

DROUGHT AND COYOTES MEDIATE THE RELATIONSHIP BETWEEN
MESOPREDATORS AND HUMAN DISTURBANCE IN CALIFORNIA

By

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ABSTRACT

DROUGHT AND COYOTES MEDIATE THE RELATIONSHIP BETWEEN MESOPREDATORS AND HUMAN DISTURBANCE IN CALIFORNIA

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Mesopredators in California are facing two major changes to their ecosystem: drought and the expansion of human disturbance. As a result, mesopredators are likely shifting their habitat use as well as their interspecies interactions to balance resource needs and risk-taking on the landscape. In response to severe drought, the California Department of Fish and Wildlife deployed 585 camera traps throughout the Mojave Desert and Central Valley documenting mammalian mesopredator presence in a drought year (2016) and a post-drought year (2017). The objectives of this study were to examine spatial patterns of mesopredator occurrence and co-occurrence with a dominant predator, the coyote (*Canis latrans*), at a large spatial scale across varying levels of human disturbance and to investigate how drought may mediate these relationships. Single-season, single-species occupancy models were used to elucidate the relationship between human disturbance, drought, and mesopredator habitat use in both ecoregions. Conditional two-species occupancy models were then fit to establish the effect coyotes may have had on subordinate mesopredators and their relationships with human disturbance during and after the drought. I found that human disturbance differentially affected both the occupancy and detection of mesopredator species and that these

relationships were sometimes mediated by drought and the presence of coyotes. Except for the domestic cat (*Felis catus*), all mesopredators showed some kind of response to drought. Detection of mesopredators in the Central Valley was typically higher in 2016, especially in low disturbance sites, indicating that species became more active during the drought to meet resource needs. However, detection and occupancy of mesopredators in the Mojave Desert tended to increase after the drought, suggesting that species were responding to an increase in resources, possibly the density of prey. Coyotes in the Mojave Desert became more detectable in high human disturbance in 2016 and less detectable in 2017, signifying that they were increasing activity in human disturbance during the drought, possibly to obtain anthropogenic resources. Additionally, subordinate species, particularly in the Central Valley, appeared to take greater risks during the drought with increased use of water sources, despite the presence of coyotes. These findings suggest that drought not only affects individual species and their relationships to human disturbance, but that it can also impact their interspecies interactions and use of different landscape features.

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INTRODUCTION

Due to human population growth, there has been an expansion of human enterprises such as agriculture, industry, and fishing which, in turn, alter land cover, wildlife populations, and biogeochemical cycles (Vitousek et al. 1997). These alterations further affect the planet through global climate change and biodiversity loss (Vitousek et al. 1997, Karl and Trenberth 2003, Maxwell et al. 2016). Of the species imperiled by human development and disturbance, large mammalian predators are considered to be especially sensitive because they often occur in low densities, need large areas of undisturbed habitat, and have been traditionally persecuted by people (Noss et al. 1996, Woodroffe 2000, Gittleman and Gompper 2005). Given this susceptibility, there has been an extreme reduction in the ranges and populations of large predators globally (Ripple et al. 2014).

In the absence of apex predators, mid-sized predators, called mesopredators, become “de facto top” predators that can shift the dynamics within an ecological community (Gittleman and Gompper 2005). This process is referred to as “mesopredator release”, defined as the expansion in density, distribution, or behavior of a middle-rank predator following the decline in density or distribution of an apex predator (Soulé et al. 1988, Prugh et al. 2009, Brashares et al. 2010). Mesopredator release is often tied to reduced intraguild predation, an extreme form of interference competition, whereby a larger dominant predator will kill and possibly eat a smaller subordinate predator which competes for a limiting resource (Polis et al. 1989). Intraguild predation by apex

predators can cause population and behavioral effects in mesopredators (Polis et al. 1989). Therefore, an ecosystem that loses the top predator releases mesopredators from this control, which can have potentially unknown ecological consequences.

Because habitat fragmentation can decrease populations of large apex predators, mesopredator release is closely associated with anthropogenic land-use change (Brashares et al. 2010). Mesopredators are naturally more abundant than large predators because they are smaller, have a wider resource base, often have an opportunistic and omnivorous diet, and are able to adjust to and thrive in diverse habitats (Gittleman and Gompper 2005, Roemer et al. 2009). Therefore, mesopredators can adjust to human-dominated landscapes and may even benefit from human food subsidies (Brashares et al. 2010).

In much of North America the coyote (*Canis latrans*) is now considered the top predator due to the extirpation of the gray wolf (*Canis lupus*, Prugh et al. 2009). Coyotes are known to kill a variety of mesopredator species and, in turn, influence the larger ecosystem through the suppression of predation on birds and rodents (Rogers and Caro 1998, Crooks and Soulé 1999, Henke and Bryant 1999, Palomares and Caro 1999, Fedriani et al. 2000). Intraguild prey species often exhibit “escape” behaviors from intraguild predators, such as coyotes, in which they may alter their spatial activity patterns to avoid overlap with the dominant predator (Polis et al. 1989, Linnell and Strand 2000). This change in spatial activity is called spatial partitioning and plays a central role in structuring predator communities (Gompper et al. 2016).

While coyotes are omnivores that are known to exploit urban areas and take advantage of human-related food, they are also predominantly associated with natural areas (Riley et al. 2003). Coyotes appear to have a tolerance threshold for urbanization in which they can utilize human-dominated landscapes but require natural areas to persist (Crooks and Soulé 1999, Ordeñana et al. 2010). Coyotes' reliance on natural areas has caused smaller mesopredators to use more urban or disturbed areas as "human shields" from coyotes; this has been found to be especially true for red foxes (*Vulpes vulpes*, Gosselink et al. 2003, Moll et al. 2018). In this way, subordinate predators can escape the pressures of a dominant predator through use of an urban refuge.

The safety of these urban refuges can be compromised, however, in times of drought when more dominant, human-averse species are also attracted to urban areas. For example, black bears (*Ursus americanus*) and mountain lions (*Puma concolor*) have been found to use areas of higher human density in times of food shortage (Baruch-Mordo et al. 2014, Blecha et al. 2018), and coyotes have been found to increase their use of anthropogenic food during the dry season and in response to low annual precipitation (Fedriani et al. 2001, Cypher et al. 2018). This is of importance because the risk of drought is increasing as climate change produces higher temperatures and evaporation rates which result in increased drying (Dai et al. 2004, Trenberth 2011). The outcome of these changes to the hydrologic cycle are droughts that set in more quickly, are more intense, and last longer (Trenberth et al. 2014). As a result, 22.6% of the world's

terrestrial mammals experience significant exposure to droughts (Ameca y Juárez et al. 2013).

The effects of human disturbance, drought, and the interaction of the two on the mesopredator community are particularly relevant in California, which has been identified as a biodiversity hotspot (Myers et al. 2000), has experienced expansive land cover change (Sleeter et al. 2011), and recently experienced the state's worst drought on record (Griffin and Anchukaitis 2014). From 1973-2000 developed land in California increased by about 37.6%, with the largest relative increase being in the Mojave Basin and Range, followed by the Central Valley of California (Sleeter et al. 2011).

Historically, both the Mojave Desert and the Central Valley were dominated by grasslands and shrublands; however, agriculture now dominates the Central Valley and loss of grasslands/shrublands to development is common in the Mojave Desert (Sleeter 2008, Sleeter et al. 2011). In addition to increased development, the Mojave Desert landscape has been impacted by livestock grazing, introduction of exotic species, mining, military activities, and off-road vehicles, some of which are exacerbated by drought (Lovich and Bainbridge 1999).

California land use, particularly agriculture, has historically been influenced by drought (Sleeter 2008) and will likely continue to be shaped by future drought (Wilson et al. 2016). This is especially true for the Central Valley of California, which is considered one of the most productive agricultural regions in the world (Faunt et al. 2016), and which has experienced an increase in farmland from 1973-2000 (Sleeter 2008). However,

this region also relies on state and federal water systems which divert surface water from the Sierra Nevada Mountains and Coast Ranges to irrigate crops (Faunt et al. 2016).

During the recent 2012-2016 drought, the lower availability of surface water led to an increase in ground water pumpage, depleting groundwater reservoirs (Faunt et al. 2016).

Future drought may lead to decreased agriculture in this region as water becomes scarce and reservoirs are depleted.

A 2016 report on the vulnerability of wildlife to extreme drought in California identified both the Central Valley and Mojave Desert as two of the top five ecoregions supporting the highest number of drought-sensitive taxa (California Department of Fish and Wildlife 2016a). Similarly, a recent study of drought impacts on an ecological community near both the Central Valley and Mojave Desert of California found that 25% of the species studied declined in abundance in response to drought (Prugh et al. 2018). Additionally, vertebrates were found to respond more strongly to long-term water deficits suggesting that longer-lasting droughts, which are becoming more common with climate change, will greatly impact vertebrates (Trenberth et al. 2014, Prugh et al. 2018). Specifically, carnivores were found to be the most impacted by drought likely due to the decline of a few keystone prey (Prugh et al. 2018).

Indeed, small mammals, a frequent prey base of mesopredators in California, are vulnerable to drought and decrease in abundance when drought conditions prevail for a year or more (Chew and Butterworth 1964, Whitford 1976, Rosen 2000). This would suggest that in times of drought, predators will have fewer resources on which to rely

which can affect competition within the guild. There has been some debate about the influence of stress, such as drought, on competition in a community; some believe competition will be greater with reduced resources while others have found it results in competitive release when more dominant species decline in numbers (Tilman 1982, Chesson and Huntly 1997, McCluney et al. 2012, Prugh et al. 2018).

The objectives of this study were to examine spatial patterns of mesopredator occurrence and co-occurrence with a dominant predator, the coyote, at a large spatial scale across varying levels of human disturbance and to investigate how drought may mediate these relationships. These co-occurrence patterns should elucidate potential spatial partitioning among mesopredators, which is reflective of competition within the guild. Co-occurrence is considered indicative of competition because observed co-occurrence in most natural communities is usually less than expected by chance (Gotelli and McCabe 2002). To address my objectives I used two years of data collected from 585 camera traps which monitored mesopredator presence in the Mojave Desert and Central Valley ecoregions of California. This data set encompassed one of the driest years (2016) and one of the wettest years (2017) on record in California (AghaKouchak et al. 2015, Gomez 2017). I used both single-season single-species and conditional two-species occupancy modeling to analyze how mesopredators responded to drought and human disturbance in the presence and absence of coyotes.

Occupancy modeling estimates two parameters: occupancy and detection probability, which can be interpreted in different ways. In this study, occupancy is

interpreted as the probability that a species used a site during the field season and therefore the probability that a camera trap was located within the home range of at least one individual and was consequently located in suitable habitat (MacKenzie et al. 2017a, Cruz et al. 2018). Occupancy is a measure reflecting behavior at the landscape-level whereas detection probability is a smaller-scale measure of behavior which reflects the magnitude of use as a response to landscape characteristics within the home range (Lewis et al. 2015a). The probability of detecting a species is both a function of density (Royle and Nichols 2003, Lewis et al. 2015b, Neilson et al. 2018, Broadley et al. 2019) and animal space use (Broadley et al. 2019) such as movement (Neilson et al. 2018, Stewart et al. 2018) and frequency of use (Lewis et al. 2015b). Using these interpretations, I did not treat detection as a nuisance parameter (Mackenzie et al. 2002) but rather as a more sensitive measure of species' relationships to habitat conditions which may be masked in occupancy estimates.

I hypothesized that the 2012-2016 drought did not cause mesopredators to shift their large-scale habitat associations as they selected home ranges (occupancy) but I did hypothesize that drought influenced mesopredator activity patterns and their relative abundance (detection probability). Because 2016 was the final year of an extreme multi-year drought (Griffin and Anchukaitis 2014), water levels were likely at their lowest and prey species' populations were reduced (Kelly et al. 2019). Extreme decreases in water availability likely result in bottom-up effects (plant-mediated) dominating a community which would ultimately lead to a decrease in the abundance of predatory species

(McCluney et al. 2012); this has been found in both mammalian and avian predators in a semi-arid and arid ecosystems of California (Iknayan and Beissinger 2018, Prugh et al. 2018). A reduction in the density of mesopredators would likely lead to a decrease in detection probability in 2016. Additionally, at very low water availability, such as in 2016, predators are thought to decrease hunting activity and instead seek refuge as a water conservation technique, leading to decreased detection probability (McCluney et al. 2012). Combined, I expected reduced density and activity of mesopredators in 2016 to result in reduced detection probability. However, following the intense rains in the winter of 2016-2017, which likely stimulated plant production and prey population growth (McCluney 2017), I expected activity and density of mesopredators to increase, resulting in increased detection probabilities.

I hypothesized that all species would be more detectable at sources of water in 2016, during the drought. Most mesopredator species are more likely to occupy sites with surface water (Rich et al. 2019a) and I believed that drought would exacerbate that relationship, regardless of species or eco-region. While kit fox are typically thought to be independent of surface water and obtain water needs through prey acquisition (Golightly and Ohmart 1984); long-distance travel in search of resources can use as much as 33% of their total energy budget (Girard 2001). Therefore, it is likely that kit fox couldn't afford to expend that much energy to obtain limited prey sources in 2016 and risked competitive interactions with other mesopredator species at water sites. I predicted that all subordinate mesopredators would increase use of water sources during the drought,

regardless of the presence of coyotes but that this risk-taking behavior would possibly decrease in 2017 when water was not as limiting.

Because the Mojave Desert is primarily wildlands without managed water systems, I thought that mesopredator response to drought would be stronger in that ecoregion. While species living in the Mojave Desert are arid-adapted, the drought experienced from 2012-2016 was unprecedented and carnivores are known to react strongly to long-term drought (Griffin and Anchukaitis 2014, Prugh et al. 2018). Additionally, open habitats are known to intensify competitive interactions (Creel et al. 2001), which could be exacerbated in times of resource shortage, such as drought. As a result, I expected to see a more dramatic difference in detection probabilities of mesopredators between 2016 and 2017 in the Mojave Desert versus the Central Valley. While the Central Valley did experience reduced water deliveries during the drought, water pumpage buffered much of the ecoregion to extreme water shortage (Faunt et al. 2016, Lund et al. 2018). However, there was still a 10% shortage in statewide agricultural water use which led to the both the reduced irrigation of some crops and fallowing of fields of annual crops (Lund et al. 2018). Therefore I still expected mesopredators to have lower detection probabilities in 2016, but not significantly different from detection probabilities in 2017, especially in areas which used irrigation (human disturbance).

I expected coyotes in both ecoregions to use human disturbance as a drought refuge and therefore be more active and detectable in human-disturbed areas during the drought due to their increased use of anthropogenic food (Cypher et al. 2018). Because

subordinate mesopredators, such as fox species, sometimes utilize disturbed areas as urban refuges from coyotes (Moll et al. 2018), I hypothesized that they might decrease their use of these areas during the drought when coyotes increased their use. Because native prey populations likely increased in 2017 in response to increased plant productivity following the rains, coyotes likely increased their use of less-disturbed areas after the drought. In response, I expected subordinate mesopredators to avoid areas of increased coyote activity and therefore increase their use of disturbed areas in 2017, resulting in higher detection probabilities.

MATERIALS AND METHODS

Site Locations

Mojave Desert

The Mojave Desert ecoregion of California covers an area of approximately 66,834 km² and is characterized by its extensive, undulating plains with short mountain ranges, playas, basins, and dunes (Bailey 1980, McNab et al. 2007). The elevation in the Mojave Desert is greatly variable from ~85 m below sea level to ~3,353 m in the mountains (Bailey 1980). The mountains of the Mojave Desert ecoregion are rocky and mostly devoid of vegetation, and the valleys are primarily characterized by creosote bush (*Larrea tridentata*)-dominated shrub communities (Bailey 1980, Griffith et al. 2016). The interior basins of the Mojave Desert ecoregion are comprised of ephemeral, shallow playa lakes which lead to alkali soils in which salt-tolerant plant communities dominate (Bailey 1980, Griffith et al. 2016). High temperatures prevail for long periods of time in the summer while winters are moderate, but occasional frosts do occur (Bailey 1980). Rains are widespread and gentle in the winter, and summer rains are characterized by rare but powerful thunderstorms (Bailey 1980). Annual precipitation in the Mojave Desert is typically ~5-25 cm in the valleys but can be much higher in the mountains (Bailey 1980).

Central Valley

The Central Valley of California is a long, flat alluvial plain which stretches between the Sierra Nevada Mountains and the Coast Ranges covering an area of

approximately 49,176 km² (Bailey 1980). Once dominated by native bunch grasses, the Central Valley is now characterized by flat, intensely-farmed plains (Griffith et al. 2016). The remnant grasslands are dominated by introduced grasses (Bailey 1980). Since the 1970s, there has been a trend of annual cropland being converted to perennial crops such as orchards and vineyards (Sleeter 2008, Faunt et al. 2016). The Central Valley has long, hot, dry summers and mild winters, during which it receives most of its rain (~15-76 cm, Bailey 1980, Griffith et al. 2016). Elevation in the Central Valley ranges only slightly from sea level to ~152 m (Bailey 1980). The Central Valley is divided into two smaller valleys, dominated by two watersheds, the Sacramento Valley and the Sacramento River to the north and the San Joaquin Valley and the San Joaquin River to the south (American Museum of Natural History 2017).

Site Selection and Study Design

Site selection was completed by California Department of Fish and Wildlife (CDFW) personnel following the Terrestrial Species Stressor Monitoring Project (TSM) protocol (California Department of Fish and Wildlife 2016b, 2017). Sites were selected within the United States Department of Agriculture (USDA)-defined Great Valley (hereafter Central Valley) and Mojave Desert ecoregions, truncated to California boundaries. A grid of hexagons (2.6 km radius) from the USDA Forest Inventory and Analysis Program (Brand et al. 2000) was used as the sampling frame and a random sample of hexagons was drawn for both ecoregions. To select site locations within each

hexagon, CDFW created a finer-scale grid of approximately 2,400 points spaced 100 m apart within each hexagon. Vegetation maps were used to calculate the total cover of key lifeforms (e.g. grasslands, cropland, playa) within each ecoregion and lifeform at each point. This information was then used to develop goals for stratified sampling of points within the random sample of hexagons. Due to the high proportion of privately owned land in the Central Valley ecoregion, opportunistic sampling often had to be utilized in addition to randomly selected points.

Within each randomly-selected hexagon, CDFW typically established one to two sampling points/study sites that were approximately one to two km apart (Figure 1). These study sites were selected by assigning random numbers to each finer-scale grid point and selecting the lowest numbered points which met stratified sampling goals and land access restrictions. Private lands were excluded from the random selection process in the Mojave Desert given the high proportion of publicly-owned land. Additional guzzlers (artificial water catchments used as a conservation tool to provide water to wildlife) and natural water features were also randomly selected to meet stratification goals in both years.

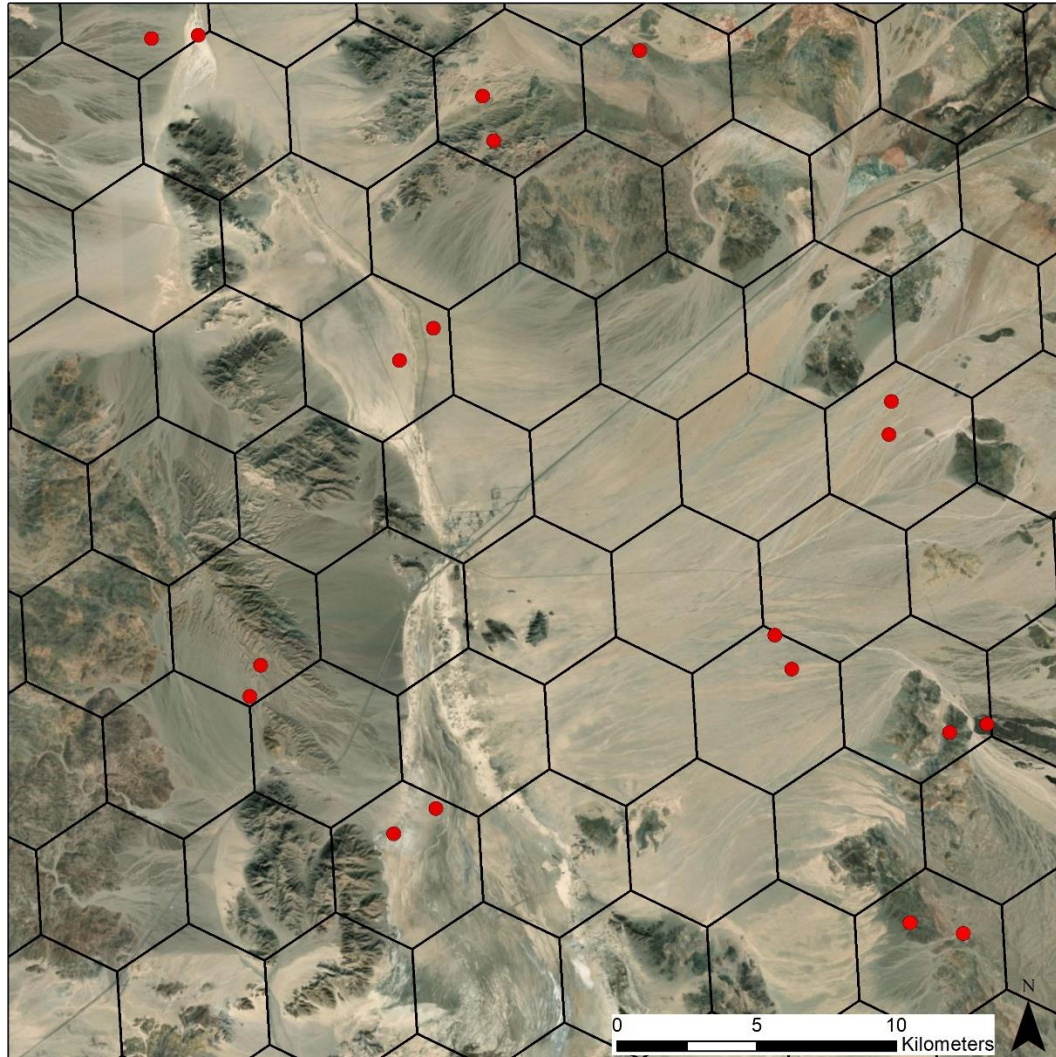


Figure 1. Map depicting USDA FIA hexagons used for site selection by CDFW within the Mojave Desert. Red dots represent TSM field sites visited during the two year study. Each study site was approximately 1-2 km from other sites within the same hexagon.

Due to a limited number of cameras, we rotated our camera traps across sites both years. After a camera trap had been deployed for at least 28 nights, cameras could be retrieved from a site and redeployed at a new site. As a result, camera trap data was collected anywhere from March to August depending on the site, as well as the year. In

2016, we deployed cameras at 229 sites in the Mojave Desert and 91 sites in the Central Valley. In 2017, we deployed cameras at 107 sites in the Mojave Desert and 184 in the Central Valley. In total, we were able to visit 611 sites over our two year study.

Camera Trap Data Collection

The protocol used for this project was developed by the TSM project (California Department of Fish and Wildlife 2016*b*, 2017), which was adapted from the Ecoregion Biodiversity Monitoring (EBM) project of CDFW (Furnas and Callas 2015). However, some details were altered to accommodate the primarily non-forested ecoregions in which we were collecting data. All procedures adhered to the animal care and use policy at Humboldt State University (HSU) and were approved by HSU Institutional Animal Care and Use Committee (IACUC), protocol number 16/17.W.08-A (September 7, 2016).

We positioned cameras to face north, when possible, to avoid direct light, and preferentially aimed cameras at game trails, burrows, or other wildlife sign. Additionally, cameras were positioned to avoid foliage or foliage was trimmed back to avoid false triggers. We pounded T-posts into the ground and Reconyx PC900 cameras were cable-locked to a hole drilled into the T-posts. However, some cameras were secured to trees or established fence posts if T-post mounting was not possible or preferable. Cameras were mounted on small wooden boards prior to deployment, which allowed them to be secured to the T-post with a U-bolt at the base and a bungee cord at the top. This made adjusting the angle of cameras with wooden shims much easier.

Cameras were baited only once at the time of camera deployment at a site. Bait was placed three to four meters in front of the camera traps, which were mounted approximately one meter above the ground, depending on specific site conditions. Bait included approximately one half to one kg salt lick, 500 mg of peanut butter- oat mixture, and 150 g of fishy cat food which was covered with sticks or rocks, if possible, to encourage animals to linger. Bait types were spaced approximately 10 cm apart.

Cameras were set to high trigger sensitivity and took three photos per trigger event, with no delay between triggers (Appendix A). We used walk tests to establish where cameras were triggering, this allowed for more accurate placement of cameras and bait. In 2017, smartphone card readers were also used to verify accuracy. Header and footer photos were taken at the time of deployment and retrieval, respectively, to ensure functionality of camera for the duration of deployment.

Cameras were deployed for approximately 28 nights although this varied due to site access limitations. Crews visited each site three times; first visits were to deploy cameras, second visits were approximately one week later to check that cameras were functioning/aimed correctly and to clear overgrown vegetation (in the Central Valley), and third visits were to collect cameras. Of the 611 sites set up over the two year study, 585 collected usable camera trap data (Figure 2). Some cameras were destroyed or stolen and some did not function properly.

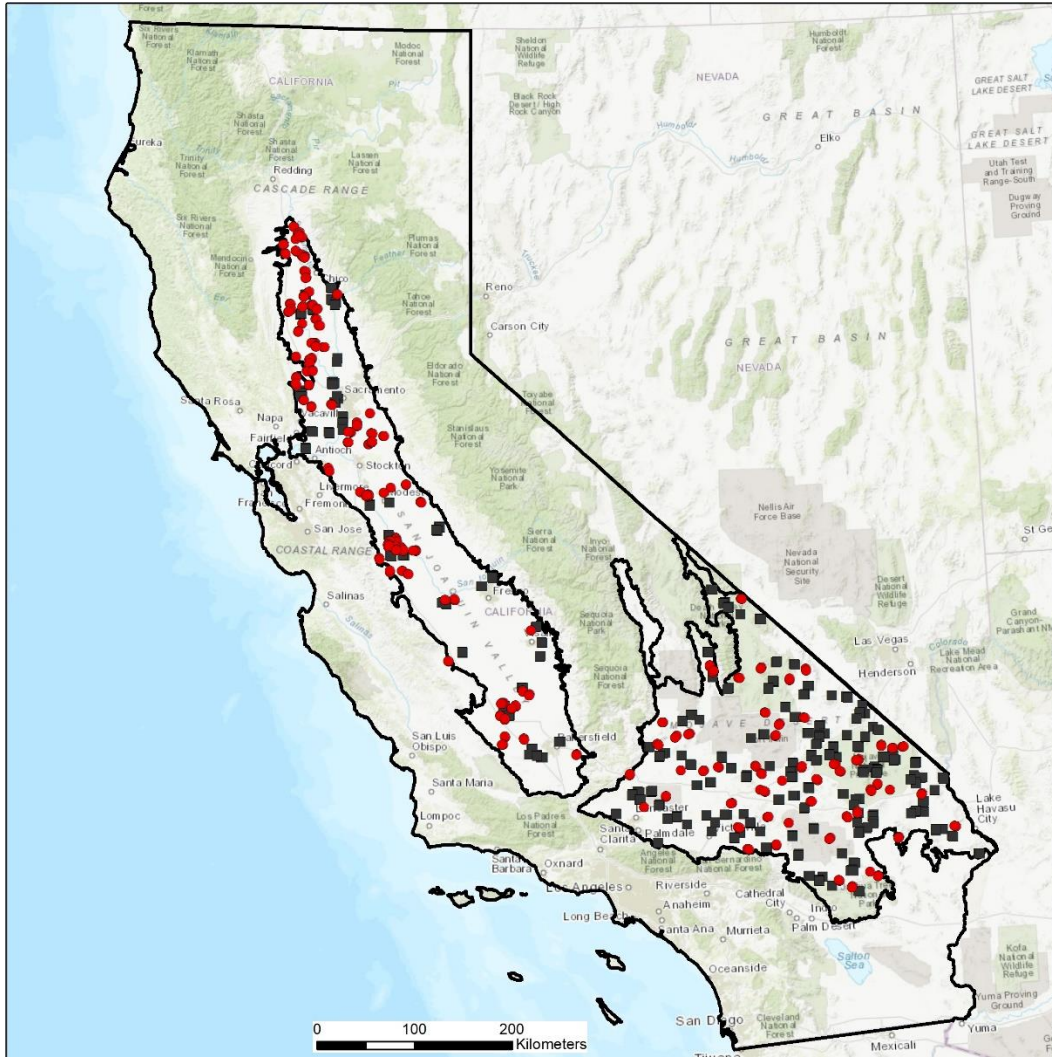


Figure 2. Map of field TSM sites used in analysis ($n=585$) in the Central Valley ($n=266$) and Mojave Desert ($n=319$) of California during our two year study. Black squares represent sites from 2016 and red dots represent sites from 2017.

Data Analysis and Occupancy Modeling

Camera trap photo processing

Photos and their associated metadata were imported onto a computer using MapView Professional. Each camera trap's photos were then processed by a CDFW technician who identified each photo detection to species level, if possible. If species identification was not possible, genus was noted and the photo was tagged for review. When processing data, each individual species was only counted once per 24 hr period (clock starting at time of deployment, not 0000 hours) and times were not noted for detections. If the camera was not aimed at the bait for more than 12 hrs in a 24 hr period (determined by the time of the camera's header photo), the camera was considered non-functional. All camera trap photos were reviewed by at least two independent observers in both 2016 and 2017. Whenever there were discrepancies between the two photo identifications, a third reviewer went through the photos once more to determine a final identification.

Single season occupancy modeling

Detection history and covariates.

Single season occupancy modeling relies on a sampling scheme wherein N sites are each surveyed T times to establish the presence or absence of a species (Mackenzie et al. 2002). In this study, a camera location was considered a site and a survey period was considered a 24 hour period. I chose to limit all camera sites to a survey period of 27 days to minimize the amount of missing data across sites and to ensure survey periods of the

same length. The input data for occupancy modeling is called a detection history and is comprised of a series of vectors of 1's and 0's representing the detection and non-detection of a species at a site. Detection histories can also include information on missing data where surveys were not conducted and detection data is therefore unavailable. In this study, days or surveys where a camera was classified as “non-functional” resulted in missing data and a “.” was used for that survey period rather than a “1” or a “0”.

I created species-specific detection histories for mesopredator species that were detected at a minimum of 5% of sites in each ecoregion each year. This value was chosen to maximize the number species retained for analysis while removing species with limited data. Following this criterion, a species needed to be detected at no fewer than five sites in 2016 and nine sites in 2017 in the Central Valley. Species that met this criterion included: coyotes, bobcats, domestic cats (*Felis catus*), raccoons (*Procyon lotor*), opossums (*Didelphis virginiana*), and striped skunks (*Mephitis mephitis*). Species which were detected by our cameras in the Central Valley but that did not have enough detections were: the long-tailed weasel (*Mustela fermata*), American mink (*Neovision vison*), gray fox (*Urocyon cinereoargenteus*), North American river otter (*Lontra canadensis*), San Joaquin kit fox (*Vulpes macrotis mutics*), red fox, American badger, and ring-tailed cat (*Bassariscus astutus*). In the Mojave Desert, a species needed to be detected at 11 sites or more in 2016 and six sites in 2017; this included coyotes, bobcats, American badgers, gray foxes, and desert kit foxes (*Vulpes macrotis arsipus*, hereafter

“kit fox”). Species that were detected in the Mojave Desert but that did not meet detection history criterion were: the opossum, striped skunk, raccoon, and western spotted skunk (*Spilogale gracilis*).

Very rarely are surveys 100% effective at detecting all individuals or species present at a site. This discrepancy between true occupancy and detected occupancy can be problematic when trying to make estimates using only detection data. For this reason, occupancy modeling uses the presence/absence detection histories from repeated samples at a site to estimate the effectiveness of surveys, called detection probability (Mackenzie et al. 2002). Detection probability is estimated to account for false absences where a species was present at a site but was never detected. In this way occupancy modeling can estimate the probability that a site is occupied while accounting for imperfect detection.

Many factors at a site may influence the behavior of a species and therefore its detectability (Lewis et al. 2015a). Occupancy modeling allows detection probability (hereafter: detection) to vary according to both site-specific and survey-specific variables, called covariates (Mackenzie et al. 2002). The presence of a species at a site is also reliant upon site-specific conditions; therefore, occupancy modeling also allows occupancy to vary by site-specific covariates. I therefore created a set of covariates I thought would impact both the detection and occupancy of mesopredators in the Mojave Desert and Central Valley (Table 1). After initial selection and extraction of covariates, I ran Pearson correlation tests in Program R Version 5.3.2 (R Core Team 2018) to evaluate collinearity of my proposed covariates and retained only one covariate from a pair of

covariates with $|r| \geq 0.50$ (Appendix B). All retained continuous covariates were

standardized in program PRESENCE 12.6 (Hines 2006) prior to analysis.

Table 1. Table of final detection and occupancy covariates selected for mesopredator single-season occupancy modeling in both the Mojave Desert and Central Valley of California.

Variable	Meaning	Ecoregion*	Parameter**
Year	Year when site sampled (2016 = drought or 2017 = post-drought)	MD, CV	p, ψ
Human Disturbance	Measure of human footprint from 14 landscape features averaged across 1 km buffer. <u>Source:</u> Human Footprint of the West (Leu et al. 2008, U.S. Geological Society 2016a)	MD, CV	p, ψ
Year*human disturbance	Interaction of year and level of human disturbance. Evaluates how drought influences relationship with human disturbance.	MD, CV	p, ψ
Guzzler	Presence of artificial water catchment.	MD	p
Year*guzzler	Interaction of year and guzzler presence. Evaluates how drought influences relationship with water source.	MD	p
Water at site	Presence of water at site in Central Valley as determined by site photos from time of camera deployment.	CV	p
Year*water at site	Interaction of year and presence of water at site. Evaluates how drought influences relationship with water source.	CV	p
Distance to water	Distance from site to perennial sources of water in Mojave Desert as well as ephemeral sources in the Central Valley. <u>Source:</u> National Hydrography Dataset and Cropscape (U.S. Department of	MD, CV	ψ

Variable	Meaning	Ecoregion*	Parameter**
	Agriculture 2016, U.S. Geological Society 2016b)		
Year*distance to water	Interaction of year and distance to water. Evaluates how drought influences relationship with water source.	MD, CV	ψ
Julian date	Represents date of survey and temperature.	MD, CV	p
Bait age	Represents time since baiting and therefore the strength of lure.	MD	p
Elevation	Elevation of site which also represents temperature and amount of shrub cover. <u>Source:</u> LANDFIRE (LANDFIRE 2016)	MD	ψ
Latitude	Latitude of site, representative of temperature and precipitation.	CV	ψ
Percent tree cover	Percentage of tree cover including orchards averaged across 1 km buffer. <u>Source:</u> Cropscape (U.S. Department of Agriculture 2016)	CV	ψ

*MD = Mojave Desert, CV = Central Valley

** ψ = occupancy probability, p = detection probability

Because sites were set up over two years, I included a binary covariate to represent the difference between the two years of data collection. Specifically, I treated 2016 (0) as a drought year and 2017 (1) as a post-drought year. Therefore, this covariate represented the effect of winter precipitation on the detection and occupancy of my study

species. I also used this covariate to create interaction terms which examined how drought (year) influenced mesopredators' relationships with other covariates.

Our study sites were also located across a gradient of human disturbance in both ecoregions. Some sites were difficult to access in remote areas of National Parks while others were located along roadsides or were next to row crops. A measure of the "human footprint" resulting from an analysis of 14 landscape structure and anthropogenic features exists for the western United States and consists of a 180 m resolution raster data set with 10 human footprint classes (Leu et al. 2008, U.S. Geological Society 2016a). Using ArcMap 10.5.1 (Esri Inc. 2017), I calculated the mean human footprint (hereafter referred to as human disturbance) within a one km buffer of all sites to use as my measure of human disturbance. A one km buffer was chosen to more accurately capture the disturbance experienced by my study species. In addition, I created a covariate representing the interaction of year and human disturbance to determine if drought influenced the relationship between the occupancy and detection of mesopredators and human disturbance.

I also created a binary covariate for the Mojave Desert representing guzzler where "0" indicated the absence of a guzzler at a site and a "1" represented the presence of a guzzler. The presence of guzzlers indicates the presence of water, a limiting resource in arid regions (Larsen et al. 2012), so I hypothesized that a guzzler on site would increase the probability of detecting my species of interest. I was also interested in whether drought mediated the relationship between mesopredators and guzzlers so I included the interaction of year and guzzler as a covariate for detection of my species. In the Central

Valley, I also created a binary covariate which indicated the presence of water at site. This covariate was generated to identify site-specific sources of water, such as irrigation, possibly missed by large-scale geospatial layers. Photos were taken at all sites at the time of camera deployment in eight directions to create a 360 degree view of the site. These photos were later used to determine whether water was present at the time of camera deployment (Smith 2019). I treated this covariate much like guzzlers in the Mojave Desert and therefore again created an interaction term between year and water at site to determine whether drought influenced the detection of mesopredators at a water source.

I also included survey-specific variables which I thought might influence the detection of my species. In the Mojave Desert I created a “bait age” covariate which indicated days since camera deployment and baiting of the camera in order to represent how attracted mesopredators would be to the site/bait as time passed and the attractant became less perceivable. In both ecoregions, I included the Julian date as a covariate because I predicted that the specific date of a survey would influence the detection probability of mesopredators. This was correlated with daily maximum temperature (Appendix B) which was extracted from PRISM (Oregon State University 2017). Therefore, I chose to retain Julian date as it likely accounted for more variability than maximum temperature itself. In the Mojave Desert, I elected to only use the first Julian date from the day of camera deployment and use bait as my only survey-specific covariate.

I hypothesized that distance to water would influence the occupancy of mesopredators so I used the National Hydrography Dataset (NHD, U.S. Geological

Society 2016) to identify locations of perennial sources of water in both ecoregions. NHD water sources were at a 1:24,000 scale and included perennial rivers, streams, lakes, and springs/seeps in the Mojave Desert and all perennial water bodies including reservoirs which held drinkable water such as decorative pools in the Central Valley. In the Mojave Desert, I also included the location of guzzlers in the ecoregion, and in the Central Valley I included the locations of aquaculture, open water, and herbaceous wetlands from Cropscape (30 m resolution, U.S. Department of Agriculture 2016). I used both NHD and Cropscape for the Central Valley because Cropscape is generated every year and can be used to identify ephemeral water. I merged all NHD water sources and additional water locations and then used ArcMap (Esri Inc. 2017) to measure the distance from all sites to water sources. I also created an interaction term between year and distance to water to examine the influence of drought on mesopredators and their spatial relationship to water.

Elevation impacts the occupancy of mesopredators in the Mojave Desert (Rich et al. 2018) so I included it as a covariate for my models. I extracted elevation for the Mojave Desert at a 30 m spatial resolution from LANDFIRE (LANDFIRE 2016) which uses 1/3 arc-second digital elevation models (DEM) from the USGS 3D Elevation Program (3DEP). Elevation was correlated with Normalized Difference Vegetation Index (NDVI), an indicator of the amount of green vegetation in an area, downloaded from the USGS National Map (eMODIS 2018). Elevation was also correlated with shrubland extracted from the National Landcover Database shrubland layer for the Great Basin in 2014 (Xian et al. 2015, U.S. Geological Society 2016c) and with mean temperature which was extracted from PRISM (Oregon State University 2017). Thus, elevation was

the only covariate correlated with others in the Mojave Desert to be retained for further analysis.

I used latitude to represent differences which impact occupancy of mesopredators between sites in the northern and southern Central Valley. Latitude was extracted from Global Positioning System (GPS) data collected at each camera site in the Central Valley and was correlated with both mean temperature and precipitation extracted from PRISM (Oregon State University 2017). Therefore, latitude was retained and the two measures of climate were eliminated. I also thought that habitat type in the Central Valley might differentially affect the occupancy of mesopredators. Therefore, I extracted either the 2016 or 2017 percent cover of water/wetlands, forest, grass/pasture, natural habitat, and “trees” from Cropscape (U.S. Department of Agriculture 2016) for all Central Valley sites. Water/wetlands were composed of: aquaculture, open water, and herbaceous wetlands; forest was composed of deciduous forest, evergreen forest, mixed forest, shrubland, and woody wetlands; natural habitat was composed of open water/wetlands, forest, and grass/pasture; and the “trees” category was composed of forest and all tree crops to account for the many orchards which provide cover in the Central Valley.

Following correlation tests, I found that human disturbance was correlated with natural cover and was close to $R = 0.50$ with grass/pasture so I chose to only retain human disturbance as a covariate. Unsurprisingly, percent forest and percent tree were correlated so I elected to only retain percent tree cover because research has shown that mesopredators also use orchards as habitat (Nogeire et al. 2013).

Goodness of fit testing.

Before doing any single-season single-species occupancy modelling I first conducted goodness of fit (GOF) testing in Program PRESENCE (Hines 2006). GOF testing diagnoses whether the underlying assumptions in the models being fit to data are met and identifies how much extra variation there is, which is termed overdispersion (Cooch and White 2019a). Single-season, single-species occupancy models assume that sites are closed to changes in occupancy, species are never falsely detected, and that detection of a species at one site is independent of detection of that species at other sites (Mackenzie et al. 2002). Therefore, if data show extra variation or overdispersion it is likely that they are violating one of these underlying assumptions of occupancy modeling.

Because photos were reviewed by three independent observers and because surveys were no longer than 27 days, I was confident that my data met the first two assumptions of constant occupancy status and no false detections. However, because our sites were typically 1-2 kilometers apart, I did not believe that our sites were independent because most mesopredators can move that distance. Therefore, I considered any overdispersion in my data to reflect a possible lack of independence between my sites. For this reason, I used occupancy models to reflect habitat use rather than true occupancy (Mackenzie 2005).

To assess the fit of occupancy models, a Pearson chi-square statistic is calculated and a parametric bootstrap procedure is used to determine if the observed statistic is unusually large (MacKenzie and Bailey 2004). This procedure results in the estimation of an overdispersion parameter \hat{c} (c-hat). A c-hat value of 1 indicates that the model fits the

data and AIC can be used for model selection, a value less than 1 suggests underdispersion and a \hat{c} value of 1 is used; a \hat{c} value over 1 suggests that there is more variation in the data than expected by the model and \hat{c} is then used to compute QAIC for model selection (MacKenzie and Bailey 2004, Cooch and White 2019a). I used 2000 bootstraps to get final \hat{c} estimates.

Initial GOF testing showed possible evidence of a “trap happy” response. Some detection histories showed patterns of consecutive detections which may have indicated that once an animal visited the bait at a camera it was more likely to return the next day and be detected again. Because of this apparent temporal autocorrelation, I created a series of binomial covariates representing Markov dependency between survey days at each site for each species (Hines et al. 2010, Furnas et al. 2017). These dependency covariates called “lagX” were based on detection histories where a “1” represented that an animal was detected within the past “X” days and a “0” indicated that it was not. I tested a variety of values for “X” to determine how long a trap response lasted for each species. I chose the best “lag” from 0 (no trap response) to 27 (a detection at any time resulted in a trap response) for each species based on which “X” value most improved model performance based on AIC (Akaike 1974) and which also improved model fit using GOF testing.

In the Central Valley I discovered that a three day dependency most improved model fit for coyotes, a 27 day dependency most improved model fit for domestic cats, and no Markov dependency covariate was necessary for bobcats or raccoons. Unfortunately, I was unable to find a Markov dependency covariate which improved c-

hat values enough for the striped skunk or the opossum, so they were excluded from analysis. Similarly, I was unable to find a dependency covariate which improved fit for my Mojave Desert species. Instead, I aggregated my detection histories such that three days of data collection were compressed into one survey occasion. This resulted in a detection history of nine surveys rather than 27 for each species and successfully dealt with the autocorrelation issue in the data.

Model building and selection.

I used a step-wise procedure to minimize the number of models I built and compared in PRESENCE. First, I compared all possible iterations of detection models while keeping a constant global occupancy model. I used Akaike's Information Criterion (Akaike 1974) corrected for small sample size (AICc, Hurvich and Tsai 1989) to evaluate candidate model performance. I used AICc despite having a large sample size because AIC and AICc converge when effective sample size is large (Cooch and White 2019b). However, I used QAICc for model selection for species where \hat{c} was greater than one (Anderson and Burnham 2002, MacKenzie and Bailey 2004).

I tested 52 detection models for each of my mesopredator species in the Mojave Desert and compared 26 detection models for bobcats and raccoons and 52 models for coyotes and domestic cats in the Central Valley. I did not model average but instead selected the most conservative detection model (model with most covariates) which showed support. Any model within two delta AIC of the top model was considered to have support (Burnham and Anderson 2004), and any model within that set which reduced deviance by at least two per additional parameter and therefore had informative

parameters (Arnold 2010) was considered competitive. Of the competitive models, the model with the most parameters was selected to be used for the next step of model selection. If a top model appeared not to converge, I examined beta estimates and eliminated any covariates which appeared to be problematic (large standard errors or estimates that were too large to allow accurate estimation). Typically, problematic betas/covariates corresponded with a lack of data about that covariate and its relationship to a species. If a top model had a problematic covariate, I would select the next top model according to my criteria which had appropriate beta estimates.

Once I selected a top detection model it was then used to test all possible occupancy models. I tested 26 occupancy models for my Mojave Desert mesopredators and 52 models for all Central Valley mesopredator species. I followed the same criterion to select a top occupancy model for each species as I used for detection models (within 2 delta AICc, no uninformative parameters, most parameterized model, no problematic beta estimates).

Because I was not able to enter specific covariate values for estimation of parameters in program PRESENCE, I then rebuilt all of my top models in program MARK Version 9.0 (White and Burnham 1999). With Program MARK I was able to specify certain covariate values and get real parameter estimates for specific scenarios of interest involving drought and human disturbance.

Conditional two-species occupancy modeling

Following single-species occupancy modeling, I conducted conditional two-species single-season occupancy modeling in PRESENCE to investigate the relationship

between subordinate mesopredators and coyotes. Conditional two-species occupancy modeling can estimate four to eight parameters and an additional derived parameter, the Species Interaction Factor (SIF, Table 2, Richmond et al. 2010, MacKenzie et al. 2017). These models estimate the probability of detection and occupancy of a subordinate species (species B) conditional upon the presence of a dominant species (species A, the coyote) (Richmond et al. 2010, MacKenzie et al. 2017).

$$\varphi = \frac{\psi^A \psi^{BA}}{\psi^A (\psi^A \psi^{BA} + (1 - \psi^A) \psi^{Ba})}$$

Table 2. All possible parameters estimated using conditional two species occupancy modeling along with one derived parameter, the Species Interaction Factor.

Parameter	Description
φ	Species Interaction Factor (SIF)
ψ^A	Probability of occupancy for species A
ψ^{BA}	Probability of occupancy for species B, given species A is present
ψ^{Ba}	Probability of occupancy for species B, given species A is absent
p^A	Probability of detection for species A, given species B is absent
r_j^A	Probability of detection for species A, given both species are present
p^B	Probability of detection for species B, given species A is absent
r_j^{BA}	Probability of detection for species B, given both species are present and species A is detected
r_j^{Ba}	Probability of detection for species B, given both species are present and species A is not detected

Conditional two-species occupancy models can be formulated differently to test hypotheses about the relationships between two species. ψ^A is always an unconditional parameter representing the occupancy of the dominant species, the coyote. However, I determined whether the occupancy of a subordinate species was conditional upon the presence of a coyote by estimating ψ^{BA} and ψ^{Ba} separately or when $\psi^{BA} = \psi^{Ba}$ and determined which model performed better according to AIC (Richmond et al. 2010). A SIF can only be estimated when the top performing model estimates ψ^{BA} and ψ^{Ba} separately. SIFs represent the ratio of how likely the two species are to co-occur compared to what would be expected under a hypothesis of independence (Richmond et al. 2010, MacKenzie et al. 2017b). If two species occur independently then the SIF is equal to 1. Alternatively, a SIF that is less than 1 indicates that species B is less likely to

co-occur with species A (avoidance), and a SIF value greater than 1 indicates that species B is more likely to co-occur with species A (aggregation, Richmond et al. 2010).

I was also able to determine whether the detection of the subordinate species was conditional on the detection of coyotes when both are present by comparing model performance when r_j^{BA} and r_j^{Ba} were estimated separately or together ($r_j^{BA}=r_j^{Ba}$, Richmond et al. 2010). I also could test whether the detection of the subordinate species was conditional on the presence of coyotes by comparing model performance when p^B was estimated separately from $r_j^{BA}=r_j^{Ba}$ or together ($p^B=r_j^{BA}=r_j^{Ba}$, Richmond et al. 2010). I did not test whether the detection probability of coyotes was conditional upon the presence of the subordinate species by comparing model performance when p^A and r_j^A were estimated separately or together (Richmond et al. 2010). Therefore $p^A=r_j^A$ in all of my models. I opted not to test this model formulation because I was not interested in how my dominant species responded to my subordinate species.

Conditional two species occupancy models can also incorporate covariates for all parameters to test how site and survey-specific variables influence the detection and occupancy of the species in the model. Because I was only interested in the subordinate species, I used the top single species occupancy model for coyotes in both ecoregions as the covariates for Species A in all models. Otherwise, I used the same global occupancy model structure for each of my subordinate species. I then followed the same stepwise procedure I used for single species modeling in my conditional two species modeling. However, when I tested all possible detection models for species B I always kept

parameters conditional (p_B , r_{BA} , r_{Ba} estimated separately and Ψ_{BA} and Ψ_{Ba} estimated separately).

Once I had a top species B detection model following my specific criteria (within 2 delta AICc, no uninformative parameters, most parameterized model, no problematic beta estimates), I then tested the formulation of my species B detection model. If there was any uncertainty among which detection model to use, I would test the formulation of both models and then selected the top model from there. Because there is not a GOF test for this kind of occupancy model I could not check for overdispersion or correct for it using QAICc, therefore all model selection was done using AICc.

When a top Species B detection model was established, I then kept that part of the model constant as I tested all possible Species B occupancy models. I repeated the same process of selecting a top model as I had used for single-species modeling and then tested formulation of my occupancy model to see if occupancy of species B was conditional upon the occupancy of species A. If the top model was conditional, I was also able to estimate a SIF. I again rebuilt all top models in Program MARK (White and Burnham 1999) in order to get real parameter estimates for scenarios of interest involving drought and human disturbance.

RESULTS

In total, data collected over 15,795 camera trap nights were analyzed from 585 cameras operating for 27 days each. Following the aggregation of 27 survey days into nine survey occasions in the Mojave Desert, there were 2,871 survey occasions included in analysis. In the Mojave Desert, five mesopredator species were detected at more than 5% of sites and were included in analysis: coyote, bobcat, badger, gray fox, and kit fox. Four mesopredator species were detected at more than 5% of sites and had acceptable global model fit to be included in analysis in the Central Valley: coyote, bobcat, domestic cat, and raccoon. Only coyote and bobcat detection histories were analyzed in both ecoregions.

Odds ratios were reported to demonstrate the relative effect covariates had on the odds of a site either being occupied or not and the odds of detection or non-detection of a species if the site was occupied. Because covariates were standardized for modeling, odds ratios represent the change in log odds of either occupancy or detection at a site based on a one standard deviation (SD) increase in a covariate of interest. An odds ratio of one represents independence between the outcome (occupancy or detection) and the covariate while an odds ratio of less than one represents a decrease in odds of occupancy or detection with an SD increase in the covariate and an odds ratio of greater than one represents an increase in the odds.

Throughout the results “uncertainty” refers to any instance where a 95% confidence interval crossed one (on the odds ratio scale), indicating some uncertainty in

the directionality of the relationship. Additionally, when creating figures, “low” and “high” values for environmental covariates represented extremes (e.g. highest level of human disturbance recorded at any site in the Mojave Desert). “Average” was the average covariate value for the ecoregion and was the covariate value around which standardization of all covariates was based.

Single-Season Single-Species Occupancy Models

Mojave Desert

In the Mojave Desert, human disturbance values at study sites ranged from 1 to 6.8 out of 10, with a median value of 3.3 and a mean value of 3.4 (Figure 3). Therefore, “low” values represent the lowest possible disturbance and “high” values of human disturbance represent medium to high disturbance on the overall disturbance scale. Distance to water in the Mojave Desert ranged from 0 m to 22.6 km, with a median value of 3.3 km and a mean of 4.7 km. Therefore “close” represents a site at water and “far” represents a site over 10 km away from a known perennial water source.

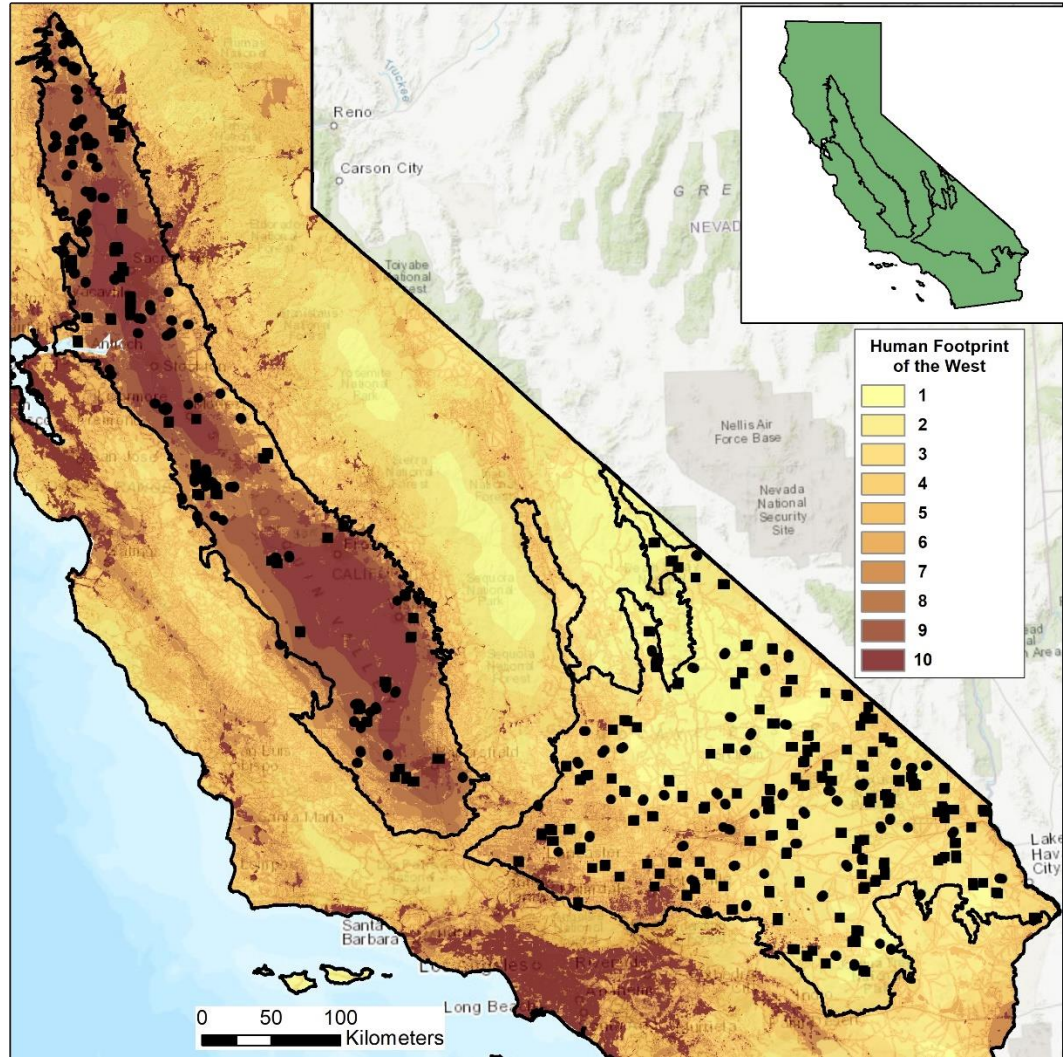


Figure 3. Map of the human footprint of the West (Leu et al. 2008) in California and all TSM study sites (black circles = 2016, black squares = 2017) in the Mojave Desert and Central Valley.

Coyote.

Coyotes were detected at a total of 99 sites out of 319 surveyed over our two year study (Appendix C). Following model selection (Appendix E), the only covariate that influenced the occupancy of coyotes in the Mojave Desert was human disturbance

(Figure 4). A one SD increase in human disturbance (1.1287) increased the odds of coyote occupancy by 26.2% (odds ratio (OR): 1.262, 95% CI [0.915, 1.741], Figure 5), but there was some uncertainty in this relationship. A one SD increase in human disturbance in 2016 also increased the odds of coyote detection by 29.4% (OR: 1.294, 95% CI [1.019, 1.644]). However, a one SD increase in human disturbance in 2017 decreased the odds of coyote detection by 45.8% (OR: 0.542, 95% CI [0.326, 0.902], Figure 6). Odds of detection in 2017 decreased by 17.3% (OR: 0.827, 95% CI: 0.516, 1.326) but there was a lot of uncertainty with this relationship. The presence of a guzzler increased the odds of coyote detection by 119.3% (OR: 2.193, 95% CI [1.425, 3.375], Figure 7) and a one SD increase in first Julian date (date of deployment, 23.2318 days) increased the odds of coyote detection by 21.1% (OR: 1.211, 95% CI [0.983, 1.492]), there was marginal uncertainty with this.

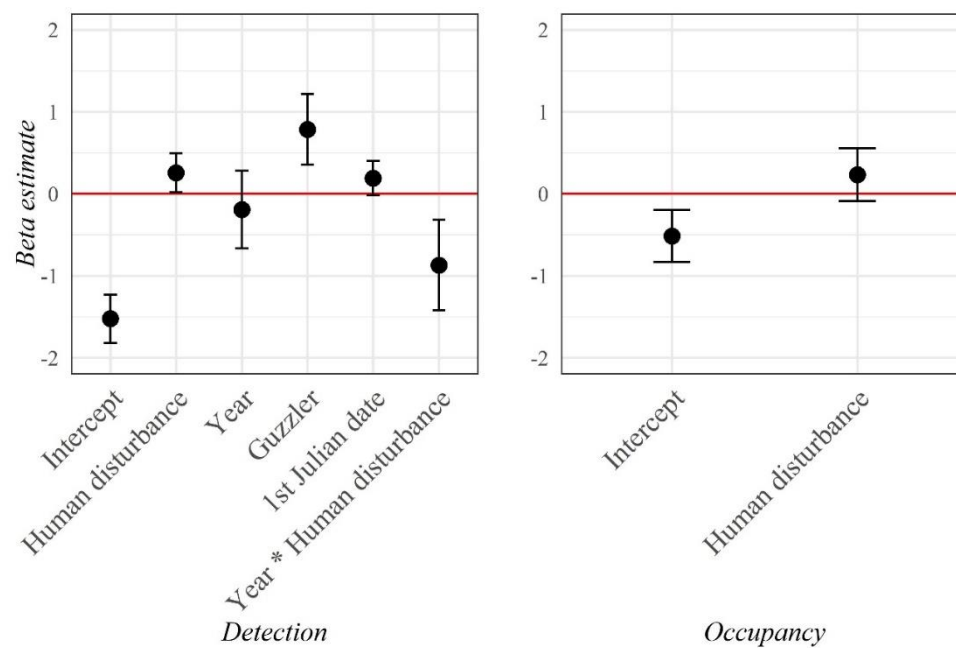


Figure 4. Beta estimates and 95% confidence intervals for covariates in top single-season single-species occupancy model for coyotes in the Mojave Desert of California.

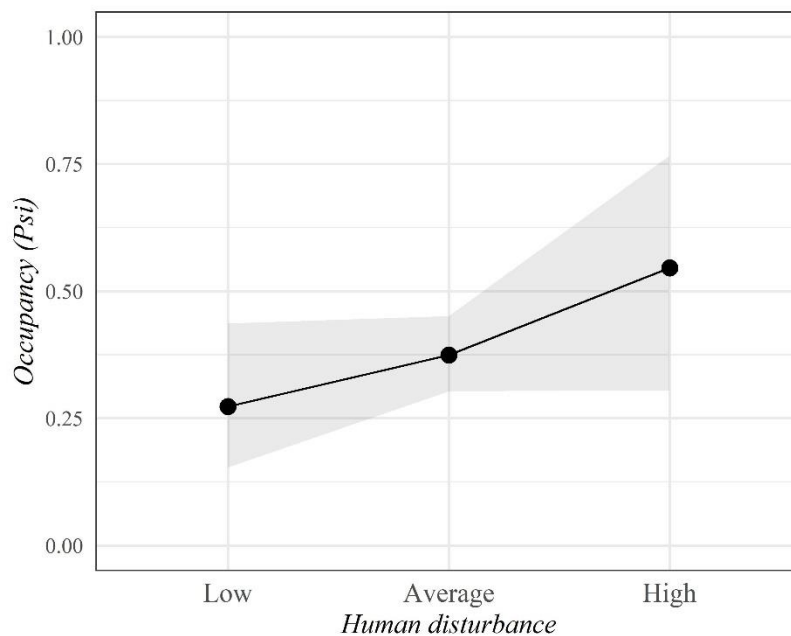


Figure 5. Occupancy estimates and 95% confidence intervals (shaded gray) for coyotes along a human disturbance gradient in the Mojave Desert of California.

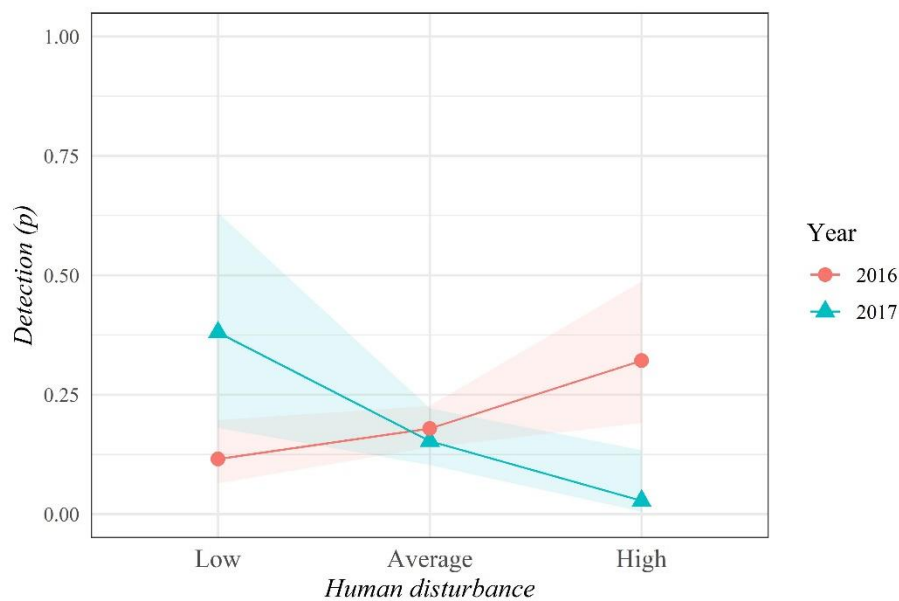


Figure 6. Detection estimates and 95% confidence intervals (shaded regions) for coyotes in 2016 and 2017 along a human disturbance gradient in the Mojave Desert of California.

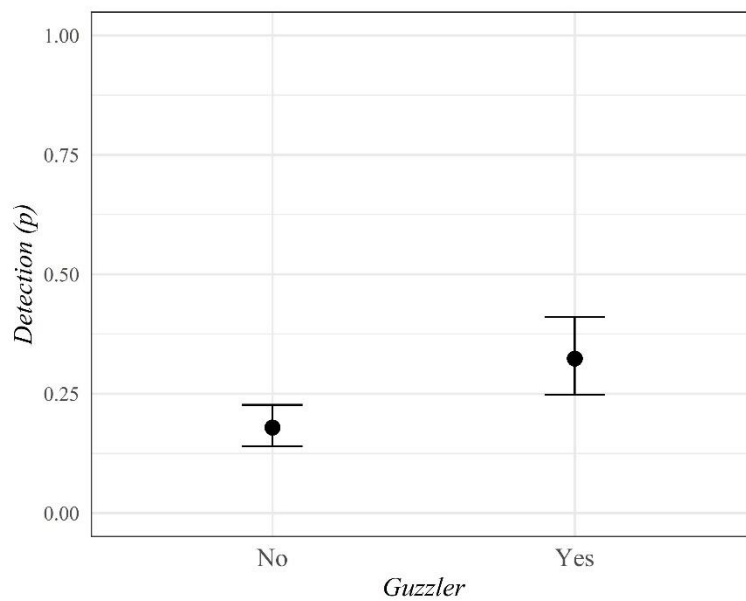


Figure 7. Detection estimates and 95% confidence intervals for coyotes at sites with and without guzzlers in the Mojave Desert of California.

Bobcat.

Bobcats were detected at a total of 53 sites out of 319 surveyed over our two year study (Appendix C). Following model selection (Appendix E), both elevation and distance to water were identified as predictors of bobcat occupancy (Figure 8). A one SD increase in elevation (360.6 m) increased the odds of bobcat occupancy by 133.3% (OR: 2.333, 95% CI [1.452, 3.748]). However a one SD increase in distance to water (4.487 km) decreased the odds of bobcat occupancy by 56.1% (OR: 0.439, 95% CI [0.234, 0.823]). Bobcat detection was positively associated with human disturbance, year, and guzzler (Figure 10). A one SD increase in human disturbance (1.1287) increased the odds of bobcat detection by 44.3% (OR: 1.443, 95% CI [1.03, 2.02], Figure 9), odds of bobcat detection in 2017 increased by 92.8% (OR: 1.928, 95% CI [1.022, 3.636], Figure 9), and presence of a guzzler increased odds of bobcat detection by 72.1% (OR: 1.721, 95% CI [0.969, 3.054], Figure 10) but there was marginal uncertainty with this.

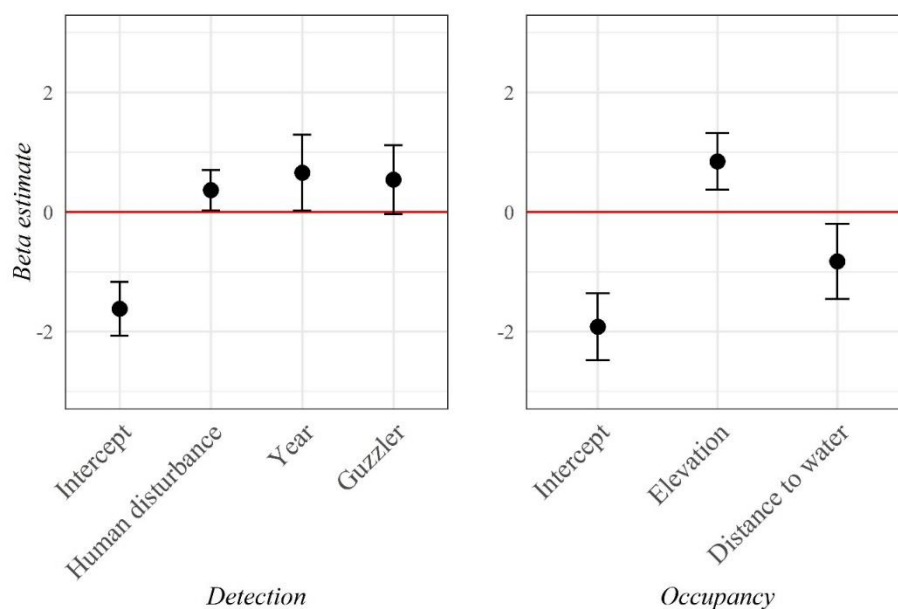


Figure 8. Beta estimates and 95% confidence intervals for covariates in top single-season- single-species occupancy model for bobcats in the Mojave Desert of California.

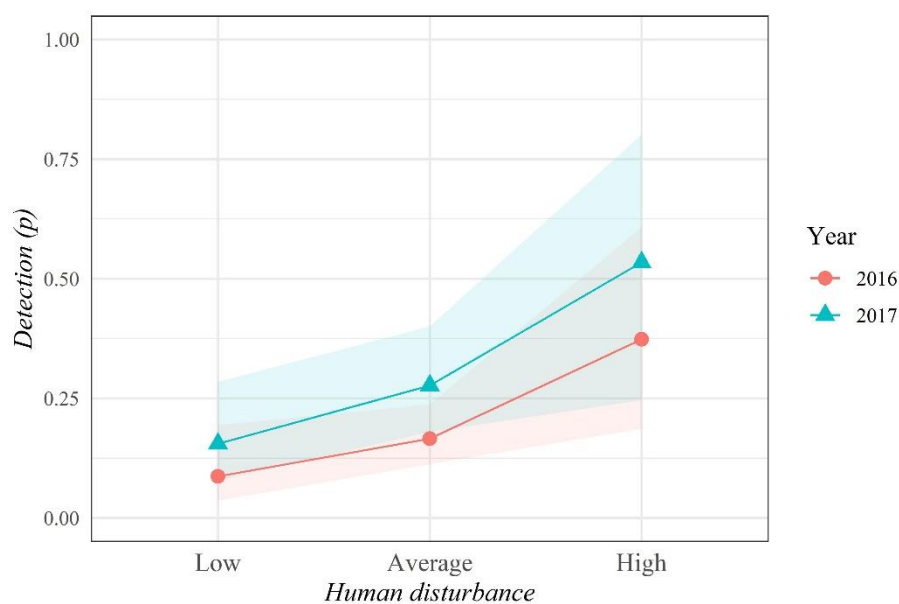


Figure 9. Detection estimates and 95% confidence intervals (shaded regions) for bobcats in 2016 and 2017 along a human disturbance gradient in the Mojave Desert of California.

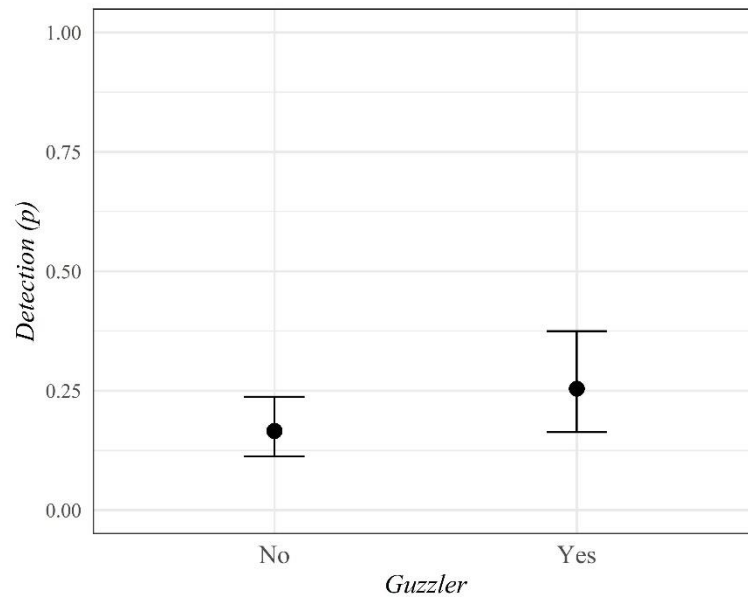


Figure 10. Detection estimates and 95% confidence intervals for bobcats at sites with and without guzzlers in the Mojave Desert of California.

Badger.

Badgers were detected at a total of 41 sites out of 319 surveyed over our two year study (Appendix C). Following model selection (Appendix E), elevation and year were identified as the only predictors influencing badger occupancy (Figure 11). A one SD increase in elevation (360.6 m) increased odds of badger occupancy by 90.1% (OR: 1.901, 95% CI [1.183, 3.053]). Odds of badger occupancy in 2017 (versus 2016) increased by 123.8% (OR: 2.238, 95% CI [0.816, 6.136]) although there was some uncertainty about this (Figure 12). The presence of a guzzler increased the odds of badger detection by 366.4% (OR: 4.664, 95% CI [2.414, 9.010], Figure 13) and a one SD increase in Julian date at time of camera deployment (23.2318 days) increased odds of badger detection by 46.4% (OR: 1.464, 95% CI [1.026, 2.087]).

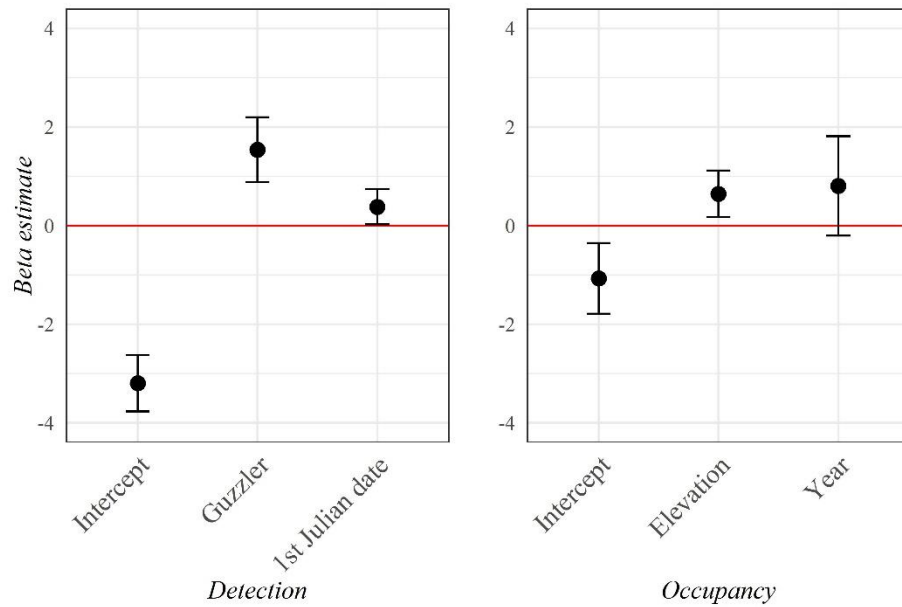


Figure 11. Beta estimates and 95% confidence intervals for covariates in top single-season single-species occupancy model for badgers in the Mojave Desert of California.

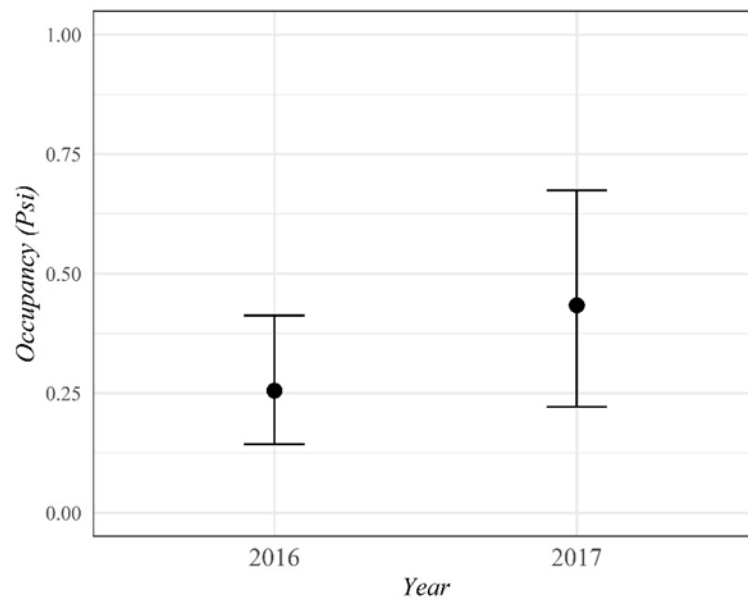


Figure 12. Occupancy estimates and 95% confidence intervals for badgers in 2016 and 2017 in the Mojave Desert of California.

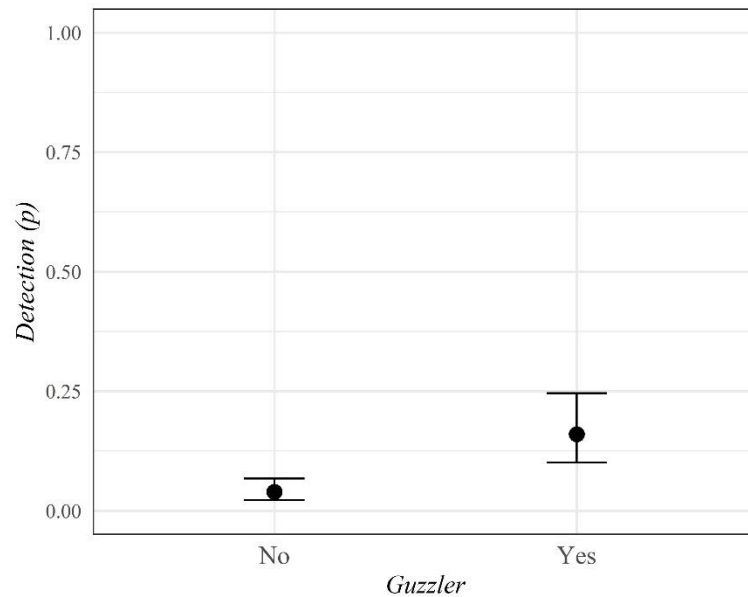


Figure 13. Detection estimates and 95% confidence intervals for badgers at sites with and without guzzlers in the Mojave Desert in California.

Gray fox.

Gray foxes were detected at a total of 18 sites out of 319 surveyed over our two year study (Appendix C). Following model selection (Appendix E), only year and bait age were identified as predictors of gray fox detection (Figure 14). Every additional day following initial deployment and baiting of camera decreased odds of gray fox detection by 49% (OR: 0.51, 95% CI [0.351, 0.739]). Odds of gray fox detection increased by 317.1% in 2017 compared to 2016 (OR: 4.171, 95% CI [1.908, 9.121], Figure 15).

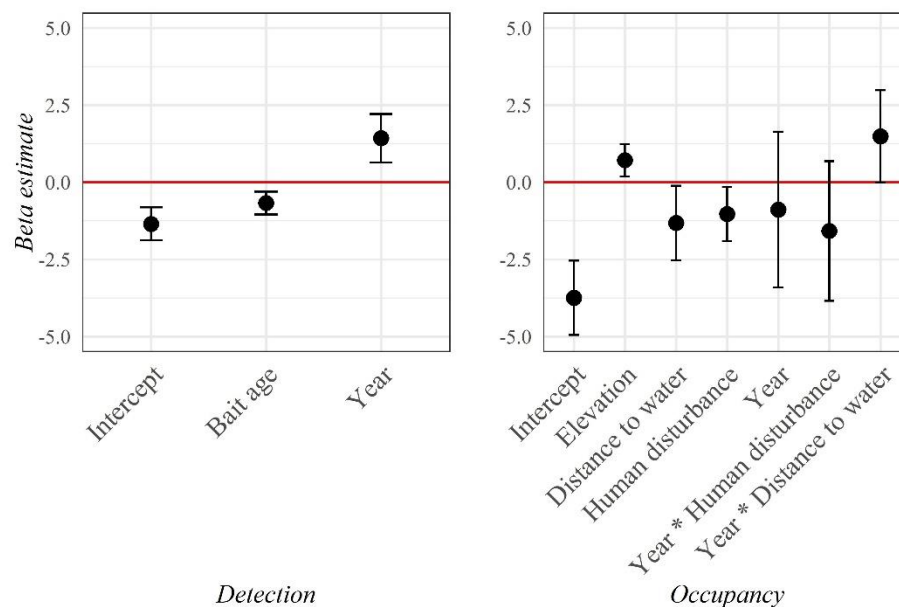


Figure 14. Beta estimates and 95% confidence intervals for covariates in top single season single-species occupancy model for gray foxes in the Mojave Desert of California.

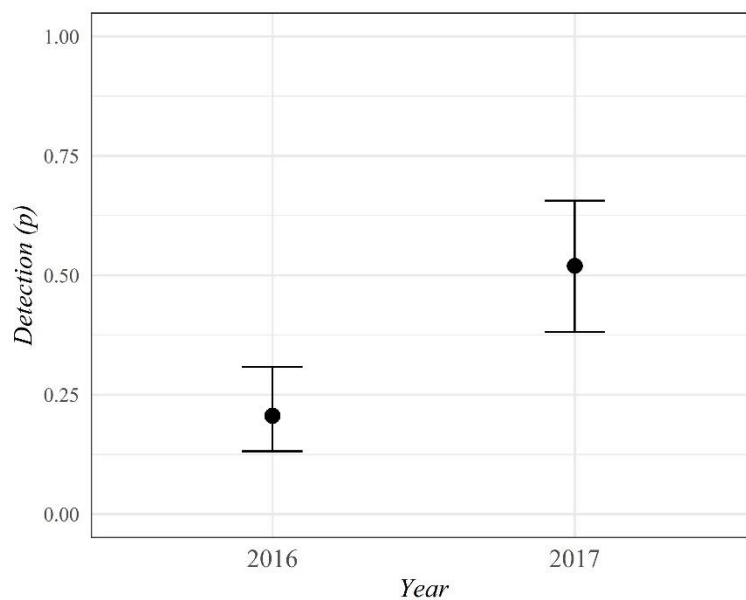


Figure 15. Detection estimates and 95% confidence intervals for gray foxes at sites in 2016 and 2017 in the Mojave Desert in California.

Odds of gray fox occupancy increased by 104.9% (OR: 2.049, 95% CI [1.216, 3.453]) with every SD increase in elevation (360.6 m). In 2017, odds of gray fox occupancy decreased by 58.8% (OR: 0.412, 95% CI [0.033, 5.164]) but there was a lot of uncertainty with this relationship. In 2016, odds of gray fox occupancy decreased by 73.3% (OR: 0.267, 95% CI [0.08, 0.892]) with every SD increase in distance to water (4.487 km); however, in 2017, odds of gray fox occupancy increased by 18.7% (OR: 1.186, 95% CI [0.486, 2.9]) with every SD increase in distance to water but there was a great deal of uncertainty in this relationship. In 2016, the odds of gray fox occupancy decreased by 64.4% (OR: 0.356, 95% CI [0.149, 0.852]) with every SD increase in human disturbance (1.1287) and in 2017, the odds of gray fox occupancy decreased by 92.7% (OR: 0.073, 95% CI [0.009, 0.607]) with every SD increase in human disturbance (Figure 16).

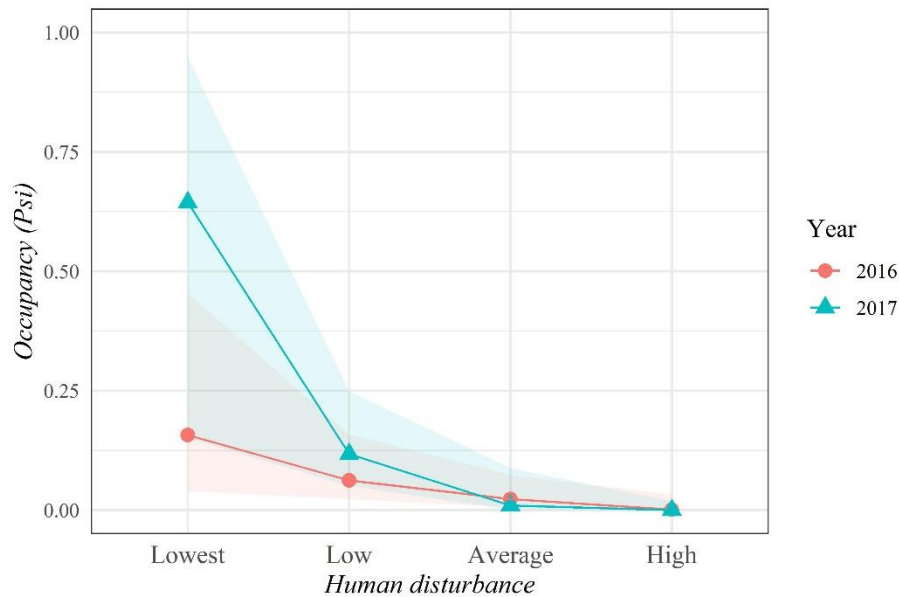


Figure 16. Occupancy estimates and 95% confidence intervals (shaded regions) for gray foxes along a human disturbance gradient in 2016 and 2017 in the Mojave Desert of California.

Kit fox.

Kit foxes were detected at a total of 133 sites out of 319 surveyed over our two year study (Appendix C). Following initial model selection (Appendix E), the interaction of year and guzzler was identified as a strong predictor of kit fox detection. However, the beta estimate and standard error for this covariate were extremely high so it was excluded from model selection. The likely explanation for the strength and uncertainty of this predictor is that kit foxes were never detected at guzzlers in 2017. Therefore, it is possible that the presence of guzzlers, particularly in 2017, influenced the detection of kit foxes, but I could not model this relationship.

After excluding the interaction of year and guzzler from analysis, guzzler was still identified as an important predictor for kit fox detection with the odds of detection decreasing by 46.3% if there was a guzzler at a site (OR: 0.537, 95% CI [0.260, 1.11], Figure 17, Figure 18), but there was uncertainty in this relationship. Odds of kit fox detection also increased from 2016 to 2017 by 102.8% (OR: 2.028, 95% CI [1.467, 2.804], Figure 18, Figure 19). Every additional day following initial deployment and baiting of camera decreased odds of kit fox detection by 43% (OR: 0.57, 95% CI [0.493, 0.658]). Finally, a one SD increase in human disturbance (1.1287) increased odds of kit fox detection by 11.6% (OR: 1.116, 95% CI [0.96, 1.298], Figure 19) but there was marginal uncertainty with this relationship.

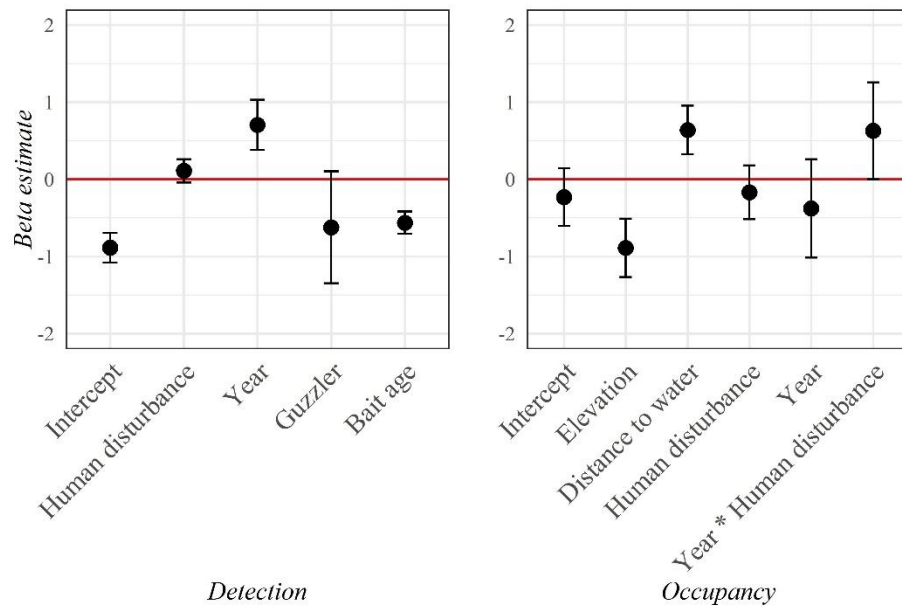


Figure 17. Beta estimates and 95% confidence intervals for covariates in top single-season single-species occupancy model for kit foxes in the Mojave Desert of California.

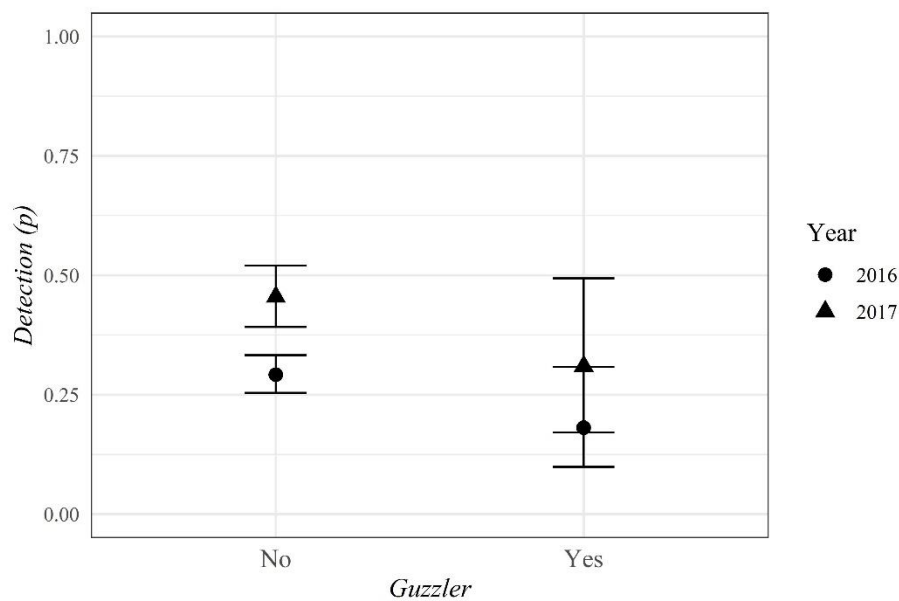


Figure 18. Detection estimates and 95% confidence intervals for kit foxes at sites with and without guzzlers in 2016 and 2017 in the Mojave Desert of California.

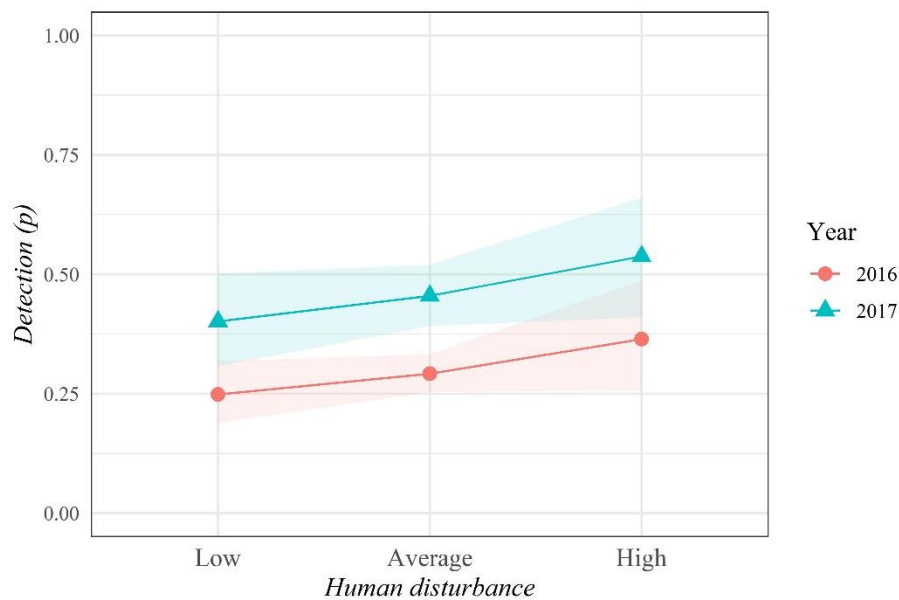


Figure 19. Detection estimates and 95% confidence intervals (shaded regions) for kit foxes along a human disturbance gradient in 2016 and 2017 in the Mojave Desert of California.

Odds of kit fox occupancy decreased by 58.9% (OR: 0.411, 95% CI [0.281, 0.6]) with every SD increase in elevation (360.6 m). With every SD increase in distance to water (4.487 km), odds of kit fox occupancy increased by 89.8% (OR: 1.898, 95% CI [1.388, 2.595]). There was uncertainty in the relationships between kit fox occupancy and year, human disturbance, and their interaction. Odds of kit fox occupancy decreased by 31.5% from 2016 to 2017 (OR: 0.685, 95% CI [0.362, 1.296], Figure 20). Odds of kit fox occupancy also decreased with every SD increase in human disturbance in 2016 by 15.6% (OR: 0.844, 95% CI [0.595, 1.196], Figure 20). However, odds of kit fox occupancy increased by 58.1% (OR: 1.581, 95% CI [0.935, 2.672], Figure 20) with every SD increase in human disturbance in 2017.

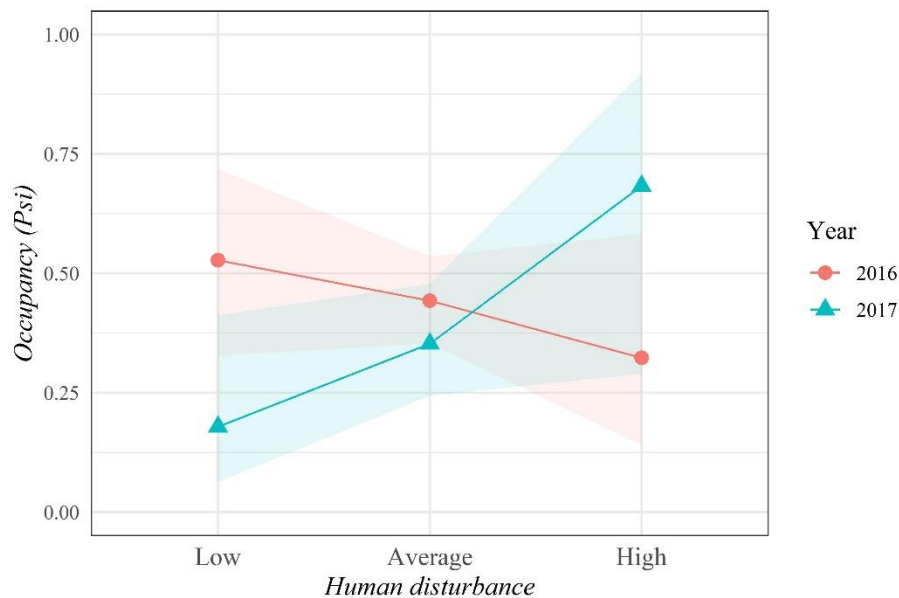


Figure 20. Occupancy estimates and 95% confidence intervals (shaded regions) for kit foxes along a human disturbance gradient in 2016 and 2017 in the Mojave Desert of California.

Central Valley

In the Central Valley, human disturbance values at study sites ranged from 4 to 10 out of 10, with a median value of 8.2 and an average value of 8.1 (Figure 3). Therefore, “low” values represent the low to mid-levels of disturbance and “high” values of human disturbance represent the highest possible disturbance on the overall disturbance scale. Distance to water in the Central Valley ranged from 0 m to 3 km, with a median value of 0.16 km and an average of 0.40 km. Therefore “close” represents a site at water and “far” represents a site only a few km away from a known perennial water source.

Coyote.

Coyotes were detected at a total of 108 sites out of 266 surveyed over our two year study (Appendix D). Following model selection (Appendix F), the only covariate that influenced the occupancy of coyotes in the Central Valley was latitude (Figure 21). A one standard deviation (SD) increase in latitude (1.396 decimal degrees) decreased the odds of coyote occupancy by 40.7% (OR: 0.593, 95% CI [0.3838, 0.917]).

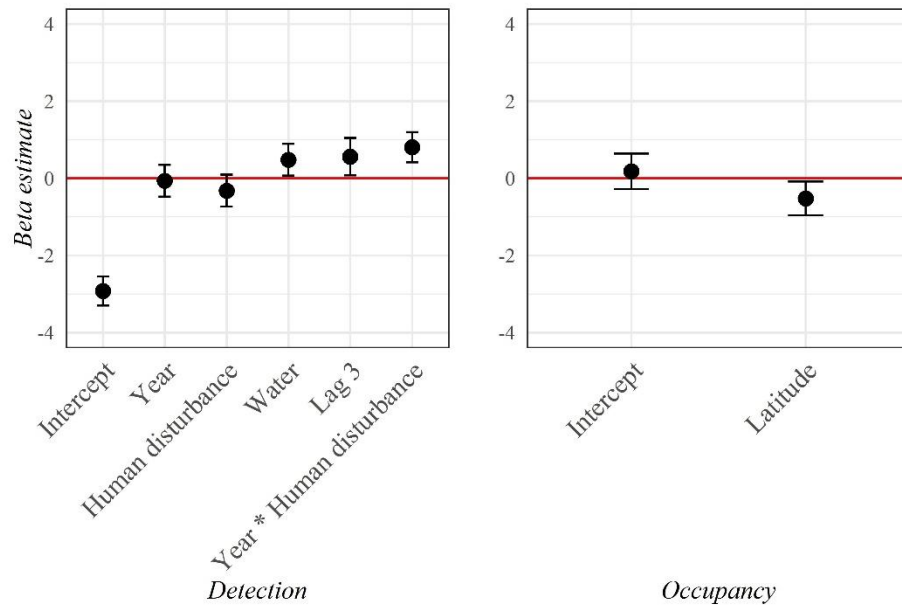


Figure 21. Beta estimates and 95% confidence intervals for covariates in top single-season single-species occupancy model for coyotes in the Central Valley of California.

Odds of coyote detection increased by 61.4% if there was water present at a site (OR: 1.614, 95% CI [1.068, 2.438], Figure 22). Odds of coyote detection also increased by 123.7% (OR: 2.237, 95% CI [1.513, 3.307]) following the detection of a coyote within the previous three days (lag 3, which represents trap response). Odds of coyote detection decreased by 6% from 2016 to 2017 (OR: 0.94, 95% CI [0.622, 1.419]) but there was uncertainty with this (Figure 23). Odds of coyote detection also decreased by 27.5% (OR: 0.725, 95% CI [0.48, 1.097]) with a one SD increase in human disturbance (1.303) in 2016, although there was uncertainty; however, odds of coyote detection increased by 26.8% (OR: 1.268, 95% CI [1.001, 1.596]) with a one SD increase in human disturbance in 2017 (Figure 23).

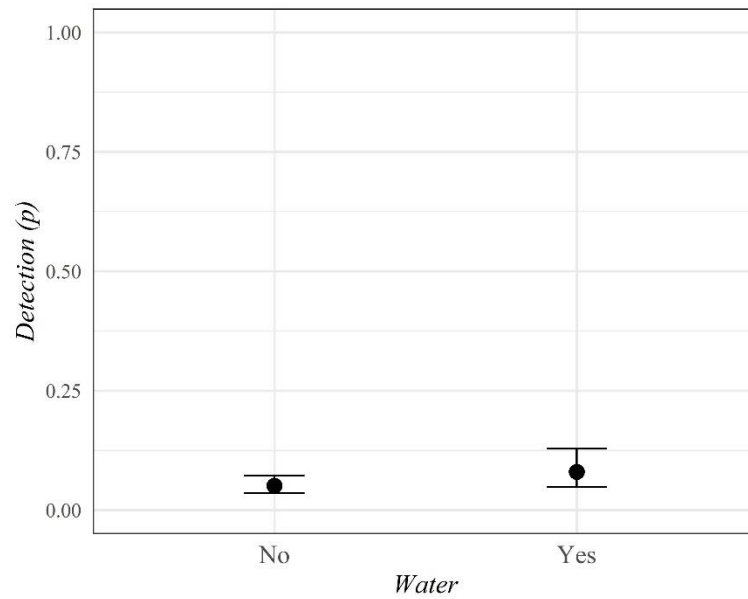


Figure 22. Detection estimates and 95% confidence intervals for coyotes at sites with and without water in the Central Valley of California.

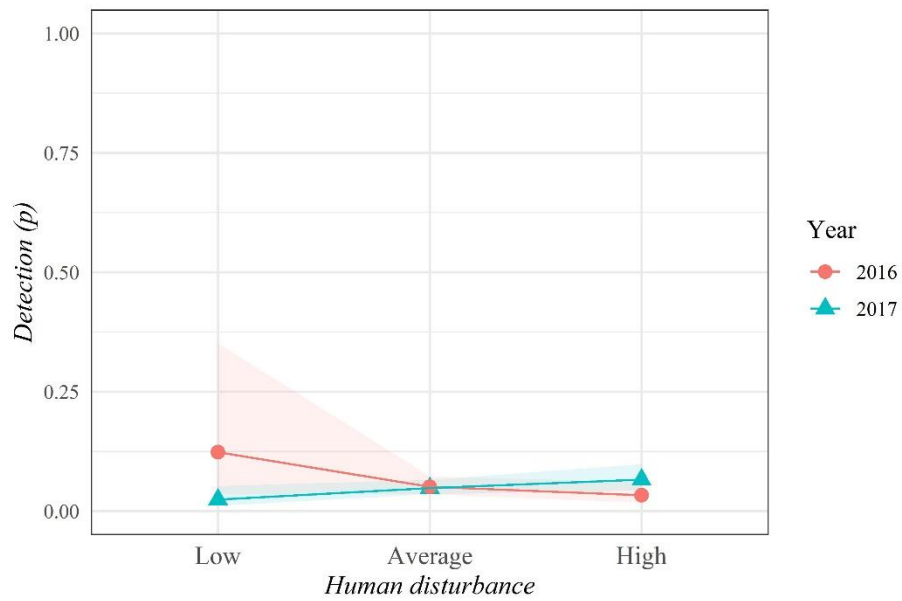


Figure 23. Detection estimates and 95% confidence intervals (shaded regions) for coyotes in 2016 and 2017 along a human disturbance gradient in the Central Valley of California.

Bobcat.

Bobcats were detected at a total of 24 sites out of 266 surveyed over our two year study (Appendix D). Following model selection (Appendix F), only year and Julian date were found to influence the detection of bobcats (Figure 24). Odds of bobcat detection decreased by 79.3% (OR: 0.207, 95% CI [0.066, 0.65], Figure 25) from 2016 to 2017 and by 58.9% (OR: 0.411, 95% CI [0.247, 0.685]) with every SD increase in Julian date (27.799 days).

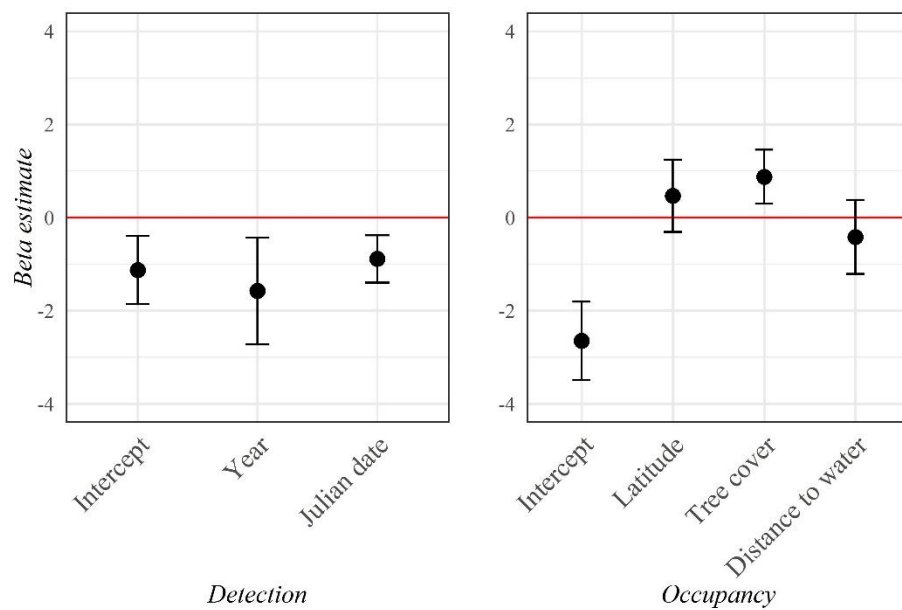


Figure 24. Beta estimates and 95% confidence intervals for covariates in top single-season single-species occupancy model for bobcats in the Central Valley of California.

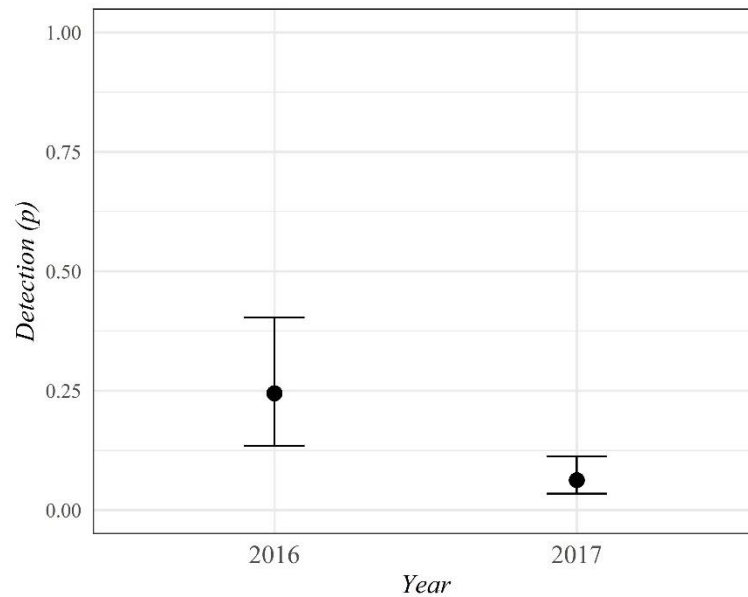


Figure 25. Detection estimates and 95% confidence intervals for bobcats in 2016 and 2017 in the Central Valley of California.

Odds of bobcat occupancy increased by 59.4% (OR: 1.594, 95% CI [0.734, 3.462]) with every SD increase in latitude (1.396 decimal degrees), but there was uncertainty with this. The odds of bobcat occupancy increased by 140.2% (OR: 2.402, 95% CI [1.342, 4.3]) with every SD increase in tree cover (20.1%). However, odds of bobcat occupancy decreased by 34.1% (OR: 0.659, 95% CI [0.298, 1.459]) with every SD increase in distance to water (509.429 m); however, there was uncertainty with this relationship.

Domestic cat.

Domestic cats were detected at a total of 32 sites out of 266 surveyed over our two year study (Appendix D). Following model selection (Appendix F), only year and Julian date were found to influence the detection of domestic cats (Figure 26). Odds of

domestic cat detection decreased by 48.1% (OR: 0.519, 95% CI [0.302, 0.892]) at sites where water was present (Figure 27). Odds of domestic cat detection also decreased by 20% (OR: 0.8, 95% CI [0.642, 0.996]) with every SD increase in Julian date (27.799 days).

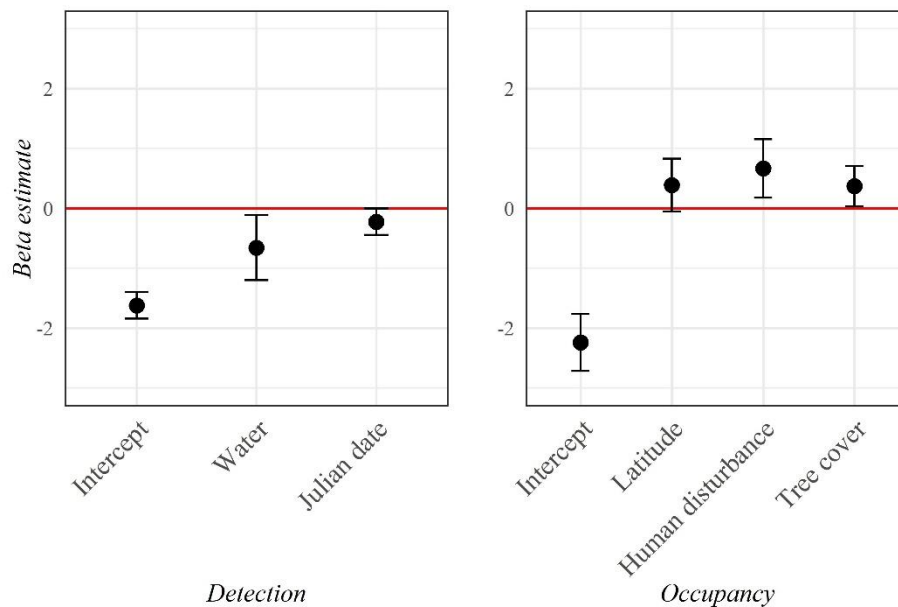


Figure 26. Beta estimates and 95% confidence intervals for covariates in top single-season single-species occupancy model for domestic cats in the Central Valley of California.

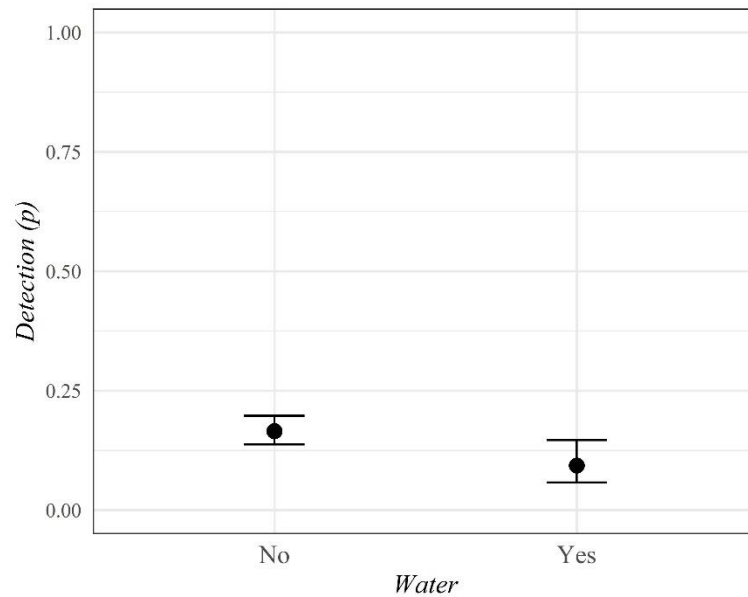


Figure 27. Detection estimates and 95% confidence intervals for domestic cats in 2016 and 2017 in the Central Valley of California.

Odds of domestic cat occupancy increased by 47.4% (OR: 1.474, 95% CI [0.948, 2.294]) with every SD increase in latitude (1.396 decimal degrees) but there was slight uncertainty with this. A one SD increase in tree cover (20.1 %) resulted in a 44.7% increase in the odds of domestic cat occupancy (OR: 1.447, 95% CI [1.035, 2.023]) and a one SD increase in human disturbance (1.303) resulted in a 94.5% increase in the odds of domestic cat occupancy (OR: 1.945, 95% CI [1.192, 3.172], Figure 28).

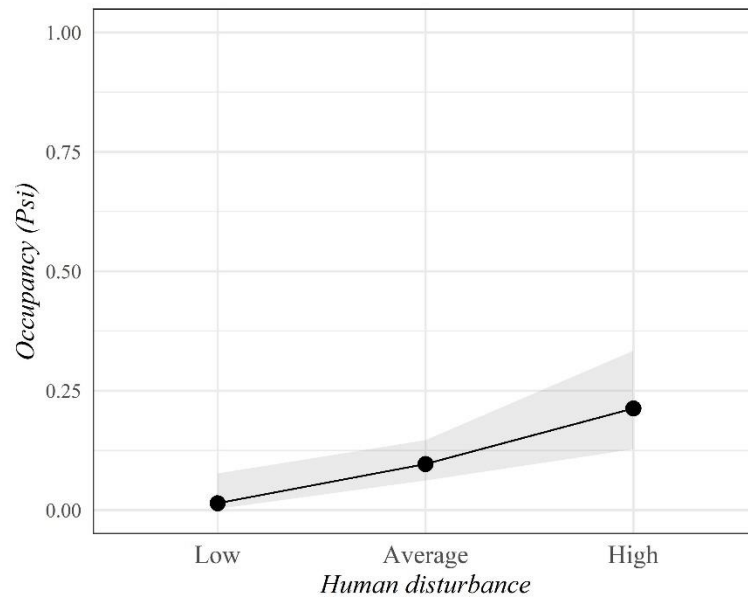


Figure 28. Occupancy estimates and 95% confidence intervals (shaded regions) for domestic cats along a human disturbance gradient in the Central Valley of California.

Raccoon.

Raccoons were detected at a total of 117 sites out of 266 surveyed over our two year study (Appendix D). Following model selection (Appendix F), year, human disturbance, and the interaction of the two affected both the detection and occupancy of raccoons (Figure 29). Odds of raccoon detection decreased by 64.3% (OR: 0.357, 95% CI [0.215, 0.591]) from 2016 to 2017 (Figure 30), but odds of raccoon occupancy increased by 261% (OR: 3.61, 95% CI [1.308, 9.966]) from 2016 to 2017 (Figure 31). A one SD increase in human disturbance in 2016 (1.303) resulted in a 51.8% decrease in the odds of raccoon detection (OR: 0.482, 95% CI [0.351, 0.66], Figure 30) and a 93.5% increase in the odds of raccoon occupancy (OR: 1.935, 95% CI [0.815, 4.592], Figure 31), but there

was uncertainty with occupancy. However, every SD increase in human disturbance in 2017 resulted in a 41.6% increase in the odds of raccoon detection (OR: 1.416, 95% CI [1.107, 1.812], Figure 30) and a 6.9% decrease in the odds of raccoon occupancy (OR: 0.931, 95% CI [0.478, 1.815], Figure 31) but there was again uncertainty with occupancy.

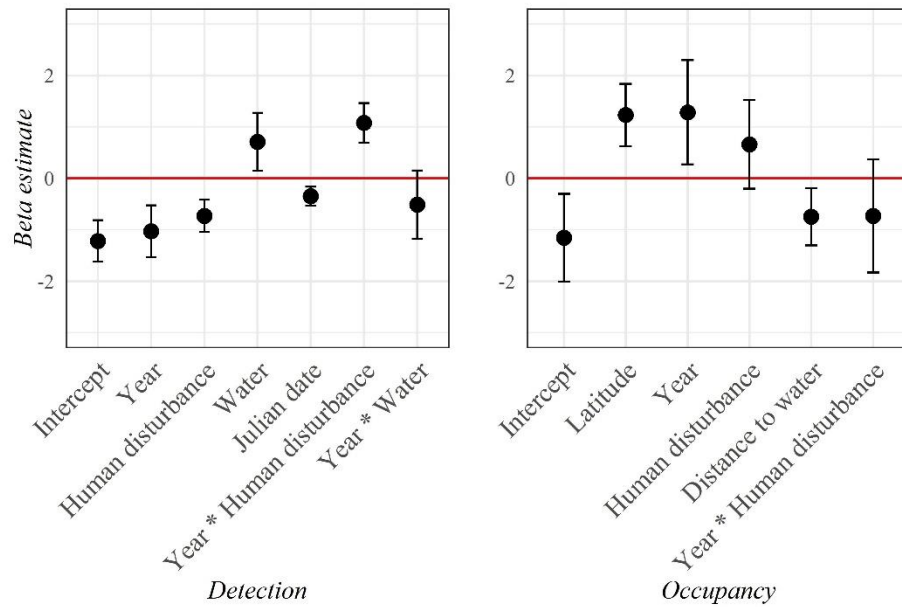


Figure 29. Beta estimates and 95% confidence intervals for covariates in top single-season single-species occupancy model for raccoons in the Central Valley of California.

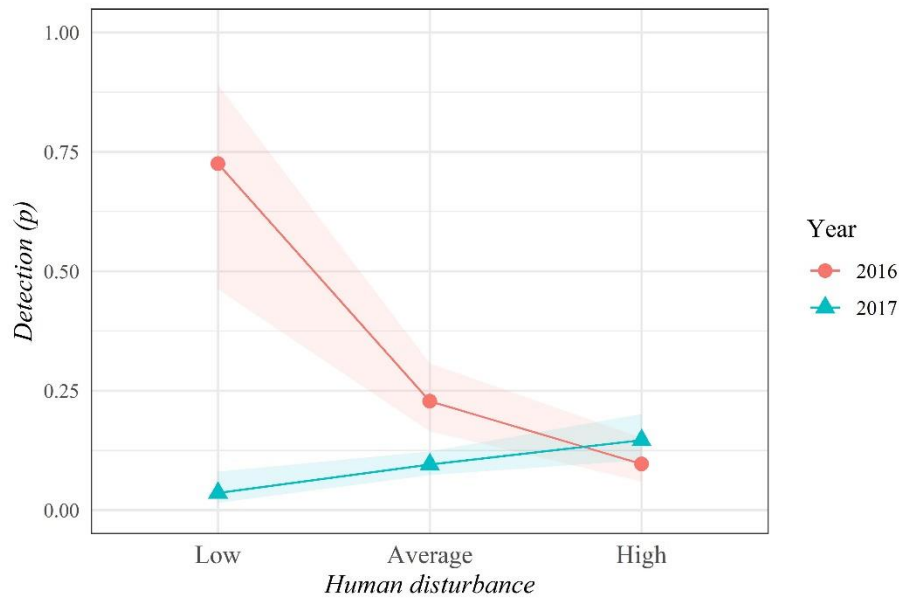


Figure 30. Detection estimates and 95% confidence intervals (shaded regions) for raccoons in 2016 and 2017 along a human disturbance gradient in the Central Valley of California.

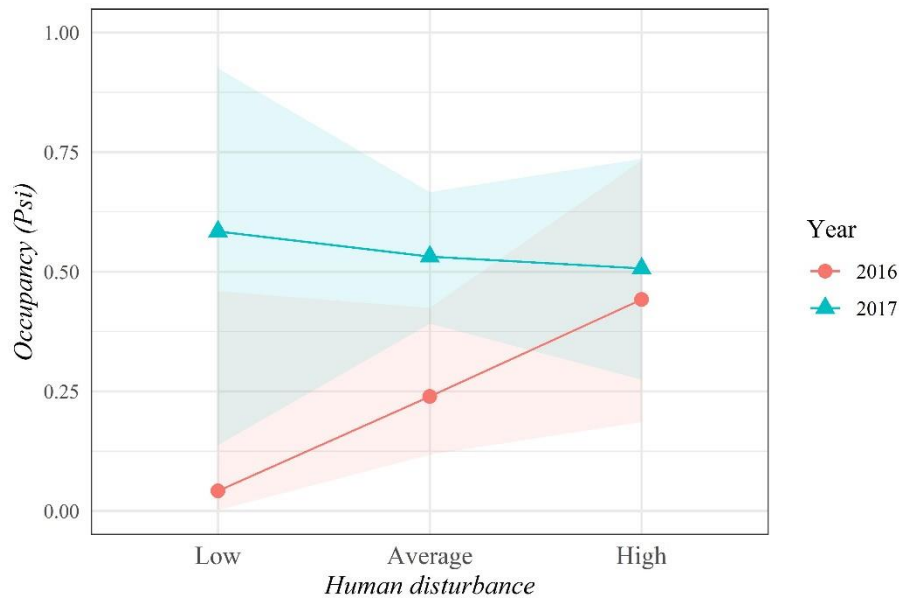


Figure 31. Occupancy estimates and 95% confidence intervals (shaded regions) for raccoons along a human disturbance gradient in 2016 and 2017 in the Central Valley of California.

The presence of water at a site in 2016 increased the odds of raccoon detection by 103.3% (OR: 2.033, 95% CI [1.159, 3.57], Figure 32). However, the presence of water at a site in 2017 only increased the odds of raccoon detection by 22.1% (OR: 1.221, 95% CI [0.857, 1.74], Figure 32) and there was uncertainty with this. Additionally, odds of raccoon detection decreased by 29.3% (OR: 0.707, 95% CI [0.588, 0.851]) with a one SD increase in Julian date (27.799 days).

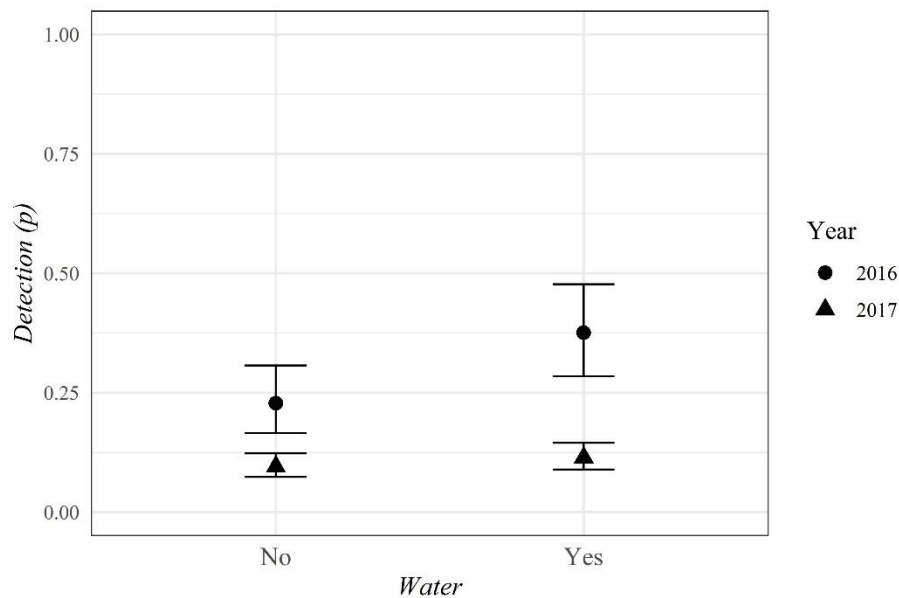


Figure 32. Detection estimates and 95% confidence intervals for raccoons at sites with and without water in 2016 and 2017 in the Central Valley of California.

A one SD increase in latitude (1.396 decimal degrees) resulted in a 242.4% increase in the odds of raccoon occupancy (OR: 3.424, 95% CI [1.871, 6.267]). Finally, odds of raccoon occupancy decreased by 52.6% (OR: 0.474, 95% CI [0.272, 0.826]) with every SD increase in distance to water (509.429 m).

Conditional Single-Season Two-Species Occupancy Models

In two-species occupancy modeling, the coyote was always treated as species A, the dominant species. Therefore, the covariates used for species A were always those from the top single species occupancy model for coyotes in either ecoregion.

Additionally, I was only interested in the responses of the subordinate species, species B, to species A, so further results will only focus on those species, and not coyotes.

Following model selection, if species B occupancy was not conditional upon the presence of coyotes then a species interaction factor (SIF) could not be calculated.

Mojave Desert

Due to limited detection data, I was unable to build a conditional two-species model for coyotes and gray foxes in the Mojave Desert. Coyotes and gray foxes were only detected together at a total of four sites, all of which were surveyed in 2016 and two of which were at guzzlers. I attempted to build a single species model for gray foxes in which I incorporated site-specific occupancy estimates for coyotes as a covariate.

However, because human disturbance was the only predictor of coyote occupancy, the two covariates were correlated and I could not model the influence of the two separately.

Coyote and bobcat.

Following model selection (Appendix G), bobcat occupancy of a site was not conditional upon the presence or absence of coyotes. However, the detection of bobcats was conditional upon the presence of coyotes at a site, but not coyote detection.

Additionally, following initial model selection, the interaction of year and distance to

water was identified as a strong predictor of bobcat occupancy. However, the beta estimate and standard error for this covariate were very high so it was excluded from model selection. The likely explanation for the strength and uncertainty of this predictor is that bobcats and coyotes were only detected together at sites with guzzlers in 2017 (five sites total) and were only detected together at four sites that were over one km from water in 2016. Therefore, it is possible that distance to water influenced the co-occurrence of bobcats and coyotes, specifically in 2017, but I could not model this relationship.

Bobcat occupancy was positively associated with elevation (Figure 33Figure 33. Beta estimates and 95% confidence intervals for covariates in top single-season two-species occupancy model for bobcats in the Mojave Desert of California.) with odds of occupancy increasing by 178.3% (OR: 2.783, 95% CI [1.708, 4.533]) with every SD increase in elevation (360.6 m). Odds of bobcat occupancy decreased by 59.9% (OR: 0.401, 95% CI [0.228, 0.704]) with every SD increase in distance to water (4.487 km). These two findings were very similar to single species modeling; however, year, human disturbance, and the interaction of the two influenced bobcat occupancy in two-species modeling as well. Odds of bobcat occupancy decreased by 59.3% (OR: 0.407, 95% CI [0.123, 1.346]) from 2016 to 2017 but there was uncertainty about this (Figure 34). One SD increase in human disturbance (1.1287) in 2016 decreased the odds of bobcat occupancy by 11.8% (OR: 0.882, 95% CI [0.439, 1.772]), but there was uncertainty with this (Figure 34). In 2017, one SD increase in human disturbance decreased the odds of bobcat occupancy by 59.9% (OR: 0.401, 95% CI [0.167, 0.962], Figure 34).

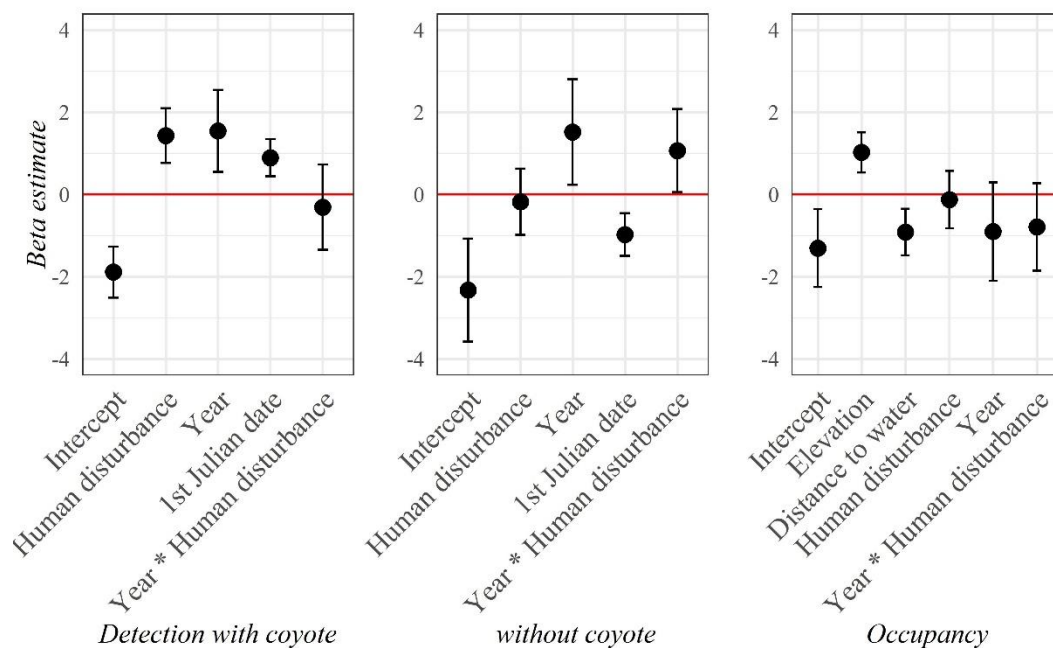


Figure 33. Beta estimates and 95% confidence intervals for covariates in top single-season two-species occupancy model for bobcats in the Mojave Desert of California.

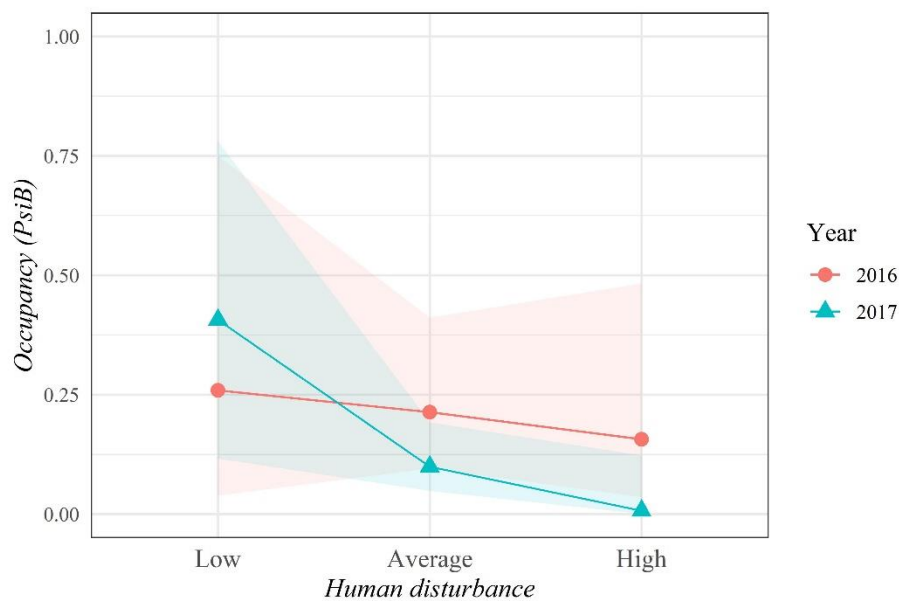


Figure 34. Occupancy estimates and 95% confidence intervals (shaded regions) for bobcats along a human disturbance gradient in 2016 and 2017 in the Mojave Desert of California.

In the absence of coyotes, odds of bobcat detection decreased by 62.3% (OR: 0.377, 95% CI [0.224, 0.635]) with every SD increase in first Julian date (23.2318 days) but increased by 144.4% (2.444, 05% CI [1.558, 3.832]) in the presence of coyotes. Odds of bobcat detection increased by 355.1% (OR: 4.551, 95% CI [1.262, 16.410]) from 2016 to 2017 in the absence of coyotes and by 368.6% (OR: 4.686, 95% CI [1.729, 12.702]) in the presence of coyotes (Figure 35). In 2016, a one SD increase in human disturbance (1.1287) decreased odds of bobcat occupancy by 16.2% (OR: 0.838, 95% CI [0.375, 1.87]) in the absence of coyotes but there was uncertainty with this (Figure 35). However, in the presence of coyotes, a one SD increase in human disturbance in 2016 increased odds of bobcat detection by 317.7% (OR: 4.177, 95% CI [2.146, 8.13], Figure 35). In 2017, a one SD increase in human disturbance increased odds of bobcat detection by 143.3% (OR: 2.433, 95% CI [1.298, 4.559]) in the absence of coyotes and by 206.9% (OR: 3.069, 95% CI [1.244, 7.584]) in the presence of coyotes (Figure 35).

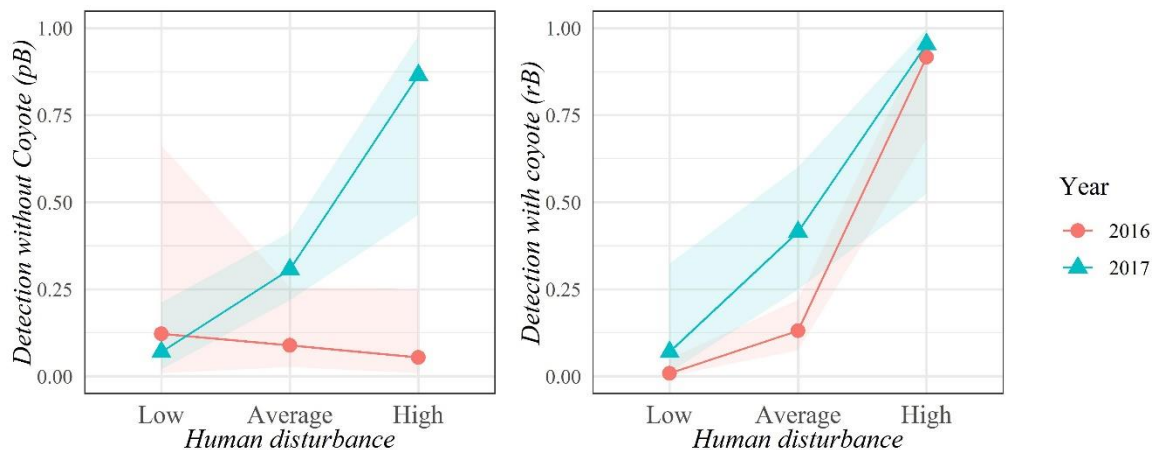


Figure 35. Detection estimates and 95% confidence intervals (shaded regions) for bobcats at sites without coyotes (left) and with coyotes (right) along a human disturbance gradient in 2016 and 2017 in the Mojave Desert of California.

Coyote and badger.

Following model selection (Appendix G), both badger occupancy and detection at a site were independent of the presence or absence of a coyote. Only elevation influenced the occupancy of badgers with a one SD increase in elevation (360.6 m) increasing the odds of badger occupancy by 90% (OR: 1.9, 95% CI [1.179, 3.064], Figure 36). Similar to single species modeling, both guzzler and first Julian date were positively associated with badger detection. The presence of a guzzler increased the odds of badger detection by 384.9% (OR: 4.849, 95% CI [2.496, 9.42]) and a one SD increase in first Julian date (23.2318 days) increased odds of badger detection by 37.3% (OR: 1.373, 95% CI [0.976, 1.932]) but there was minor uncertainty with this relationship.

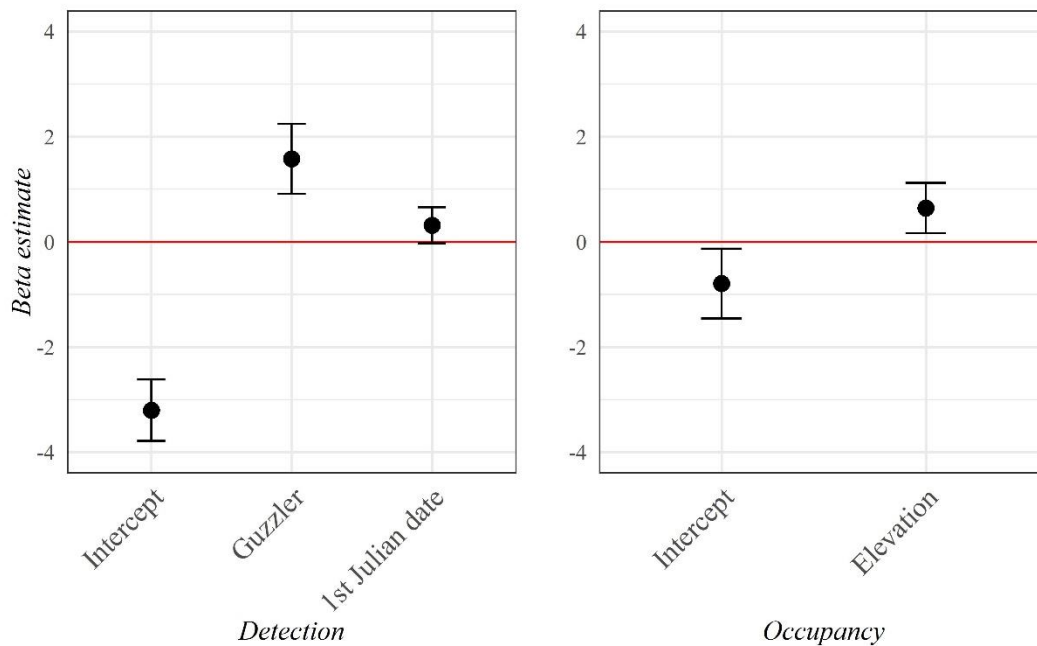


Figure 36. Beta estimates and 95% confidence intervals for covariates in top single-season two-species occupancy model for badgers in the Mojave Desert of California.

Coyote and kit fox.

Following model selection (Appendix G), kit fox occupancy of a site was not conditional upon the presence or absence of coyotes. However, the detection of kit foxes was conditional upon the presence of coyotes at a site, but not coyote detection.

Additionally, following initial model selection, guzzler was identified as a strong predictor of kit fox detection. However, the beta estimate and standard error for this covariate were extremely high so it was excluded from model selection. The likely explanation for the strength and uncertainty of this predictor is that kit foxes and coyotes were only detected together at four sites with guzzlers, all in 2016. Therefore, it is possible that the presence of guzzlers influenced the co-occurrence of kit foxes and coyotes, but I could not model this relationship.

The covariates in the top occupancy model for kit foxes remained unchanged following two-species occupancy modeling (Figure 37). Odds of kit fox occupancy decreased by 68.7% (OR: 0.313, 95% CI [0.204, 0.479]) with every SD increase in elevation (360.6 m) but odds of kit fox occupancy increased by 80.1% (OR: 1.801, 95% CI [1.326, 2.447]) with every SD increase in distance to water (4.487 km). Kit fox occupancy decreased by 50.6% (OR: 0.494, 95% CI [0.263, 0.927]) from 2016 to 2017 (Figure 38) and by 25.6% (OR: 0.744, 95% CI [0.521, 1.062]) with every SD increase in human disturbance (1.1287) in 2016 (Figure 38), but there was uncertainty with this. However, odds of kit fox occupancy increased by 65% (OR: 1.65, 95% CI [1.013, 2.688]) with every SD increase in human disturbance in 2017 (Figure 38).

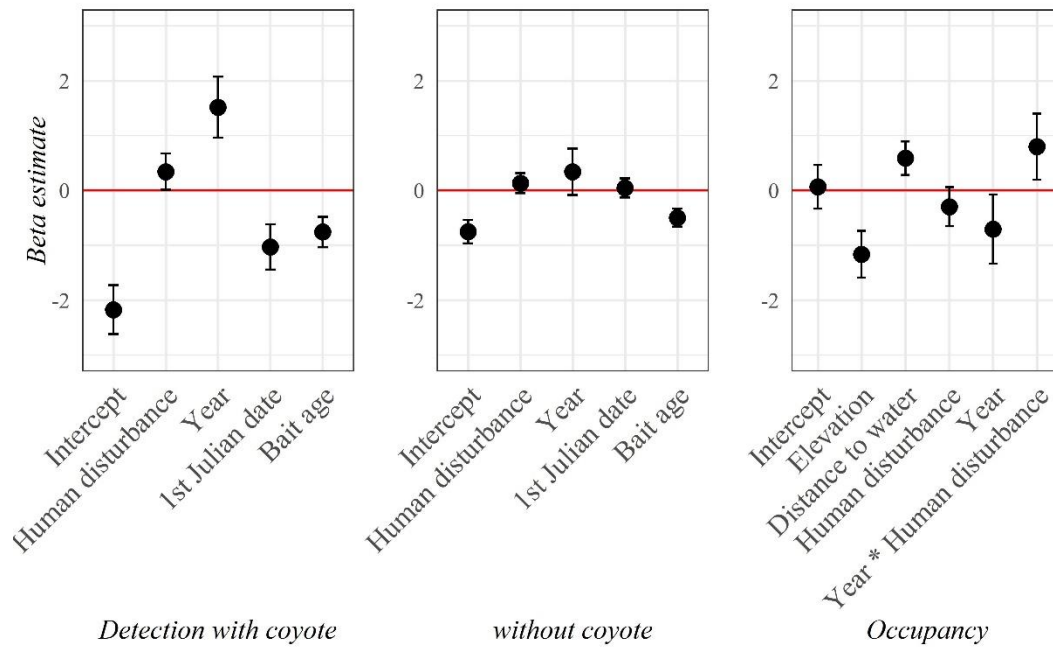


Figure 37. Beta estimates and 95% confidence intervals for covariates in top single-season two-species occupancy model for kit foxes in the Mojave Desert of California.

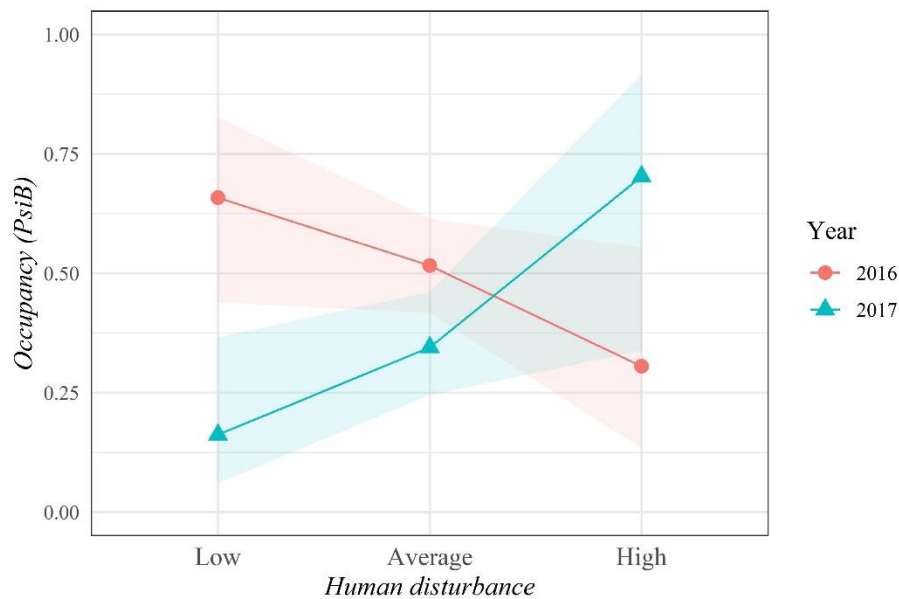


Figure 38. Occupancy estimates and 95% confidence intervals (shaded regions) for kit foxes along a human disturbance gradient in 2016 and 2017 in the Mojave Desert of California.

In the absence of coyotes, odds of kit fox detection increased by 4.8% (OR: 1.048, 95% CI [0.882, 1.244]) with every SD increase in first Julian date (23.2318 days) but there was uncertainty with this. However, in the presence of coyotes, odds of kit fox detection decreased by 62.2% (OR: 0.358, 95% CI [0.236, 0.541]) with every SD increase in Julian date. In the absence of coyotes, odds of kit fox detection increased by 40.7% (OR: 1.407, 95% CI [0.921, 2.149]) from 2016 to 2017 (Figure 39) but there was uncertainty with this. In the presence of coyotes, odds of kit fox detection increased by 356.5% (OR: 4.565, 95% CI [2.619, 7.958]) from 2016 to 2017 (Figure 39). Each additional day following initial deployment and baiting of cameras decreased odds of kit fox occupancy by 39.1% (OR: 0.609, 95% CI [0.517, 0.718]) in the absence of coyotes and by 53.2% (OR: 0.468, 95% CI [0.355, 0.618]) in the presence of coyotes. One SD increase in human disturbance (1.1287) increased odds of kit fox detection by 14.3% (OR: 1.143, 95% CI [0.954, 1.37]) in the absence of coyotes, but there was slight uncertainty with this (Figure 39). In the presence of coyotes, a one SD increase in human disturbance increased the odds of kit fox detection by 40.9% (OR: 1.409, 95% CI [1.009, 1.967], Figure 39).

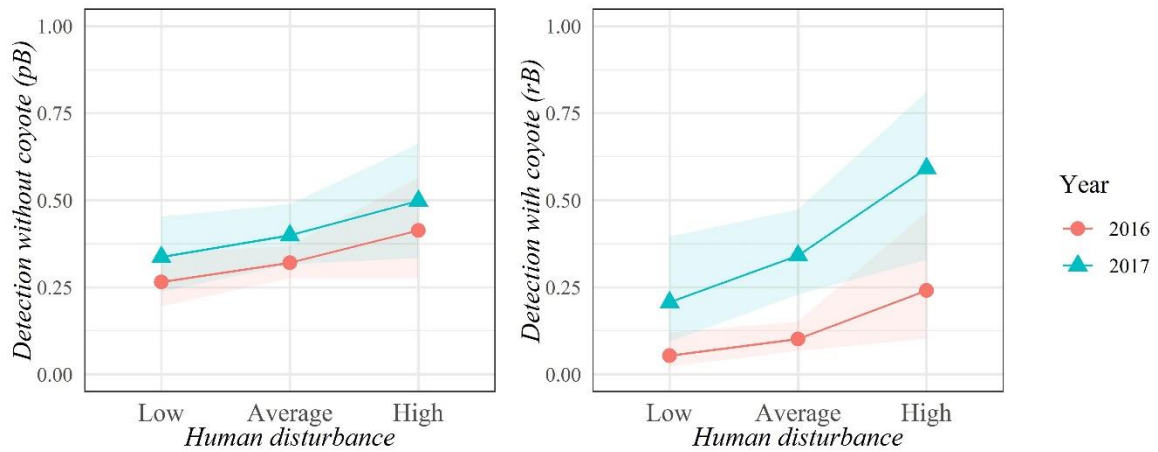


Figure 39. Detection estimates and 95% confidence intervals (shaded regions) for kit foxes at sites without coyotes (left) and with coyotes (right) along a human disturbance gradient in 2016 and 2017 in the Mojave Desert of California.

Central Valley

Coyote and bobcat.

Following model selection (Appendix H), bobcat occupancy of a site was not conditional upon the presence or absence of coyotes. However, the detection of bobcats was conditional upon the presence of coyotes at a site, but not coyote detection. Additionally, following initial model selection, year was identified as a strong predictor of bobcat occupancy. However, the beta estimate and standard error for this covariate were extremely high so it was excluded from model selection. As a result, all interaction terms were also dropped from further analysis. The likely explanation for the strength and uncertainty of this predictor is that bobcats and coyotes were only detected together at four sites in 2016 and bobcats were only detected at four sites without coyotes in 2016. Therefore, it is possible that year influenced the co-occurrence of bobcats and coyotes,

and the relationship between co-occurrence and other covariates, but I could not model these relationships.

Similar to single species modeling, latitude, tree cover, and distance to water influenced the occupancy of bobcats (Figure 40). Odds of bobcat occupancy increased by 75.7% (OR: 1.757, 95% CI [0.988, 3.125]) with each SD increase in latitude (1.396 degrees) and there was marginal uncertainty with this. Odds of bobcat occupancy also increased by 136.2% (OR: 2.362, 95% CI [1.488, 3.747]) with every SD increase in percent tree cover (20.1%). However, odds of bobcat occupancy decreased by 35% (OR: 0.65, 95% CI [0.362, 1.166]) with every SD increase in distance to water (509.429 m) but there was some uncertainty with this.

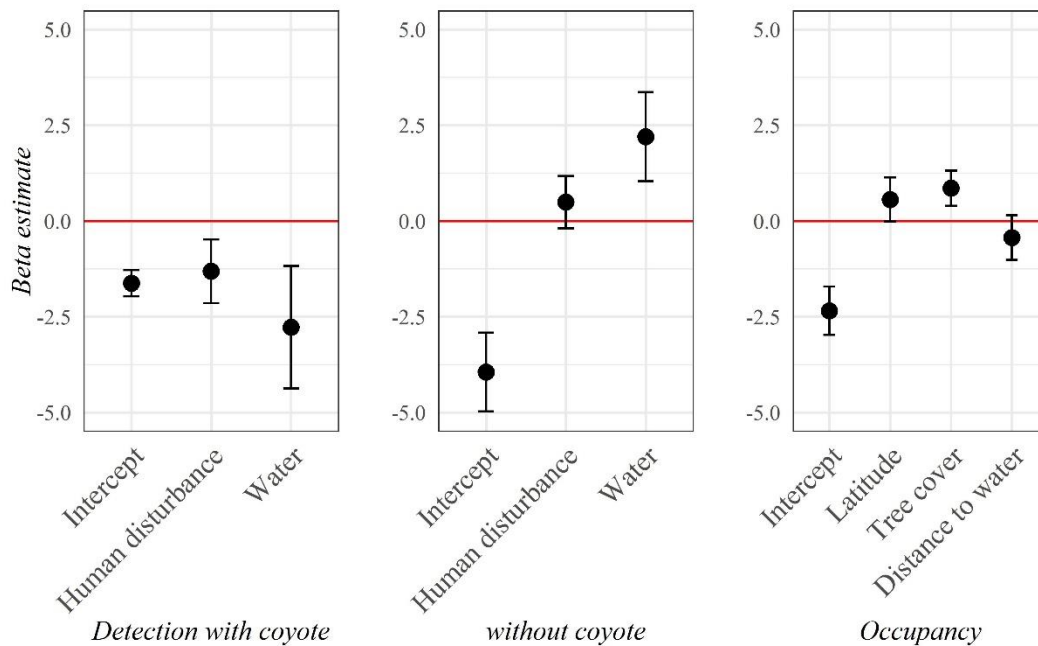


Figure 40. Beta estimates and 95% confidence intervals for covariates in top single-season two-species occupancy model for bobcats in the Central Valley of California.

If water was present at a site, odds of bobcat detection increased by 805.9% (OR: 9.059, 95% CI [2.834, 28.96]) in the absence of coyotes; however, odds of bobcat detection decreased by 93.8% (OR: 0.062, 95% CI [0.013, 0.310]) if coyotes were present (Figure 41). In the presence of coyotes, odds of bobcat detection also decreased by 73.1% (OR: 0.269, 95% CI [0.117, 0.619]) with every SD increase in human disturbance (1.303); however, odds of bobcat detection increased by 64% (OR: 1.64, 95% CI [0.829, 3.247]) with each SD increase in human disturbance in the absence of coyotes, but there was uncertainty with this (Figure 41).

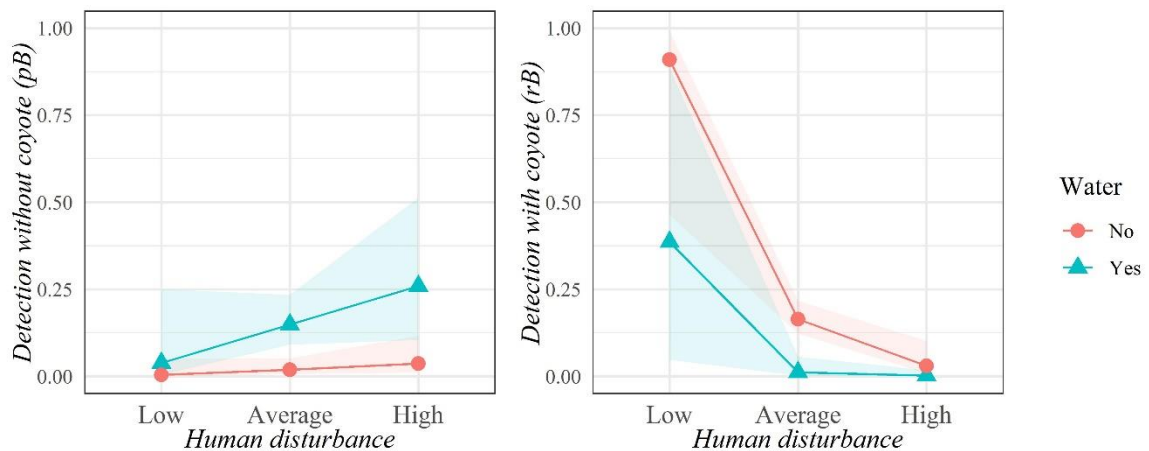


Figure 41. Detection estimates and 95% confidence intervals (shaded regions) for bobcats at sites without coyotes (left) and with coyotes (right) along a human disturbance gradient at sites with and without water in the Central Valley of California.

Coyote and domestic cat.

Following model selection (Appendix H), domestic cat occupancy of a site was conditional upon the presence of coyotes. Therefore, I was able to estimate a (SIF) for domestic cats and coyotes. Additionally, the detection of domestic cats was conditional

upon both the presence and detection of coyotes at a site (Figure 42). Following initial model selection, year was identified as a strong predictor of domestic cat detection. However, the beta for this covariate was extremely high so it was excluded from model selection. As a result, all interaction terms were also dropped from further analysis. The likely explanation for the strength and uncertainty of this predictor is that domestic cats and coyotes were only detected together at one site in 2016. Therefore, it is possible that year influenced the co-occurrence of domestic cats and coyotes, and the relationship between co-occurrence and other covariates, but I could not model these relationships.

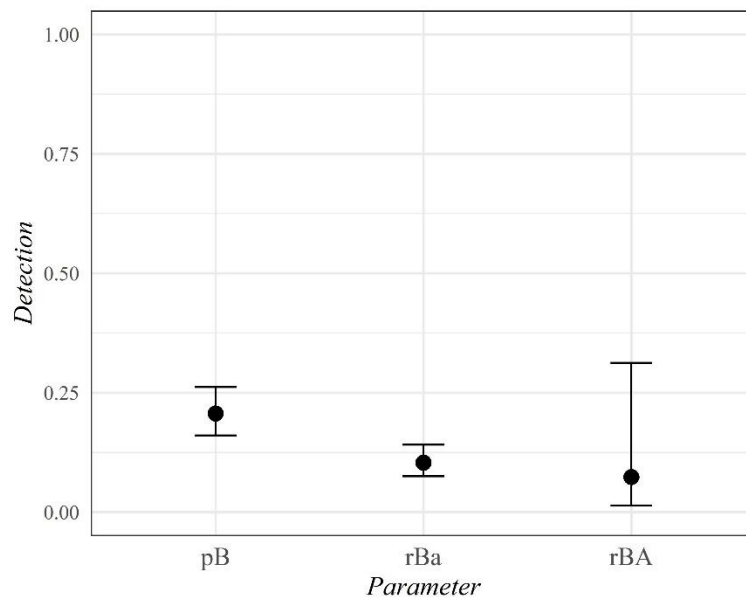


Figure 42. Detection estimates and 95% confidence intervals for domestic cats at an average site in the Central Valley of California without coyotes (pB), with coyotes (rBa), and with coyote detection (rBA).

The only covariate which affected the detection of domestic cats in two-species modeling was Julian date (Figure 43). In the absence of coyotes, odds of domestic cat

detection increased by 48.7% (OR: 1.487, 95% CI [1.138, 1.941]) with every SD increase in Julian date (27.799 days). However, at sites where coyotes were present but not detected, odds of domestic cat detection decreased by 65% (OR: 0.35, 95% CI [0.236, 0.519]) with an SD increase in Julian date and decreased by 83% (OR: 0.17, 95% CI [0.026, 1.112]) per SD increase in Julian date at sites where coyotes were present and detected, but there was uncertainty with this.

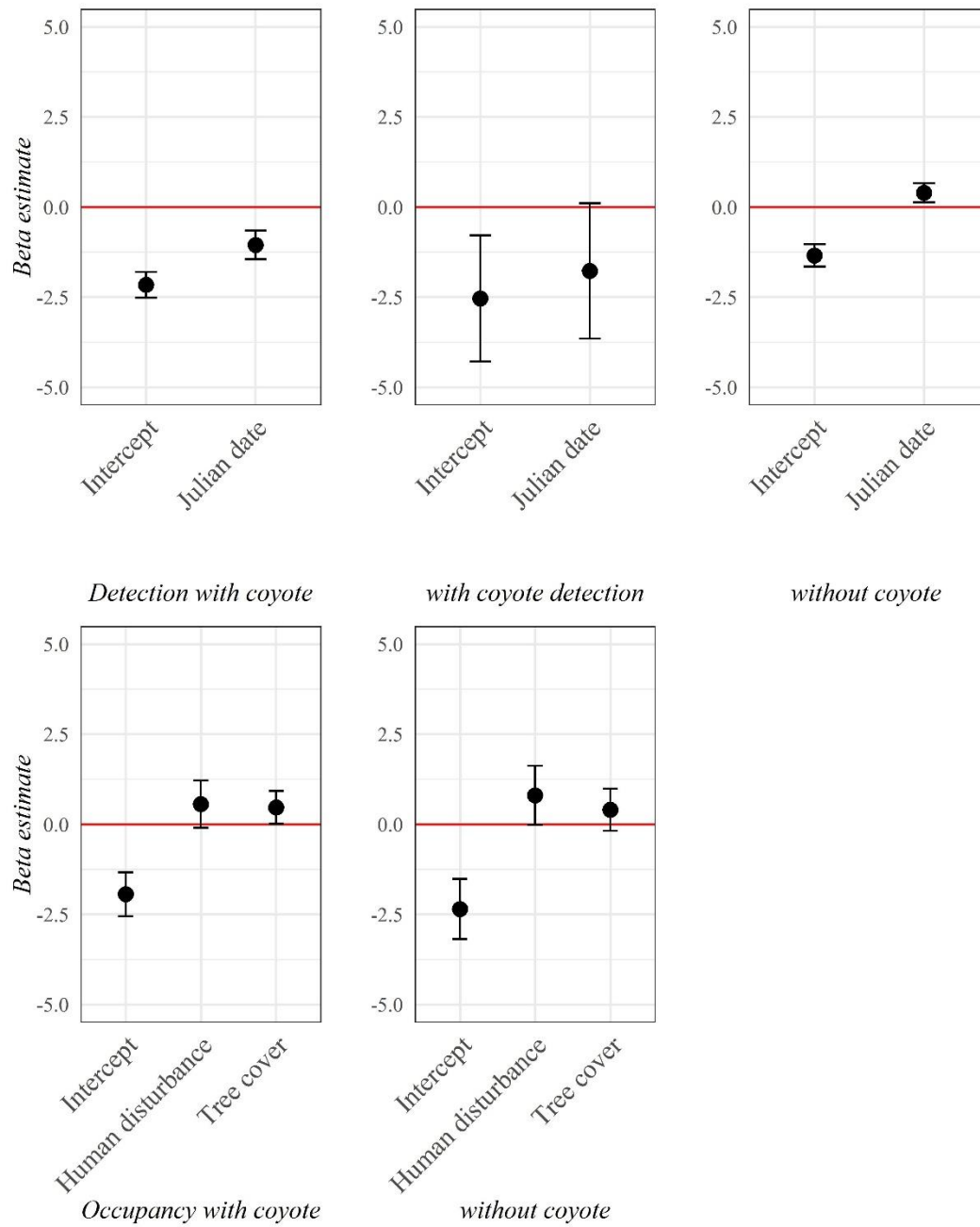


Figure 43. Beta estimates and 95% confidence intervals for covariates in top single-season two-species occupancy model for domestic cats in the Central Valley of California.

Odds of domestic cat occupancy were positively influenced by both human disturbance and tree cover regardless of the presence of coyotes (Figure 43). A one SD increase in percent tree cover (20.1%) increased odds of domestic cat occupancy by 59.8% (OR: 1.598, 95% CI [1.013, 2.52]) at sites where coyotes were present and by 49.9% (OR: 1.499, 95% CI [0.834, 2.696]) at sites without coyotes, but there was uncertainty with this. A one SD increase in human disturbance (1.303) increased odds of domestic cat occupancy by 75.1% (OR: 1.751, 95% CI [0.905, 3.388]) in the presence of coyotes and increased by 123.4% (OR: 2.234, 95% CI [0.982, 5.081]) in the absence of coyotes, although there was some uncertainty with both of these (Figure 44).

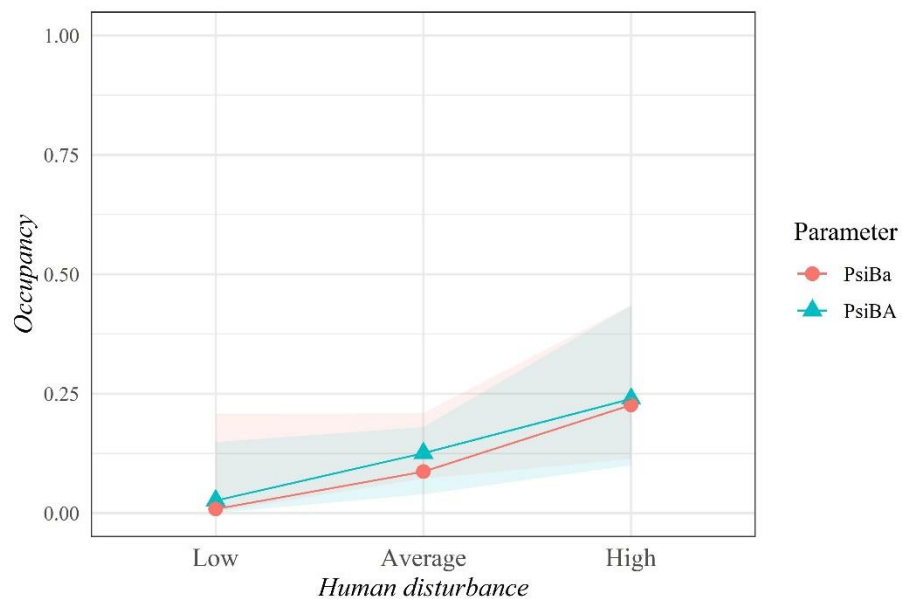


Figure 44. Occupancy estimates and 95% confidence intervals (shaded regions) for domestic cats along a human disturbance gradient in the presence of coyotes (PsiBA) and absence of coyotes(PsiBa) in the Central Valley of California.

The SIF for domestic cats and coyotes appeared to decrease with increasing human disturbance but remained above 1 suggesting possible aggregation of the two species (Figure 45). However, the uncertainty with this derived parameter was large, especially at sites with low human disturbance where domestic cats were less likely to occur.

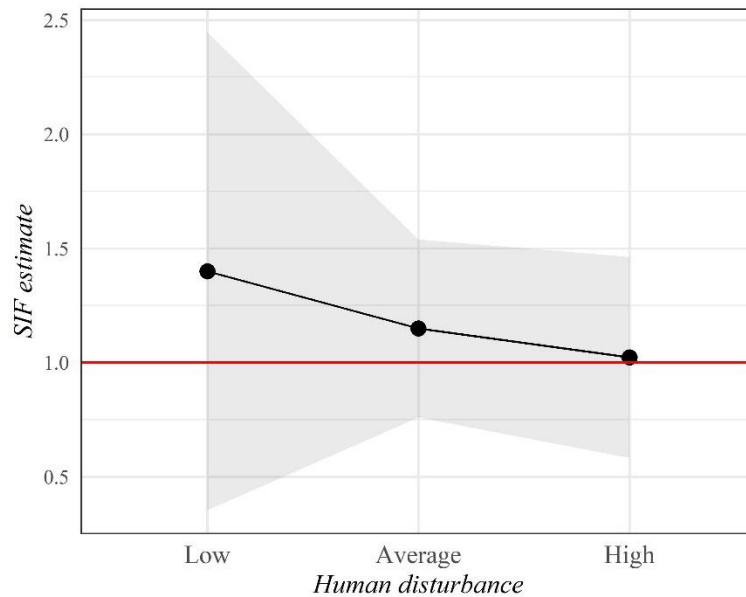


Figure 45. Species Interaction Factor (SIF) estimates and 95% confidence intervals (shaded gray) for domestic cats and coyotes along a human disturbance gradient in the Central Valley of California. The red line represents a SIF of 1, indicating the two species occupy a site independently of one another.

Coyote and raccoon.

Following model selection (Appendix H), raccoon occupancy of a site was not conditional upon the presence or absence of coyotes. However, the detection of raccoons was conditional upon the presence of coyotes at a site, but not coyote detection.

With the exception of the interaction of year and human disturbance, the top occupancy model for raccoons following two-species modeling was the same as that from single species modeling (Figure 46). Odds of raccoon occupancy increased by 266.8% (OR: 3.668, 95% CI [2.283, 5.895]) with one SD increase in latitude (1.396 decimal degrees). However, odds of raccoon occupancy decreased by 51.2% (OR: 0.488, 95% CI [0.32, 0.745]) with a one SD increase in distance to water (509.429 m). A one SD increase in human disturbance (1.303) increased the odds of raccoon occupancy by 20.5% (OR: 1.205, 95% CI [0.837, 1.736]) while odds of raccoon occupancy increased by 101.8% (OR: 2.018, 95% CI [0.881, 4.62]) from 2016 to 2017 but there was uncertainty with both of these (Figure 47).

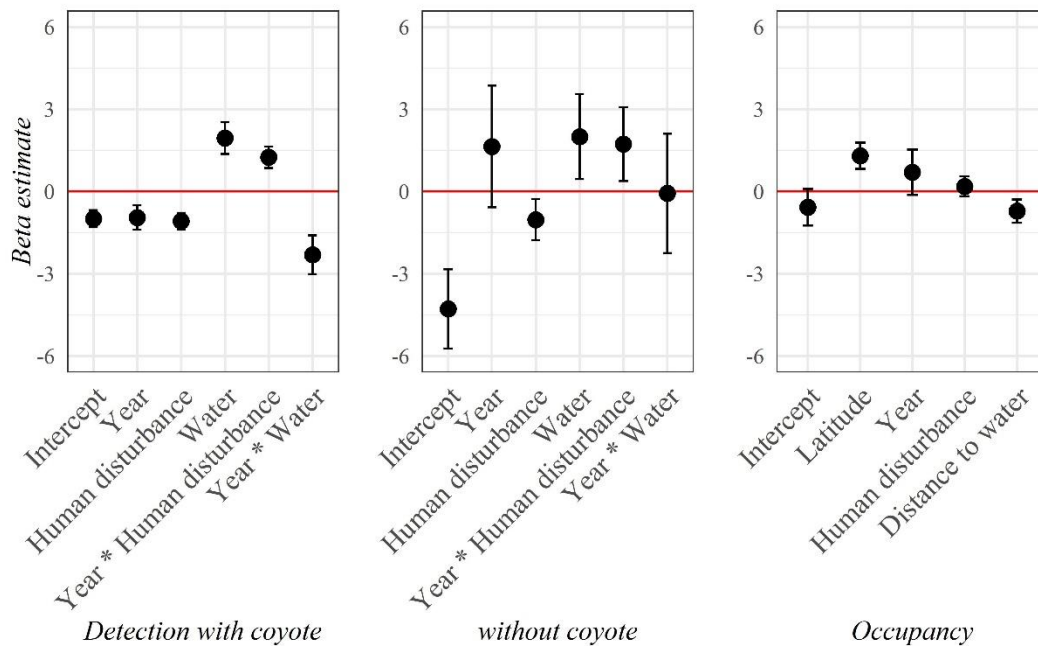


Figure 46. Beta estimates and 95% confidence intervals for covariates in top single-season two-species occupancy model for raccoons in the Central Valley of California.

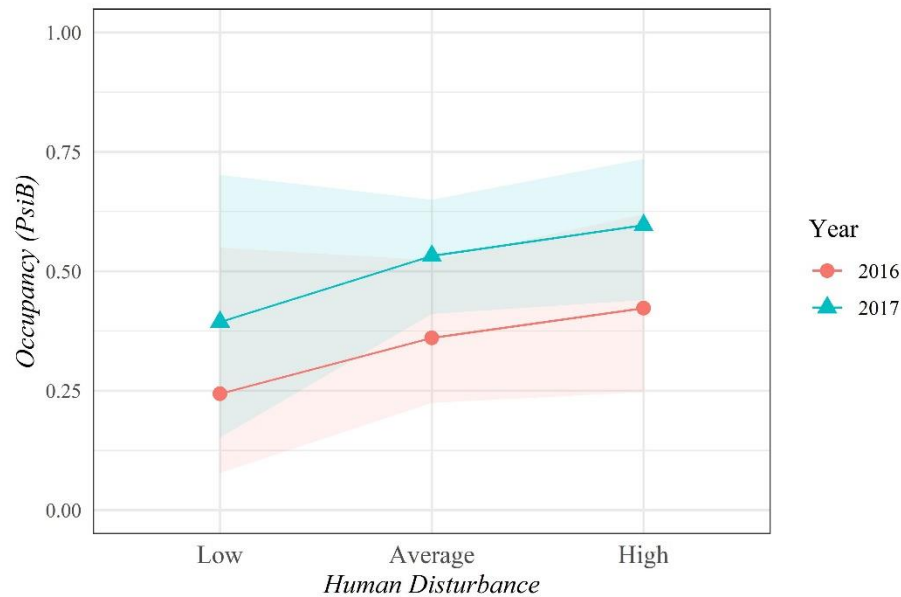


Figure 47. Occupancy estimates and 95% confidence intervals (shaded regions) for raccoons along a human disturbance gradient in 2016 and 2017 in the Central Valley of California.

From 2016 to 2017, odds of raccoon detection decreased by 61.3% (OR: 0.387, 95% CI [0.248, 0.603]) at sites with coyotes and increased by 415.5% (OR: 5.156, 95% CI [0.561, 47.359]), at sites without coyotes but there was a lot of uncertainty with this (Figure 48). In the absence of coyotes, odds of raccoon detection increased by 640.3% (OR: 7.403, 95% CI [1.574, 34.824]) at sites with water in 2016 (Figure 49). Similarly, when coyotes were present, odds of raccoon detection increased by 601.7% (OR: 7.017, 95% CI [3.923, 12.55]) at sites with water in 2016 (Figure 49). In 2017, odds of raccoon detection at sites with water increased by 590.8% (OR: 6.908, 95% CI [1.481, 32.253]) if coyotes were absent but decreased by 30.4% (OR: 0.696, 95% CI [0.468, 1.034]) if coyotes were present, but there was uncertainty with the latter (Figure 49).

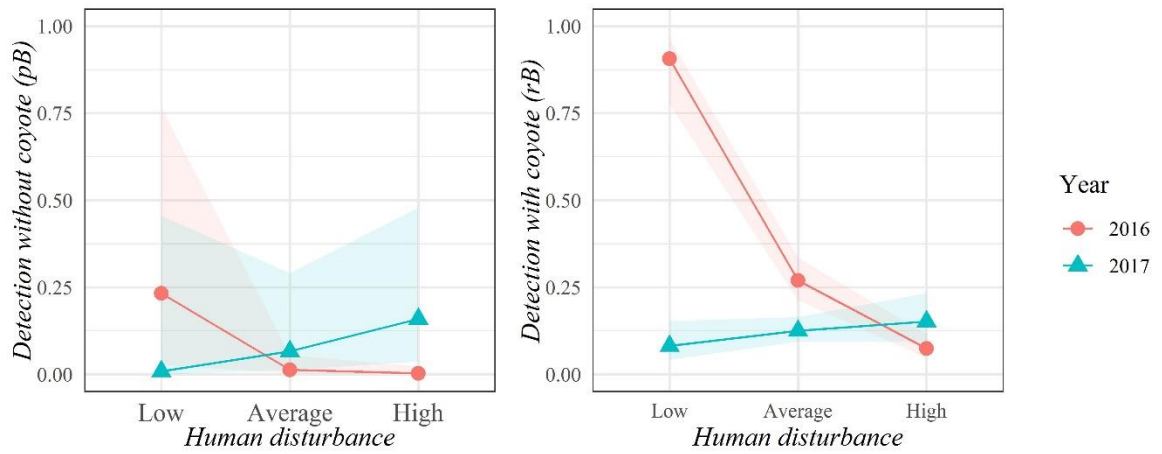


Figure 48. Detection estimates and 95% confidence intervals (shaded regions) for raccoons at sites without coyotes (left) and with coyotes (right) along a human disturbance gradient in 2016 and 2017 in the Central Valley of California.

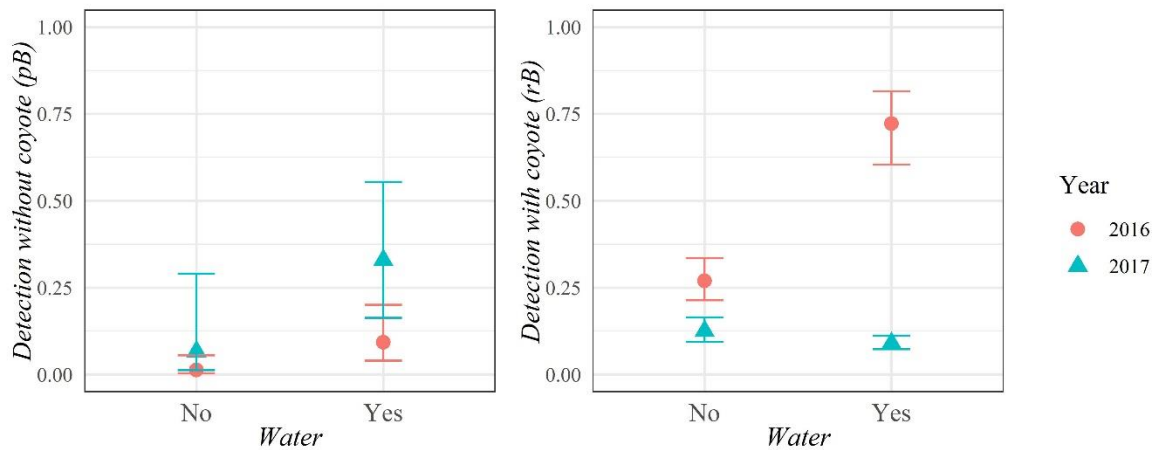


Figure 49. Detection estimates and 95% confidence intervals for raccoons at sites without coyotes (left) and with coyotes (right) at sites with and without water in the Central Valley of California.

In 2016, a one SD increase in human disturbance (1.303) decreased the odds of raccoon detection by 64.3% (OR: 0.357, 95% CI [0.168, 0.758]) if coyotes were absent and by 66.3% (OR: 0.337, 95% CI [0.248, 0.457]) if coyotes were present (Figure 48).

However, in 2017, a one SD increase in human disturbance increased the odds of raccoon detection by 101.6% (OR: 2.016, 95% CI [0.657, 6.185]) if coyotes were absent and by 17.2% (OR: 1.172, 95% CI [0.918, 1.497]) if coyotes were present, but there was uncertainty in both of these relationships (Figure 48).

DISCUSSION

Long-term drought clearly influences mesopredators in California. The only species in this study which was unaffected by drought was the domestic cat, a subsidized pet that doesn't rely upon natural resources for survival. Drought impacted not only how species utilized the landscape, but also how they responded to an apex predator, the coyote. All species, besides the badger, responded in some way to the presence of coyotes, suggesting that coyotes impact the guild, and likely the entire community. However, my work showed that some mesopredators appeared to take greater risks in the presence of coyotes during the drought, particularly in order to obtain water. Animals will make different risk assessments under stress which can alter the effectiveness of top-down control in an ecosystem (Bleicher 2017). Mesopredators, which avoided open water after the drought when coyotes were present, utilized the same water sources as coyotes during the drought, risking aggressive competitive interactions.

Additionally, human disturbance differentially affected both the occupancy and detection of mesopredator species, relationships which were sometimes mediated by the presence of drought and coyotes. Therefore, the safety of urban shields can shift for mesopredators dependent upon drought and how drought influences the behavior of other species within the mesopredator guild.

Interpretation of results relating to elevation, latitude, tree cover, and Julian date are in the appendices (Appendix I&Appendix J).

Coyotes and subordinate species

Coyotes only affected the occupancy of one species, the domestic cat.

Interestingly, the species interaction factor (SIF) between the two was marginally greater than one, suggesting the possibility of aggregation. However, the SIF decreased slightly with greater human disturbance in the Central Valley suggesting that the effect of coyotes on cats may instead be human-mediated. A previous study in southern California found that almost half of cat owners restricted their cat's outdoor activity when they believed coyotes were in the area (Crooks and Soulé 1999). It is possible that cat owners in more urban areas are choosing to keep their cats indoors when they believe coyotes are present. Less urban areas may be inhabited by more feral and/or farm cats with fewer restrictions on their movement, which could explain the higher SIF values in less disturbed areas.

Domestic cats were also the only species whose detection was influenced not just by the presence of coyotes, but also the detection of coyotes. Domestic cat detection was lower when coyotes were present, especially if they were detected. This indicates that domestic cats and/or their owners respond not only to the occupancy of an area by coyotes but also their activity. Unfortunately, due to data shortage I was unable to include year in my domestic cat-coyote models and was therefore unable to examine how drought might mediate the relationship between cats and coyotes and their relationship with their habitat.

Badgers were the only species whose detection was unaffected by the presence of coyotes. Coyotes and badgers sometimes hunt in tandem for small mammals, such as

ground squirrels, suggesting that badgers might actually benefit from the presence of coyotes (Minta et al. 1992, Thornton et al. 2018). However, a recent study of coyote diet in the Mojave Desert found that coyotes prefer rabbits as a source of prey (Cypher et al. 2018) which might indicate that such hunting associations are less important in the Mojave Desert. My study did not document any such partnerships but did indicate that badgers do not avoid coyotes spatially or behaviorally.

The presence of coyotes affected the detection of bobcats and kit foxes in the Mojave Desert and bobcats and raccoons in the Central Valley. This may indicate that while coyotes may not influence the spatial distribution of these species, they do influence other species' activity patterns and behavior. In all species pairs, detection of the subordinate species was not consistently lower or higher dependent upon the presence of coyotes. Rather, these relationships were driven by habitat and drought covariates.

Drought and mesopredator occupancy and detection

The badger was the only species in the Mojave Desert whose occupancy was influenced by drought. While there was some uncertainty, single species modeling indicated that badger occupancy increased from 2016 to 2017. Similarly, as I hypothesized, the detection probability of bobcats, kit foxes, and gray foxes increased from 2016 to 2017. These responses may have been driven by prey availability. Rodents are a frequent prey base of mesopredators, especially badgers (Long 1973), which rely on winter annual vegetation and precipitation for successful reproduction in arid ecosystems (Beatley 1969). Due to the prolonged drought that persisted in 2016, rodent populations

were low during our first year of data collection (Kelly et al. 2019). However, rodent populations can rapidly respond to drought conditions ending (Bradley et al. 2006) which indicates that rodent populations could have been higher in 2017. Mesopredator densities, reproductive success, and spatial overlap have all been tied to prey availability and density (White and Ralls 1993, Fuller and Sievert 2001) which might explain changes in mesopredator detection. In 2016, when rodent availability was reduced, mesopredators such as bobcats and foxes may not have been able to obtain the resources necessary for successful reproduction, resulting in reduced densities and therefore detection. Similarly, a study of kit foxes during a drought found that kit fox reduced overlap of home ranges during prey scarcity (White and Ralls 1993) which could also influence detection probability. Badgers, on the other hand, may have expanded their use of the landscape as rodent populations increased in 2017, which would result in increased occupancy in the Mojave Desert ecoregion following the drought.

Unlike bobcats in the Mojave Desert, bobcat detection in the Central Valley decreased from 2016 to 2017. This was not as I hypothesized and may indicate that bobcat populations were partially buffered to drought but differently than I expected. This response may indicate a behavioral response in which bobcats were more actively searching for resources during the drought. At intermediate water availability prey can function as both a source of energy and water which may lead to increased hunting behavior in predators to meet resource needs (McCluney et al. 2012). It is possible that bobcats increased their activity to acquire more prey during the drought in 2016 and reduced hunting activities in 2017 when surface water was more readily available.

Additionally, bobcats are known to diversify their diets in times of food scarcity (McKinney and Smith 2007) which may have caused Central Valley bobcats to forage more intensely in 2016 to meet their resource needs. In this case, detection probability may have been driven by increased activity rather than abundance and could explain the difference between the two ecoregions. If true, this would indicate that bobcats in the Central Valley were protected from some of the more severe bottom-up effects of drought that likely reduced reproductive potential and abundance of mesopredators in the Mojave Desert. Unfortunately, I was unable to model the effects of drought on coyote-bobcat interactions in the Central Valley due to a lack of data.

When accounting for coyote presence and absence using two-species occupancy modeling, year was positively correlated with raccoon occupancy in the Central Valley. The increase of raccoon occupancy in 2017 may reflect raccoons' broader use of the landscape as more habitats became suitable with the end of the drought. Raccoons are known to utilize aquatic habitats (Stuewer 1943, Gehrt and Fritzell 1998) which were likely limited in 2016 during the drought but may have expanded following the high winter precipitation levels and flooding of early 2017 (Wang et al. 2017).

Access to water and drought

Mojave Desert

Guzzlers represent manmade water sources in the Mojave Desert that have been shown to increase occupancy of most mammalian predators (Rich et al. 2019a). My modeling showed similar patterns with higher coyote, bobcat, and badger detection

probabilities at guzzlers and lower kit fox detection. This aligns with previous findings where mesopredators were differentially attracted to guzzlers, with kit fox using them the least (O'Brien et al. 2006, Atwood et al. 2011, Rich et al. 2019a). In fact, subordinate species, such as kit foxes, are less likely to use guzzlers than more dominant predators, such as the coyote, suggesting coyote presence may mediate the relationship between other species and water (Atwood et al. 2011, Rich et al. 2019a).

All of our kit fox detections at guzzlers occurred in 2016. I therefore had to drop the interaction of year and guzzler from modeling but it does provide anecdotal evidence that kit fox may only use guzzlers during times of scarcity, such as drought, as I had predicted. Kit fox meet their water needs through acquisition of prey, such as rodents (Golightly and Ohmart 1984), but may have struggled to meet these needs in 2016 when rodent populations declined (Kelly et al. 2019). As a result, kit fox may have been forced to utilize free standing water in 2016 and risk competitive interactions with coyotes, but again avoided guzzlers in 2017 when rodent populations likely recovered.

In addition to guzzlers, I examined species' relationships with distance to natural water sources and again found kit foxes to be relatively independent of water. Kit fox occupancy increased with distance to water while bobcat occupancy decreased. Interestingly, gray fox response to distance to water was possibly influenced by drought with gray fox occupancy decreasing with distance to water in 2016 but increasing in 2017. I only included perennial water in my distance to water measure which may indicate that gray foxes were able to make use of ephemeral water bodies in 2017 and therefore able to move further from perennial sources, increasing their overall occupancy

on the landscape. Additionally, I included guzzlers within my distance to water measure so gray fox response could partially account for attraction to guzzlers in 2016 (see Rich et al. 2019).

Central Valley

Coyote detection was positively associated with water at site in the Central Valley while domestic cat detection was negatively correlated. Coyotes are attracted to sources of water (O'Brien et al. 2006, Atwood et al. 2011, Rich et al. 2019a) and Central Valley coyotes appear to follow this pattern, regardless of drought. Domestic cats, on the other hand, probably do not require access to water as their owners supply it. Domestic cats' aversion to water at a site may also represent their avoidance of habitats frequented by coyotes. Two-species modeling for domestic cats and coyotes confirmed that coyote presence and detection influence both the occupancy and detection of domestic cats but their species interaction factor seems to indicate that cats did not spatially avoid coyotes. However, cats are less likely to occur with coyotes present (Crooks and Soulé 1999) so it is possible that while not avoiding coyotes directly, domestic cats are avoiding areas of high coyote activity.

Water at site only influenced bobcat detection when accounting for the presence of coyotes in two-species occupancy modeling. In the presence of coyotes, bobcat detection decreased at sites with water while bobcat detection increased at sites with water if coyotes were absent, which may indicate that while bobcats do not avoid coyotes (Lesmeister et al. 2015, Wang et al. 2015, Baker 2016), they do alter their use of water sources to avoid interactions with coyotes. Despite altering their use of water sources,

bobcat occupancy was consistently higher closer to water, regardless of coyote presence. Therefore, while bobcat might respond behaviorally to coyotes, they do not appear to alter their overall habitat use.

Similar to bobcats, raccoon occupancy was negatively correlated with distance to water regardless of coyote presence. However, raccoon detection at water was driven by drought. During the drought, raccoon detection was higher at sites with water but in 2017 raccoons were just as likely to be detected at sites without water. This likely indicates that raccoons were more reliant on fewer sources of water and frequented them more often in 2016 when other water sources may have been dry. This obligate relationship with diminished sources of water likely relaxed in 2017 when high precipitation levels resulted in replenished surface water in the ecoregion (California Department of Water Resources 2017). The interaction of year and water at a site was also in the top two-species model for raccoon detection. In 2016, regardless of coyote presence, raccoons were always much more active at sites with water, as I had predicted. However, following the drought, raccoons became marginally less active at sites with water if coyotes were present, but remained just as active at sites with water if coyotes were absent. During the drought, raccoons likely had to use any sources of water available and risk interactions with coyotes. But in 2017, perhaps they adjusted their use of water as a means to avoid interacting with coyotes. While my research, like previous research, indicates that raccoons do not directly avoid coyotes (Gehrt and Prange 2007, Lesmeister et al. 2015), there does appear to be evidence that drought influences how raccoons respond to coyote presence at water.

Human disturbance and drought

Mojave Desert

The level of human disturbance in the Mojave Desert is relatively low so relationships between species and disturbance represent their response to low to mid-level disturbance. Additionally, this human disturbance measure did not encapsulate all disturbance types such as grazing or recreation like off-highway vehicles (Leu et al. 2008) which greatly impact this landscape and whose impacts are exacerbated by drought (Lovich and Bainbridge 1999, Czech et al. 2000). However, at a large scale, the Human Footprint of the West (Leu et al. 2008) accurately represents general human disturbance in both ecoregions.

Badgers were the only species unaffected by human disturbance. However, previous research of European badgers (*Meles meles*) found badgers to alter feeding behavior and vigilance in response to the sound of humans (Clinchy et al. 2016). While European and American badgers are in different subfamilies, European badgers may still indicate how American badgers might respond to humans. It is possible that in the Mojave Desert, badgers do not alter their use of a landscape in response to mid-level human disturbance but might respond at a finer scale, undetectable by my occupancy modeling.

Unlike badgers, both coyote occupancy and detection were influenced by human disturbance in the Mojave Desert. Coyote occupancy was always positively correlated with human disturbance regardless of year which was unsurprising given the low levels

of disturbance in the ecoregion and coyotes' ability to exploit human-modified areas (Crooks 2002, Riley et al. 2003, Gehrt et al. 2010, Ordeñana et al. 2010). While coyote occupancy was always positively associated with human disturbance, coyote detection probability was influenced by drought. As I had hypothesized, coyotes were more likely to be detected at sites of higher disturbance in 2016 but after the drought coyotes were more likely to be detected at sites of lower disturbance in 2017. This suggests that while coyotes are always more likely to be in areas of higher human disturbance, they increased their use of these areas during the drought. This finding matches previous work where Mojave Desert coyotes increased their dietary diversity during the drought and expanded their use of anthropogenic food (Cypher et al. 2018).

In contrast to coyotes, gray fox occupancy was negatively associated with human disturbance both during and after the drought. This aligns with recent research that has also found gray foxes to be sensitive to human disturbance (Ordeñana et al. 2010, Wang et al. 2015, Baker and Leberg 2018). However, there is the possibility that drought mediates gray foxes' relationship with human-modified areas as they were marginally more likely to be in average to highly disturbed sites in the drought year. It is possible that in times of resource shortage, such as drought, gray fox will seek out anthropogenic sources of food and water, similar to other predators (Baruch-Mordo et al. 2014, Blecha et al. 2018, Cypher et al. 2018).

Due to a limited number of gray fox detections, I was unable to conduct two-species occupancy modeling with gray foxes and coyotes. However, it is worth noting that it is possible that gray fox aversion to human disturbance may also reflect their

avoidance of coyotes. Because higher human disturbance was the only predictor of coyote presence, the two are closely correlated in the Mojave Desert. Interestingly, gray foxes may be attracted to and thrive in urban areas (Crooks 2002, Riley et al. 2003, Bidlack 2007); however, they also avoid coyotes both spatially and behaviorally (Wang et al. 2015, Baker 2016). Therefore, it is possible that Mojave Desert gray fox avoid disturbance as a means to avoid coyotes rather than humans. A study in northern California further supports this possibility where gray foxes reached their highest densities in areas near urbanization where coyotes had been extirpated from the urban zone (Riley 2006).

The other Mojave Desert fox species, the kit fox, had the opposite relationship with drought and human disturbance. As I had hypothesized, kit foxes were attracted to higher human disturbance in 2017, our post-drought year, and were less likely to occupy sites of human disturbance in 2016, our drought year. This remained true following two-species occupancy modeling. As an arid-adapted species, the kit fox may not need anthropogenic resources available in times of drought and may actually outcompete other species when there is a resource shortage. However, kit foxes are known to inhabit urban areas and to benefit physiologically in urban areas in times of drought (Cypher and Frost 1999). This could suggest that kit fox may typically be attracted to human-disturbed areas where there are anthropogenic resources and that their avoidance of higher disturbance sites in 2016 could be in response to coyotes' increased activity in those areas during the drought. This aligns with a study from Utah where kit foxes foraged in resource-scarce habitats as a form of spatial isolation from coyotes (Kozlowski et al. 2012).

While kit fox occupancy was influenced by drought, kit fox detection probability was independent of year. Kit fox were consistently more likely to be detected in areas of higher human disturbance, even after accounting for coyote presence. Kit foxes are known to use anthropogenic food (Iossa et al. 2010) so their increased activity in higher disturbed areas could indicate that they are using these areas to search for food.

Bobcats were more detectable in areas of higher human disturbance both during and after the drought, which I had not expected. While bobcats have been identified as resident urban carnivores (Iossa et al. 2010), bobcats' relationship with human disturbance is somewhat debated with some studies finding them to be marginally affected by human disturbance (Baker and Leberg 2018), while others have found bobcats to be very susceptible to and less detectable in human disturbance (Riley 2006, Ordeñana et al. 2010, Goad et al. 2014, Wang et al. 2015). Interestingly, when accounting for the presence of coyotes in two-species occupancy modeling, the interaction of human disturbance and year came up in the top occupancy model as well as the top detection model for bobcats in the Mojave Desert. While bobcat occupancy remained independent of coyotes, modeling showed that in both years bobcat occupancy was negatively correlated with human disturbance, a relationship that was more extreme in 2017. This may indicate a possible drought response where bobcats were slightly more likely to be found in human disturbance when resources were scarce in 2016.

Unlike bobcat occupancy, bobcat detection was influenced by the presence of coyotes and this influenced the relationship between bobcat detection and human disturbance. In 2016, detection at sites without coyotes was negatively correlated with

human disturbance while detection at sites with coyotes was positively correlated with human disturbance. However, in 2017, regardless of the presence or absence of coyotes, bobcat detection was positively associated with human disturbance. Human disturbance was relatively low in the ecoregion and higher levels typically corresponded with the presence and density of roads. While there is not a consensus, some studies have found road verges to function as refuges which support greater abundances of small mammals, such as rodents (Peter et al. 2013, Ruiz-Capillas et al. 2013). Bobcats are a more specialized predator than coyotes and primarily consume rodents or lagomorphs depending on prey availability (Beasom and Moore 1977, Delibes and Hiraldo 1987, Delibes et al. 1997, McKinney and Smith 2007). Coyotes are known to preferentially prey upon lagomorphs in the Mojave Desert (Cypher et al. 2018) and it has been suggested that rodents are a more important source of prey for bobcats in western states (Delibes and Hiraldo 1987, McKinney and Smith 2007). Therefore, bobcats may use roads for foraging, even in times of prey scarcity, such as in 2016, if coyotes are present and preferentially hunting lagomorphs. It is also possible that bobcats utilize roads as foraging grounds for rodents when these prey are abundant, such as in 2017. This may explain the positive relationship between bobcat detection and human disturbance in 2017, despite the presence of coyotes. Additionally, coyotes were more detectable in lower disturbance in 2017 which might suggest that bobcats were also adjusting their activity patterns to avoid conflict with coyotes.

Interestingly, during the drought, bobcats were still more detectable in higher disturbance sites where coyotes were present despite coyotes' increased activities in these

areas in 2016. While this could still suggest bobcats' use of roads for hunting rodents, there may be another explanation. Both coyotes and bobcats diversify their diets during drought and bobcats even include fruits and seeds in their diet when rodent diversity and abundance decrease (McKinney and Smith 2007). Perhaps when both species were present in the same area during the drought, both species increased their activity in human-disturbed areas in search of a broader array of resources.

Bobcat detection during the drought at sites without coyotes was consistently very low, although there was a downward trend in detection as disturbance increased. This may indicate that in the absence of coyotes, and when rodent density was low, bobcats may have become less active overall but focused their foraging efforts on other native prey in undisturbed areas. In the absence of coyotes, bobcats may have been able to include more lagomorphs in their diet as a prey-switching response to reduced rodent density (Neale and Sacks 2001). Additionally, bobcats likely preyed upon other taxonomic groups such as lizards, a known source of prey for carnivores, such as bobcats, in arid ecoregions (Delibes et al. 1997). Despite bobcats' use of disturbed areas, they are typically considered sensitive to human disturbance (Crooks 2002, Tigas et al. 2002, Riley et al. 2003). Therefore, bobcats may prefer more natural areas, especially if there is not a preferred prey source in more developed areas. However, bobcats may have only been able to utilize natural areas during the drought if coyotes were absent and not competing for shared resources.

Central Valley

High intensity human disturbance tends to radiate from areas suitable for agriculture (Leu et al. 2008). Therefore, as one of the most productive agricultural regions in the world (Faunt et al. 2016), the Central Valley is dominated by high levels of human disturbance. As a result, relationships between species and disturbance in this region represent their response to mid to high-level disturbance. Additionally, all mesopredator species had some response to human disturbance, reinforcing both the impact of human disturbance on the landscape in this ecoregion and on the species which live within the landscape.

Unlike coyotes in the Mojave Desert, occupancy of coyotes in the Central Valley was not associated with human disturbance. However, not as hypothesized, coyotes were more active and detectable in high human disturbance sites in 2017 and less detectable at high human disturbance sites in 2016. Overall, coyote detection was lower in the Central Valley ecoregion and the difference in detection between the two years was less extreme than in the Mojave Desert. While this result is the opposite of that in the Mojave Desert it is important to remember that the levels of human disturbance are very different between the two ecoregions.

Coyote detection was highest in 2016 in low disturbance sites which may suggest that coyotes were more active in natural areas during the drought than they were in 2017. As noted earlier, prey populations were likely low, and coyotes are known to diversify their diets when prey is scarce (Neale and Sacks 2001). As a result, coyotes may have had to spend more time foraging and move more to access the resources they needed in

natural habitats during the drought. Conversely, more disturbed sites likely represented landscapes dominated by irrigated agriculture which offer year round food and water subsidies to coyotes. For example, coyotes are known to utilize domestic fruit trees during the dry season (Fedriani et al. 2001) and will chew on irrigation pipes to access water if surface water is unavailable (Moran 1981, Jones 1987, Timm et al. 2008). As a result, coyotes likely did not have to forage as much to achieve their resource needs in these more disturbed areas in 2016.

After the drought, it is probable that natural prey populations began to recover so coyotes could more efficiently utilize prey in natural habitats. With decreased movement and foraging, coyote detection dropped in these areas in 2017. However, detection probabilities for coyotes in more disturbed sites in 2017 were very similar to those in 2016. It is likely that the highly manipulated and controlled agricultural landscapes offered similar resources during and after the drought; and, as a result, coyote activity in these areas did not change much between the two years.

Raccoons, like coyotes, were also more detectable at higher human disturbance sites in 2017 than in 2016. What was more obvious, however, was how much more detectable raccoons were at low disturbance sites in 2016 compared to 2017. Similar to coyotes, this might indicate that raccoons had to forage more during the drought to meet their resource needs, especially in less disturbed areas where natural resources may have been limited. While raccoons eat a diversity of food, they are selective when food is plentiful and diversify when resources are scarce (Lotze and Anderson 1979) which may explain their higher detection rates in more natural areas during the drought. However, as

human disturbance increased and anthropogenic food became more available, perhaps raccoons didn't have to search as actively for resources which led to lower detection rates. Alternatively, in 2017, when the drought was over, raccoons may have been able to become more selective with their resources in lower disturbed sites, lowering their detection probability. Alternatively, raccoons may have had to search slightly more in urban areas following the drought where they rely upon seeking out anthropogenic resources, as they did in 2016. Another study in California found raccoon detection probabilities to increase with human development (Wang et al. 2015) which may further support that raccoon detection patterns in 2016 were unusual. Following two-species occupancy modeling, I discovered that raccoon detection followed the same pattern with human disturbance regardless of coyote presence. However, the positive effect of human disturbance on raccoon detection in 2017 was much stronger in the absence of coyotes which could suggest that raccoons adjust the magnitude of their activity in disturbed areas if coyotes are present.

Unlike detection, raccoon occupancy was positively correlated with human disturbance in 2016 but negatively in 2017 which suggests that raccoons were attracted to human disturbance during the drought year but not after the drought. While a drought response is predictable for this species as they are known to utilize aquatic habitats (Stuewer 1943, Gehrt and Fritzell 1998), it is surprising that as a human-associated species (Hadidian et al. 2010) they were less likely to occupy human disturbance sites in 2017. However, the negative effect of human disturbance in 2017 was minor so it is possible that the relationship to human disturbance was weakened following the drought

but not necessarily negative. This is reinforced by two-species occupancy modeling which showed raccoon occupancy to be positively associated with human disturbance regardless of year.

Similarly, domestic cat occupancy was always positively associated with human disturbance which makes sense as they are a subsidized predator which rely on their owners for resources (Crooks and Soulé 1999). While domestic cat detection and occupancy were conditional on coyote detection and occupancy, the presence of coyotes did not influence domestic cats' relationship with human disturbance. Regardless of coyote occupancy, there were virtually no domestic cats in low disturbance areas which reinforces their reliance on humans.

In the Central Valley, bobcats only responded to human disturbance when coyote presence was taken into account. Like bobcats in the Mojave Desert, bobcat occupancy was independent of coyote occupancy but their detection was influenced by coyote presence. Due to a lack of data I could not examine the influence of drought on bobcats while accounting for the occupancy of coyotes. However, I could examine how coyotes influenced the relationship between bobcats and human disturbance during both years of data collection. In the Central Valley, bobcats were more likely to be detected at higher human disturbance sites if coyotes were absent and less likely to be detected at disturbed sites if coyotes were present. Although bobcats do not appear to spatially avoid coyotes, they do appear to shift their activity patterns more than other species conditional upon the presence of coyotes. While bobcats are thought to avoid human disturbances such as development and recreation (George and Crooks 2006, Goad et al. 2014, Wang et al.

2015), they may be attracted to other disturbances, such as agriculture, which may provide good hunting grounds. Bobcats' main source of prey are small mammals, particularly rodents (Fedriani et al. 2000, McKinney and Smith 2007), which are known pests in agriculture (Gebhardt et al. 2011, Baldwin et al. 2014). In the absence of coyotes, bobcats may utilize agricultural areas as hunting grounds but avoid them when coyotes are in the area.

Management Implications

My research suggests that human disturbance may serve as drought refugia in California. Species in the Central Valley may have even been buffered to some of the more extreme effects of drought (e.g. reproductive potential) because of the managed landscape and water systems, which ensure productive agriculture in the region. While agricultural lands are not typically considered and managed as wildlife habitat, future conservation may need to redefine these areas as important for the persistence of wildlife in the region, especially during drought. However, it is also important to recognize that increased use of habitat in close proximity to humans can be problematic. For example, my research revealed that coyotes in the Mojave Desert increased their use of human disturbance during the drought, likely in search of anthropogenic resources. While this may have physiologically benefited coyotes, it also likely increased the probability of human-coyote conflict. This is already apparent in California where reports of human-wildlife conflict with mesopredators, including coyotes, are becoming more common during times of lower annual precipitation (Furnas 2017). Future conservation of

landscapes used as wildlife drought refuges will only succeed if there is not an increased possibility of conflict. Therefore, additional research should focus on understanding what kinds of conflicts are being reported during drought. This will allow managers to address the sources of these problems and manage for them in the future.

This research and other studies that resulted from the Terrestrial Species Stressor Monitoring project show the value of large scale monitoring, specifically the use of non-invasive data collection. We have been able to use this data to answer a suite of questions related to wildlife in California that will hopefully help in future management. However, it is important to note that while our research covered a large area it also only covered two years. While these two years reflect precipitation extremes and can be used as a proxy for drought, it is valuable to have data across many years and varied precipitation levels. Data should continue to be collected at these sites, and additional sites within urban areas should be added to further address the impact of human disturbance. Current research is already underway by another graduate student (C. Moura) that has revisited some TSM sites and added urban sites in the Sacramento area of the Central Valley. Hopefully more projects will be able to utilize our sites for future data collection as a means to create a long term dataset. The continued use of standardized data collection across large areas, and preferably over long time periods, will allow scientists to keep track of wildlife populations and examine how they are responding to changes in the landscape and climate.

Mesopredators in California are facing two major changes to their ecosystem: drought and the expansion of human disturbance. The risk of drought, such as the one

which gripped California from 2012-2016, is increasing (Diffenbaugh et al. 2015), while future projections predict the replacement of 12 million acres of wild and agricultural lands with exurban development in California (Mann et al. 2014). Such changes to the landscape and climate influence not only the spatial ecology of mesopredators but also how they interact with their habitat and other species, including humans.

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APPENDIX A

Appendix A. Advanced settings for Reconyx PC900 camera traps used to collect data in 2016 and 2017 for CDFW Terrestrial Species Stressor Monitoring Program.

Tab	Sub-category	Selection
Trigger	Motion Sensor	ON
	Sensitivity	High
	Pictures per trigger	3
	Picture Interval	1 second
	Quiet Period	No Delay
Time Lapse	AM Period	OFF
	PM Period	OFF
Resolution		1080p
Night Mode	Balanced	
	Illuminator	ON
Date/Time/Temp	Temp	Celsius
Codeloc		None (unless at a site with risk of theft)
User Label	Change	HexID (12345A)

APPENDIX B

Appendix B. Pearson correlation tables for proposed detection and occupancy covariates in the Mojave Desert and Central Valley. * indicates coefficients where $r \geq 0.50$ indicating collinearity.

Pearson correlation coefficients for proposed detection covariates in the Mojave Desert.

	Guzzler	Human disturb.	Year	1st Julian date	Maximum temp.
Guzzler		0.002	0.037	0.022	-0.088
Human disturb.			-0.072	-0.157	-0.137
Year				-0.267	-0.174
1st Julian date					0.691*
Maximum temp.					

Pearson correlation coefficients for proposed detection covariates in the Central Valley.

	Year	Water	Human disturb.	1st Julian Date	Maximum temp.
Year		0.129	-0.115	-0.367	-0.258
Water			-0.087	-0.221	-0.213
Human disturb.				-0.074	0.058
1st Julian Date					0.680*
Maximum temp.					

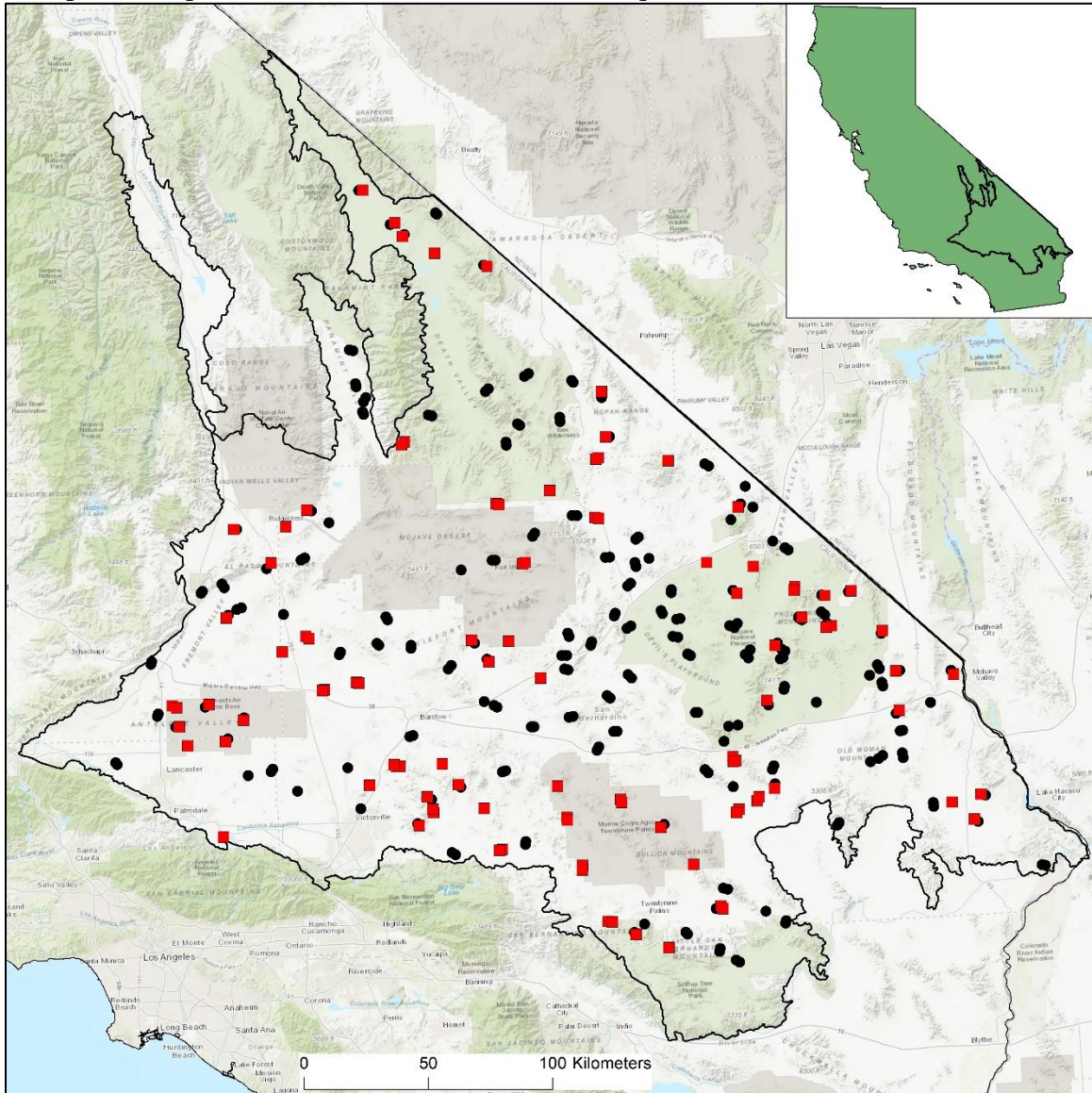
Pearson correlation coefficients for proposed occupancy covariates in the Mojave Desert.

	Elevation	Dist. to water	Human disturb.	Year	NDVI	% Shrub	Mean temp.
Elevation		-0.266	0.154	0.044	0.669*	0.629*	-0.822*
Dist. to water			-0.117	-0.104	-0.305	-0.240	0.245
Human disturb.				-0.072	0.190	0.307	-0.250
Year					0.290	-0.085	-0.494
NDVI						0.731*	-0.669*
% Shrub							-0.500*
Mean temp.							

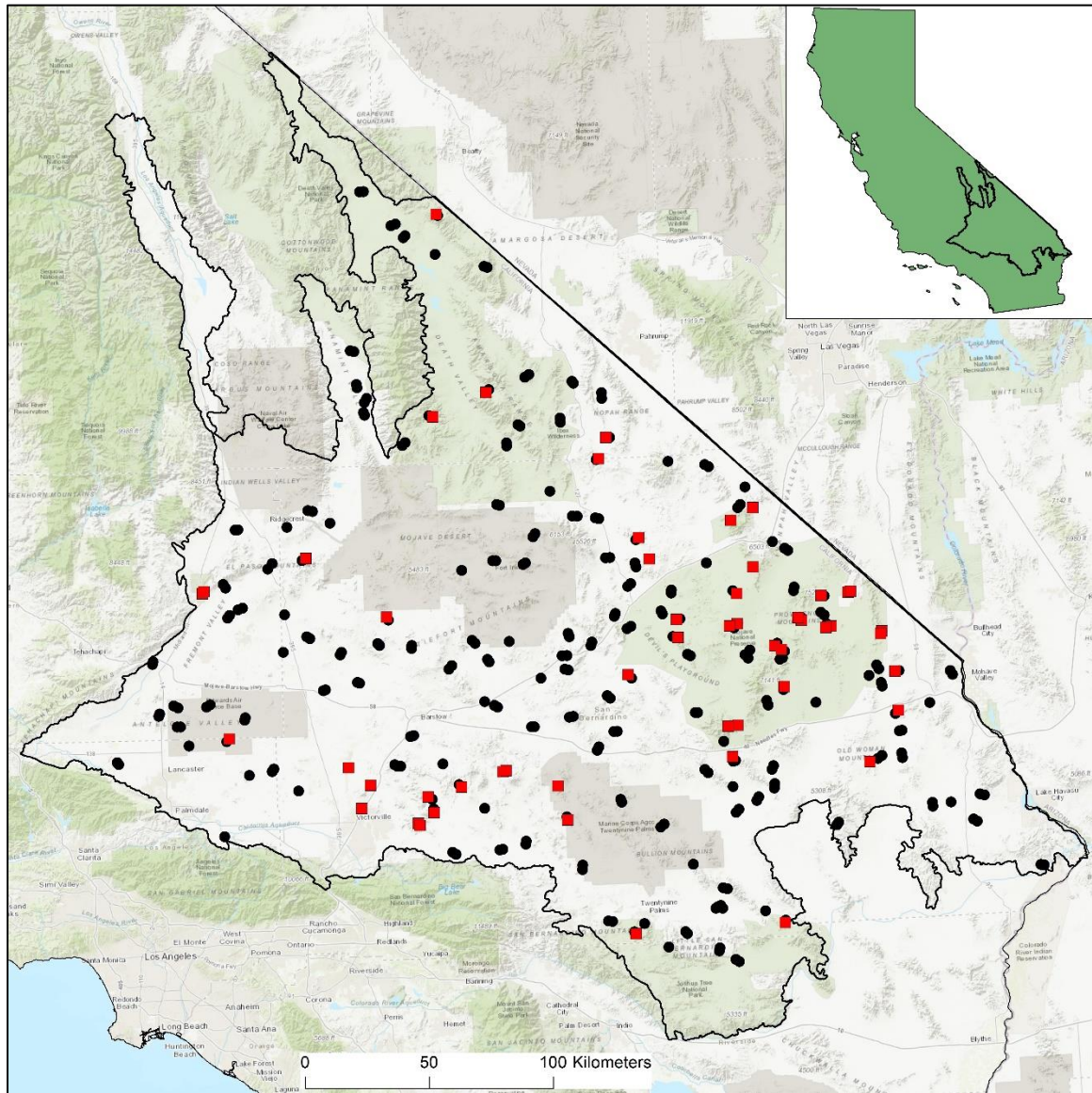
[illegible]

APPENDIX C

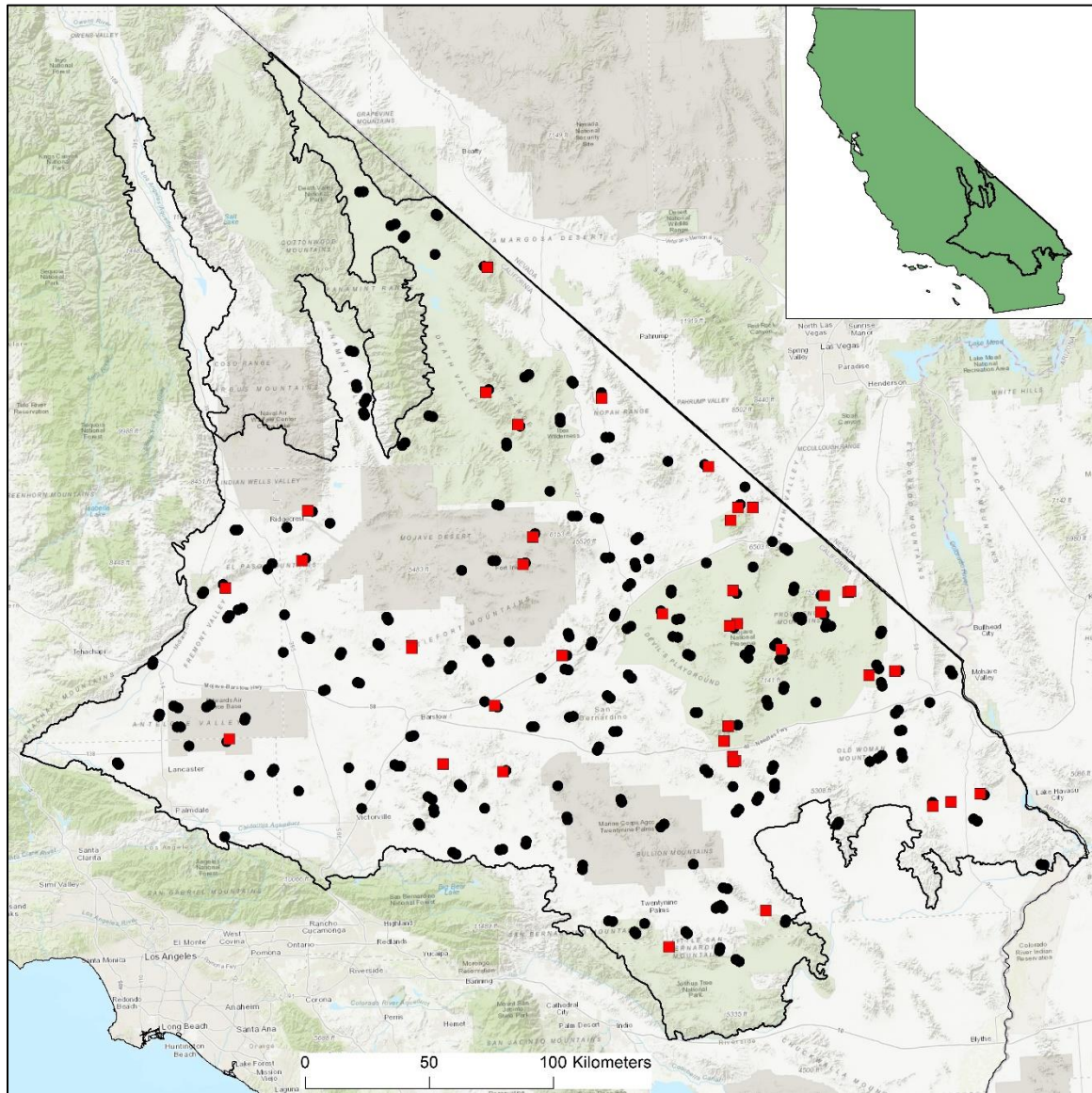
Appendix C. Maps of all sites in the Mojave Desert (black dots) and sites where each mesopredator species was detected on camera (red squares).



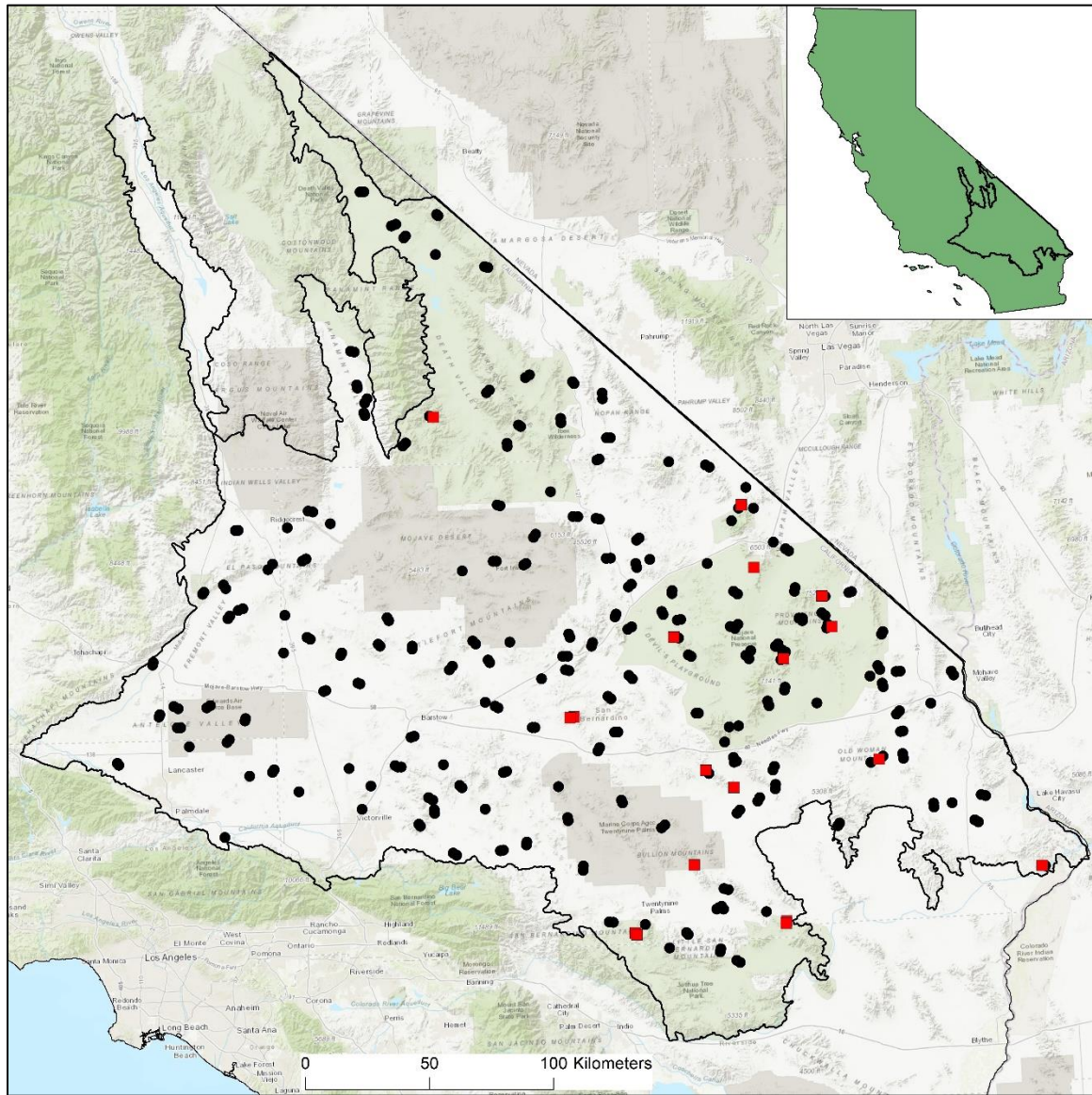
Map of all sites in the Mojave Desert (black dots) and sites where coyotes were detected on camera (red squares). Coyotes were detected at 99 out of 319 sites overall (naïve occupancy: 31%), in 2016 coyotes were detected at 72 out of 217 sites (naïve occupancy: 33%), and in 2017 coyotes were detected at 27 out of 102 sites (naïve occupancy: 26%).



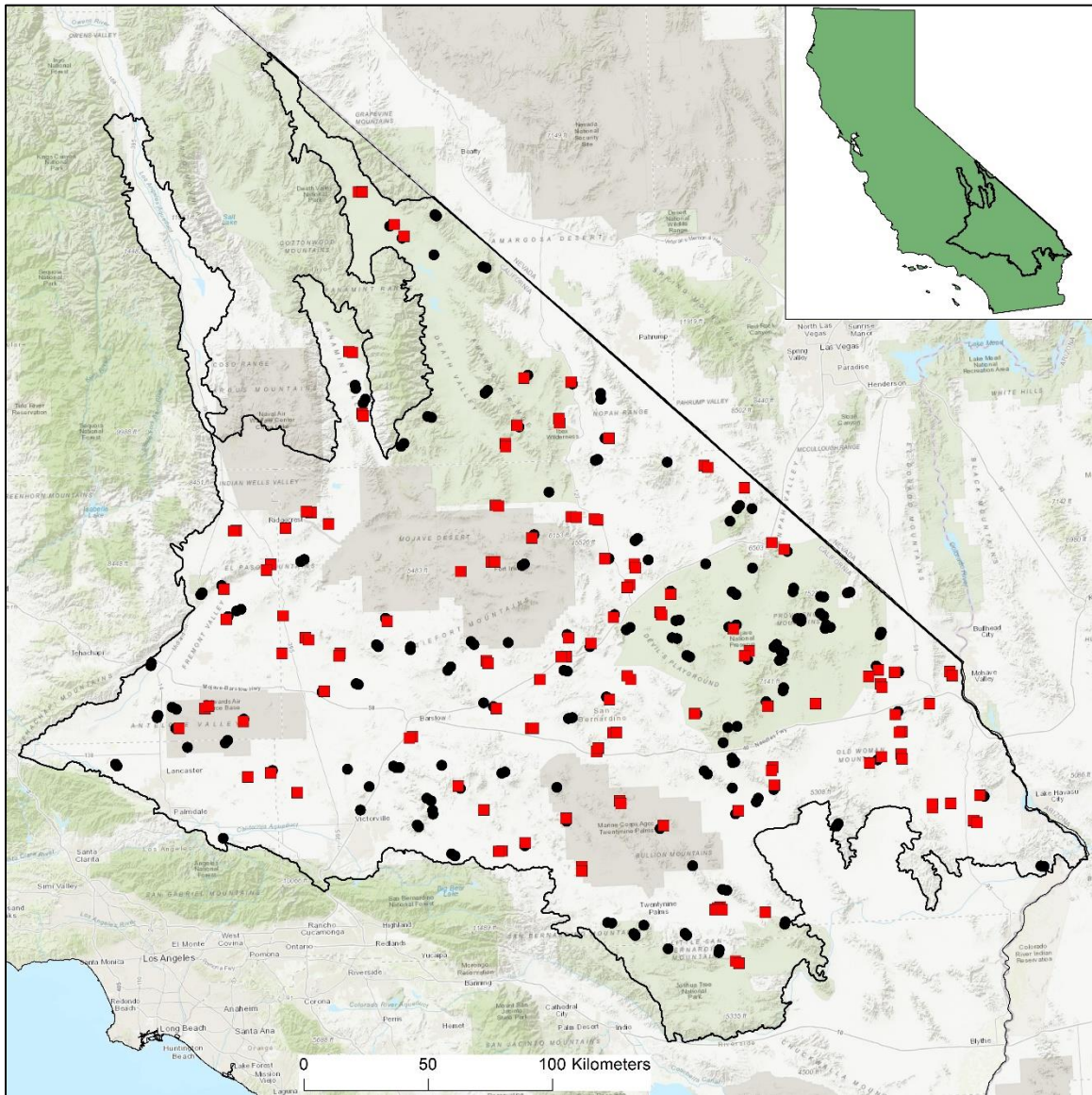
Map of all sites in the Mojave Desert (black dots) and sites where bobcats were detected on camera (red squares). Bobcats were detected at 53 out of 319 sites overall (naïve occupancy: 17%), in 2016 bobcats were detected at 34 out of 217 sites (naïve occupancy: 16%), and in 2017 bobcats were detected at 19 out of 102 sites (naïve occupancy: 19%).



Map of all sites in the Mojave Desert (black dots) and sites where badgers were detected on camera (red squares). Badgers were detected at 41 out of 319 sites overall (naïve occupancy: 13%), in 2016 badgers were detected at 24 out of 217 sites (naïve occupancy: 11%), and in 2017 badgers were detected at 17 out of 102 sites (naïve occupancy: 17%).



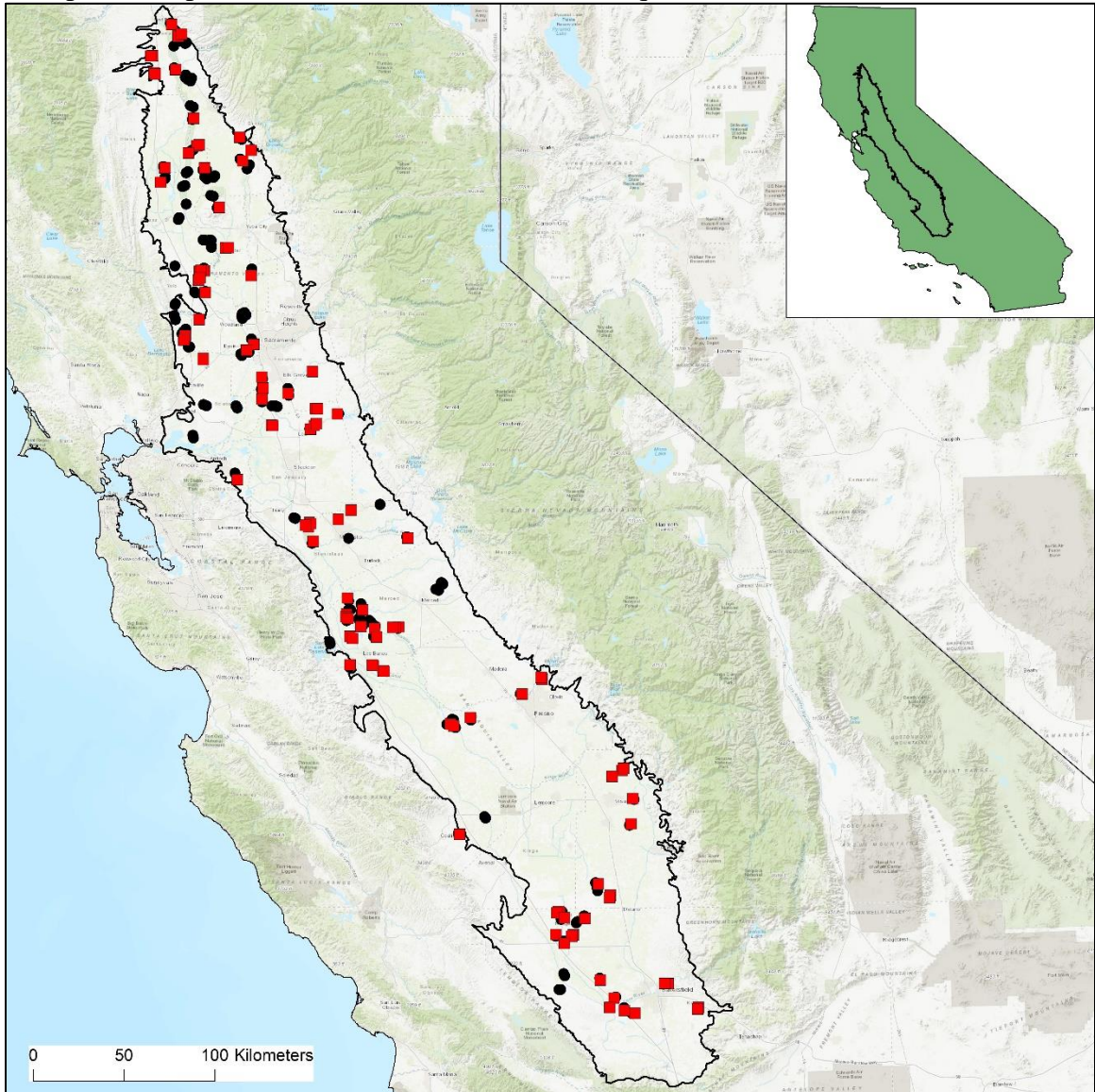
Map of all sites in the Mojave Desert (black dots) and sites where gray foxes were detected on camera (red squares). Gray foxes were detected at 18 out of 319 sites overall (naïve occupancy: 6%), in 2016 gray foxes were detected at 12 out of 217 sites (naïve occupancy: 6%), and in 2017 gray foxes were detected at 6 out of 102 sites (naïve occupancy: 6%).



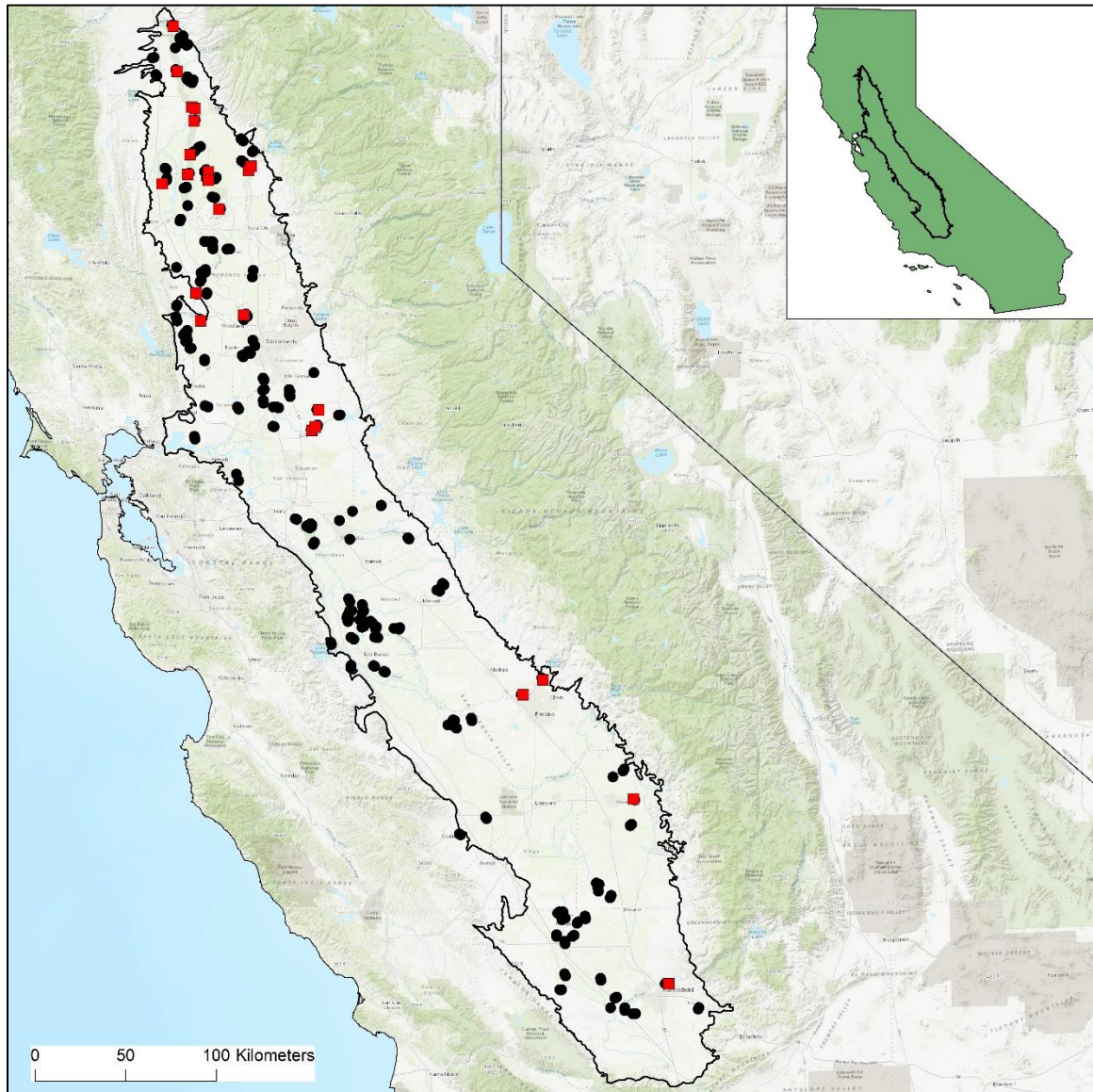
Map of all sites in the Mojave Desert (black dots) and sites where kit foxes were detected on camera (red squares). Kit foxes were detected at 133 out of 319 sites overall (naïve occupancy: 42%), in 2016 kit foxes were detected at 98 out of 217 sites (naïve occupancy: 45%), and in 2017 kit foxes were detected at 35 out of 102 sites (naïve occupancy: 34%).

APPENDIX D

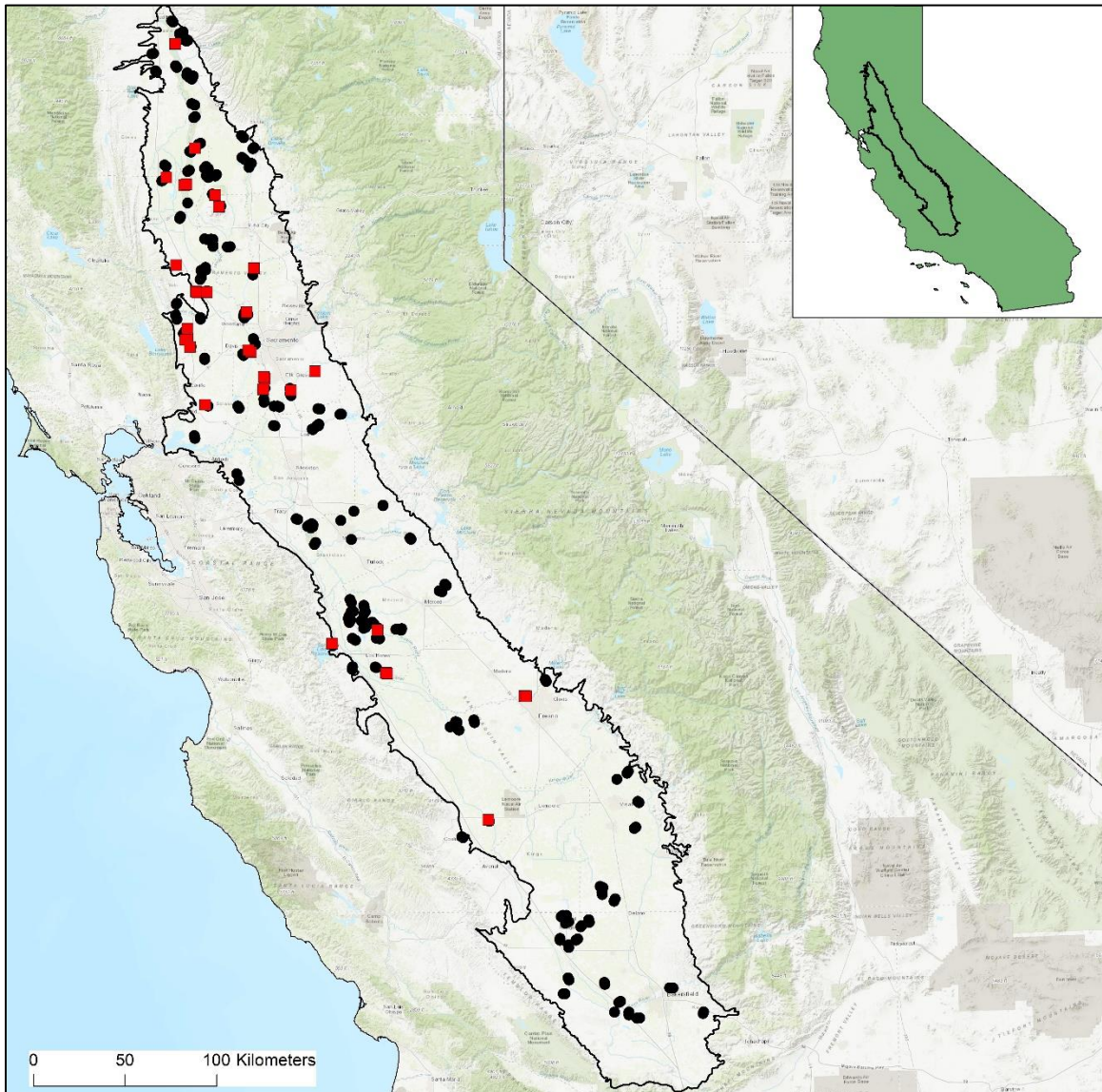
Appendix D. Maps of all sites in the Central Valley (black dots) and sites where each mesopredator species was detected on camera (red squares).



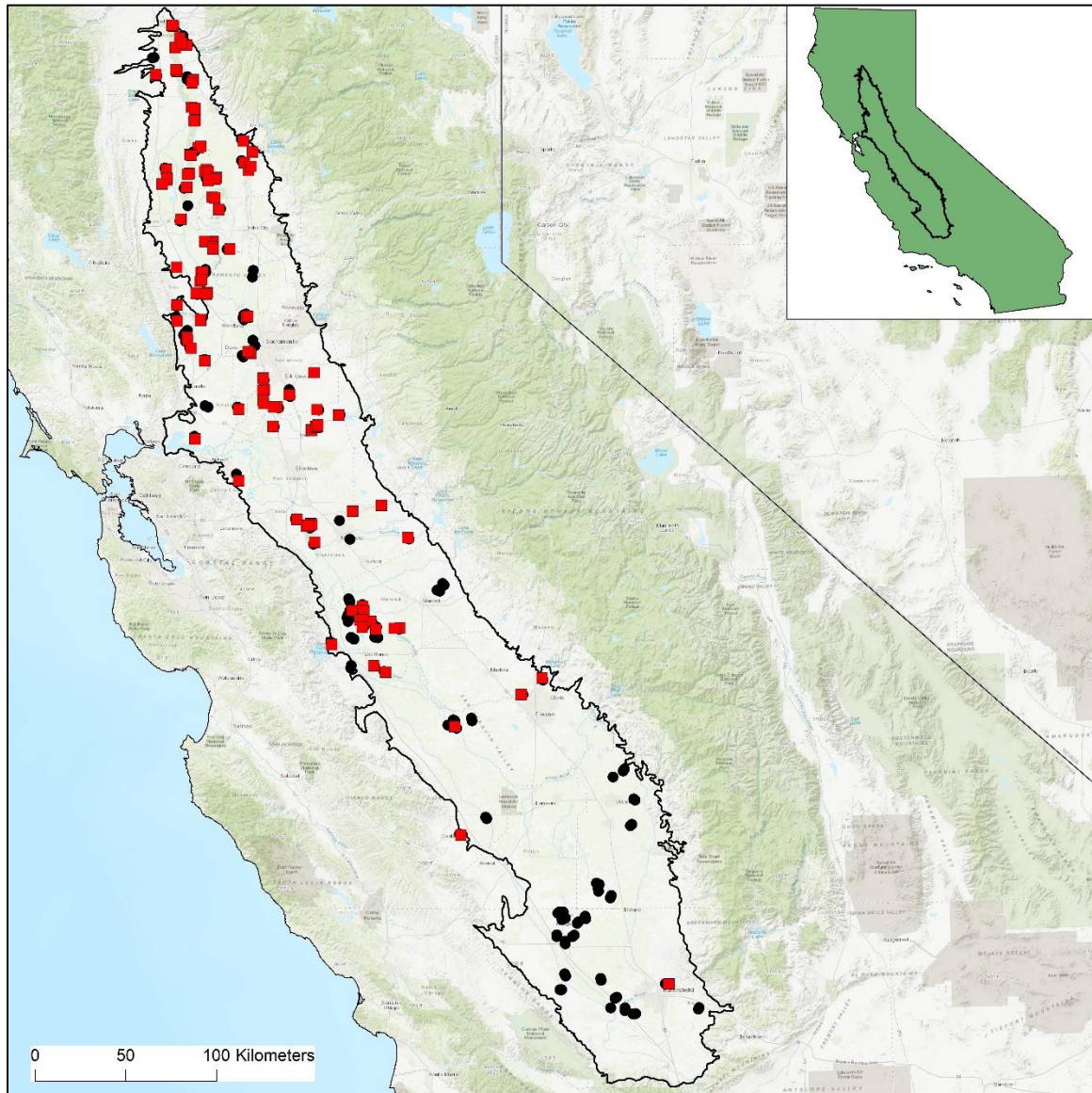
Map of all sites in the Central Valley (black dots) and sites where coyotes were detected on camera (red squares). Coyotes were detected at 108 out of 266 sites overall (naïve occupancy: 41%), in 2016 coyotes were detected at 34 out of 86 sites (naïve occupancy: 40%), and in 2017 coyotes were detected at 74 out of 180 sites (naïve occupancy: 41%).



Map of all sites in the Central Valley (black dots) and sites where bobcats were detected on camera (red squares). Bobcats were detected at 24 out of 266 sites overall (naïve occupancy: 9%), in 2016 bobcats were detected at 8 out of 86 sites (naïve occupancy: 9%), and in 2017 bobcats were detected at 16 out of 180 sites (naïve occupancy: 9%).



Map of all sites in the Central Valley (black dots) and sites where domestic cats were detected on camera (red squares). Domestic cats were detected at 32 out of 266 sites overall (naïve occupancy: 12%), in 2016 domestic cats were detected at 7 out of 86 sites (naïve occupancy: 8%), and in 2017 domestic cats were detected at 25 out of 180 sites (naïve occupancy: 14%).



Map of all sites in the Central Valley (black dots) and sites where raccoons were detected on camera (red squares). Raccoons were detected at 117 out of 266 sites overall (naïve occupancy: 44%), in 2016 raccoons were detected at 24 out of 86 sites (naïve occupancy: 28%), and in 2017 raccoons were detected at 93 out of 180 sites (naïve occupancy: 52%).

APPENDIX E

Appendix E. Top single species detection (p) and occupancy (psi) models (within 2 delta AICc) for Mojave Desert mesopredators.

Models used for interpretation are highlighted in gray and were selected using the following criteria: within 2 delta AICc, no uninformative parameters, most parameterized (conservative) model, and no problematic beta estimates. Detection models were built with a global occupancy model: $\text{psi}(\text{elev} + \text{water} + \text{hd} + \text{yr} + \text{yr} * \text{hd} + \text{yr} * \text{water})$, occupancy models were built with the top selected detection model; 52 detection models and 26 occupancy models were built and tested for all species.

K = number of parameters, elev = elevation, water = distance to water, hd = human disturbance, yr = year, $\text{yr} * \text{hd}$ = interaction of year and human disturbance, $\text{yr} * \text{water}$ = interaction of year and distance to water, guzz = guzzler, $\text{yr} * \text{guzz}$ = interaction of year and guzzler, 1jul = first Julian date, bait = bait age.

Top detection (above black line) and occupancy (below black line) models for coyote.
Over dispersion parameter, $\hat{c} = 1.2738$.

Model	QAICc	ΔQAICc	AIC wgt	Model Likelihood	#K	Deviance
psi (global), p(hd+yr+guzz+1jul+yr*hd)	1061.74	0	0.215	1	13	1317.8
psi(global), p(hd+yr+guzz+yr*hd)	1062.53	0.79	0.1448	0.6737	12	1321.58
psi(.), p(hd+yr+guzz+1jul+yr*hd)	1052.35	0	0.1618	1	7	1322.19
psi(hd), p(hd+yr+guzz+1jul+yr*hd)	1052.41	0.06	0.1570	0.9704	8	1319.59
psi(yr), p(hd+yr+guzz+1jul+yr*hd)	1053.82	1.47	0.0776	0.4795	8	1321.38
psi(water), p(hd+yr+guzz+1jul+yr*hd)	1053.97	1.62	0.0720	0.4449	8	1321.57
psi(elev), p(hd+yr+guzz+1jul+yr*hd)	1054.06	1.71	0.0688	0.4253	8	1321.69
psi(water+hd), p(hd+yr+guzz+1jul+yr*hd)	1054.17	1.82	0.0651	0.4025	9	1319.13
psi(elev+hd), p(hd+yr+guzz+1jul+yr*hd)	1054.33	1.98	0.0601	0.3716	9	1319.33
psi(hd+yr), p(hd+yr+guzz+1jul+yr*hd)	1054.39	2.04	0.0583	0.3606	9	1319.41

Top detection (above black line) and occupancy (below black line) models for bobcat.
Over dispersion parameter, $\hat{c} = 1.4753$.

Model	QAICc	Δ QAICc	AIC wgt	Model Likelihood	#K	Deviance
psi(global), p(hd+yr+guzz)	540.26	0	0.1097	1	11	763.32
psi(global), p(hd+yr+guzz+yr*hd)	541.41	1.15	0.0617	0.5627	12	761.83
psi(global), p(guzz)	541.43	1.17	0.0611	0.5571	9	771.36
psi(global), p(hd+guzz)	541.71	1.45	0.0531	0.4843	10	768.62
psi(global), p(hd+yr)	541.79	1.53	0.0511	0.4653	10	768.74
psi(global), p(hd+yr+guzz+1jul)	541.83	1.57	0.05	0.4561	12	762.45
psi(global), p(hd+yr+yr*hd)	541.99	1.73	0.0462	0.4211	11	765.87
psi(global), p(yr+guzz)	542.13	1.87	0.0431	0.3926	10	769.24
psi(global), p(hd+yr+guzz+bait)	542.27	2.01	0.0402	0.366	12	763.1
psi(elev+water), p(hd+yr+guzz)	534.77	0	0.4171	1	7	767.76
psi(elev+water+hd), p(hd+yr+guzz)	536.67	1.9	0.1613	0.3867	8	767.46
psi(elev+water+yr), p(hd+yr+guzz)	536.83	2.06	0.1489	0.357	8	767.69

Top detection (above black line) and occupancy (below black line) models for badger.

Over dispersion parameter, $\hat{c} = 0.8247$; use $\hat{c} = 1$.

Model	AICc	$\Delta AICc$	AIC wgt	Model Likelihood	#K	Deviance
psi(global), p(guzz+1jul)	527.11	0	0.1641	1	10	506.4
psi(global), p(guzz)	528.23	1.12	0.0937	0.5712	9	509.65
psi(global), p(guzz+1jul+bait)	528.53	1.42	0.0807	0.4916	11	505.67
psi(global), p(yr+guzz+1jul)	528.54	1.43	0.0803	0.4892	11	505.68
psi(global), p(hd+guzz+1jul)	528.97	1.86	0.0648	0.3946	11	506.11
psi(elev+yr), p(guzz+1julian)	521.15	0	0.20876	1	6	508.88
psi(elev), p(guzz+1julian)	521.69	0.54	0.15937	0.7634	5	511.5
psi(elev+hd+yr), p(guzz+1julian)	522.68	1.53	0.09714	0.4653	7	508.32
psi(elev+hd), p(guzz+1julian)	522.9	1.75	0.08703	0.4169	6	510.63
psi(elev+hd+yr+yr*hd), p(guzz+1julian)	523.11	1.96	0.07835	0.3753	8	506.65
psi(elev+water+yr), p(guzz+1julian)	523.11	1.96	0.07835	0.3753	7	508.75

Top detection (above black line) and occupancy (below black line) models for gray fox.

Over dispersion parameter, $\hat{c} = 0.6325$; use $\hat{c} = 1$.

Model	AICc	$\Delta AICc$	AIC wgt	Model Likelihood	#K	Deviance
psi(global), p(yr+bait)	305.58	0	0.2106	1	10	284.87
psi(global), p(yr+guzz+bait)	306.71	1.13	0.1197	0.5684	11	283.85
psi(global), p(hd+yr+bait+yr*hd)	307.27	1.69	0.0905	0.4296	12	282.25
psi(global), p(yr+1jul+bait)	307.44	1.86	0.0831	0.3946	11	284.58
psi(global), p(hd+yr+bait)	307.67	2.09	0.0741	0.3517	11	284.81
psi(elev+water+hd+yr+hd*yr+water*yr), p(yr+bait)	305.58	0	0.35803	1	10	284.87
psi(elev+water+hd+yr+water*yr), p(yr+bait)	305.77	0.19	0.32558	0.9094	9	287.19

Top detection (above black line) and occupancy (below black line) models for kit fox. From set of 42 models excluding interaction of year and guzzler which performed well but resulted in problematic beta estimates.

Over dispersion parameter, c-hat 1.2368 (excludes interaction of year and guzzler from global model).

Model	QAICc	ΔQAICc	AIC wgt	Model Likelihood	#K	Deviance
psi(global),p(yr+guzz+bait)	1447.5	0	0.1818	1	11	1761.99
psi(global),p(hd+yr+guzz+bait)	1447.61	0.11	0.172	0.9465	12	1759.46
psi(global),p(yr+bait)	1448.47	0.97	0.1119	0.6157	10	1765.85
psi(global),p(hd+yr+bait)	1448.7	1.2	0.0998	0.5488	11	1763.48
psi(global),p(yr+guzz+1jul+bait)	1448.99	1.49	0.0863	0.4747	12	1761.17
psi(global),p(hd+yr+guzz+1jul+bait)	1449.23	1.73	0.0765	0.4211	13	1758.77
psi(elev+water),p(hd+yr+guzz+bait)	1445.15	0	0.28316	1	8	1767
psi(elev+water+yr),p(hd+yr+guzz+bait)	1445.9	0.75	0.19461	0.6873	9	1765.31
psi(elev+water+hd+yr+hd*yr),p(hd+yr+guzz+bait)	1446.25	1.1	0.16337	0.5769	11	1760.45
psi(elev+water+hd),p(hd+yr+guzz+bait)	1447.23	2.08	0.10008	0.3535	9	1766.95

APPENDIX F

Appendix F. Top single species detection (p) and occupancy (psi) models (within 2 delta AICc) for Central Valley mesopredators.

Models used for interpretation are highlighted in gray and were selected using the following criteria: within 2 delta AICc, no uninformative parameter, most parameterized (conservative) model, and no problematic beta estimates. Detection models were built with a global occupancy model: $\text{psi}(\text{lat}+\text{yr}+\text{HD}+\text{trees}+\text{d_water}+\text{yr}*\text{HD}+\text{yr}*\text{d_water})$, occupancy models were built with the top selected detection model; 52 detection models were tested for coyotes and domestic cats, 26 detection models were tested for bobcats and raccoons, and 52 occupancy models were built and tested for all species.

K = number of parameters, lat = latitude, d_water = distance to water, hd = human disturbance, yr = year, yr*hd = interaction of year and human disturbance, yr*d_water = interaction of year and distance to water, trees = percent tree cover, water = water at site, julian = Julian date, lagX = represents X day trap response.

Top detection (above black line) and occupancy (below black line) models for coyote.

Over dispersion parameter, c-hat = 1.4311.

Model	QAICc	ΔQAICc	AIC wgt	Model Likelihood	#K	Deviance
psi(global), p(yr+hd+water+lag3+yr*hd)	1397.19	0	0.2644	1	14	1957.05
psi(global), p(water+lag3)	1399.12	1.93	0.1007	0.381	11	1969.31
psi(global), p(yr+hd+water+lag3+yr*hd+yr*water)	1399.25	2.06	0.0944	0.357	15	1956.78
psi(lat), p(yr+hd+water+lag3+yr*hd)	1387.74	0	0.2099	1	8	1962.3
psi(lat+yr), p(yr+hd+water+lag3+yr*hd)	1389.01	1.27	0.1112	0.5299	9	1961.05
psi(lat+d_water), p(yr+HD+water+lag3+yr*hd)	1389.68	1.94	0.0796	0.3791	9	1962.01
psi(lat+HD), p(yr+hd+water+lag3+yr*hd)	1389.76	2.02	0.0764	0.3642	9	1962.12

Top detection (above black line) and occupancy (below black line) models for bobcat.

Over dispersion parameter, $\hat{c} = 1.9887$.

Model	QAICc	ΔQAICc	AIC wgt	Model Likelihood	#K	Deviance
psi(global), p(yr+julian)	313.66	0	0.3739	1	11	577.95
psi(global), p(yr+water+julian)	315.49	1.83	0.1498	0.4005	12	577.24
psi(global), p(yr+hd+julian)	315.76	2.1	0.1308	0.3499	12	577.77
psi(trees), p(yr+julian)	304.65	0	0.1534	1	5	585.51
psi(lat+trees), p(yr+julian)	304.91	0.26	0.1347	0.8781	6	581.86
psi(trees+d_water), p(yr+julian)	305.15	0.5	0.1194	0.7788	6	582.35
psi(lat+trees+d_water), p(yr+julian)	305.72	1.07	0.0898	0.5857	7	579.29
psi(hd+trees), p(yr+julian)	306.74	2.09	0.0539	0.3517	6	585.5
psi(yr+trees), p(yr+julian)	306.74	2.09	0.0539	0.3517	6	585.51

Top detection (above black line) and occupancy (below black line) models for domestic cat.
 Over dispersion parameter, $\hat{c} = 0.8284$; use $\hat{c} = 1$.

Model	AICc	Δ AICc	AIC wgt	Model Likelihood	#K	Deviance
psi(global), p(water+julian)	914.39	0	0.1164	1	11	891.35
psi(global), p(water+julian+lag27)	914.97	0.58	0.0871	0.7483	12	889.74
psi(global), p(yr+water+lag27+yr*water)	915.52	1.13	0.0661	0.5684	13	888.08
psi(global), p(hd+water+julian)	915.98	1.59	0.0525	0.4516	12	890.75
psi(global), p(water+lag27)	916.13	1.74	0.0488	0.419	11	893.09
psi(global), p(yr+water+lag27)	916.26	1.87	0.0457	0.3926	12	891.03
psi(global), p(yr+water+julian)	916.26	1.87	0.0457	0.3926	12	891.03
psi(global), p(water)	916.34	1.95	0.0439	0.3772	10	895.48
psi(lat+hd+trees),p(water+julian)	911.15	0	0.0894	1	7	896.72
psi(lat+yr+hd+trees),p(water+julian)	911.47	0.32	0.0762	0.8521	8	894.91
psi(yr+hd+trees),p(water+julian)	911.48	0.33	0.0758	0.8479	7	897.05
psi(yr+hd+trees+d_water),p(water+julian)	911.86	0.71	0.0627	0.7012	8	895.3
psi(lat+hd+trees+d_water),p(water+julian)	912.04	0.89	0.0573	0.6408	8	895.48
psi(lat+yr+hd+trees+yr*hd),p(water+julian)	912.11	0.96	0.0553	0.6188	9	893.41
psi(hd+trees),p(water+julian)	912.29	1.14	0.0506	0.5655	6	899.97
psi(lat+yr+hd+trees+d_water),p(water+julian)	912.32	1.17	0.0498	0.5571	9	893.62
psi(yr+hd+trees+yr*hd),p(water+julian)	912.45	1.3	0.0467	0.522	8	895.89
psi(hd+trees+d_water),p(water+julian)	912.61	1.46	0.0431	0.4819	7	898.18
psi(yr+hd+trees+d_water+yr*hd),p(water+julian)	912.88	1.73	0.0377	0.4211	9	894.18
psi(yr+hd+trees+d_water+yr*d_water),p(water+julian)	913.13	1.98	0.0332	0.3716	9	894.43
psi(lat+yr+hd+trees+d_water+yr*hd),p(water+julian)	913.19	2.04	0.0322	0.3606	10	892.33

Top detection (above black line) and occupancy (below black line) models for raccoon.
Over dispersion parameter, $\hat{c} = 1.93$.

Model	QAICc	Δ QAICc	AIC wgt	Model Likelihood	#K	Deviance
psi(global), p(yr+hd+water+julian+yr*hd+yr*water)	1452.94	0	0.4565	1	15	2742.56
psi(global), p(yr+hd+water+julian+yr*hd)	1453.09	0.15	0.4235	0.9277	14	2747.19
psi(lat+yr+d_water), p(yr+hd+water+julian+yr*hd+yr*water)	1448.36	0	0.1935	1	11	2750.86
psi(lat+yr+trees+d_water), p(yr+hd+water+julian+yr*hd+yr*water)	1448.76	0.4	0.1584	0.8187	12	2747.41
psi(lat+yr+hd+d_water), p(yr+hd+water+julian+yr*hd+yr*water)	1449.9	1.54	0.0896	0.463	12	2749.6
psi(lat+yr+hd+d_water+yr*hd), p(yr+hd+water+julian+yr*hd+yr*water)	1450.24	1.88	0.0756	0.3906	13	2746

APPENDIX G

Appendix G. Top two species detection (pB, pA, rBa, rBA) and occupancy (psiA, psiBA, psiBa) models (within 4 delta AICc following testing of formulations) for Mojave Desert mesopredators.

Models used for interpretation are highlighted in gray and were selected using the following criteria: within 2 delta AICc, no uninformative parameters, most parameterized (conservative) model, and no problematic beta estimates. All models were built with a constant coyote (species A) model: psi(hd), p(hd+yr+guzz+1jul+yr*hd) where detection was unconditional (pA=rA). Species B detection models were built with a global occupancy model: psiBA(elev+water+hd+yr+yr*hd+yr*water), psiBa(elev+water+hd+yr+yr*hd+yr*water), and with all parameters estimated separately (conditional formulation). Once a top detection model was selected, the formulation (conditional versus unconditional) was tested (tested formulation of all models within 2 delta AIC) and the top performing formulation was used to build occupancy models. Once a top occupancy model was selected its formulation was also tested to select a final top model. 52 detection models with 3 formulations and 26 occupancy models with 2 formulations were built and tested for all species.

K = number of parameters, e = elevation, w = distance to water, h = human disturbance, y = year, y*h = interaction of year and human disturbance, y*w = interaction of year and distance to water, g = guzzler, y*g = interaction of year and guzzler, j = first Julian date, b = bait age.

Top detection (above black line) and occupancy (below black line) models for coyote (species A) and bobcat (species B). Interaction of year and distance to water performed well as a predictor of psiB but resulted in problematic betas so the next top model without that covariate was selected as the best model.

Model	AICc	Δ AICc	AIC wgt	Model Likelihood	#K	Deviance
psiA, psiBA, psiBa, pA=rA, pB(h+y+j+y*h), rBA=rBa	2098.19	0	0.592	1	32	2026.81
psiA, psiBA, psiBa, pA=rA, pB(h+y+j+b+y*h), rBA=rBa	2099.91	1.72	0.2505	0.4232	34	2023.53
psiA,psiBA,psiBa, pA=rA, pB(h+y+j+y*h), rBA, rBa	2102.36	4.17	0.0736	0.1243	37	2018.35
psiA, psiBA(e+w+h+y+y*h+y*w), psiBa, pA=rA, pB(h+y+j+y*h), rBA=rBa	2098.19	0	0.2716	1	32	2026.81
psiA, psiBA(e+w+h+y+y*h)=psiBa, pA=rA, pB(h+y+j+y*h), rBA=rBa	2098.4	0.21	0.2445	0.9003	24	2046.32
psiA, psiBA(e+w+h+y+y*w),psiBa, pA=rA, pB(h+y+j+y*h), rBA=rBa	2098.8	0.61	0.2002	0.7371	30	2032.34
psiA, psiBA(e+w+y+y*w),psiBa, pA=rA, pB(h+y+j+y*h), rBA=rBa	2100.45	2.26	0.0877	0.323	28	2038.85
psiA, psiBA(e+w+h+y+y*h+y*w)=psiBa, pA=rA, pB(h+y+j+y*h), rBA=rBa	2100.76	2.57	0.0751	0.2767	25	2046.32
psiA, psiBA(e+w+h+y+y*h),psiBa, pA=rA, pB(h+y+j+y*h), rBA=rBa	2101.04	2.85	0.0653	0.2405	30	2034.58

Top detection (above black line) and occupancy (below black line) models for coyote (species A) and badger (species B).

Model	AICc	Δ AICc	AIC wgt	Model Likelihood	#K	Deviance
psiA, psiBA, psiBa, pA, pB(g+j)=rBA=rBa	1876.82	0	0.5207	1	25	1822.38
psiA, psiBA, psiBa, pA, pB(g)=rBA=rBa	1877.84	1.02	0.3127	0.6005	24	1825.76
psiA, psiBA, psiBa, pA, pB(g), rBA=rBa	1880.28	3.46	0.0923	0.1773	26	1823.47
psiA, psiBA(e)=psiBa, pA=rA, pB(g+j)=rBA=rBa	1858.28	0	0.5665	1	13	1831.09
psiA, psiBA(e), psiBa, pA=rA, pB(g+j)=rBA=rBa	1860.47	2.19	0.1895	0.3345	15	1828.89
psiA, psiBA(e+y), psiBa, pA=rA, pB(g+j)=rBA=rBa	1862	3.72	0.0882	0.1557	17	1825.97

Top detection (above black line) and occupancy (below black line) models for coyote (species A) and kit fox (species B). Guzzler performed well as a predictor of pB but resulted in problematic betas. All competitive detection models had guzzler as a covariate so a new set of 24 detection models were tested without guzzler to select a top detection model for species B.

Model	AICc	Δ AICc	AIC wgt	Model Likelihood	#K	Deviance
psiA, psiBA, psiBa, pA, pB(h+y+j+b), rBA=rBa	3098.13	0	0.9821	1	32	3026.75
psiA, psiBA(e+w+h+y+y*h)=psiBa, pA=rA, pB(h+y+j+b), rBA=rBa	3088.3	0	0.8497	1	24	3036.22

APPENDIX H

Appendix H. Top two species detection (pB, pA, rBa, rBA) and occupancy (psiA, psiBA, psiBa) models (within 4 delta AICc following testing of formulations) for Central Valley mesopredators.

Models used for interpretation are highlighted in gray and were selected using the following criteria: within 2 delta AICc, no uninformative parameters, most parameterized (conservative) model, and no problematic beta estimates. All models were built with a constant coyote (species A) model: $\psi(l)$, $p(y+h+w+lx+y*h)$ where detection was unconditional ($pA=rA$). Species B detection models were built with a global occupancy model: $\psi BA(l+y+h+t+d_w+y*h+y*d_w)$, $\psi Ba(l+y+h+t+d_w+y*h+y*d_w)$, and with all parameters estimated separately (conditional formulation). Once a top detection model was selected, the formulation (conditional versus unconditional) was tested (tested formulation of all models within 2 delta AIC) and the top performing formulation was used to build occupancy models. Once a top occupancy model was selected its formulation was also tested to select a final top model. 28 detection models with 3 formulations were built and tested for bobcats and raccoons while 53 detection models with 3 formulations were built and tested for domestic cats; 53 occupancy models with 2 formulations were tested for all species.

K = number of parameters, l = latitude, d_w = distance to water, h = human disturbance, y = year, y*h = interaction of year and human disturbance, y*d_w = interaction of year and distance to water, t = percent tree cover, w = water at site, j = Julian date, lx = represents X day trap response.

Top detection (above black line) and occupancy (below black line) models for coyote (species A) and bobcat (species B). Year performed well for psiB but resulted in problematic beta estimates so a new model set of 17 models with two formulations was created without year as a covariate.

Model	AICc	Δ AICc	AIC wgt	Model Likelihood	#K	Deviance
psiA,psiBA, psiBa,, pA=rA, pB(h+w), rBA=rBa	2565.15	0	0.9565	1	30	2497.24
psiA, psiBA(l+t+d_w)=psiBa, pA=rA, pB(h+w), rBA=rBa	2568	0	0.3746	1	18	2529.23
psiA, psiBA(l+t+d_w), psiBa, pA=rA, pB(h+w), rBA=rBa	2568.88	0.88	0.2413	0.644	22	2520.72
psiA, psiBA(t+d_w), psiBa, pA=rA, pB(h+w), rBA=rBa	2570.16	2.16	0.1272	0.3396	20	2526.73
psiA, psiBA(l+h+t+d_w), psiBa, pA=rA, pB(h+w), rBA=rBa	2570.91	2.91	0.0874	0.2334	24	2517.93
psiA, psiBA(l+t), psiBa, pA=rA, pB(h+w), rBA=rBa	2571.61	3.61	0.0616	0.1645	20	2528.18
psiA, psiBA(l+h+t), psiBa, pA=rA, pB(h+w), rBA=rBa	2572.16	4.16	0.0468	0.1249	22	2524

Top detection (above black line) and occupancy (below black line) models for coyote (species A) and domestic cat (species B). Year performed well for pB but resulted in problematic beta estimates so a new model set of 17 models with three formulations was created without year as a covariate.

Model	AICc	Δ AICc	AIC wgt	Model Likelihood	#K	Deviance
psiA, psiBA, psiBa, pA=rA, pB(j), rBA ,rBa	2894.86	0	0.3551	1	30	2826.95
psiA, psiBA, psiBa, pA=rA, pB(w), rBA, rBa	2896	1.14	0.2008	0.5655	30	2828.09
psiA, psiBA, psiBa, pA=rA, pB(lx), rBA, rBa	2896.25	1.39	0.1772	0.4991	30	2828.34
psiA, psiBA, psiBa, pA=rA, pB(h), rBA, rBa	2897.22	2.36	0.1091	0.3073	30	2829.31
psiA, psiBA, psiBa, pA=rA, pB(j), rBA=rBa	2898.95	4.09	0.0459	0.1294	28	2836.1
psiA, psiBA(h+t), psiBa, pA=rA, pB(j), rBA ,rBa	2881.59	0	0.2836	1	20	2838.16
psiA, psiBA(l+h+t), psiBa, pA=rA, pB(j), rBA ,rBa	2882.42	0.83	0.1873	0.6603	22	2834.26
psiA, psiBA(h+t+d_w), psiBa, pA=rA, pB(j), rBA ,rBa	2883.04	1.45	0.1373	0.4843	22	2834.88
psiA, psiBA(l+h+t+d_w), psiBa, pA=rA, pB(j), rBA ,rBa	2884.42	2.83	0.0689	0.2429	24	2831.44
psiA, psiBA(l+h+d_w), psiBa, pA=rA, pB(j), rBA ,rBa	2884.56	2.97	0.0642	0.2265	22	2836.4
psiA, psiBA(h+d_w), psiBa, pA=rA, pB(j), rBA ,rBa	2884.83	3.24	0.0561	0.1979	20	2841.4
psiA, psiBA(y+h+t+d_w), psiBa, pA=rA, pB(j), rBA ,rBa	2885.34	3.75	0.0435	0.1534	24	2832.36
psiA, psiBA(l+y+h+t), psiBa, pA=rA, pB(j), rBA ,rBa	2885.42	3.83	0.0418	0.1473	24	2832.44

Top detection (above black line) and occupancy (below black line) models for coyote (species A) and raccoon (species B).

Model	AICc	ΔAICc	AIC wgt	Model Likelihood	#K	Deviance
psiA, psiBA, psiBa, pA=rA, pB(y+h+w+y*h+y*w), rBA=rBa	4712.14	0	0.9723	1	36	4628.51
psiA, psiBA(l+y+h+w)=psiBa, pA=rA, pB(y+h+w+y*h+y*w), rBA=rBa	4697.8	0	0.914578	1	25	4642.38

APPENDIX I

Appendix I. Interpretation of results following single and two-species occupancy modeling regarding habitat variables and mesopredators.

Akin to previous work, elevation influenced the occupancy of all Mojave Desert mesopredators, with the exception of the coyote (Rich et al. 2018). Occupancy of bobcats, gray foxes, and badgers was greater in higher elevations while occupancy of kit foxes was higher in lower elevations. Because elevation was correlated with several other habitat variables (NDVI, percent shrub cover, and mean temperature) any relationship with elevation likely indicates a more complex habitat association. For example, kit fox occupancy is positively associated with high maximum temperatures (Rich et al. 2019b) and flat terrain with sparse vegetation (Egoscue 1962). Additionally, use of underground dens buffer this species from extreme temperatures (Golightly and Ohmart 1984) which likely allows them to persist in lower elevations.

Unlike the Mojave Desert, the topography of the Central Valley is mostly invariable. Instead, latitude better represents differences in temperature and precipitation throughout the ecoregion. The northern latitudes of the Central Valley are positively correlated with precipitation while the southern Central Valley experiences higher mean temperatures. Latitude was the only variable that influenced Central Valley coyote occupancy with higher coyote occupancy in the southern Central Valley. Conversely, bobcat, domestic cat, and raccoon occupancies were higher in more

northern latitudes. This may reflect mesopredators' response to precipitation and temperature. Previous work has found that coyote occupancy decreases with higher precipitation while other species' occupancy increased with precipitation in the Central Valley (Rich et al. 2018).

Only felids responded to percent tree cover in the Central Valley with occupancy of both bobcats and domestic cats increasing with percent cover. Domestic cats have been found to have a strong preference for forested areas (Krauze-Gryz et al. 2012) and bobcats are known to utilize orchard cover in southern California (Nogeire et al. 2013). This relationship with cover may be related to felid hunting strategies, as all felids, other than the cheetah (*Acinonyx jubatus*), are ambush hunters (Martín-Serra et al. 2016) and therefore rely on cover to hunt successfully.

APPENDIX J

Appendix J. Interpretation of results following single and two-species occupancy modeling regarding time of year (Julian date) and mesopredators.

Time of year was an important predictor for mesopredator detection and this relationship appeared to be influenced by the presence or absence of coyotes. Both coyote and badger detection were positively correlated with Julian date in the Mojave Desert suggesting that both species were more active and/or abundant during May-July. Both badgers and coyotes give birth in the spring (March-April/May) with lactation lasting through early summer (June, Long 1973, Sacks 2005). As a result, any young of the year were inactive for the beginning of our field study in March-April but became active later as they got older and big enough to leave their dens. Badgers' relationship with Julian date did not change when accounting for coyote presence. However, following two-species occupancy modeling, Julian date became a clear predictor of both bobcat and kit fox detection in the Mojave Desert and the presence of coyotes influenced these relationships.

Kit fox detection at sites where coyotes were present was negatively associated with Julian date while there was essentially no relationship between kit fox detection and Julian date at sites without coyotes. This seems to indicate that kit fox may alter their activity patterns to avoid interactions with coyotes later in the year. It has been suggested that kit fox are able to coexist with coyotes partially due to their year-round

use of dens (White et al. 1995) which may explain why kit fox do not avoid coyotes spatially but only behaviorally. Kit fox may preferentially stay in their dens in early summer when coyotes are more active and potentially abundant as a means to avoid intraguild competition and predation.

In contrast, bobcats were more detectable later in the summer if coyotes were present and less detectable if coyotes were absent in the Mojave Desert. Previous research has shown that bobcats will avoid overlapping with areas of core use by coyotes during the reproductive season (spring) when coyotes behave more territorially (Neale and Sacks 2001). As a result, bobcats may be less active earlier in the season when coyotes are protecting their territory and their young but will increase activity once the reproductive season is over. However, in the absence of coyotes, bobcats appear to be more active in the spring. This may reflect bobcats avoiding higher temperatures (Rich et al. 2018). This relationship was consistent in the Central Valley where bobcats were more detectable earlier in the year.

Bobcats, domestic cats, and raccoons all had higher probability of detection in the Central Valley earlier in the year. However, following two-species occupancy modeling, only domestic cats still responded to Julian date when accounting for coyote presence. In the absence of coyotes, domestic cats appeared to be more active later in the summer but this relationship flipped at sites where coyotes were present. This may reflect a human response to coyotes where owners typically let their cats outside more in the summer if there is no threat of coyote depredation. However, if coyote families

become active in the area in the summer, cat owners may stop allowing their cats to go outside as young coyotes leave their dens and explore the area.