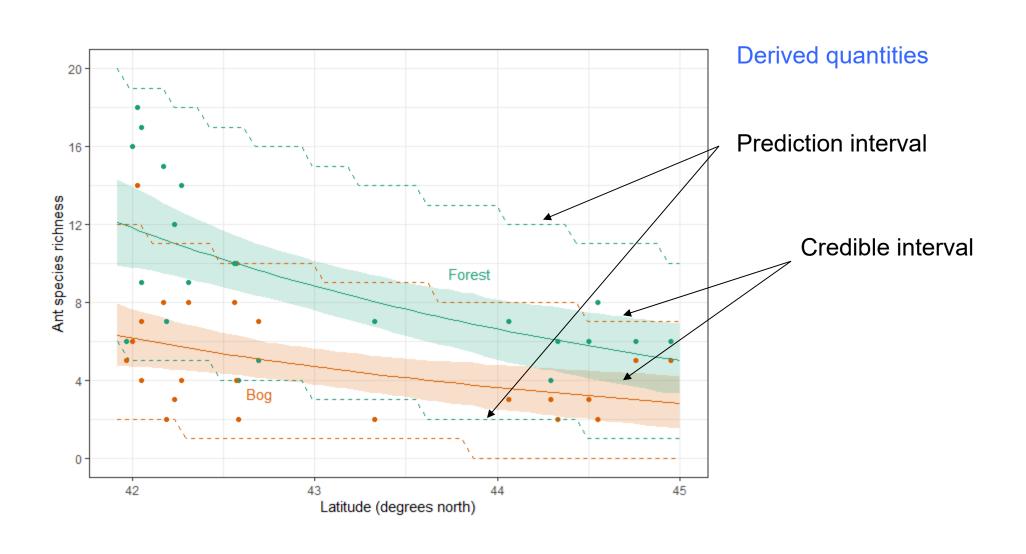
# Today

- Ants GLM, Bayesian (rethinking)
  - working with posterior samples
  - derived quantities
  - Answer to: How different is species richness between habitats?
- Ants GLM, frequentist
  - model formulae
- Ants GLM, Bayesian (rstanarm)
  - model checking

# Bayesian model - ants

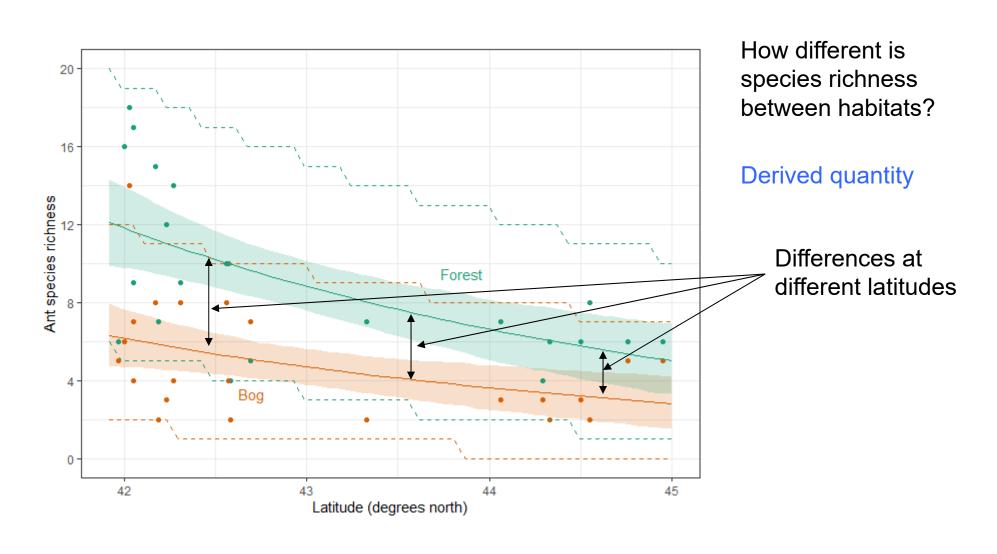


```
# Initialize a grid of latitudes, scaled the same as we scaled the data
lat_upr <- (45 - mean_lat) / sd_lat</pre>
                                                  Keep scaling factors
lat_lwr \leftarrow (41.92 - mean_lat) / sd_lat
latitude <- seg(from=lat_lwr, to=lat_upr, length.out=50)</pre>
# Initialize storage
n <- length(latitude)</pre>
hpdi_bog <- matrix(NA, nrow=n, ncol=5) #to store hpdi values and mean
colnames (hpdi_bog) <- c("mnmu","mulo95","muhi95","ppdlo95","ppdhi95")</pre>
hpdi_forest <- matrix(NA, nrow=n, ncol=5)
colnames(hpdi_forest) <- c("mnmu","mulo95","muhi95","ppdlo95","ppdhi95")</pre>
# For each latitude, form the posterior
for ( i in 1:n ) {
    # First form samples for the linear predictor \eta
    eta_bog <- samples$beta_0 +
                samples$beta_2 * latitude[i]
                                                        Model on linear predictor scale
    eta_forest <- samples$beta_0 +
                   samples\beta_1 +
                                                        Sampled parameters (vectors 36000)
                   samples$beta_2 * latitude[i] +
                   samples$beta_3 * latitude[i]
    # Then use inverse link for samples of the posterior \mu
    mu_bog <- exp(eta_bog)</pre>
                                        Mean species richness
    mu_forest <- exp(eta_forest)</pre>
    # Sample from Poisson to get the posterior predictive distribution
    ppd_bog <- rpois(n=length(mu_bog), lambda=mu_bog)</pre>
                                                                      Simulate data generating process
    ppd_forest <- rpois(n=length(mu_forest), lambda=mu_forest)</pre>
                                                                      Once for each sample
    # Mean and intervals of these samples
    hpdi_bog[i,1] <- mean(mu_bog)
    hpdi_bog[i,2:3] \leftarrow HPDI(mu_bog, prob=0.95)
    #hpdi_bog[i,4:5] <- HPDI(ppd_bog, prob=0.95)</pre>
    hpdi\_bog[i,4:5] \leftarrow quantile(ppd\_bog, prob=c(0.025,0.975)) \#CPI
    hpdi_forest[i,1] <- mean(mu_forest)
    hpdi_forest[i,2:3] <- HPDI(mu_forest, prob=0.95)
    #hpdi_forest[i,4:5] <- HPDI(ppd_forest, prob=0.95)</pre>
    hpdi_forest[i,4:5] <- quantile(ppd_forest, prob=c(0.025,0.975)) #CPI
```

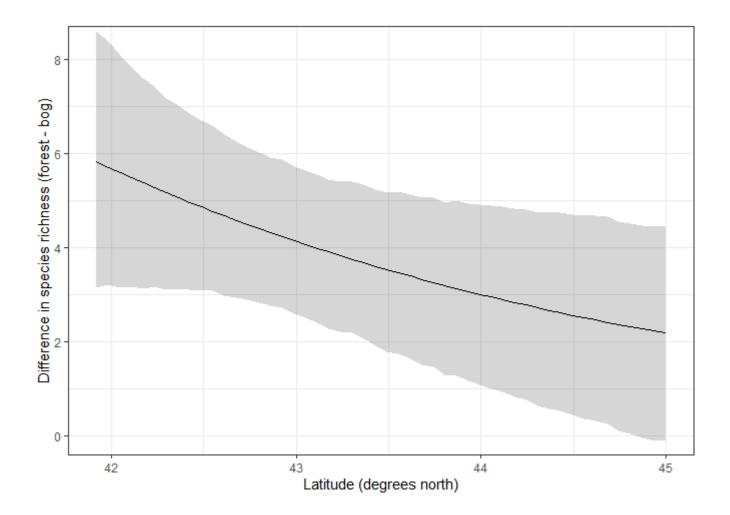
#### Package in tidy format for plotting

```
latitude <- latitude * sd_lat + meRevetse the standardization
predsbog <- data.frame(habitat=rep("bog", n), latitude, hpdi_bog)
predsforest <- data.frame(habitat=rep("forest", n), latitude, hpdi_forest)
preds <- rbind(predsbog, predsforest)
```

# Bayesian model - ants



```
# Initialize variables and storage
lat_lwr \leftarrow (41.92 - mean_lat) / sd_lat
lat\_upr <- (45 - mean\_lat) / sd\_lat
latitude <- seg(from=lat_lwr, to=lat_upr, length.out=50)</pre>
n <- length(latitude)</pre>
forest_bog_diff <- matrix(NA, nrow=n, ncol=3) #to store mean and hpdi values
colnames(forest_bog_diff) <- c("mndiff", "difflo95", "diffhi95")</pre>
# For each latitude, form the posterior
for ( i in 1:n ) {
    # First form samples for the linear predictor \eta
    eta_bog <- samples$beta_0 +
                samples$beta_2 * latitude[i]
    eta_forest <- samples$beta_0 +
                   samples$beta_1 +
                   samples$beta_2 * latitude[i] +
                   samples$beta_3 * latitude[i]
    # Then use inverse link for samples of the posterior \mu
    mu_bog <- exp(eta_bog)</pre>
    mu_forest <- exp(eta_forest)</pre>
    # Now calculate the habitat difference (derived quantity)
    diff <- mu_forest - mu_bog</pre>
                                        Here's the derived quantity. Output: 36000 samples.
    # Mean and intervals of these samples
    forest_bog_diff[i,1] <- mean(diff)</pre>
    forest_bog_diff[i,2:3] <- HPDI(diff, prob=0.95)</pre>
    #forest_bog_diff[i,2:3] <- quantile(diff, prob=c(0.025,0.975)) #CPI</pre>
```



## Model formulae

$$y \sim x1 * x2 + x3 / x4$$

### equivalent to:

$$y \sim 1 + x1 + x2 + x1:x2 + x3 + x3:x4$$

## Model formula

$$\eta_i = \beta_0 intercept_i + \beta_1 forest_i + \beta_2 latitude_i + \beta_3 forest_i \times latitude_i$$

### Model formula

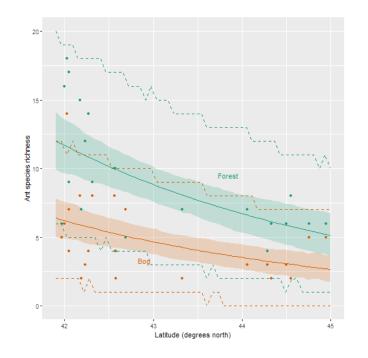
#### **Equivalent:**

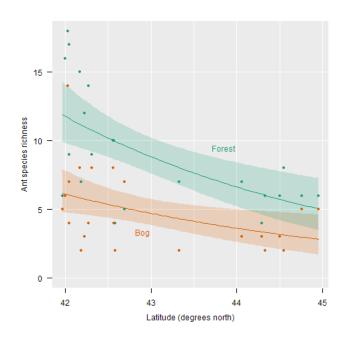
```
richness ~ habitat * latitude  
richness ~ 1 + habitat + latitude + habitat:latitude  
\eta_i = \beta_0 intercept_i + \beta_1 forest_i + \beta_2 latitude_i + \beta_3 forest_i \times latitude_i
```

## Model matrix (design matrix)

Data				Model	matrix		
habitat	latitude	richness	i	ntercept	forest	latitude	forest:latitude
forest	42	16		1	1	42	42
forest	42.56	10		1	1	42.56	42.56
forest	43.33	7		1	1	43.33	43.33
forest	44.76	6		1	1	44.76	44.76
bog	42.17	8	model.matrix(fit	.) 1	0	42.17	0
bog	42.57	4		1	0	42.57	0
bog	44.06	3		1	0	44.06	0
bog	44.95	5		<b>▼</b> 1	<b>7</b> 0	44.95	0
	$\eta_i = f$	$B_0$ inter	$cept_i + \beta_1 fore$	$est_i + \beta_i$	latitude	$+\beta_3$ for	$est_i \times latitud$

eta ~ 1 + forest + latitude + forest:latitude





Bayesian

Frequentist (w approx intervals)

Comparing inference algorithms for frequentist and Bayesian approaches to model means and predictions so far:

Tool	Mean	Uncertainty of mean	Uncertainty of prediction
lm	predict()	predict(int="confidence")	predict(int="prediction")
glm	predict(type= "response")	predict(se.fit=TRUE)	via bootstrap
		or via bootstrap	
stan_glm	mean(pmu)	hpdi(pmu), cpi(pmu)	hpdi(ppd), cpi(ppd)

#### where:

- pmu <- posterior\_linpred(transform = TRUE), Of pmu <- posterior\_epred()
- ppd <- posterior\_predict()</li>