SEMs with presence ants, standardized coefficients

> #Model attack####

> model8\_1<-lm(phen\_int~meanT+moist\_per+meanT:moist\_per,as.data.frame(allplants))

> model8\_2<-glm(Mrub\_sch\_s\_pres~meanT+moist\_per+meanT:moist\_per,as.data.frame(allplants),family="binomial")

> model8\_3<-lm(suit\_neigh~meanT+moist\_per+meanT:moist\_per,as.data.frame(allplants))

> model8\_4<-glm(attack\_f~phen\_int+Mrub\_sch\_s\_pres+phen\_int:Mrub\_sch\_s\_pres+suit\_neigh+meanT+moist\_per,as.data.frame(allplants),family="binomial")

> model8\_5<-lm(seeds\_per\_fl~phen\_int+meanT+moist\_per+attack\_f,as.data.frame(allplants))

$Fisher.C

fisher.c df p.value

1 10.43 10 0.404

$AIC

AIC AICc K n

1 64.43 67.979 27 454

Class Family Link n R.squared

1 lm gaussian identity 8848 0.1150905

2 glm binomial logit 8852 0.1825483

3 lm gaussian identity 8852 0.3702739

4 glm binomial logit 8848 0.3749710

5 lm gaussian identity 454 0.1883276

response predictor estimate std.error p.value

1 phen\_int moist\_per -0.37965854 0.011448715 0.0000 \*\*\*

2 phen\_int meanT -0.14054179 0.011546385 0.0000 \*\*\*

3 phen\_int meanT:moist\_per 0.05310500 0.011305695 0.0000 \*\*\*

4 Mrub\_sch\_s\_pres moist\_per -1.15084324 0.030799348 0.0000 \*\*\*

5 Mrub\_sch\_s\_pres meanT:moist\_per 0.48466854 0.030527831 0.0000 \*\*\*

6 Mrub\_sch\_s\_pres meanT 0.08647461 0.031385579 0.0059 \*\*

7 suit\_neigh moist\_per 0.44011146 0.009650630 0.0000 \*\*\*

8 suit\_neigh meanT:moist\_per 0.35209050 0.009533297 0.0000 \*\*\*

9 suit\_neigh meanT 0.11253369 0.009735974 0.0000 \*\*\*

10 attack\_f suit\_neigh -1.90271005 0.089117369 0.0000 \*\*\*

11 attack\_f phen\_int 1.26004704 0.089253108 0.0000 \*\*\*

12 attack\_f meanT 0.70824749 0.058016167 0.0000 \*\*\*

13 attack\_f moist\_per 0.43839493 0.059152928 0.0000 \*\*\*

14 attack\_f phen\_int:Mrub\_sch\_s\_pres 0.31278939 0.149664323 0.0366 \*

15 attack\_f Mrub\_sch\_s\_pres -0.24889610 0.157773527 0.1147

16 seeds\_per\_fl attack\_f1 -0.89887030 0.094058664 0.0000 \*\*\*

17 seeds\_per\_fl phen\_int 0.10518473 0.068389375 0.1247

18 seeds\_per\_fl meanT -0.05517473 0.049988814 0.2703

19 seeds\_per\_fl moist\_per -0.02278059 0.044558101 0.6094

20 ~~ phen\_int ~~ Mrub\_sch\_s\_pres -0.01628804 NA 0.9373

21 ~~ phen\_int ~~ suit\_neigh -0.02217326 NA 0.9815

22 ~~ suit\_neigh ~~ Mrub\_sch\_s\_pres -0.05899978 NA 1.0000

> #Model n eggs####

>

> model9\_1<-lm(phen\_int~meanT+moist\_per+meanT:moist\_per,as.data.frame(allplants))

> model9\_2<-glm(Mrub\_sch\_s\_pres~meanT+moist\_per+meanT:moist\_per,as.data.frame(allplants),family="binomial")

> model9\_3<-lm(suit\_neigh~meanT+moist\_per+meanT:moist\_per,as.data.frame(allplants))

> model9\_4<-glm.nb(n\_eggs\_max~phen\_int+Mrub\_sch\_s\_pres+suit\_neigh+meanT+moist\_per,subset(as.data.frame(allplants),n\_eggs\_max>0))

> model9\_5<-lm(seeds\_per\_fl~phen\_int+meanT+moist\_per+scale(n\_eggs\_max),subset(as.data.frame(allplants),n\_eggs\_max>0))

$Fisher.C

fisher.c df p.value

1 7.49 8 0.485

$AIC

AIC AICc K n

1 61.49 72.29 27 168

Class Family Link n R.squared

1 lm gaussian identity 8848 0.1150905

2 glm binomial logit 8852 0.1825483

3 lm gaussian identity 8852 0.3702739

4 negbin Negative Binomial log 731 0.1493221

5 lm gaussian identity 168 0.1209474

response predictor estimate std.error p.value

1 phen\_int moist\_per -0.37965854 0.011448715 0.0000 \*\*\*

2 phen\_int meanT -0.14054179 0.011546385 0.0000 \*\*\*

3 phen\_int meanT:moist\_per 0.05310500 0.011305695 0.0000 \*\*\*

4 Mrub\_sch\_s\_pres moist\_per -1.15084324 0.030799348 0.0000 \*\*\*

5 Mrub\_sch\_s\_pres meanT:moist\_per 0.48466854 0.030527831 0.0000 \*\*\*

6 Mrub\_sch\_s\_pres meanT 0.08647461 0.031385579 0.0059 \*\*

7 suit\_neigh moist\_per 0.44011146 0.009650630 0.0000 \*\*\*

8 suit\_neigh meanT:moist\_per 0.35209050 0.009533297 0.0000 \*\*\*

9 suit\_neigh meanT 0.11253369 0.009735974 0.0000 \*\*\*

10 n\_eggs\_max suit\_neigh -2.04385440 0.078305323 0.0000 \*\*\*

11 n\_eggs\_max phen\_int 1.57142263 0.068153859 0.0000 \*\*\*

12 n\_eggs\_max meanT 0.76439236 0.057873316 0.0000 \*\*\*

13 n\_eggs\_max moist\_per 0.55606746 0.062056183 0.0000 \*\*\*

14 n\_eggs\_max Mrub\_sch\_s\_pres 0.09911743 0.108154082 0.3594

15 seeds\_per\_fl scale(n\_eggs\_max) -0.16242619 0.020322152 0.0000 \*\*\*

16 seeds\_per\_fl meanT -0.07170348 0.051205344 0.1621

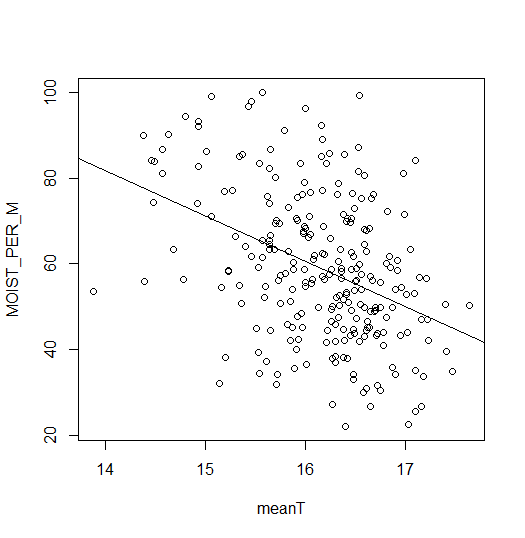
17 seeds\_per\_fl phen\_int 0.07917703 0.070120206 0.2594

18 seeds\_per\_fl moist\_per -0.02202963 0.045756780 0.6304

19 ~~ phen\_int ~~ Mrub\_sch\_s\_pres -0.01628804 NA 0.9373

20 ~~ phen\_int ~~ suit\_neigh -0.02217326 NA 0.9815

21 ~~ suit\_neigh ~~ Mrub\_sch\_s\_pres -0.05899978 NA 1.0000

Relation among temperature and moisture, “real” values (from data points)

Correlation: -0.4048787

> with(data\_pts,summary(lm(MOIST\_PER\_M~meanT)))

Call:

lm(formula = MOIST\_PER\_M ~ meanT)

Residuals:

Min 1Q Median 3Q Max

-37.447 -10.837 -0.717 9.872 44.173

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 229.320 24.528 9.349 < 2e-16 \*\*\*

meanT -10.543 1.518 -6.945 3.36e-11 \*\*\*

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Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 15.65 on 246 degrees of freedom

(6 observations deleted due to missingness)

Multiple R-squared: 0.1639, Adjusted R-squared: 0.1605

F-statistic: 48.23 on 1 and 246 DF, p-value: 3.359e-11

PCA with all values (could also make PCA with data points and interpolate those axes)

|  |  |
| --- | --- |
|  |  |

Importance of components:

PC1 PC2

Standard deviation 1.1701 0.7943

Proportion of Variance 0.6846 0.3154

Cumulative Proportion 0.6846 1.0000

Standard deviations (1, .., p=2):

[1] 1.1701088 0.7942578

Rotation (n x k) = (2 x 2):

PC1 PC2

allplants$meanT 0.7071068 0.7071068

allplants$moist\_per -0.7071068 0.7071068

SEMs with PC1+PC2 instead of temperature and moisture, standardized coefficients

After model selection based on AICc

> #Model attack####

> model10\_1<-lm(phen\_int~PC1+PC2,as.data.frame(allplants))

> model10\_2<-glm(Mrub\_sch\_s\_pres~PC1+PC2,as.data.frame(allplants),family="binomial")

> model10\_3<-lm(suit\_neigh~PC1+PC2,as.data.frame(allplants))

> model10\_4<-glm(attack\_f~phen\_int+Mrub\_sch\_s\_pres+phen\_int:Mrub\_sch\_s\_pres+suit\_neigh+PC1+PC2,as.data.frame(allplants),family="binomial")

> model10\_5<-lm(seeds\_per\_fl~phen\_int+attack\_f,as.data.frame(allplants))

$Fisher.C

fisher.c df p.value

1 27.82 18 0.065

$AIC

AIC AICc K n

1 71.82 74.168 22 454

Class Family Link n R.squared

1 lm gaussian identity 8848 0.1128828

2 glm binomial logit 8852 0.1572797

3 lm gaussian identity 8852 0.2731941

4 glm binomial logit 8848 0.3749710

5 lm gaussian identity 454 0.1860952

response predictor estimate std.error p.value

1 phen\_int PC2 -0.2708633 0.010017908 0.0000 \*\*\*

2 phen\_int PC1 0.1989511 0.010013814 0.0000 \*\*\*

3 Mrub\_sch\_s\_pres PC1 0.8692477 0.028337828 0.0000 \*\*\*

4 Mrub\_sch\_s\_pres PC2 -0.4876318 0.025602813 0.0000 \*\*\*

5 suit\_neigh PC2 0.4513440 0.009062794 0.0000 \*\*\*

6 suit\_neigh PC1 -0.2635957 0.009062794 0.0000 \*\*\*

7 attack\_f suit\_neigh -1.9027101 0.089117369 0.0000 \*\*\*

8 attack\_f phen\_int 1.2600470 0.089253108 0.0000 \*\*\*

9 attack\_f PC2 0.6439831 0.057831865 0.0000 \*\*\*

10 attack\_f PC1 0.2232738 0.046264299 0.0000 \*\*\*

11 attack\_f phen\_int:Mrub\_sch\_s\_pres 0.3127894 0.149664323 0.0366 \*

12 attack\_f Mrub\_sch\_s\_pres -0.2488961 0.157773527 0.1147

13 seeds\_per\_fl attack\_f1 -0.9187378 0.090954914 0.0000 \*\*\*

14 seeds\_per\_fl phen\_int 0.1086748 0.068253759 0.1120

#Model n eggs####

> model11\_1<-lm(phen\_int~PC1+PC2,as.data.frame(allplants))

> model11\_2<-glm(Mrub\_sch\_s\_pres~PC1+PC2,as.data.frame(allplants),family="binomial")

> model11\_3<-lm(suit\_neigh~PC1+PC2,as.data.frame(allplants))

> model11\_4<-glm.nb(n\_eggs\_max~phen\_int+suit\_neigh+PC1+PC2,subset(as.data.frame(allplants),n\_eggs\_max>0))

> model11\_5<-lm(seeds\_per\_fl~scale(n\_eggs\_max),subset(as.data.frame(allplants),n\_eggs\_max>0))

$Fisher.C

fisher.c df p.value

1 18.18 18 0.444

$AIC

AIC AICc K n

1 58.18 63.894 20 168

Class Family Link n R.squared

1 lm gaussian identity 8848 0.11288285

2 glm binomial logit 8852 0.15727972

3 lm gaussian identity 8852 0.27319414

4 negbin Negative Binomial log 731 0.14924581

5 lm gaussian identity 168 0.07334824

response predictor estimate std.error p.value

1 phen\_int PC2 -0.2708633 0.010017908 0e+00 \*\*\*

2 phen\_int PC1 0.1989511 0.010013814 0e+00 \*\*\*

3 Mrub\_sch\_s\_pres PC1 0.8692477 0.028337828 0e+00 \*\*\*

4 Mrub\_sch\_s\_pres PC2 -0.4876318 0.025602813 0e+00 \*\*\*

5 suit\_neigh PC2 0.4513440 0.009062794 0e+00 \*\*\*

6 suit\_neigh PC1 -0.2635957 0.009062794 0e+00 \*\*\*

7 n\_eggs\_max suit\_neigh -2.0485015 0.078199928 0e+00 \*\*\*

8 n\_eggs\_max phen\_int 1.5765818 0.068160965 0e+00 \*\*\*

9 n\_eggs\_max PC2 0.7321932 0.057856431 0e+00 \*\*\*

10 n\_eggs\_max PC1 0.1810611 0.046823896 1e-04 \*\*\*

11 seeds\_per\_fl scale(n\_eggs\_max) -0.1623548 0.019068619 0e+00 \*\*\*

Relation among temperature and seeds

|  |  |  |
| --- | --- | --- |
| All plants | Plants with eggs | Plants without eggs |
|  |  |  |
| \* | NS | NS |

N=454 for the model with all plants (all plants where seed data was available)

Difference with other models of the path analyses where n>8000