

Appendix II

Notebook MT5751 - Project 3 Occupancy Estimation

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I) Notebook Setup

```
{r}
# Load libraries
library(tidyverse)
library(corrplot)
library(ggplot2)
library(MuMin)
library(unmarked)
library(tidyr)
library(car)
library(AICcmodavg)
library(dplyr)

# Load Data
library(statsecol)

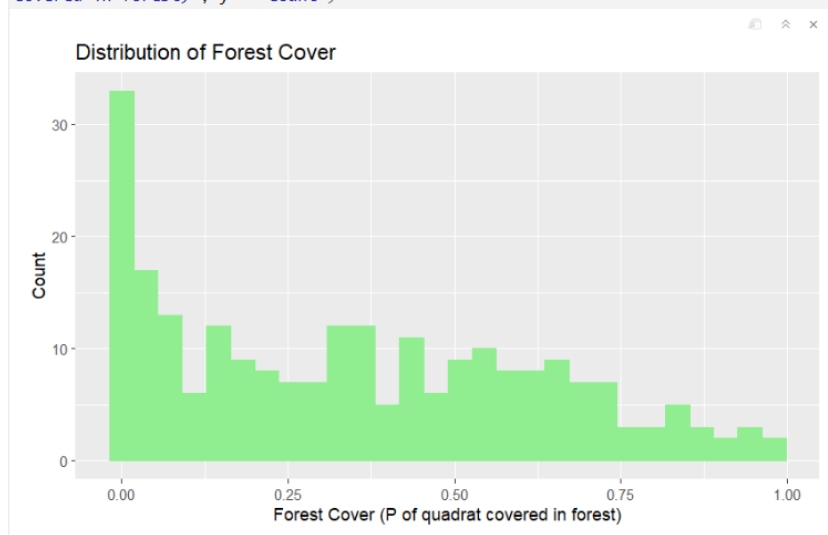
# Save the data frame
data(willow)
willow_df <- willow
str(willow_df)

willow_df <- as.data.frame(sapply(willow_df, as.numeric))
```

II) Data exploration

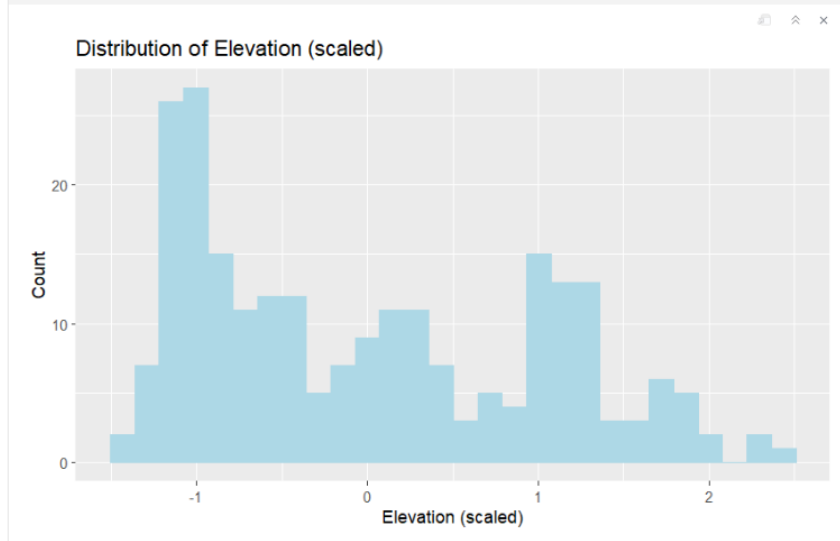
A) Distribution of forest Cover

```
{r}
ggplot(data = willow_df, aes(x = forest)) +
  geom_histogram(bins = 28, fill = 'lightgreen', color = 'lightgreen') +
  labs(title = "Distribution of Forest Cover", x = "Forest Cover (P of quadrat covered in forest)", y = "Count")
```



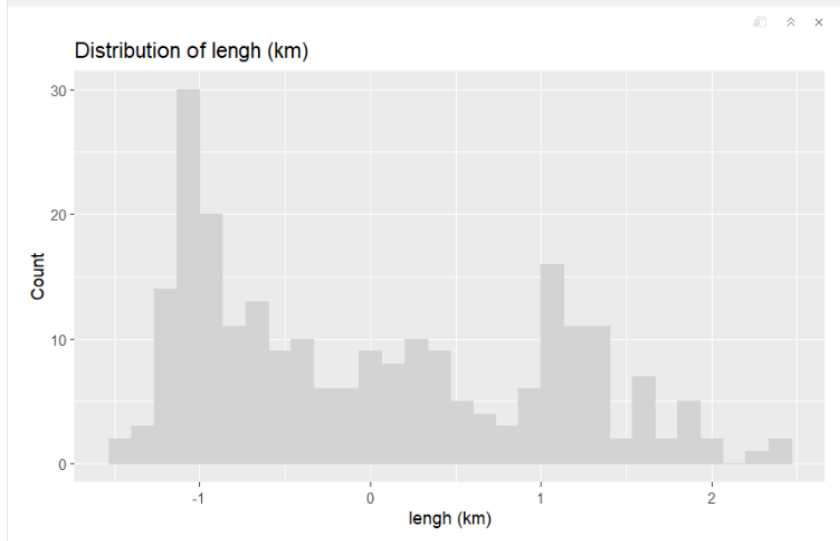
B) Distribution of elevation

```
{r}  
ggplot(data = willow_df, aes(x = elev)) +  
  geom_histogram(bins = 28, fill = 'lightblue', color = 'lightblue') +  
  labs(title = "Distribution of Elevation (scaled)", x = "Elevation (scaled)", y =  
    "Count")
```



D) Distribution of length

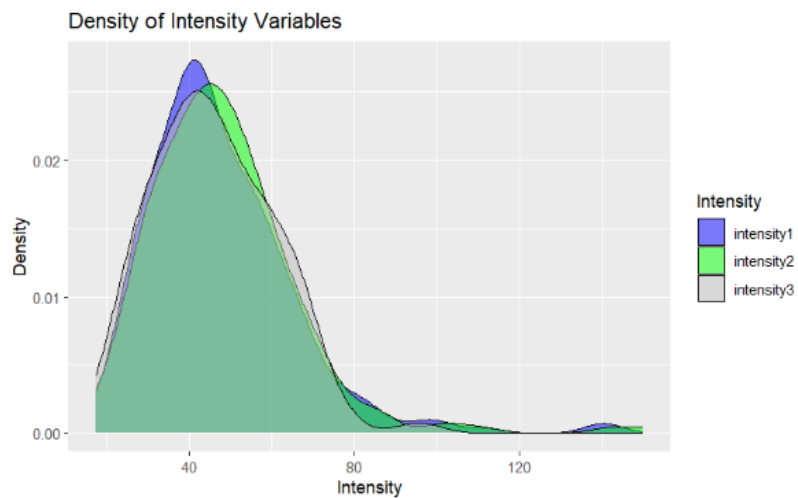
```
{r}  
ggplot(data = willow_df, aes(x = elev)) +  
  geom_histogram(bins = 30, fill = 'lightgrey', color = 'lightgrey') +  
  labs(title = "Distribution of length (km)", x = "length (km)", y = "Count")#  
Introduction
```



E) Distribution of intensity per visit

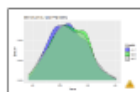
```
{r}  
# Convert intensity to numeric  
willow_df$intensity2 <- as.numeric(willow_df$intensity2)  
willow_df$intensity3 <- as.numeric(willow_df$intensity3)  
  
# Reshape data  
willow_df_long <- pivot_longer(willow_df, cols = starts_with("intensity"), names_to =  
= "variable", values_to = "value")  
  
# Create plot  
effort_willow_df_long <- ggplot(willow_df_long, aes(x = value, fill = variable)) +  
  geom_density(alpha = 0.5) +  
  xlab("Intensity") +  
  ylab("Density") +  
  ggtitle("Density of Intensity Variables") +  
  scale_fill_manual(name = "Intensity", values = c("intensity1" = "blue",  
"intensity2" = "green", "intensity3" = "grey"))  
effort_willow_df_long
```

Warning: [38;5;232mRemoved 46 rows containing non-finite values ('stat_density()'). [39m

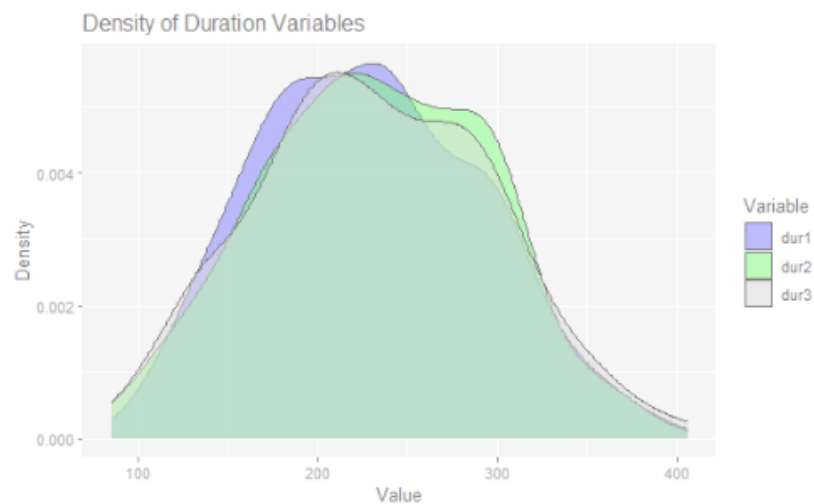


E) Distribution of Duration per visit

```
{r}  
# Convert dur to numeric  
willow_df$dur2 <- as.numeric(willow_df$dur2)  
willow_df$dur3 <- as.numeric(willow_df$dur3)  
  
# Reshape data  
willow_df_dur <- pivot_longer(willow_df, cols = starts_with("dur"),  
                              names_to = "variable", values_to = "value")  
  
# Create a plot  
willow_plot_dur <- ggplot(willow_df_dur, aes(x = value, fill = variable)) +  
  geom_density(alpha = 0.5) +  
  xlab("Value") +  
  ylab("Density") +  
  ggtitle("Density of Duration Variables") +  
  scale_fill_manual(name = "Variable",  
                    values = c("dur1" = "blue", "dur2" = "green", "dur3" = "grey"))  
  
willow_plot_dur
```



Warning: [38;5;232mRemoved 46 rows containing non-finite values ('stat_density()'). [39m



F) Distribution of days since the start of the year on each occasion

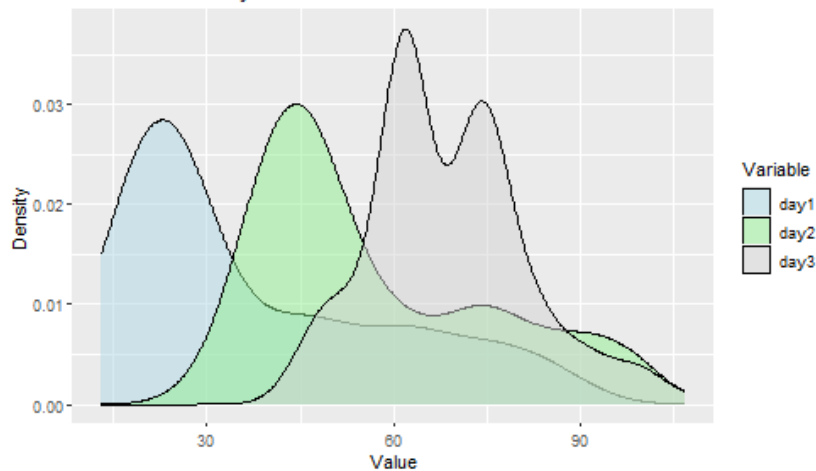
```
{r}
# Convert day to numeric
willow_df$day3 <- as.numeric(willow_df$day3)
apply(select(willow_df, starts_with("day")), c(class))

# Pivot the data
willow_df %>%
  pivot_longer(cols = starts_with("day"), names_to = "variable", values_to =
"value") %>%
  ggplot(aes(x = value, fill = variable)) +
  geom_density(alpha = 0.5) +
  labs(x = "Value", y = "Density", title = "Distribution of Days Since the Start of
the Year on Each Occasion") +
  scale_fill_manual(name = "Variable", values = c("lightblue", "lightgreen",
"lightgrey"))
```



Warning: Removed 42 rows containing non-finite values ('stat_density()').

Distribution of Days Since the Start of the Year on Each Occasion



H) Sampling period

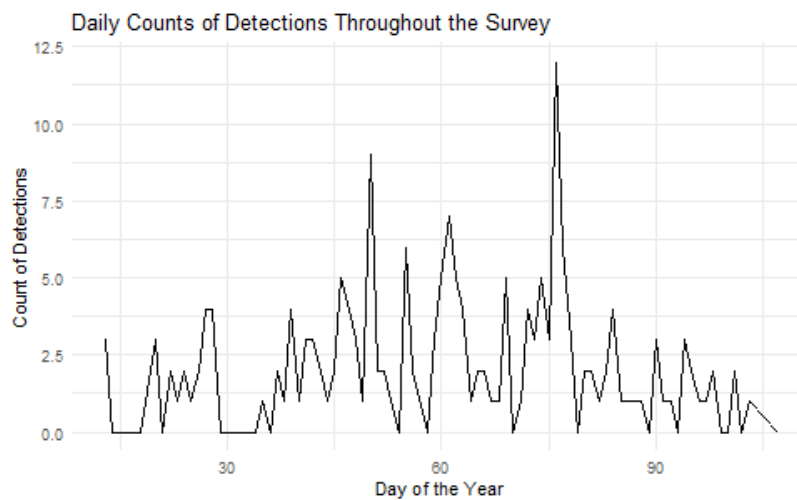
```
{r}
# Reshape Data
data_range <- melt(willow_df, id.vars = c("day1", "day2", "day3"),
  measure.vars = c("y.1", "y.2", "y.3"),
  variable.name = "survey", value.name = "detection")

# Create a new column
data_range$day_of_survey <- ifelse(data_range$survey == "y.1", data$day1,
  ifelse(data_range$survey == "y.2", data$day2,
  data$day3))

# Aggregate counts
Counts <- data_range %>%
  group_by(day_of_survey) %>%
  summarise(detection_count = sum(detection, na.rm = TRUE))

# Plot
ggplot(Counts, aes(x = day_of_survey, y = detection_count)) +
  geom_line() +
  labs(title = "Daily Counts of Detections Throughout the Survey",
    x = "Day of the Year", y = "Count of Detections") +
  theme_minimal()
```

Warning: Removed 1 row containing missing values ('geom_line()').



III) "unmarked" frame object

```
{r}
# Create Dataframe
UM_willow_df <- unmarkedFrameOccu(
  y = willow_df[, c("y.1", "y.2", "y.3")],
  siteCovs = data.frame(forest = willow_df$forest,
                        elev = willow_df$elev,
                        length = willow_df$length,
                        elevsq = willow_df$elevsq),
  obsCovs = list(intensity = willow_df[, c("intensity1", "intensity2", "intensity3"
)],
                  dur = willow_df[, c("dur1", "dur2", "dur3")],
                  day = willow_df[, c("day1", "day2", "day3")])
)
summary(UM_willow_df)
```

unmarkedFrame Object

237 sites
Maximum number of observations per site: 3
Mean number of observations per site: 2.81
Sites with at least one detection: 79

Tabulation of y observations:

	0	1	<NA>
	483	182	46

Site-level covariates:

	forest	elev	length	elevsq
Min.	:0.0000	Min. :-1.4429	Min. :1.200	Min. :0.000016
1st Qu.:	0.0800	1st Qu.: -0.9478	1st Qu.: 4.200	1st Qu.: 0.219154
Median :	0.3300	Median : -0.1742	Median : 5.000	Median : 0.957877
Mean :	0.3479	Mean : 0.0000	Mean : 5.103	Mean : 0.995781
3rd Qu.:	0.5700	3rd Qu.: 0.9862	3rd Qu.: 5.900	3rd Qu.: 1.337285
Max. :	0.9800	Max. : 2.4251	Max. : 9.400	Max. : 5.881141

Observation-level covariates:

	intensity	dur	day
Min.	: 17.31	Min. : 85.0	Min. : 13.00
1st Qu.:	35.96	1st Qu.:180.0	1st Qu.: 38.00
Median :	45.00	Median :230.0	Median : 52.00
Mean :	47.39	Mean :230.7	Mean : 53.66
3rd Qu.:	56.82	3rd Qu.:280.0	3rd Qu.: 72.00
Max. :	150.00	Max. :406.0	Max. :107.00
NA's :	46	NA's :46	NA's :42

VI) Full Vs Null Model Fit

```
{r}  
# Full model with all covariates  
willow_f <- occu(formula = ~ day + intensity + dur ~ length + forest + elev + elevsq  
, data = UM_willow_df)
```

```
# Output  
willow_fu <- summary(willow_f)
```

DESCRIPTION: A table of 4 rows and 4 columns.
The first column is the parameter name, the second is the estimate, the third is the standard error, and the fourth is the p-value.

data.frame

data.frame

Description: df [4 × 4]

	Estimate <dbl>	SE <dbl>	z <dbl>	P(> z) <dbl>
(Intercept)	-1.177485517	0.911853607	-1.2913098	0.1965962668
day	0.004413742	0.008216376	0.5371885	0.5911374383
intensity	-0.027203567	0.014335565	-1.8976278	0.0577451263
dur	0.014312274	0.004274964	3.3479285	0.0008141802

4 rows

```
{r}  
# Null model with no covariates  
willow_n <- occu(formula = ~ 1 ~ 1, data = UM_willow_df)
```

```
# Output  
willow_nu <- summary(willow_n)
```

DESCRIPTION: A table of 1 row and 4 columns.
The first column is the parameter name, the second is the estimate, the third is the standard error, and the fourth is the p-value.

data.frame

data.frame

Description: df [1 × 4]

	Estimate <dbl>	SE <dbl>	z <dbl>	P(> z) <dbl>
(Intercept)	1.324917	0.1741857	7.606344	2.819586e-14

1 row

VI) Model Selection

```
{r}
# Define full model with interactions
full <- occu(formula = ~ day + dur + intensity + day:dur + day:intensity +
intensity:dur ~ length + elev + elevsq + forest + forest:elev + forest:elevsq, data
= UM_willow_df)

# dredge
Dredge_output_with_interaction <- suppresswarnings(dredge(full, rank = "AIC"))

# Print the first 5 rows of the output
Dredge_output_with_interaction[1:5, ]
```

Fixed terms are "p(Int)" and "psi(Int)"
Global model call: occu(formula = ~day + dur + intensity + day:dur + day:intensity +
+ intensity:dur ~ length + elev + elevsq + forest + forest:elev +
forest:elevsq, data = UM_willow_df)

Model selection table

	p(Int)	psi(Int)	p(day)	p(dur)	p(int)	psi(elev)	psi(elvs)	psi(frs)
psi(lng)	psi(elev:frs)	psi(elvs:frs)	df					
3527	-1.035	-1.1070		0.014260	-0.02560	1.152	-0.9610	2.347
3.726	2.908	9						
3523	-1.196	-1.0580		0.009622		1.149	-0.9950	2.175
3.376	2.718	8						
3528	-1.121	-1.0610	0.003252	0.013980	-0.02603	1.189	-1.0050	2.242
3.485	2.823	10						
4039	-1.072	-0.9566		0.014560	-0.02651	1.124	-0.9365	2.419
-0.03579	3.832		2.946	10				
4035	-1.158	-1.2620		0.009483		1.183	-1.0110	2.151
0.04346	3.300		2.647	9				
	logLik	AIC	delta	weight				
3527	-199.797	417.6	0.00	0.329				
3523	-200.882	417.8	0.17	0.302				
3528	-199.711	419.4	1.83	0.132				
4039	-199.797	419.6	2.00	0.121				
4035	-200.841	419.7	2.09	0.116				

Models ranked by AIC(x)

B) Define best models

```
{r}
# Best model 1
Best_1 <- occu(formula = ~ dur + intensity ~ elev + elevsq + forest + (elev:forest) + (elevsq:forest), data=UM_willow_df)

# Best model 2
Best_2 <- occu(formula = ~ dur ~ elev + forest + elevsq + (elev:forest) + (elevsq:forest), data=UM_willow_df)

# Best model 3
Best_3 <- occu(formula = ~ day + intensity + dur ~ elev + forest + elevsq + (elev:forest) + (elevsq:forest), data=UM_willow_df)

# Best model 4
Best_4 <- occu(formula = ~ intensity + dur ~ length + elev + forest + elevsq + (elev:forest) + (elevsq:forest), data=UM_willow_df)

# Best model 5
Best_5 <- occu(formula = ~ intensity + dur ~ elev + forest + elevsq + (elev:forest), data=UM_willow_df)

# Best model 6
Best_6 <- occu(formula = ~ intensity + dur ~ elev + forest + elevsq, data=UM_willow_df)
```

C) regularized occupancy

```
{r}
# Define a range of lambda values to test
lamb_vals <- 10^seq(-4, -1, length.out = 30)

# Initialize vector
AIC_vals <- numeric(length(lamb_vals))

# Loop over lambda values, fit model each time, and record AIC
for (i in seq_along(lamb_vals)) {
  model <- occuPEN(~ intensity + dur ~ elev + forest + elevsq + (elev:forest),
                  data = UM_willow_df,
                  lambda = lamb_vals[i])
  AIC_vals[i] <- AIC(model)
}

# Find lambda with lowest AIC
min_lamb <- lamb_vals[which.min(AIC_vals)]

# Fit best model
Best_5_reg <- occuPEN(~ intensity + dur ~ elev + forest + elevsq + (elevsq:forest),
                    data = UM_willow_df,
                    lambda = min_lamb)
```

VI) Model Evaluation

A) Multicollinearity

```
{r}
# Best model 1
vif_results <- vif(Best_1, type = 'state')
print("VIF Results for Best Model 1:")
print(vif_results)
vif_results_1 <- vif(mod = Best_1, type = 'det')
print(vif_results_1)

# Best model 2
print("VIF Results for Best Model 2:")
vif_results_1 <- vif(mod = Best_2, type = 'state')
print(vif_results_1)

# Best model 3
vif_results <- vif(mod = Best_3, type = 'state')
print("VIF Results for Best Model 3:")
print(vif_results)
vif_results_1 <- vif(mod = Best_3, type = 'det')
print(vif_results_1)

# Best model 4
vif_results <- vif(mod = Best_4, type = 'state')
print("VIF Results for Best Model 4:")
print(vif_results)
vif_results_1 <- vif(mod = Best_4, type = 'det')
print(vif_results_1)

# Best model 5
vif_results <- vif(mod = Best_5, type = 'state')
print("VIF Results for Best Model 5:")
print(vif_results)
vif_results_1 <- vif(mod = Best_5, type = 'det')
print(vif_results_1)

# Best model 5
vif_results <- vif(mod = Best_5, type = 'state')
print("VIF Results for Best Model 5:")
print(vif_results)
vif_results_1 <- vif(mod = Best_5, type = 'det')
print(vif_results_1)

# Best model 6
vif_results <- vif(mod = Best_6, type = 'state')
print("VIF Results for Best Model 6:")
print(vif_results)
vif_results_1 <- vif(mod = Best_6, type = 'det')
print(vif_results_1)
```

B) Goodness-of-fit

I) Model with both interactions

```
{r}
# Create a suppress warning wrapper
suppressWarningsWrapper <- function(...) {
  suppressWarnings({
    mb.gof.test(...)
  })
}

GOF_WILLOW_1 <- suppressWarningsWrapper(Best_1, nsim = 5, plot.hist = FALSE)
print(GOF_WILLOW_1)
```

II) Model with one interactions

```
{r}
GOF_WILLOW_2 <- suppressWarningsWrapper(Best_5, nsim = 5, plot.hist = FALSE)
print(GOF_WILLOW_2)
```

III) Model with no interaction

```
{r}
GOF_WILLOW_3 <- suppressWarningsWrapper(Best_5, nsim = 50, plot.hist = FALSE)
print(GOF_WILLOW_3)
```

B) Cross validation

I) Model with both interactions

```
{r}
(kFold_1 = crossVal(Best_1, method="kfold", folds=10))
```

Normal: 0.0000 (20.00%)
Task: Mean Squared Error
Data: 0.0000 (20.00%)

data.frame

data.frame

Description: df [1 × 2]

	Estimate <dbl>	SD <dbl>
Mean absolute err...	0.2396447	0.036333

1 row

II) Model with one interactions

```
{r}
(kFold_2 = crossVal(Best_5, method="kfold", folds=10))
```

Normal: 0.0000 (20.00%)
Task: Mean Squared Error
Data: 0.0000 (20.00%)

data.frame

data.frame

Description: df [1 × 2]

	Estimate <dbl>	SD <dbl>
Mean absolute err...	0.253979	0.05142638

1 row

III) Model with no interaction

```
{r}
(kFold_3 = crossVal(Best_6, method="kfold", folds=10))
```

Normal: 0.0000 (20.00%)
Task: Mean Squared Error
Data: 0.0000 (20.00%)

data.frame

data.frame

Description: df [1 × 2]

	Estimate <dbl>	SD <dbl>
Mean absolute err...	0.2591313	0.03737407

1 row

IV) Model With one interaction and regularization

```
{r}
(kFold_3 = crossVal(Best_5_reg, method="kfold", folds=10))
```

Normal: 0.0000 (20.00%)
Task: Mean Squared Error
Data: 0.0000 (20.00%)

data.frame

data.frame

Description: df [1 × 2]

	Estimate <dbl>	SD <dbl>
Mean absolute err...	0.2489738	0.02977029

1 row

VII) Effects plots

A) Detection

a) Duration

```
{r}
# Create a dummy data frame with the mean intensity
Duration_df <- data.frame(dur = seq(
  min(UM_willow_df@obsCovs$dur, na.rm=TRUE),
                                max(UM_willow_df@obsCovs$dur, na.rm=TRUE),
                                length = 30),
  intensity = mean(UM_willow_df@obsCovs$intensity, na.rm=TRUE)
))

# Create predictions
Duration_df <- predict(Best_5,type="det",newdata = Duration_df, append = TRUE)

# Plot the results
Effects_duration <- ggplot(data = Duration_df, aes(x = dur, y = Predicted)) +
  geom_ribbon(aes(ymin=lower, ymax=upper), fill="#808080", alpha=0.1) +
  geom_line(size=1,color="#ADD8E6") +
  ylab("Pr(Detection)") + xlab("Survey Duration (Min)") + ylim(0,1) + theme_bw()

Effects_duration
```

b) Intensity

```
{r}
# Create dummy data frame
Intensity_df <- data.frame(
  dur = mean(UM_willow_df@obsCovs$dur, na.rm = TRUE),
  intensity = seq(
    min(UM_willow_df@obsCovs$intensity, na.rm = TRUE),
    max(UM_willow_df@obsCovs$intensity, na.rm = TRUE),
    length.out = 30))

# Create predictions
Intensity_df <- predict(Best_5,type="det",newdata = Intensity_df, append = TRUE)

# Plot the results
Effects_Intensity <- ggplot(data = Intensity_df, aes(x = intensity, y = Predicted))
+
  geom_ribbon(aes(ymin=lower, ymax=upper), fill="#808080", alpha=0.1) +
  geom_line(size=1,color="#228B22") +
  ylab("Pr(Detection)") + xlab("Intensity of search (duration/length) ") + ylim(0,1)
+ theme_bw()

Effects_Intensity
```

A) Occupancy

a) Elevation

```
{r}
# Set mean and standard deviation of elevation
avgElevation <- 1182.574
elevationSD <- 646.333

# Create sequence so that it can be squared
elev_seq <- seq(min(UM_willow_df@siteCovs$elev, na.rm = TRUE),
               max(UM_willow_df@siteCovs$elev, na.rm = TRUE),
               length = 30)

# Create dummy data frame
elevation_df <- data.frame(
  elev = elev_seq,
  elevsq = elev_seq^2, # Square elevation
  forest = mean(UM_willow_df@siteCovs$forest, na.rm = TRUE))

# Create predictions
elevation_df <- predict(Best_5, type = "state", newdata = pred_psi_ele, append = TRUE)

# Plot the results
elevation_effects <- ggplot(data = elevation_df, aes(x = (elev * elevationSD +
  avgElevation), y = Predicted)) +

  geom_ribbon(aes(ymin = lower, ymax = upper), fill = "#5B84B1FF", alpha = 0.1) +
  geom_line(size = 1, color = "#5B84B1FF") +
  ylab("Pr(Occupancy)") + xlab("Elevation (m)") + ylim(0, 1) + theme_bw()

elevation_effects
```

C) Forest

```
{r}
# Create prediction data frame
Forest_df <- data.frame(
  forest = seq(min(UM_willow_df@siteCovs$forest, na.rm = TRUE),
               max(UM_willow_df@siteCovs$forest, na.rm = TRUE),
               length = 30),
  elev = mean(UM_willow_df@siteCovs$elev, na.rm = TRUE),
  elevsq = (mean(UM_willow_df@siteCovs$elev, na.rm = TRUE))^2)

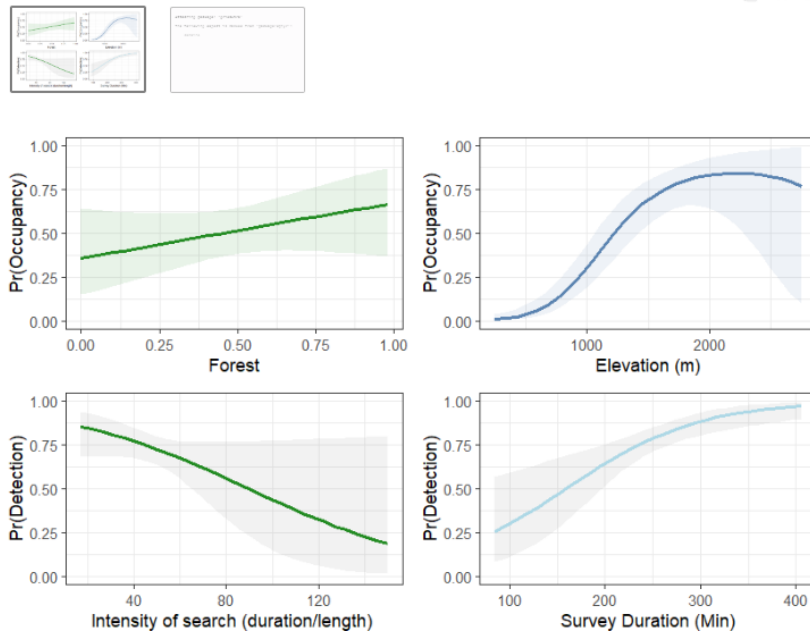
# Generate predictions
Forest_df <- predict(Best_5, type = "state", newdata = Forest_df, append = TRUE)

# Create plot
Plot_forest <- ggplot(data = Forest_df, aes(x = forest, y = Predicted)) +
  geom_ribbon(aes(ymin = lower, ymax = upper), fill = "#228B22", alpha = 0.1) +
  geom_line(size = 1, color = "#228B22") +
  ylab("Pr(Occupancy)") + xlab("Forest") + ylim(0, 1) + theme_bw()

Plot_forest
```

```
{r}
library(gridExtra)

combined_plot <- grid.arrange(Plot_forest, elevation_effects, Effects_Intensity,
  Effects_duration, ncol = 2, nrow = 2)
ggsave("combined_plot.png", combined_plot, width = 10, height = 10)
```



VII) Prediction

A) Detection prediction

```
{r}
# Define quadrats
quadList <- c(25, 62, 150, 203)
# Initialize lists
detectionPred <- vector("list", length = length(quadList))
detectionCounter <- 1

# Loop for each quadrat
for (quad in quadList) {
  # Data values
  quadData <- data.frame(intensity = UM_willow_df@obsCovs$intensity[quad],
                        dur = UM_willow_df@obsCovs$dur[quad],
                        elev = UM_willow_df@siteCovs$elev[quad],
                        elevsq = UM_willow_df@siteCovs$elevsq[quad],
                        forest = UM_willow_df@siteCovs$forest[quad])

  # Prediction
  detectionPred[[detectionCounter]] <- predict(Best_5, type = "det", newdata =
quadData, append = TRUE)
  detectionCounter <- detectionCounter + 1}

# Format df
detectionDF <- do.call(rbind, lapply(detectionPred, unlist)) %>% round(3)
rownames(detectionDF) <- paste0("Quad ", quadList)
colnames(detectionDF) <- c("Predictedval", "Std", "Lower", "Upper", "Int", "Dur",
"Elev", "Eles", "Forest")

# Adjusting elevation
detectionDF[, "Elev"] <- detectionDF[, "Elev"] * elevationSD + avgElevation

detectionDF
```

	Predictedval	Std	Lower	Upper	Int	Dur	Elev	Eles	Forest
Quad 25	0.577	0.085	0.408	0.730	43.42	165	620.2643	0.758	0.03
Quad 62	0.748	0.051	0.636	0.834	36.84	210	370.1334	1.581	0.14
Quad 150	0.739	0.068	0.588	0.849	27.54	190	1660.2141	0.546	0.86
Quad 203	0.816	0.042	0.720	0.885	36.92	240	1980.1489	1.522	0.06

A) Occupancy prediction

```
{r}
# Initialize lists
occupancyPred <- vector("list", length = length(quadList))
occupancyCounter <- 1

# Loop for each quadrat
for (quad in quadList) {
  # append values to data frame
  quadData <- data.frame(intensity = UM_willow_df@obsCovs$intensity[quad],
                        dur = UM_willow_df@obsCovs$dur[quad],
                        elev = UM_willow_df@siteCovs$elev[quad],
                        elevsq = UM_willow_df@siteCovs$elevsq[quad],
                        forest = UM_willow_df@siteCovs$forest[quad])

  # Prediction
  occupancyPred[[occupancyCounter]] <- predict(Best_5, type = "state", newdata =
quadData, append = TRUE)
  occupancyCounter <- occupancyCounter + 1}

# Format df
occupancyDF <- do.call(rbind, lapply(occupancyPred, unlist)) %>% round(3)
rownames(occupancyDF) <- paste0("Quad ", quadList)
colnames(occupancyDF) <- c("Predictedval", "Std", "Lower", "Upper", "Int", "Dur",
"Elev", "Eles", "Forest")

# Adjusting elevation
occupancyDF[, "Elev"] <- occupancyDF[, "Elev"] * elevationSD + avgElevation

occupancyDF
```

	Predictedval	Std	Lower	Upper	Int	Dur	Elev	Eles	Forest
Quad 25	0.023	0.014	0.007	0.072	43.42	165	620.2643	0.758	0.03
Quad 62	0.005	0.004	0.001	0.021	36.84	210	370.1334	1.581	0.14
Quad 150	0.934	0.035	0.822	0.977	27.54	190	1660.2141	0.546	0.86
Quad 203	0.482	0.086	0.321	0.646	36.92	240	1980.1489	1.522	0.06