Monaro and Werriwa CTGW CEEC Analyses

Code for regression models

library(rstanarm)  
library(ggeffects)  
library(matrixStats)  
library(tidyr)  
library(projpred)  
library(lme4)  
library(bayesplot)  
library(forcats)  
library(gridExtra)

# LOAD ALL REQUIRED DATA from specified directory   
  
#Exercise 1 data - id of CEEC using real plots  
ex1\_ceec<-read.csv("Ex1\_expobs.csv", header=TRUE)#all obs  
ex1\_sum<-read.csv("Ex1\_sitelevel.csv", header=TRUE)#site level data  
ex1\_ceec$N<-1  
#common sites assessed by all experts  
ex1\_common<-subset(ex1\_ceec, SITE\_ID=="EL20" | SITE\_ID=="EL46" | SITE\_ID=="EL77" |  
 SITE\_ID=="EL27"| SITE\_ID=="EL35" |  
 SITE\_ID=="EL53" | SITE\_ID=="EL65" | SITE\_ID=="EL61" |SITE\_ID=="EL7" |  
 SITE\_ID=="EL26" | SITE\_ID=="EL73"| SITE\_ID=="EL41"| SITE\_ID=="EL18"|SITE\_ID=="EL95")  
  
#clusters as factor in summary data  
ex1\_sum$Final\_cluster <- factor(ex1\_sum$Final\_cluster, levels = c("Other", "CTGW"))  
ex1\_sum$SITE\_ID<-ex1\_sum$Site  
  
  
#####Exercise 2. - id of CEEC, low condition threshold and restoration likelihood  
  
Ex2\_all<-read.csv("Ex2\_expobs.csv", header=TRUE)#all obs

## Experiment 1

#Prepare for modeling  
  
ex1\_ceec$CEEC\_beta<-(ex1\_ceec$LIKELY\*(409-1)+0.5)/409#response variable, to ensure no values of 1 or 0  
  
#standardise fixed effect variables  
ex1\_ceec$Snow\_gum\_ca<-(ex1\_ceec$Epauc-mean(ex1\_ceec$Epauc))/sd(ex1\_ceec$Epauc)#snow gum c/a  
ex1\_ceec$Charact\_spp<-(ex1\_ceec$Charct\_spp-mean(ex1\_ceec$Charct\_spp))/sd(ex1\_ceec$Charct\_spp)#richness characteristic spp  
ex1\_ceec$Non\_charact\_trees<-(ex1\_ceec$Non\_eucR-mean(ex1\_ceec$Non\_eucR))/sd(ex1\_ceec$Non\_eucR)#richness of non-characteristic trees  
  
  
x\_epauc<- mean(ex1\_ceec$Epauc)#mean Epauc ca  
# [1] 1.124694  
sd\_epauc<- sd(ex1\_ceec$Epauc)# sd Epauc  
# [1] 1.31231  
x\_cspp<-mean(ex1\_ceec$Charct\_spp)#mean richness char. spp  
# [1] 14.62347  
sd\_cspp<- sd(ex1\_ceec$Charct\_spp)#sd char spp  
# [1] 6.612528  
x\_nc<- mean(ex1\_ceec$Non\_eucR)#mean richness non-char spp  
# [1] 0.9070905  
sd\_nc<- sd(ex1\_ceec$Non\_eucR)#sd non char spp  
# [1] 1.32701

#run beta regression models  
  
#use default priors for fixed and random effects ie ~ normal(location = [0,0,0], scale = [2.5,2.5,2.5]);   
# ~ decov(reg. = 1, conc. = 1, shape = 1, scale = 1)  
  
model.seed <- 1  
load('m1.1.rda')  
#model  
 m1.1<-stan\_glmer(CEEC\_beta~Snow\_gum\_ca+Charact\_spp+Non\_charact\_trees+  
 (1|Exp\_Code)+(1|SITE\_ID),   
 data=ex1\_ceec, family=mgcv::betar, seed=model.seed)  
  
prior\_summary(m1.1)#default priors  
  
# Priors for model 'm1.1'   
# ------  
# Intercept (after predictors centered)  
# ~ normal(location = 0, scale = 10)  
#   
# Coefficients  
# Specified prior:  
# ~ normal(location = [0,0,0], scale = [2.5,2.5,2.5])  
# Adjusted prior:  
# ~ normal(location = [0,0,0], scale = [2.50,2.50,2.50])  
#   
# Covariance  
# ~ decov(reg. = 1, conc. = 1, shape = 1, scale = 1)  
  
summary(m1.1)  
#m1.1  
  
save(m1.1, file="m1.1.rda")  
  
pi\_m1.1<-posterior\_interval(m1.1, prob=0.95)  
  
#plot results & check model trace and autocorrelation  
color\_scheme\_set("gray")  
p1<-plot(m1.1, "areas", pars=c("(Intercept)","Charact\_spp","Snow\_gum\_ca",  
 "Non\_charact\_trees"),  
 prob = 0.95, prob\_outer = 1)+  
 geom\_vline(xintercept = 0, linetype="dotted")+xlab("Coefficient")+  
 scale\_y\_discrete(labels = c("(Intercept)"= "Intercept", "Snow\_gum\_ca"="Snow gum C/A","Charact\_spp"="Characteristic spp","Non\_charact\_trees"="Non-characteristic tree spp"))  
  
  
p2<-plot(m1.1, "areas", pars=c("b[(Intercept) Exp\_Code:1]","b[(Intercept) Exp\_Code:2]","b[(Intercept) Exp\_Code:3]","b[(Intercept) Exp\_Code:4]",  
 "b[(Intercept) Exp\_Code:5]","b[(Intercept) Exp\_Code:6]","b[(Intercept) Exp\_Code:7]","b[(Intercept) Exp\_Code:8]",  
 "b[(Intercept) Exp\_Code:9]","b[(Intercept) Exp\_Code:10]","b[(Intercept) Exp\_Code:11]","b[(Intercept) Exp\_Code:12]",  
 "b[(Intercept) Exp\_Code:13]","b[(Intercept) Exp\_Code:14]","b[(Intercept) Exp\_Code:15]","b[(Intercept) Exp\_Code:16]"),  
 prob = 0.95, prob\_outer = 1)+ geom\_vline(xintercept = 0,linetype="dotted")+xlab("Coefficient")+  
 scale\_y\_discrete(labels = c("b[(Intercept) Exp\_Code:1]"="Exp 1","b[(Intercept) Exp\_Code:2]"="Exp 2","b[(Intercept) Exp\_Code:3]"="Exp 3","b[(Intercept) Exp\_Code:4]"="Exp 4",  
 "b[(Intercept) Exp\_Code:5]"="Exp 5","b[(Intercept) Exp\_Code:6]"="Exp 6","b[(Intercept) Exp\_Code:7]"="Exp 7","b[(Intercept) Exp\_Code:8]"="Exp 8",  
 "b[(Intercept) Exp\_Code:9]"="Exp 9","b[(Intercept) Exp\_Code:10]"="Exp 10","b[(Intercept) Exp\_Code:11]"= "Exp 11","b[(Intercept) Exp\_Code:12]"="Exp 12",  
 "b[(Intercept) Exp\_Code:13]"="Exp 13","b[(Intercept) Exp\_Code:14]"="Exp 14","b[(Intercept) Exp\_Code:15]"="Exp 15","b[(Intercept) Exp\_Code:16]"="Exp 16"))  
p2  
  
  
  
  
plot(m1.1, "trace", pars=c("(Intercept)","Snow\_gum\_ca","Charact\_spp",  
 "Non\_charact\_trees"))  
plot(m1.1, "acf", pars=c("(Intercept)","Snow\_gum\_ca","Charact\_spp",  
 "Non\_charact\_trees"))  
  
# draw from the posterior distribution of the conditional mean  
  
ppm1.1<-posterior\_linpred(m1.1, draws = 3000, transform=TRUE)  
  
# posterior distribution of phi  
  
phi1 <- as.data.frame(m1.1)$`(phi)`  
#then draw from a beta distribution to get the posterior predictive distribution  
  
PPD1.1 <- matrix(rbeta(prod(dim(ppm1.1)), shape1 = ppm1.1 \* phi1, shape2 = (1 - ppm1.1) \* phi1),  
 nrow = nrow(ppm1.1), ncol = ncol(ppm1.1))

#model of distance coefficient from fuzzy clustering  
#this is the comparative model to examine the relative effect of snow gum,   
#charact spp numbers and non-characteristic tree spp cf. expert derived models  
  
ex1\_sum$Dist\_beta<-(ex1\_sum$Distance\*(100-1)+0.5)/100#to ensure no values of 1 or 0; numeric likeliood  
  
  
#standardise covariates# only required if not already run  
 ex1\_sum$Snow\_gum\_ca<-(ex1\_sum$Epauc-x\_epauc)/sd\_epauc  
 ex1\_sum$Charact\_spp<-(ex1\_sum$CharSpp-x\_cspp)/sd\_cspp  
ex1\_sum$Non\_charact\_trees<-(ex1\_sum$Non\_eucR-x\_nc)/sd\_nc  
  
# Priors for model 'm2.1'   
# ------  
# Intercept (after predictors centered)  
# ~ normal(location = 0, scale = 10)  
#   
# Coefficients  
# Specified prior:  
# ~ normal(location = [0,0,0], scale = [2.5,2.5,2.5])  
# Adjusted prior:  
# ~ normal(location = [0,0,0], scale = [2.47,2.59,1.80])  
  
#model  
# m2.1<-stan\_glm(Dist\_beta~Snow\_gum\_ca+Charact\_spp+Non\_charact\_trees,   
#data=ex1\_sum, family=mgcv::betar, seed=model.seed)  
  
save(m2.1, file="m2.1.rda")  
prior\_summary(m2.1)  
  
summary(m2.1)  
m2.1  
  
posterior\_interval(m2.1, prob=0.95)  
  
plot(m2.1, "trace", pars=c("(Intercept)","Snow\_gum\_ca","Charact\_spp",  
 "Non\_charact\_trees"))  
plot(m2.1, "acf", pars=c("(Intercept)","Snow\_gum\_ca","Charact\_spp",  
 "Non\_charact\_trees"))  
  
#plot of effects  
color\_scheme\_set("gray")  
  
p3<-plot(m2.1, "areas", pars=c("(Intercept)","Charact\_spp","Snow\_gum\_ca",  
 "Non\_charact\_trees"),  
 prob = 0.95, prob\_outer = 1)+  
 geom\_vline(xintercept = 0, linetype="dotted")+ xlab("Coefficient")+  
 scale\_y\_discrete(labels = c("(Intercept)"= "Intercept", "Snow\_gum\_ca"="Snow gum C/A","Charact\_spp"="Characteristic spp","Non\_charact\_trees"="Non-characteristic tree spp"))  
  
   
# draw from the posterior distribution of the conditional mean  
  
ppm2.1<-posterior\_linpred(m2.1, draws = 3000, transform=TRUE)  
  
# posterior distribution of phi  
  
phi2 <- as.data.frame(m2.1)$`(phi)`  
#then draw from a beta distribution to get the posterior predictive distribution  
  
PPD2.1 <- matrix(rbeta(prod(dim(ppm2.1)), shape1 = ppm2.1 \* phi2, shape2 = (1 - ppm2.1) \* phi2),  
 nrow = nrow(ppm2.1), ncol = ncol(ppm2.1))  
  
  
#plot posterior draws and observed  
  
bayesplot\_grid(  
 ppc\_dens\_overlay(ex1\_ceec$CEEC\_beta, PPD1.1[1:100, ])+  
 ggplot2::xlab("Likelihood"), ppc\_dens\_overlay(ex1\_sum$Dist\_beta, PPD2.1[1:100, ])+  
 ggplot2::xlab("Membership Coefficient"),   
 titles = c("A. Expert likelihoods", "B. Numeric membership coefficients"),  
 grid\_args = list(ncol = 2)  
)

## Experiment 2

#deal with covariates  
  
#use means and SD from first exercise for those covariates that overlap  
  
#Non characteristic trees are 0 in all plots  
Ex2\_all$Non\_eucR<-0  
Ex2\_all$Non\_charact\_trees<-(Ex2\_all$Non\_eucR-x\_nc)/sd\_nc  
Ex2\_all$Snow\_gum\_ca<-(Ex2\_all$Epauc-x\_epauc)/sd\_epauc  
Ex2\_all$Charact\_spp<-(Ex2\_all$MonaroSpp-x\_cspp)/sd\_cspp  
  
Ex2\_all$Distance\_s<-(Ex2\_all$Distance-mean(Ex2\_all$Distance))/sd(Ex2\_all$Distance)#new variable for likelihood CTGW analysis  
  
Ex2\_all$Large\_treeNs<-(Ex2\_all$Large\_treeN-mean(Ex2\_all$Large\_treeN))/sd(Ex2\_all$Large\_treeN)#new variable  
Ex2\_all$ForbRs<-(Ex2\_all$ForbR-mean(Ex2\_all$ForbR))/sd(Ex2\_all$ForbR)#new variable  
Ex2\_all$Stumps<-factor(Ex2\_all$Stumps)#new variable  
Ex2\_all$N\_Eratio<-(Ex2\_all$ForbC+Ex2\_all$GrassC)/(Ex2\_all$ExoticC)#new variable  
Ex2\_all$N\_Eratios<-(Ex2\_all$N\_Eratio-mean(Ex2\_all$N\_Eratio))/sd(Ex2\_all$N\_Eratio)#new variable  
  
Ex2\_all$N<-1  
  
  
  
#response variables  
Ex2\_all$CEEC\_beta<-(Ex2\_all$MOST\_LIKELY\*(358-1)+0.5)/358 #prob CTGW CEEC  
Ex2\_all$Rest\_beta<-(Ex2\_all$MOST\_LIKELY\_R\*(358-1)+0.5)/358#prob restoration success  
Ex2\_all$LC\_beta<-(Ex2\_all$MOST\_LIKELY\_LC\*(358-1)+0.5)/358#prob low condition threshold

#Run model - probability CEEC  
  
#priors from model 1.1  
  
# > m1.1  
# stan\_glmer  
# family: beta [logit, link.phi=log]  
# formula: CEEC\_beta ~ Snow\_gum\_ca + Charact\_spp + Non\_charact\_trees + (1 |   
# Exp\_Code) + (1 | SITE\_ID)  
# observations: 409  
# ------  
# Median MAD\_SD  
# (Intercept) -0.2 0.1   
# Snow\_gum\_ca 1.0 0.1   
# Charact\_spp 0.4 0.1   
# Non\_charact\_trees -0.7 0.1   
# (phi) 3.9 0.3   
#   
# Error terms:  
# Groups Name Std.Dev.  
# SITE\_ID (Intercept) 0.66   
# Exp\_Code (Intercept) 0.21   
# Num. levels: SITE\_ID 101, Exp\_Code 16   
  
priorB <- normal(location = c(1.0,0.4,0,0), scale = c(0.1,0.1,2.5,2.5), autoscale = FALSE)  
priorInt<-normal(location=-0.2,scale=0.1, autoscale= FALSE)  
  
  
#model  
nm1.1<-stan\_glmer(CEEC\_beta~Snow\_gum\_ca+Charact\_spp+Distance\_s+Stumps+  
 (1|Exp\_Code)+(1|SITE\_ID), data=Ex2\_all,  
 prior=priorB, prior\_intercept = priorInt,  
 family=mgcv::betar, seed=model.seed)  
  
  
summary(nm1.1)  
nm1.1  
  
save(nm1.1, file="nm1.1.rda")  
  
ppi\_nm1.1<-posterior\_interval(nm1.1, prob=0.95)  
  
plot(nm1.1, "trace", pars=c("(Intercept)","Snow\_gum\_ca","Charact\_spp",  
 "Distance\_s","Stumps1"))  
plot(nm1.1, "acf", pars=c("(Intercept)","Snow\_gum\_ca","Charact\_spp",  
 "Distance\_s","Stumps1"))  
  
pexp2<-plot(nm1.1, "areas", pars=c("b[(Intercept) Exp\_Code:1]","b[(Intercept) Exp\_Code:2]","b[(Intercept) Exp\_Code:3]","b[(Intercept) Exp\_Code:4]",  
 "b[(Intercept) Exp\_Code:5]","b[(Intercept) Exp\_Code:6]","b[(Intercept) Exp\_Code:7]","b[(Intercept) Exp\_Code:8]",  
 "b[(Intercept) Exp\_Code:9]","b[(Intercept) Exp\_Code:10]","b[(Intercept) Exp\_Code:11]","b[(Intercept) Exp\_Code:12]",  
 "b[(Intercept) Exp\_Code:13]","b[(Intercept) Exp\_Code:14]","b[(Intercept) Exp\_Code:15]","b[(Intercept) Exp\_Code:16]"),  
 prob = 0.95, prob\_outer = 1)+ geom\_vline(xintercept = 0,linetype="dotted")+xlab("Coefficient")+  
 scale\_y\_discrete(labels = c("b[(Intercept) Exp\_Code:1]"="Exp 1","b[(Intercept) Exp\_Code:2]"="Exp 2","b[(Intercept) Exp\_Code:3]"="Exp 3","b[(Intercept) Exp\_Code:4]"="Exp 4",  
 "b[(Intercept) Exp\_Code:5]"="Exp 5","b[(Intercept) Exp\_Code:6]"="Exp 6","b[(Intercept) Exp\_Code:7]"="Exp 7","b[(Intercept) Exp\_Code:8]"="Exp 8",  
 "b[(Intercept) Exp\_Code:9]"="Exp 9","b[(Intercept) Exp\_Code:10]"="Exp 10","b[(Intercept) Exp\_Code:11]"= "Exp 11","b[(Intercept) Exp\_Code:12]"="Exp 12",  
 "b[(Intercept) Exp\_Code:13]"="Exp 13","b[(Intercept) Exp\_Code:14]"="Exp 14","b[(Intercept) Exp\_Code:15]"="Exp 15","b[(Intercept) Exp\_Code:16]"="Exp 16"))  
pexp2  
  
ggsave("Expert\_pars\_experiment2.png", pexp2, dpi=300, height=6, width=6)  
  
#parameter estimates  
  
color\_scheme\_set("gray")  
pexp2.1<-plot(nm1.1, "areas", pars=c("(Intercept)","Charact\_spp","Snow\_gum\_ca",  
 "Distance\_s","Stumps1"),  
 prob = 0.95, prob\_outer = 1)+  
 geom\_vline(xintercept = 0, linetype="dotted")+xlab("Coefficient")+  
 scale\_y\_discrete(labels = c("(Intercept)"="Intercept","Charact\_spp"="Characteristic spp","Snow\_gum\_ca"="Snow gum C/A","Distance\_s"=" Distance to snow gum","Stumps1"="Stumps - Present"))  
  
  
#model fit  
  
  
y<-Ex2\_all$CEEC\_beta  
yrep1<-posterior\_predict(nm1.1, draws=100)  
  
  
  
bayesplot\_grid(  
 ppc\_dens\_overlay(y,yrep1)  
+xlab("Likelihood"))

#model restoration likelihood  
#is likelihood correlated with likelihood of CEEC? Possibly experts are more optimistic if the community is the CEEC?  
  
  
#Model  
r1.1<-stan\_glmer(Rest\_beta~CTGW+ForbRs+N\_Eratios+Large\_treeNs+  
 (1|Exp\_Code)+(1|SITE\_ID), data=Ex2\_rest,  
 family=mgcv::betar, seed=model.seed)  
  
prior\_summary(r1.1)#default priors  
summary(r1.1)  
r1.1  
  
save(r1.1, file="r1.1.rda")  
ppI\_r1.1<-posterior\_interval(r1.1, prob=0.95)  
  
  
plot(r1.1, "trace", pars=c("(Intercept)","CTGW",  
 "N\_Eratios","Large\_treeNs","ForbRs"))  
plot(r1.1, "acf", pars=c("(Intercept)","CTGW",  
 "N\_Eratios","Large\_treeNs","ForbRs"))  
  
pexp2\_rest<-plot(r1.1, "areas", pars=c("b[(Intercept) Exp\_Code:1]","b[(Intercept) Exp\_Code:2]","b[(Intercept) Exp\_Code:3]","b[(Intercept) Exp\_Code:4]",  
 "b[(Intercept) Exp\_Code:5]","b[(Intercept) Exp\_Code:6]","b[(Intercept) Exp\_Code:7]","b[(Intercept) Exp\_Code:8]",  
 "b[(Intercept) Exp\_Code:9]","b[(Intercept) Exp\_Code:10]","b[(Intercept) Exp\_Code:11]","b[(Intercept) Exp\_Code:12]",  
 "b[(Intercept) Exp\_Code:13]","b[(Intercept) Exp\_Code:14]","b[(Intercept) Exp\_Code:15]","b[(Intercept) Exp\_Code:16]"),  
 prob = 0.95, prob\_outer = 1)+ geom\_vline(xintercept = 0,linetype="dotted")+xlab("Coefficient")+  
 scale\_y\_discrete(labels = c("b[(Intercept) Exp\_Code:1]"="Exp 1","b[(Intercept) Exp\_Code:2]"="Exp 2","b[(Intercept) Exp\_Code:3]"="Exp 3","b[(Intercept) Exp\_Code:4]"="Exp 4",  
 "b[(Intercept) Exp\_Code:5]"="Exp 5","b[(Intercept) Exp\_Code:6]"="Exp 6","b[(Intercept) Exp\_Code:7]"="Exp 7","b[(Intercept) Exp\_Code:8]"="Exp 8",  
 "b[(Intercept) Exp\_Code:9]"="Exp 9","b[(Intercept) Exp\_Code:10]"="Exp 10","b[(Intercept) Exp\_Code:11]"= "Exp 11","b[(Intercept) Exp\_Code:12]"="Exp 12",  
 "b[(Intercept) Exp\_Code:13]"="Exp 13","b[(Intercept) Exp\_Code:14]"="Exp 14","b[(Intercept) Exp\_Code:15]"="Exp 15","b[(Intercept) Exp\_Code:16]"="Exp 16"))  
  
  
#model fit  
  
  
y2<-Ex2\_rest$Rest\_beta  
yrep2<-posterior\_predict(r1.1, draws=100)  
  
  
bayesplot\_grid(  
 ppc\_dens\_overlay(y2,yrep2)  
+xlab("Likelihood"))  
  
  
  
  
#parameter estimates  
  
pexp2.2<-plot(r1.1, "areas", pars=c("(Intercept)", "CTGWCTGW",  
 "N\_Eratios","Large\_treeNs","ForbRs"),  
 prob = 0.95, prob\_outer = 1)+  
 geom\_vline(xintercept = 0, linetype="dotted")+xlab("Coefficient")+  
 scale\_y\_discrete(labels = c("(Intercept)"="Intercept","CTGWCTGW"="CTGW",  
 "ForbRs"="Native Forb R",  
 "Large\_treeNs"="Large Trees",  
 "N\_Eratios"="N:E Cover"))

#model low condition likelihood  
#is likelihood correlated with likelihood of CEEC? Possibly experts are more optimistic if the community is the CEEC?  
  
# Model  
L1.1<-stan\_glmer(LC\_beta~CTGW+ForbRs+N\_Eratios+Large\_treeNs+  
 (1|Exp\_Code)+(1|SITE\_ID), data=Ex2\_all,  
 family=mgcv::betar, seed=model.seed)  
prior\_summary(L1.1)  
  
summary(L1.1)  
L1.1  
  
save(L1.1, file="L1.1.rda")  
  
  
  
  
ppI\_L1.1<-posterior\_interval(L1.1, prob=0.95)  
  
plot(L1.1, "trace", pars=c("(Intercept)","CTGWCTGW",  
 "N\_Eratios","Large\_treeNs","ForbRs","CTGWCTGW:ForbRs","CTGWCTGW:N\_Eratios","CTGWCTGW:Large\_treeNs"))  
plot(L1.1, "acf", pars=c("(Intercept)","CTGWCTGW",  
 "N\_Eratios","Large\_treeNs","ForbRs","CTGWCTGW:ForbRs","CTGWCTGW:N\_Eratios","CTGWCTGW:Large\_treeNs"))  
  
  
pexp2\_L1.1<-plot(L1.1, "areas", pars=c("b[(Intercept) Exp\_Code:1]","b[(Intercept) Exp\_Code:2]","b[(Intercept) Exp\_Code:3]","b[(Intercept) Exp\_Code:4]",  
 "b[(Intercept) Exp\_Code:5]","b[(Intercept) Exp\_Code:6]","b[(Intercept) Exp\_Code:7]","b[(Intercept) Exp\_Code:8]",  
 "b[(Intercept) Exp\_Code:9]","b[(Intercept) Exp\_Code:10]","b[(Intercept) Exp\_Code:11]","b[(Intercept) Exp\_Code:12]",  
 "b[(Intercept) Exp\_Code:13]","b[(Intercept) Exp\_Code:14]","b[(Intercept) Exp\_Code:15]","b[(Intercept) Exp\_Code:16]"),  
 prob = 0.95, prob\_outer = 1)+ geom\_vline(xintercept = 0,linetype="dotted")+xlab("Coefficient")+  
 scale\_y\_discrete(labels = c("b[(Intercept) Exp\_Code:1]"="Exp 1","b[(Intercept) Exp\_Code:2]"="Exp 2","b[(Intercept) Exp\_Code:3]"="Exp 3","b[(Intercept) Exp\_Code:4]"="Exp 4",  
 "b[(Intercept) Exp\_Code:5]"="Exp 5","b[(Intercept) Exp\_Code:6]"="Exp 6","b[(Intercept) Exp\_Code:7]"="Exp 7","b[(Intercept) Exp\_Code:8]"="Exp 8",  
 "b[(Intercept) Exp\_Code:9]"="Exp 9","b[(Intercept) Exp\_Code:10]"="Exp 10","b[(Intercept) Exp\_Code:11]"= "Exp 11","b[(Intercept) Exp\_Code:12]"="Exp 12",  
 "b[(Intercept) Exp\_Code:13]"="Exp 13","b[(Intercept) Exp\_Code:14]"="Exp 14","b[(Intercept) Exp\_Code:15]"="Exp 15","b[(Intercept) Exp\_Code:16]"="Exp 16"))  
  
  
  
#model fit  
  
y3<-Ex2\_all$LC\_beta  
yrep3<-posterior\_predict(L1.1, draws=100)  
  
  
  
bayesplot\_grid(  
 ppc\_dens\_overlay(y3,yrep3)  
+xlab("Likelihood"))  
  
  
#parameter estimates  
  
pexp2.3<-plot(L1.1, "areas", pars=c("(Intercept)","CTGWCTGW",  
 "N\_Eratios","Large\_treeNs","ForbRs"),  
 prob = 0.95, prob\_outer = 1)+  
 geom\_vline(xintercept = 0, linetype="dotted")+xlab("Coefficient")+  
 scale\_y\_discrete(labels = c("(Intercept)"="Intercept","CTGWCTGW"="CTGW",  
 "ForbRs"="Native Forb R",  
 "Large\_treeNs"="Large Trees",  
 "N\_Eratios"="N:E Cover"))