

1 Supplementary Information

2 Disentangling the legacies of climate and management on tree growth

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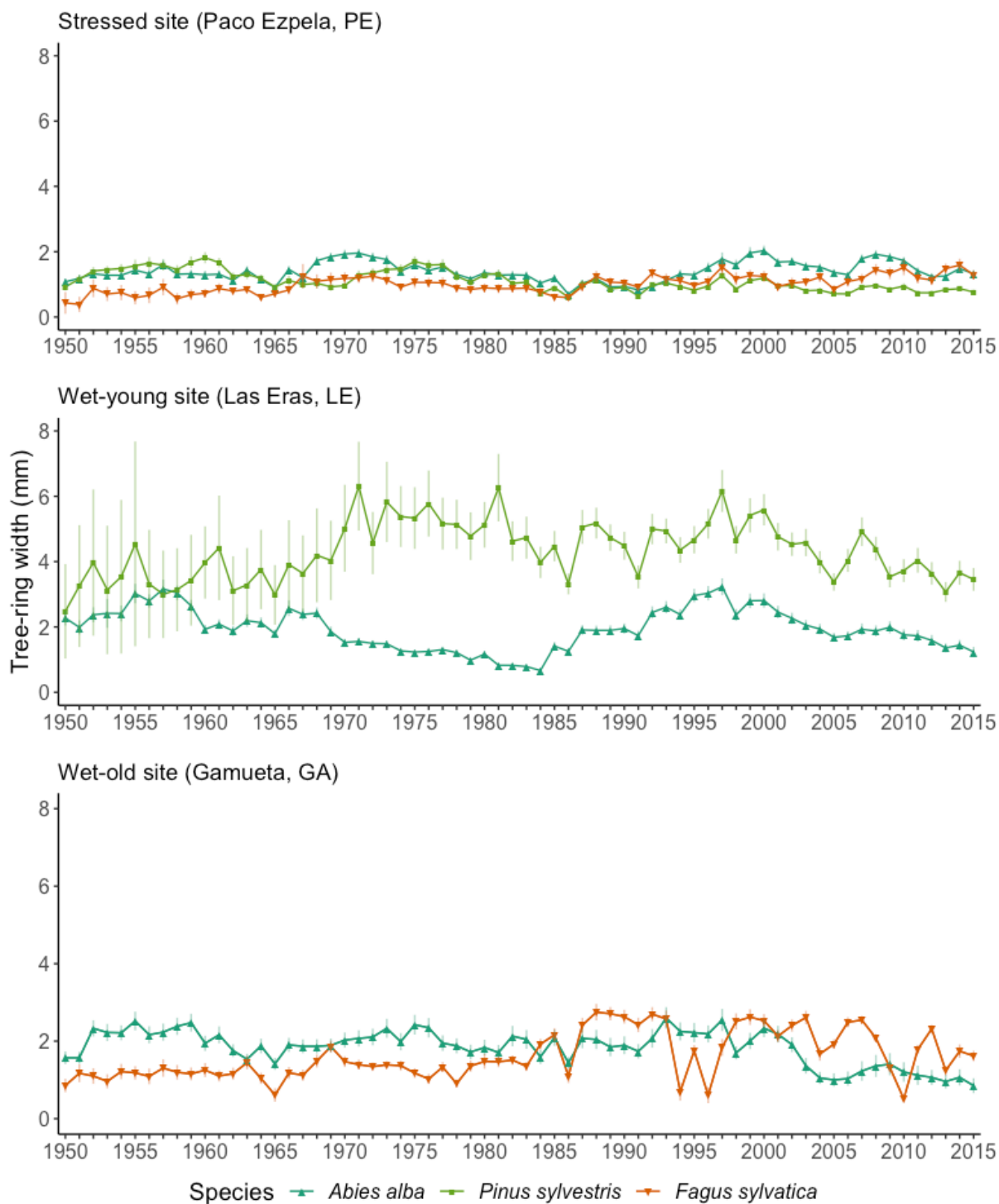
4 González, Gabriel Sangüesa-Barreda & Kiona Ogle

5 **Appendix S1.** Soil properties in the three study sites.

Site	Sands (%)	Silt (%)	Clays (%)	Soil pH
Paco Ezpela (PE) (Stressed site)	45.58	41.20	13.22	6.0
Las Eras (LE) / Gamueta (GA) (Wet sites)	27.21	56.44	16.35	6.5

6

7 **Appendix S2.** Time series plots of average tree-ring widths for the three tree species (*Abies alba*,
 8 *Pinus sylvestris* and *Fagus sylvatica*) in the study sites (stressed, wet-young and wet-old sites).



9

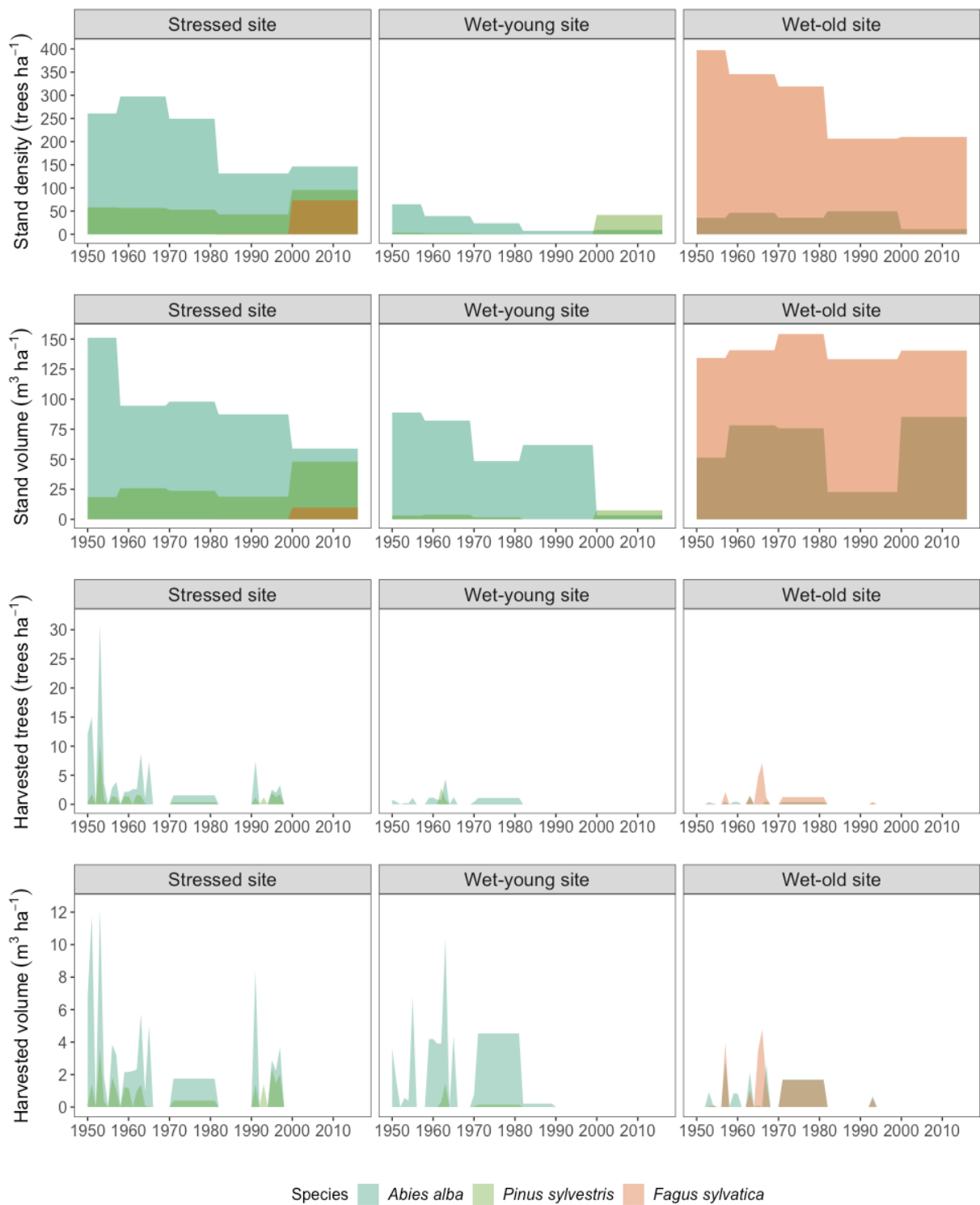
10 **Appendix S3.** Cross-dating statistics for the tree-ring series.

Site	Tree species	Correlation with master series	Correlation between trees	Best-replicated period	Expressed Population Signal	Variance in first eigenvector (%)
Paco	<i>Abies alba</i>	0.59	0.35	1944-2016	0.95	37.2
Ezpela	<i>Pinus sylvestris</i>	0.47	0.27	1942-2016	0.86	27.4
	<i>Fagus sylvatica</i>	0.42	0.25	1967-2016	0.87	29.4
Las Eras	<i>Abies alba</i>	0.63	0.50	1952-2016	0.98	64.7
	<i>Pinus sylvestris</i>	0.52	0.26	1978-2016	0.85	38.1
Gamueta	<i>Abies alba</i>	0.49	0.30	1863-2016	0.88	36.8
	<i>Fagus sylvatica</i>	0.63	0.49	1961-2016	0.96	52.4

11
12 The Expressed Population Signal (EPS) measures how well replicated is a chronology or mean site series. A threshold value of
13 EPS > 0.85 is usually considered to define well-replicated chronologies (Wigley et al. 1984).

14
15 Wigley TML, Briffa KR, Jones PD (1984) On the average value of correlated time series, with applications in dendroclimatology
16 and hydrometeorology. J Appl Meteorol 23:201-213.
17

18 **Appendix S4.** Stand density, stand volume, harvested trees, and harvested volume for each target
 19 species at each study site. Colors correspond to different species and columns to different sites.



21 Appendix S5. SAM model code implemented in JAGS.

22 R Packages

```
23 library(dplR)
24 library(vegan)
25 library(rjags)
26 load.module("dic")
27 library(ggplot2)
28 library(mcmcplots)
29 library(coda)
```

30 1.- Construct antecedent variables

```
31
32 model{
33   for(v in 1:Nv){ # variable 1=precipitation, 2=temperature
34     for(t in 1:Nlag){ # Lag (in years) up to 5
35       for(m in 1:12){ # month 1-12
36         ant.Mean1[m,t,v] <- delta[m,t,v]*((v==1)*meanppt[m]+(v==2)*meantave[m])
37         ant.Mean1.real[m,t,v] <- weight[m,t,v]*((v==1)*meanppt[m]+(v==2)*meantave[m])
38       }
39       ant.Mean2[t,v]<-sum(ant.Mean1[1:12,t,v])
40       ant.Mean2.real[t,v]<-sum(ant.Mean1.real[1:12,t,v])
41     }
42     ant.Mean[v]<-sum(ant.Mean2[1:5,v])
43     ant.Mean.real[v]<-sum(ant.Mean2.real[1:5,v])
44   }
45   # Compute antecedent climate variables for time "block" into the past t
46   for(v in 1:Nv){
47     for(j in 1:Nblocks){ #block, 1-38
48       deltaX[j,v] ~ dgamma(1,1)
49       weightX[j,v] <- deltaX[j,v]/sum(deltaX[,v])
50     }
51   }
52   # Compute sum of deltas needed for computing importance weights
53   for(v in 1:Nv){
54     for(t in 1:Nlag){
55       sumD1[t,v] <- sum(delta[,t,v]) # sum deltas across months
56     }
57     sumD[v] <- sum(sumD1[,v]) # sum deltas across lags
58   }
59   # Compute importance weights of interest
60   for(v in 1:Nv){
61     for(t in 1:Nlag){
62       # Compute yearly weights
63       yr.w[t,v] <- sum(weight[,t,v])
64       # Define monthly importance weights for every month x year into past:
65       for(m in 1:12){
66         delta[m,t,v] <- (deltaX[block[t,m],v]/BlockSize[t])*(1-(t==1)*step(m-9.5))
67         weight[m,t,v] <- delta[m,t,v]/sumD[v]
68         weightOrdered[(t-1)*12 + (12-m+1),v] <- weight[m,t,v]
69       }
70     }
71   }
72
73   # Construct the antecedent variable
74   # We use a computational "trick" to speed convergence time, multiplying the climate data by
75   the nonidentifiable weight (delta) rather than weight.
```

```

76 for(v in 1:Nv){
77   for(t in 1:Nlag){
78     for(m in 1:12){
79       for(i in 1:Nyears){
80         antX1[i,m,t,v] <- delta[m,t,v]*((v==1)*ppt[(i+5)-t+1, 1+m] +
81           (v==2)*tave[(i+5)-t+1, 1+m])
82 # Compute the real antX
83   antX1.real[i,m,t,v] <- weight[m,t,v]*((v==1)*ppt[(i+5)-t+1, 1+m] +
84     (v==2)*tave[(i+5)-t+1, 1+m])
85   }
86 }
87 }
88 }
89 # Compute the antecedent variable by summing the weighted climate variables
90 for(v in 1:Nv){
91   for(i in 1:Nyears){
92     for(t in 1:Nlag){
93       ant.sum1[i,t,v] <- sum(antX1[i,,t,v])
94       ant.sum1.real[i,t,v] <- sum(antX1.real[i,,t,v])
95     }
96 # Monitor the ant.sum2.real to extract antX changes over time
97   ant.sum2[i,v] <- sum(ant.sum1[i,,v])
98   ant.sum2.real[i,v] <- sum(ant.sum1.real[i,,v])
99   antX[i,v] <- ant.sum2[i,v] - ant.Mean[v]
100   antX.real[i,v] <- ant.sum2.real[i,v] - ant.Mean.real[v]
101 }
102 }
103 # Compute cumulative monthly weights
104 for(v in 1:Nv){
105   for(t in 1:(12*Nlag)){
106     cum.weight[t,v] <- sum(weightOrdered[1:t,v])
107   }
108   for(m in 1:12){
109     for(t in 1:Nlag){
110       alpha[m,t,v] <- weight[m,t,v]/yr.w[t,v]
111     }
112   }
113 }

```

114 2.- Likelihood for log tree-ring width data:

```

115 for(i in 1:Nobs){
116   LogWidth[i] ~ dnorm(mu.LogWidth[i], tau)
117   LogWidth.rep[i] ~ dnorm(mu.LogWidth[i], tau) # Replicated data for evaluating model fit
118   sq.diff[i] <- pow(LogWidth.rep[i]-LogWidth[i],2)
119   resid[i] <- LogWidth[i]-mu.LogWidth[i]
120   Dsum <- sum(sq.diff[]) #Total sum of squared differences

```

121 3.- Mean model with effect of age, antecedent climate effects (antX) and past ring-width 122 (LogAR1)

```

123 mu.LogWidth[i] <- a[1,CoreID[i]] + a[2,CoreID[i]]*Age[i] + a[3,CoreID[i]]*antX[yrID[i],1] +
124 a[4,CoreID[i]]*antX[yrID[i],2] + a[5,CoreID[i]]*antX[yrID[i],1]*antX[yrID[i],2] +
125 a[6,CoreID[i]]*(LogAR1[i]-log(Meanwidth+1)) + a[7,CoreID[i]]*HI[i] +
126 a[8,CoreID[i]]*HI[i]*antX[yrID[i],1] + a[9,CoreID[i]]*HI[i]*antX[yrID[i],2]
127 LogAR1[i] ~ dnorm(0,0.0001) # For missing data
128 }

```

129 4.- Compute identifiable parameters

```
130 for(c in 1:Ncores){
131   a_star[1,c]<-a[1,c]
132   a_star[2,c]<-a[2,c]
133   a_star[3,c]<-a[3,c]*sumD[1]
134   a_star[4,c]<-a[4,c]*sumD[2]
135   a_star[5,c]<-a[5,c]*sumD[1]*sumD[2]
136   a_star[6,c]<-a[6,c]
137   a_star[7,c]<-a[7,c]
138   a_star[8,c]<-a[8,c]*sumD[1]
139   a_star[9,c]<-a[9,c]*sumD[2]
140 }
141 mu.a_star[1]<-mu.a[1]
142 mu.a_star[2]<-mu.a[2]
143 mu.a_star[3]<-mu.a[3]*sumD[1]
144 mu.a_star[4]<-mu.a[4]*sumD[2]
145 mu.a_star[5]<-mu.a[5]*sumD[1]*sumD[2]
146 mu.a_star[6]<-mu.a[6]
147 mu.a_star[7]<-mu.a[7]
148 mu.a_star[8]<-mu.a[8]*sumD[1]
149 mu.a_star[9]<-mu.a[9]*sumD[2]
```

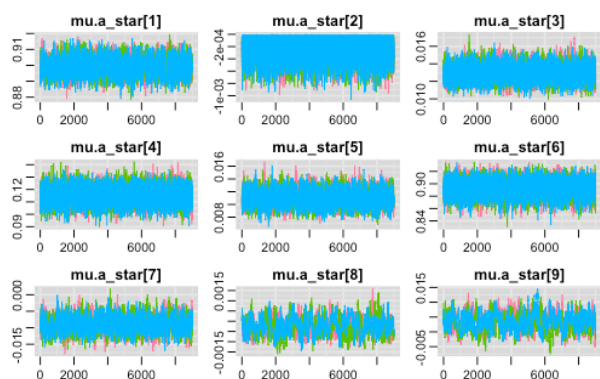
150 5.- Prior distributions

151 Assign hierarchical priors to the core-level effects in the mean model, and assign relatively non-
152 informative priors to population-level parameters

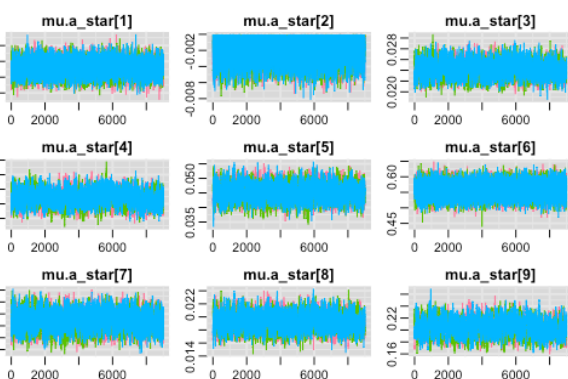
```
153 # Intercept
154 for(c in 1:Ncores){
155   # Core-level hierarchical prior
156   a[1,c] ~ dnorm(mu.a[1],tau.a[1])T(0,4)
157 }
158 # Age effect
159 for(c in 1:Ncores){
160   # Core-level hierarchical prior
161   a[2,c] ~ dnorm(mu.a[2],tau.a[2])T(,0)
162 }
163 # Other parameters
164 for(k in 3:9){
165   for(c in 1:Ncores){
166     # Core-level hierarchical prior
167     a[k,c] ~ dnorm(mu.a[k],tau.a[k])
168   }
169 }
170 # Sigs
171 for(k in 1:9){
172   tau.a[k] <- pow(sig.a[k],-2)
173   sig.a[k] ~ dunif(0,100)
174 }
175 # Hierarchical means
176 mu.a[1] ~ dnorm(0,0.0001)T(0,4)
177 mu.a[2] ~ dnorm(0,0.0001)T(,0)
178 for(k in 3:9){
179   mu.a[k] ~ dnorm(0,0.0001)
180 }
181 sig ~ dunif(0,100)
182 tau <- pow(sig,-2)
183 }
```


184 **Appendix S6.** Trace plots for assessing convergence for the population parameters μ_{α_k} .
185 Convergence was formally assessed via the potential scale reduction factor (Gelman and Rubin
186 1992), for all parameters, not just the population-level parameters (see methods section).

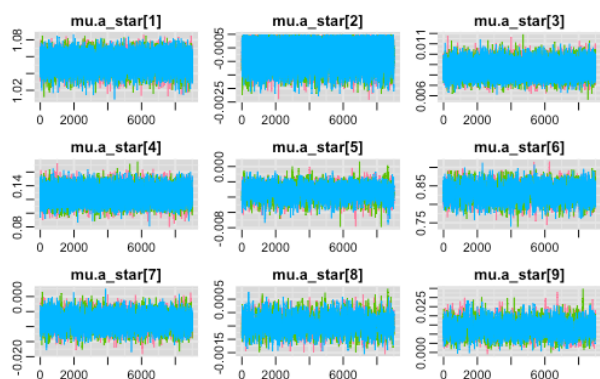
Abies alba stressed site



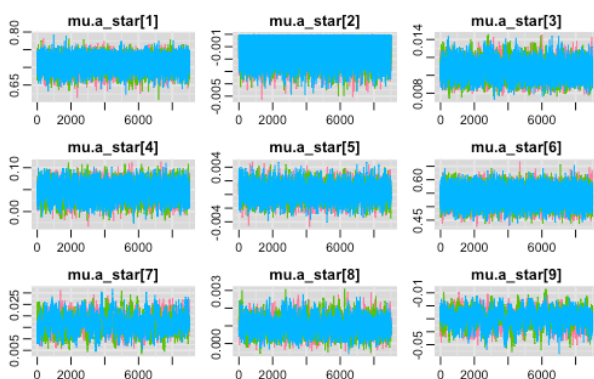
Abies alba wet-young site



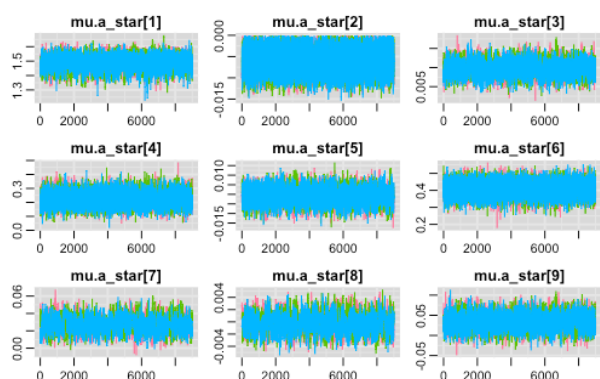
Abies alba wet-old site



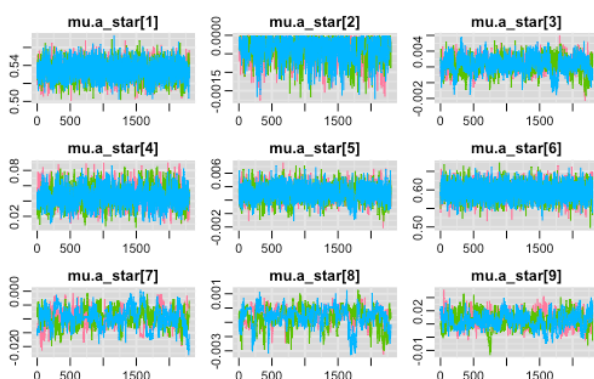
Pinus sylvestris stressed site



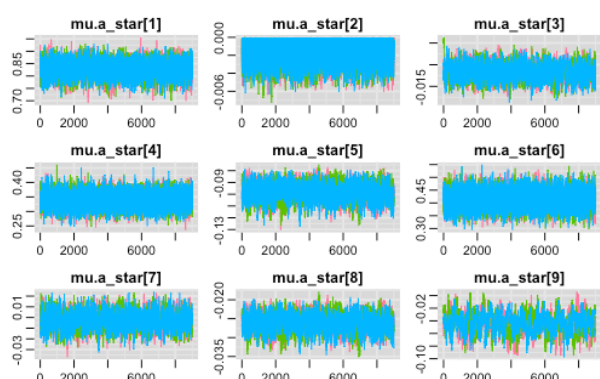
Pinus sylvestris wet-young site



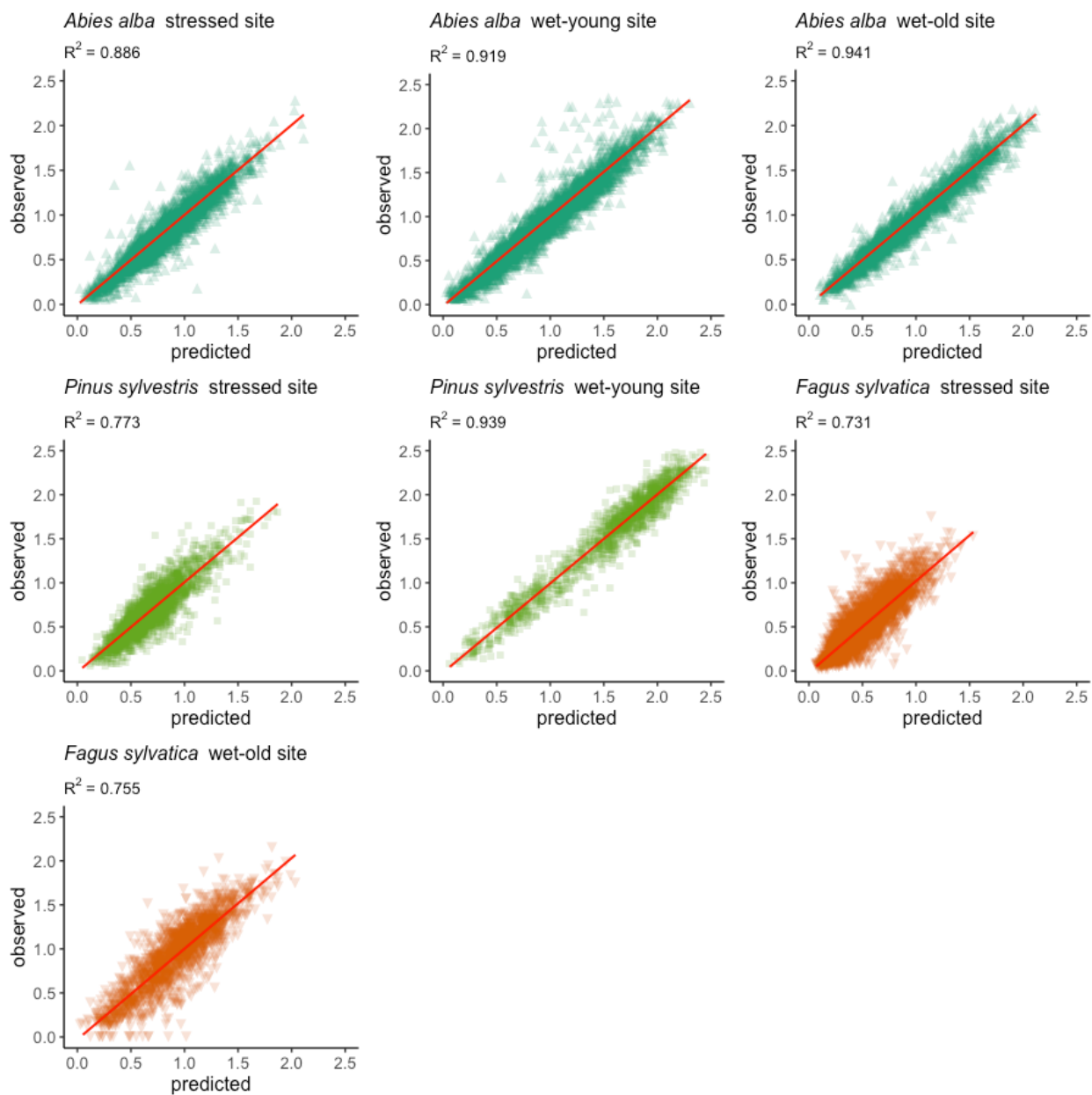
Fagus sylvatica stressed site



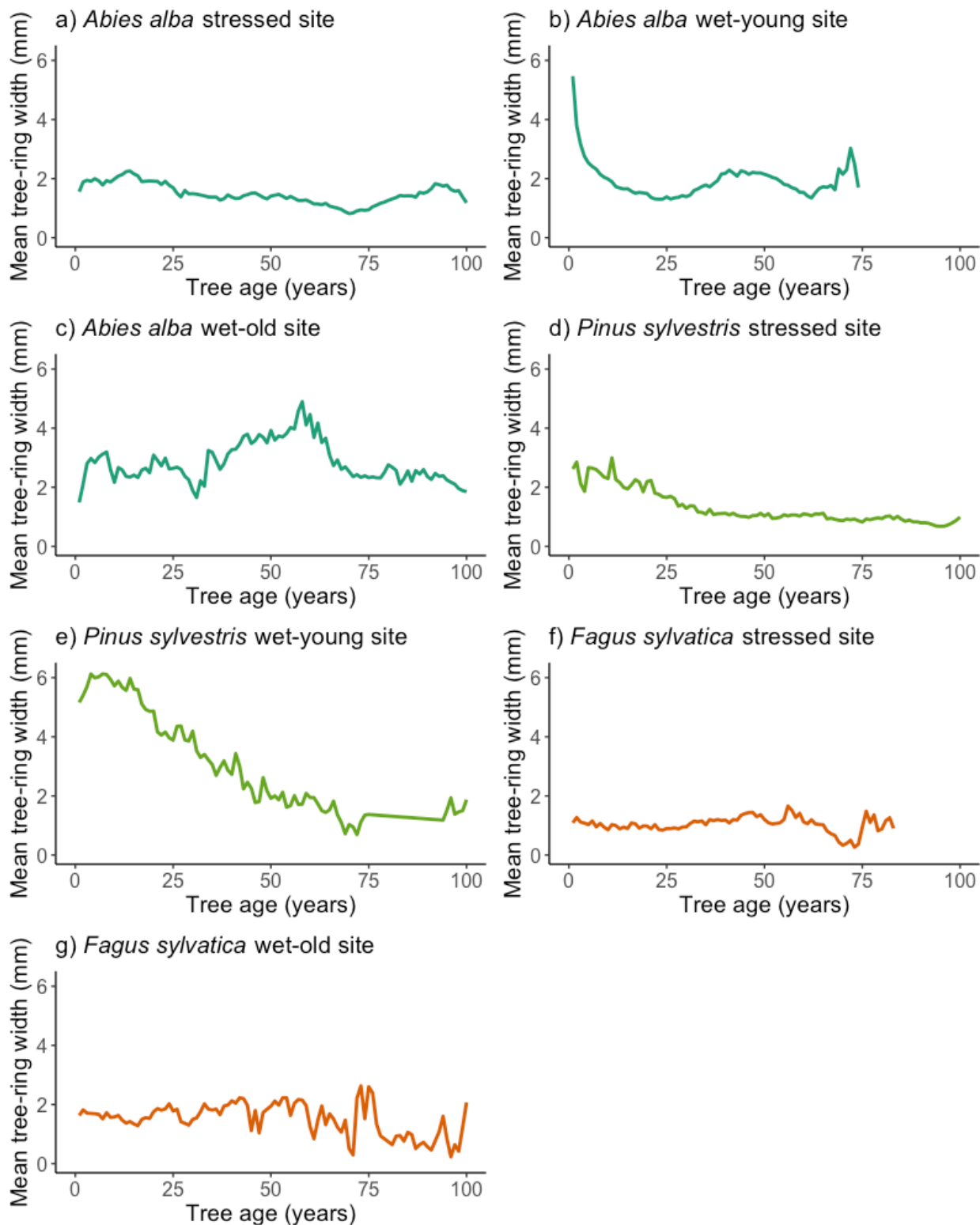
Fagus sylvatica wet-old site



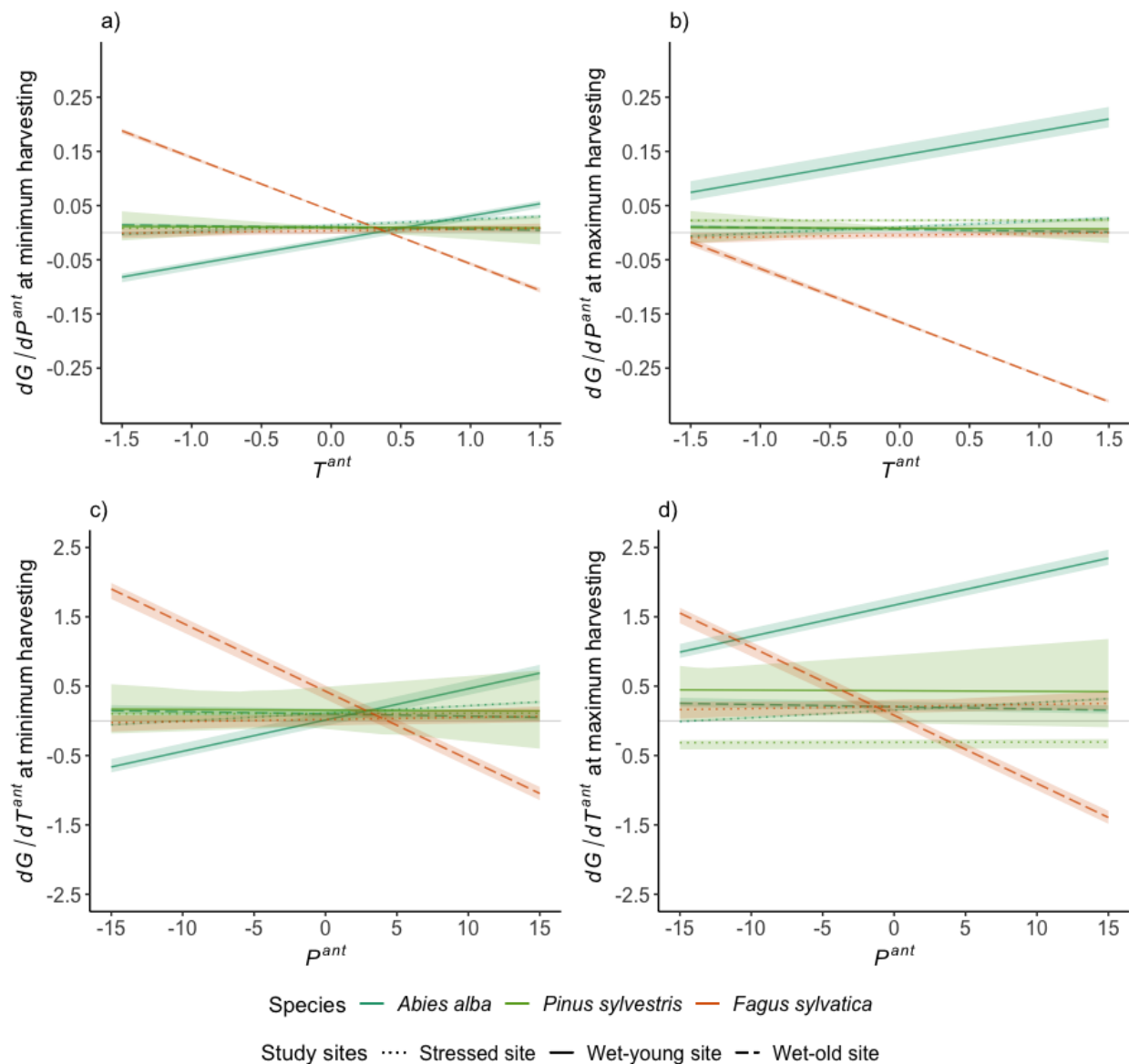
191 **Appendix S7.** Plots of observed vs. predicted (replicated data) tree growth (G) for each species-
 192 site combination. Coefficients of determination (R^2) from regressions of observed vs. predicted
 193 growth values, defined as $G = \log(r+1)$, are shown above each panel.



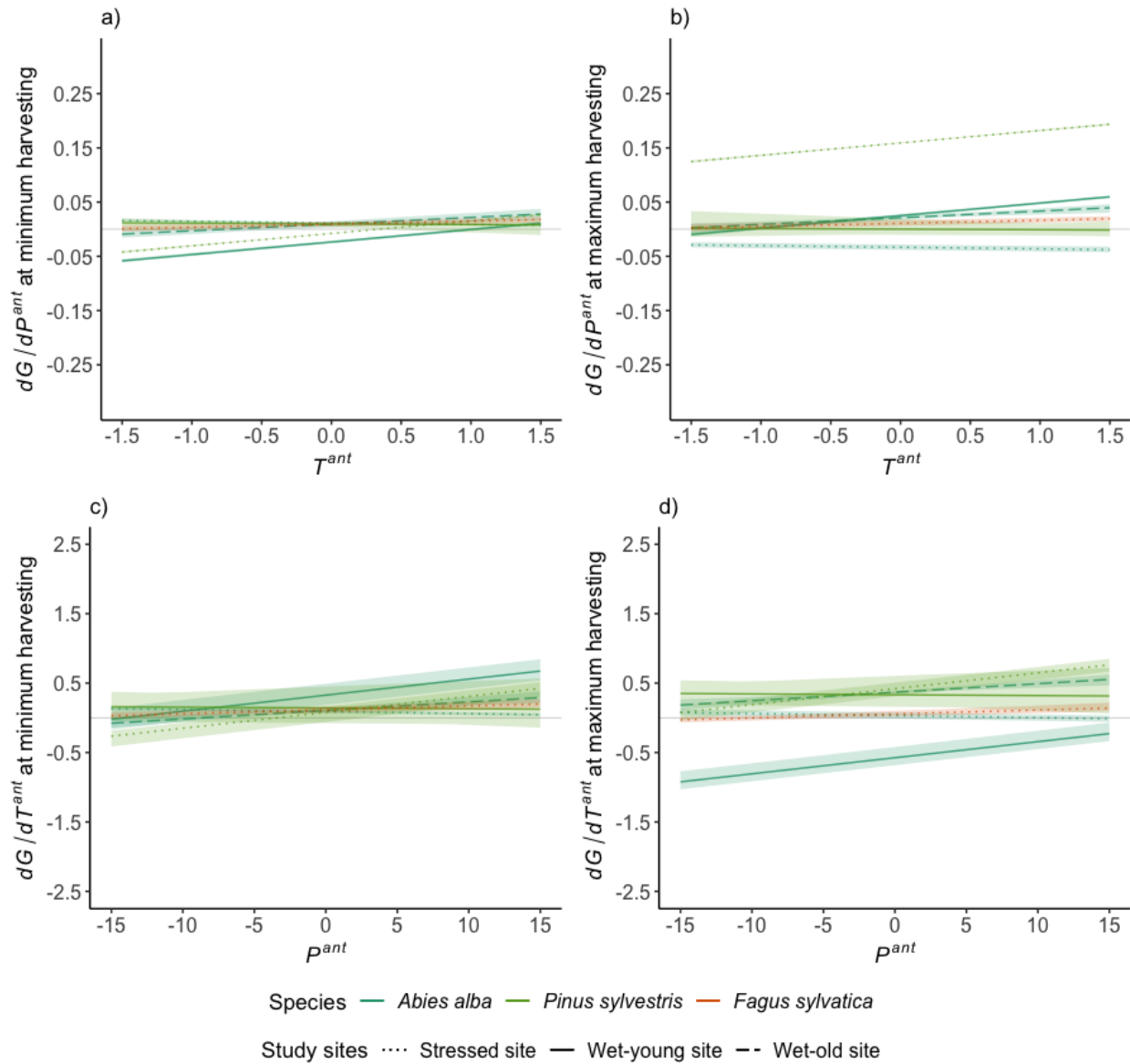
Appendix S8. Relationships between mean tree-ring width and tree age for each species-site combination over the period 1950-2016 represented up to 100 years.



Appendix S9. Estimates of the net sensitivity of tree growth (G , see Eqn 1) to changes in P^{ant} (a, b) and T^{ant} (c, d), under minimum (a, c) and maximum (b, d) values of harvesting intensity in terms of number of trees removed from the stand (HI) for each target tree species in the three study sites.



202 **Appendix S10.** Estimates of the net sensitivity of tree growth (G , see Eqn 1) to changes in P^{ant} (a,
 203 b) and T^{ant} (c, d), under minimum (a, c) and maximum (b, d) values of harvesting intensity in terms
 204 of wood volume removed from the stand (HI) for the subset of tree species and study sites for
 205 which models converged.



206