

# Summary

## Introduction

Rapid environmental change, IPCC, estimated temperature rise.

Trend to precocity in plants, flowering time, etc. Advance in phenology.

**Problem:** Understanding (and predicting?) long-lived plant adaptation to climate change

Based on previously developed demographic and quantitative genetics model (see ), added fluctuating environments. Made theoretical predictions. Estimated fluctuations using data from phenological data (PHENOFIT).

## Materials and Methods

### Population model

We used a previously developed model with stage-structure (Sandell et al. 2014, master's thesis). We considered to have a population of trees split in two classes, immature (I) and mature (M). The mature individuals are the only one to reproduce. Each year, an immature individual can survive with a probability  $s_I$ , mature and reproduce with a probability of  $m$ . At the same time, a mature individual has a probability  $s_M$  to survive. First-time reproducers, i.e. immature that became mature and reproduce the same year, have a fecundity of  $f_1$ , while experienced reproducers, those who already reproduced at least once, have a fecundity of  $f_2$ . Produced seeds have a probability  $s_0$  to survive and become immature. The standard parameters set is given in (Table 1). The population census is just before reproduction, giving the following Lefkovich matrix (Caswell, 2001):

$$A = \begin{pmatrix} a_{II} & a_{IM} \\ a_{MI} & a_{MM} \end{pmatrix} = \begin{pmatrix} s_0 m f_1 + s_I(1 - m) & s_0 f_2 \\ s_M m & s_M \end{pmatrix} \quad (1)$$

Where  $a_{ij}$  describes the contribution of stage  $j$  individuals to stage  $i$  the next year. With given initial conditions we can compute the number of individuals in the two stages by iterating matrix multiplication by  $A$ .

From the original model (Sandell et al. 2014, master's thesis) we implemented density-dependence, so that population will not continuously increase but reach a plateau (see Figure 1). We chose to implement density-dependence through seed germination and survival parameter  $s_0$  using a Beverton-Holt function to avoid chaotic behaviors (Caswell, 2001):

$$s_0 = \frac{s_{0,max}}{1 + k_I N_I + k_M N_M} \quad (2)$$

with  $k_I$  and  $k_M$  the weights of immature ( $N_I$ ) and mature ( $N_M$ ) population respectively.  $s_{0,max}$  is the maximum achievable  $s_0$ .

### Life-history traits

We considered certain life-history trait  $s_I$ ,  $f_1$ ,  $f_2$  as gaussian for each individual such as:

$$s_I(z) = s_I(\theta_s) \exp\left(-\frac{(z - \theta_s)^2}{2\omega_s}\right) \quad (3)$$

We have similar expressions for  $f_1$  and  $f_2$ . Averaging over the population it gives:

$$\overline{s_I}(\overline{z_I}) = s_I(\theta_s) \sqrt{\frac{\omega_s}{\omega_s + P_I}} \exp\left(-\frac{(\overline{z_I} - \theta_s)^2}{2(\omega_s + P_I)}\right) \quad (4)$$

Again, we obtain similar expressions for  $\overline{f_1}$  and  $\overline{f_2}$ .

## Iterations at each time step

Assuming the phenotype has a Gaussian distribution, the mean genotypic value of matures and immatures at the next timestep is given by (Barfield et al. 2011 Eq.5) :

$$\overline{g_I}' = (c_{IM}\overline{g_M} + c_{II}\overline{g_I})(c_{IM}G_M\beta_{a_{IM}} + c_{II}G_I\beta_{a_{II}}) \quad (5a)$$

$$\overline{g_M}' = (c_{MI}\overline{g_I} + c_{MM}\overline{g_M})(c_{MI}G_I\beta_{a_{MI}} + c_{MM}G_M\beta_{a_{MM}}) \quad (5b)$$

With  $c_{ij}$  defined as in (Barfield et al., 2011), that is  $c_{ij} = \frac{n_j \overline{a_{ij}}}{n_i'}$ , it is the contribution of stage  $j$  individuals to next years pool of stage  $i$  individuals, as a fraction of  $i$  individuals at the next time step  $n_i'$ ; and  $\beta_{a_{II}}$  the gradient of selection as  $\beta_{a_{IM}} = \frac{\partial \ln \overline{a_{IM}}}{\partial \overline{z_M}}$ .

The first term is a weighted average of mean genotypes contributing to this stage; while the second shows the effect of selection.

A similar recursion is given in (Barfield et al., 2011) for phenotypes. They depend on terms of direct transition from one stage to the other  $\overline{t_{ij}}$  and births  $\overline{f_{ij}}$  (and we have  $\overline{a_{ij}} = \overline{t_{ij}} + \overline{f_{ij}}$ ):

$$\overline{z_I}' = c_{II}^t(\overline{z_I} + P_I\beta_{t_{II}}) + c_{II}^f(\overline{g_I} + G_I\beta_{f_{II}}) + c_{IM}^f(\overline{g_M} + G_M\beta_{f_{IM}}) \quad (6a)$$

$$\overline{z_M}' = c_{MI}^t(\overline{z_I} + P_I + \beta_{t_{MI}}) + c_{MM}^t(\overline{z_M} + P_M + \beta_{t_{MM}}) \quad (6b)$$

With  $\beta_{t_{II}}$  the gradient of selection defined as above in Equation 5a, i.e.  $\beta_{t_{II}} = \frac{\partial \ln \overline{t_{II}}}{\partial \overline{z_I}}$ ;  $c_{ij}^t$  the contribution by direct transition of stage  $j$  to stage  $i$  and  $c_{ij}^f$  the contribution by birth.

## Approximation under weak selection

Under weak selection, the mean phenotype in the population  $\overline{z}$  follow the given approximations under constant environment from (Engen et al., 2011):

$$\overline{z_{eq}} = \frac{\gamma_f \theta_f + \gamma_s \theta_s}{\gamma_f + \gamma_s} \quad (7)$$

With,

$$\gamma_f = \frac{v_I u_I s_0 m \overline{f_1}}{\lambda(P_I + \omega_f)} + \frac{v_I u_M \frac{G_M}{G_I} s_0 \overline{f_2}}{\lambda(P_M + \omega_f)} \quad (8a)$$

and

$$\gamma_s = \frac{v_I u_I \overline{s_I}(1 - m)}{\lambda(P_I + \omega_s)} \quad (8b)$$

$\gamma_f$  and  $\gamma_s$  represent the respective weight of each of the optimum in the trade-off for  $\overline{z_{eq}}$ . Indeed, if  $\theta_f = \theta_s$  then  $\overline{z_{eq}} = \theta_f = \theta_s$ . But if  $\theta_f \neq \theta_s$ , then the trade-off depends on  $\gamma_f$  and  $\gamma_s$  and the ratio between them.

## Fluctuating environment

To mimic environmental fluctuations, the optimums are fluctuating around a given as such:

$$\begin{cases} \theta_f(t) = \bar{\theta}_f + \alpha_f \xi_f \\ \theta_s(t) = \bar{\theta}_s + \alpha_s \xi_s \end{cases} \quad (9)$$

$\alpha_i$  is the sensitivity of  $\theta_i$  to noise  $\xi_i$ .  $\xi_f$  and  $\xi_s$  are noise vectors drawn at each time step from a bi-variate normal distribution with respectively  $\sigma_f^2$  and  $\sigma_s^2$  variances and correlation  $\rho_N$ . Thus we get normal fluctuations, correlated with a correlation coefficient of  $\rho_N$ .

Under varying environment, i.e. optimums, we get another approximation under weak selection from (Engen et al., 2011) describing the change of mean phenotype:

$$\Delta \bar{z}(t) = -G_I \gamma (\bar{z}(t) - \theta_v(t)) \quad (10)$$

With

$$\gamma = \gamma_f + \gamma_s \quad (11a)$$

$$\theta_v(t) = \bar{z}_{eq} + \xi_v \quad (11b)$$

$$\xi_v = \frac{\alpha_f \xi_f + \alpha_s \xi_s}{\alpha_f + \alpha_s} \quad (11c)$$

We see that the change in the mean phenotype depends on the sensitivity of the optimums as well as on the magnitude of the variations.

## Trend in change

To induce a trend in the variation of the optimums we use the same formula as above but adding a term depending on time  $kt$ :

$$\theta_i(t) = \bar{\theta}_i + kt + \xi_i \quad (12)$$

With  $k$  having a negative value, the optimums decrease with time.

## Phenofit data

PHENOFIT is a phenology model including several models, from environmental and phenological data it simulates populations of trees to predict their range (Morin et al., 2008).

On 6 localities (see Figure 3) we had modeled bud burst date and predicted fitnesses  $\pm 21$  days around this date (predicted fitness if bud burst date were modeled date +1 day, -1 day, etc.) from these data we predicted the optimums fluctuations. Considering the mean fecundity as a Gaussian function with the same form as  $f_1$  in Equation 4:

$$\beta = \frac{\partial \ln fec}{\partial \bar{z}} = \frac{\theta_f - \bar{z}}{\omega_f + \sigma_z^2} \quad (13)$$

Using (Lande and Arnold, 1983), with  $z$  Gaussian,  $p(z)$  the distribution of  $z$  in the population,  $f(z)$  the fitness associated with  $z$  and  $\bar{f}$  the mean fitness in the population:

$$\beta = \frac{\text{cov}(z, \frac{f(z)}{\bar{z}})}{\sigma_z^2} \quad (14)$$

From (13) and (14) we can express  $\theta_f$ :

$$\theta_f = \frac{\text{cov}(z, \frac{f(z)}{\bar{z}})}{\sigma_z^2}(\omega_f + \sigma_z^2) + \bar{z} \quad (15)$$

In our estimations we considered  $p(z)$  to be Gaussian around the modeled date by PHENOFIT, with a variance of  $P_I = 40$  as in our analytic model. We normalized this distribution so that all dates in the population would be in the 21 days interval around the modeled date.

## General analyses

All statistical analyses were made using R, graphics were drawn using ggplot2.

## Results

### Constant environment and density-dependence

From Sandell et al., we simulated populations. With the introduction of density-dependence, the blablabla...

**Figure1:** See Fig. 1

Introduction of DD should decrease mean phenotype (lower  $s_0$ ) and limit population size

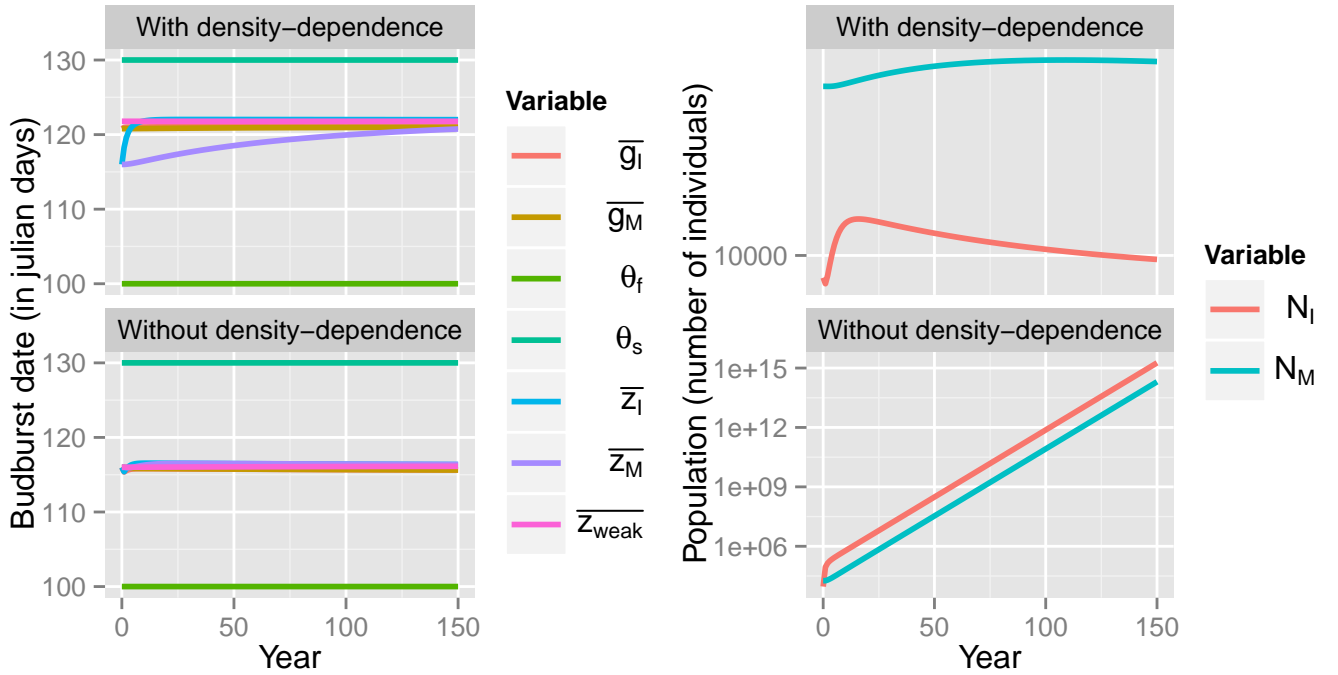


Figure 1: **Effect of density-dependence on phenotypes and populations.**

### Fluctuating optimums

The noises were drawn from a bivariate normal distribution to make the optimums fluctuate. We varied the correlation between them.

**Figure2:** See Fig. 2

Explain in the text correlation of  $z_I$  with  $\theta_s(t)$

Parameter	Notation	Value
<b>Life Cycle</b>		
Optimal phenotype for fecundity	$\theta_f$	100
Optimal phenotype for immature survival	$\theta_s$	130
Fecundity function width	$\omega_f$	400
Survival function width	$\omega_s$	400
Heritability	$h^2$	0.5
Phenotypic variance of immatures	$P_I$	40
Phenotypic variance of matures	$P_M$	40
Genotypic variance of immatures	$G_I = P_I \times h^2$	20
Genotypic variance of matures	$G_M$	20
Survival of immature at phenotypic optimum	$\overline{s_I}(\bar{z} = \theta_s)$	0.8
Fecundity of first time reproducers at optimum	$\overline{f_1}(\bar{z} = \theta_f)$	100
Fecundity of experienced reproducers at optimum	$\overline{f_2}(\bar{z} = \theta_f)$	200
Maturation rate of immature	$m$	0.02
Combined survival and germination rate of seed	$s_0$	0.03
Survival of mature stage	$s_M$	0.99
<b>Density-dependence</b>		
Maximum $s_0$ in density-dependence function	$s_{0,max}$	0.12
Decreasing factor due to immatures	$k_I$	0.001
Decreasing factor due to matures	$k_M$	0.005
<b>Fluctuations</b>		
Sensitivity of optimum for fecundity to fluctuation	$\alpha_f$	5
Sensitivity of optimum for survival to fluctuation	$\alpha_s$	5
Noise variance for fecundity	$\sigma_{\xi_f}^2$	3.725
Noise variance for survival	$\sigma_{\xi_s}^2$	3.725
Correlation between noises	$\rho_N$	0.5
Trend coefficient	$k$	-0.15

Table 1: Standard parameter set

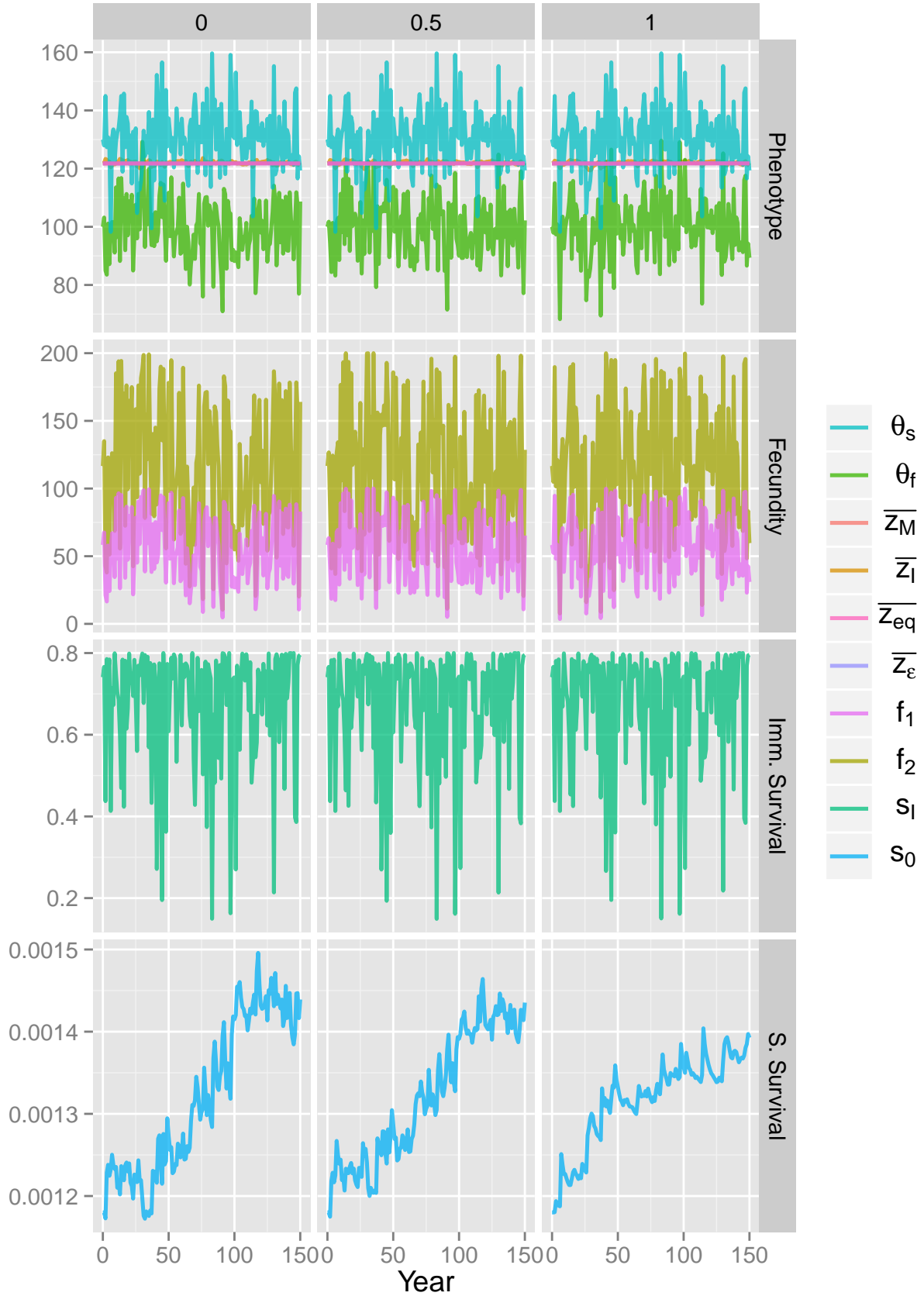


Figure 2: **Effect of the correlation of fluctuations on phenotypes and life-history traits.** Correlation coefficient  $\rho_N$  values of noises are indicated on the top.

## Trend in the environment

Decreasing optimums through time to mimic the advance in phenology with climate change.

**Figure:** Trend 2 panels with and without fluctuations, simulations results phenotype/time (with and without DD)

## Estimation of the fluctuations

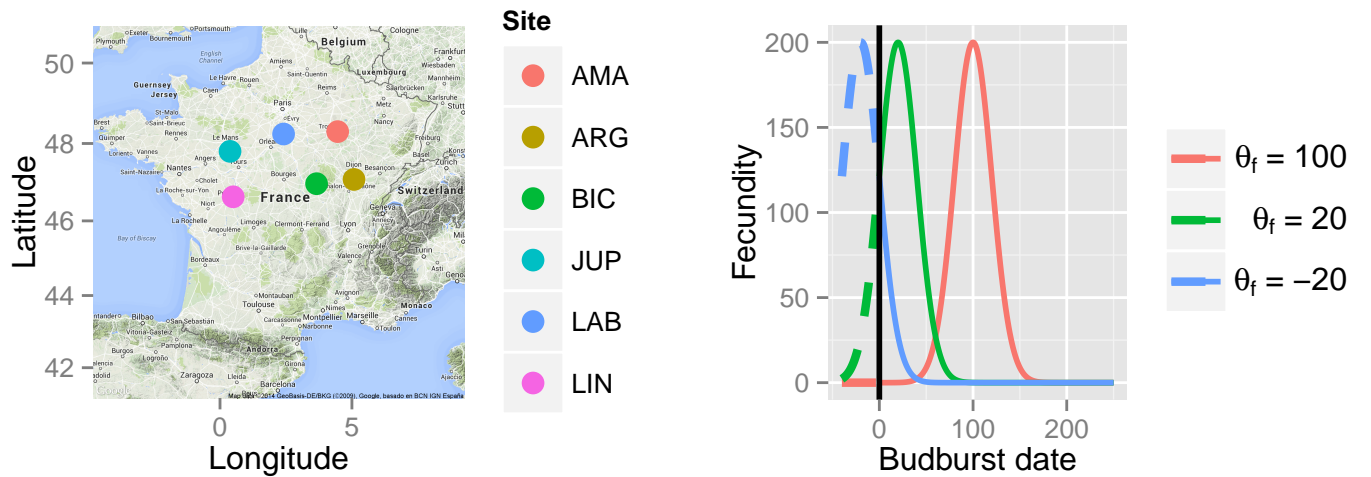
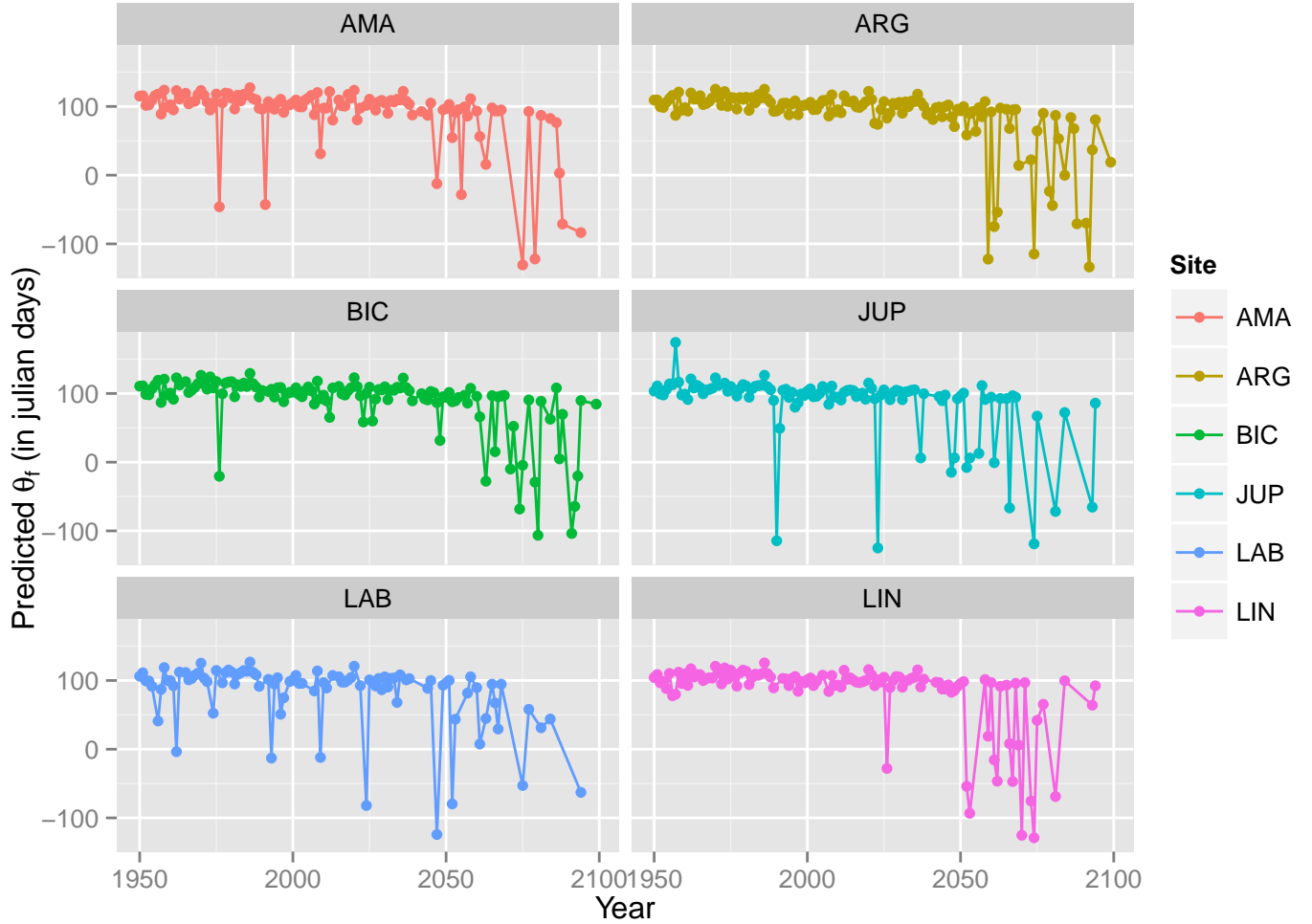


Figure 3:  $\theta_f$  estimations from PHENOFIT data.

From phenofit.

**Figure:** Fig. 3

**Table:** table with slope and noise variance estimates for all years, years before 2001 (simulated climate close to real one), after 2001 (projection in climate evolution)

## Discussion

Difference in  $\bar{z}$  and  $\bar{g}$  with fluctuations because of selection on viability.

Increasing number of extreme events from predictions.

## Authors Contributions and Acknowledgments

## References

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