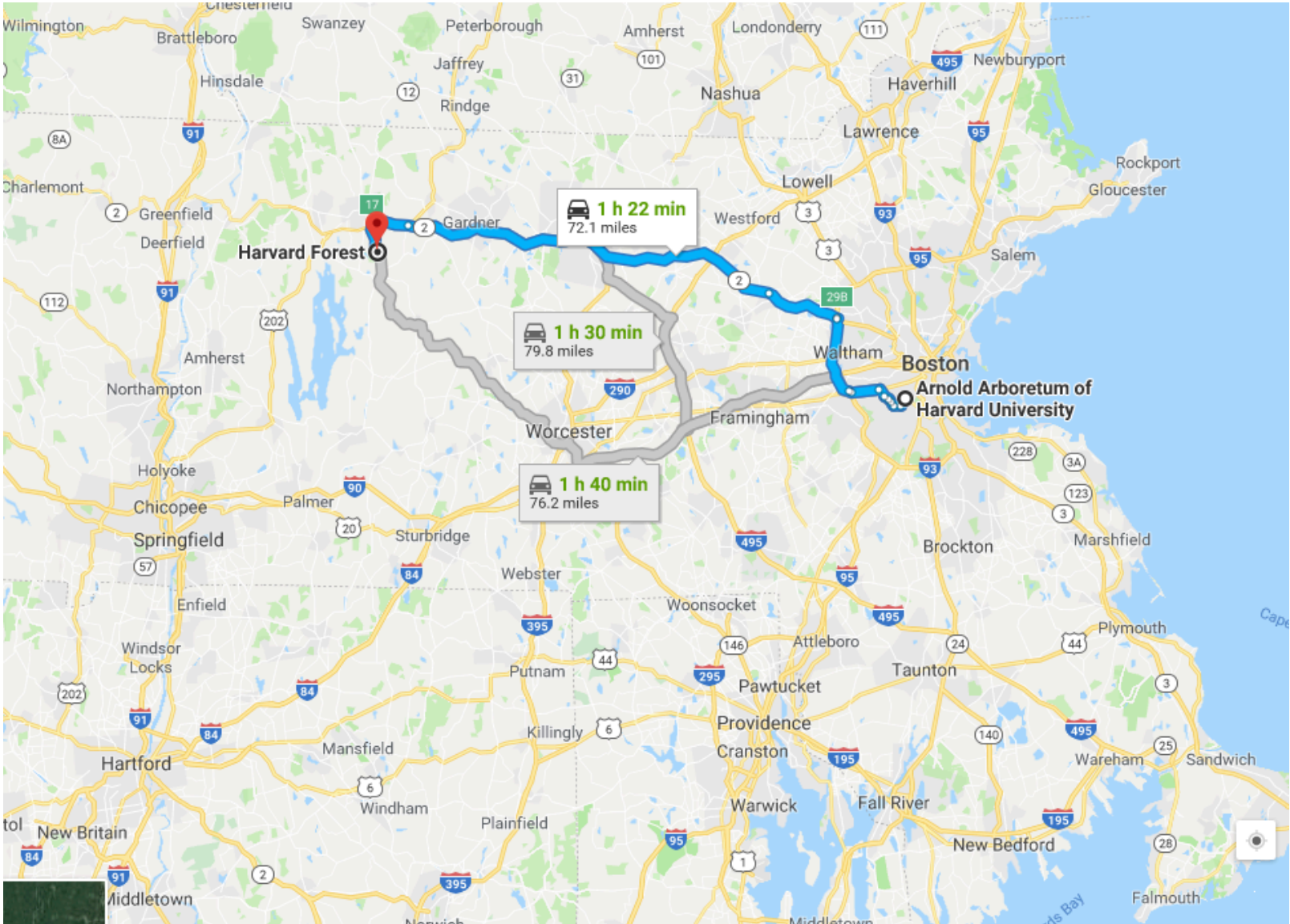


# Study Question:



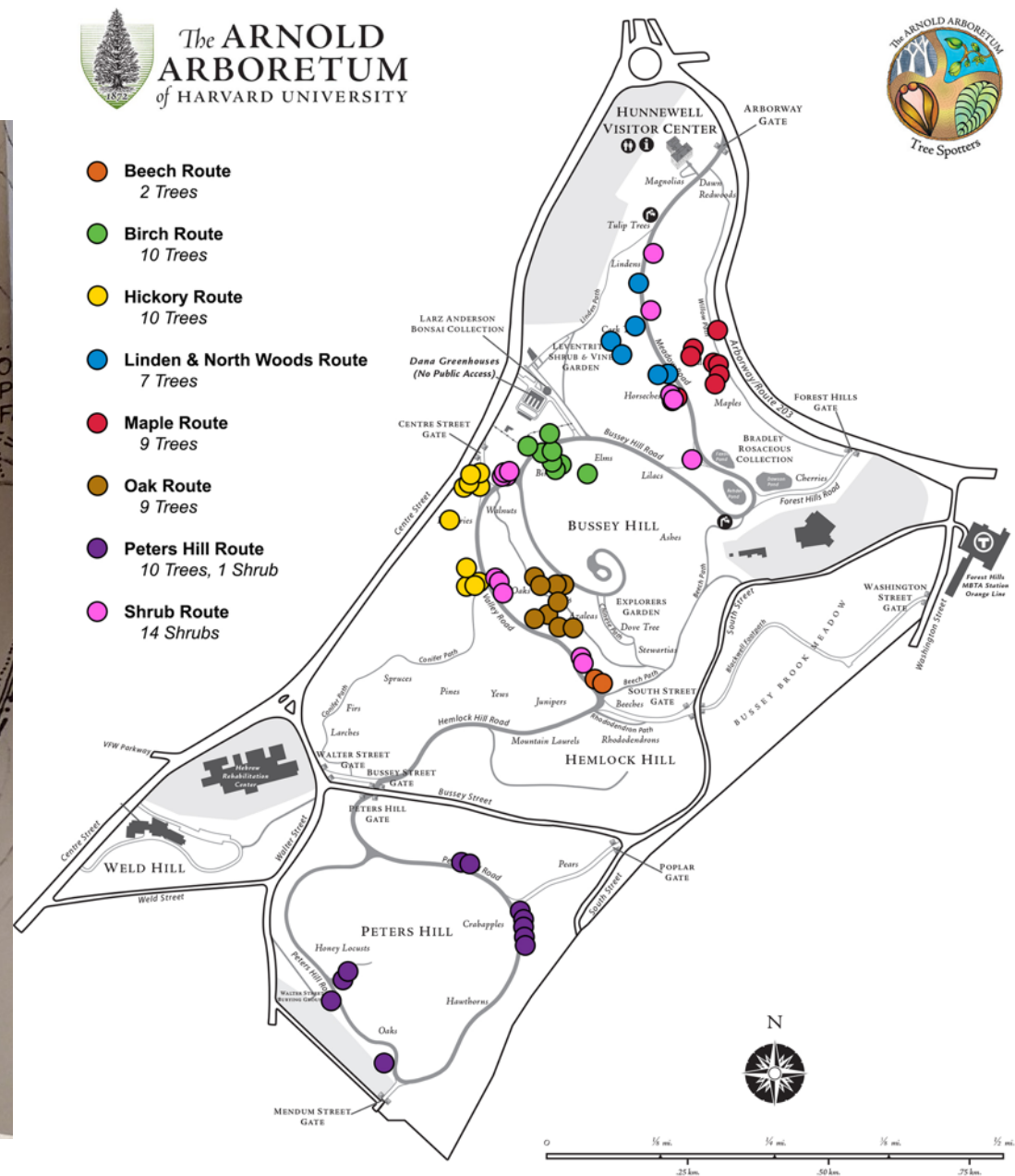
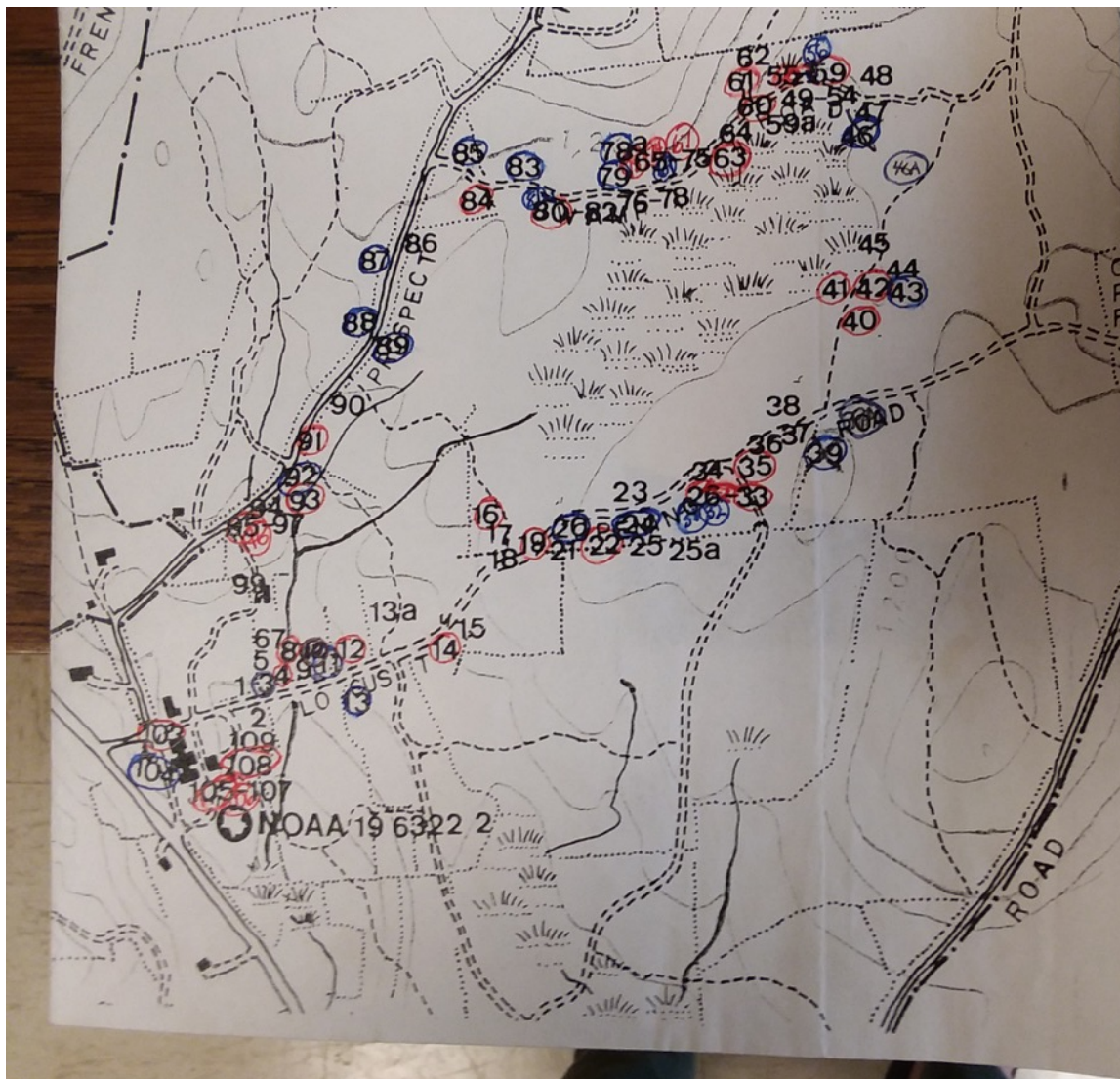
HARVARD FOREST



ARNOLD ARBORETUM







## APPROACH 1:

How do GDDs to leafout compare between hobo logger data and weather station data?

And how do these compare across sites?

$$\text{GDDs} \sim 1 + (1 \mid \text{species})$$

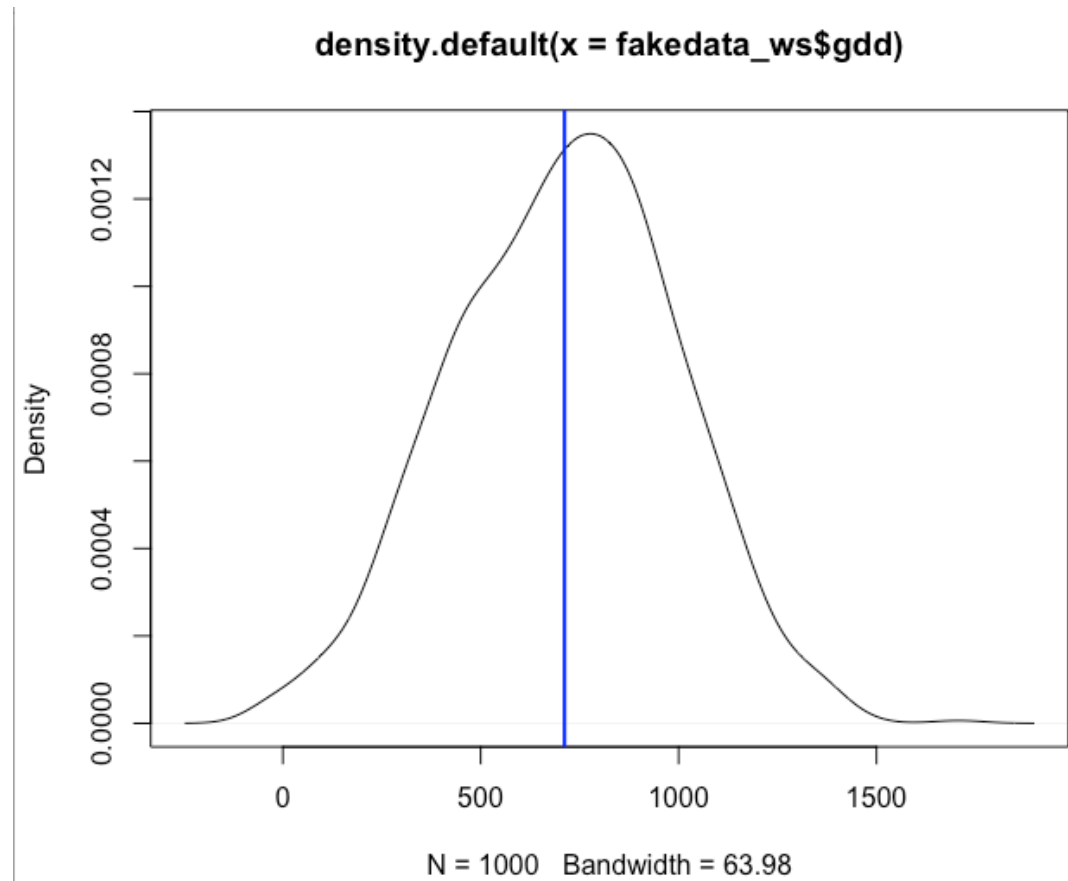
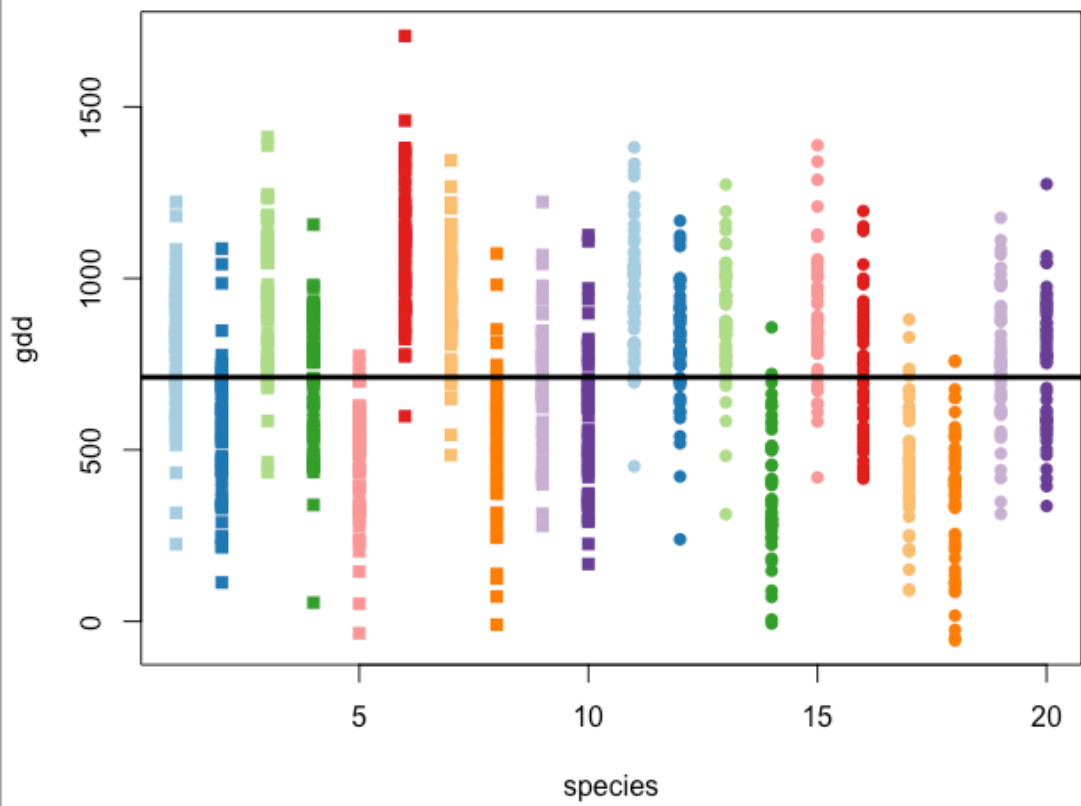
$$y_i \sim N(\mu_i, \sigma)$$

$$y_i = \alpha_i + \sigma$$

```

35 ### WEATHER STATION DATA MODEL SIMULATION
36 ### Okay, now let's make some fake data using help Rethinking, Gelman, OSPREE and Geoff
37 # 1) Let's make the observations much higher than the actual data to build a good model.
38 nsp = 20 # number of species
39 ntot = 50 # numbers of obs per species.
40
41 sample_a <- list(int.env = rnorm(1000, 700, 200))
42
43 # 2) Now, we will make varying intercepts
44 int.samples <- sapply(sample_a, FUN = function(x){
45   sample(x, size = nsp * ntot, replace = TRUE)})
46
47 # 4) We need to make a random intercept model for each species
48 baseinter <- list(intercept = mean(int.samples))
49 baseinter.mat <- matrix(unlist(baseinter), ncol = length(baseinter), nrow = nsp * ntot, byrow = TRUE)
50 ## From Geoff's simulate-linear.R code in OSPREE: Which parameters are random?
51 random.inter <- grep(pattern = paste("intercept", collapse = "|"), x = names(baseinter))
52 # Generate random intercepts (by species)
53 for(i in 1:length(random.inter)){
54   baseinter.mat[, i] <- sapply(1:nsp, FUN = function(X){
55     rep(rnorm(n = 1, mean = baseinter[[random.inter[i]]], sd = 200), ntot)})
56
57 # 5) Calculate response
58 response <- sapply(1:nrow(int.samples), FUN = function(x){
59   rnorm(n = 1, mean = baseinter.mat[x, ], sd = 200)})
60
61 # 6) Make a dataframe of fake data
62 fakedata_ws <- cbind(data.frame(species = as.vector(sapply(1:nsp, FUN = function(x) rep(x, ntot))),
63   gdd = response))

```





```

74
75 ## PRIOR PREDICTIVE CHECK time!!
76 # Now I will follow the workflow from the Gabry et al., 2019 paper
77 ## Using vague priors
78 nsims <- length(fakedata_ws$species)
79 alpha <- rnorm(20, 700, 200)
80 sigma <- runif(20, 0, 200)
81
82 data1 <- data.frame(
83   gdd = fakedata_ws$gdd,
84   sim = alpha[fakedata_ws$species] +
85     rnorm(nsims, mean = 0, sd = sigma)
86 )
87
88 xysim_labs <- labs(
89   x = "Observed GDD",
90   y = "Simulated data"
91 )
92
93 theme_set(bayesplot::theme_default(base_size = 18))
94 theme_update(axis.text = element_text(size = 20))
95
96 ggplot(data1, aes(x = gdd, y = sim)) +
97   geom_point(alpha = 0.1, color = "red") +
98   xysim_labs + coord_cartesian(xlim=c(0, 1500), ylim=c(0,1500)) + geom_abline(intercept=0, slope=1)
99

```

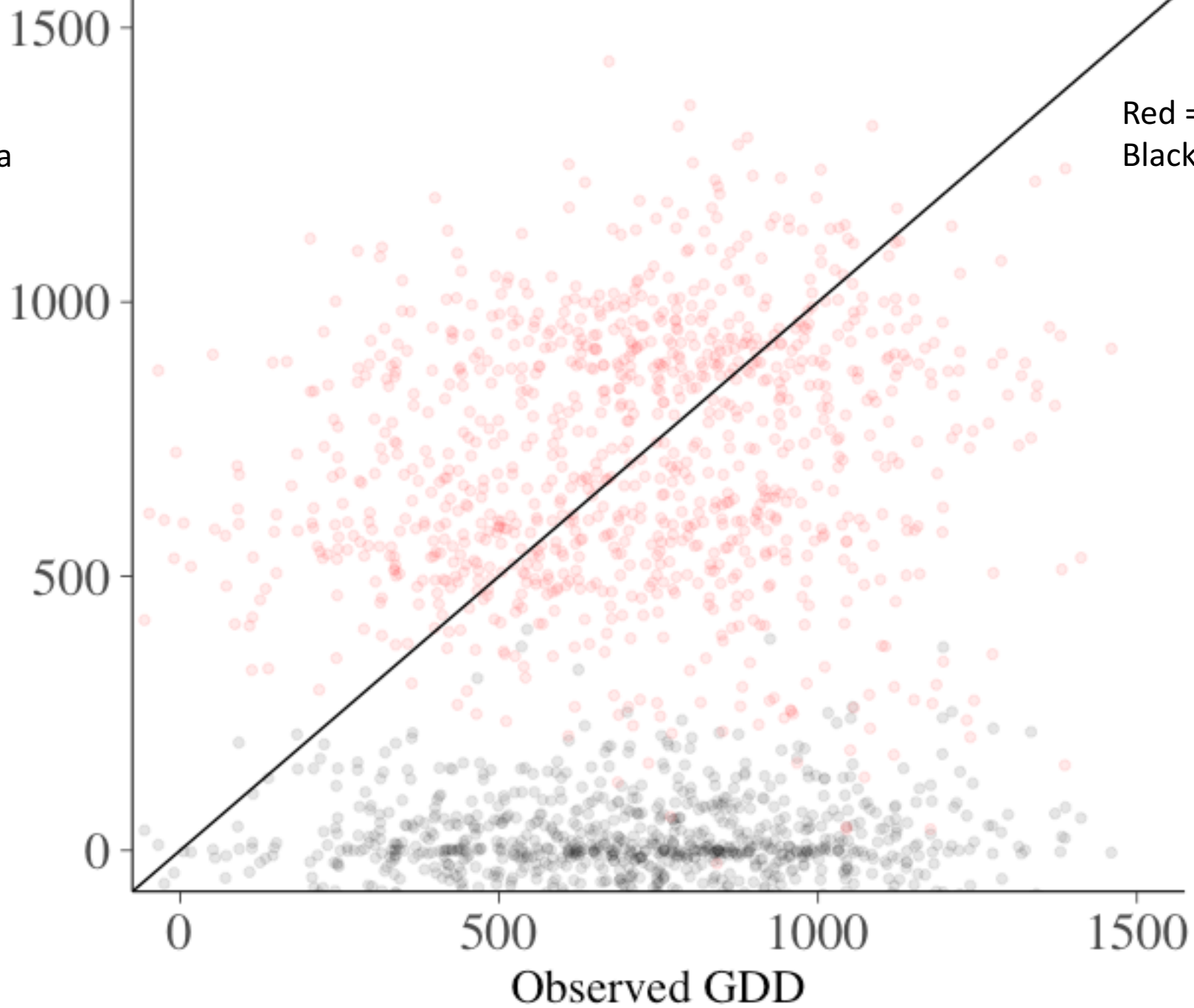
```

100 ## Using weakly informative priors
101 alpha2 <- rnorm(20, 0, 1)
102 sigma2 <- runif(20, 0, 1)
103

```

Weather Station Data

Simulated data





Hobo Logger Data

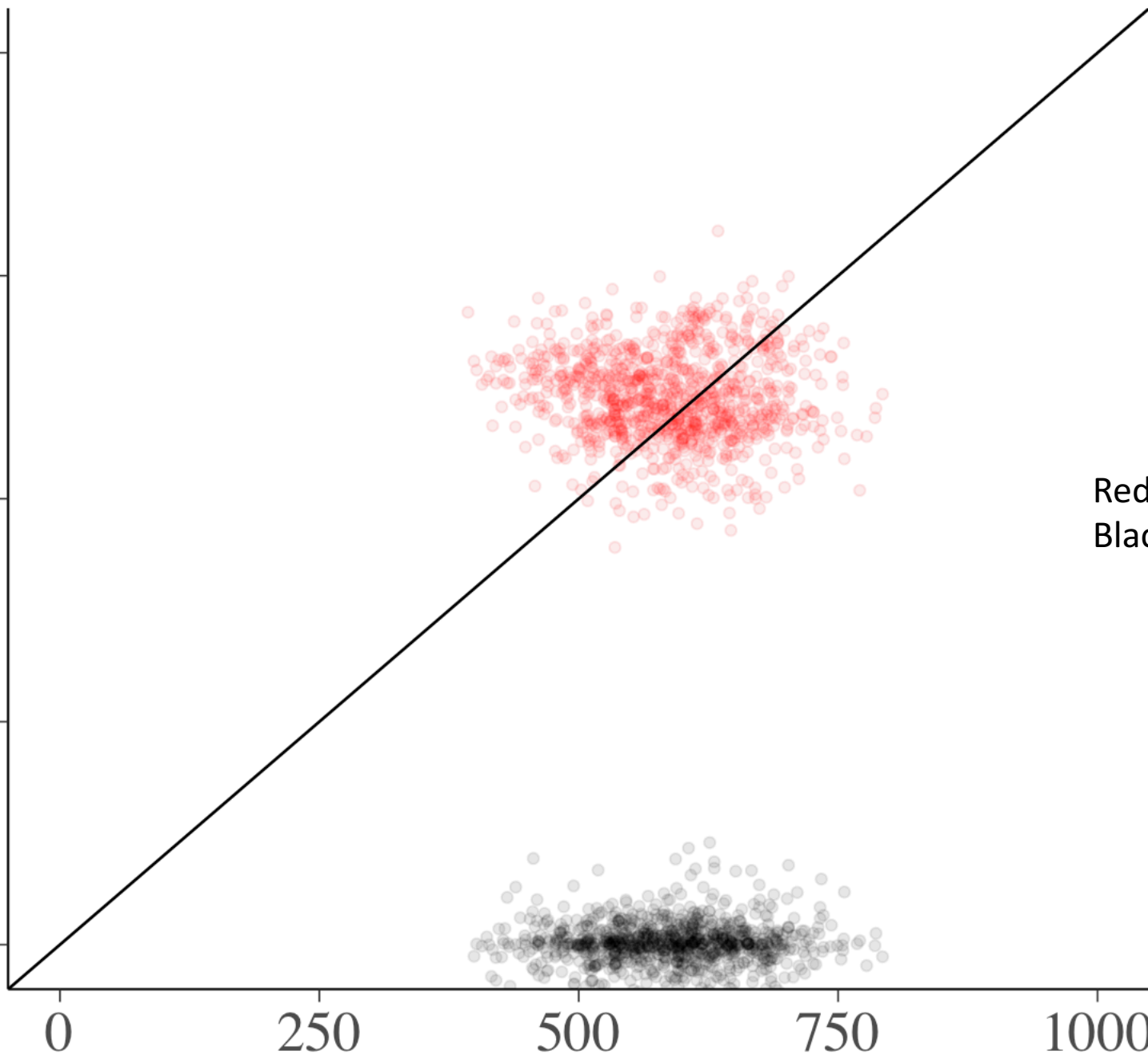
Simulated data

1000  
750  
500  
250  
0

0 250 500 750 1000

Observed GDD

Red = vague priors  
Black = weakly informative



## APPROACH 2:

Let's try and see if there's an 'urban' effect by combining sites into one model.

Again compare weather station data to hobo logger data in separate models

$$\text{GDDlo} \sim \text{urban} + (\text{urban} | \text{species})$$

$$y_i \sim N(\mu_i, \sigma)$$

$$y_i = \alpha_i + \beta x_i + \sigma$$

Weather Station Data

Simulated data

0

500

1000

1500

0

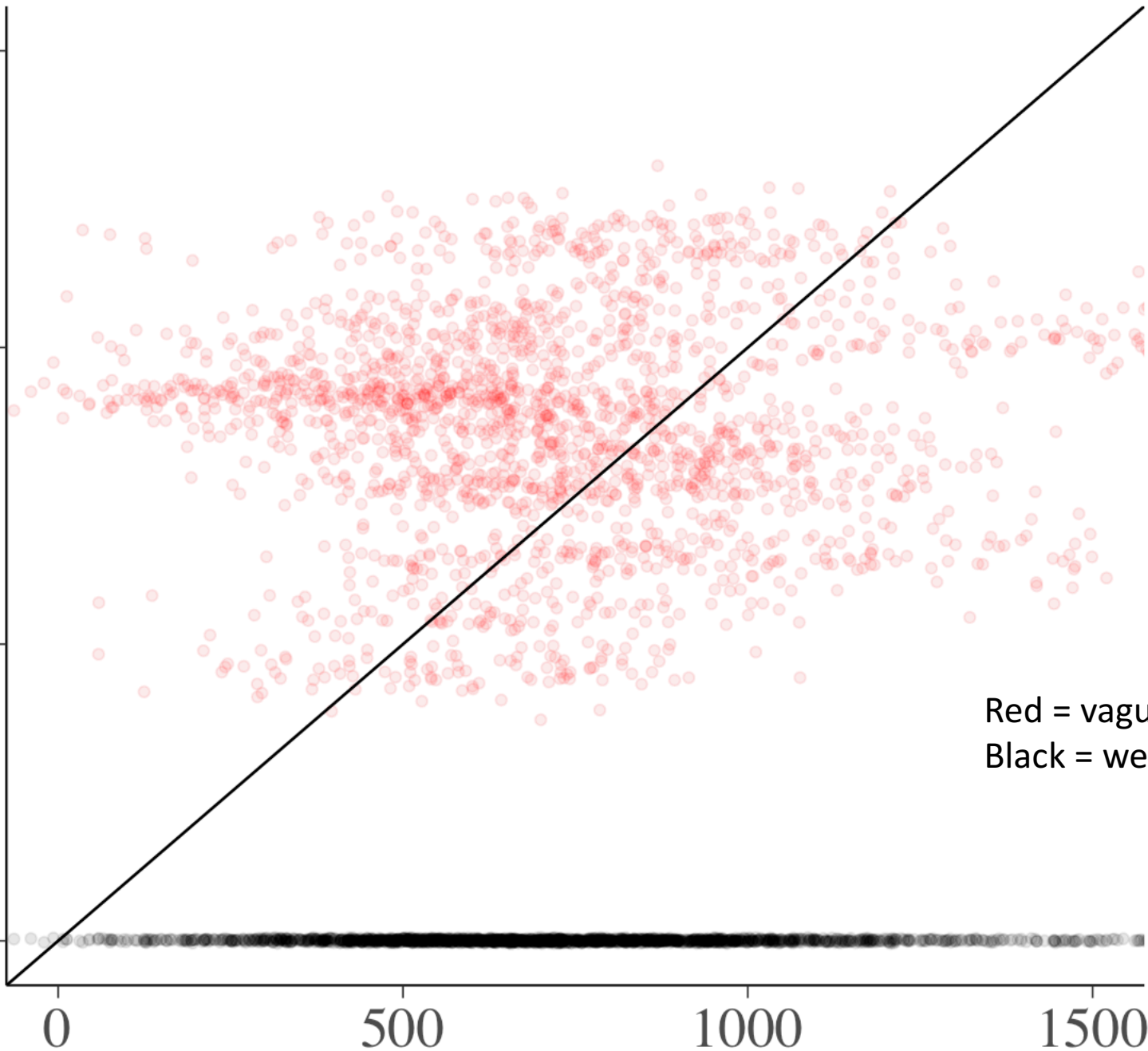
500

1000

1500

Observed GDD

Red = vague priors  
Black = weakly informative





Hobo Logger Data

Simulated data

