34-66<sup>th</sup> and 67-  
310 100<sup>th</sup> percentiles of LTC, respectively, computed across the natural distribution range of the  
311 species.

312

## 313 **RESULTS**

314 We found both *in-situ* and *ex-situ* models with significant terms for LTC, RCC and their  
315 interaction on individual tree height in *Q. petraea* whereas only the *in-situ* model was found  
316 significant for *A. alba*. In *Q. petraea*, selected *in-situ* and *ex-situ* models were based on the  
317 maximum temperature of the warmest month (Tmax). In *A. alba*, the selected *in-situ* model  
318 was based on the potential evapotranspiration of the warmest month (PETmax). Both *in-situ*

319 and *ex-situ* models indicated significant negative interaction between LTC and RCC (Table 1)  
320 and positive interaction between LTC and STC (Table 2) in both species. Hence, average  
321 plasticity differed among regions and provenances for both species.

322 *In-situ* selected models indicated significant positive effects of tree age and neighbour basal  
323 area on tree height (Table 1, Fig. S4.1). Tree height increased with increasing neighbour basal  
324 area in *A. alba* ( $P = 0.07$ ) and with neighbour basal area towards warmer regions in *Q.*  
325 *petraea* (positive interaction between BAc and LTC,  $P = 0.02$ ; Table 1).

326

### 327 **Statistical approximation of provenance and plasticity effects**

#### 328 *Sessile oak (Quercus petraea)*

329 Validation using common garden data indicated that predictions of tree height variation  
330 among provenances and among sites using the *in-situ* model were significantly correlated  
331 with observations in common gardens in *Q. petraea* ( $P < 0.001$  for estimates of provenance  
332 and plasticity effects, and the total component of tree height, Fig. S6.3). Validation using *ex-*  
333 *situ* model predictions showed high correlations between *in-situ* and *ex-situ* model  
334 predictions of the provenance and plasticity effects, and their interaction (Table 2, Fig. 2). We  
335 found significant quadratic responses of height to Tmax for the provenance effect (Fig. 2a),  
336 plasticity (Fig. 2b) and the total (Fig. 2c) variation, that were similar between *in-situ* and *ex-*  
337 *situ* models with high correlations between paired predictions ( $r > 0.80$ ,  $P < 0.001$ ). We found  
338 high correlations between *ex-situ* and *in-situ* model paired predictions of cold ( $r = 0.65$ ,  $P <$   
339  $0.001$ ), core ( $r = 0.99$ ,  $P < 0.001$ ) and warm provenance mean reaction norms ( $r = 0.97$ ,  $P <$   
340  $0.001$ ). Both models showed similar patterns in Tmax optimums (i.e. Tmax values  
341 corresponding to maximum predicted heights) among cold, core and warm provenances that  
342 were respectively warmer and colder for warm and cold provenances (Kruskal-Wallis tests,  $P$

343 < 0.001, Fig. 2d-e). The *in-situ* model, however, showed higher differences in optimums  
344 among provenances (Fig. 2e).

345

#### 346 *Silver fir (Abies alba)*

347 In *A. alba*, the *in-situ* model showed significant quadratic responses of tree height to PETmax  
348 for the provenance and plasticity effects (Table 2). Validation using common garden data  
349 indicated that the *in-situ* model significantly predicted tree height variation among  
350 provenances in common gardens (provenance effect:  $r = 0.44$ ,  $P < 0.01$ , Fig. 3a) and among  
351 sites (plasticity effect:  $r = 0.72$ ,  $P < 0.001$ , Fig. 3b). The correlation was weak for the total  
352 variation ( $r = 0.20$ ,  $P = 0.06$ , Fig. 3c, Fig. S7.3). The *in-situ* model predicted warmer  
353 optimums for warm provenances and colder optimums for cold provenances (Kruskal-Wallis  
354 tests,  $P < 0.001$ , Fig. 3d).

355

#### 356 **Range-wide spatial predictions of tree height**

357 In *Q. petraea*, both the *ex-situ* and *in-situ* models predicted very similar spatial patterns (Fig.  
358 4) in the relative variation of tree height for provenance and plasticity effects, and their  
359 interaction, despite differences in absolute values for total variation for a given age and  
360 neighbour basal area (Fig. 4g-h). These differences are explained by the differences in tree  
361 age estimation between the two datasets (i.e. age is measured at breast height in NFI and as  
362 the time since sowing in common gardens). The quadratic response of tree height to LTC  
363 (Fig. 2a) predicted that trees living at the warm limit of the species range were the shortest,  
364 which is illustrated by the short heights predicted over southern Europe from the provenance  
365 effect (transparent colours, Fig. 4a-b). Similarly, trees inhabiting the warmest conditions in  
366 the southernmost part of the species distribution range were also predicted to be shorter from  
367 the phenotypic plasticity effect (Fig. 4c-d). Spatial predictions of interaction effects showed

368 an opposite pattern with increasing height towards warmer climates (Fig. 4e-f). Total  
369 variation followed spatial patterns of the provenance and plasticity effects (Fig. 4g-h). In *A.*  
370 *alba*, trees inhabiting cold climates (e.g. high elevation areas in the Alps) were predicted to be  
371 shorter according to the *in-situ* model (Fig. 5). In warm climates, the provenance effect (Fig.  
372 4a) and provenance  $\times$  plasticity interaction (Fig. 5c) predicted taller trees while plasticity  
373 predicted smaller trees over southern Europe (Fig. 5b).

374

## 375 **DISCUSSION**

### 376 **Can the effects of the provenance and phenotypic plasticity in tree height be inferred** 377 **from *in-situ* observations?**

378 To date, disentangling the sources of phenotypic variation has only been addressed by  
379 analysing common gardens or reciprocal transplant experiments (e.g. Kawecki & Ebert,  
380 2004; Hoffmann & Sgrò, 2011; Blanquart *et al.*, 2013; Latreille & Pichot, 2017), using  
381 similar approaches as those that we named here *ex-situ* models. However, as common garden  
382 data are often scarce, we propose an alternative method for understanding the causes of  
383 phenotypic variation: using increasingly abundant data from field observations, such as NFI.  
384 Using the rationale of *ex-situ* models based on common garden data, we defined *in-situ*  
385 models based on NFI data and thoroughly validated *in-situ* model predictions with raw data  
386 coming from common gardens and with predictions from *ex-situ* models.

387 Overall, our results show that *in-situ* models correctly predicted phenotypic patterns  
388 observed in common gardens (Table 2, Figs 2-5), suggesting that field observations (NFI) can  
389 be used to statistically approximate the range-wide intraspecific variation in tree height that is  
390 attributable to differences among provenances, plasticity and their interaction. In particular,  
391 our results suggest that differences among provenances that are related to their climate of  
392 origin can be statistically approximated using field measurements by modelling trait variation



393 as a function of the long-term regional climate (LTC), while the recent climate change (RCC)  
394 and its components (STC - LTC) can be used to estimate the plastic response of the trait.

395 In both species, the most parsimonious models (both *in-situ* and *ex-situ*) were based on  
396 climatic variables related to summer temperature: PETmax in *A. alba* and Tmax in *Q.*  
397 *petraea*. This underlies the high sensitivity of *Abies alba* to the evaporative demand in  
398 summer (Lebourgeois *et al.*, 2013) and that temperature chiefly drove differences in tree  
399 height among *Q. petraea* provenances while drought mostly drove plastic responses for tree  
400 height and survival in this species (Sáenz-Romero *et al.*, 2017).

401

#### 402 **Common patterns of among-provenance variation in tree height plasticity: implications** 403 **for species distribution ranges under climate change**

404 In both species, we found hump-shaped relationships between height and climate for the  
405 provenance (long-term climate) and plasticity effects (short-term climate) and a positive  
406 interaction effect between them (Table 2, Figs 2-3). The latter indicated that climatic optima  
407 of provenances co-vary positively with their climate of origin: warmer provenances grow  
408 taller in warmer climates and colder provenances grow taller in colder climates (Figs 2d-e  
409 and 3d), suggesting local adaptation in both species and that plasticity differs significantly  
410 among populations (Wang *et al.*, 2006; Leites *et al.*, 2012; Münzbergová *et al.*, 2017; Sáenz-  
411 Romero *et al.*, 2017). This consistency between *A. alba* (a mountain evergreen conifer tree)  
412 and *Q. petraea* (a temperate deciduous broadleaved tree) points to potential common patterns  
413 in local adaptation and plasticity among tree species, as recently indicated in boreal conifer  
414 trees (Pedlar & McKenney, 2017).

415 Our spatial predictions of phenotypic plasticity suggest that tree height of warm provenances  
416 has decreased in response to recent climate warming, mostly in southern Europe (Figs 4-5).

417 These results suggest that recent warming may have pushed species at the warmest boundary

418 of the distribution range beyond their tolerance limits, that is corroborated by a higher  
419 mortality in warmest/driest range margins for *A. alba*, *Q. petraea* and other European tree  
420 species (Cailleret *et al.*, 2014; Benito Garzón *et al.*, 2018). Furthermore, we found that the  
421 effect of neighbour basal area on tree height was dependent on the climate of the bioclimatic  
422 region in *Q. petraea*, emphasising that tree sensitivity to biotic interaction (e.g. competition)  
423 may change along climatic gradients (Gomez-Aparicio *et al.*, 2011; Kunstler *et al.*, 2016).

424

### 425 **Limitations and perspectives**

426 Our approach needs an extensive network of common gardens to well identify reaction norms  
427 that are at the basis of the models. For instance, in *A. alba* models that are based in  
428 significantly less data than those of *Q. petraea*, we did not find any significant *ex-situ* model.

429 Another limitation of our approach comes from the large difference in the age of trees  
430 (older in NFI data) and the fact that NFI data rely on dominant trees, that might partly  
431 explained that a stronger signal of local adaptation (i.e. higher differences in climatic optima)  
432 was found using NFI data for *Q. petraea* (Fig. 2d).

433 Finally, the among-provenances differences found by our approach are not only related to  
434 local adaptation, but also to neutral, adaptive and even maladaptive components of genetic  
435 variation that were not taken into account. New analysis using genomic data across species  
436 ranges is the natural next step to fully understand genetic effects (including neutral, adaptive  
437 and maladaptive components of genetic variation) in natural and common garden populations  
438 (Fitzpatrick & Keller, 2015; Bay *et al.*, 2018; Josephs *et al.*, 2019).

439

### 440 **CONCLUSION**

441 We show that phenotypic plasticity, provenance effects and their interaction can be  
442 statistically approximated using field observations of wild tree populations subject to recent

443 climate warming. However, further studies are needed to determine whether the ability of *in-*  
444 *situ* models to predict trends in common garden experiments represent a shared underlying  
445 cause that can be generalized to other situations, i.e. whether climate variations at different  
446 scales can be used to separate local adaptation and plastic responses to climate in field  
447 conditions. The modelling framework used in our study could be applied to many species and  
448 traits, offering a promising avenue to enhance our understanding of local adaptation and  
449 plasticity patterns across large geographical gradients.

450

## 451 REFERENCES

- Alberto, F.J., Aitken, S.N., Alía, R., González-Martínez, S.C., Hänninen, H., Kremer, A., Lefèvre, F., Lenormand, T., Yeaman, S., Whetten, R. & Savolainen, O. (2013) Potential for evolutionary responses to climate change – evidence from tree populations. *Global Change Biology*, **19**, 1645–1661.
- Bay, R.A., Harrigan, R.J., Underwood, V.L., Gibbs, H.L., Smith, T.B. & Ruegg, K. (2018) Genomic signals of selection predict climate-driven population declines in a migratory bird. *Science*, **359**, 83–86.
- Benito Garzón, M., Alía, R., Robson, T.M. & Zavala, M.A. (2011) Intra-specific variability and plasticity influence potential tree species distributions under climate change. *Global Ecology and Biogeography*, **20**, 766–778.
- Benito Garzón, M., González-Muñoz, N., Wigneron, J.-P., Moisy, C., Fernández-Manjarrés, J. & Delzon, S. (2018) The legacy of water deficit on populations having experienced negative hydraulic safety margin. *Global Ecology and Biogeography*, **27**, 346–356.
- Benito Garzón, M., Robson, T.M. & Hampe, A. (2019)  $\Delta$ TraitSDM: species distribution models that account for local adaptation and phenotypic plasticity. *New Phytologist*, <https://doi.org/10.1111/nph.15716>.
- Blanquart, F., Kaltz, O., Nuismer, S.L. & Gandon, S. (2013) A practical guide to measuring local adaptation. *Ecology Letters*, **16**, 1195–1205.
- Cailleret, M., Nourtier, M., Amm, A., Durand-Gillmann, M. & Davi, H. (2014) Drought-induced decline and mortality of silver fir differ among three sites in Southern France. *Annals of Forest Science*, **71**, 643–657.
- Chevin, L.-M., Lande, R. & Mace, G.M. (2010) Adaptation, Plasticity, and Extinction in a Changing Environment: Towards a Predictive Theory. *PLOS Biology*, **8**, e1000357.
- Diaz, S., Hodgson, J.G., Thompson, K., Cabido, M., Cornelissen, J.H.C., Jalili, A., Montserrat-Martí, G., Grime, J.P., Zarrinkamar, F., Asri, Y. & others (2004) The plant traits that drive ecosystems: evidence from three continents. *Journal of vegetation science*, **15**, 295–304.
- Díaz, S., Kattge, J., Cornelissen, J.H.C., Wright, I.J., Lavorel, S., Dray, S., Reu, B., Kleyer, M., Wirth, C., Colin Prentice, I., Garnier, E., Bönsch, G., Westoby, M., Poorter, H., Reich, P.B., Moles, A.T., Dickie, J., Gillison, A.N., Zanne, A.E., Chave, J., Joseph Wright, S., Sheremet'ev, S.N., Jactel, H., Baraloto, C., Cerabolini, B., Pierce, S.,

- Shipley, B., Kirkup, D., Casanoves, F., Joswig, J.S., Günther, A., Falczuk, V., Rüger, N., Mahecha, M.D. & Gorné, L.D. (2016) The global spectrum of plant form and function. *Nature*, **529**, 167–171.
- Duputié, A., Rutschmann, A., Ronce, O. & Chuine, I. (2015) Phenological plasticity will not help all species adapt to climate change. *Global Change Biology*, **21**, 3062–3073.
- Fady, B., Cottrell, J., Ackzell, L., Alía, R., Muys, B., Prada, A. & González-Martínez, S.C. (2016) Forests and global change: what can genetics contribute to the major forest management and policy challenges of the twenty-first century? *Regional Environmental Change*, **16**, 927–939.
- Fitzpatrick, M.C. & Keller, S.R. (2015) Ecological genomics meets community-level modelling of biodiversity: mapping the genomic landscape of current and future environmental adaptation. *Ecology Letters*, **18**, 1–16.
- Frank, A., Howe, G.T., Sperisen, C., Brang, P., St Clair, J.B., Schmatz, D.R. & Heiri, C. (2017) Risk of genetic maladaptation due to climate change in three major European tree species. *Global Change Biology*.
- Fréjaville, T. & Benito Garzón, M. (2018) The EuMedClim Database: Yearly Climate Data (1901–2014) of 1 km Resolution Grids for Europe and the Mediterranean Basin. *Frontiers in Ecology and Evolution*, **6**.
- Gomez-Aparicio, L., Garcia-Valdes, R., Ruiz-Benito, P. & Zavala, M.A. (2011) Disentangling the relative importance of climate, size and competition on tree growth in Iberian forests: Implications for forest management under global change. *Global Change Biology*, **17**, 2400–2414.
- Harris, I., Jones, P. d., Osborn, T. j. & Lister, D. h. (2014) Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. *International Journal of Climatology*, **34**, 623–642.
- Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G. & Jarvis, A. (2005) Very high resolution interpolated climate surfaces for global land areas. *International journal of climatology*, **25**, 1965–1978.
- Hoffmann, A.A. & Sgrò, C.M. (2011) Climate change and evolutionary adaptation. *Nature*, **470**, 479–485.
- Josephs, E.B., Berg, J.J., Ross-Ibarra, J. & Coop, G. (2019) Detecting adaptive differentiation in structured populations with genomic data and common gardens. *Genetics*, <https://doi.org/10.1534/genetics.118.301786>.
- Kawecki, T.J. & Ebert, D. (2004) Conceptual issues in local adaptation. *Ecology letters*, **7**, 1225–1241.
- Kremer, A., Ronce, O., Robledo-Arnuncio, J.J., Guillaume, F., Bohrer, G., Nathan, R., Bridle, J.R., Gomulkiewicz, R., Klein, E.K., Ritland, K., Kuparinen, A., Gerber, S. & Schueler, S. (2012) Long-distance gene flow and adaptation of forest trees to rapid climate change. *Ecology Letters*, **15**, 378–392.
- Kunstler, G., Falster, D., Coomes, D.A., Hui, F., Kooyman, R.M., Laughlin, D.C., Poorter, L., Vanderwel, M., Vieilledent, G., Wright, S.J. & others (2016) Plant functional traits have globally consistent effects on competition. *Nature*, **529**, 204–207.
- Latreille, A.C. & Pichot, C. (2017) Local-scale diversity and adaptation along elevational gradients assessed by reciprocal transplant experiments: lack of local adaptation in silver fir populations. *Annals of Forest Science*, **74**, 77.
- Lebourgeois, F., Gomez, N., Pinto, P. & Mérian, P. (2013) Mixed stands reduce *Abies alba* tree-ring sensitivity to summer drought in the Vosges mountains, western Europe. *Forest Ecology and management*, **303**, 61–71.

- Leimu, R. & Fischer, M. (2008) A Meta-Analysis of Local Adaptation in Plants. *PLOS ONE*, **3**, e4010.
- Leites, L.P., Robinson, A.P., Rehfeldt, G.E., Marshall, J.D. & Crookston, N.L. (2012) Height-growth response to climatic changes differs among populations of Douglas-fir: a novel analysis of historic data. *Ecological Applications*, **22**, 154–165.
- Matyas, C. (1994) Modeling climate change effects with provenance test data. *Tree Physiology*, **14**, 797–804.
- Mimura, M. & Aitken, S.N. (2010) Local adaptation at the range peripheries of Sitka spruce. *Journal of evolutionary biology*, **23**, 249–258.
- Münzbergová, Z., Hadincová, V., Skálová, H. & Vandvik, V. (2017) Genetic differentiation and plasticity interact along temperature and precipitation gradients to determine plant performance under climate change. *Journal of Ecology*, **105**, 1358–1373.
- Nakagawa, S. & Schielzeth, H. (2013) A general and simple method for obtaining R<sup>2</sup> from generalized linear mixed-effects models. *Methods in Ecology and Evolution*, **4**, 133–142.
- Nicotra, A.B., Atkin, O.K., Bonser, S.P., Davidson, A.M., Finnegan, E.J., Mathesius, U., Poot, P., Purugganan, M.D., Richards, C.L., Valladares, F. & van Kleunen, M. (2010) Plant phenotypic plasticity in a changing climate. *Trends in Plant Science*, **15**, 684–692.
- Pedlar, J.H. & McKenney, D.W. (2017) Assessing the anticipated growth response of northern conifer populations to a warming climate. *Scientific Reports*, **7**.
- Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D. & R Core Team (2015) nlme: Linear and Nonlinear Mixed Effects Models. R package version 3.1–120. <http://CRAN.R-project.org/package=nlme>.
- R Core Team (2013) *R: A language and environment for statistical computing*, R Foundation for Statistical Computing, Vienna, Austria.
- Ratcliffe, S., Liebergesell, M., Ruiz-Benito, P., Madrigal Gonzalez, J., Muñoz Castañeda, J.M., Kändler, G., Lehtonen, A., Dahlgren, J., Kattge, J., Peñuelas, J. & others (2016) Modes of functional biodiversity control on tree productivity across the European continent. *Global ecology and biogeography*, **25**, 251–262.
- Rehfeldt, G.E., Tchebakova, N.M., Parfenova, Y.I., Wykoff, W.R., Kuzmina, N.A. & Milyutin, L.I. (2002) Intraspecific responses to climate in *Pinus sylvestris*. *Global Change Biology*, **8**, 912–929.
- Ruiz-Benito, P., Ratcliffe, S., Zavala, M.A., Martínez-Vilalta, J., Vilà-Cabrera, A., Lloret, F., Madrigal-González, J., Wirth, C., Greenwood, S., Kändler, G., Lehtonen, A., Kattge, J., Dahlgren, J. & Jump, A.S. (2017) Climate- and successional-related changes in functional composition of European forests are strongly driven by tree mortality. *Global Change Biology*, **23**, 4162–4176.
- Sáenz-Romero, C., Lamy, J.-B., Ducousso, A., Musch, B., Ehrenmann, F., Delzon, S., Cavers, S., Chalupka, W., Dağdaş, S., Hansen, J.K., Lee, S.J., Liesebach, M., Rau, H.-M., Psomas, A., Schneck, V., Steiner, W., Zimmermann, N.E. & Kremer, A. (2017) Adaptive and plastic responses of *Quercus petraea* populations to climate across Europe. *Global Change Biology*, **23**, 2831–2847.
- Savolainen, O., Lascoux, M. & Merilä, J. (2013) Ecological genomics of local adaptation. *Nature Reviews Genetics*, **14**, 807–820.
- Savolainen, O., Pyhäjärvi, T. & Knürr, T. (2007) Gene flow and local adaptation in trees. *Annual Review of Ecology, Evolution, and Systematics*, 595–619.
- Shipley, B., Vile, D. & Garnier, E. (2006) From plant traits to plant communities: a statistical mechanistic approach to biodiversity. *Science*, **314**, 812–814.

- Valladares, F., Matesanz, S., Guilhaumon, F., Araújo, M.B., Balaguer, L., Benito-Garzón, M., Cornwell, W., Gianoli, E., Kleunen, M., Naya, D.E. & others (2014) The effects of phenotypic plasticity and local adaptation on forecasts of species range shifts under climate change. *Ecology letters*, **17**, 1351–1364.
- Valladares, F., Sanchez-Gomez, D. & Zavala, M.A. (2006) Quantitative estimation of phenotypic plasticity: bridging the gap between the evolutionary concept and its ecological applications. *Journal of Ecology*, **94**, 1103–1116.
- Wang, T., Hamann, A., Yanchuk, A., O’neill, G.A. & Aitken, S.N. (2006) Use of response functions in selecting lodgepole pine populations for future climates. *Global Change Biology*, **12**, 2404–2416.
- Yeaman, S., Hodgins, K.A., Lotterhos, K.E., Suren, H., Nadeau, S., Degner, J.C., Nurkowski, K.A., Smets, P., Wang, T., Gray, L.K., Liepe, K.J., Hamann, A., Holliday, J.A., Whitlock, M.C., Rieseberg, L.H. & Aitken, S.N. (2016) Convergent local adaptation to climate in distantly related conifers. *Science*, **353**, 1431–1433.

453 **DATA ACCESSIBILITY**

454 Raw data can be freely accessed online for French National Forest Inventories

455 (<http://inventaire-forestier.ign.fr>), *Quercus petraea*

456 (<https://arachne.pierroton.inra.fr/QuercusPortal/>) and *Abies alba* common gardens (online

457 repository, under process). Climate data used for this study are available online

458 (<http://gentree.data.inra.fr/climate/>). R codes used for data analyses can be obtained from the

459 correspondence author upon request.

460

461 **BIOSKETCH**

462 The authors' research aims to understand how ecological and evolutionary processes drive the

463 effects of global changes on forests, by merging expertise in ecological modelling, genetics

464 and conservation.

465 T.F. and M.B.G. conceived and designed the study; T.F. conducted the data analyses; T.F. and

466 M.B.G. wrote the manuscript that was commented and improved by B.F., A.K. and A.D.

467 **TABLES**

468 **Table 1** Estimates of *in-situ* and *ex-situ* linear mixed-effect models of individual tree height  
469 data (log-transformed). *In-situ* models were fit on 5376 trees (height measurements) in 3617  
470 plots nested in 22 bioclimatic regions (random groups) for *Q. petraea* and on 1304 trees in  
471 904 plots nested in 15 bioclimatic regions for *A. alba*. Bioclimatic regions were added as  
472 random effects in *in-situ* model for *Q. petraea* but not for *A. alba*. *Ex-situ* models were fit on  
473 130241 trees (height measurements) from 141 provenances that were planted in 591 blocs  
474 nested in 13 sites (random groups) for *Q. petraea* and on 13314 trees from 47 provenances  
475 planted in 166 blocs nested in 6 sites for *A. alba*. No significant *ex-situ* models were found in  
476 *A. alba*. The climatic variable used to compute LTC and RCC is the maximal temperature of  
477 the warmest month in *Quercus petraea* and the potential evapotranspiration of the warmest  
478 month in *Abies alba*. The percentage of the variance explained by the models is measured by  
479 the marginal (fixed effects, m) and conditional (both fixed and random effects, c) adjusted R<sup>2</sup>.  
480 ‘Df’ degree of freedom, ‘BAc’ sum of basal area of neighbouring competitor trees, ‘LTC’  
481 long-term climate, ‘RCC’ recent climate change.

482

483 **Table 2** Mean bootstrap estimates ( $\pm$  SD) of tree height variation due to provenance and  
484 plasticity effects, and their interaction, computed from *in-situ* (NFI) model and *ex-situ*  
485 (common garden) model. ‘x’ and ‘x<sup>2</sup>’ indicate linear and quadratic terms respectively.  
486 Significant differences of bootstrapped values (n = 200) to null values were tested using t-  
487 tests; all are significant at  $P < 0.001$ .



488 **Table 1**

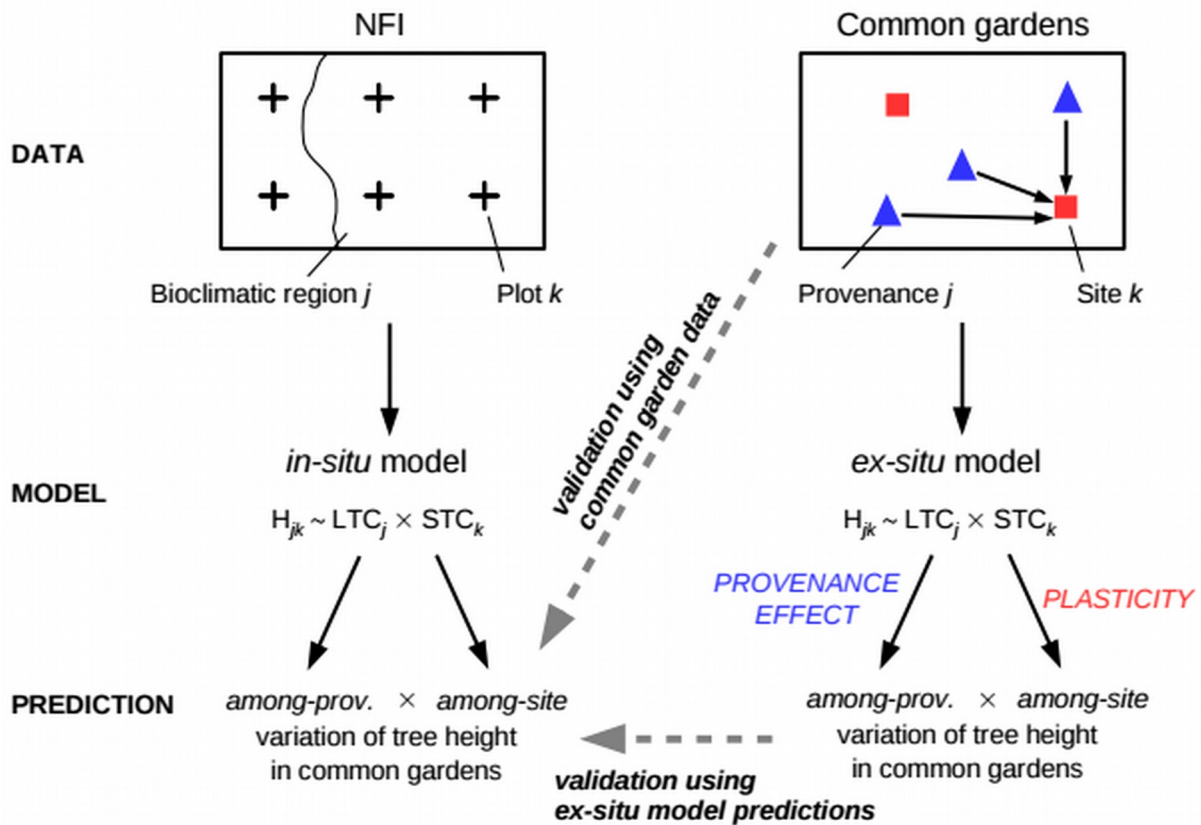
<i>Quercus petraea</i>	<i>in-situ</i>				<i>ex-situ</i>			
	Estimate (±SE)	Df	t-value	P	Estimate (±SE)	Df	t-value	P
Intercept	-13.40 (4.07)	3589	-3.3	0.001	-12.38 (2.23)	129643	-5.54	<0.001
log(age)	0.311 (0.009)	1758	34.53	<0.001	1.322 (0.008)	129643	167.71	<0.001
log(BAc)	-0.171 (0.133)	1758	-1.29	0.197				
LTC	1.269 (0.354)	19	3.59	0.002	0.903 (0.181)	129643	5	<0.001
LTC <sup>2</sup>	-0.028 (0.008)	19	-3.58	0.002	-0.020 (0.004)	129643	-5.55	<0.001
RCC	0.440 (0.118)	3589	3.72	<0.001	0.730 (0.182)	129643	4.01	<0.001
RCC <sup>2</sup>	-0.017 (0.003)	3589	-5.22	<0.001	-0.018 (0.004)	129643	-4.95	<0.001
LTC:RCC	-0.018 (0.005)	3589	-4.02	<0.001	-0.031 (0.007)	129643	-4.26	<0.001
log(BAc):LTC	0.013 (0.006)	1758	2.38	0.017				
log(age):RCC	0.009 (0.007)	1758	1.3	0.193	-0.012 (0.003)	129643	-3.63	<0.001
R2 (m/c) (%)	41/91				26/65			
<i>Abies alba</i>	Estimate (±SE)	Df	t-value	P				
Intercept	0.732 (0.649)	898	-1.13	0.259				
log(age)	0.319 (0.014)	396	23.57	<0.001				
log(BAc)	0.224 (0.123)	396	1.82	0.069				
LTC	0.024 (0.008)	898	2.95	0.003				
LTC <sup>2</sup>	-7.3 10 <sup>-5</sup> (2.8 10 <sup>-5</sup> )	898	-2.63	0.009				
RCC	0.009 (0.006)	898	1.46	0.146				
RCC <sup>2</sup>	-9.9 10 <sup>-5</sup> (2.3 10 <sup>-5</sup> )	898	-4.36	<0.001				
LTC:RCC	-8.3 10 <sup>-5</sup> (3.8 10 <sup>-5</sup> )	898	-2.17	0.030				
log(BAc):LTC	-2.4 10 <sup>-4</sup> (9.5 10 <sup>-4</sup> )	396	-0.25	0.803				
log(age):RCC	0.002 (8.4 10 <sup>-4</sup> )	396	1.92	0.056				
R2 (m/c) (%)	49/86							

489

490 **Table 2**

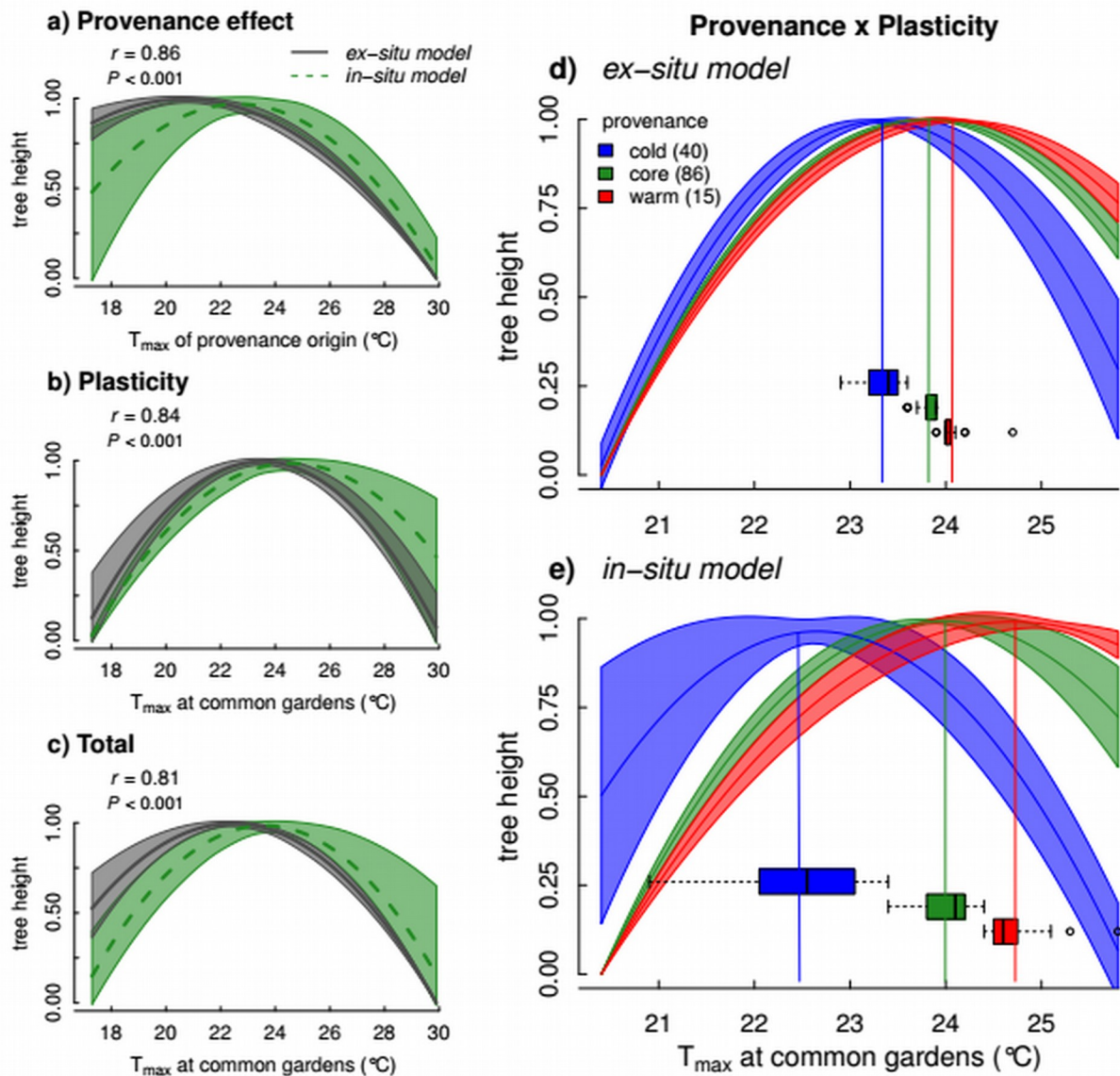
	Provenance effect		Phenotypic plasticity		interaction
	x	x <sup>2</sup>	x	x <sup>2</sup>	
<i>Quercus petraea</i> <i>ex-situ</i> model	0.191 (0.026)	-7.3 10 <sup>-3</sup> (0.35 10 <sup>-3</sup> )	0.712 (0.169)	-0.017 (0.003)	4.6 10 <sup>-3</sup> (0.68 10 <sup>-3</sup> )
<i>Quercus petraea</i> <i>in-situ</i> model	0.548 (0.365)	-0.022 (0.009)	0.465 (0.122)	-0.018 (0.003)	0.018 (0.007)
<i>Abies alba</i> <i>in-situ</i> model	0.014 (0.007)	-8.6 10 <sup>-5</sup> (2.1 10 <sup>-5</sup> )	0.010 (0.007)	-9.2 10 <sup>-5</sup> (2.1 10 <sup>-5</sup> )	1.0 10 <sup>-4</sup> (0.4 10 <sup>-4</sup> )

491



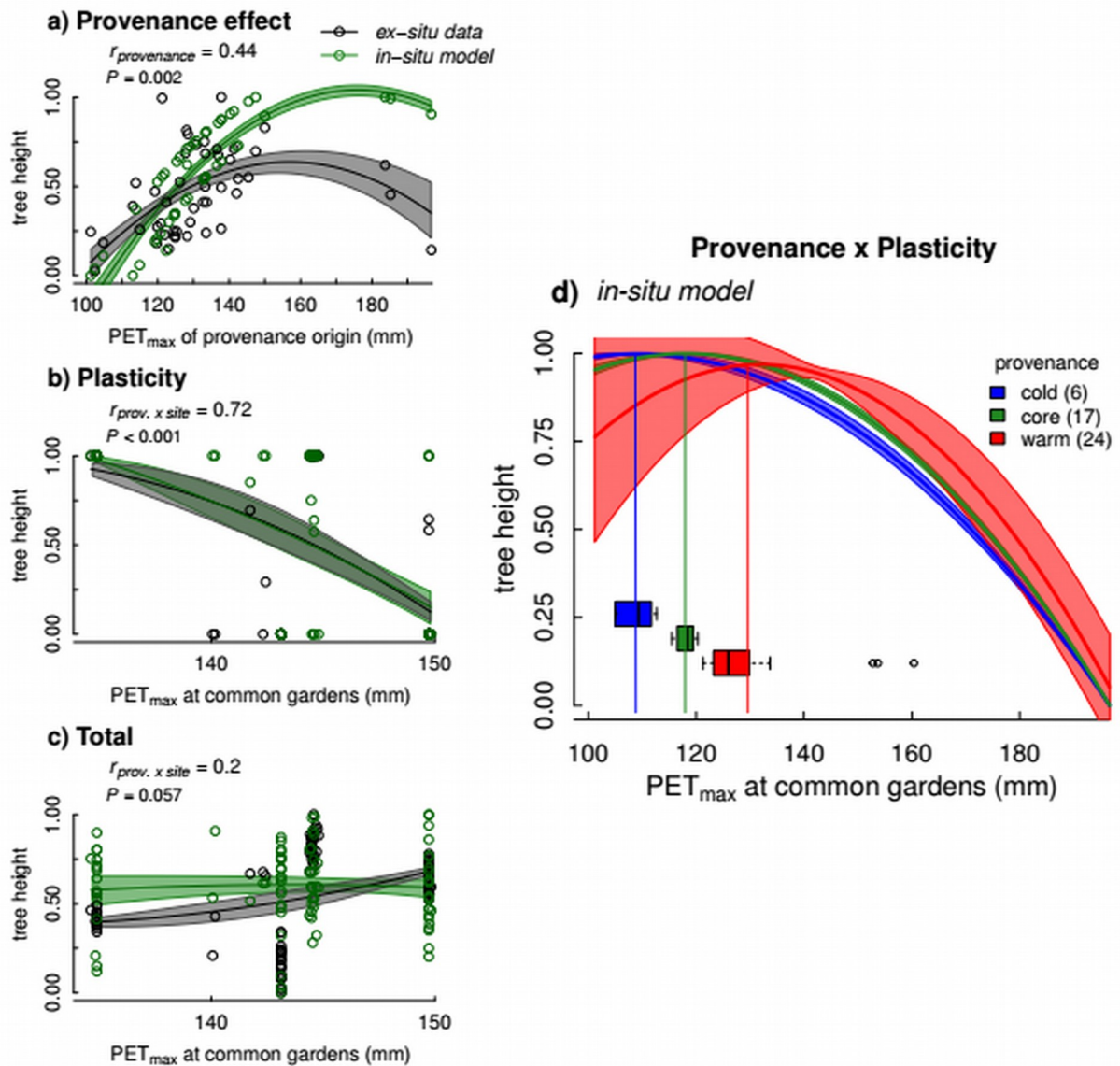
493

494 **Figure 1** Workflow of the modelling approach and validation methods. We used individual  
 495 tree height data from National Forest Inventories (NFI) to calibrate a mixed-effect model  
 496 ('*in-situ* model') as a function of long-term climate (LTC) of the bioclimatic region and short-  
 497 term climate (STC) of the forest plot to disentangle local adaptation, plasticity and their  
 498 interaction on intraspecific trait variation. To validate our approach, we compared *in-situ*  
 499 model predictions with independent observations of tree height variation in common gardens  
 500 where trait differences among populations of different geographical origin (i.e., the  
 501 provenance) and their plasticity can be separated. *In-situ* model predictions of tree height  
 502 variation among provenances and among planting sites were compared to observations in  
 503 common gardens (*validation using common garden data*) and to predictions from a parallel  
 504 model calibrated using common garden data (*validation using ex-situ model predictions*).  
 505 *Validation using ex-situ model predictions* needs common garden data covering large climatic  
 506 gradients (as is the case of *Quercus petraea* in this study) which is not always feasible, while  
 507 *validation using common garden data* can be used also with scarce common data networks  
 508 (as is the case of *Abies alba* in this study).



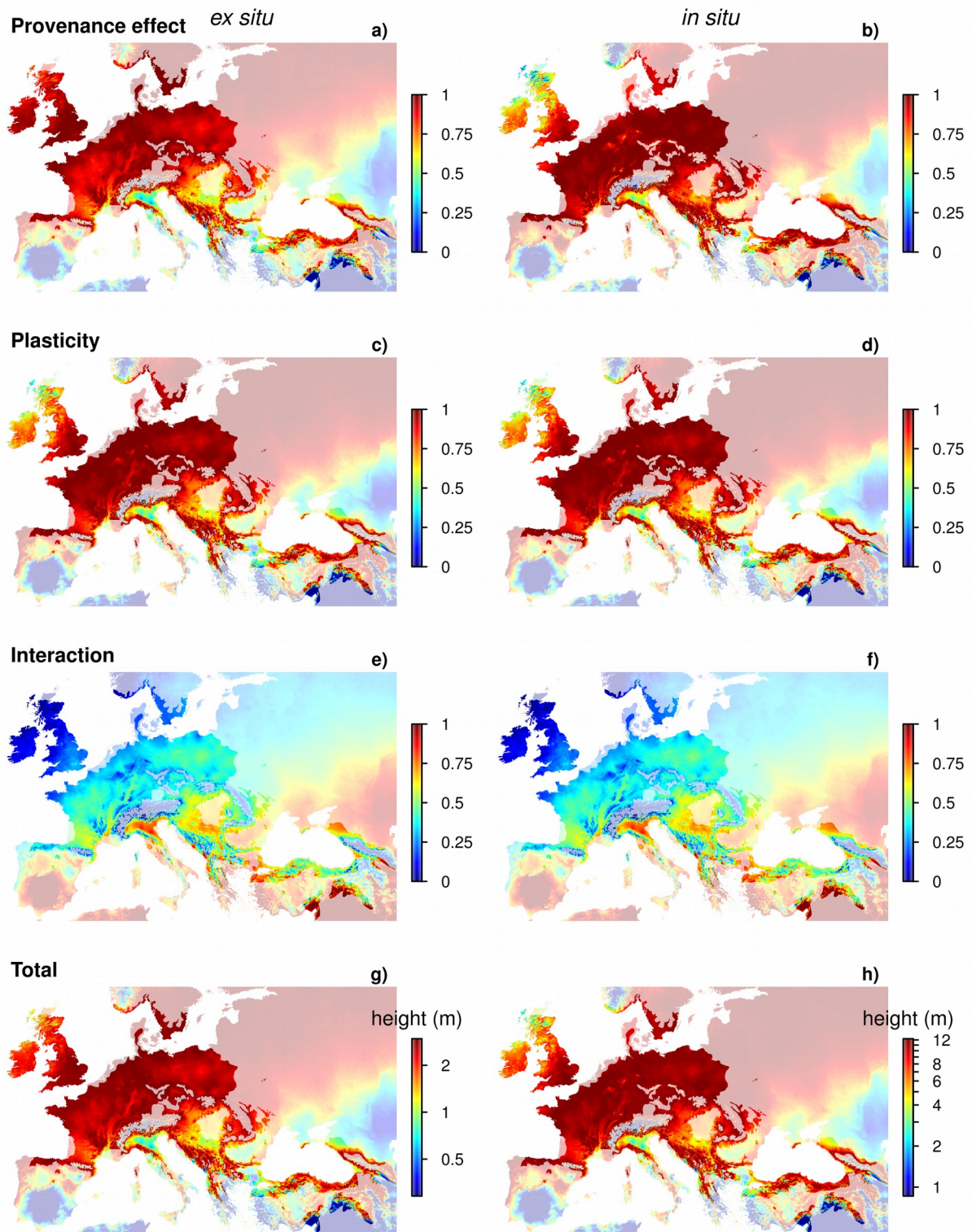
509

510 **Figure 2** Comparison of *in-situ* model (NFI) and *ex-situ* model (common gardens)  
 511 predictions of provenance (a) and plasticity effects (b), and the total component (c) of tree  
 512 height variation, recorded in common gardens in *Quercus petraea*. Pearson correlation  
 513 coefficients between *ex-situ* and *in-situ* model predictions are reported. (d-e) Model  
 514 predictions of plastic responses among provenances (provenance  $\times$  plasticity interaction).  
 515 Temperature optima for cold, core and warm provenances are indicated by horizontal  
 516 boxplots; vertical coloured lines indicate mean optimum values. Significant differences in  
 517 temperature optimum were tested using Kruskal-Wallis tests:  $\chi^2 = 105.2$  in d) and  $\chi^2 = 104.2$   
 518 in e),  $P < 0.001$  for both. Shaded areas and lines represent the standard deviation around  
 519 average model predictions (computed by bootstrapping in a-c). Predictions were scaled  
 520 between 0–1 independently for *in-situ* and *ex-situ* models. Model parameters (coefficients  
 521 and significance) are presented in Table 1. Validation analyses using common garden data are  
 522 presented in Appendix S3.



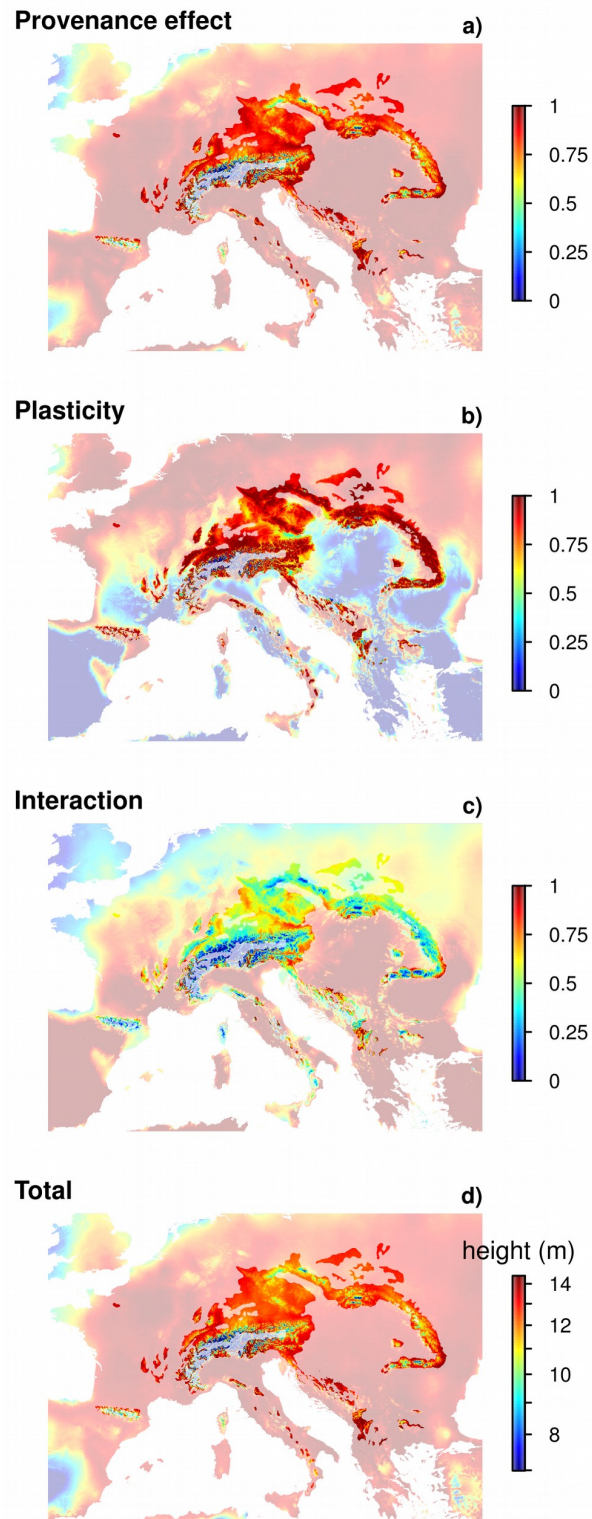
523

524 **Figure 3** Comparison of *in-situ* (NFI) model predictions and common garden data (*ex-situ*)  
 525 estimates of provenance (a) and plasticity effects (b), and the total component (c) of tree  
 526 height variation, recorded in common gardens in *Abies alba*. Points represent provenance  
 527 means in a) and provenance-by-site means in b-c that were computed according to the  
 528 validation method using common garden data (see Fig. 1). Computation of provenance and  
 529 plasticity effects, and the total variation is described in Appendix S3. Pearson correlation  
 530 coefficients between *ex-situ* data and *in-situ* model predictions are reported. (d) *In-situ* model  
 531 predictions of plastic responses among provenances (provenance  $\times$  plasticity interaction).  
 532 Temperature optima for cold, core and warm provenances are indicated by horizontal  
 533 boxplots; vertical coloured lines indicate mean optimum values. Significant differences in  
 534 temperature optimum were tested using Kruskal-Wallis tests:  $\chi^2 = 105.2$ ,  $P < 0.001$ . Shaded  
 535 areas and lines represent the standard deviation around average model predictions (computed  
 536 by bootstrapping in a-c). Height values were scaled between 0–1 independently for *in-situ*  
 537 predictions and common garden data. *In-situ* model parameters (coefficients and significance)  
 538 are presented in Table 1.



539

540 **Figure 4** Spatial predictions of *Quercus petraea* range-wide variation in tree height using *ex*-  
 541 *situ* (a, c, e, g) and *in-situ* models (b, d, f, h). Maps indicate the provenance effect (a-b),  
 542 plasticity (c-d), their interaction (e-f) and the total variation of tree height (g-h). The shaded  
 543 area represents model predictions outside the natural distribution range of the species.  
 544 Predictions are for 12-years-old trees, with neighbour basal area set to average conditions (30  
 545  $\text{m}^2 \text{ha}^{-1}$ ) in the *in-situ* model.



546

547 **Figure 5** Spatial predictions of *Abies alba* range-wide variation in tree height using the *in-*  
 548 *situ* model. Maps indicate the provenance effect (a), plasticity (b), their interaction (c) and the  
 549 total variation of tree height (d). The shaded area represents model predictions outside the  
 550 natural distribution range of the species. Predictions are for 12-years-old trees, with  
 551 neighbour basal area set to average conditions ( $30 \text{ m}^2 \text{ ha}^{-1}$ ).

552

## SUPPORTING INFORMATION

553

### 554 **Inferring phenotypic plasticity and population responses to climate across tree species** 555 **ranges using forest inventory data**

556

557

558 Thibaut Fréjaville, Bruno Fady, Antoine Kremer, Alexis Ducouso, Marta Benito-Garzón

559

560

#### 561 **Appendix S1 Phenotypic and climate data**

562 **Fig. S1.1** Maps of *NFI* and *common garden* tree height data for *Quercus petraea* and *Abies*  
563 *alba*.

564 **Fig. S2.1** Principal component Analysis of climatic conditions across *NFI* and *common*  
565 *garden* data for *Quercus petraea* and *Abies alba*.

566 **Fig. S3.1** Temporal trends (1901–2014) in annual mean temperature across species ranges.

567 **Fig. S4.1** Tree height variation as a function of tree age and neighbour basal area.

568 **Table S1** Description of the 6 common gardens used for measuring tree height on *Abies alba*  
569 provenances.

**Table S2** Description of *Abies alba* provenances planted in the 6 common gardens.

570

#### 571 **Appendix S2 Bioclimatic regionalisation of species' natural distribution ranges**

572 **Fig. S5.2** Maps of bioclimatic regions within the natural distribution range of *Quercus*  
573 *petraea* and *Abies alba*.

574

#### 575 **Appendix S3 Model Validation**

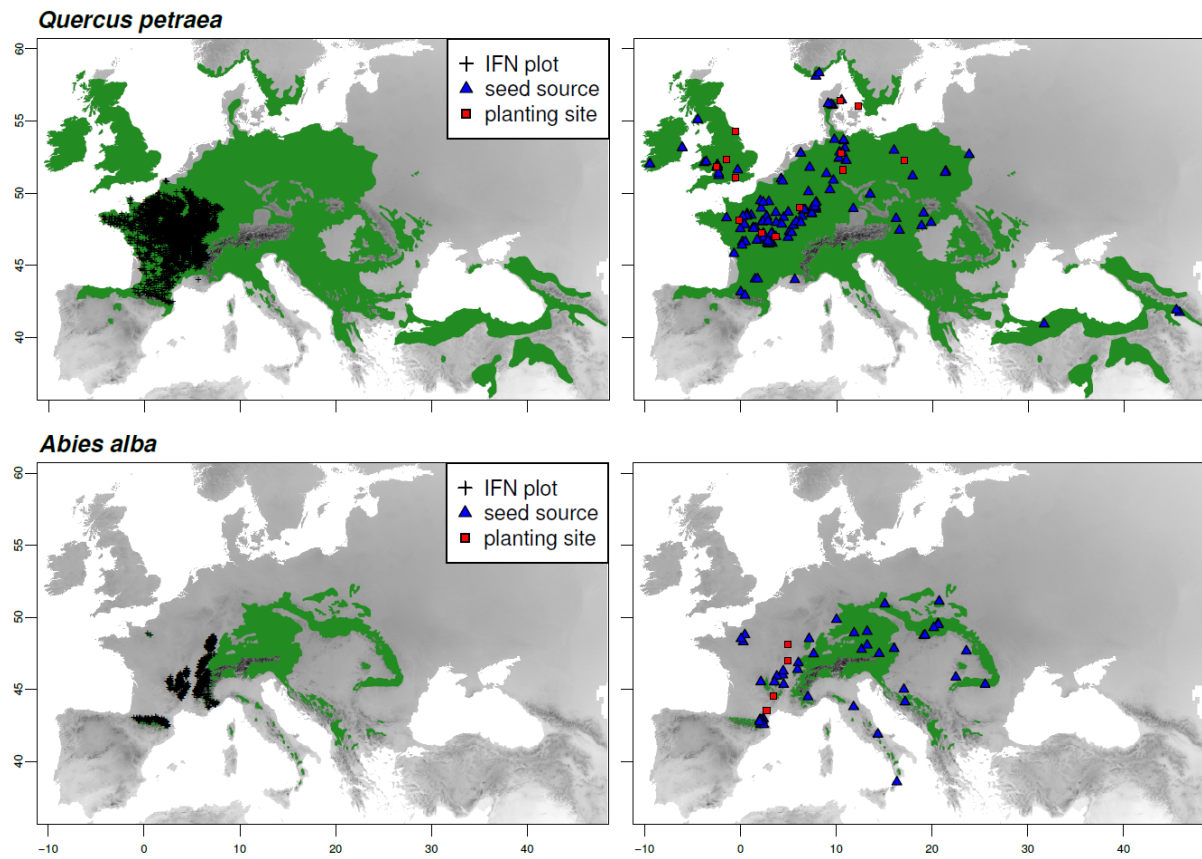
576 *Validation using common garden data*

**Fig. S6.3** Correlation between *in-situ* model predictions and common garden data estimates  
of provenance and plasticity effects and the total component of variation in tree height in  
*Quercus petraea*.

**Fig. S7.3** Correlation between *in-situ* model predictions and common garden data estimates  
of provenances and plasticity effects and the total component of variation in tree height in  
*Abies alba*.

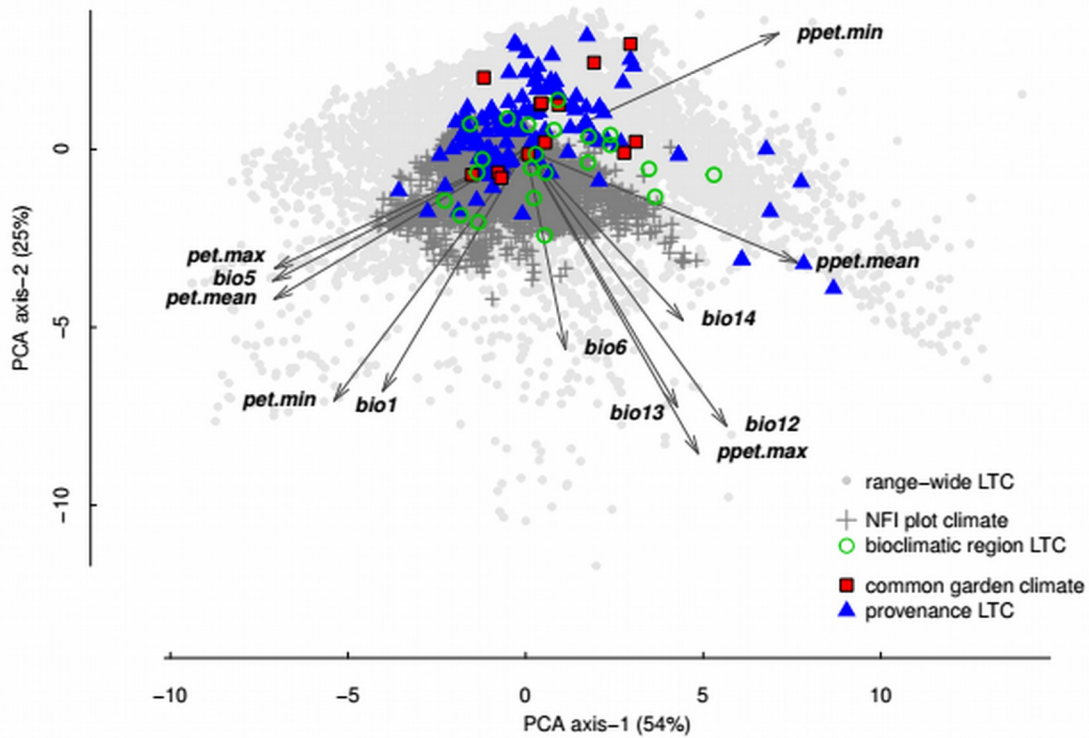
577 *Validation using ex-situ model predictions*



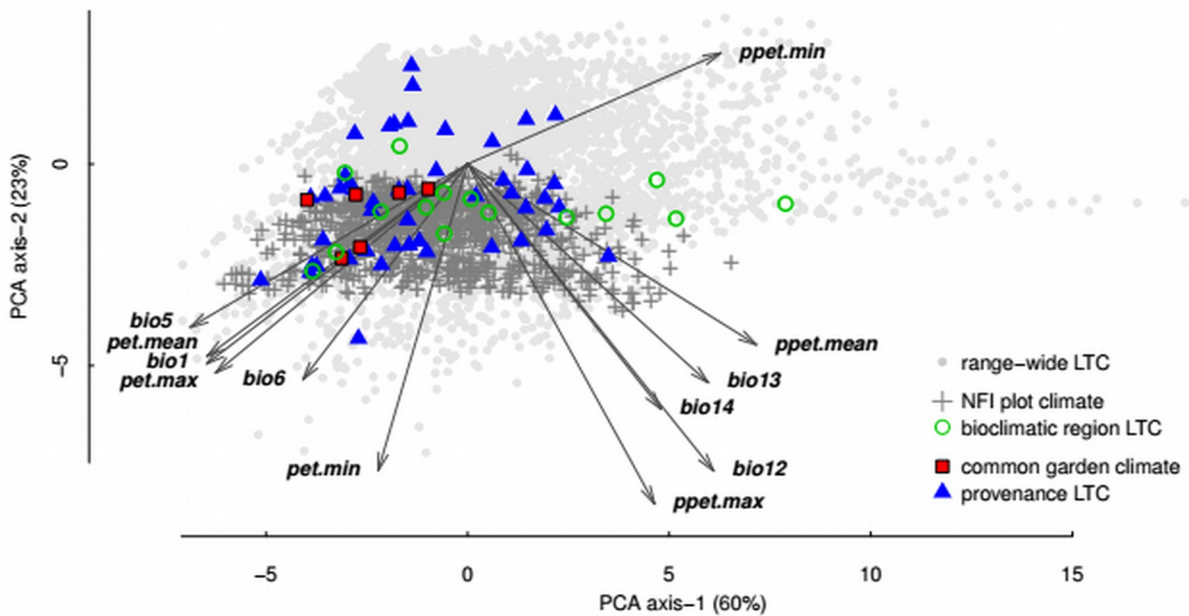


**Figure S1.1** Geographic distribution of French National Forest Inventory data (NFI) and common garden experiments within the natural distribution range of *Quercus petraea* and *Abies alba*. Black crosses represent NFI temporary forest plots (left panels) in which height, age and diameter at breast height were measured on dominant trees, within the natural distribution range of the species (green area; <http://www.euforgen.org>). Common garden experiments (right panels) consist of planted trees from provenances (seed sources, blue triangles) covering the species distribution range in common gardens (genetic trials, red squares).

a) *Quercus petraea*

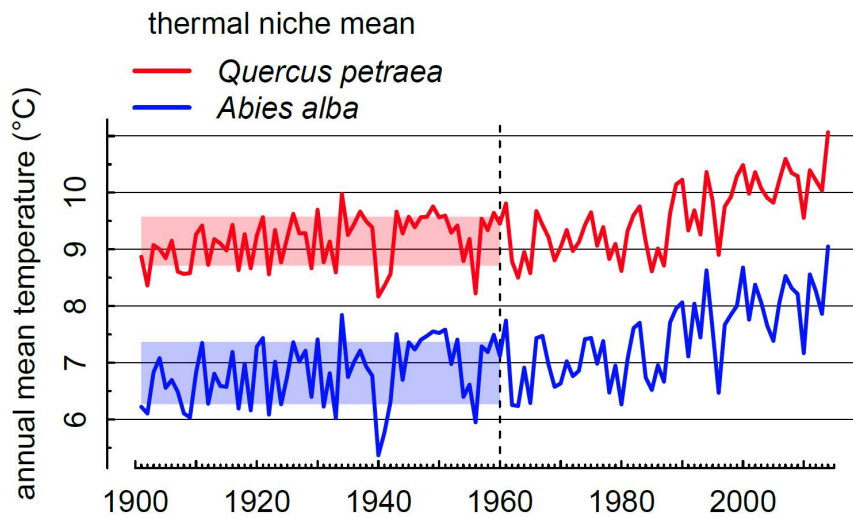


b) *Abies alba*

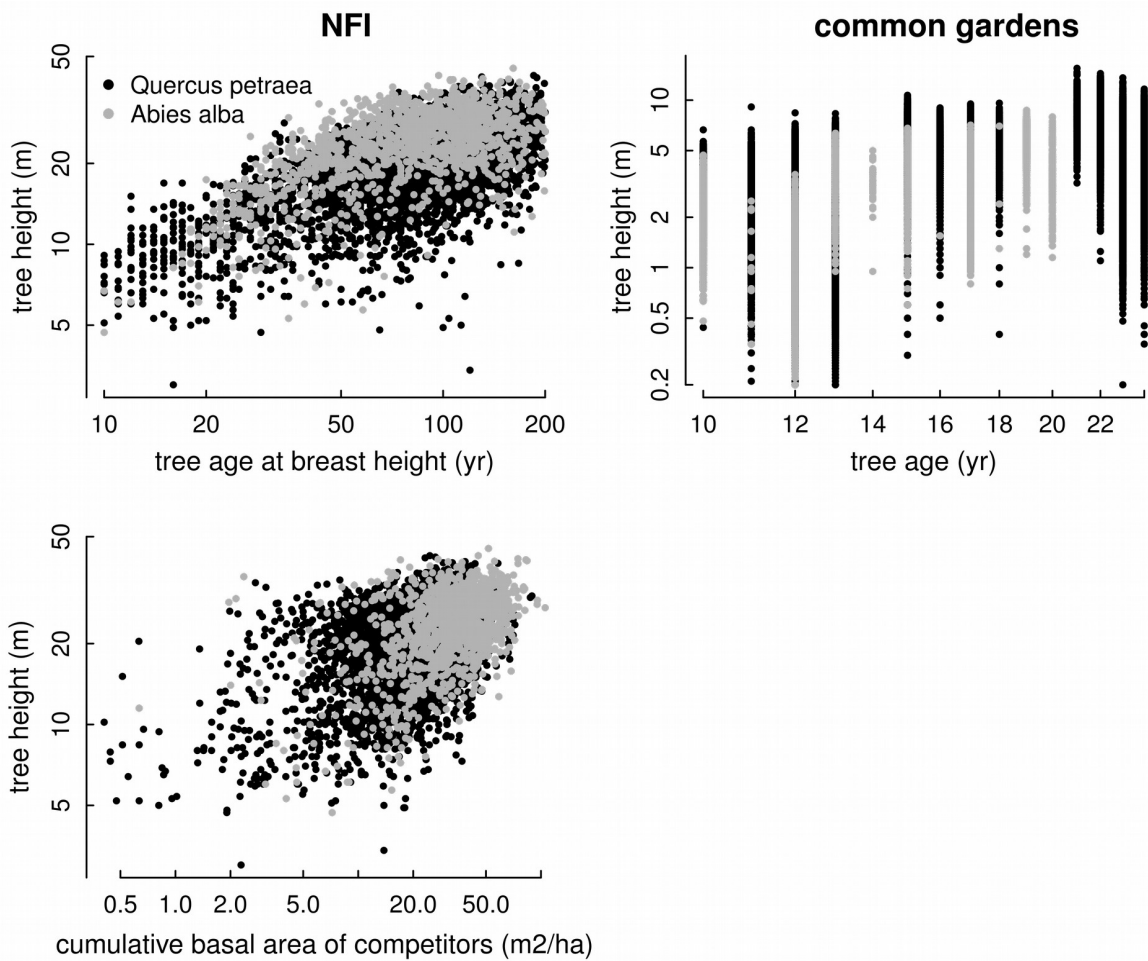


**Figure S2.1** Principal component analysis (PCA) of short-term climate at *in-situ* National Forest Inventory (NFI) plots (grey crosses) and *ex-situ* common gardens (red squares), and of long-term climate (LTC) of origin of populations planted in common gardens ('provenance', blue triangles) and of bioclimatic regions covered by NFI plots (black circles, see Appendix S2) for *Quercus petraea* (a) and *Abies alba* (b). The LTC distribution across the species natural distribution range is indicated by grey dots. Short-term climate represents the 10-yr means before tree measurements and LTC the 1901–1960 means. The climatic variance explained by the first two PCA axes is indicated in brackets. The PCA was computed using

the following climatic variables downscaled from EuMedClim: ‘bio1’ annual mean temperature, ‘bio5’ maximum temperature of the warmest month, ‘bio6’ minimum temperature of the coldest month, ‘bio12’ annual precipitation, ‘bio13’ maximum precipitation of the wettest month, ‘bio14’ minimum precipitation of the driest month, ‘pet.mean’ annual potential evapotranspiration, ‘pet.max’ potential evapotranspiration of the warmest month, ‘pet.min’ potential evapotranspiration of the coldest month, ‘ppet.mean’ annual water balance (precipitation minus evapotranspiration), ‘ppet.max’ water balance of the wettest month, ‘ppet.min’ water balance of the driest month.



**Figure S3.1** Temporal variation (1901–2014) in annual mean temperature (from <http://gentree.data.inra.fr/climate/>) averaged within the natural distribution range of *Quercus petraea* (red) and *Abies alba* (blue). Shaded area represents the standard deviation around the long-term average climate (1901–1960), prior to the acceleration of climate warming during the decades following 1960. The shapes of species distribution maps used to compute the temporal variation of the thermal niches were sourced from Euforgen (<http://www.euforgen.org>).



**Figure S4.1** Tree height variation as a function of tree age (top) and neighbour basal area (bottom) in *Quercus petraea* (black) and *Abies alba* (grey) in National Forest Inventories (NFI, left) and common gardens (right). Neighbour basal area was assumed to be constant between and within common gardens. Tree age was estimated using wood increment cores collected at breast height (1.30 m) in NFI plots, whereas tree age is the time between the height measurement and the sowing date in common gardens. Note a log scale on both axes.

**Table S1** Description of the 6 French common gardens used for measuring phenotypic traits on *Abies alba* provenances. Data include: test site code (as in Table S3), name of forest where the site is located, name of region where the site is located, latitude (in degree decimal, to the 4<sup>th</sup> decimal point), longitude (in degree decimal to the 4<sup>th</sup> decimal point), elevation (m a.s.l.), total size of the test site (in hectare), plantation density (trees per hectare) and number of *A. alba* provenances tested in the study (N).

Site code	Site name	Latitude	Longitude	Elevation	Planting date	Size	Density	N
60301	Bois Génard	48.1167	4.9833	320	1972	3	2500	2
70201	Rouvre Sur Aube	47.0167	4.9667	410	1967	3.88	2500	21
70203	La Brugère	44.5667	3.4517	1110	1967	3.22	2000	16
70402	Les Chauvets	44.5667	3.4483	1050	1972	4.31	2500	20
70502	Somail Chinchidou	43.5333	2.7333	920	1973	0.29	10000	35
70503	Somail Sagnassol	43.5361	2.7347	973	1973	0.42	2500	33

Note: the test site may contain other genetic material than the populations tested in this study, e.g. other species irrelevant to this study.

**Table S2** Description of *Abies alba* Mill. provenances in the 6 common gardens. Data include: population code number and name, geographic coordinates in degree decimal, country of origin, and number of blocks (replicates) per site where the population is planted. ‘B&H’ Bosnia & Herzegovina, ‘Czech’ Czech Republic.

Pop. code	Pop. name	Latitude	Longitude	Country	60301	70201	70203	70402	70502	70503
36549	FORE	45.517	3.550	France		5	5			
36550	GRBO	45.350	4.517	France		5	5			
36555	RUHP	47.767	12.650	Germany					80	32
36556	BEAR	42.967	2.400	France		5	5			
36557	RIAL	42.950	2.367	France		5				
36558	NEBS	42.900	2.133	France		5	5			
36559	PUIV	42.900	2.033	France		6	5			
36560	CALL II	42.850	2.117	France		5	5			
36561	FANG II	42.833	2.283	France		5				
36562	Lafa	42.767	2.000	France		6	5			
36563	BALC	42.583	2.100	France		7	5			
36564	CANG	42.550	2.450	France		6	5			
36565	JOUX II	46.850	6.050	France		5	5			
36566	DONO	48.517	7.167	France		5	5			
36567	BOAJ	46.283	4.467	France		5	5			
36568	MOLL	46.000	4.433	France		5				
36569	BONO II	45.917	3.800	France		5	5			
36570	JASO	45.533	2.133	France		5				
36571	ECOU II	48.517	0.067	France		7	5			
36572	PERS	48.300	0.300	France		5				
36573	LASU	47.667	23.583	Romania		6	5			
36574	PRAH	45.350	25.550	Romania		8	5			
36575	BLIZ	51.117	20.750	Poland					80	32
36576	LA-SU II	45.850	22.483	Romania	5				80	32
36577	KURN	49.850	10.033	Germany					80	32
36578	PRAZ	44.483	7.050	Italy					80	32
36579	KOZA	45.000	17.063	B&H					80	32
36580	FANG IV	42.817	2.267	France				5	80	32
36581	ZWIE	49.017	13.233	Germany					80	32
36582	CALL IV	42.869	2.087	France					80	32
36583	CAMA	43.800	11.817	Italy					80	32
36585	TRIE	47.486	14.486	Austria					80	32
36586	RYTR	49.490	20.668	Poland					80	32
36588	KOBE	48.067	13.233	Austria					80	32
36589	VODC	44.135	17.189	B&H					80	32
36590	KELH	48.917	11.868	Germany					80	32
36591	SEVR II	48.791	0.464	France				6	80	
36592	JOUX III	46.376	5.972	France	5			5	80	32
36594	ROSE	41.900	14.350	Italy					80	32
36596	HOHE	47.834	16.048	Austria					80	32
36597	STSA	49.563	20.636	Poland					80	32
36598	SBRU	38.583	16.333	Italy					80	32
36602	BANS	48.733	19.149	Slovakia					80	32
36603	SLLU	48.767	19.275	Slovakia					80	32
36604	PODS	49.283	20.183	Slovakia					80	32
36606	FRYD	50.921	15.079	Czech					80	32
36607	LOCH	47.457	7.640	Switzerland					80	32

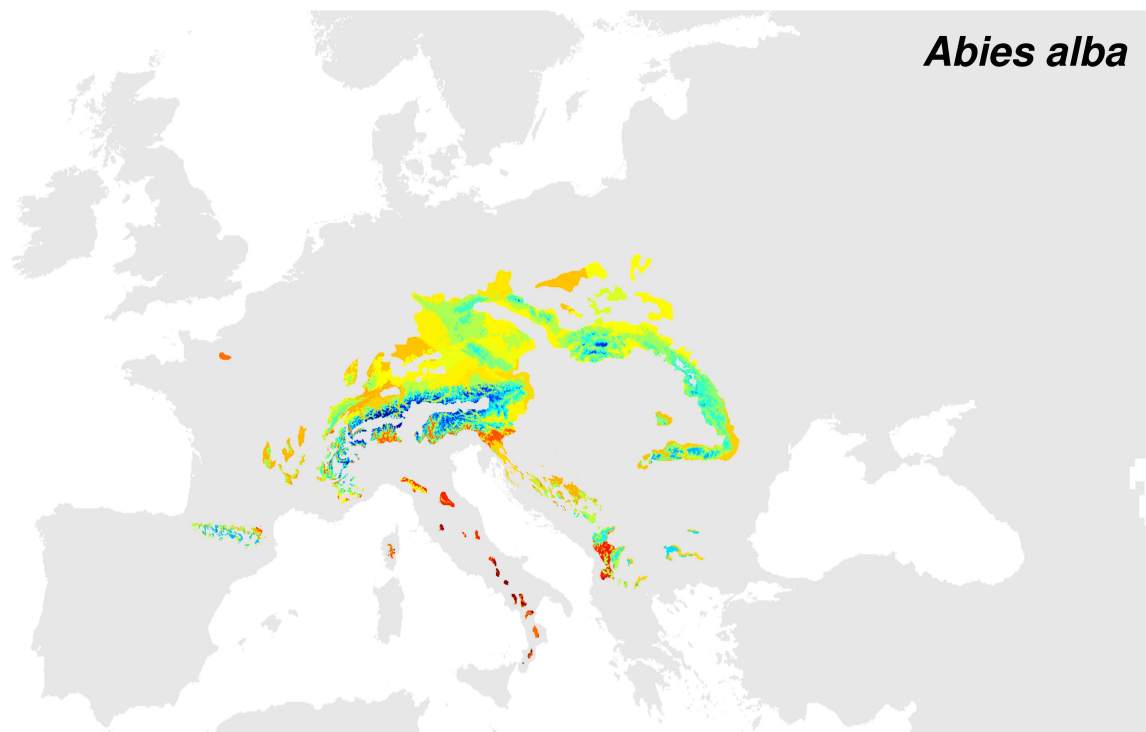
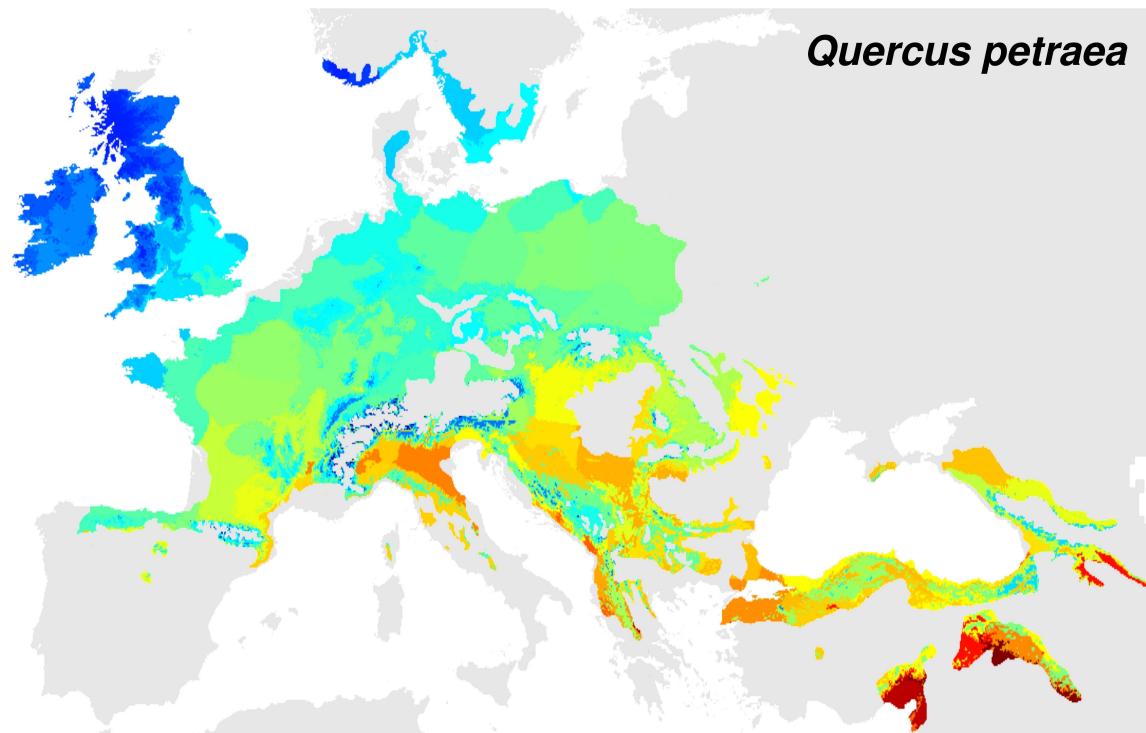
## 580 **Appendix S2 Bioclimatic regionalisation of species natural distribution ranges**

581 In contrast to the common garden experiments, the geographical origin of the seed source  
582 (i.e., the provenance) is unknown for NFI observations. To overcome this major limitation,  
583 we made the neutral assumption that the trees have a local origin. In other words, we assume  
584 that potential seed sources were mostly from local provenances within the bioclimatic region  
585 with a low probability of long-distance transfer. We therefore performed a fine bioclimatic  
586 partitioning of the species' natural distribution range (Figure S5.2). The long-term climate of  
587 origin (LTC) was estimated as the long-term (1901-1960) average climate of the bioclimatic  
588 region in NFI. The recent climate change (RCC) is estimated as the difference between the  
589 recent short-term climate (STC) experienced by the tree in the NFI plot (averaged over the  
590 last decade of growth before tree height measurement) and the estimated LTC for the  
591 corresponding climatic variable.

592 For each species, the natural distribution range (<http://www.euforgen.org>) was partitioned  
593 into bioclimatic regions by K-means clustering using the R package *vegan* (Oksanen et al.  
594 2013) (Figure S5.2). We used the Caliński–Harabasz criterion (Caliński & Harabasz 1974) to  
595 select a statistically optimal number of regions (K = 70 for *A. alba*; K = 90 for *Q. petraea*)  
596 from a range of K (10 to 200 in steps of 10). Partitioning of bioclimatic regions was  
597 performed on Z-scores (standardised data) of long-term (1901–1960) averages of the  
598 following four climatic parameters: minimum temperature of the coldest month (°C),  
599 maximum temperature of the warmest month (°C), and total precipitation in the driest and the  
600 wettest months (mm); in addition to the latitude and longitude of the plots.

### **References:**

- Caliński, T. & Harabasz, J. (1974) A dendrite method for cluster analysis. *Commun. Stat.* 3, 1–27.
- Oksanen, J. et al. (2013) *vegan*: Community Ecology Package. R package version 2.0-7.
- Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D. & R Core Team (2015) *nlme*: Linear and Nonlinear Mixed Effects Models. R package version 3.1–120. [HttpCRANR-Proj.](http://CRAN.R-project.org)



**Figure S5.2** Bioclimatic regions within the natural distribution range of *Quercus petraea* (top) and *Abies alba* (bottom). Colour gradient represents differences in long-term regional average (1901–1960) of annual mean temperature, from blue (coldest regions) to red (warmest regions). Discontinuous areas of similar colour indicate a similar long-term mean temperature between bioclimatic regions. Number of bioclimatic regions across species ranges:  $N = 90$  and  $N = 70$  for *Q. petraea* and for *A. alba* respectively.



## 601 **Appendix S3 Model validation**

### 602 *Validation using common garden data*

603 In the case of validation by comparing the predictions of *in-situ* models with raw common  
604 garden data, we standardized both predictions and raw data for differences in provenances,  
605 sites, age and neighbour basal area. First, the *in-situ* model was used to predict the mean  
606 height of each provenance in each site ('provenance-by-site' means) from equation 3 (main  
607 text), using the LTC of the provenance and the STC of the site (i.e. common garden) for a  
608 given age (12-year-old trees, i.e. the most common age at the time of height measurements  
609 across common gardens in both species) and neighbour basal area (30 m<sup>2</sup> ha<sup>-1</sup>). Second,  
610 common garden data were standardized across ages using a linear mixed-effect model, where  
611 the log of tree height was regressed against the log of age with the provenance and the site set  
612 as random effects. In particular, we used model residuals computed from fixed effects only  
613 (i.e. age) to compute provenance-by-site means for common garden observations. Third,  
614 provenance-by-site means of common garden observations and *in-situ* model predictions  
615 were standardized as follows, before comparing them using Pearson correlation coefficients.

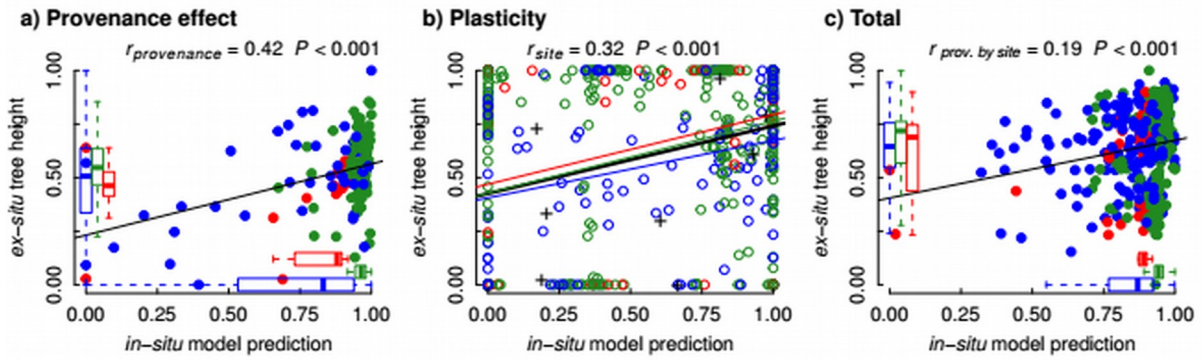
616 To estimate differences in tree height among provenances (provenance effect), provenance-  
617 by-site means were standardized (height values scaled between 0-1) independently for each  
618 site. In this way, we focused on height differences among provenances after accounting for  
619 differences in environmental conditions among sites (i.e. phenotypic plasticity effect). Then,  
620 we computed mean values by provenance. Pearson coefficients indicated significant  
621 correlations between common garden data and *in-situ* model predictions for the provenance  
622 effect in *Quercus petraea* (Fig. S6.3a) and *Abies alba* (Fig. S7.3a). Moreover, *in-situ* model  
623 predictions well predicted tree height differences among cold, core and warm provenances, as  
624 indicated by boxplots (Figs S6.3a and S7.3a).

625 To estimate plasticity, provenance-by-site means were standardized (height values scaled  
626 between 0-1) independently for each provenance. In this way, we focused on height  
627 differences among sites after accounting for the provenance effect. Pearson coefficients  
628 indicated significant correlations between common garden data and *in-situ* model predictions  
629 for the plastic component in *Q. petraea* (Fig. S6.3b) and *A. alba* (Fig. S7.3b). Considering  
630 cold, core and warm provenances separately, correlations were still significant at  $P < 0.05$ .

631 To estimate the total component of variation (sum of provenance effect and provenance  
632 plasticity effect), provenance-by-site means were standardized across all data (height values  
633 scaled between 0-1). Pearson coefficients indicated weak correlations in both species,  
634 significant in *Q. petraea* at  $P < 0.001$  (Fig. S6.3c) and in *A. alba* at  $P < 0.10$  (Fig. S7.3c). *In-*  
635 *situ* model predictions reasonably predicted height differences among cold, core and warm  
636 provenances, as indicated by boxplots (Figs S6.3c and S7.3c).

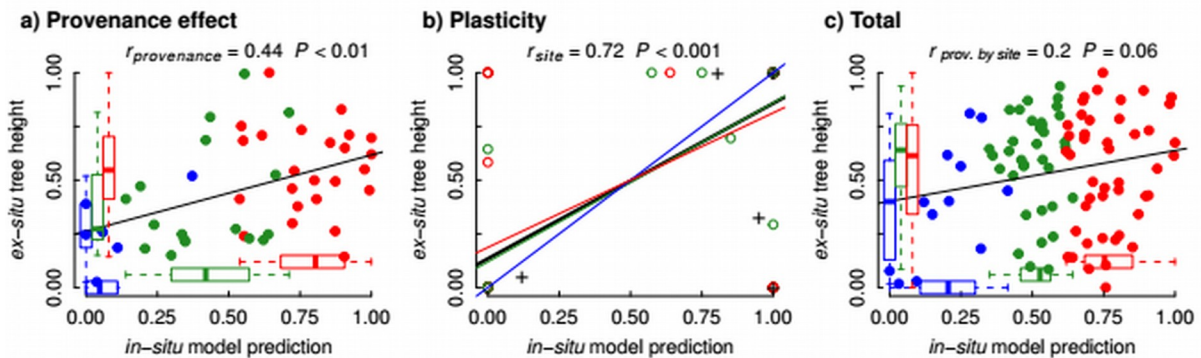
637

638



639

640 **Fig S6.3** Pearson correlation coefficients between *in-situ* model predictions (calibrated on  
 641 NFI) and common garden data estimates of provenance (a) and plasticity effects (b) and of  
 642 the total component of tree height variation (c) across *Quercus petraea* provenances. Points  
 643 represent provenance means in a) and provenance-by-site means in b) and c). Tree height  
 644 differences among cold (blue), core (green) and warm provenances (red) for common garden  
 645 data and *in-situ* model predictions are indicated by boxplots in a) and c). Regression lines in  
 646 b) illustrate correlations for phenotypic plasticity between common garden data and *in-situ*  
 647 model predictions for cold (blue), core (green), warm (red) and all provenances (black); all  
 648 are significant at  $P < 0.05$ ; crosses indicate mean site values.



**Fig S7.3** Pearson correlation coefficients between *in-situ* model predictions (calibrated on  
 NFI) and common garden data estimates of provenance (a) and plasticity effects (b) and of  
 the total component of tree height variation (c) across *Abies alba* provenances. Points  
 represent provenance means in a) and provenance-by-site means in b) and c). Tree height  
 differences among cold (blue), core (green) and warm provenances (red) for common garden  
 data and *in-situ* model predictions are indicated by boxplots in a) and c). Regression lines in  
 b) illustrate correlations for phenotypic plasticity between common garden data and *in-situ*  
 model predictions for cold (blue), core (green), warm (red) and all provenances (black); all  
 are significant at  $P < 0.05$ ; crosses indicate mean site values.

649

650 *Validation using ex-situ model predictions*

651 In the case of validation by comparing the predictions of both models, we predicted  
652 provenance and plasticity effects, and their interaction, as a function of LTC and STC  
653 conditions in common gardens. In particular, using equation 3 (main text) we predicted the  
654 relative variation of tree height as a function of  $LTC_j$  (i.e., the provenance effect) by fixing  
655  $STC_k$  to mean observed values across common gardens (i.e., for average climate of planting  
656 sites). Reciprocally, the relative variation of tree height as a function of  $STC_k$  (i.e., the  
657 phenotypic plasticity effect) was fitted by fixing  $LTC_j$  to mean observed values across  
658 provenances (i.e., for a mean-climate provenance). To predict plastic responses of each  
659 provenance  $j$ , we fitted height as a function of  $STC_k$  and the interaction term  $LTC_j \times STC_k$ . For  
660 this, we scaled predicted values between 0–1 independently for each provenance  $j$  to focus on  
661 the relative variation of height among provenances. The total component of variation was  
662 fitted as a function of  $LTC_j$ ,  $STC_k$  and  $LTC_j \times STC_k$ , i.e. the sum of provenance and plasticity  
663 effects and their interaction. Covariates in equation 2 (main text) were fixed to constant  
664 values, i.e. *age* (the most common age in common garden data, 12-year-old trees), *BAC* (mean  
665 observed value in NFI,  $\sim 30 \text{ m}^2 \text{ ha}^{-1}$ ) and their interaction with  $RCC_{jk}$  and  $LTC_j$ , respectively.  
666 Confidence intervals (SD) of predicted values along  $STC_k$  and  $LTC_j$  gradients were computed  
667 by bootstrapping, i.e., 200 model runs on 50% randomly sampled trees with replacement. In  
668 the comparison of plasticity among provenances, confidence intervals (SD) of predicted  
669 values along  $STC_k$  were computed among ‘cold’, ‘core’ and ‘warm’ provenances.