Annexure I

R script

```
library(readr)
library(lme4)
library(spm)
#Read in file
bear_presence <- read.csv("E:/R studio/Sloth_bear_R2019_R2020.csv")
#Convert binary variables to factors
bear_presence$`Season`<-as.factor(bear_presence$Season)
bear_presence$`SB presence sign`<-as.factor(bear_presence$SB.presence.sign)
bear_presence$`Presence of food`<-as.factor(bear_presence$Presence.of.food)
bear_presence$`Habitat Type`<-as.factor(bear_presence$Habitat.Type)
bear_presence$`Zizyphus spp`<-as.factor(bear_presence$Zizyphus.spp)
bear_presence$`Cassia Fistula`<-as.factor(bear_presence$Cassia.Fistula)
bear_presence$`Grewia Flavesecnes`<-as.factor(bear_presence$Grewia.Flavesecnes)
bear_presence$`Diosyros melanoxylon`<-as.factor(bear_presence$Diosyros.melanoxylon)
```

#Data visualization

Hide

```
plot(bear_presence$`SB presence sign`~bear_presence$Season)
plot(bear_presence$Season~bear_presence$`Presence of food`)

#Because all the habitat variables are exactly the same between seasons, we really cannot do much beyond acco
unt for those differences.

mcnemar.test(bear_presence$`SB presence sign`,bear_presence$Season)

#lm1=glmer(bear_presence$SB.presence.sign~bear_presence$Season+(1|bear_presence$S..No.),family = bino
mial)
lm1=glmer(bear_presence$SB.presence.sign~bear_presence$Season+ (1|bear_presence$S..No.),family = binom
ial)

summary(lm1)

plot(lm1)
```

```
library(readr)
Results
library(lme4)
## Loading required package: Matrix
library(spm)
#Read in file
bear_presence <- read.csv("E:/R studio/Sloth_bear_R2019_R2020.csv")
#Convert binary variables to factors
bear_presence$`Season`<-as.factor(bear_presence$Season)
bear_presence$`SB presence sign`<-as.factor(bear_presence$SB.presence.sign)
bear_presence$`Presence of food`<-as.factor(bear_presence$Presence.of.food)
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bear_presence$`Diosyros melanoxylon`<-as.factor(bear_presence$Diosyros.melanoxylon)
```
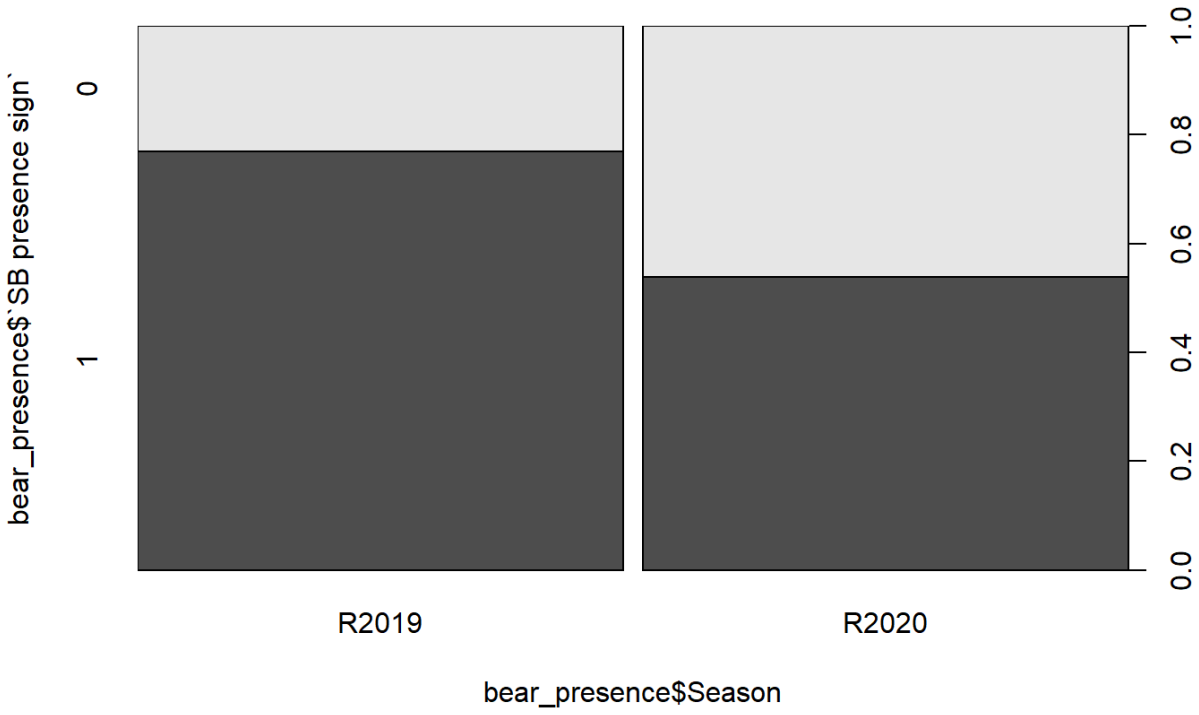
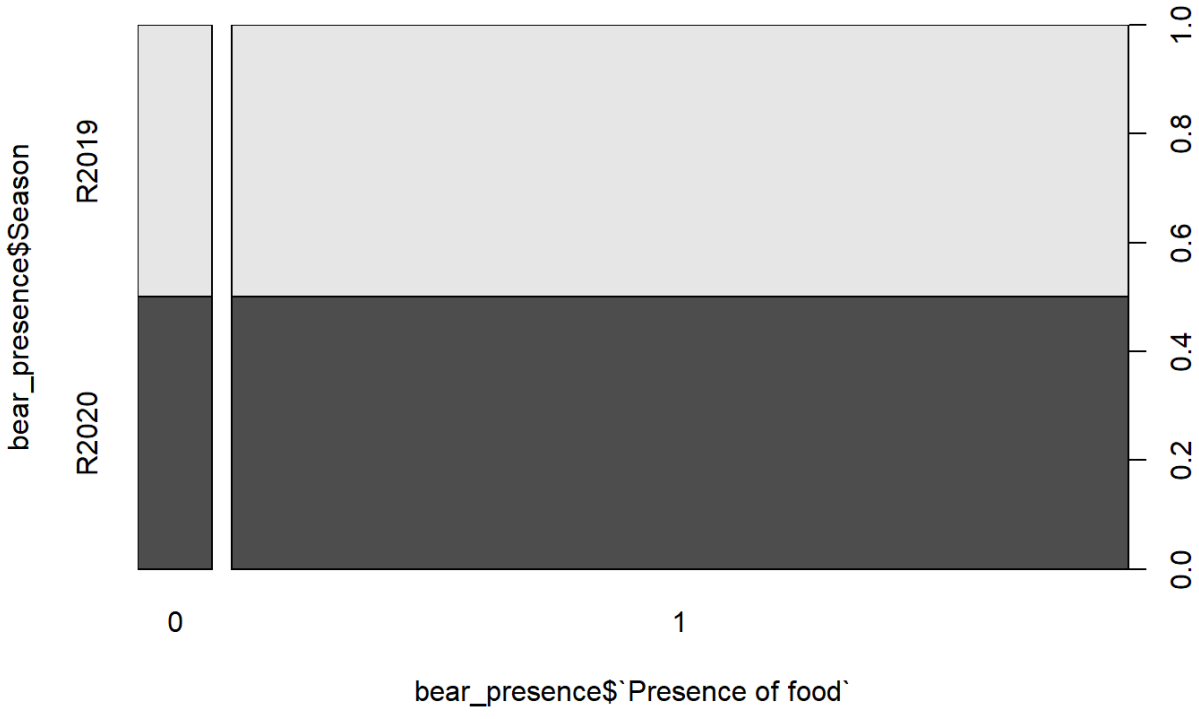

#Data visualization

```
plot(bear_presence$`SB presence sign`~bear_presence$Season)
```




```
plot(bear_presence$Season~bear_presence$`Presence of food`)
```



```
#Because all the habitat variables are exactly the same between seasons, we really cannot do much beyond acco
unt for those differences.


mcnemar.test(bear_presence$`SB presence sign`,bear_presence$Season)
##
##  McNemar's Chi-squared test with continuity correction
##
## data:  bear_presence$`SB presence sign` and bear_presence$Season
## McNemar's chi-squared = 1.5312, df = 1, p-value = 0.2159
#lm1=glmer(bear_presence$SB.presence.sign~bear_presence$Season+(1|bear_presence$S..No.),family = bino
mial)
lm1=glmer(bear_presence$SB.presence.sign~bear_presence$Season+ (1|bear_presence$S..No.),family = binom
ial)


summary(lm1)
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: bear_presence$SB.presence.sign ~ bear_presence$Season + (1 |
##     bear_presence$S..No.)
##
##      AIC      BIC   logLik deviance df.resid
##     69.1     75.0    -31.6     63.1       49
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.8329 -0.9661  0.3780  0.7173  1.0351
##
## Random effects:
##  Groups              Name        Variance Std.Dev.
##  bear_presence$S..No. (Intercept) 1.022    1.011
## Number of obs: 52, groups:  bear_presence$S..No., 26
##
## Fixed effects:
##                             Estimate Std. Error z value Pr(>|z|)
## (Intercept)                  1.4707     0.6618   2.222   0.0263 *
## bear_presence$SeasonR2020  -1.2808     0.7469  -1.715   0.0864 .
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr)
## br_p$SR2020 -0.768
plot(lm1)
```

Annexure II

Table. S. 1 (a). Pair wise matrix used for calculating the weighted sum for resistance score.

Layers	Conflict zone	Land use land cover	Road	Rail	Settlements	Slope	Water bodies	Forest
Conflict zone	1	2	3	3	3	3	3	5
LU/LC	0.50	1	3	3	2	3	2	5
Roads	0.50	0.33	1	0.25	1	2	2	3
Rails	0.33	0.33	0.25	1	0.33	2	3	3
Settlements	0.33	0.5	1	3.03	1	3	3	5
Slope	0.33	0.33	0.50	0.5	0.33	1	2	5
Water bodies	0.33	0.5	0.50	0.33	0.33	0.5	1	4
Forests	0.20	0.20	0.33	0.33	0.20	0.2	0.25	1
SUM	3.53	5.20	9.58	11.45	8.20	14.7	16.25	31

Table. S.2. (b). Standardized Decision Matrix used for calculating resistance score.

Standardized Decision matrix									Sum	Weight (%)	Weighted criteria
Conflict zone	0.28	0.57	0.85	0.85	0.85	0.85	0.85	1.42	6.51	23.02	0.81
LU/LC	0.14	0.28	0.85	0.85	0.57	0.85	0.57	1.42	5.52	19.52	0.69
Road	0.14	0.09	0.28	0.07	0.28	0.57	0.57	0.85	2.85	10.09	0.36
Rail	0.09	0.09	0.07	0.28	0.09	0.57	0.85	0.85	2.90	10.26	0.36
Settlements	0.09	0.14	0.28	0.86	0.28	0.85	0.85	1.42	4.77	16.88	0.60
Slope	0.09	0.09	0.14	0.14	0.09	0.28	0.57	1.42	2.83	10.01	0.35
Water bodies	0.09	0.14	0.14	0.09	0.09	0.14	0.28	1.13	2.12	7.51	0.27
Forest	0.06	0.06	0.09	0.09	0.06	0.06	0.07	0.28	0.77	2.72	0.10
SUM									**28.28**	**100**	**3.53**

Table. S.3. (c). Normalised decision Matrix used for calculating consistency index and ratio

Conflict zone	0.81	1.38	1.07	1.09	1.79	1.06	0.80	0.48	8.48	10.42
LU/LC	0.41	0.69	1.07	1.09	1.19	1.06	0.53	0.48	6.52	9.45
Road	0.41	0.23	0.36	0.09	0.60	0.71	0.53	0.29	3.21	8.99
Rail	0.27	0.27	0.09	0.36	0.20	0.71	0.80	0.29	2.98	8.23
Settlements	0.27	0.34	0.36	1.10	0.60	1.06	0.80	0.48	5.01	8.39
Slope	0.27	0.23	0.18	0.18	0.20	0.35	0.53	0.48	2.42	6.85
Water bodies	0.27	0.34	0.18	0.12	0.20	0.18	0.27	0.38	1.94	7.31
Forest	0.16	0.14	0.12	0.12	0.12	0.07	0.07	0.10	0.89	9.29