Lathyrus ms3: Selective agents

Contents

D	ata preparation	1
H	stograms for interaction variables	3
1.	Effects of yearly intensity of interactions on selection Graphs of interaction effects	
2.	Models interactions ~ climate (across years)	8
	Number of seeds per flower	9
	Proportion of seeds escaping predation	10
	Grazing	11
	FFD	13
	Fitness	14
	Correlation n fl - FFD	15
3.	Models interactions ~ climate (within years)	15
	Number of seeds per flower	15
	Proportion of seeds escaping predation	
	Grazing	18
	Fitness	19
	Correlation n fl - FFD	21
4.	Models without climate (across years)	21
5.	Models without climate (within years)	22

Data preparation

Load data, keep variables needed and merge

```
data_selag<-read.table("C:/Users/user/Dropbox/SU/Projects/lathyrus/lathyrus_ms1/data/clean/alldata_weather="mean_weather">data_selag<-read.table("C:/Users/user/Dropbox/SU/Projects/lathyrus/lathyrus_ms1/data/clean/alldata_weather="mean_weather">data_clean/alldata_weather="mean_weather">data_clean/alldata_weather="mean_weather">data_clean/alldata_weather="mean_weather">data_clean/alldata_weather="mean_weather">data_clean/alldata_weather="mean_weather">data_clean/alldata_weather="mean_weather">data_clean/alldata_weather="mean_weather">data_clean/alldata_clean/alldata_weather="mean_weather">data_clean/alldata_clean/alldata_weather="mean_weather">data_clean/alldata_clean/alldata_weather="mean_weather">data_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean/alldata_clean
```

```
is.na(n_fl))) # Remove rows with all these NAs
names(data_selag)
                          "FFD"
    [1] "year"
                                            "id"
                                                              "ruta"
##
                                            "vernal"
    [5] "genet"
                          "data"
                                                              "grazing"
    [9] "shoot_vol"
                          "n fr"
                                            "n ovules"
                                                              "FFD corr"
## [13] "period"
                          "n_seeds"
                                            "n_intact_seeds"
                                                              "n fl"
                                            "mean_5"
## [17] "mean_3"
                          "mean_4"
                                                              "mean 6"
data_selag<-subset(data_selag, year!=1995) # Remove data from 1995 due to problems with predation
```

List of variables in data set:

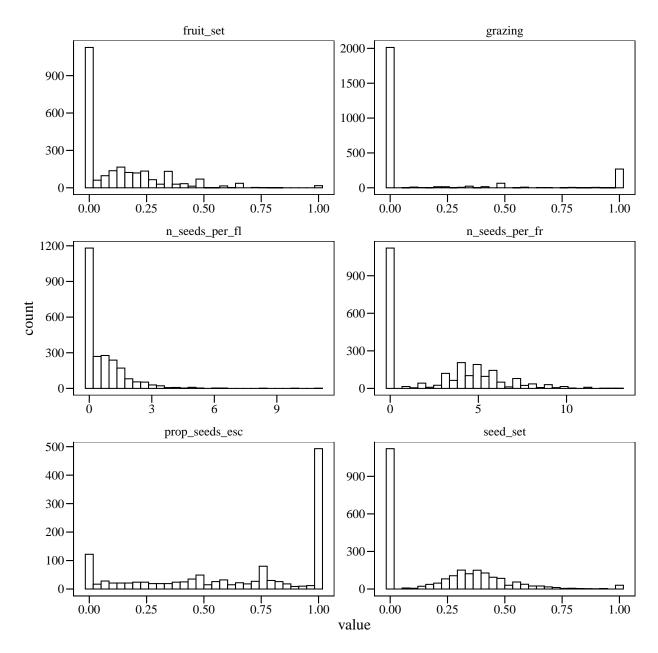
- year
- FFD: first flowering date (as number of days from vernal equinox)
- id: individual identifier (including "old" for individuals in period 1987-1996 and "new" for individuals in period 2006-2017)
- ruta, genet: identifiers for plots and ids in old data
- data: 1 if data available, 0 if not
- vernal: date of vernal equinox in each year
- grazing: proportion of grazing by deer
- shoot vol: shoot volume
- n fr: number of fruits
- n ovules: number of ovules
- FFD corr: first flowering date (as a date)
- period: "old" for 1987-1996 and "new" for 2006-2017
- n seeds: number of seeds
- n_intact_seeds: number of intact (non-predated) seeds
- n_fl: number of flowers
- mean_3/4/5/6: average of daily mean temperatures for March/April/May/June

Interactions that we will focus on:

- Pollination: number of seeds per flower
- Seed predation: proportion of seeds escaping predation
- Grazing (by deer) before flowering: proportion of grazing

Calculate fruit set, seed set, number of seeds per fruit, number of seeds per flower, proportion of predated seeds

Histograms for interaction variables



Using only mean temperatures. Using grazing as a proportion, and for 2008-2015 use values of proportion of aboveground volume.

- 1987-1996: grazing = proportion of flowers removed
- 2006: grazing = proportion of grazed shoots
- 2007-2015: grazing = proportion of aboveground volume removed
- 2016-2017: grazing = proportion of flowers removed

1. Effects of yearly intensity of interactions on selection

Because grazing influences (decreases) the number of seeds per flower, we calculate residuals of number of seeds per flower on grazing to use in the model.

In this model, we use: fitness relativized within years, FFD and n_fl standardized within years, interactions standardized accross years. Main effects of interactions are not included because fitness was relativized within years.

```
N = 2376
```

```
data_selag$n_seeds_per_fl_res<-with(data_selag,ifelse(is.na(n_seeds_per_fl),NA,
                                            residuals(lm(n seeds per fl~grazing corr,
                                                data=data_selag))))
data_selag_means<-data_selag%>%
  group_by(year)%>%
  dplyr::summarise(n_seeds_per_fl_mean=mean(n_seeds_per_fl,na.rm=T),
                   n seeds per fl res mean=mean(n seeds per fl res,na.rm=T),
                   grazing_mean=mean(grazing_corr,na.rm=T),
                   prop_seeds_esc_mean=mean(prop_seeds_esc,na.rm=T),
                   FFD_mean=mean(FFD,na.rm=T),
                   FFD_sd=sd(FFD,na.rm=T),
                   n_fl_mean=mean(n_fl,na.rm=T),
                   n_fl_sd=sd(n_fl,na.rm=T),
                   n_intact_seeds_mean=mean(n_intact_seeds,na.rm=T))
data_selag<-data_selag\\^\lambda\left_join(data_selag_means,by="year")</pre>
# Standardize interactions accross years
data_selag$n_seeds_per_fl_mean_s<-scale(data_selag$n_seeds_per_fl_mean)
data_selag$n_seeds_per_fl_res_mean_s<-scale(data_selag$n_seeds_per_fl_res_mean)
data_selag$grazing_mean_s<-scale(data_selag$grazing_mean)</pre>
data_selag$prop_seeds_esc_mean_s<-scale(data_selag$prop_seeds_esc_mean)
# Relativize fitness within years and standardize FFD and n_fl within years
data selag$n intact seeds rel y<-with(data selag,n intact seeds/n intact seeds mean)
data_selag$FFD_s_y<-with(data_selag,(FFD-FFD_mean)/FFD_sd)</pre>
data_selag$n_fl_s_y<-with(data_selag,(n_fl-n_fl_mean)/n_fl_sd)
mod int sel GLM<-lm(n intact seeds rel y ~ FFD s y+n fl s y+
               FFD_s_y:n_seeds_per_fl_res_mean_s+FFD_s_y:grazing_mean_s+FFD_s_y:prop_seeds_esc_mean_s,
               data_selag)
mod_int_sel_GLMM<-lmer(n_intact_seeds_rel_y ~ FFD_s_y+n_fl_s_y+</pre>
               FFD_s_y:n_seeds_per_fl_res_mean_s+FFD_s_y:grazing_mean_s+FFD_s_y:prop_seeds_esc_mean_s+
                 (1|id),data_selag)
# Results of models (t-tests)
kable(summary(mod_int_sel_GLM)$coefficients,digits=c(3,3,2,3))
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.032	0.042	24.31	0.000
FFD_s_y	-0.293	0.050	-5.83	0.000
n_fl_s_y	0.405	0.048	8.48	0.000
FFD_s_y:n_seeds_per_fl_res_mean_s	-0.032	0.040	-0.80	0.425
FFD_s_y:grazing_mean_s	0.132	0.032	4.08	0.000
$FFD_s_y:prop_seeds_esc_mean_s$	0.029	0.041	0.71	0.477

kable(summary(mod_int_sel_GLMM)\$coefficients,digits=c(3,3,1,2,3))

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	1.025	0.045	774.7	22.86	0.000
FFD_s_y	-0.301	0.051	2325.2	-5.96	0.000
n_fl_s_y	0.388	0.049	2044.4	7.99	0.000
FFD_s_y:n_seeds_per_fl_res_mean_s	-0.033	0.040	2343.2	-0.82	0.412
FFD_s_y:grazing_mean_s	0.134	0.032	2359.5	4.16	0.000
FFD_s_y:prop_seeds_esc_mean_s	0.026	0.041	2369.9	0.62	0.533

Analysis of variance/ deviance (F-test for GLM, Wald chi-square tests for GLMM) kable(Anova(mod_int_sel_GLM))

	Sum Sq	Df	F value	Pr(>F)
FFD_s_y	134.437195	1	31.3766367	0.0000000
n_fl_s_y	307.867556	1	71.8539869	0.0000000
FFD_s_y:n_seeds_per_fl_res_mean_s	2.727113	1	0.6364879	0.4250654
FFD_s_y:grazing_mean_s	71.239904	1	16.6268611	0.0000470
FFD_s_y:prop_seeds_esc_mean_s	2.164351	1	0.5051433	0.4773188
Residuals	10154.566777	2370	NA	NA

kable(Anova(mod_int_sel_GLM))

	а а	D.C.	- I	D (D)
	Sum Sq	Df	F value	$\Pr(>F)$
FFD_s_y	134.437195	1	31.3766367	0.0000000
n_fl_s_y	307.867556	1	71.8539869	0.0000000
FFD_s_y:n_seeds_per_fl_res_mean_s	2.727113	1	0.6364879	0.4250654
FFD_s_y:grazing_mean_s	71.239904	1	16.6268611	0.0000470
FFD_s_y:prop_seeds_esc_mean_s	2.164351	1	0.5051433	0.4773188
Residuals	10154.566777	2370	NA	NA

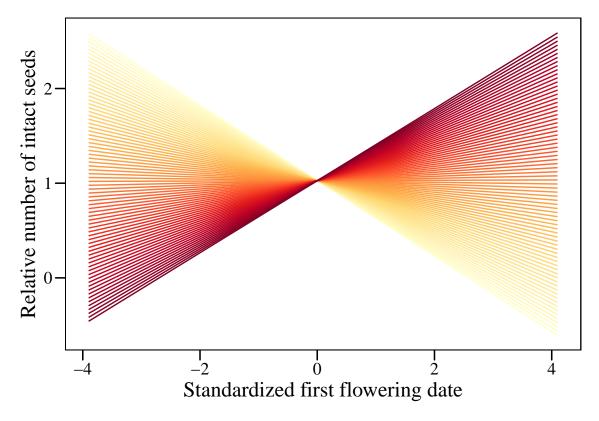
Significant effect of all grazing on selection.

${\bf Graphs\ of\ interaction\ effects}$

Graphs based on GLMMs with non-standardized interactions - to show real values of interactions in the color bars.

Proportion of grazing





• The slope of the relationship among fitness and FFD is more positive in years with higher proportions of grazing → selection for later flowering in those years

Effects on selection gradients for each year

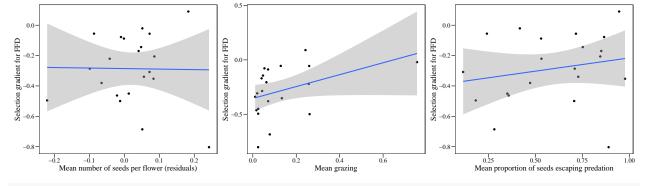
```
selgrads_FFD<-data.frame(data_selag %>% group_by(year) %>%
  do(model = lm(n_intact_seeds_rel_y ~ FFD_s_y+n_fl_s_y, data = .)) %>% tidy(model))
selgrads_FFD$sig<-ifelse(selgrads_FFD$p.value<0.05,"*","")
kable(subset(selgrads_FFD,term=="FFD_s_y"),digits=3) #Linear selection gradients for FFD</pre>
```

	year	term	estimate	std.error	statistic	p.value	sig
2	1987	FFD_s_y	-0.078	0.088	-0.883	0.378	
5	1988	FFD_s_y	-0.088	0.111	-0.789	0.431	
8	1989	FFD_s_y	-0.144	0.143	-1.010	0.315	
11	1990	FFD_s_y	-0.286	0.175	-1.631	0.105	
14	1991	FFD_s_y	-0.353	0.098	-3.597	0.000	*
17	1992	FFD_s_y	-0.463	0.199	-2.323	0.022	*
20	1993	FFD_s_y	-0.340	0.152	-2.236	0.027	*
23	1994	FFD_s_y	-0.499	0.213	-2.340	0.020	*
26	1996	FFD_s_y	-0.170	0.101	-1.684	0.095	
29	2006	FFD s y	-0.221	0.123	-1.796	0.076	

	year	term	estimate	std.error	statistic	p.value	sig
32	2007	FFD_s_y	-0.380	0.135	-2.816	0.006	*
35	2008	FFD_s_y	-0.206	0.115	-1.796	0.076	
38	2009	FFD_s_y	-0.056	0.353	-0.158	0.875	
41	2010	FFD_s_y	-0.495	0.201	-2.459	0.016	*
44	2011	FFD_s_y	-0.308	0.230	-1.338	0.185	
47	2012	FFD_s_y	-0.685	0.216	-3.174	0.002	*
50	2013	FFD_s_y	-0.450	0.351	-1.284	0.204	
53	2014	FFD_s_y	-0.803	0.218	-3.676	0.001	*
56	2015	FFD_s_y	0.090	0.341	0.264	0.794	
59	2016	FFD_s_y	-0.056	0.100	-0.563	0.575	
62	2017	FFD_s_y	-0.021	0.608	-0.034	0.973	

#FFD * (selection for early flowering) in 1991,1992,1993,1994,2007,2010,2012,2014 (as in EL paper)

```
data_selag_means<-data_selag_means%>%
  left_join(subset(selgrads_FFD,term=="FFD_s_y")[c(1,3)])
grid.arrange(
  ggplot(data_selag_means,aes(x=n_seeds_per_fl_res_mean,y=estimate))+my_theme()+
  geom_point()+geom_smooth(method="lm")+ylab("Selection gradient for FFD")+
  xlab("Mean number of seeds per flower (residuals)"),
  ggplot(data_selag_means,aes(x=grazing_mean,y=estimate))+my_theme()+
  geom_point()+geom_smooth(method="lm")+ylab("Selection gradient for FFD")+
  xlab("Mean grazing"),
  ggplot(data_selag_means,aes(x=prop_seeds_esc_mean,y=estimate))+my_theme()+
  geom_point()+geom_smooth(method="lm")+ylab("Selection gradient for FFD")+
  xlab("Mean proportion of seeds escaping predation"),
  ncol=3)
```



kable(summary(lm(estimate~n_seeds_per_fl_res_mean,data_selag_means))\$coefficients)

	Estimate	Std. Error	t value	$\Pr(> t)$
(Intercept) n_seeds_per_fl_res_mean	-0.2855260 -0.0340912		-5.4723276 -0.0641067	

kable(summary(lm(estimate~grazing_mean,data_selag_means))\$coefficients)

	Estimate	Std. Error	t value	$\Pr(> t)$
(Intercept)	-0.3546187	0.0584607	-6.065936	0.0000078
grazing_mean	0.5466662	0.2826267	1.934234	0.0681187

Estimate Std. Error	t value	$\Pr(> t)$
---------------------	---------	-------------

kable(summary(lm(estimate~prop_seeds_esc_mean,data_selag_means))\$coefficients)

	Estimate	Std. Error	t value	$\Pr(> t)$
(Intercept) prop seeds esc mean	-0.3896223	0.1236889 0.1907548	0.200020	0.000=.=0

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.5189983	0.1355472	-3.8289128	0.0013438
n_seeds_per_fl_res_mean	-0.5782329	0.5835095	-0.9909572	0.3356026
grazing_mean	0.5875429	0.2859367	2.0548003	0.0556002
$prop_seeds_esc_mean$	0.2891049	0.2123263	1.3616066	0.1910960

No significant effects of yearly mean interactions on yearly selection gradients (but effect of grazing is ALMOST significant)

2. Models interactions ~ climate (across years)

Model selections for later constructing a path diagram.

Calculate successes/failures for grazing

```
data_selag$grazing_success<-round(with(data_selag,ifelse(is.na(grazing_corr),NA,
                                                    ifelse(year<1997|year>2015,grazing_corr*n_fl,
                                                    ifelse(year>2006&year<2016,grazing_corr*shoot_vol,
                                                           999)))))
data_selag$grazing_failure<-round(with(data_selag,ifelse(is.na(grazing_corr),NA,
                                                    ifelse(year<1997|year>2015,n_fl-grazing_success,
                                                           ifelse(year>2006&year<2016,
                                                                  shoot_vol-grazing_success,
                                                                  999)))))
grazing_success_2006<-read.table(</pre>
  "C:/Users/user/Dropbox/SU/Projects/lathyrus/lathyrus_ms3/data/grazing_success_2006.csv",
  header=T, sep=", ", dec=".")
data_selag<-data_selag%>%
  left_join(grazing_success_2006)
data_selag$grazing_success<-with(data_selag,ifelse(year==2006,gr_success,grazing_success))
data_selag$grazing_failure<-with(data_selag,ifelse(year==2006,gr_failure,grazing_failure))
data_selag$gr_success<-NULL
data_selag$gr_failure<-NULL
```

In these models, we use: fitness relativized across years, FFD, n_fl and climatic variables standardized across years, interactions not standardized (because interactions cannot be standardized when used as responses, so we do not standardize them at all).

```
data_selag$n_intact_seeds_rel<-data_selag$n_intact_seeds/mean(data_selag$n_intact_seeds,na.rm=T)
data_selag$FFD_s<-(data_selag$FFD_mean(data_selag$FFD,na.rm=T))/sd(data_selag$FFD,na.rm=T)
data_selag$n_fl_s<-(data_selag$n_fl_mean(data_selag$n_fl,na.rm=T))/sd(data_selag$n_fl,na.rm=T)
data_selag$mean_3_s<-(data_selag$mean_3-mean(data_selag$mean_3,na.rm=T))/sd(data_selag$mean_3,na.rm=T)
data_selag$mean_4_s<-(data_selag$mean_4-mean(data_selag$mean_4,na.rm=T))/sd(data_selag$mean_4,na.rm=T)
data_selag$mean_5_s<-(data_selag$mean_5-mean(data_selag$mean_5,na.rm=T))/sd(data_selag$mean_5,na.rm=T)
data_selag$mean_6_s<-(data_selag$mean_6-mean(data_selag$mean_6,na.rm=T))/sd(data_selag$mean_6,na.rm=T)
```

Number of seeds per flower

```
data selag subset1<-subset(data selag,!is.na(n seeds per fl)&!is.na(FFD s))
globmod_n_seeds_per_fl_path_GLM<-glm(round(n_seeds_per_fl)~mean_3_s+mean_4_s+mean_5_s+
                                        FFD_s+n_fl_s+grazing_corr,data=data_selag_subset1,
                                      family="poisson",na.action="na.fail")
globmod_n_seeds_per_fl_path_GLMM<-glmer(round(n_seeds_per_fl)~mean_3_s+mean_4_s+mean_5_s+
                                        FFD_s+n_fl_s+grazing_corr+(1|id),data=data_selag_subset1,
                                        family="poisson",na.action="na.fail")
clusterType <- if(length(find.package("snow", quiet = TRUE))) "SOCK" else "PSOCK"</pre>
clust1 <- try(makeCluster(getOption("cl.cores", 3), type = clusterType))</pre>
clusterExport(clust1, "data_selag_subset1")
clusterEvalQ(clust1, library(lme4))
## [[1]]
## [1] "lme4"
                    "Matrix"
                                "stats"
                                             "graphics"
                                                         "grDevices" "utils"
## [7] "datasets"
                   "methods"
                                "base"
## [[2]]
## [1] "lme4"
                    "Matrix"
                                "stats"
                                                         "grDevices" "utils"
                                             "graphics"
## [7] "datasets"
                   "methods"
                                "base"
##
## [[3]]
## [1] "lme4"
                   "Matrix"
                                "stats"
                                                         "grDevices" "utils"
                                             "graphics"
## [7] "datasets"
                                "base"
                   "methods"
modsel_n_seeds_per_fl_path_GLM<-pdredge(globmod_n_seeds_per_fl_path_GLM,cluster=clust1)</pre>
modsel_n_seeds_per_fl_path_GLMM<-pdredge(globmod_n_seeds_per_fl_path_GLMM,cluster=clust1)</pre>
```

Coefficients of averaged model and R square of the best model

	Estimate	Std. Error	Adjusted SE	z value	$\Pr(> z)$
(Intercept)	-0.322	0.028	0.028	11.68	0.000
FFD_s	-0.424	0.039	0.039	10.84	0.000
$grazing_corr$	-2.311	0.218	0.218	10.60	0.000
$mean_4_s$	-0.106	0.028	0.028	3.82	0.000
$mean_5_s$	-0.350	0.041	0.041	8.56	0.000
n_fl_s	-0.349	0.043	0.043	8.02	0.000
$mean_3_s$	-0.013	0.024	0.024	0.53	0.593

	Estimate	Std. Error	Adjusted SE	z value	$\Pr(> z)$
(Intercept)	-0.484	0.042	0.042	11.46	0.000
FFD_s	-0.450	0.044	0.044	10.16	0.000
grazing_corr	-2.435	0.227	0.227	10.74	0.000
$mean_4_s$	-0.126	0.031	0.031	4.11	0.000
$mean_5_s$	-0.359	0.045	0.045	8.06	0.000
n_fl_s	-0.358	0.048	0.048	7.49	0.000
$mean_3_s$	-0.019	0.029	0.029	0.65	0.518

```
r.squaredGLMM(get.models(modsel_n_seeds_per_fl_path_GLM,
                         subset=1)$"59") # R square of best model
##
                   R2m
                             R2c
             0.2602587 0.2602587
## delta
## lognormal 0.3664307 0.3664307
## trigamma 0.1460169 0.1460169
r.squaredGLMM(get.models(modsel_n_seeds_per_fl_path_GLMM,
                         subset=1)$"59") # R square of best model
##
                   R2m
                             R2c
             0.2426189 0.3839025
## delta
## lognormal 0.3187817 0.5044170
## trigamma 0.1481666 0.2344480
```

Proportion of seeds escaping predation

```
data_selag_subset2<-subset(subset(data_selag,n_seeds>0),!is.na(n_intact_seeds)&!is.na(n_fl_s)&!is.na(FF.
globmod_prop_seeds_esc_path_GLM<-glm(cbind(round(n_intact_seeds),round(n_pred_seeds))~</pre>
                                      mean_3_s+mean_4_s+mean_5_s+mean_6_s+n_fl_s+FFD_s,
                                      data=data_selag_subset2,family="binomial",na.action="na.fail")
globmod_prop_seeds_esc_path_GLMM<-glmer(cbind(round(n_intact_seeds),round(n_pred_seeds))~</pre>
                                      mean_3_s+mean_4_s+mean_5_s+mean_6_s+n_fl_s+FFD_s+
                                      (1|id),data=data_selag_subset2,family="binomial",na.action="na.fai
clusterType <- if(length(find.package("snow", quiet = TRUE))) "SOCK" else "PSOCK"</pre>
clust2 <- try(makeCluster(getOption("cl.cores", 3), type = clusterType))</pre>
clusterExport(clust2, "data_selag_subset2")
clusterEvalQ(clust2, library(lme4))
## [[1]]
## [1] "lme4"
                   "Matrix"
                                "stats"
                                                         "grDevices" "utils"
                                             "graphics"
## [7] "datasets"
                   "methods"
                                "base"
##
## [[2]]
                   "Matrix"
## [1] "lme4"
                                "stats"
                                             "graphics"
                                                         "grDevices" "utils"
## [7] "datasets"
                   "methods"
                                "base"
##
## [[3]]
## [1] "lme4"
                   "Matrix"
                                "stats"
                                             "graphics"
                                                         "grDevices" "utils"
```

```
## [7] "datasets" "methods" "base"

modsel_prop_seeds_esc_path_GLM<-pdredge(globmod_prop_seeds_esc_path_GLM,cluster=clust2)
modsel_prop_seeds_esc_path_GLMM<-pdredge(globmod_prop_seeds_esc_path_GLMM,cluster=clust2)</pre>
```

Coefficients of averaged model and R square of the best model

	Estimate	Std. Error	z value	Pr(> z)
	Listinate	oud: Ellor	Z varae	
(Intercept)	0.864	0.022	40.02	0
FFD_s	-0.205	0.027	-7.69	0
$mean_3_s$	0.256	0.021	12.03	0
$mean_4_s$	-0.197	0.021	-9.49	0
$mean_5_s$	-0.369	0.041	-9.10	0
$mean_6_s$	-0.541	0.023	-23.04	0
n_fl_s	-0.089	0.010	-9.04	0

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	1.412	0.085	16.64	0
FFD_s	-0.755	0.043	-17.74	0
$mean_3_s$	0.184	0.028	6.52	0
$mean_4_s$	-0.148	0.028	-5.30	0
$mean_5_s$	-0.777	0.062	-12.62	0
$mean_6_s$	-0.556	0.035	-15.92	0
n_fl_s	-0.135	0.017	-7.98	0

Grazing

```
globmod_grazing_path_GLMM<-glmer(cbind(grazing_success,grazing_failure)~mean_3_s+mean_4_s+mean_5_s+
                                    n_fl_s+FFD_s+(1|id),data = data_selag_subset3,
                                  family="binomial",na.action="na.fail")
clusterType <- if(length(find.package("snow", quiet = TRUE))) "SOCK" else "PSOCK"</pre>
clust3 <- try(makeCluster(getOption("cl.cores", 3), type = clusterType))</pre>
clusterExport(clust3, "data_selag_subset3")
clusterEvalQ(clust3, library(lme4))
## [[1]]
## [1] "lme4"
                    "Matrix"
                                "stats"
                                             "graphics"
                                                         "grDevices" "utils"
## [7] "datasets"
                   "methods"
                                "base"
##
## [[2]]
## [1] "lme4"
                    "Matrix"
                                "stats"
                                             "graphics"
                                                         "grDevices" "utils"
                   "methods"
## [7] "datasets"
                                "base"
##
## [[3]]
## [1] "lme4"
                    "Matrix"
                                "stats"
                                             "graphics"
                                                         "grDevices" "utils"
                                "base"
## [7] "datasets" "methods"
modsel_grazing_path_GLM<-pdredge(globmod_grazing_path_GLM,cluster=clust3)</pre>
modsel_grazing_path_GLMM<-pdredge(globmod_grazing_path_GLMM,cluster=clust3)</pre>
```

Coefficients of averaged model and R square of the best model

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-3.075	0.008	-391.61	0
FFD_s	-0.300	0.006	-47.30	0
$mean_3_s$	0.340	0.006	59.96	0
$mean_4_s$	-0.036	0.004	-8.72	0
$mean_5_s$	-1.233	0.018	-69.95	0
n_fl_s	-0.056	0.002	-32.89	0

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-6.991	0	-86312.76	0
FFD_s	-0.367	0	-4529.72	0
$mean_3_s$	0.360	0	4447.35	0
$mean_4_s$	-0.161	0	-1985.97	0
$mean_5_s$	-1.206	0	-14894.35	0
n_fl_s	-0.097	0	-1200.12	0

```
## R2m R2c
## theoretical 0.16815795 0.16815795
```

```
## delta
               0.02700909 0.02700909
r.squaredGLMM(get.models(modsel_grazing_path_GLMM,
                          subset=1)$"31") # R square of best model, failed to converge, nearly unidentif
                         R.2m
                                    R2c
## theoretical 0.0209904595 0.87921411
               0.0004176369 0.01749329
FFD
data selag subset4<-subset(data selag,!is.na(FFD s))</pre>
globmod_FFD_path_GLM<-lm(FFD_s~mean_3_s+mean_4_s+mean_5_s,data = data_selag_subset4,na.action="na.fail"
globmod_FFD_path_GLMM<-lmer(FFD_s~mean_3_s+mean_4_s+mean_5_s+(1|id),
                             data = data_selag_subset4,na.action="na.fail")
clusterType <- if(length(find.package("snow", quiet = TRUE))) "SOCK" else "PSOCK"</pre>
clust4 <- try(makeCluster(getOption("cl.cores", 3), type = clusterType))</pre>
clusterExport(clust4, "data_selag_subset4")
clusterEvalQ(clust4, library(lme4))
## [[1]]
## [1] "lme4"
                                                         "grDevices" "utils"
                   "Matrix"
                                "stats"
                                             "graphics"
## [7] "datasets"
                   "methods"
                                "base"
##
## [[2]]
## [1] "lme4"
                   "Matrix"
                                "stats"
                                             "graphics"
                                                         "grDevices" "utils"
## [7] "datasets" "methods"
                                "base"
##
## [[3]]
## [1] "lme4"
                   "Matrix"
                                "stats"
                                             "graphics"
                                                         "grDevices" "utils"
## [7] "datasets" "methods"
                                "base"
modsel_FFD_path_GLM<-pdredge(globmod_FFD_path_GLM,cluster=clust4)</pre>
modsel_FFD_path_GLMM<-pdredge(globmod_FFD_path_GLMM,cluster=clust4)</pre>
Coefficients of averaged model and R square of the best model
kable(summary(get.models(modsel_FFD_path_GLM,
                          subset=1)$"7")$coefficients,digits=c(3,3,2,3)) # Coefs best model
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.042	0.016	2.71	0.007
$mean_3_s$	-0.050	0.017	-2.98	0.003
$mean_4_s$	-0.316	0.015	-20.49	0.000
$mean_5_s$	-0.643	0.021	-30.80	0.000

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	0.078	0.018	744.3	4.20	0
$mean_3_s$	-0.067	0.016	2211.8	-4.20	0
$mean_4_s$	-0.281	0.015	2309.7	-18.75	0

Fitness

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-0.0456230		-2.183021	0.0_000_
n_fl_s	0.2433366	0.0073956	32.902738	0.0000000

kable(summary(mod_n_intact_seeds1_GLMM)\$coefficients)

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-0.3284973	0.0411383	-7.985198	0
n_fl_s	0.3250654	0.0162972	19.946087	0

kable(summary(mod n intact seeds2 GLM)\$coefficients)

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-0.3650931	0.0244360	-14.94081	0
$n_seeds_per_fl$	0.3861005	0.0089547	43.11731	0

```
kable(summary(mod_n_intact_seeds2_GLMM)$coefficients)
```

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-0.7910685	0.0455259	-17.37623	0
$n_seeds_per_fl$	0.5168424	0.0176238	29.32642	0

kable(summary(mod_n_intact_seeds3_GLM)\$coefficients)

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-0.6441175	0.0641699	-10.03769	0
$prop_seeds_esc$	1.7177269	0.0738609	23.25623	0

kable(summary(mod_n_intact_seeds3_GLMM)\$coefficients)

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-1.007795	0.0782787	-12.87445	0
$prop_seeds_esc$	1.956197	0.0838087	23.34122	0

Correlation n fl - FFD

```
with(data_selag,cor.test(n_fl_s,FFD_s)) # -0.372 *

##

## Pearson's product-moment correlation

##

## data: n_fl_s and FFD_s

## t = -19.502, df = 2374, p-value < 2.2e-16

## alternative hypothesis: true correlation is not equal to 0

## 95 percent confidence interval:

## -0.4057461 -0.3364104

## sample estimates:

## cor

## -0.3715963</pre>
```

3. Models interactions ~ climate (within years)

Model selections for later constructing a path diagram.

In these models, we use: fitness relativized within years, FFD and n_fl standardized within years and climatic variables standardized across years, interactions not standardized (because interactions cannot be standardized when used as responses, so we do not standardize them at all).

In this model, we do not include effects of temperature on FFD.

Number of seeds per flower

```
globmod_n_seeds_per_fl_path_GLM_y<-glm(round(n_seeds_per_fl)~mean_3_s+mean_4_s+mean_5_s+
FFD_s_y+n_fl_s_y+grazing_corr,data=data_selag_subset1,
```

```
family="poisson",na.action="na.fail")
globmod_n_seeds_per_fl_path_GLMM_y<-glmer(round(n_seeds_per_fl)~mean_3_s+mean_4_s+mean_5_s+
                                        FFD_s_y+n_fl_s_y+grazing_corr+(1|id),data=data_selag_subset1,
                                        family="poisson",na.action="na.fail")
clusterType <- if(length(find.package("snow", quiet = TRUE))) "SOCK" else "PSOCK"</pre>
clust1 <- try(makeCluster(getOption("cl.cores", 3), type = clusterType))</pre>
clusterExport(clust1, "data selag subset1")
clusterEvalQ(clust1, library(lme4))
## [[1]]
## [1] "lme4"
                   "Matrix"
                                "stats"
                                             "graphics"
                                                         "grDevices" "utils"
## [7] "datasets"
                   "methods"
                                "base"
##
## [[2]]
                   "Matrix"
                                "stats"
## [1] "lme4"
                                             "graphics"
                                                         "grDevices" "utils"
## [7] "datasets"
                   "methods"
                                "base"
## [[3]]
## [1] "lme4"
                   "Matrix"
                                "stats"
                                                         "grDevices" "utils"
                                             "graphics"
## [7] "datasets"
                                "base"
                   "methods"
modsel_n_seeds_per_fl_path_GLM_y<-pdredge(globmod_n_seeds_per_fl_path_GLM_y,cluster=clust1)</pre>
modsel_n_seeds_per_fl_path_GLMM_y<-pdredge(globmod_n_seeds_per_fl_path_GLMM_y,cluster=clust1)</pre>
```

Coefficients of averaged model and R square of the best model

	Estimate	Std. Error	Adjusted SE	z value	$\Pr(> z)$
(Intercept)	-0.335	0.027	0.027	12.33	0.000
FFD_s_y	-0.279	0.030	0.030	9.41	0.000
grazing_corr	-2.241	0.216	0.216	10.37	0.000
$mean_5_s$	-0.086	0.031	0.031	2.73	0.006
$n_fl_s_y$	-0.295	0.036	0.036	8.29	0.000
$mean_4_s$	0.007	0.016	0.016	0.41	0.678
$\underline{\text{mean}}\underline{3}\underline{\text{s}}$	0.007	0.017	0.017	0.40	0.689

	Estimate	Std. Error	Adjusted SE	z value	$\Pr(> z)$
(Intercept)	-0.335	0.027	0.027	12.33	0.000
FFD_s_y	-0.279	0.030	0.030	9.41	0.000
$grazing_corr$	-2.241	0.216	0.216	10.37	0.000
$mean_5_s$	-0.086	0.031	0.031	2.73	0.006
$n_fl_s_y$	-0.295	0.036	0.036	8.29	0.000
$mean_4_s$	0.007	0.016	0.016	0.41	0.678
$\underline{\text{mean}}\underline{-3}\underline{-\text{s}}$	0.007	0.017	0.017	0.40	0.689

```
r.squaredGLMM(get.models(modsel_n_seeds_per_fl_path_GLM_y,
                          subset=1)$"51") # R square of best model
##
                   R2m
             0.2450620 0.2450620
## delta
## lognormal 0.3479506 0.3479506
## trigamma 0.1362621 0.1362621
r.squaredGLMM(get.models(modsel_n_seeds_per_fl_path_GLM_y,
                          subset=1)$"51") # R square of best model
##
                   R<sub>2</sub>m
## delta
             0.2450620 0.2450620
## lognormal 0.3479506 0.3479506
## trigamma 0.1362621 0.1362621
```

Proportion of seeds escaping predation

```
globmod_prop_seeds_esc_path_GLM_y<-glm(cbind(round(n_intact_seeds),round(n_pred_seeds))~</pre>
                                         \label{lem:mean_3_s+mean_4_s+mean_5_s+mean_6_s+FFD_s_y+n_fl_s_y} \\ \text{mean_3_s+mean_4_s+mean_5_s+mean_6_s+FFD_s_y+n_fl_s_y},
                                         data=data_selag_subset2,family="binomial",na.action="na.fail")
globmod_prop_seeds_esc_path_GLMM_y<-glmer(cbind(round(n_intact_seeds),round(n_pred_seeds))~</pre>
                                         mean_3_s+mean_4_s+mean_5_s+mean_6_s+FFD_s_y+n_fl_s_y+
                                         (1|id),data=data_selag_subset2,family="binomial",na.action="na.fai
clusterType <- if(length(find.package("snow", quiet = TRUE))) "SOCK" else "PSOCK"</pre>
clust2 <- try(makeCluster(getOption("cl.cores", 3), type = clusterType))</pre>
clusterExport(clust2, "data_selag_subset2")
clusterEvalQ(clust2, library(lme4))
## [[1]]
## [1] "lme4"
                     "Matrix"
                                  "stats"
                                                "graphics"
                                                             "grDevices" "utils"
## [7] "datasets"
                     "methods"
                                  "base"
##
## [[2]]
## [1] "lme4"
                     "Matrix"
                                  "stats"
                                                "graphics"
                                                             "grDevices" "utils"
## [7] "datasets"
                     "methods"
                                  "base"
##
## [[3]]
## [1] "lme4"
                     "Matrix"
                                  "stats"
                                                "graphics"
                                                             "grDevices" "utils"
## [7] "datasets"
                                  "base"
                     "methods"
modsel_prop_seeds_esc_path_GLM_y<-pdredge(globmod_prop_seeds_esc_path_GLM_y,cluster=clust2)
modsel_prop_seeds_esc_path_GLMM_y<-pdredge(globmod_prop_seeds_esc_path_GLMM_y,cluster=clust2)</pre>
```

Coefficients of averaged model and R square of the best model

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	0.975	0.023	42.21	0
FFD_s_y	0.085	0.022	3.90	0
$mean_3_s$	0.282	0.021	13.35	0
mean 4 s	-0.143	0.018	-7.90	0

	Estimate	Std. Error	z value	$\Pr(> z)$
$mean_5_s$	-0.232	0.036	-6.39	0
$mean_6_s$	-0.554	0.024	-23.47	0
$n_fl_s_y$	-0.079	0.013	-6.23	0

	Estimate	Std. Error	Adjusted SE	z value	Pr(> z)
(Intercept)	1.497	0.070	0.07	21.495	0.000
$mean_3_s$	0.299	0.028	0.03	10.842	0.000
$mean_4_s$	0.027	0.029	0.03	0.925	0.355
$mean_5_s$	-0.338	0.051	0.05	6.577	0.000
$mean_6_s$	-0.565	0.031	0.03	18.017	0.000
$n_fl_s_y$	-0.068	0.021	0.02	3.283	0.001
FFD_s_y	0.017	0.026	0.03	0.649	0.516

Grazing

```
data_selag_subset3<-subset(data_selag,!is.na(grazing_success)&!is.na(FFD_s)&!is.na(n_f1))
globmod_grazing_path_GLM_y<-glm(cbind(grazing_success,grazing_failure)~mean_3_s+mean_4_s+mean_5_s+
                                n_fl_s_y+FFD_s_y,data = data_selag_subset3,
                              family="binomial",na.action="na.fail")
globmod_grazing_path_GLMM_y<-glmer(cbind(grazing_success,grazing_failure)~mean_3_s+mean_4_s+mean_5_s+
                                    n_fl_s_y+FFD_s_y+(1|id),data = data_selag_subset3,
                                  family="binomial",na.action="na.fail")
clusterType <- if(length(find.package("snow", quiet = TRUE))) "SOCK" else "PSOCK"</pre>
clust3 <- try(makeCluster(getOption("cl.cores", 3), type = clusterType))</pre>
clusterExport(clust3, "data_selag_subset3")
clusterEvalQ(clust3, library(lme4))
## [[1]]
## [1] "lme4"
                   "Matrix"
                                "stats"
                                            "graphics" "grDevices" "utils"
## [7] "datasets"
                   "methods"
                                "base"
##
## [[2]]
## [1] "lme4"
                   "Matrix"
                                "stats"
                                            "graphics"
                                                        "grDevices" "utils"
```

```
## [7] "datasets" "methods" "base"

##
## [[3]]
## [1] "lme4" "Matrix" "stats" "graphics" "grDevices" "utils"

## [7] "datasets" "methods" "base"

modsel_grazing_path_GLM_y<-pdredge(globmod_grazing_path_GLM_y,cluster=clust3)
modsel_grazing_path_GLMM_y<-pdredge(globmod_grazing_path_GLMM_y,cluster=clust3)</pre>
```

Coefficients of averaged model and R square of the best model

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-2.981	0.008	-389.73	0
FFD_s_y	-0.095	0.005	-17.56	0
$mean_3_s$	0.404	0.005	75.81	0
$mean_4_s$	0.035	0.004	9.58	0
$mean_5_s$	-1.037	0.017	-61.25	0
$n_fl_s_y$	-0.069	0.003	-20.66	0

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-7.891	0.372	-21.20	0
FFD_s_y	-0.138	0.007	-18.46	0
$mean_3_s$	0.412	0.006	68.46	0
$mean_4_s$	-0.075	0.004	-16.97	0
$mean_5_s$	-0.982	0.021	-46.19	0
$n_fl_s_y$	-0.173	0.005	-33.68	0

Fitness

```
mod_n_intact_seeds1_GLM_y<-glm(round(n_intact_seeds_rel_y)~n_fl_s_y,data_selag,family="poisson")
mod_n_intact_seeds2_GLM_y<-glm(round(n_intact_seeds_rel_y)~n_seeds_per_fl,data_selag,</pre>
```

kable(summary(mod_n_intact_seeds1_GLM_y)\$coefficients)

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-0.0594166	0.0213785	-2.779272	0.0054481
$n_fl_s_y$	0.3448890	0.0138490	24.903467	0.0000000

kable(summary(mod_n_intact_seeds1_GLMM_y)\$coefficients)

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-0.4248847	0.0453297	-9.373213	0
n_fl_s_y	0.2996889	0.0193150	15.515851	0

kable(summary(mod_n_intact_seeds2_GLM_y)\$coefficients)

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-0.3486902	0.0243480	-14.32109	0
$n_seeds_per_fl$	0.3787594	0.0091228	41.51796	0

kable(summary(mod_n_intact_seeds2_GLMM_y)\$coefficients)

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-0.8702585	0.0488369	-17.81970	0
${\tt n_seeds_per_fl}$	0.5200799	0.0186002	27.96095	0

kable(summary(mod_n_intact_seeds3_GLM_y)\$coefficients)

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-0.0190455	0.0517786	-0.3678267	0.7130025
$prop_seeds_esc$	0.9345432	0.0631235	14.8049894	0.0000000

kable(summary(mod_n_intact_seeds3_GLMM_y)\$coefficients)

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept) prop_seeds_esc	-0.3672086 1.0833125	$0.0685563 \\ 0.0742927$	-5.356305 14.581677	1e-07 0e+00

Correlation n fl - FFD

```
## ## Pearson's product-moment correlation
## ## data: n_fl_s_y and FFD_s_y
## t = -24.948, df = 2374, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## -0.4870403 -0.4232984
## sample estimates:
## cor
## -0.4557535</pre>
```

4. Models without climate (across years)

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-0.327	0.026	-12.37	0
FFD_s	-0.182	0.028	-6.48	0
grazing_corr	-2.212	0.216	-10.23	0
n_fl_s	-0.237	0.039	-6.04	0

kable(summary(mod_n_seeds_per_fl_noclim_GLMM)\$coefficients,digits=c(3,3,2,3))

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-0.481	0.041	-11.70	0
FFD_s	-0.183	0.031	-5.86	0
$grazing_corr$	-2.306	0.224	-10.31	0
n_fl_s	-0.227	0.043	-5.33	0

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	0.762	0.018	42.18	0
FFD_s	0.140	0.016	8.61	0
n_fl_s	-0.092	0.009	-10.24	0

kable(summary(mod_prop_seeds_esc_noclim_GLMM)\$coefficients,,digits=c(3,3,2,3))

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	1.456	0.088	16.46	0
FFD_s	-0.338	0.028	-12.26	0
n_fl_s	-0.077	0.015	-5.02	0

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-3.314	0.007	-500.70	0
n_fl_s FFD_s	-0.064 -0.327	$0.002 \\ 0.006$	-35.70 -58.29	$0 \\ 0$

kable(summary(mod_grazing_noclim_GLMM)\$coefficients,digits=c(3,3,2,3))

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-7.472	0.348	-21.47	0
n_fl_s FFD_s	-0.085	0.002 0.007	-34.80 -47.82	0
FFD_S	-0.328	0.007	-47.82	U

5. Models without climate (within years)

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-0.340	0.027	-12.73	0
FFD_s_y	-0.278	0.030	-9.40	0
$grazing_corr$	-2.229	0.216	-10.34	0
$n_fl_s_y$	-0.295	0.036	-8.30	0

kable(summary(mod_n_seeds_per_fl_noclim_GLMM_y)\$coefficients,digits=c(3,3,2,3))

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-0.511	0.042	-12.30	0
FFD_s_y	-0.295	0.034	-8.81	0
grazing_corr	-2.344	0.224	-10.48	0

	Estimate	Std. Error	z value	$\Pr(> z)$
n_fl_s_y	-0.313	0.040	-7.93	0

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	0.693	0.019	36.51	0.000
FFD_s_y	0.035	0.021	1.69	0.091
$n_fl_s_y$	-0.090	0.012	-7.49	0.000

kable(summary(mod_prop_seeds_esc_noclim_GLMM_y)\$coefficients,,digits=c(3,3,2,3))

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	1.386	0.080	17.25	0.000
FFD_s_y	-0.085	0.031	-2.72	0.007
$n_fl_s_y$	-0.109	0.022	-4.94	0.000

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept) n fl s y	-3.082 -0.069	0.005 0.003	-660.71 -20.71	0
FFD_s_y	-0.117	0.005	-20.71	0

kable(summary(mod_grazing_noclim_GLMM_y)\$coefficients,digits=c(3,3,2,3))

	Estimate	Std. Error	z value	$\Pr(> z)$
(Intercept)	-7.629	0.355	-21.46	0
$n_fl_s_y$	-0.137	0.005	-26.57	0
FFD_s_y	-0.143	0.007	-19.58	0