Evaluating differences between observers surveying for rails at night on ATVs

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Introduction

Rails are very difficult to detect, which makes surveying for them, and assessing the success of those surveys, very challenging (Conway, Nadeau, and Piest 2010; Melvin and Gibbs 1996). Rails are difficult to detect because they don't vocalize regularly in the fall, and do not respond to vocalizations, and their behavior has them dense in vegetation most of the time (Conway, Nadeau, and Piest 2010; Budka and Osiejuk 2013; Conway et al. 1993; Conway and Gibbs 2001). Rails are also reluctant to flush out of the vegetation until you are very close to them. This is one of the reasons they are the least studied group of birds in North America and why there are no standard survey methods for them outside of the breeding season (Conway 2011).

My projects overall goals are to understand how different kinds of wetland management impact both rails and watefowl during their fall migration. A large part of my data collection is done by going out and surveying the locations of birds in a variety of different wetland impoundments. In 2013 and 2014 my project did double surveys each night, in which a wetland impoundment was surveyed two times, by two different people, in a short period of time (3 hours). These surveys are done from ATVs driving transects after sunset with a spotlight under a distance sampling framework which takes the distance from the survey line to estimate detection probability and generate abundance estimates (Kissling and Garton 2006; Thomas et al. 2010; Royle, Dawson, and Bates 2004).

Since rails are active during the day other then responding to our presence in the wetland we are assuming that they are sleeping or still the rest of the night. I did some preliminary telemetry work tracking rail's response to ATVs during the past two falls and have not detected one moving more then 10 meters in response to an ATV. As a result we hope that these two surveys on the same night are surveying the same birds in roughly the same locations. I wanted to use this point pattern analysis to examine the differences in marked point patterns from the same night. To do this I will look at the closest point between the two point patterns and examine the distribution of these distances and how they are arranged throughout the wetland impoundments.

Methods

I have a marked point patterns of observations of Sora (*Porzana carolina*) on 13 different public properties in 45 different wetland units across 6 months of surveys (3 months in each year). I will summarize the differences in pattern at the wetland level, as that is the unit of interest to my project as a whole and is the unit at which we consider the survey to be completed.

Across that time period we had four different observers (four in 2013 and two returning in 2014). For the purposes of this project we are just going to look at 2014, since there are only two observers so its simpler. If these patterns work for two observers I will expand them to the four from 2013 in the future.

First I subsetted out the 2014 data and removed four of the sites because they had very few observations and were creating very high distance values. Then I re-projected it from lat/long to UTM.

```
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 3.1.3
```

```
## Loading required package: methods
```

```r
library(rgdal)
```

```
## Loading required package: sp
## rgdal: version: 0.8-16, (SVN revision 498)
## Geospatial Data Abstraction Library extensions to R successfully loaded
## Loaded GDAL runtime: GDAL 1.9.2, released 2012/10/08
## Path to GDAL shared files: /Library/Frameworks/R.framework/Versions/3.1/Resources/library/rgdal/gdal
## Loaded PROJ.4 runtime: Rel. 4.8.0, 6 March 2012, [PJ_VERSION: 480]
## Path to PROJ.4 shared files: /Library/Frameworks/R.framework/Versions/3.1/Resources/library/rgdal/pro
```

```r
library(gridExtra)
```

```
## Loading required package: grid
```

```r
library(AICcmodavg)
library(spatstat)
```

```
## Warning: package 'spatstat' was built under R version 3.1.2
```

```
##
## spatstat 1.40-0       (nickname: 'Do The Maths')
## For an introduction to spatstat, type 'beginner'
##
## Note: R version 3.1.1 (2014-07-10) is more than 9 months old; we strongly recommend upgrading to the
```

```r
setwd("/Users/AurielFournier/Documents/data")
dat <- read.csv("all_birds.csv")
dat <- na.omit(dat)
dat <- dat[dat$species=="sora",]
## I am removing these three sites because they have very few points, and were causing most, but not al
dat <- dat[dat$canwr!="tmpca"&dat$canwr!="osca"&dat$canwr!="ccnwr"&dat$canwr!="tsca",]

## reprojecting the points into utm
utm <- as.data.frame(project(cbind(dat$long, dat$lat), "+proj=utm +zone=15 ellps=WGS84"))
colnames(utm) <- c("utm_w","utm_n")

dat <- cbind(dat, utm)
# taking only the 2014 points
dat4 <- dat[dat$year==2014,]

#figuring out how many unique survey days we have. jdate = julian date
jdate4 <- unique(dat4$jdate)
```

Then I created a list where each object in the list is a data frame of just the observations from that day.

```r
# creating list to put each days points into seperately.
list4 <- list()
## so this takes each day adn makes a list with each unique date being a level in the lsit
# removes days in which only one observer saw birds
for(i in 1:length(jdate4)){
```

```
  dat <- dat4[dat4$jdate==jdate4[i],]
  if (length(unique(dat$obs))>1){
  list4[[i]] <- dat}
}

##
```

Then I wrote a for loop to use the crossdist function from the spatstat package to calculate the distance from each point to every other point in another set of points, and vise versa. These are then rbind-ed together into one master dataset.

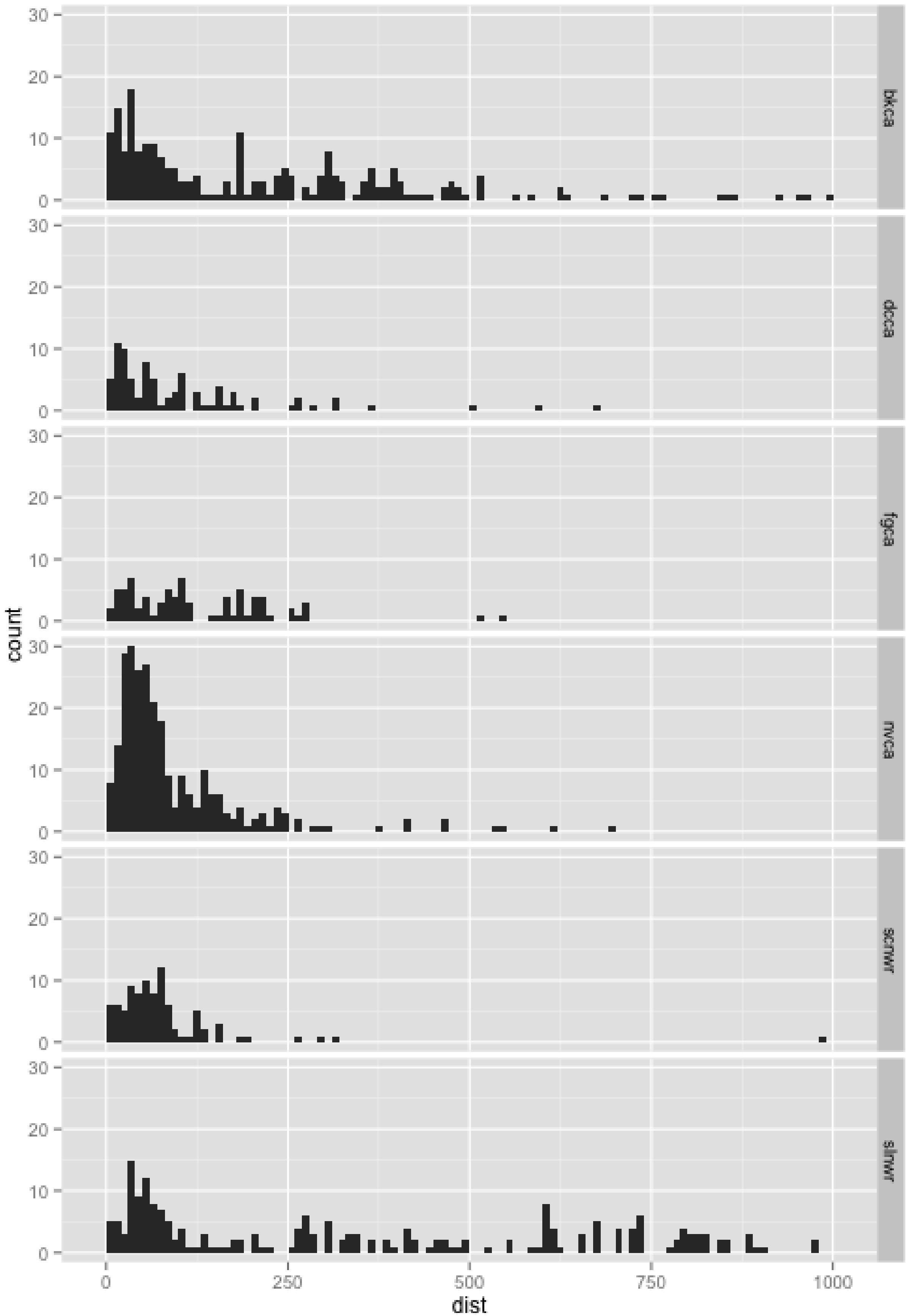
```
dist4 <- list()
newdf <- list()

dista <- list()
newdfa <- list()
for (i in c(1:length(list4))){
  # takes one element out of the list and makes it a data frame
  df <- as.data.frame(list4[[i]])
  if (nrow(df)>1){
    # splits the points from one night into two point patterns, one for me (A) and one for Nick (N)
    a <- df[df$obs=="N",]
    b <- df[df$obs=="A",]
    # figures out the distance between all the a points and the n points
    cdf <- crossdist(a$utm_w, a$utm_n, b$utm_w, b$utm_n)
    # finds the shortest distance for each point (row)
    c <- apply(cdf, 1, min)
    #figures out the distance between all the n points and the a points
    cdf2 <- crossdist(b$utm_w, b$utm_n, a$utm_w, a$utm_n)
    # finds the shortest distance for each point (row)
    d <- apply(cdf2, 1, min)
    # cbinding together the distances with their respective points, then stacking the points together w
    newdfa[[i]] <- rbind(cbind(a, dist=c),cbind(b,dist=d))
  }
  }

# binding together all the objects from the above for loop
dist <- do.call(rbind, newdfa)
# cutting out the outliers (those over 1000 meters, which are all instances where the nearest point was
dist <- dist[dist$dist<=1000,]

dist$scale <- as.numeric(scale(dist$dist))
```

```
ggplot()+
  geom_histogram(data=dist, aes(x=dist), binwidth=10)+
  facet_grid(canwr ~ .)
```


count
dist
0
250
500
750
1000
0
10
20
30
bkca
dcca
fgca
nvca
scnwr
slnwr

```r
ggplot()+
  geom_histogram(data=dist, aes(x=scale), binwidth=0.01)+
  facet_grid(canwr ~ .)
```

```
## Warning: position_stack requires constant width: output may be incorrect
## Warning: position_stack requires constant width: output may be incorrect
## Warning: position_stack requires constant width: output may be incorrect
## Warning: position_stack requires constant width: output may be incorrect
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## Warning: position_stack requires constant width: output may be incorrect
```

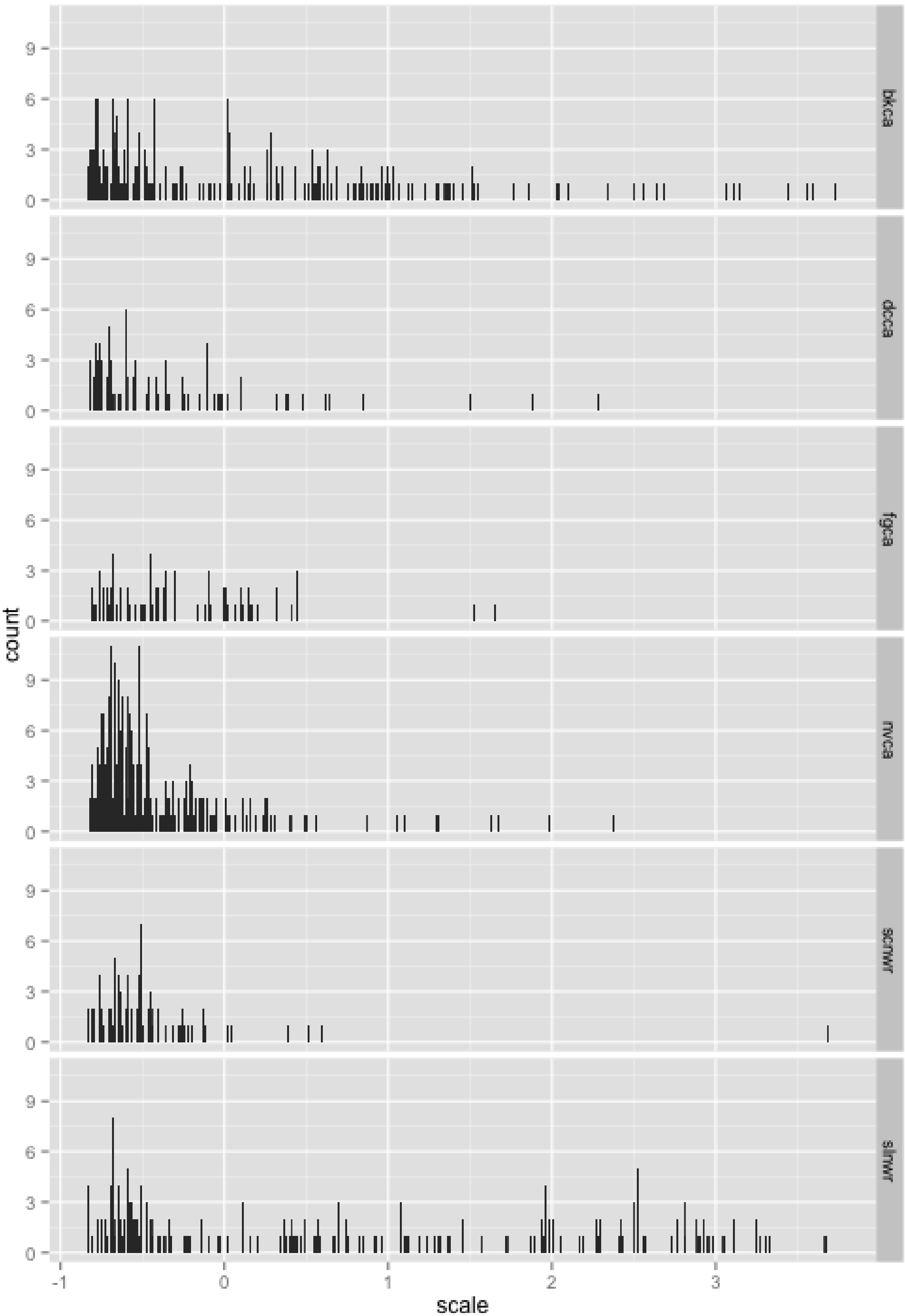

count
scale
bkca
dcca
fgca
nvca
scmwr
slmwr
-1
0
1
2
3
0
3
6
9

```r
model <- lm(data=dist, scale ~ canwr)

uni <- unique(dist$canwr)

canwr <- list()

for(i in 1:6){
  canwr[[i]] <- dist[dist$canwr==uni[i],]
}

library(BSDA)
```

```
## Warning: package 'BSDA' was built under R version 3.1.2

## Loading required package: e1071

## Warning: package 'e1071' was built under R version 3.1.2

## Loading required package: lattice
##
## Attaching package: 'lattice'
##
## The following object is masked from 'package:spatstat':
##
##     panel.histogram
##
##
## Attaching package: 'BSDA'
##
## The following object is masked from 'package:datasets':
##
##     Orange
```

```r
z <- list()

for(i in 1:6){
  df <- canwr[[i]]
  z[[i]] <- z.test(df$scale, mu=0, sigma.x=1)
}

z
```

```
## [[1]]
##
##  One-sample z-Test
##
## data:  df$scale
## z = 11.17, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  0.6416 0.9147
## sample estimates:
```

```
## mean of x
##    0.7782
##
##
## [[2]]
##
##  One-sample z-Test
##
## data:  df$scale
## z = -6.682, p-value = 2.363e-11
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.5319 -0.2906
## sample estimates:
## mean of x
##   -0.4112
##
##
## [[3]]
##
##  One-sample z-Test
##
## data:  df$scale
## z = -3.158, p-value = 0.001589
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.5584 -0.1307
## sample estimates:
## mean of x
##   -0.3446
##
##
## [[4]]
##
##  One-sample z-Test
##
## data:  df$scale
## z = 2.642, p-value = 0.008249
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  0.04596 0.31024
## sample estimates:
## mean of x
##    0.1781
##
##
## [[5]]
##
##  One-sample z-Test
##
## data:  df$scale
## z = -2.338, p-value = 0.01936
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
```

```
##  -0.48670 -0.04286
## sample estimates:
## mean of x
##   -0.2648
##
##
## [[6]]
##
##  One-sample z-Test
##
## data:  df$scale
## z = -4.356, p-value = 1.322e-05
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.6658 -0.2526
## sample estimates:
## mean of x
##   -0.4592
```

So something weird is happening at Swan Lake NWR (slnwr) but the rest seem... vaguely normally distributed.

```r
model <- lm(data=dist, dist ~ canwr)
summary(model)
```

```
##
## Call:
## lm(formula = dist ~ canwr, data = dist)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -348.0  -87.3  -35.1   65.2  898.5
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)    220.5       12.9   17.07  < 2e-16 ***
## canwrdcca     -113.4       24.6   -4.61  4.5e-06 ***
## canwrfgca      -96.1       25.3   -3.80  0.00015 ***
## canwrnvca     -127.9       17.5   -7.31  5.8e-13 ***
## canwrscnwr    -138.3       24.0   -5.77  1.1e-08 ***
## canwrslnwr     130.2       18.6    7.01  4.6e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 192 on 936 degrees of freedom
## Multiple R-squared:  0.224,  Adjusted R-squared:  0.22
## F-statistic:   54 on 5 and 936 DF,  p-value: <2e-16
```

Discussion

In 2013 and 2014 we put out radio transmitters on rails and tracked them in response to the ATVs. We never observed a rail moving more then 10 meters from its original location in response to an ATV. Based on our efforts catching rails at night we know that once they fly/or run from an ATV they typical stop and stay where they end up. At night they are sleeping, so they likely return to sleeping after we disturb them. Based on this I do not think they are actively moving around the impoundment during the night, at least not large distances.

Based on the model outputs from the distance sampling based surveys that we do (that generated these point patterns) detection probability for a Sora is low ~30%. So the fact that most of these points don't have a close (<50m) neighbor isn't surprising.

What I find most intriguing is that on some properties the farther distance points are clustered, which based on my knowledge of the area makes sense, since most of them are in areas with very thick/tall vegetation that makes detection very difficult, so detection probability is probably lower there.

I'm not sure expanding this project to 2013 is worth examining since this has reinforced my ideas that detection is low, but does prompt thinking about how we should be thinking about repeat surveys

References

Budka, Michał, and Tomasz S. Osiejuk. 2013. "Neighbour–stranger call discrimination in a nocturnal rail species, the Corncrake Crex crex." *Journal of Ornithology* 154 (3): 685–94. doi:10.1007/s10336-013-0933-8.

Conway, Courtney J. 2011. "Standardized North American Marsh Bird Monitoring Protocol." *Waterbirds* 34 (3). Tucson, AZ: U.S. Geological Survey, Arizona Cooperative Fish; Wildlife Research Unit: 319–46. doi:10.1675/063.034.0307.

Conway, Courtney J., and James P. Gibbs. 2001. *Factors influencing detection probability and the benefits of call broadcast surveys for monitoring marsh birds.* Laurel, MD: USGS, Patuxent Wildlife Research CEnter.

Conway, Courtney J., William R Eddleman, Stanley H Anderson, and Louis R. Hanebury. 1993. "Season Changes in Yuma Clapper Rail Vocalization Rate and Habitat Use." *The Journal of Wildlife Management* 57 (2): 282–90.

Conway, Courtney J., Christopher P. Nadeau, and Linden Piest. 2010. "Fire helps restore natural disturbance regime to benefit rare and endangered marsh birds endemic to the Colorado River." *Ecological Applications* 20 (7): 2024–35. http://www.ncbi.nlm.nih.gov/pubmed/21049887.

Kissling, Michelle L., and Edward O. Garton. 2006. "Estimating Detection Probability and Density From Point-Count Surveys: A Combination of Distance and Double-Observer Sampling." *The Auk* 123 (3): 735–52.

Melvin, Scott M., and James P. Gibbs. 1996. "Sora." In *The Birds of North America*, 250.

Royle, J. Andrew, Deanna K. Dawson, and Scott Bates. 2004. "Modeling Abundance Effects in Distance Sampling." *Ecology* 85 (6): 1591–97. doi:10.1890/03-3127.

Thomas, Len, Stephen T Buckland, Eric a Rexstad, Jeff L Laake, Samantha Strindberg, Sharon L Hedley, Jon Rb Bishop, Tiago a Marques, and Kenneth P Burnham. 2010. "Distance software: design and analysis of distance sampling surveys for estimating population size." *The Journal of Applied Ecology* 47 (1): 5–14. doi:10.1111/j.1365-2664.2009.01737.x.