Buds Experiment

FALSE SPRING EVENTS

CATHERINE CHAMBERLAIN

False Spring Risk

Interested in time between leaf budburst and leafout,
when frost tolerance is lowest but risk is still relatively high.

BUDBURST → LEAFOUT

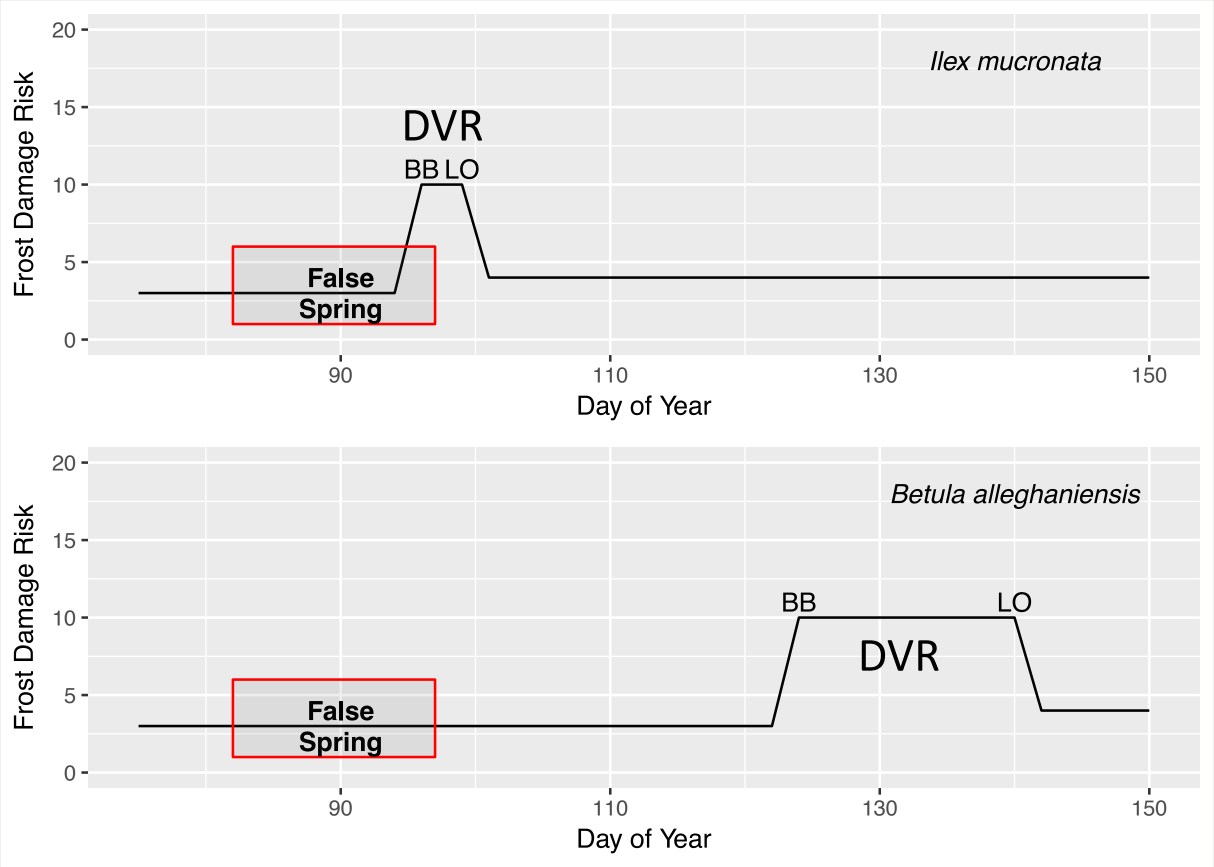
DURATION OF VEGETATIVE RISK

Alnus incana - budburst

Betula populifolia - leafout

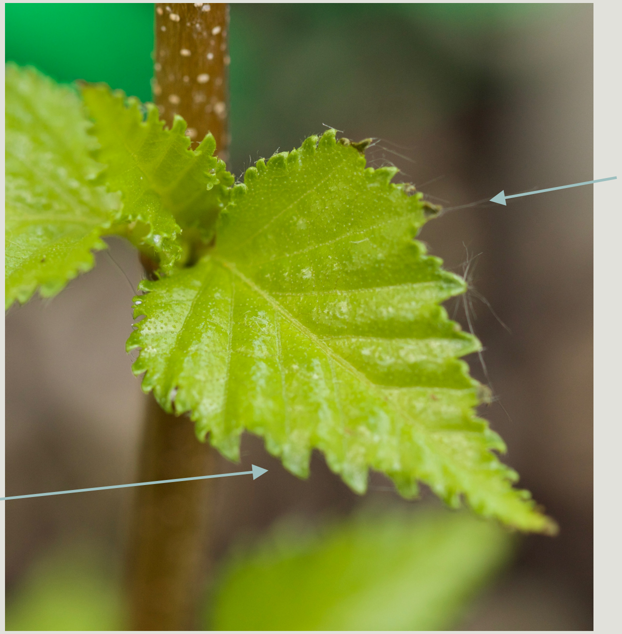
STRATEGIES:

Avoidance



Tolerance

Trichomes on young leaves



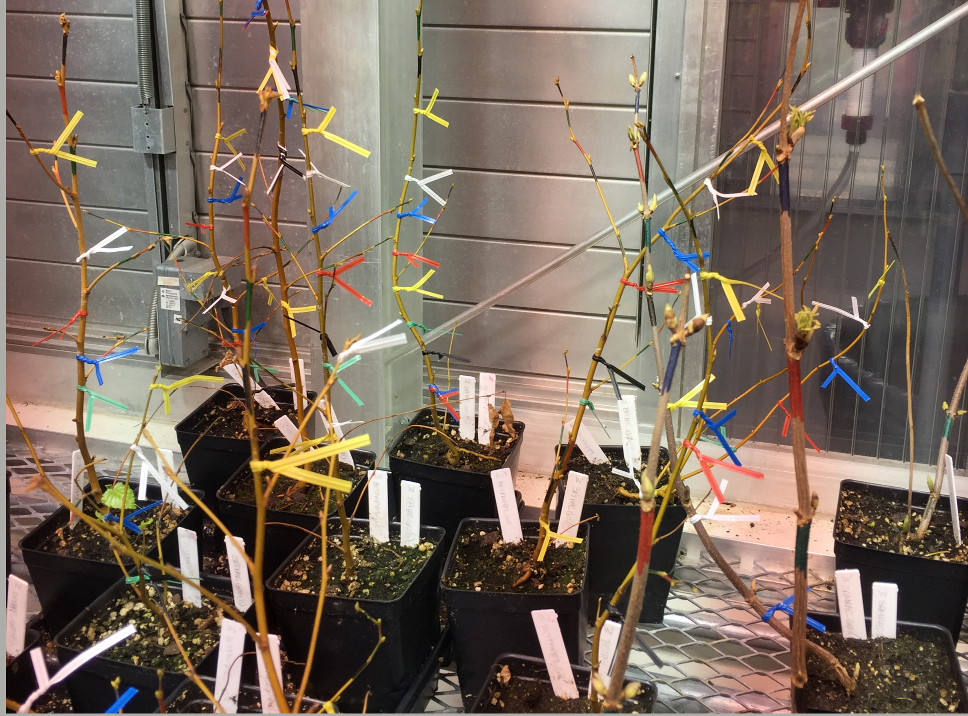
Serrations along leave margins

Buds Experiment

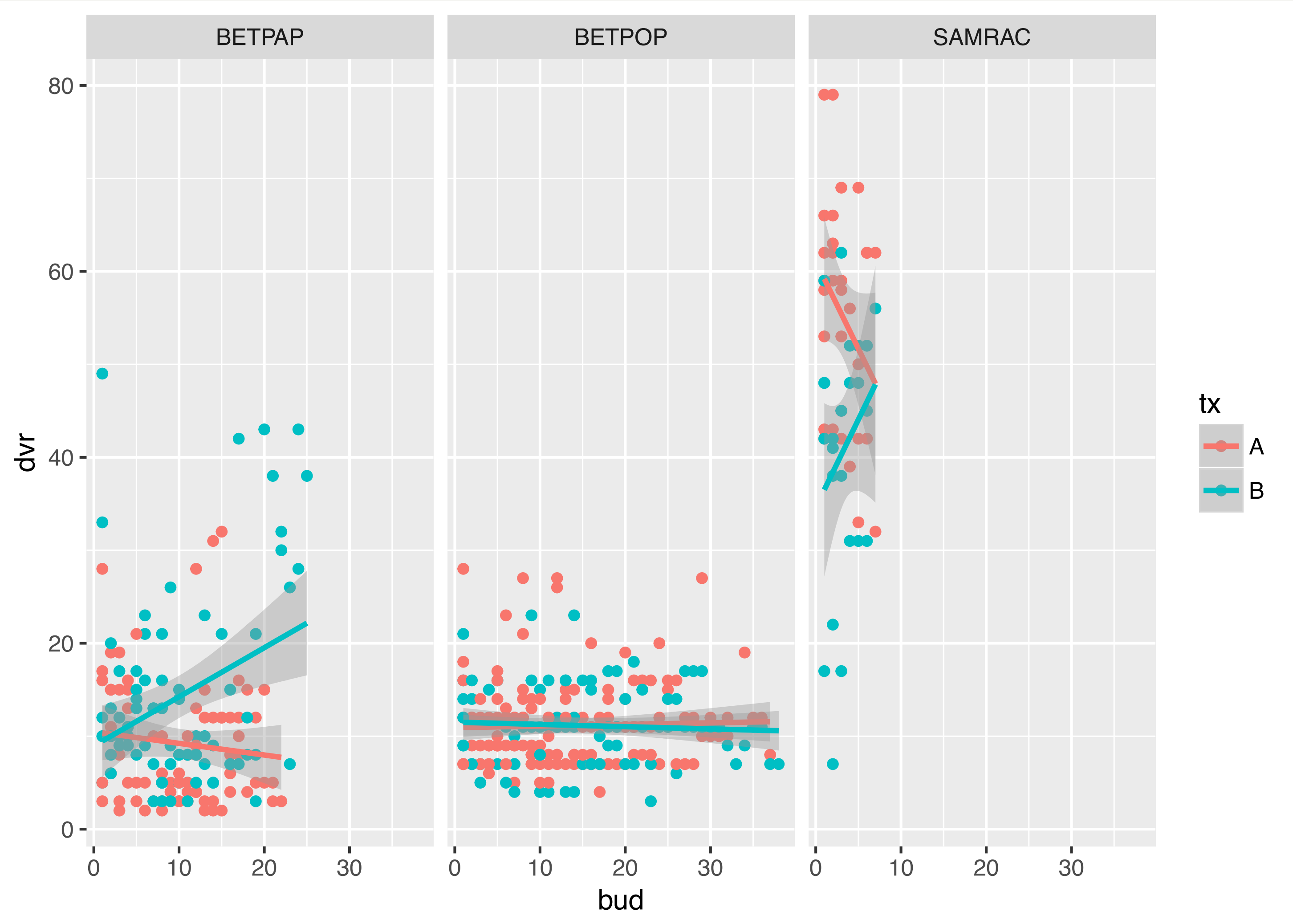
Freezing Experiment with greenhouse individuals

Put individuals in growth chamber at

-3degC between budburst and leafout




BETPAP
BETPOP
dvr
bud
0
10
20
30
40
50
as.factor(tx)
A
B



Sambucus racemosa hit by pests…

Species: 2-3 -- BETPAP, BETPOP, SAMRAC (?)
Individuals: 14-18
Buds: 6-36
TX: Control vs. Freeze

$$dvr \sim tx + species + (1|individual)$$

DVR: Duration of Vegetative Risk

FAKE DATA: 2 ways (still testing...)

Apply Version

```r
nrep <- 22
nind <- 7; ind_sd<-0.1
nsp <- 2; sp_sd<-0.3
ntx <- 2; tx_sd<-1


## Generate Random Y Response Data that follows studies nesting structure
rep_means <- rnorm(nrep, mean = 11, sd = 3)
ind_means <- lapply(rep_means, function(x) rnorm(nind, mean = x, sd = ind_sd))
sp_means <- lapply(ind_means, function(x) rnorm(nsp, mean = x, sd = sp_sd) )
tx_means <- lapply(unlist(sp_means), function(x) rnorm(ntx, mean = x, sd = tx_sd))


## Put Together X Predictor Matrix
ntot <-  nsp * ntx * nind * nrep
x_mat <- data.frame(buds = rep(1:(nrep), each = ntot/nrep),
                    species = rep(1:(nsp), each = nrep*nind*nsp),
                    tx =   rep( 1:(ntx), each=nsp*nind),
                    ind =  rep(1:(nind), each=nrep))

## Add in response for full fake dataset
x_mat <- x_mat[order(x_mat$species, x_mat$tx, x_mat$ind),]
#x_mat$dvr<-rnorm(n_pops, mean = 11, sd = 5)
x_mat$dvr <- unlist(tx_means)
fake_data <- x_mat

# now fix the levels to 0/1 (not 1/2) as R does
fake_data$tx <- as.numeric(fake_data$tx)
fake_data$tx[fake_data$tx==1] <- 0
fake_data$tx[fake_data$tx==2] <- 1
```

Looping

```r
##### Again, now with individuals.

baseinter = 11 # baseline intercept across all individuals
spint <- baseinter + c(1:nind)-mean(1:nind) # different intercepts by individual

fake <- vector()

for(i in 1:nind){ # loop over individual (random effect)

  # Give individuals different difference values, drawn from normal
  coeff <- c(spint[i],
             rnorm(1, spdiff, spdiff.sd),
             rnorm(1, txdiff, txdiff.sd)
  )

  dvr <- rnorm(n = length(tx), mean = mm %*% coeff, sd = 0.1)

  fakex <- data.frame(dvr, ind = i, sp, tx)

  fake <- rbind(fake, fakex)
  }

summary(lm(dvr ~ (sp+tx)^2, data = fake)) # sanity check
```

Stan_glmer (dvr ~ tx + species + (1|ind))

Fake: apply version

```
stan_glmer
 family:  gaussian [identity]
 formula: dvr ~ tx + species + (1 | ind)
------

Estimates:
            Median MAD_SD
(Intercept) 10.0    0.4
tx          -0.2    0.3
species      0.2    0.3
sigma        3.3    0.1

Error terms:
 Groups   Name        Std.Dev.
 ind      (Intercept) 0.19
 Residual             3.33
Num. levels: ind 7

Sample avg. posterior predictive
distribution of y (X = xbar):
         Median MAD_SD
mean_PPD 10.2    0.2
```

Fake: loop version

```
stan_glmer
 family:  gaussian [identity]
 formula: dvr ~ tx + sp + (1 | ind)
------

Estimates:
            Median MAD_SD
(Intercept) 10.5    0.7
tx           2.7    0.1
sp           0.5    0.1
sigma        0.7    0.0

Error terms:
 Groups   Name        Std.Dev.
 ind      (Intercept) 1.94
 Residual             0.73
Num. levels: ind 7

Sample avg. posterior predictive
distribution of y (X = xbar):
         Median MAD_SD
mean_PPD 12.6    0.0
```

Real!

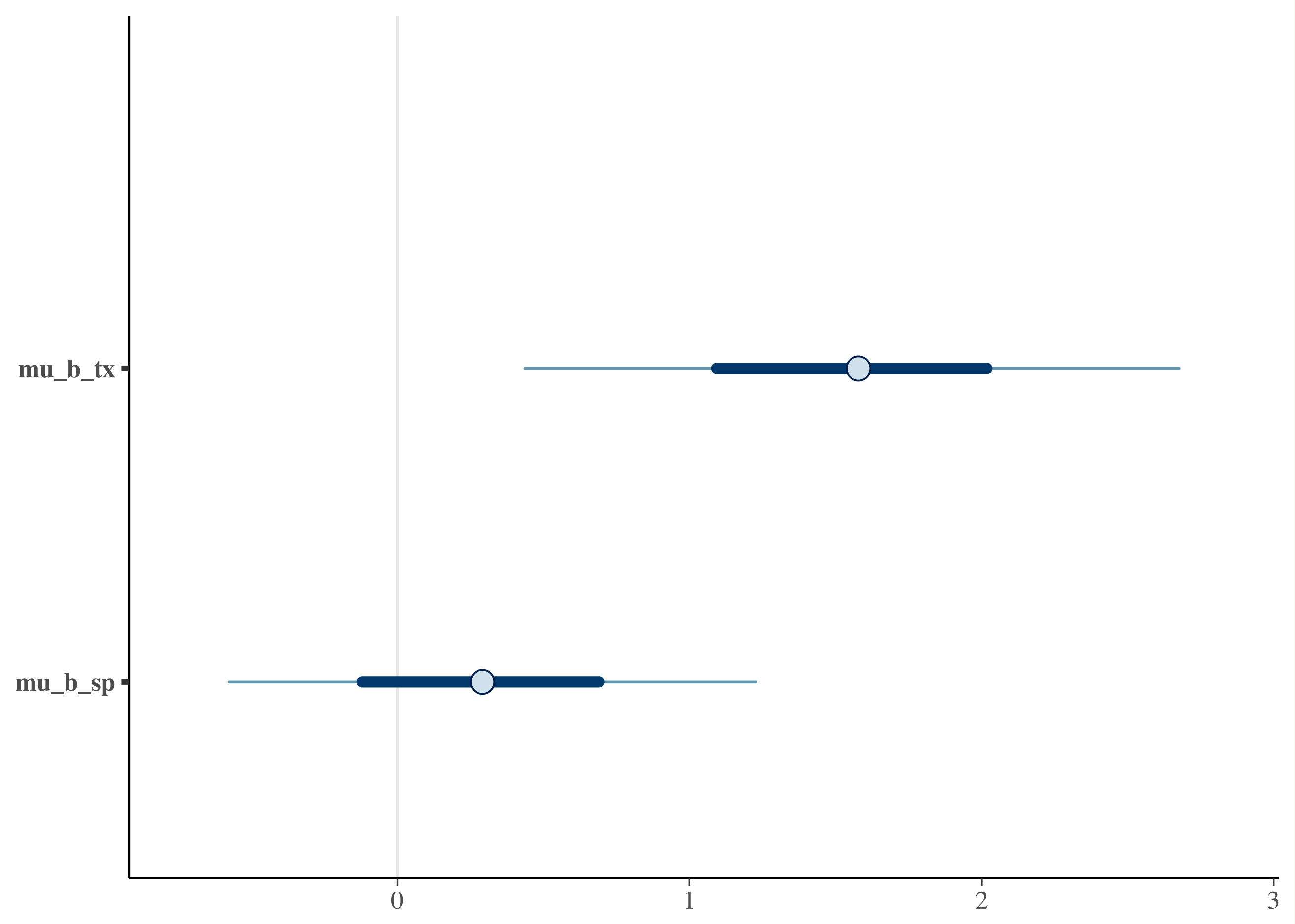
```
stan_glmer
 family:  gaussian [identity]
 formula: dvr ~ tx + sp + (1 | ind)
------

Estimates:
            Median MAD_SD
(Intercept) 10.5    1.8
tx           1.5    0.6
sp           0.4    0.7
sigma        6.3    0.2

Error terms:
 Groups   Name        Std.Dev.
 ind      (Intercept) 3.7
 Residual             6.3
Num. levels: ind 8

Sample avg. posterior predictive
distribution of y (X = xbar):
         Median MAD_SD
mean_PPD 11.4    0.4
```

Stan Model

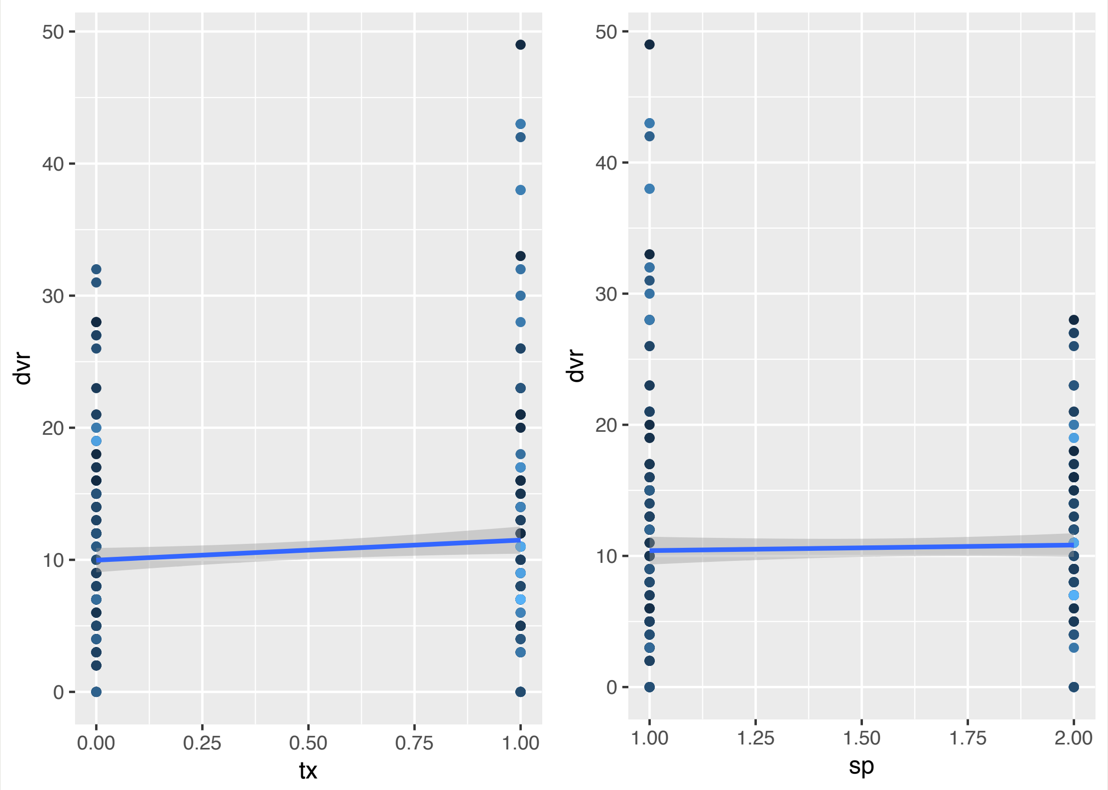
```
data {
  int<lower=0> N;
  int<lower=0> n_ind;
  int<lower=0> n_sp;
  int<lower=1, upper=n_ind> ind[N];
  vector[N] dvr;
  vector[N] tx;
  vector[N] sp;

}

parameters {
  vector[n_ind] a_ind;
  vector[n_ind] b_tx;
  vector[n_ind] b_sp;

  real mu_a;
  real mu_b_tx;
  real mu_b_sp;

  real<lower=0> sigma_b_tx;
  real<lower=0> sigma_b_sp;

  real<lower=0> sigma_a;

  real<lower=0> sigma_y;

}
```

```
transformed parameters {
    vector[N] y_hat;

  for(i in 1:N){
    y_hat[i] = a_ind[ind[i]] +
    b_sp[ind[i]] * sp[i] +
    b_tx[ind[i]] * tx[i]
    ;

    }

}

model {
  // Priors. Make them flat
  mu_b_tx ~ normal(0, 5);
  mu_b_sp ~ normal(0, 2);

  sigma_b_tx ~ normal(0, 1);
  sigma_b_sp ~ normal(0, .5);

  a_ind ~ normal(mu_a, sigma_a);

  b_tx ~ normal(mu_b_tx, sigma_b_tx);
  b_sp ~ normal(mu_b_sp, sigma_b_sp);

  dvr ~ normal(y_hat, sigma_y);

}
```

Real Data Output

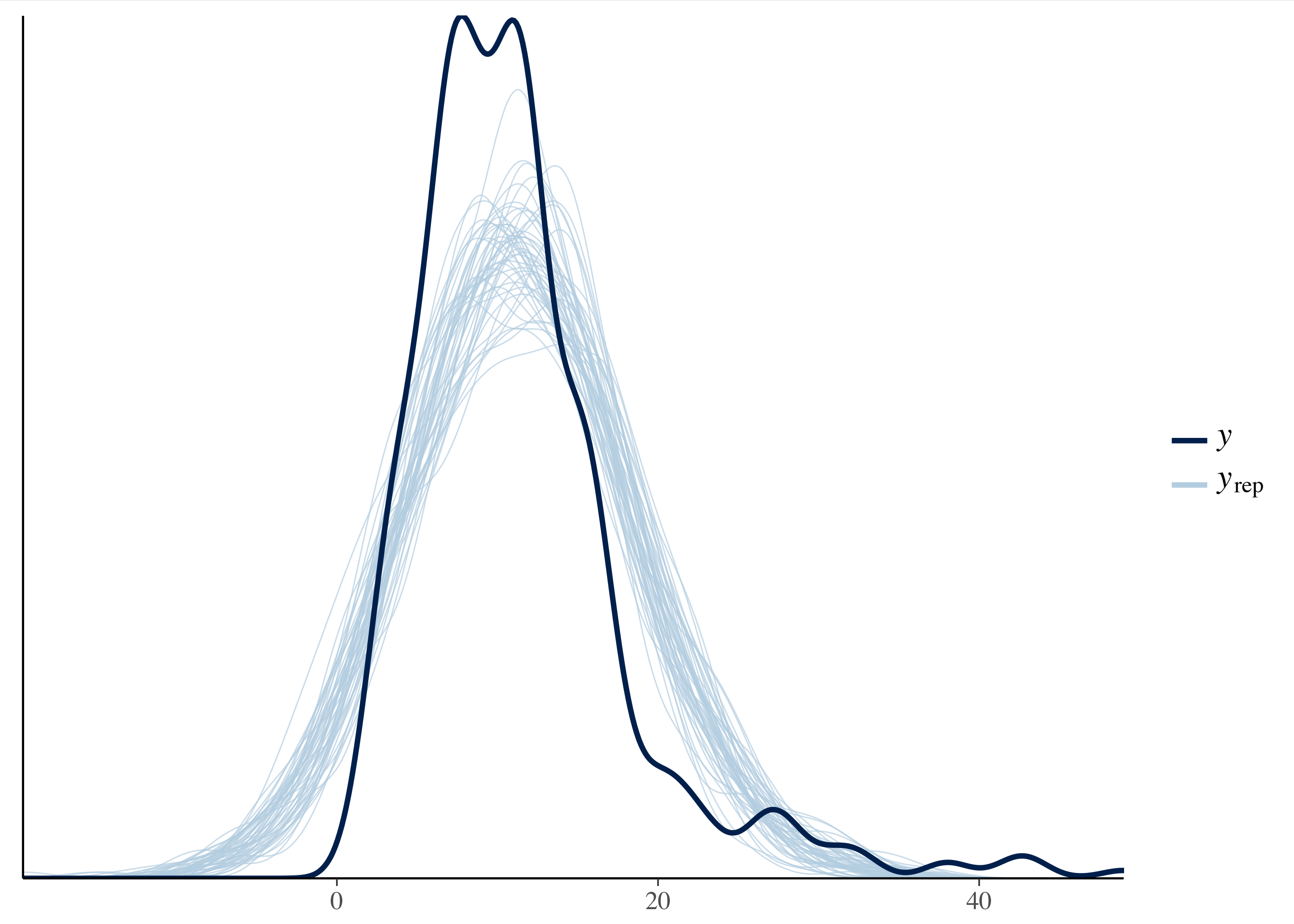


BETPAP = Sp 1
BETPOP = Sp 2

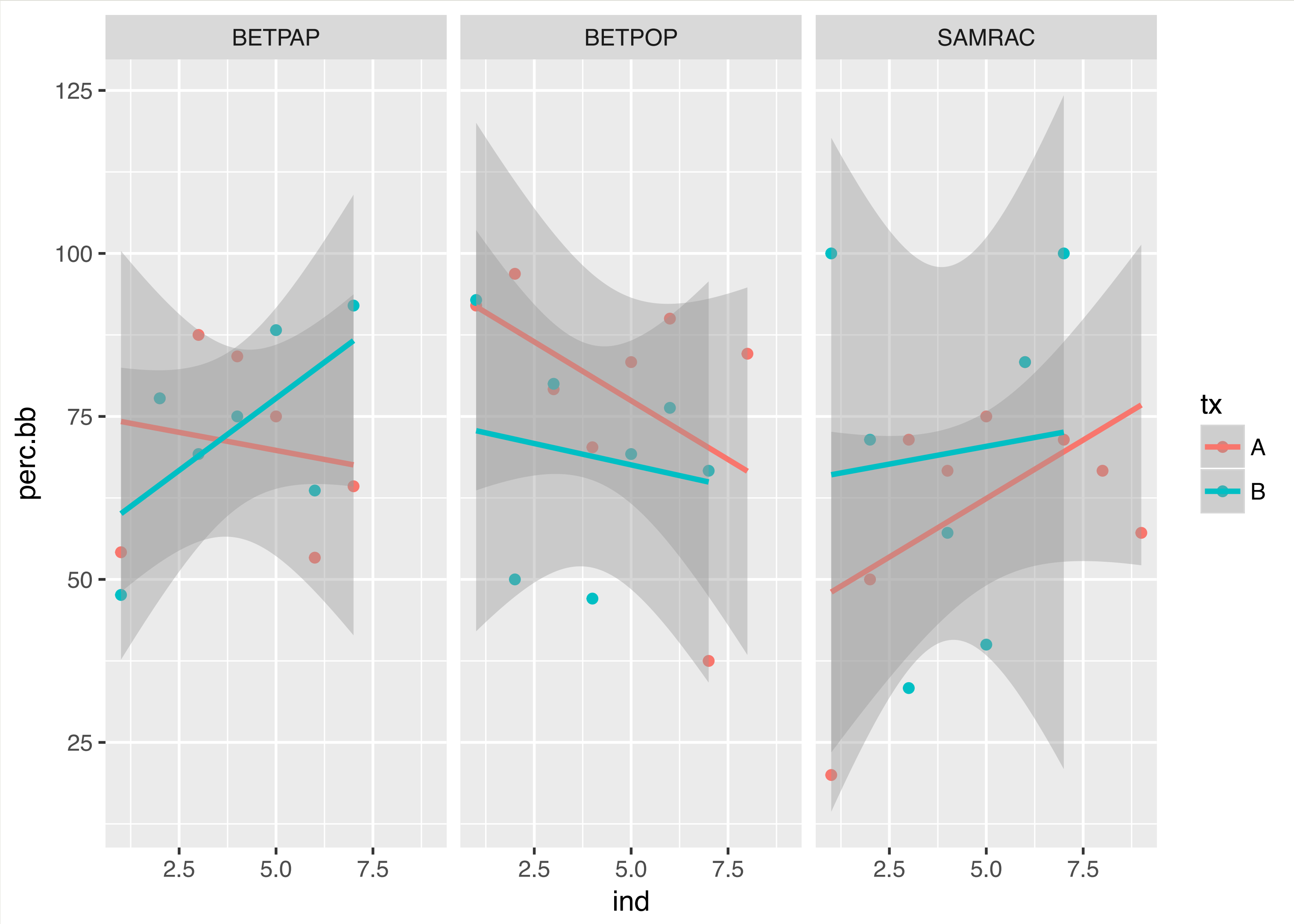


dvr ~ tx + species + (1|individual)

PP_Check



Percent Budburst Model: percBB ~ tx + species

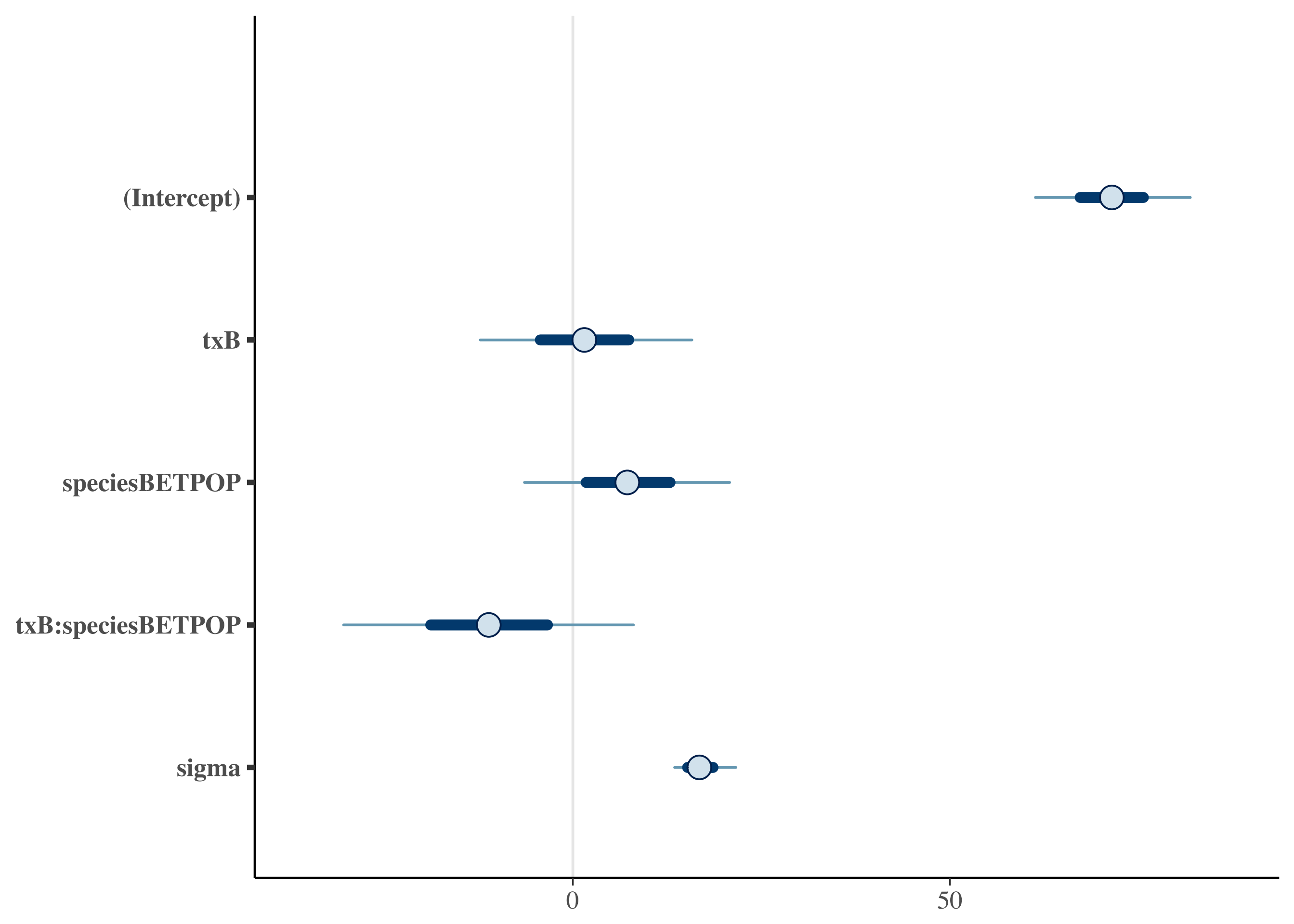


Dove straight into the Real data...

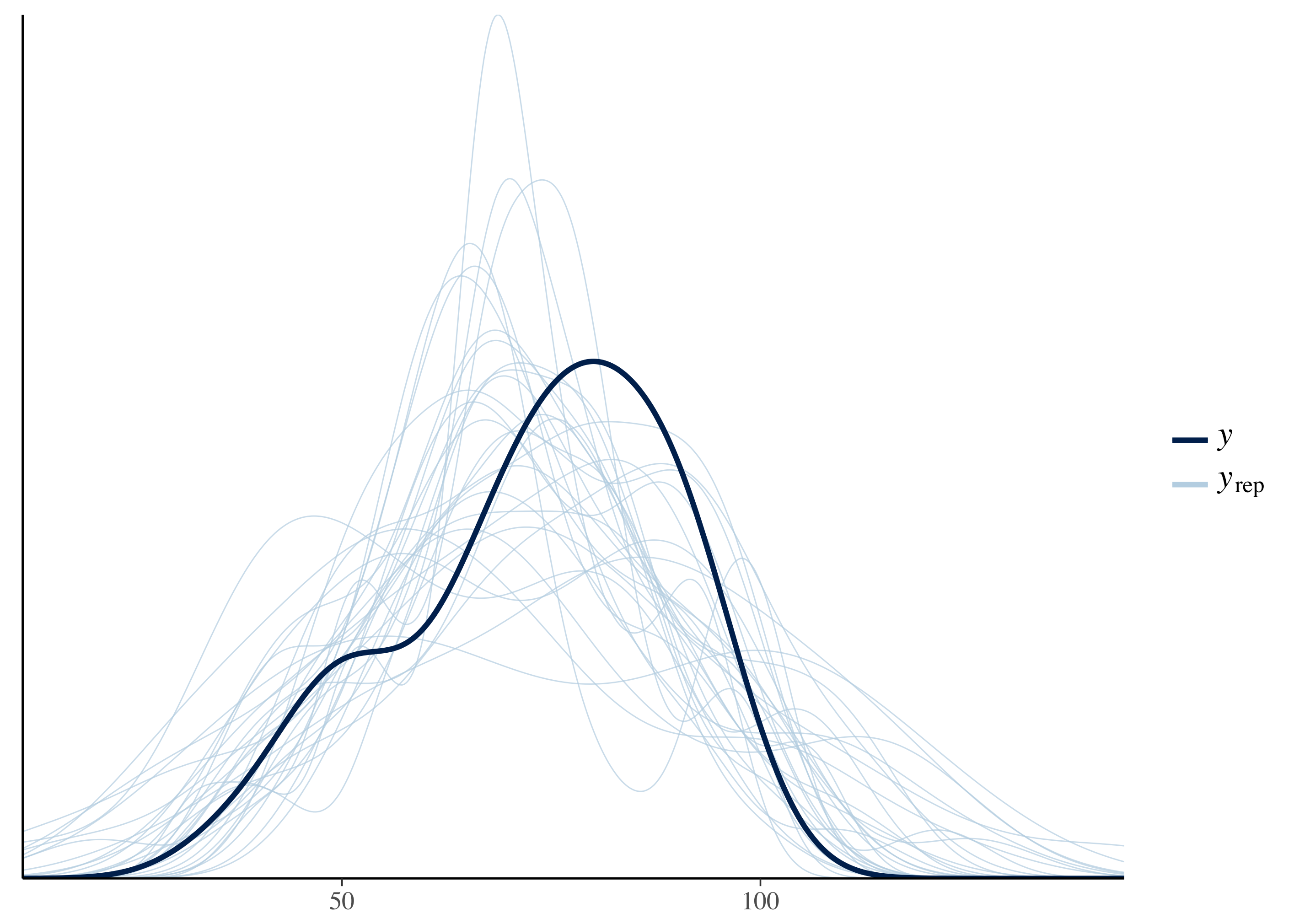
** Need to make fake data and start learning about Beta Distribution models

** Not including *Sambucus racemosa*

```
stan_glm
 family:  gaussian [identity]
 formula: perc.bb ~ tx + species
------

Estimates:
              Median MAD_SD
(Intercept)   74.1    5.4
txB           -3.9    6.2
speciesBETPOP  2.0    6.2
sigma         16.8    2.3

Sample avg. posterior predictive
distribution of y (X = xbar):
         Median MAD_SD
mean_PPD 73.3    4.4
```



PP_check



Next Steps…

1. Make models for each species: incorporate *Sambucus racemosa*

2. Work on Posterior Predictive Checks

3. Try to learn about Beta Distribution models

    a) % budburst ~ tx + species + (1|individual)

4. Somehow evaluate both models