Summary of camera trap data, SAGW, 2022

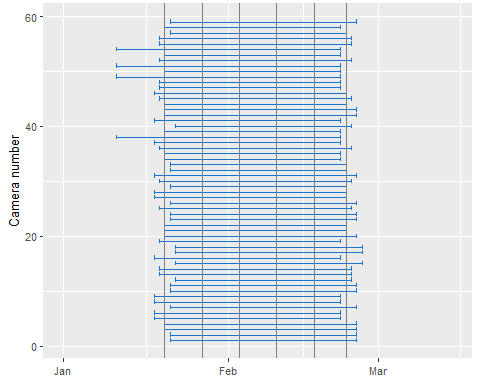
2023-06-06

# Effort

A total of 59 cameras were deployed in SAGW between 2022-01-11 and 2022-01-22 and were retrieved between 2022-02-22 and 2022-02-26. We delineated a total of 5 sampling occasions that were each 7 days long.

| Occasion | Start | End |
| --- | --- | --- |
| 1 | 2022-01-20 | 2022-01-26 |
| 2 | 2022-01-27 | 2022-02-02 |
| 3 | 2022-02-03 | 2022-02-09 |
| 4 | 2022-02-10 | 2022-02-16 |
| 5 | 2022-02-17 | 2022-02-23 |

In the figure below, each horizontal blue line represents a camera deployment. The gray vertical lines denote the beginning and end of the 5 consecutive sampling occasions.



# Detections

We detected a total of 11 mammal species on the 59 cameras during the 5 sampling occasions. For each species in the table below, we list the total number of photographs obtained (multiple photos may occur at the same camera location in the same day), the number of detections to be used in an occupancy modeling framework (maximum of one detection per location per sampling period), and unique number of camera locations where the species was photographed.

| Common name | Scientific name | No. photos | No. detections | No. locations |
| --- | --- | --- | --- | --- |
| Javelina | *Peccary tajacu* | 685 | 53 | 26 |
| Mule deer | *Odocoileus hemionus* | 548 | 68 | 36 |
| Black-tailed jackrabbit | *Lepus californicus* | 191 | 36 | 15 |
| Coyote | *Canis latrans* | 188 | 68 | 31 |
| Gray fox | *Urocyon cinereoargenteus* | 170 | 67 | 31 |
| Desert cottontail | *Sylvilagus audubonii* | 117 | 56 | 21 |
| Unknown jackrabbit | *Lepus sp.* | 113 | 31 | 12 |
| Bobcat | *Lynx rufus* | 48 | 23 | 15 |
| Feral dog | *Canis familiaris* | 9 | 3 | 2 |
| American badger | *Taxidea taxus* | 3 | 3 | 3 |
| Unknown skunk | *Mephitidae* | 1 | 1 | 1 |

# Modeling approach

## Occupancy models

For each species with a sufficient number of detections (% detection rate; here, 1 species), we used single-season occupancy models to estimate the probability of occurrence and the probability of detection given occurrence (MacKenzie et al. 2002). To estimate these parameters, we generated encounter histories for each camera location, where a “1” denotes that the species was detected at least once during a sampling occasion and a “0” indicates that the species was not detected. For example, an encounter history of “10011” would indicate that a species was photographed at least once during the first, fourth, and fifth sampling occasions and was not photographed during the second and third sampling occasions.

We used a Bayesian framework to estimate model parameters, as this made it easier to estimate derived parameters (e.g., proportion of area occupied across the entire park) with associated uncertainties and to incorporate random effects that can account for uncertainties beyond that explained by covariates in the model. We fit models in R using the spOccupancy package (Doser et al. 2022). For each model, we ran 3 Markov chains initiated at random values for 8000 iterations. We discarded the first 4000 iterations and retained 1 of every 8 iterations thereafter, using the remaining 1500 samples (across all the chains) to summarize the posterior distribution.

## Model selection

We identifed a number of spatial covariates for the Tucson Mountain District of Saguaro National Park that could explain variation in occurrence probabilities, detection probabilities, or both.

Something about where we obtained spatial data?

* candidate model set (general)
* how a model for inference was selected

# Species 1 (create species sections in a loop since the number of species will change across parks and years?)

i = 1  
SPECIES <- spp\_table$Species\_code[i]  
spp\_name <- tolower(spp\_table$common[i])  
spp\_plural <- paste0(spp\_name, "s")  
  
# Load best model and attributes  
model\_list <- readRDS(paste0("output/single-season-models/", PARK, "-",  
 SPECIES, "-", YEAR, ".rds"))  
best <- model\_list$model  
psi\_model <- model\_list$psi\_model  
p\_model <- model\_list$p\_model  
  
  
# Extract names of covariates (with and without "\_z" subscripts) from best model  
psi\_covs\_z <- create\_cov\_list(psi\_model)  
if (length(psi\_covs\_z) == 1 & any(psi\_covs\_z == "1")) {  
 psi\_covs\_z <- character(0)  
 psi\_covs <- character(0)  
} else {  
 psi\_covs <- psi\_covs\_z %>% str\_remove\_all(pattern = "\_z")  
}  
p\_covs\_z <- create\_cov\_list(p\_model)  
if (length(p\_covs\_z) == 1 & any(p\_covs\_z == "1")) {  
 p\_covs\_z <- character(0)  
 p\_covs <- character(0)  
} else {  
 p\_covs <- p\_covs\_z %>% str\_remove\_all(pattern = "\_z")  
}  
  
# Create table with summary stats that can be saved to file  
occ\_estimates <- parameter\_estimates(model = best,  
 parameter = "occ",  
 lower\_ci = 0.025,  
 upper\_ci = 0.975)  
det\_estimates <- parameter\_estimates(model = best,  
 parameter = "det",  
 lower\_ci = 0.025,  
 upper\_ci = 0.975)  
occ\_estimates <- occ\_estimates %>%  
 rename(Covariate = Parameter) %>%  
 mutate(Parameter = "Occurrence", .before = "Covariate")  
det\_estimates <- det\_estimates %>%  
 rename(Covariate = Parameter) %>%  
 mutate(Parameter = "Detection", .before = "Covariate")  
estimates <- rbind(occ\_estimates, det\_estimates)  
  
psi\_model

## occ   
## "~ elev\_z + vegclass2 + vegclass3"

p\_model

## det   
## "~ 1"

psi\_covs\_z

## [1] "elev\_z" "vegclass2" "vegclass3"

psi\_covs

## [1] "elev" "vegclass2" "vegclass3"

p\_covs\_z

## character(0)

p\_covs

## character(0)

head(covariates)

## parameter park short\_name formula axis\_label  
## 1 either all boundary boundary\_z Distance to park boundary (m)  
## 2 either all aspect east\_z + north\_z <NA>  
## 3 either all east east\_z Eastness  
## 4 either all north north\_z Northness  
## 5 either all elev elev\_z Elevation (m)  
## 6 either all elev2 elev\_z + I(elev\_z^2) Elevation (m)

# Add something to calculate the number of covariates for each parameter  
# Need to create wording to describe vegclasses and quadratic effects

## Model used for inference

The highest-ranking model for coyotes included XX covariates in the occurrence part of the model and XX covariates in the detection part of the model.

**Table X.** Parameter estimates from a model for coyote in the Tucson Mountain District of Saguaro National Park, 2022. SD = Standard deviation and 95% CI = 95% credible interval. Rhat values between 1 and 1.05 indicate that the model has converged. ESS = effective sample size; values > 400 are usually sufficient. f values indicate the proportion of posterior samples that are < 0 if the mean is < 0 or the proportion of samples that are > 0 if the mean is > 0. Estimates are on the logit scale and all continuous covariates have been standardized by their respective means and standard deviations.

| Parameter | Covariate | Mean | SD | 95% CI | Rhat | ESS | f |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Occurrence | (Intercept) | 1.18 | 0.61 | 0.04, 2.42 | 1 | 1375 | 0.98 |
| Occurrence | elev\_z | -1.63 | 0.67 | -3.04, -0.45 | 1 | 1294 | 1.00 |
| Occurrence | vegclass2 | -2.08 | 0.99 | -4.03, -0.19 | 1 | 1379 | 0.98 |
| Occurrence | vegclass3 | -1.43 | 0.92 | -3.26, 0.34 | 1 | 1500 | 0.94 |
| Detection | (Intercept) | -0.38 | 0.17 | -0.73, -0.04 | 1 | 1500 | 0.99 |

Table with overall estimate (or estimates by vegclass)

## Estimated occurrence probabilities

Map

## Estimated covariate effects on occurrence and/or detection probabilities

Figures with captions

Two examples of how to do things in a loop: