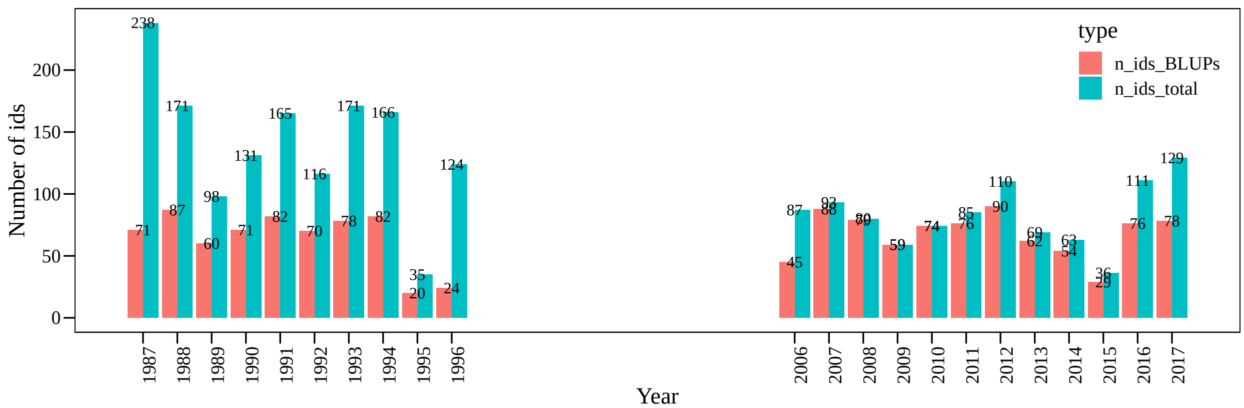
Lathyrus ms2: Selection on reaction norms - Phenotypic selection analyses using BLUPs

Contents

These analyses are just a starting point, they should eventually be replaced by Bayesian analyses.

Year-wise analyses

How many individuals do we have for each year?



The number of individuals where BLUPs are available are always lower than the total number of individuals.

Calculation of relative fitness and standardized intercept and slope within each year.

```
data_4yrs<-data_4yrs %>%
  group_by(year) %>%
  mutate(n_intact_seeds_rel_yr=n_intact_seeds/mean(n_intact_seeds)) %>% # Rel. fitness
  mutate(BLUP_int_std_yr=(BLUP_int-mean(BLUP_int))/sd(BLUP_int)) %>%    # Std. intercept
  mutate(BLUP_slope_std_yr=(BLUP_slope-mean(BLUP_slope))/sd(BLUP_slope))%>% # Std. slope
  ungroup()
```

Phenotypic selection models for each year: relative fitness against standardized BLUP intercept and slope

```
# Extract out common code with function
yr_model <- function(df) {
  lm(n_intact_seeds_rel_yr ~ BLUP_int_std_yr + BLUP_slope_std_yr, data = df)
}
```

```r
yr_models <- data_4yrs%>%
    group_by(year)%>%
    nest()%>%
    mutate(model = map(data, yr_model))%>%       # Repeat common code using map function
    mutate(coefs = map(model, broom::tidy))%>%   # Tidy df - a row for each coef
    unnest(coefs)                                # List of dfs back into regular df

# Years where intercept and/or slope show a significant effect on fitness
# (i.e. there is selection on RNs)
subset(yr_models,p.value<0.05&!term=="(Intercept)")
```

```
## # A tibble: 7 x 6
##    year term               estimate std.error statistic  p.value
##   <int> <chr>                 <dbl>     <dbl>     <dbl>    <dbl>
## 1  2012 BLUP_int_std_yr      -1.52      0.654     -2.32 0.0229
## 2  2014 BLUP_int_std_yr      -2.43      0.621     -3.91 0.000275
## 3  2014 BLUP_slope_std_yr     2.08      0.621      3.36 0.00150
## 4  2016 BLUP_int_std_yr      -0.977     0.397     -2.46 0.0164
## 5  2016 BLUP_slope_std_yr     0.907     0.397      2.28 0.0253
## 6  1990 BLUP_slope_std_yr    -1.08      0.437     -2.47 0.0159
## 7  1992 BLUP_slope_std_yr     1.18      0.485      2.44 0.0174
```

But intercept and slope of RNs are highly correlated…

```r
with(data_4yrs,cor(BLUP_int_std_yr,BLUP_slope_std_yr))
```

```
## [1] 0.9231341
```

… so maybe we should not use them together in the same model.

Models with only slope of the RN.

```r
# Extract out common code with function
yr_model_slope <- function(df) {
  lm(n_intact_seeds_rel_yr ~ BLUP_slope_std_yr, data = df)
}

yr_models_slope <- data_4yrs%>%
  group_by(year)%>%
  nest()%>%
  mutate(model = map(data, yr_model_slope))%>%
  mutate(coefs = map(model, broom::tidy))%>%   # Tidy df - a row for each coef
  unnest(coefs)                                # List of dfs back into regular df

# Years where slope shows a significant effect on fitness
# (i.e. there is selection on RN slope)
subset(yr_models_slope,p.value<0.05&!term=="(Intercept)")
```

```
## # A tibble: 4 x 6
##    year term               estimate std.error statistic p.value
##   <int> <chr>                 <dbl>     <dbl>     <dbl>   <dbl>
## 1  2007 BLUP_slope_std_yr    -0.290     0.117     -2.48 0.0152
## 2  2008 BLUP_slope_std_yr    -0.422     0.126     -3.36 0.00122
## 3  2011 BLUP_slope_std_yr    -0.444     0.219     -2.03 0.0463
## 4  1995 BLUP_slope_std_yr     0.661     0.261      2.53 0.0208
```

Models with only intercept of the RN.

```
# Extract out common code with function
yr_model_int <- function(df) {
  lm(n_intact_seeds_rel_yr ~ BLUP_int_std_yr, data = df)
}

yr_models_int <- data_4yrs%>%
  group_by(year)%>%
  nest()%>%
  mutate(model = map(data, yr_model_int))%>%
  mutate(coefs = map(model, broom::tidy))%>%   # Tidy df - a row for each coef
  unnest(coefs)                                # List of dfs back into regular df

# Years where intercept shows a significant effect on fitness
# (i.e. there is selection on RN intercept)
subset(yr_models_int,p.value<0.05&!term=="(Intercept)")
```

```
## # A tibble: 4 x 6
##    year term            estimate std.error statistic p.value
##   <int> <chr>              <dbl>     <dbl>     <dbl>   <dbl>
## 1  2007 BLUP_int_std_yr   -0.284     0.117     -2.43 0.0173
## 2  2008 BLUP_int_std_yr   -0.390     0.127     -3.08 0.00290
## 3  2014 BLUP_int_std_yr   -0.427     0.191     -2.24 0.0295
## 4  1989 BLUP_int_std_yr   -0.376     0.164     -2.29 0.0259
```

Are estimates of selection on RNs related to temperature?

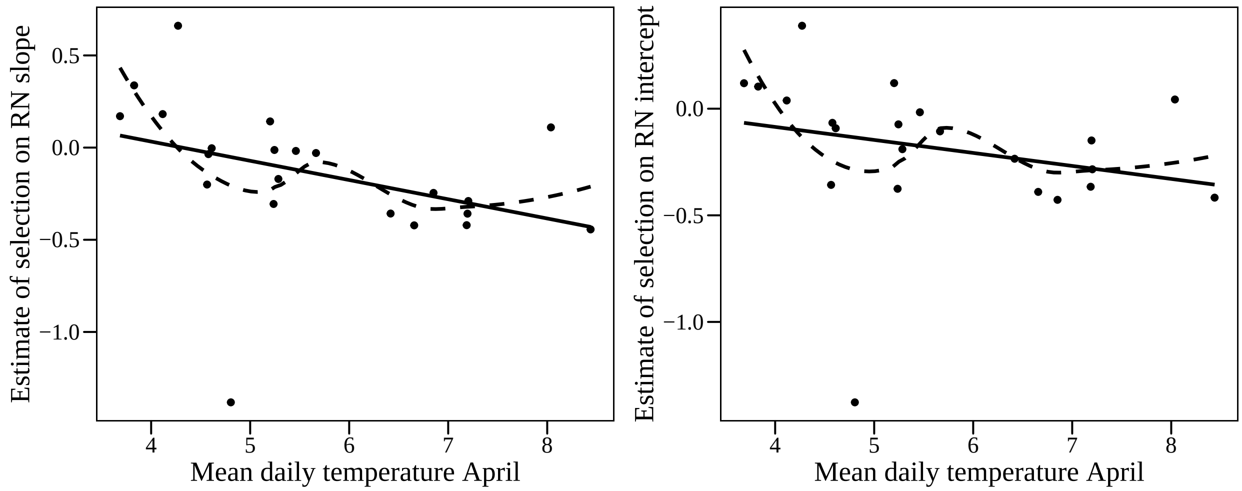
Merge estimates of selection on RNs with previous data and get summarized data by year

```
(data_4yrs_summ<-data_4yrs %>%
  group_by(year)%>%
  summarise(mean_4=mean(mean_4))%>%
  select(year,mean_4)%>%
  right_join(yr_models_slope%>%
               filter(!term=="(Intercept)")%>%
               select(year,term,estimate)%>%
               spread(key = term, value = estimate)%>%  # Long to wide format
               rename(estim_slope_yr=BLUP_slope_std_yr),
             by = "year")%>%
  right_join(yr_models_int%>%
               filter(!term=="(Intercept)")%>%
               select(year,term,estimate)%>%
               spread(key = term, value = estimate)%>%  # Long to wide format
               rename(estim_int_yr=BLUP_int_std_yr),
             by = "year"))
```

```
## # A tibble: 22 x 4
##     year mean_4 estim_slope_yr estim_int_yr
##    <int>  <dbl>          <dbl>        <dbl>
##  1  1987   4.58        -0.0355      -0.0663
##  2  1988   3.69         0.170        0.120
##  3  1989   5.24        -0.306       -0.376
##  4  1990   7.20        -0.358       -0.149
```

```
## 5 1991 5.24 -0.0130 -0.0734
## 6 1992 3.83 0.338 0.104
## 7 1993 5.46 -0.0181 -0.0167
## 8 1994 6.42 -0.358 -0.235
## 9 1995 4.27 0.661 0.389
## 10 1996 5.20 0.142 0.120
## # ... with 12 more rows
```

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



According to the graphs it seems that with increasing temperatures, selection favors lower (more negative) slopes and lower elevations of the RNs.

The year 2017 is an outlier with a very negative slope and intercept of the RN. This might be because only 4 out of 78 plants produced seeds in 2017.

```
nrow(subset(data_4yrs,year==2017&n_intact_seeds>0))
```

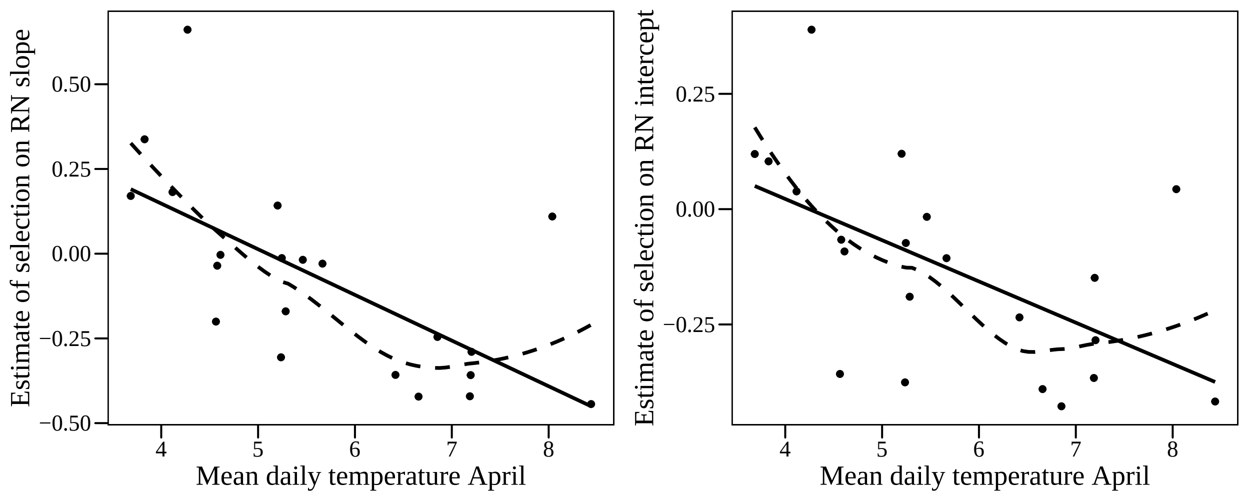
```
## [1] 4
```

```
nrow(subset(data_4yrs,year==2017))
```

```
## [1] 78
```

Graphs with 2017 removed:

```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



Models with all years (NS)

```
tidy(lm(estim_slope_yr~mean_4,data_4yrs_summ))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)    0.450    0.345       1.31  0.207
## 2 mean_4        -0.104    0.0592     -1.76  0.0935
```

```
tidy(lm(estim_int_yr~mean_4,data_4yrs_summ))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)   0.158     0.313      0.506   0.619
## 2 mean_4       -0.0610    0.0538    -1.13    0.270
```

Models without 2017 (significant)

```
tidy(lm(estim_slope_yr~mean_4,subset(data_4yrs_summ,!year==2017)))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)    0.687    0.205       3.35 0.00338
## 2 mean_4        -0.135    0.0350     -3.85 0.00108
```

```
tidy(lm(estim_int_yr~mean_4,subset(data_4yrs_summ,!year==2017)))
```

```
## # A tibble: 2 x 5
##   term        estimate std.error statistic p.value
##   <chr>          <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)   0.380     0.175       2.17 0.0427
## 2 mean_4       -0.0894    0.0298     -3.00 0.00737
```

The slope and intercept of the reaction norm decrease with increasing temperatures (when removing 2017).

Should we also remove 2017 from the calculations of RN parameters (BLUPs)?

Analyses with all years

n = number of reproductive events (mixed models)

Are there among-year differences in selection on RN parameters?

We use models including the interaction between yearly-standardized RN parameters and year. The main effect of year was not included as fitness was relativized within years prior to analysis. Plant individual was included as a random effect.

Slope of the RN

```
summary(lmer(n_intact_seeds_rel_yr ~ BLUP_slope_std_yr+BLUP_slope_std_yr:year+
             (1|id),data = data_4yrs))
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
## n_intact_seeds_rel_yr ~ BLUP_slope_std_yr + BLUP_slope_std_yr:year +
##     (1 | id)
##    Data: data_4yrs
##
## REML criterion at convergence: 6375.3
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.3896 -0.4374 -0.2901  0.1623 23.8850
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  id       (Intercept) 0.1589   0.3987
##  Residual             4.4957   2.1203
## Number of obs: 1455, groups:  id, 243
##
## Fixed effects:
##                         Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)             0.991667   0.061738 289.678497  16.062   <2e-16
## BLUP_slope_std_yr      28.178686  11.526435 383.992860   2.445   0.0149
## BLUP_slope_std_yr:year -0.014168   0.005758 382.683755  -2.461   0.0143
##
## (Intercept)            ***
## BLUP_slope_std_yr      *
## BLUP_slope_std_yr:year *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) BLUP_s__
## BLUP_slp_s_  0.010
```

```
## BLUP_slp__: -0.010 -1.000
## fit warnings:
## Some predictor variables are on very different scales: consider rescaling
```

```r
Anova(lmer(n_intact_seeds_rel_yr ~ BLUP_slope_std_yr+BLUP_slope_std_yr:year+
             (1|id),data = data_4yrs),type="II")
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: n_intact_seeds_rel_yr
##                          Chisq Df Pr(>Chisq)
## BLUP_slope_std_yr      8.8659  1   0.002905 **
## BLUP_slope_std_yr:year 6.0553  1   0.013864 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Intercept of the RN

```r
summary(lmer(n_intact_seeds_rel_yr ~ BLUP_int_std_yr+BLUP_int_std_yr:year+
             (1|id),data = data_4yrs))
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: n_intact_seeds_rel_yr ~ BLUP_int_std_yr + BLUP_int_std_yr:year +
##     (1 | id)
##    Data: data_4yrs
##
## REML criterion at convergence: 6370
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.3908 -0.4412 -0.2753  0.1567 23.8905
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  id       (Intercept) 0.1453   0.3812
##  Residual             4.4902   2.1190
## Number of obs: 1455, groups:  id, 243
##
## Fixed effects:
##                         Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)             0.993056   0.061215 290.650320  16.222  < 2e-16 ***
## BLUP_int_std_yr        31.457188  11.453799 377.336222   2.746  0.00631 **
## BLUP_int_std_yr:year   -0.015824   0.005721 376.029969  -2.766  0.00596 **
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) BLUP_n__
## BLUP_nt_st_  0.007
## BLUP_nt_s_: -0.007 -1.000
## fit warnings:
## Some predictor variables are on very different scales: consider rescaling
```

```r
Anova(lmer(n_intact_seeds_rel_yr ~ BLUP_int_std_yr+BLUP_int_std_yr:year+
             (1|id),data = data_4yrs),type="II")
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: n_intact_seeds_rel_yr
##                         Chisq Df Pr(>Chisq)
## BLUP_int_std_yr       12.8799  1  0.0003321 ***
## BLUP_int_std_yr:year   7.6495  1  0.0056787 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Yes, there are differences among years in selection on RN slope and intercept.

Are differences in selection on RN parameters among years related to spring temperature?

Slope of the RN

```r
summary(lmer(n_intact_seeds_rel_yr ~ BLUP_slope_std_yr+BLUP_slope_std_yr:mean_4+
             (1|id),data = data_4yrs))
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
## n_intact_seeds_rel_yr ~ BLUP_slope_std_yr + BLUP_slope_std_yr:mean_4 +
##     (1 | id)
##    Data: data_4yrs
##
## REML criterion at convergence: 6372.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.3359 -0.4350 -0.2935  0.1654 24.1037
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  id       (Intercept) 0.1628   0.4035
##  Residual             4.4965   2.1205
## Number of obs: 1455, groups:  id, 243
```

```
##
## Fixed effects:
##                           Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)                0.99039    0.06188  291.94487  16.005   <2e-16
## BLUP_slope_std_yr          0.34284    0.24865 1449.27856   1.379   0.1682
## BLUP_slope_std_yr:mean_4  -0.09362    0.04275 1442.13306  -2.190   0.0287
##
## (Intercept)              ***
## BLUP_slope_std_yr
## BLUP_slope_std_yr:mean_4 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) BLUP_s__
## BLUP_slp_s_ -0.001
## BLUP_s__:_4 -0.003 -0.968
```

```
Anova(lmer(n_intact_seeds_rel_yr ~ BLUP_slope_std_yr+BLUP_slope_std_yr:mean_4+
             (1|id),data = data_4yrs),type="II")
```

```
## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: n_intact_seeds_rel_yr
##                           Chisq Df Pr(>Chisq)
## BLUP_slope_std_yr        8.8097  1   0.002996 **
## BLUP_slope_std_yr:mean_4 4.7973  1   0.028504 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Removing 2017:

```
summary(lmer(n_intact_seeds_rel_yr ~ BLUP_slope_std_yr+BLUP_slope_std_yr:mean_4+
             (1|id),data = subset(data_4yrs,!year==2017)))
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
## n_intact_seeds_rel_yr ~ BLUP_slope_std_yr + BLUP_slope_std_yr:mean_4 +
##     (1 | id)
##    Data: subset(data_4yrs, !year == 2017)
##
## REML criterion at convergence: 5206.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.7297 -0.5385 -0.3338  0.2399  8.3561
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  id       (Intercept) 0.2812   0.5303
##  Residual             2.3288   1.5261
## Number of obs: 1377, groups:  id, 243
##
## Fixed effects:
##                           Estimate Std. Error         df t value Pr(>|t|)
```

```
## (Intercept)                  0.98292    0.05409  257.38378  18.171  < 2e-16
## BLUP_slope_std_yr            0.63029    0.18810 1370.52707   3.351 0.000828
## BLUP_slope_std_yr:mean_4   -0.13240    0.03192 1349.41617  -4.148 3.56e-05
##
## (Intercept)               ***
## BLUP_slope_std_yr         ***
## BLUP_slope_std_yr:mean_4 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) BLUP_s__
## BLUP_slp_s_ -0.003
## BLUP_s__:_4 -0.006 -0.958
```

```
Anova(lmer(n_intact_seeds_rel_yr ~ BLUP_slope_std_yr+BLUP_slope_std_yr:mean_4+
             (1|id),data = subset(data_4yrs,!year==2017)),type="II")
```

```
## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: n_intact_seeds_rel_yr
##                            Chisq Df Pr(>Chisq)
## BLUP_slope_std_yr         4.6997  1    0.03017 *
## BLUP_slope_std_yr:mean_4 17.2083  1   3.35e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Intercept of the RN

```
summary(lmer(n_intact_seeds_rel_yr ~ BLUP_int_std_yr+BLUP_int_std_yr:mean_4+
             (1|id),data = data_4yrs))
```

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
## n_intact_seeds_rel_yr ~ BLUP_int_std_yr + BLUP_int_std_yr:mean_4 +
##     (1 | id)
##    Data: data_4yrs
##
## REML criterion at convergence: 6372.3
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.2904 -0.4369 -0.2888  0.1522 24.0486
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  id       (Intercept) 0.1557   0.3946
##  Residual             4.5016   2.1217
## Number of obs: 1455, groups:  id, 243
##
## Fixed effects:
##                           Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)                0.99150    0.06166  291.71034  16.081   <2e-16
## BLUP_int_std_yr            0.05206    0.24878 1450.82714   0.209    0.834
```

```
## BLUP_int_std_yr:mean_4   -0.04840    0.04276 1444.03562  -1.132    0.258
##
## (Intercept)            ***
## BLUP_int_std_yr
## BLUP_int_std_yr:mean_4
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) BLUP_n__
## BLUP_nt_st_ -0.002
## BLUP_n__:_4 -0.002 -0.968
```

```r
Anova(lmer(n_intact_seeds_rel_yr ~ BLUP_int_std_yr+BLUP_int_std_yr:mean_4+
             (1|id),data = data_4yrs),type="II")
```

```
## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: n_intact_seeds_rel_yr
##                          Chisq Df Pr(>Chisq)
## BLUP_int_std_yr        12.6551  1  0.0003746 ***
## BLUP_int_std_yr:mean_4  1.2811  1  0.2576995
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Removing 2017:

```r
summary(lmer(n_intact_seeds_rel_yr ~ BLUP_int_std_yr+BLUP_int_std_yr:mean_4+
             (1|id),data = subset(data_4yrs,!year==2017)))
```

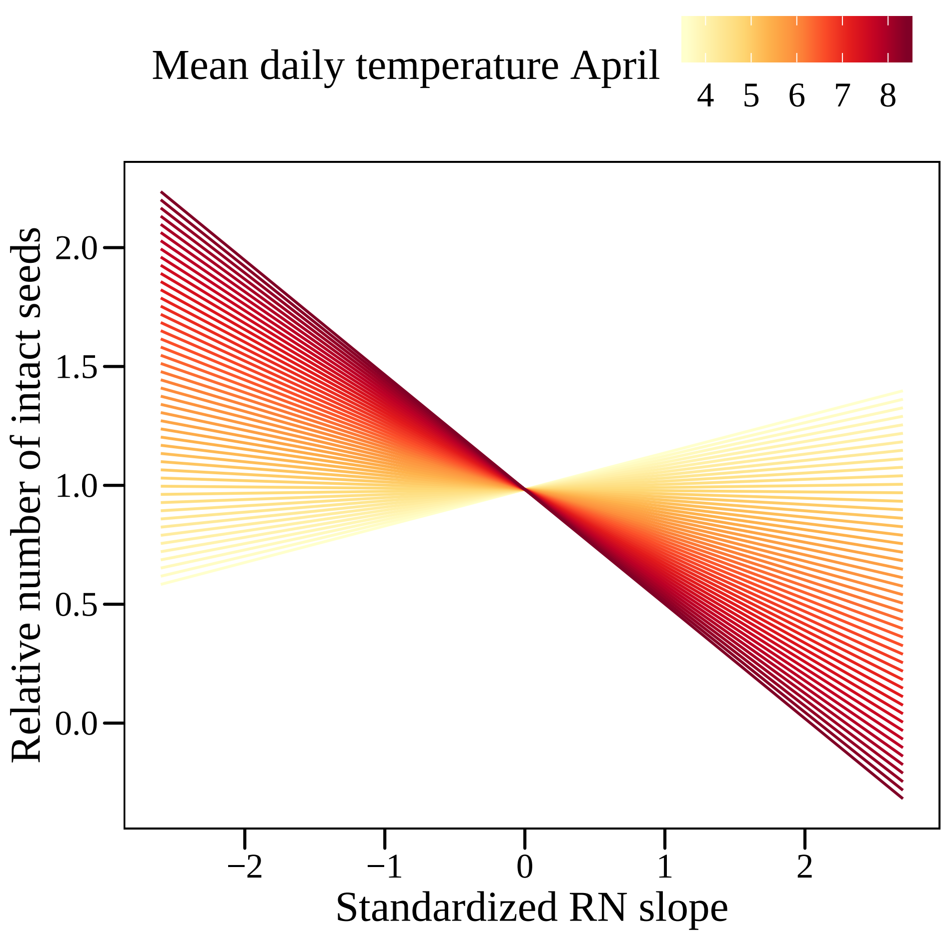
```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula:
## n_intact_seeds_rel_yr ~ BLUP_int_std_yr + BLUP_int_std_yr:mean_4 +
##     (1 | id)
##    Data: subset(data_4yrs, !year == 2017)
##
## REML criterion at convergence: 5213.1
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.7099 -0.5390 -0.3462  0.2384  8.3768
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  id       (Intercept) 0.2717   0.5213
##  Residual             2.3471   1.5320
## Number of obs: 1377, groups:  id, 243
##
## Fixed effects:
##                         Estimate Std. Error         df t value Pr(>|t|)
## (Intercept)              0.98462    0.05385  257.54529  18.284   <2e-16
## BLUP_int_std_yr          0.30601    0.18899 1373.12747   1.619   0.1056
## BLUP_int_std_yr:mean_4  -0.08217    0.03204 1353.15765  -2.565   0.0104
##
## (Intercept)            ***
```

```
## BLUP_int_std_yr
## BLUP_int_std_yr:mean_4 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) BLUP_n__
## BLUP_nt_st_ -0.005
## BLUP_n__:_4 -0.005 -0.958
```

```r
Anova(lmer(n_intact_seeds_rel_yr ~ BLUP_int_std_yr+BLUP_int_std_yr:mean_4+
             (1|id),data = subset(data_4yrs,!year==2017)),type="II")
```

```
## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: n_intact_seeds_rel_yr
##                         Chisq Df Pr(>Chisq)
## BLUP_int_std_yr        8.6192  1   0.003326 **
## BLUP_int_std_yr:mean_4 6.5786  1   0.010321 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Yes, differences in selection on RN slope and intercept among years are related to spring temperature.



Again, according to the graph it seems that with increasing temperatures, selection favors lower (more negative) slopes (and therefore lower elevations) of the RNs.

n = number of individuals (linear models)

Calculation of mean fitness (sum of fitness divided by number of years from first year when each id appeared to last year of each period). Then calculate relative fitness and standardized intercept and slope over all years.

With 3 years of data:

```
data_3yrs<-data_3yrs%>%
  mutate(period=ifelse(str_detect(as.character(id), "^o")==TRUE,"old","new"),
         n_years_from_first=ifelse(period=="old",1996-(first_yr-1),2017-(first_yr-1)))

(data_3yrs_total<-data_3yrs %>%
  group_by(id)%>%
  summarise(n_years=n(),n_years_from_first=mean(n_years_from_first),
            mean_fitness=sum(n_intact_seeds)/mean(n_years_from_first))%>%
  mutate(mean_fitness_rel=mean_fitness/mean(mean_fitness)))         # Rel. fitness
```

```
## # A tibble: 359 x 5
##    id      n_years n_years_from_first mean_fitness mean_fitness_rel
##    <fct>     <int>              <dbl>        <dbl>            <dbl>
##  1 new_10       11                 12       14.3             5.18
##  2 new_100       8                 11        4.24            1.53
##  3 new_101       9                 11        2.45            0.885
##  4 new_102      10                 11        6.12            2.21
##  5 new_103      10                 11        3.92            1.41
##  6 new_104       6                 11        1.73            0.623
##  7 new_106       7                 11        1.90            0.684
##  8 new_107       8                 11        3.27            1.18
##  9 new_108       7                 11        1.28            0.462
## 10 new_109      10                 11        0.180           0.0651
## # ... with 349 more rows
```

With 4 years of data:

```
data_4yrs<-data_4yrs%>%
  mutate(period=ifelse(str_detect(as.character(id), "^o")==TRUE,"old","new"),
         n_years_from_first=ifelse(period=="old",1996-(first_yr-1),2017-(first_yr-1)))

(data_4yrs_total<-data_4yrs %>%
  group_by(id)%>%
  summarise(n_years=n(),n_years_from_first=mean(n_years_from_first),
            mean_fitness=sum(n_intact_seeds)/mean(n_years_from_first),
            BLUP_int=mean(BLUP_int),BLUP_slope=mean(BLUP_slope))%>%
  mutate(mean_fitness_rel=mean_fitness/mean(mean_fitness)) %>%          # Rel. fitness
  mutate(BLUP_int_std=(BLUP_int-mean(BLUP_int))/sd(BLUP_int)) %>%      # Std. intercept
  mutate(BLUP_slope_std=(BLUP_slope-mean(BLUP_slope))/sd(BLUP_slope))) # Std. slope
```

```
## # A tibble: 243 x 9
##    id    n_years n_years_from_fi~ mean_fitness BLUP_int BLUP_slope
##    <fct>   <int>            <dbl>        <dbl>    <dbl>      <dbl>
##  1 new_~      11               12        14.3    -2.15      -0.896
##  2 new_~       8               11         4.24   -2.10      -0.809
##  3 new_~       9               11         2.45    0.596     -0.0622
```

```
##  4 new_~      10              11        6.12   -2.02      -0.782
##  5 new_~      10              11        3.92    0.243      0.0800
##  6 new_~       6              11        1.73    1.61       0.708
##  7 new_~       7              11        1.90    0.386      0.155
##  8 new_~       8              11        3.27    0.985      0.0892
##  9 new_~       7              11        1.28    0.372      0.0814
## 10 new_~      10              11        0.180  -0.0427     0.0828
## # ... with 233 more rows, and 3 more variables: mean_fitness_rel <dbl>,
## #   BLUP_int_std <dbl>, BLUP_slope_std <dbl>
```

With 5 years of data:

```
data_5yrs<-data_5yrs%>%
  mutate(period=ifelse(str_detect(as.character(id), "^o")==TRUE,"old","new"),
         n_years_from_first=ifelse(period=="old",1996-(first_yr-1),2017-(first_yr-1)))

(data_5yrs_total<-data_5yrs %>%
  group_by(id)%>%
  summarise(n_years=n(),n_years_from_first=mean(n_years_from_first),
            mean_fitness=sum(n_intact_seeds)/mean(n_years_from_first))%>%
  mutate(mean_fitness_rel=mean_fitness/mean(mean_fitness)))         # Rel. fitness
```

```
## # A tibble: 156 x 5
##    id      n_years n_years_from_first mean_fitness mean_fitness_rel
##    <fct>     <int>              <dbl>        <dbl>            <dbl>
##  1 new_10       11                 12       14.3             3.41
##  2 new_100       8                 11        4.24            1.01
##  3 new_101       9                 11        2.45            0.583
##  4 new_102      10                 11        6.12            1.46
##  5 new_103      10                 11        3.92            0.933
##  6 new_104       6                 11        1.73            0.411
##  7 new_106       7                 11        1.90            0.451
##  8 new_107       8                 11        3.27            0.778
##  9 new_108       7                 11        1.28            0.304
## 10 new_109      10                 11        0.180           0.0429
## # ... with 146 more rows
```

Phenotypic selection models performed only with RN slope (because of high correlation with RN intercept)

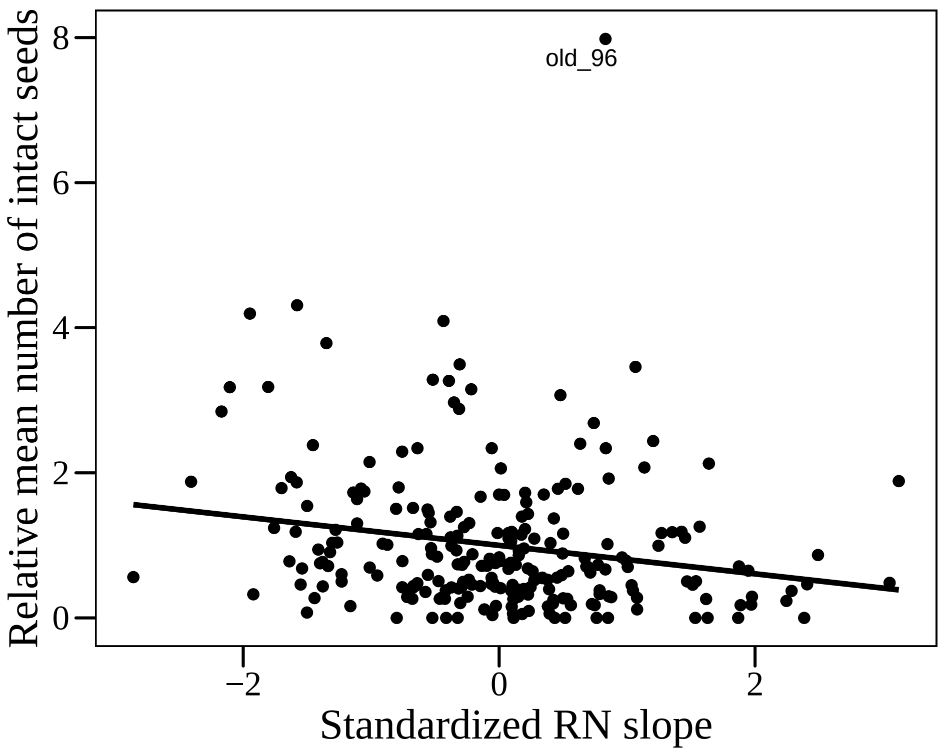
```
summary(lm(mean_fitness_rel ~ BLUP_slope_std,data = data_4yrs_total))
```

```
##
## Call:
## lm(formula = mean_fitness_rel ~ BLUP_slope_std, data = data_4yrs_total)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.2213 -0.6227 -0.2435  0.3432  7.1447
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)     1.00000    0.06164   16.22  < 2e-16 ***
## BLUP_slope_std -0.19642    0.06176   -3.18  0.00166 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 0.9608 on 241 degrees of freedom
## Multiple R-squared:  0.04028,    Adjusted R-squared:  0.03629
## F-statistic: 10.11 on 1 and 241 DF,  p-value: 0.001665
```

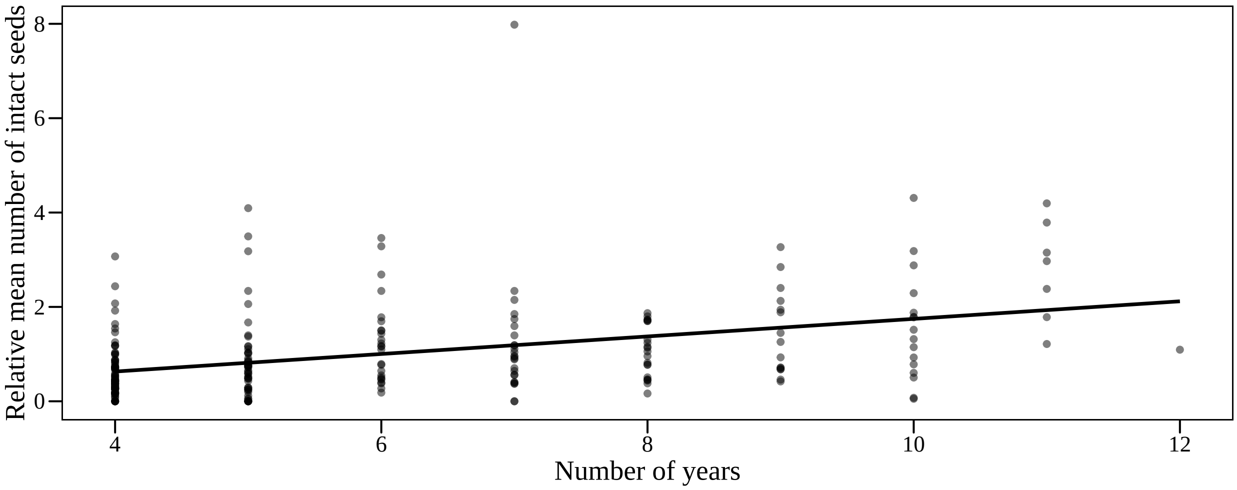
```r
Anova(lm(mean_fitness_rel ~ BLUP_slope_std,data = data_4yrs_total))
```

```
## Anova Table (Type II tests)
##
## Response: mean_fitness_rel
##                 Sum Sq  Df F value   Pr(>F)
## BLUP_slope_std   9.337   1  10.114 0.001665 **
## Residuals      222.485 241
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



Over all years, (mean) fitness is higher for individuals with more negative slopes (and therefore lower elevations) of the RNs, i.e. for individuals that have greater plasticity across temperatures.

POTENTIAL PROBLEM: Mean fitness over all years increases with the number of years that an individual has been recorded flowering.




```
##
## Call:
## lm(formula = mean_fitness_rel ~ n_years, data = data_4yrs_total)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.6937 -0.5239 -0.2079  0.3125  6.7931
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.11400    0.17137  -0.665    0.507
## n_years      0.18605    0.02696   6.901 4.54e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8962 on 241 degrees of freedom
## Multiple R-squared:  0.165,  Adjusted R-squared:  0.1615
## F-statistic: 47.62 on 1 and 241 DF,  p-value: 4.541e-11
```