Occupancy Modeling

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Goal: Determine reliability of MegaDetector for monthly presence/absence data of species at site

MegaDetector

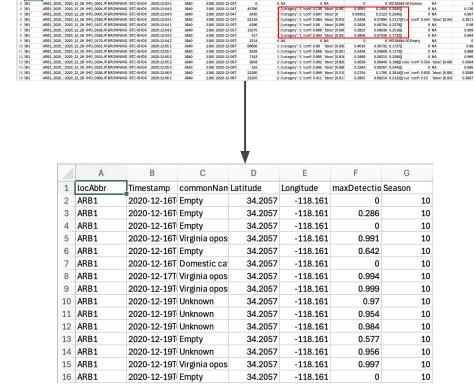
- Computer vision model
 - Identifies animals vs. humans vs. empty
 - Does not classify species
- Some data loss due to low confidence
- How impactful is this data loss?





Data Cleaning

- Grouping species
 - Handling misspellings and rare species
- Converting to actual .csv file
 - No commas within entry
- Selecting relevant columns
- Converting to proper format
- Calculating season



Setting Up the Files

```
# For each entry in dataTrame
for (i in innow(df.cur)) {
    # Get values of interest
    season < df.cur\$cascon(]
    location < df.cur\$cascon(]
    location < df.cur\$cascon(]

# Get name of day column
day_column_name <- paste0("Day_", relative_day)

# Convert current entry's corresponding cell in cur_grid to 1
    cur_grid[cur_grid\$cascon == season & cur_grid\$locAbbr == location, day_column_name] <- 1
}

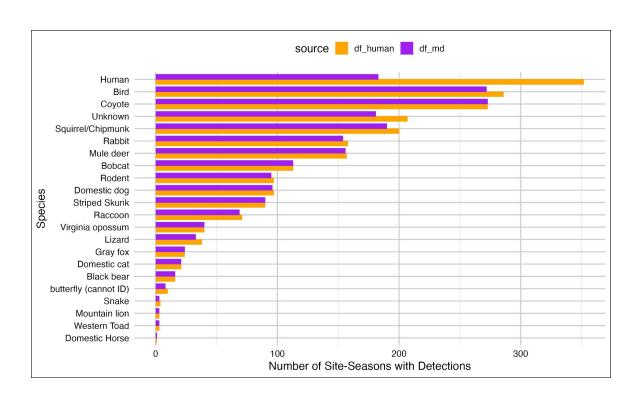
# Add column specifying source
updated_grid <- cur_grid \%%
mutate(\source = df_name)
# Add dataTrame to list
    results_list[[df_name]] <- updated_grid
}

* Put NO data below Human data
complete_grid <- bind_nows(results_list)
```

A	в с	D	Е	F	G	Н	1	- 1	K	L	M	N	0		BJ	BK	BL	BM	BN
1 Species	SeasonNumit Site 6	Latitude	Longitude	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10		Day_57	Day_58	Day_59	Day_60	Treatment
100 Coyote		34.1269			NA	NA.	NA.	NA.	NA.	NA.	NA	NA.	NA.		NA.	NA.	NA	NA	df_human
101 Coyote		34.1265	-118.21	NA	NA	NA	NA.	NA	NA	NA.	NA	NA	NA.		NA.	NA.	NA	NA	df_human
102 Coyote		34.218	-118.159		0	0	0	0	0	0	0	0	0	0	NA.	NA.	NA	NA.	df_human
103 Coyote		34.2174	-118.16	NA.	NA	NA	NA.	NA	NA	NA.	NA	NA	NA.		NA.	NA.	NA	NA.	df_human
104 Coyote		34.1557	-118.168	NA.		0	0	0	0	0	0	0	0	0	NA.	NA.	NA	NA.	df_human
105 Coyote		34,1545	-118.168	NA.	NA	NA	NA.	NA	NA	NA.	NA	NA	NA.		NA.	NA.	NA	NA.	df_human
106 Coyote		34.1548	541 -118.168 NA	NA.	NA	NA	NA.	NA	NA NA	NA NA	NA NA	NA NA 0	NA NA	0	NA.	NA.	NA	NA.	df_human
107 Coyote		34,1541		NA.	NA	NA	NA.	NA							NA.	NA.	NA	NA.	df_human
108 Coyote	6 SAB1	34.1294		NA.	NA	NA		0							NA.	NA.	NA	NA.	df_human
109 Coyote	6 SPS1	34.1243	-118.167		1	0	0	0	0	0	0	0	0	1	NA.	NA.	NA	NA.	df_human
110 Coyote	6 SPS2	34.1242	-118.167 N	NA.	NA	NA	NA.	NA	NA.	NA.	NA	NA.	NA.		NA.	NA.	NA	NA.	df_human
111 Covote	6 SPS3	34.1244	-118.167	NA.	NA	NA.	NA.	NA	NA	NA.	NA	NA	NA.		NA.	NA.	NA	NA.	df_human
12 Coyote	6 SPS4	34.1246	-118.167	NA.	NA	NA.	NA.	NA	NA	NA.	NA	NA	NA.		NA.	NA.	NA	NA.	df_human
113 Covote	6 SUN1	34.1771	-118.238	NA.	NA	NA.	NA.	NA	NA	NA.	NA	NA	NA.		NA.	NA.	NA	NA.	df_human
114 Coyote	6 SUN2	34.1761	-118.237	NA.	NA	NA.	NA.	NA	NA	NA.	NA	NA	NA.		NA.	NA.	NA	NA.	df_human
115 Covote	6 TCR1 6 TMC1 6 TMC2 6 WAV1 6 WAV2 6 WAV3 6 WAV4	34.2523	-118.328	NA.	NA	NA.	NA.	NA	NA	NA.	NA	NA	NA.		NA.	NA.	NA	NA.	df_human
116 Covote		34.1757	-118.181		0	0	0	1	1	0	1	1	0	1	NA.	NA.	NA	NA.	df_human
117 Covote		34.1756	-118.181	NA	NA	NA.	NA.	NA	NA	NA.	NA	NA	NA.		NA.	NA.	NA	NA.	df_human
118 Coyote		34.243	-118.311	NA	NA.	NA	NA	NA.	NA	NA	NA	NA	NA.			0	0	0	0 df_human
119 Coyote		34.2477	-118.306	NA.	NA	NA.	NA.	NA.	NA	NA.	NA	NA	NA.		NA.	NA.	NA	NA.	df_human
120 Coyote		34.2462	-118.294	NA.	NA	NA.	NA.	NA.	NA	NA.	NA	NA	NA.		NA.	NA.	NA	NA.	df_human
21 Coyote		34.2472	-118.305	NA.	NA	NA.	NA.	NA.	NA NA NA	NA.	NA	NA NA NA	NA NA NA		NA.	NA.	NA	NA.	df_human
22 Coyote	6 WHT1	34.2713	-118.351	-118.351 NA NA -118.319 NA NA -118.316 NA NA	NA	NA.	NA.	NA.		NA.	NA NA NA				NA.	NA.	NA	NA.	df_human
123 Coyote	6 WTP1 6 WTP2	34.2213	-118.319		NA	NA.	NA NA	NA.		NA.						1 NA	NA	NA.	df_human
124 Coyote		34.2208	-118.31		NA	NA.		NA		NA.					NA.	NA.	NA	NA.	df_human
125 Coyote	6 WWD1	34.2166	-118.258		0	0	0	0	0	0	0	0	0	0		0	0	0	0 df_human
26 Coyote	6 WWD2 6 HOL1 7 ARB1	34.2166	-118.258	NA.	NA.	NA	NA	NA.	NA	NA	NA	NA	NA.		NA.	NA.	NA	NA	df_human
27 Coyote		34.0395	-118.216	NA.	NA	NA	NA	NA.	NA	NA	NA	NA	NA.		NA.	NA	NA	NA	df_human
128 Coyote		34.2057	34.2057 -118.161 NA	NA.	NA	NA.	NA.	NA	NA	NA	NA	NA.		NA.	NA	NA	NA	df_human	
129 Covote	7 AST1	34.1382	-118.167	NA.	NA		0	1	0	0	0	1	0	0		0	0	0	0 df human

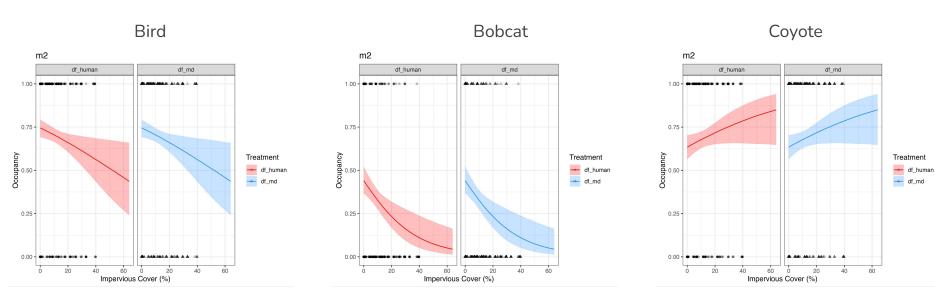
- Expanding day columns
 - Mark inactive as NA and active as 0
- For each image of species, put
 1 in cell for Season, Site, Day
 - Repeat for images with ≥ 0.8 confidence for MD
- Checking for accuracy
 - Took a surprising amount of time (and stress)
 - For photos with low confidence, often other photos that day that are above confidence threshold
- Run Occupancy Modeling File for each Species

Comparing number of Site-Seasons with detections from human-approved images with MD data. (Data loss per species)



5 models:

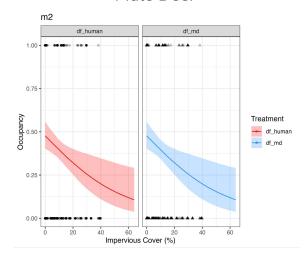
- 1. m1: intercept-only (average)
- 2. m2: Impervious as predictor
- 3. m3: Treatment as predictor (human vs. MD)
- 4. m4: Combined Impervious and Treatment
- 5. m5: Interaction of Impervious and Treatment



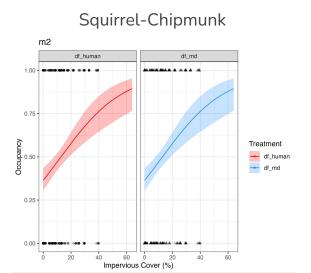
Interesting graphs of best models for some species

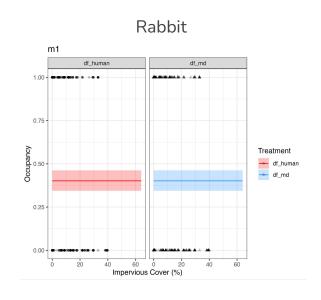
Human m5 1.00 0.75 0.00 0.20 0.00 Impervious Cover (%)

Mule Deer



m2 typically the best model (Impervious alone is best predictor), which is good news! MD seems to not have a substantive impact on predicting occupancy rates.





Next Steps

- Explore more locations (not just Los Angeles)
- Test different confidence thresholds
- Check smaller species groups
- What else?

