The Human-Wildlife Interface: A Case Study of Bobcat & Coyote Conflict in California

by
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Abstract

California is one of the most biodiverse regions in the world, and is facing growing challenges to managing and protecting wildlife. State agencies and wildlife organizations are dedicated to fostering peaceful coexistence between residents and wildlife, particularly with predator populations as urban development expands into wild habitat. My research focuses on two medium sized predators in California, coyotes (*Canis latrans*) and bobcats (*Lynx rufus*); two species whose populations are pervasive throughout the state, and often the root of conflict with humans. As anthropogenic pressures on predator populations increase, we need to understand the dynamics driving spatial and temporal patterns of conflict to protect humans and wildlife. My research looks broadly at the state of California to understand what variables are driving conflict, particularly the highest form of conflict: depredation events. Using conflict data reported to California's Department Fish and Wildlife, these analyses tested the relationship between depredation events and high value environmental resources (water, NDVI), land attributes (elevation, public parks, cropland, grazing), and socio-economic variables (population mean, median income). Separate occupancy models for both species found that percent water, elevation, and vegetative cover have a positive relationship with depredation events caused by both species. In addition, coyote depredation has a negative relationship with park area and crop area per site; bobcat depredation has a positive relationship with grazing area per site. The results show that state agencies can focus their efforts to protect and educate communities in areas with high water availability, high elevation, and high vegetative cover, all three variables that are positively related to depredation events for both species. State agencies have data repositories on conflict with wildlife throughout the state that can be used to understand how conflict evolves as pressures increase - and use data-informed strategies to protect humans and wildlife. The goal of my research is to provide insight into spatial and temporal drivers of conflict with coyotes and bobcats so state wildlife agencies can tailor wildlife education programs and other efforts to reduce conflict in areas that are more likely to experience higher rates of depredation.

Introduction

The global human population surpassed 8 billion people in 2022 (Baker et al., 2023), and has had a marked impact on biodiversity in urban areas around the globe. Cities in developed countries have seen an increase in urban populations from 10% in 1900 to over 50% in the 21st century (Grimm et al., 2008). Global biodiversity is largely threatened by habitat loss and fragmentation, both consequences of urban and suburban expansion (Markovchick-Nicholls et al., 2008). In the United States, urbanization poses a greater threat to local biodiversity than any other anthropogenic activity (McKinney, 2002). California is particularly vulnerable as one of the most biodiverse states in the country, and boasts a range of land cover types and topographic diversity (Barbour & Kueppers, 2012). The confluence of increasing urbanization and high biodiversity in California presents a significant challenge for those responsible for conservation, urban planning, farming, infrastructural development, and more. California's cities are experiencing urban sprawl, and as development expands into new areas, opportunities for human-wildlife conflict increases.

Coyotes (*Canis latrans*) are medium-sized canids that occupy all habitat types and urban areas across California. As habitat generalists, coyotes have been able to adapt to the expanding urban interface, which has increased the prevalence of human-wildlife encounters (Baker & Timm, 2016). In many urban and suburban areas across the US, coyotes are now the largest carnivore present due to development, urbanization, and a reduction in apex carnivores (Weckel & Wincorn, 2016; White & Gehrt, 2009). Between 1977 and 2015, there were 165 reported coyote attacks on people–including adults and children–within the state (Baker & Timm, 2016). In an analysis of coyote reports within California between 2017 and 2019, researchers found that the number of reports was strongly positively correlated with human population numbers and median income of a county (Heeren et al., 2020). The range for coyotes has expanded over time across the United States, in part due to the reduction in apex carnivore populations such as the gray wolf (*Canis lupus*) (Baker 1998).

Bobcat (*Lynx rufus*) populations provide unique insight into habitat connectivity dynamics in California because of their wide-ranging habitat needs and low population densities (Ruell et al., 2009). Like coyotes, bobcats are habitat generalists (Schmidt et al., 2023), but are likely to be more populous in low urban density areas (Ruell et al., 2009). Data shows that bobcats prefer spacious green areas as urban development encroaches on preferred habitat types (Lombardi et al., 2017). A 2019 study on bobcat behavior in Southern California found the species preferred coastal sage scrub and grassland 76-84% of the time compared to urban areas for diurnal habitat use, while nocturnal activity saw urban use double (Dunagan et al., 2019). Research on bobcat diet has found the species has a food preference for mammalian prey, even in urban areas

(Dunagan et al., 2019; Larson et al., 2015). Conflict patterns between humans and bobcats can help us understand how bobcat populations are shifting as urbanization increases.

Urban development has transformed the state of California in the past few decades, with documented negative effects on coyotes and bobcats, including reproductive ability, diet, cognition, and extrinsic factors (Schmidt et al., 2023). Habitat fragmentation can lead to niche partitioning in urban areas. A study that focused on coyote resource use and diet found that coyotes change their diet depending on the resources available, from cultivated urban crops to domesticated animals (Larson et al., 2020). As urban areas have expanded, interaction between humans and wildlife has increased, presenting an ongoing challenge for wildlife agencies tasked with the job of reducing conflict and fostering coexistence (Larson et al., 2020).

The state of California is facing difficult environmental issues that will continue to worsen over time. The state has a wide diversity of geography and ecosystems, which will continue to suffer under the evolving impact of climate change and anthropogenic development. Apex predator populations key to these ecosystems are in decline, with programs and resources set aside to protect predator species threatened with extinction (Marshall et al., 2016). Mesopredator populations are growing, taking the place of larger predators as the primary source of human-wildlife conflict in many regions throughout the state (Marshall et al., 2016). There are competing priorities to protect predators and domesticated ranch animals, as well as predator and prey populations (Marshall et al., 2016). There are historically challenging relationships between ranchers and predators that have informed wildlife management decisions and policies (Marshall et al., 2016). Coyotes and bobcats represent highly adaptive species that inhabit ecosystems throughout the state, and will continue to be the source of high rates of human-wildlife conflict as urban areas expand into less developed areas.

Citizen or community science is a term used to describe data received from individuals who volunteer the information based on their personal experience, regardless of expertise (Nagy et al., 2012). Databases that hold citizen reported information can be a helpful way for scientists to analyze a situation when there are limited resources to conduct data collection. While citizen reported data is limited for a multitude of reasons, the information can still be used in a way that advances human understanding of the natural world, particularly in occupancy models (Goswami et al., 2015; Nagy et al., 2012). This is notable for large areas, like the state of California where targeted studies to understand ecological changes are expensive and resource-intensive. Databases that contain citizen reported information provide a resource for scientists to deepen their understanding of expansive geographic areas that are difficult to study otherwise.

A study of coyote occupancy in New York City used camera traps to validate the accuracy of a separate study that built an occupancy model to predict patterns of coyote occupancy using citizen-science provided data (Nagy et al., 2012). This validation offers support for research that uses citizen reported data to extrapolate information to help wildlife managers understand ecosystems and wildlife movement within urban and suburban areas. The key to using citizen science data is ensuring that the results of the model continue to reflect the limitations of the data type. In the study in New York City, the researchers concluded that the separate study employing an occupancy model accurately predicted where conflict between humans and coyotes would occur (Nagy et al., 2012).

My research aims to interrogate the spatial and temporal drivers of conflict between humans and two mesopredator species - coyotes and bobcats - throughout the state of California over a five year period. The goal is to understand on a broader scale, the nature of the highest level of conflict (depredation), and what the spatial-temporal drivers of conflict are. This analysis was conducted using citizen-reported data on presence, general nuisance, potential harm, and depredation, and asked four main questions: Where is conflict happening throughout the state? Is there a time when there is more conflict? What is driving conflict with mesopredators? How can we use this information to reduce conflict? To address these questions, I analyzed environmental variables important to predator habitat preference: water availability, elevation, vegetative cover, public park area, crop area, and grazing area. Included in the analysis were human-activity related variables: average human population, median income, and year of occurrence. My analysis tested the relationship between the independent variables and the dependent variable: depredation events caused by both coyotes and bobcats.

Literature Review

California

As a state with varied topography, geography, soil communities, and a global 'hotspot' for species diversity, California is facing difficult conservation management decisions as climate change threatens ecosystems across the state (Barbour & Kueppers, 2012). Many management strategies are reactionary, built within systems set up to respond to species management once their populations hit critically low levels, instead of proactive plans to monitor and protect whole ecosystems (Barbour & Kueppers, 2012). Urban infrastructure and anthropogenic development decisions are not made with local ecosystems as a top priority; conservation action plans are formed after lasting impact has been made on local species (Barbour & Kueppers, 2012). California's ecosystems have already experienced broad-scale changes from predator population decrease, shifts in bird migration, and an increase in breadth and duration of wildfires (Barbour & Kueppers, 2012). Evolving climate change and ecosystem fragmentation will create new challenges to protecting predator populations throughout the state in the future (Barbour & Kueppers, 2012).

The state of California boasts large areas of public and private owned rangeland, which can be of use to species of concern as the state's populous areas continue to sprawl and expand. Wildlife management agencies have continuously explored the best strategies to protect areas for species with broad ranging habitats. Rangeland is important for many reasons from feeding human populations, storing carbon long-term, and providing habitat connection between protected habitats for range species (Farley et al., 2017). One solution to habitat reduction throughout the state has been an ongoing discussion with ranchers to set up incentive programs that deter land development, and explore forms of compensation to protect land for ecosystem services (Farley et al., 2017). Rancher relations are important because 95% of endangered species in the US have some of their habitat on privately owned rangeland (Marshall et al., 2016). The complicated nature of land management and development underscores the importance of adaptive management strategies to protect endangered predator populations. As wildlife agencies pool resources to protect declining predator populations, they need flexible policy that will allow them to change and adapt (Marshall et al., 2016).

Urbanization

Coyotes have had a growing presence in urban America over the past few decades; from Los Angeles, Chicago, to New York City, most urban cities in America have coyote populations (Gese et al., 2012). While human activity and land type is variable in each of these cities, coyotes have shown an adaptability that allows them to persist on a wide variety of food sources including domestic animals, garbage, domestic gardens, wild animals, and pet food (Gese et al., 2012). A study on coyote behavior in the city of Chicago found that preference for habitat type within the city changed by the season with smaller ranges during pup-rearing periods, and larger ranges when prey availability is low (Gese et al., 2012). Coyotes are often the top predator in urban cities, with research showing avoidance behavior in more densely populated areas and selective behavior for areas with vegetative cover, water, and low development (Gehrt et al., 2011). Density estimates showed much higher rates of coyotes in cities compared to rural areas (Gese et al., 2012).

A study that tracked coyotes in Chicago found that they exhibited avoidance behavior in developed areas, with preference for less developed, riparian and forested areas (Gehrt et al., 2011). However, as urbanization increased, so did coyote populations because there was enough preferential habitat and growing food sources that provided an environment where coyote populations could thrive. Effective management of coyotes in Chicago included educational programs encouraging residents not to feed wildlife. At the same time, authorities targeted the removal of a male coyote who was responsible for predating domestic animals. The result was coexistence for seven years, after targeted individual removal, paired with education programs (Gehrt et al., 2011).

Southern California is a region that has seen many studies focused on bobcat ecology, due to the layered threats to bobcats and the diversity of other species there. In Southern California, bobcat populations are becoming more isolated due to habitat fragmentation and urbanization (Ruell et al., 2012). A study on the ecology of gray foxes (*Urocyon cinereoargenteus*), coyotes, and bobcats in Southern California found that bobcats have a preference for larger areas of undeveloped habitat, and scat samples showed less dietary variety compared to the other two carnivores (coyotes and foxes) (Larson et al., 2015). While bobcats are habitat generalists, they show a high preference for isolated areas, and a diet of rodents, birds, and other wild prey (Larson et al., 2015). Bobcat habitat use in urban areas can be found to follow trends in prey populations, where natural prey can be found, bobcats can be found as well (Dunagan et al., 2019).

Successful coexistence and wildlife management programs center around local communities, as offered in a study on the two most populated areas in the United States: Los Angeles County, and Chicago's Cook County, both home to thousands of coyotes. Using insight from parallel surveys in both counties, researchers suggest that the most impactful management strategies can pinpoint gaps in local knowledge to reduce high risk behavior (leaving food out, having bird feeders, growing vegetable gardens) disseminated by wildlife agencies (Elliot et al., 2016). These adaptive and context-dependent strategies will continue to be increasingly important for management of mesopredator populations in California, and other highly populated areas in the United States for the foreseeable future.

Livestock management

As coyote and bobcat populations have increased over time, wildlife managers have researched and applied different techniques to reduce incidents of livestock conflict. As ranchers suffered losses to their sheep herds in the 1990's due to coyote predation, researchers hypothesized that coyotes had higher predation rates on sheep after denning, and studied the effects of coyote sterilization on sheep herd size over a three year period (Bromley & Gese, 2001). Sterilization turned out to be an effective short-term management strategy, but longer studies have yet to be conducted (Mitchell et al., 2004). There is a wide swath of effective nonlethal techniques that managers employ that include building protective fencing, safeguarding more vulnerable individuals in a herd, obtaining guard dogs and other reactive animals (Mitchell et al., 2004). At the moment, lethal control remains a common practice for predator control, in large part because it is a cost effective management strategy. There is growing evidence that predation risk modeling can be used to predict conflict 'hot-spots' for livestock managers to increase protection before predation takes place, but is an expensive tool for preventative management (Miller, 2015).

Wildlife management authorities have the paradoxical challenge of protecting declining predator populations while addressing the conflict that they cause with people, particularly livestock managers. Apex predator populations are in decline all over the world, which threatens the relationships they have within local ecosystem communities (McInturff et al., 2021). Due to historic interactions between predators and livestock managers, wildlife authorities are also having to address perceived risk, a socio-ecological aspect of conservation (McInturff et al., 2021). Risk perception is an important aspect of conflict management because of the connection to livestock management, and predator management decisions (McInturff et al., 2021). Research on reduction of predator-livestock conflict has often been from the perspective of economic loss, with a net negative impact on predator populations (Graham et al., 2005).

Rangeland management represents an ongoing challenge that California's resource agencies face: protecting livestock from natural predators and protecting land from development at a time when ranchers can use economic support. Between 1987 and 2003, the livestock industry in the Northwestern United States lost about USD 11,076.49 annually to predation, a loss that was not evenly distributed, and can often impact specific regions and livestock ranches more than others (Muhly & Musiani, 2009). As conservationists work to protect apex predator populations, there is an indirect impact that livestock ranchers bear the brunt of. While there are compensation programs for livestock depredation events, predator presence can have an indirect impact on herds that is difficult to quantify, but manifests in livestock weight loss, reproductive ability, and overall health (Macon et al., 2018). Ranchers throughout the United States disproportionately pay the price for returning predator populations, an important factor for wildlife agencies to be aware of (Steele et al., 2013). There is an area where conservationists and ranchers have common interest: protecting land from developers (Muhly & Musiani, 2009). A pilot approach to predator conservation has risen in the form of 'Pay for Presence' programs that compensate ranchers for the indirect costs of growing predator populations without requiring proof of predation events (Macon, 2020).

Research gap

Projections show that 70% of the world's population will live in urban areas by 2050 (Weckel & Wincorn, 2016), which underscores the importance of understanding the dynamic interactions between humans and mesopredators in California. Mesopredator populations have grown throughout the state and country due to the local and regional extirpation of apex predators, including mountain lions (*Puma concolor*), wolves, and bears (Dyck et al., 2022). Research has focused on the diet of urban coyotes, estimation of home range for both coyotes and bobcats in Southern California (Riley et al., 2003), but has not looked more broadly at the entirety of the state of California (McInturff et al., 2021). Decades of research has focused on the role of coyotes and bobcats as top predators in urban areas, and interspecific interactions (Dyck et al., 2022), but has not spatially examined regional conflict with humans, and the drivers of said conflict. The primary objective of this study is to understand broad-scale drivers not just of occurrence but of the highest level of conflict – depredation events – caused by coyotes and bobcats.

In the past fifty years, research on coyotes and bobcats in the United States has focused on their ecology, presence, and conflict with humans in urban areas (Gehrt et al., 2011; Lombardi et al., 2017). There is a growing need for data that helps wildlife agencies understand where to target their efforts, in a world that is seeing an increase in human-wildlife interactions. Predation risk models are helping connect researchers with management authorities around the world. For example, in Montana, ecologists shared a conflict risk map with livestock ranchers, that showed what areas were most at risk for high conflict with grizzly bears (*Ursus arctos horribilis*) (based off of data modeling and reported conflict), which reduced bear conflict by 96% from 2003 to 2010 (Clark et al., 2014; Miller, 2015). For effective coexistence, there is a gap in the literature that analyzes broad ranging high-level conflict such as depredation events, and where depredation is occurring in different ecosystem types (Mitchell et al., 2004). My research here aims to advance our understanding of the drivers of depredation by coyotes and bobcats throughout one of the most biodiverse states in the country.

As the human-wildlife interface expands, there will be increasing opportunities for interaction and conflict with coyotes and bobcats. To understand the spatial and temporal dynamics of reported conflict, researchers can employ occupancy modeling (Waldron et al., 2013). There is bias and imperfection in conflict report data, which is accounted for in occupancy models. Detection imperfection refers to data flaws that occur with observation and reporting bias (Goswami et al., 2015). For example, if a remote area has less reported conflict because it does not see as much human foot traffic, that does not necessarily mean that it sees zero depredation, but that depredation has not been detected in the area. Another possibility is that depredation occurs, but the observer does not know of the reporting system, and so it goes unaccounted for. An occupancy model takes these possibilities into account. Goswami et al. argue that occupancy modeling is well suited to analyze citizen reported data because of its detection imperfection, and occupancy models are an effective way to evaluate conflict with such data (Goswami et al., 2015).

Occupancy models are becoming more common tools for researchers looking to understand conflict dynamics with citizen reported data, and have produced interesting results (Waldron et al., 2013). Occupancy models are used to take spatial and temporal variables of interest and test their influence on species presence or absence to provide insight into the risk or likelihood of human-wildlife encounters (Waldron et al., 2013). Researchers wanted to understand the likelihood of crop and livestock depredation events caused by elephants in India, and employed a novel occupancy model to understand the spatiotemporal drivers (Goswami et al., 2015). Occupancy modeling has been employed by ecologists studying coyotes to understand the different drivers of predation, looking at environmental and socio-economic variables to understand the complex nature of conflict with livestock ranchers (McInturff et al., 2021).

In recognition of increasing rates of human-wildlife conflict, this study will spatially examine and assess human-mesopredator conflict to identify hot and cold spots and further understand the ecological and socio-economic drivers of high and low conflict areas statewide. The goal is to provide analysis to wildlife management agencies that will assist in their mediation of conflict incidents throughout the year in California. Based on what we know about conflict patterns throughout the state of California, my research is analyzing multiple covariates including high value environmental resources (water, NDVI), land attributes (elevation, public parks, cropland, grazing), and socio-economic variables (population mean, median income). I hypothesize that conflict will occur in areas with high value environmental resources and prey: water, human population, NDVI, park area, and grazing area. Based on changing work and home life dynamics for humans during the pandemic, I hypothesize that conflict will be higher in 2020 for both species. I hypothesize that drivers of conflict will be NDVI, park area, and grazing area. The purpose is to use the statistical modeling results to inform management decisions that will help to reduce future conflict.

Methods

Study Area

This research encompasses the state of California, a biodiversity hotspot well known for its topographic diversity, soil richness, and healthy ecosystems. California is home to the highest number of federally listed species in all the United States (Farley et al., 2017), and has widespread livestock grazing, the state's most extensive land use (Huntsinger & Bartolome, 2014). Ranchers graze their livestock across a variety of Mediterranean ecosystems including grasslands, hardwood forests, and chaparral, as well as desert ecosystems including sagebrush grasslands, coniferous forests, montane meadows, and barren landscapes (Barry & Huntsinger, 2021). Coyotes and bobcats can be found throughout the state, as their adaptive ability allows them to find resources in many different ecosystem types. It also presents an ongoing challenge to understanding where rates of conflict with both species will occur.

Data

The data used for analysis is directly from California Department of Fish and Wildlife's Wildlife Incident Reporting system. The system allows anyone to log on and report an incident with wildlife throughout the state. The Wildlife Incident Reporting website's front end captures information that includes the species, manner of interaction, date, and location. The system organizes each incident under four categories of ascending conflict: sighting (the species was observed); general nuisance (species was observed engaging in nuisance activity); potential human conflict (species was observed and the observer felt threatened in some way); depredation (species was observed to have injured or killed household pets or livestock). California's Wildlife Incident Reporting program came online in 2019, so the timeline for the data in this analysis is from 2019 to 2023 for all incidents with coyotes and bobcats. This data is held and managed by California's Department of Fish and Wildlife, and was obtained via the Freedom of Information Act. This analysis will focus on the most severe incidents with coyotes and bobcats, and analyze the data that was categorized as 'depredation' for the analysis. This is to focus our analysis of the data to understand what might be driving the most severe level of human-wildlife interaction (predation events) across the state.

Analyses

Using a combination of R statistical software, ArcGIS, and Google Earth Engine, I explored the relationship between our dependent and independent variables. US Census data was used for the 8,057 census tracts (total sites), to calculate area of water per site, and for socio-economic variables: average human population and median income. A digital elevation model, and land cover data from Data Basin were used to calculate average elevation across the state per site, and average grazing area per site, respectively. Land cover data from California's Department of Fish and Wildlife was used to calculate crop area per site, and Google Earth Engine was used to calculate Normalized Difference Vegetation Index (NDVI) per site.

A single-season occupancy model was used to statistically analyze the relationship between the dependent variable 'depredation events', and the following covariates: median income, water cover, average elevation, human population mean, vegetative cover, area of public park space, area of cropland, area of grazing land, and year. I configured one model per species to compare the results of drivers of depredation for coyotes versus for bobcats. I used an occupancy model because it is well suited to citizen reported data, as it accounts for detection imperfection, and allows for spatial and temporal analysis of variables (Nagy et al., 2012). The occupancy model is set up to account for three possible outcomes: wildlife is present and an observer sees it, wildlife is present and an observer does not see it, wildlife is not present. The variable outcomes, and potential for not observing a species when it is in fact present is a crucial reason as to why this research used an occupancy model to analyze citizen reported data - the detection portion of the occupancy model accounts for this possibility (Fidino et al., 2022; Goswami et al., 2015; Waldron et al., 2013).

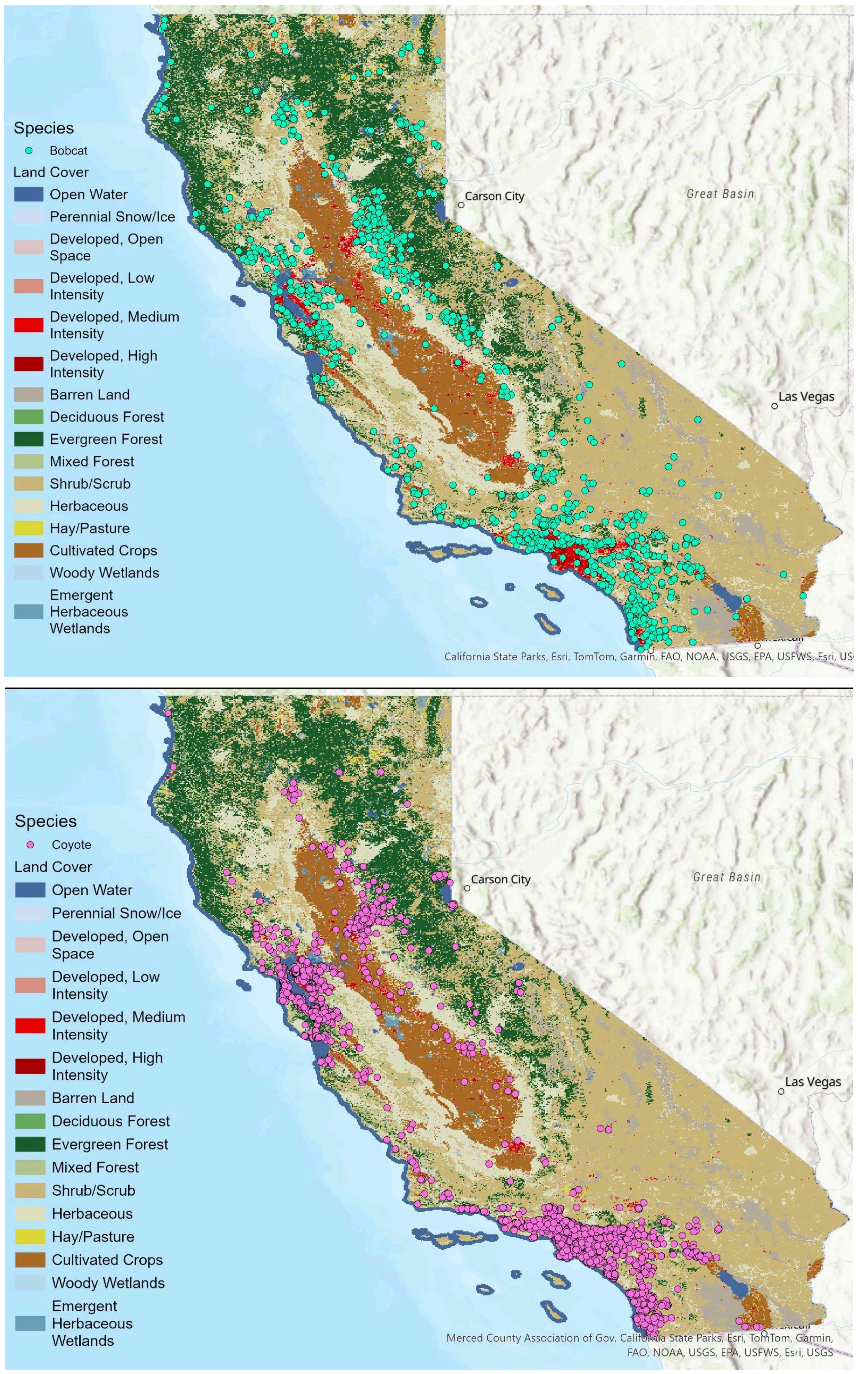
The occupancy model for each species uses sourced Census tract data to create 8,057 unique sites throughout the state, using a US Census shapefile data layer from 2018 (s = 8,057). The human population mean and median income covariates were added from Census data on population count per tract in the same year. To add vegetative cover, or specifically greenness, as a covariate, I sourced a data layer from Landsat 8 at 90 m resolution, and then calculated the Normalized Difference Vegetation Index (NDVI) using the equation: NDVI = (NIR - R) / (NIR + R), clipped to the extent of the state of California. The average value for NDVI was calculated for each census tract (s=8,057) to create a variable for each site. Using data layers from Data Basin, and California's Department of Fish and Wildlife, I calculated the average elevation, percent of public park area (local park, state park or forest, regional park, county park, national park or forest), cropland area, and grazing land area per census tract.

In R, I used the *unmarked* package to create the occupancy model for each species where our number of sites s = 8,057. In our model, occupancy of a site is represented by $y_i = 1$, no occupancy of a site is represented by $y_i = 0$. Our data are represented by y in the equation $y_i|z_i$~Bernoulli($p*z_i$) where z is the true occupancy of each site, i represents each individual site (Census tract), and p is the detection probability (Johnson et al., 2013). The covariates for each boundary were scaled to have a mean of zero, and a standard deviation of one, then fitted to the second half of the double-right sided model. Because our analysis focuses on depredation events only for both of these models, "occupancy" represents the probability of depredation. So the results of our model show the relationship between depredation events and our covariates of interest.

In addition to the occupancy models for depredation events, I used an abundance model for significant covariates for both species: water, elevation, NDVI, park area, cropland, and grazing area. An occupancy model looks at the depredation in binary terms (one for presence, zero for absence), while the abundance model looks at the entire count and therefore provides more information on variation in the relative frequency of occurrence. To validate the occupancy and abundance results, I applied a multivariate regression model to a standardized measure of depredation - the proportion of depredation (highest conflict) events out of total reported events, per site, per year in separate models for both species. Using the multivariate regression model, I tested the proportion of depredation over total conflict per year as dependent variables, and the same numeric covariates from our occupancy and abundance models as independent variables: median income, water, elevation, NDVI, park area, cropland, and grazing.

Results

Conflict: Spatial



Figures 1 & 2: Land use across the state of California with the coordinates of each depredation event from 2019 to 2023 for bobcats (top) and coyotes (bottom).

To get a sense of depredation events for coyotes and bobcats throughout the state during the timeline in question, I mapped the longitude and latitude coordinates for both species separately to compare across a map of California Land Cover Type, sourced from the USGS National Land Cover dataset. There is a distinct difference in the nature of depredation conflict comparing coyotes to bobcats. In Figures 1 and 2, coyote depredation happens more tightly concentrated around the three major urban areas in California: the San Francisco Bay Area, the Greater Los Angeles Area, and around the Capital, Sacramento. Bobcat depredation is also focused in these areas, but much more spread out in the suburban landscape. Bobcat depredation events are in general, more spread out throughout the state, with data points in forested areas in the north, along the Pacific coast, in the deserted areas towards Nevada, and along the Central Valley wherein lies the bulk of California's agriculture.

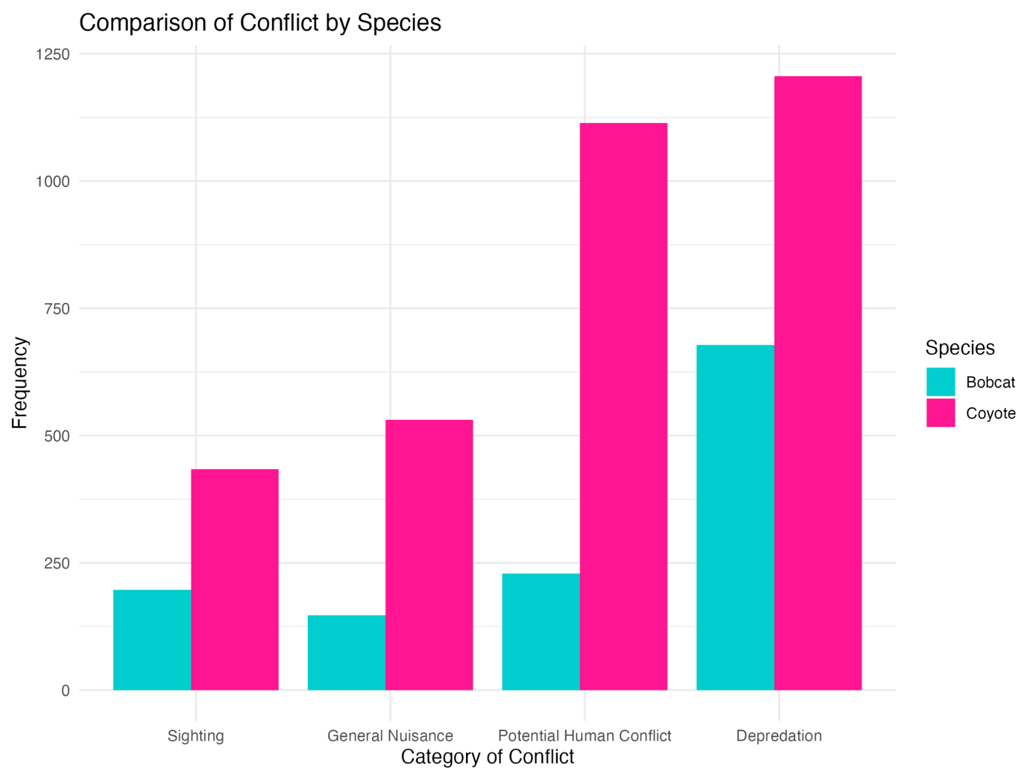


Figure 3: Plot of Category of Conflict (Sighting, General Nuisance, Potential Human Conflict, Depredation) from least to greatest frequency.

Overall, data collected by CDFW's Wildlife Incident Reporting indicated that the rate of incidence increases with the escalating conflict category for both species (Figure 3). This informed the decision to focus mainly on depredation events for both species. As the highest form of conflict, and the highest reported conflict during the time period of interest, depredation became the dependent variable of interest for this research.

Conflict: Temporal

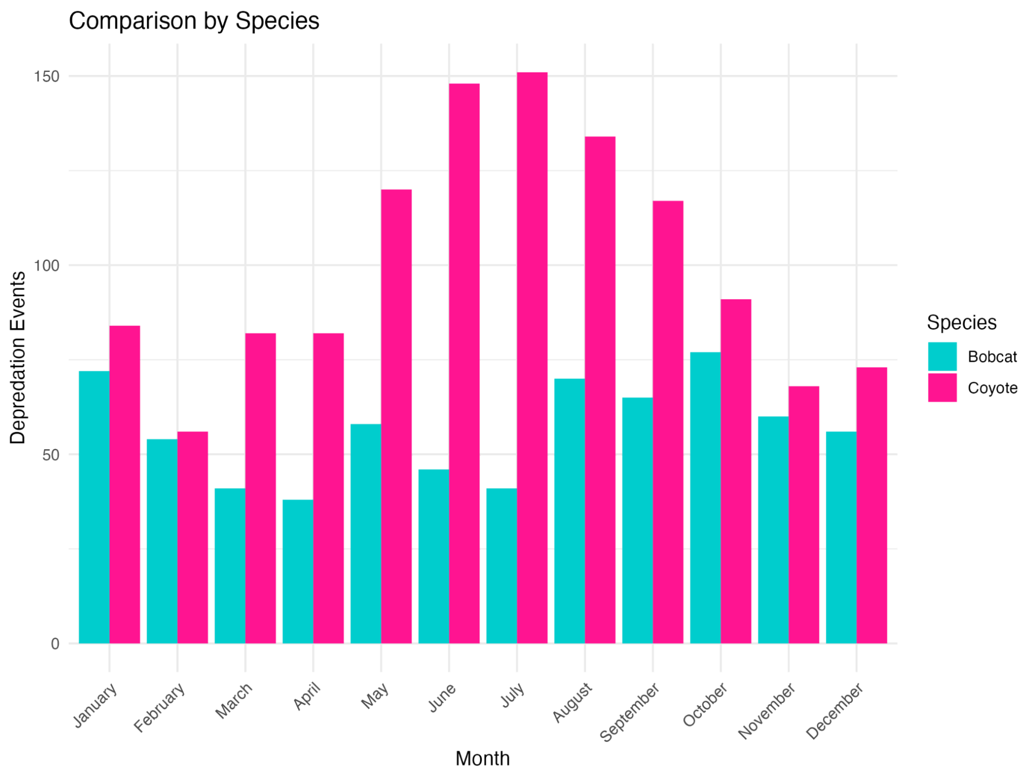


Figure 4: Number of depredation events reported by species and month.

Depredation events for coyotes peak starting in late Spring and throughout the Summer (Figure 4). Depredation events for bobcats are much more stagnant throughout the year, with a slight peak in January.

Occupancy Model Results

After running a Pearson's correlation test, I removed nightlight pollution from the list of independent variables because the correlation coefficient value was above 0.7 with NDVI, and deemed too highly correlated to be included in the occupancy models. I proceeded with the covariates: water, elevation, human population mean, NDVI, park area, cropland, and grazing. Water and NDVI have a weak negative relationship, but remained as part of the analysis.

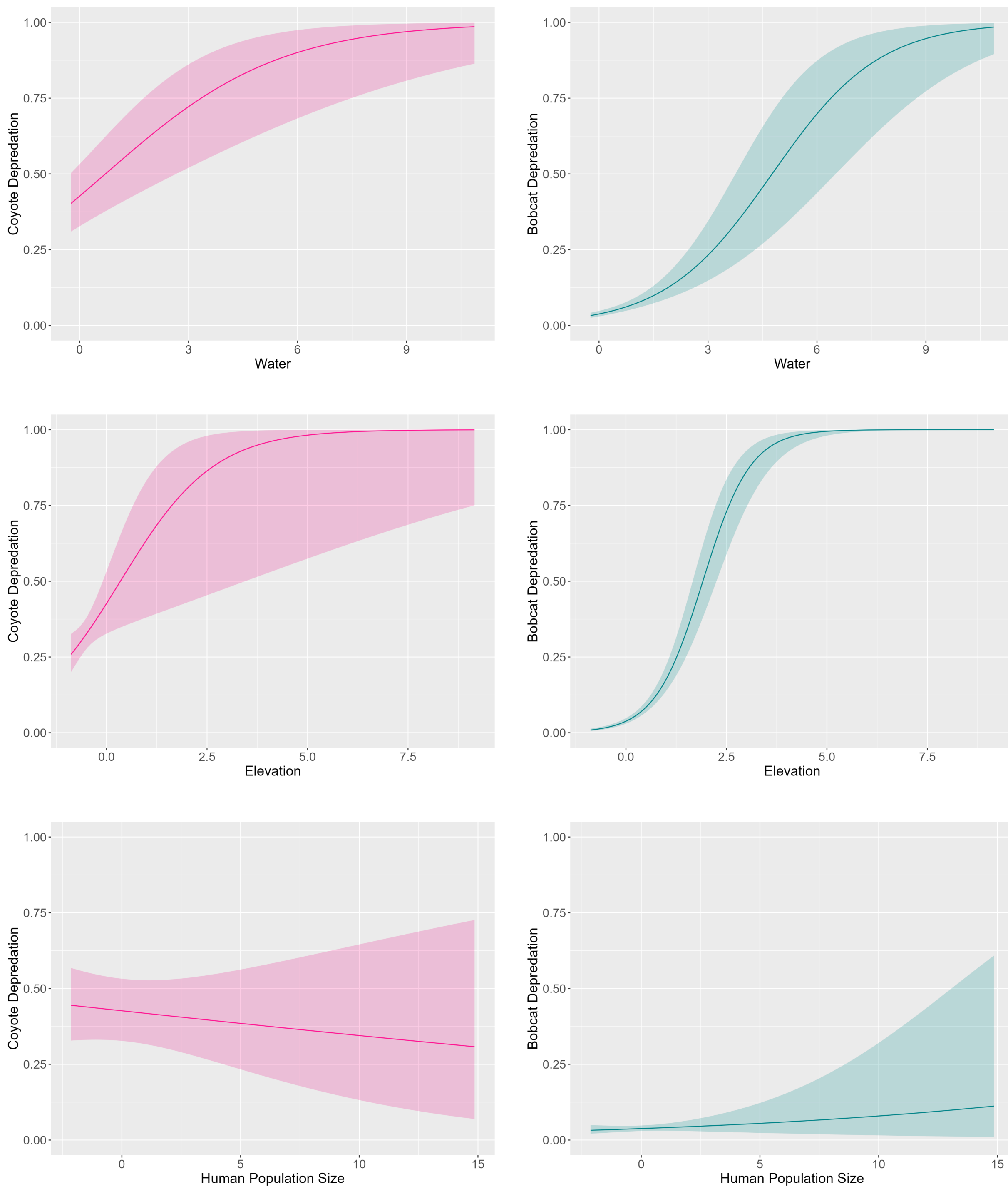
Table 1: Occupancy model results for coyote depredation, with significance codes.

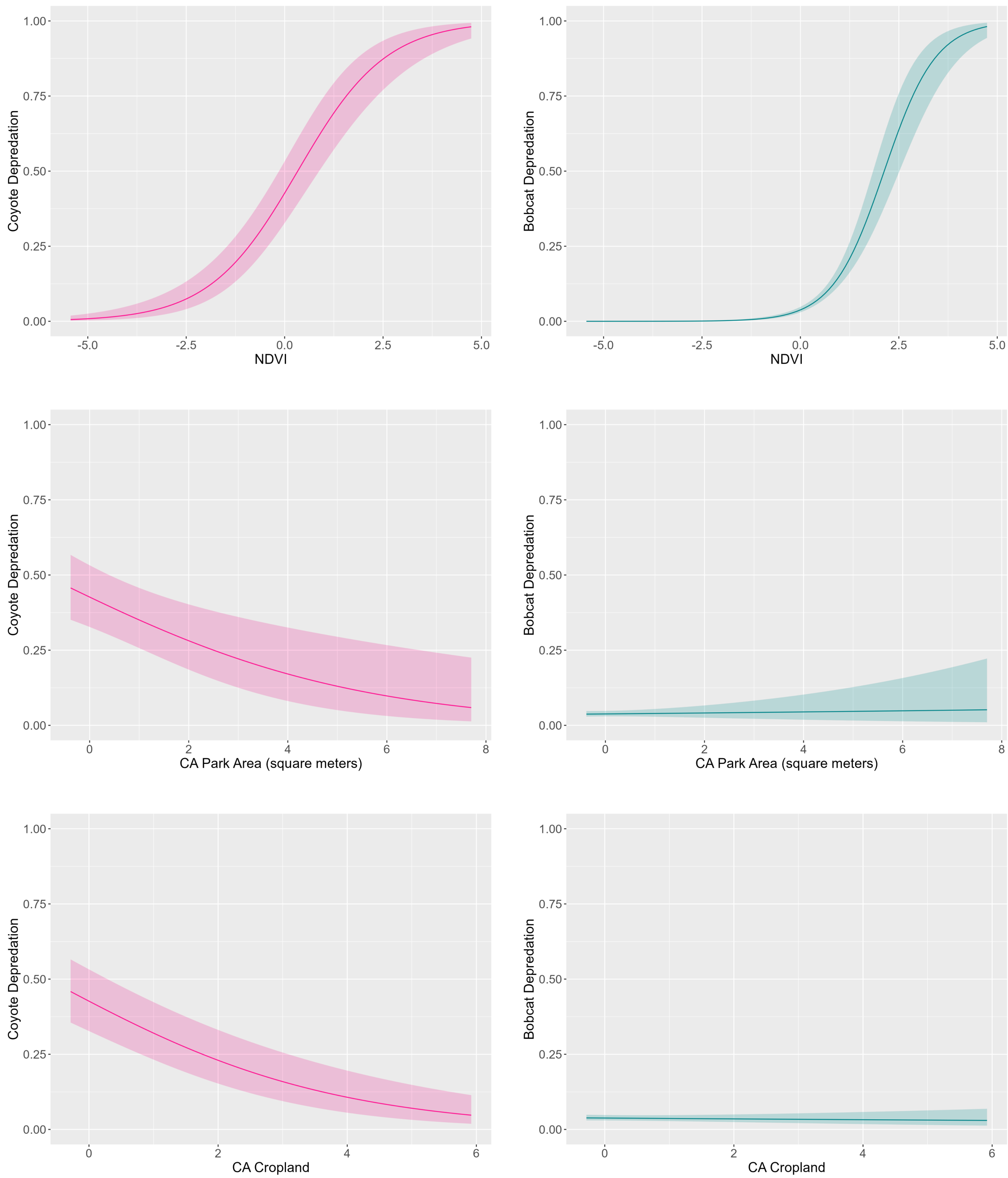
Coyote Occupancy Results				
	Estimate	**SE**	**z**	**P(>|z|)**
(Intercept)	-0.2956239	0.21672021	-1.3640809	1.73E-01
Water	0.41669207	0.10191877	4.0884725	***4.34E-05

Elevation	0.8583774	0.33999425	2.5246821	*1.16E-02
PopulationMean	-0.03459071	0.05963472	-0.5800431	5.62E-01
NDVI	0.89030405	0.10883424	8.180367	***2.83E-16
parkarea	-0.32100518	0.10134308	-3.1675096	**1.54E-03
cropland	-0.45647985	0.07474187	-6.1074182	***1.01E-09
grazing	0.11300553	0.09724748	1.1620407	2.45E-01
	Estimate	**SE**	**z**	**P(>|z|)**
(Intercept)	-2.88863375	0.09625308	-30.0108186	***7.09E-198
Median_Income	0.33282188	0.03448866	9.650182	***4.91E-22
coyote_2019	-0.16956813	0.10157872	-1.6693274	9.51E-02
coyote_2020	-0.40307311	0.10779133	-3.7393834	***1.84E-04
coyote_2021	-0.05375918	0.09888391	-0.5436596	5.87E-01
coyote_2022	0.05134622	0.09664194	0.5313037	5.95E-01
Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1				

Table 2: Occupancy model results for bobcat depredation, with significance codes.

Bobcat Occupancy Results				
	Estimate	**SE**	**z**	**P(>|z|)**
(Intercept)	-3.22874155	0.12593821	-25.6375064	***5.83E-145
Water	0.80313253	0.11173389	7.1879046	***6.58E-13
Elevation	1.73009973	0.14223169	12.1639543	***4.84E-34
PopulationMean	0.06951958	0.08849344	0.7855901	4.32E-01
NDVI	1.57878828	0.14378646	10.9800901	***4.76E-28
parkarea	0.08597721	0.11569056	0.7431653	4.57E-01
cropland	-0.05665389	0.07510713	-0.7543077	4.51E-01
grazing	0.55129539	0.07732149	7.1299116	***1.00E-12
	Estimate	**SE**	**z**	**P(>|z|)**
(Intercept)	-2.27806803	0.12190342	-18.6874822	***6.26E-78
Median_Income	-0.05800463	0.04841177	-1.1981513	2.31E-01
bobcat_2019	0.04808547	0.15495234	0.3103243	7.56E-01
bobcat_2020	0.1925598	0.15077987	1.2770923	2.02E-01
bobcat_2021	0.29336727	0.14816029	1.9800669	*4.77E-02
bobcat_2022	0.29338884	0.14815975	1.9802196	*4.77E-02
Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1				


Coyote Depredation
Water
Bobcat Depredation
Water
Coyote Depredation
Elevation
Bobcat Depredation
Elevation
Coyote Depredation
Human Population Size
Bobcat Depredation
Human Population Size


Coyote Depredation
Bobcat Depredation
1.00
0.75
0.50
0.25
0.00
-5.0
-2.5
0.0
2.5
5.0
NDVI
0
2
4
6
8
CA Park Area (square meters)
CA Cropland

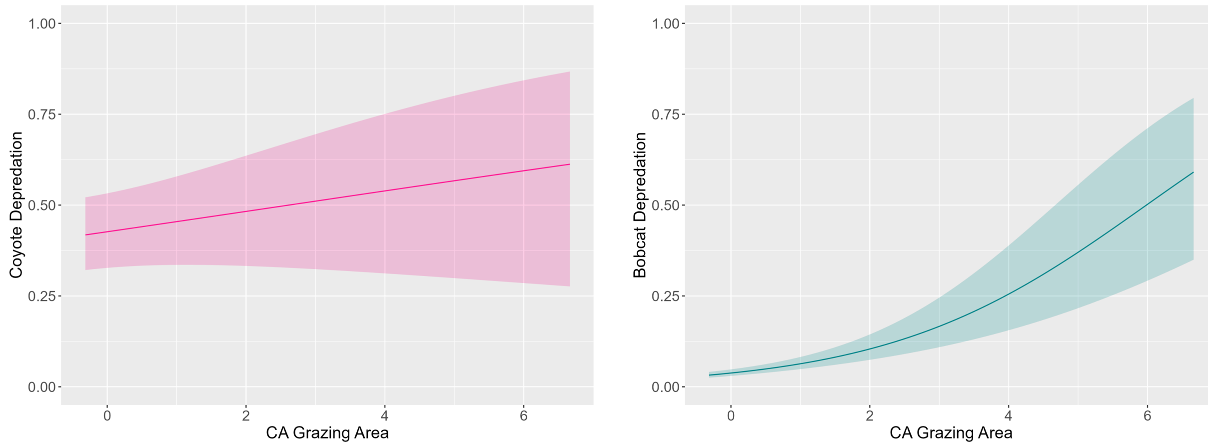
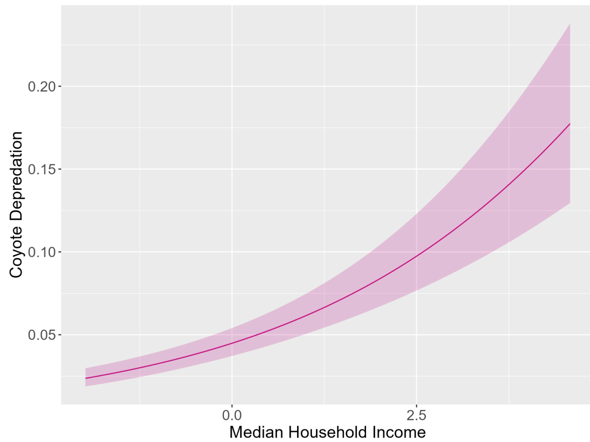


Figure 5: Occupancy model plots of the relationship between coyote depredation (left) and bobcat depredation (right), with the covariates from top to bottom: **water, **elevation, human population mean, **NDVI, *park area, *cropland, *grazing *('*' = significant for depredation by one species, '**' = significant for depredation by both species*).

The likelihood of depredation for both species had a significant positive relationship with water, elevation, and NDVI (Figure 5). For each one unit increase in area of water, the probability of coyote depredation increases by 0.42 and the probability of bobcat depredation increases by 0.80 (Tables 1 and 2). For each one unit increase in elevation, the probability of coyote depredation increases by 0.86 and the probability of bobcat depredation increases by 1.73. For each one unit increase in NDVI, coyote depredation increases by 0.89 and bobcat depredation increases by 1.58.

Park area and cropland were two covariates that only had a significant relationship with coyote depredation, while grazing only had a significant relationship with bobcat depredation. For every one unit increase in park area and cropland, coyote depredation decreases by 0.32, and 0.46, respectively (Table 1). For every one unit increase in grazing, bobcat depredation increased by 0.55 (Table 2).



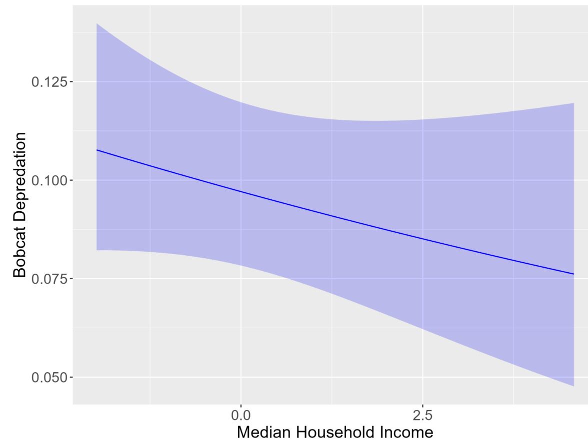


Figure 6: Relationship between coyote depredation (left) and bobcat depredation (right) and area median income. Median income only had a statistically significant relationship with coyote depredation.

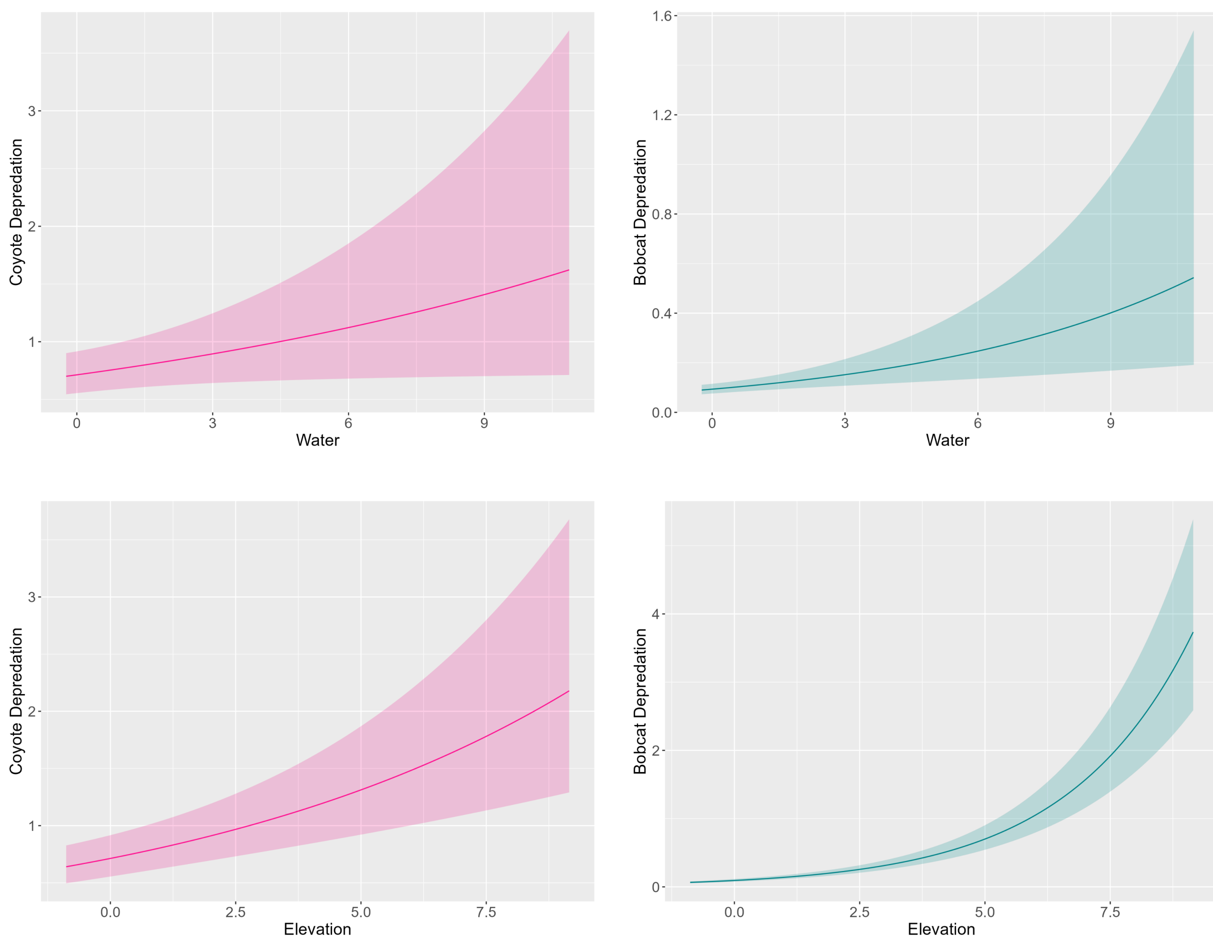
Median income had a significant positive relationship with the likelihood of reported coyote depredation, but not with the likelihood of reported bobcat depredation. For each one unit increase in median income, there was a 0.33 increase in likelihood of reported coyote depredation. In 2022 there was the highest likelihood of reported coyote depredation, while in 2021 and 2022, there was the highest likelihood of reported bobcat depredation compared to the other years (Figures 11 and 12). In 2020, there was the lowest likelihood of reported coyote depredation, while in 2019 and 2023, there was the lowest likelihood of reported bobcat depredation (Figures 11 and 12).

Abundance Model Results

Table 3: Abundance model results for coyote and bobcat depredation, with significance codes.

Coyote Abundance Results				
	Estimate	**SE**	**z**	**P(>|z|)**
(Intercept)	-0.3378731	0.12784761	-2.64278	**8.22E-03
Water	0.07558202	0.03682584	2.052418	*4.01E-02
Elevation	0.12198456	0.02584102	4.720578	***2.35E-06
NDVI	0.32656805	0.02822435	11.570438	***5.82E-31
cropland	-0.25298016	0.04632818	-5.460611	***4.74E-08
parkarea	-0.1137215	0.03097329	-3.671599	***2.41E-04
Bobcat Abundance Results				
	Estimate	**SE**	**z**	**P(>|z|)**

(Intercept)	-2.3691711	0.10562105	-22.430861	***1.97E-111
Water	0.1617871	0.04830483	3.349295	***8.10E-04
Elevation	0.4027003	0.01895301	21.247305	***3.49E-100
NDVI	0.4286259	0.03331186	12.867064	***6.90E-38
grazing	0.3957576	0.01965723	20.132931	***3.80E-90
Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1				



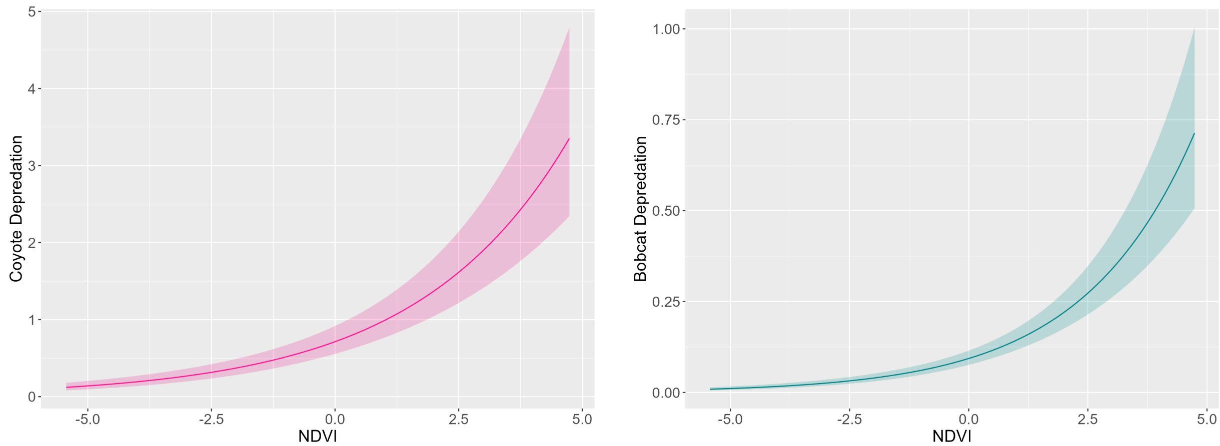


Figure 7: Relationship between coyote depredation (left) and bobcat depredation (right), comparing covariates from the abundance model: water, elevation, and NDVI. All three covariates were significant for both species in the occupancy and abundance models.

Abundance of depredation events for both species has a significant positive relationship with water, elevation and NDVI. As water increases by one unit, abundance of coyote depredation increases by 0.08 and abundance of bobcat depredation increases by 0.16. As elevation increases by one unit, abundance of coyote depredation increases by 0.12 and abundance of bobcat depredation increases by 0.40. As NDVI increases by one unit, abundance of coyote depredation increases by 0.33 and abundance of bobcat depredation increases by 0.43.

Grazing was only significant for bobcat depredation, for every one unit increase in grazing, bobcat depredation abundance increases by 0.40. Cropland and park area covariates had a significant negative relationship with abundance of coyote depredation events. As cropland increases by one unit, abundance of coyote depredation events decreases by 0.25. As park area increases by one unit, abundance of coyote depredation events decreases by 0.11.

Multivariate Regression Model Results

Table 4: Results of the multivariate regression model for coyote depredation.

lm(formula = PC_2019 + PC_2020 + PC_2021 + PC_2022 + PC_2023 ~ Median_Income + Water + Elevation + PopulationMean + NDVI + park_area + graze_area + crop_area, data = coyote_glm)				
Residuals:				
Min	1Q	Median	3Q	Max
-0.4126	-0.135	-0.0925	-0.053	3.7696
Coefficients:				
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.03941	0.014838	-2.65601	**0.007923
Median_Income	9.04E-07	1.10E-07	8.186896	***3.09E-16
Water	0.099624	0.046383	2.147876	*0.031753
Elevation	0.000107	1.64E-05	6.521896	***7.36E-11
PopulationMean	-8.67E-07	1.71E-06	-0.50832	0.611242
NDVI	0.265109	0.041024	6.462274	***1.09E-10
park_area	-0.15135	0.036147	-4.18705	***2.86E-05
graze_area	0.051146	0.029053	1.760411	0.078376
crop_area	-0.1041	0.026975	-3.85921	***0.000115
Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1				
Residual standard error: 0.3491 on 8048 degrees of freedom				
Multiple R-squared: 0.03016, Adjusted R-squared: 0.0292				
F-statistic: 31.29 on 8 and 8048 DF, p-value: < 2.2e-16				

Table 5: Results of the multivariate regression model for bobcat depredation.

lm(formula = P_2019 + P_2020 + P_2021 + P_2022 + P_2023 ~ Median_Income + Water + Elevation + PopulationMean + NDVI + park_area + graze_area + crop_area, data = bobcat_glm)				
Residuals:				
Min	1Q	Median	3Q	Max
-0.761	-0.0673	-0.0195	0.0158	4.3567
Coefficients:				
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.11981	0.012278	-9.75824	***2.26E-22
Median_Income	-1.31E-07	9.13E-08	-1.43276	0.151966
Water	0.219705	0.038381	5.724317	***1.08E-08
Elevation	0.000244	1.35E-05	17.9941	***5.27E-71

PopulationMean	2.09E-06	1.41E-06	1.480331	0.138824
NDVI	0.408696	0.033947	12.03928	***4.25E-33
park_area	-0.01946	0.029911	-0.65047	0.515408
graze_area	0.456759	0.024041	18.99914	***9.02E-79
crop_area	-0.06231	0.022321	-2.79166	**0.005256
Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1				
Residual standard error: 0.2889 on 8048 degrees of freedom				
Multiple R-squared: 0.1496, Adjusted R-squared: 0.1488				
F-statistic: 177 on 8 and 8048 DF, p-value: < 2.2e-16				

The regression model showed a significant positive relationship between median income, water, elevation, and NDVI for proportion of coyote depredation events. The proportion of coyote depredation had a significant negative relationship with park area and crop area. The same regression model for proportion of bobcat depredation events found a significant positive relationship with covariates water, elevation, NDVI, and grazing. The only result from the regression model that was different from the occupancy model was the relationship between bobcat depredation and crop area. The occupancy model did not find a significant relationship between bobcat occupancy and crop area, but the regression model found a significant negative relationship between proportion of bobcat depredation and crop area with a p-value of 0.00525.

Discussion

Where is conflict happening throughout the state?

The occupancy model, abundance model, and multivariate regression model all showed nearly identical results between the covariates of interest and depredation events for coyotes and bobcats. The occupancy and abundance models found that as water, elevation, and NDVI increase across each site, so do depredation events caused by both species. In contrast, as park area and cropland area increase across sites, coyote depredation decreases. Furthermore, as grazing area increases across sites, bobcat depredation increases.

Similar results across all three model types makes this analysis more robust, and emphasizes the potential that citizen reported data use has in predation risk modeling. It also provides an opportunity to investigate the circumstances where results did not match up. In the occupancy and abundance models, crop area was not a significant variable for bobcat depredation, however it was a significant variable in the regression model. Two studies analyzing the relationship between environmental variables and carnivore predation found that agriculture was not a significant variable for predation events (Klees van Bommel et al., 2020; Treves et al., 2004).

The multivariate regression looked at the ratio of depredation events to total conflict, which means that it is possible that total conflict is driven by cropland, but would require further investigation to be sure. This covariate should continue to be of interest as drivers of conflict may change as the urban-wildlife interface increases.

As predicted, higher rates of conflict (depredation) are happening where there is water availability and higher levels of greenness. Areas with these features are where people like to build homes, or take part in recreational activities, an overlap in preferred habitat by humans and wildlife that leads to conflict. As seen in Chicago, coyotes preferred habitat at the edge of urban areas that fit a particular niche: water availability, vegetative cover, and low development (within populated areas). While coyotes are adaptive, they have a preference for this type of habitat. Public parks and agriculture had a negative relationship with coyote depredation. Agricultural areas tend to be at low elevation, and have low levels of vegetative cover, so it stands to reason that coyote depredation would decrease in these areas. Public parks tend to have vegetated areas, but it is possible that there is not enough food or prey availability in parks for coyotes compared to other areas that are nearby parks such as neighborhoods. Bobcat depredation is more likely to occur in areas with livestock grazing, which aligns with the previously referenced study that found bobcats prefer mammalian prey (Larson et al., 2015).

From analysis of the latitude and longitude of coyote and bobcat depredation, this high level of conflict is taking place throughout the state of California, in heavily forested areas, around urban areas, along the coast, and in the desert. Depredation caused by coyotes is more likely to occur in areas with water availability, higher elevation, and high vegetative cover. Depredation is less likely to occur in areas that have higher levels of cropland and public park space. Depredation caused by bobcats is also likely to occur in areas that have water availability, high elevation, high vegetative cover, and grazing land. This means that the data shows where the highest level of conflict is occurring. It occurs elsewhere throughout the state, but these covariates are statistically significant.

Is there a time when there is more conflict?

In Figure 4, there is a trend in coyote depredation over the five year period, with a spike in reported depredation starting in late Spring, to late Summer. Bobcat depredation reports do not follow the same trend, and are relatively stagnant throughout the year. There are potential ecological explanations for this, considering denning for coyotes occurs from mid-March to mid-May, and there are bigger pups to feed during the summer months (Sacks, 2005). This also coincides with a high period of recreation and outdoor time in the state of California. People spend more time outside, and may be more assured to allow their domestic pets outside as well, which makes them vulnerable to fall prey to local mesopredators.

As this data is citizen science derived, it is hard to make conclusions as to why there are patterns over time, without further statistical analysis and controlled data collection. Further exploration is needed to be able to substantiate the patterns. In terms of application, this means that communities that have high incidents of coyote sightings are likely going to be more at risk of depredation at the end of Spring and throughout the Summer, so state wildlife agencies can take further precautionary measures in those areas to educate communities.

The data in this analysis was reported from 2019 to 2023, during the COVID-19 pandemic, which had an effect on people's day to day lives. California went into lockdown in early 2020, which is the year that shows the lowest rate of coyote depredation probability in Figure 11 (Jenkins et al., 2021). In 2020, people spent more time at home, and a large majority of the workforce shifted to full remote. This meant more time at home with family and domestic animals, and we know that coyotes exhibit selective behavior that avoids areas that have higher population density (Gehrt et al., 2011). It's possible that there were fewer rates of depredation during this time period because people were generally in and around their homes, creating an environment with too much human presence, making it too risky for coyotes to predate.

Bobcat depredation probability was highest in 2021 and 2022, the two years following the lock down COVID-19 restrictions (Kupfer et al., 2021). It is hard to draw significant conclusions that will predict future temporal trends in the data. A study on wildlife mortality during the pandemic found that incidents of large mammals killed in vehicle collisions decreased in early 2020 during the COVID lockdown in California (Shilling et al., 2021). If wildlife vehicle collisions decreased in 2020, wildlife population numbers may have increased in 2021 and 2022, leading to higher competition for resources, and more depredation events by bobcats. A study using iNaturalist observations before and during the pandemic found that mountain lions changed behavior by venturing further into urban areas during the pandemic, but the results showed coyotes and bobcats did not change behavior in urban areas (Vardi et al., 2021).

What is driving conflict with mesopredators?

From the results of our occupancy models, there are different drivers of conflict for coyotes compared to bobcats. The biotic drivers of conflict for coyotes are greenness (NDVI), park area, and crop area. The abiotic drivers of conflict for coyotes are water and elevation. The biotic drivers of conflict for bobcats are greenness (NDVI) and grazing area. The abiotic drivers of conflict for bobcats are water and elevation. As water, elevation, and NDVI increase, so does abundance of depredation events for both species.

Water availability and greenness (NDVI) are two covariates that have a significant positive relationship with depredation events for both species, and are outcomes that were predicted. Elevation has a significant positive relationship with depredation events for both species, but was not predicted. Studies on behavior for coyotes and bobcats demonstrated that both species prefer less developed, more vegetative areas (Gehrt et al., 2011; Ruell et al., 2012). Areas with water, elevation, and greenness happen to be where both humans prefer to be as well, whether it is for recreation or building a home. We know that coyotes and bobcats are habitat generalists that are able to reside in dense urban areas, but prefer urban edge. Communities at the urban edge have food sources that are included in coyote diet: domestic animals, garbage, domestic gardens, wild animals, and pet food (Gese et al., 2012), as well as food sources preferred by bobcats: rodents, birds, and other wild prey (Larson et al., 2015). This means that areas in California that are close to water sources, higher elevation, and have high levels of green cover can be the focus of Wildlife Watch, and other programs that monitor the area for predator species, to make sure the community is protected.

The analysis shows that as park area and crop area increase, coyote depredation decreases. Areas with cropland may have lower coyote depredation due to the fact that there is often less vegetative cover, less human activity, and therefore less food and prey availability. However, it is surprising that areas with more public park space would have decreased coyote depredation events, as these are higher in greenness. Further analysis is necessary to understand these relationships, but park areas have less food availability for coyotes compared to the edge of urban areas. Park area and cropland were not significant covariates for bobcat depredation in any of the models for this analysis. For the time being, wildlife agencies can continue to focus coexistence efforts in areas with high water, elevation, and NDVI.

Median income has inverse effects on coyote and bobcat depredation, meaning as income increases, coyote depredation increases, but bobcat depredation decreases. However, the relationship is only statistically significant for coyotes. There are a few possible explanations for this. It is possible that median income is only statistically significant for coyotes because coyotes are more social animals, which leads to more brazen behavior with and around humans. Because coyotes are pack animals, they may feel more comfortable predating in urban areas than bobcats, who are more solitary animals. Wildlife Watch may consider conflict programs in areas where there is higher median income, to educate residents about coyote depredation and conflict.

How can we use this information to reduce conflict?

The California Department of Fish and Wildlife is continuing to collect this citizen science data on all manner of predators within the state (including the species in this study), coyotes, bobcats, bears, mountain lions, and wolves. Our analysis of the relationship between depredation events with coyotes and bobcats can help California Department of Fish and Wildlife to decide where to focus actions focused on mitigating conflict, and educating communities about how to protect their pets and livestock from depredation. Because water, NDVI and elevation are both positively correlated with depredation events for both species, areas in California at higher elevation with more vegetation and water can be prioritized for education programs. Grazing area was significant for bobcat predation events, Wildlife Watch can also include regions in California with higher levels of livestock grazing to educate farmers how to protect their domestic animals from bobcats.

Occupancy models are a novel method for analysis that can be employed to understand the drivers of depredation, given the growing portfolio of data that the state has. The overlapping significance in the results demonstrates the power of citizen reported data. Models that simulate changing ecological pressures such as fire regimes and other dynamic covariates such as population growth and urbanization will continue to be useful predictors of conflict (Spencer et al., 2011). Research that broadens our understanding of predator response to evolving built environments, and predator population dynamics over time will continue to improve wildlife management impact (Schmidt et al., 2023).

Conclusion

Future research

Human-wildlife conflict is a conservation challenge that will continue to grow as urban areas expand into natural habitat. Research that looks at ecological and socio-ecological drivers of conflict, including the perception of risk and how it factors into decisions to reduce wild predator populations will continue to advance our understanding of these dynamic relationships (McInturff et al., 2021). Occupancy models are a useful tool for wildlife managers to understand evolving pressures and changing predator populations. Models that simulate changing ecological pressures such as fire regimes and percent cover, along with changing socio-ecological pressures such as population growth and urbanization will continue to be useful methods of analysis for wildlife managers and policy makers in charge of wildlife protections (Spencer et al., 2011). As climate change continues to impact landscapes and ecosystems, multi-site and multi-scale analysis will aid in our understanding of ecosystems and how they respond to such changes (Schmidt et al., 2023).

It is encouraging to see studies conducted with the goal of confirming novel methods of data interpretation as in Nagy et al.'s 2012 research on coyote occupancy in New York City. Many wildlife agencies have reporting systems in place to track predation reports, and other incidents that humans have with wildlife. As the world's population continues to grow, and the likelihood of human-wildlife interaction increases, these databases have the potential to continuously improve the effectiveness of wildlife management. Future studies will continue to conduct research that examines the human-wildlife interface, to inform how citizen science data can be used most effectively. Other future research that ties into this space will explore what effective wildlife management strategies look like in an increasingly urbanized world.

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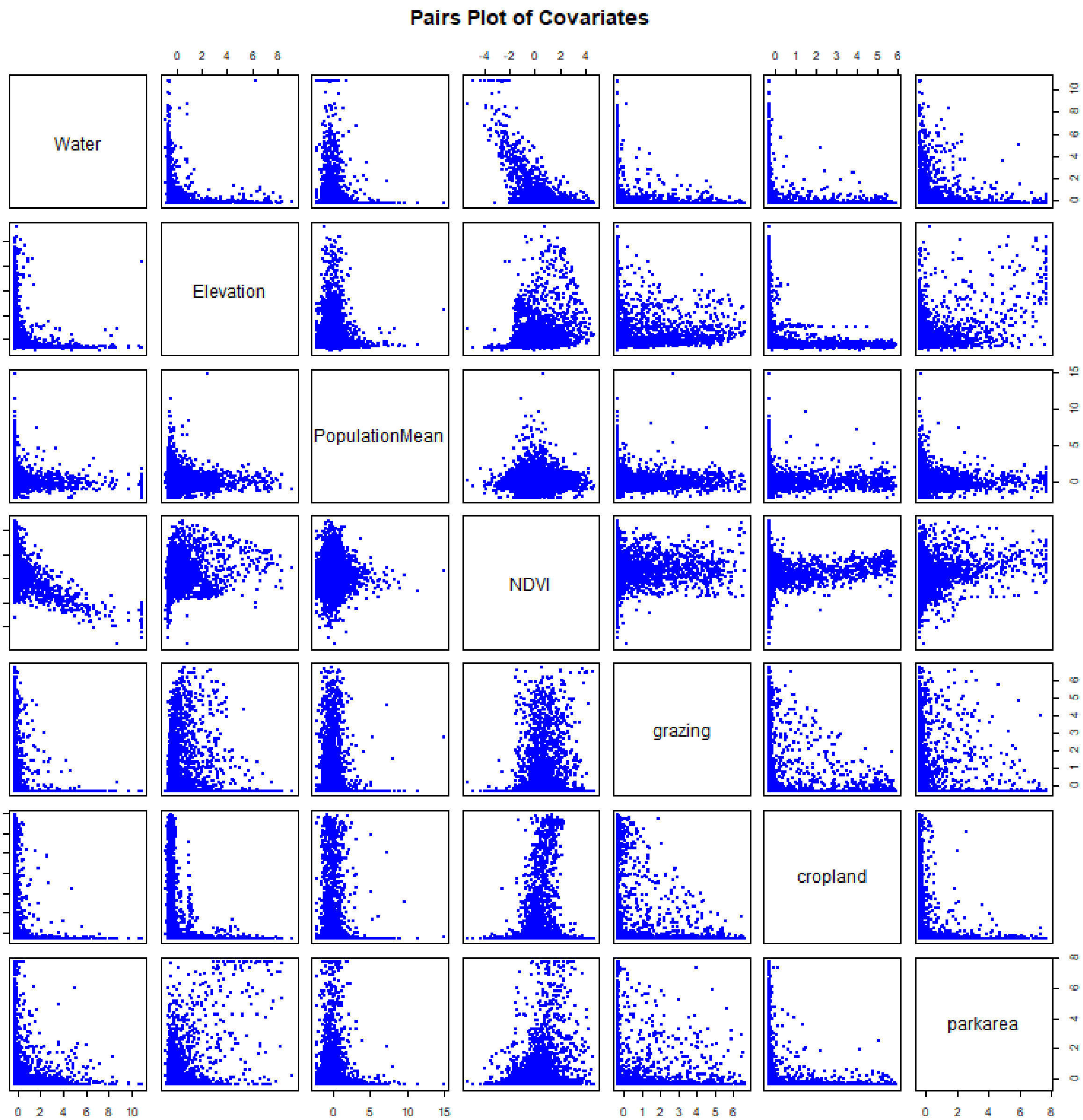

Figure 8: Relationships between covariates: water, elevation, human population mean, NDVI, grazing, cropland, and park area.

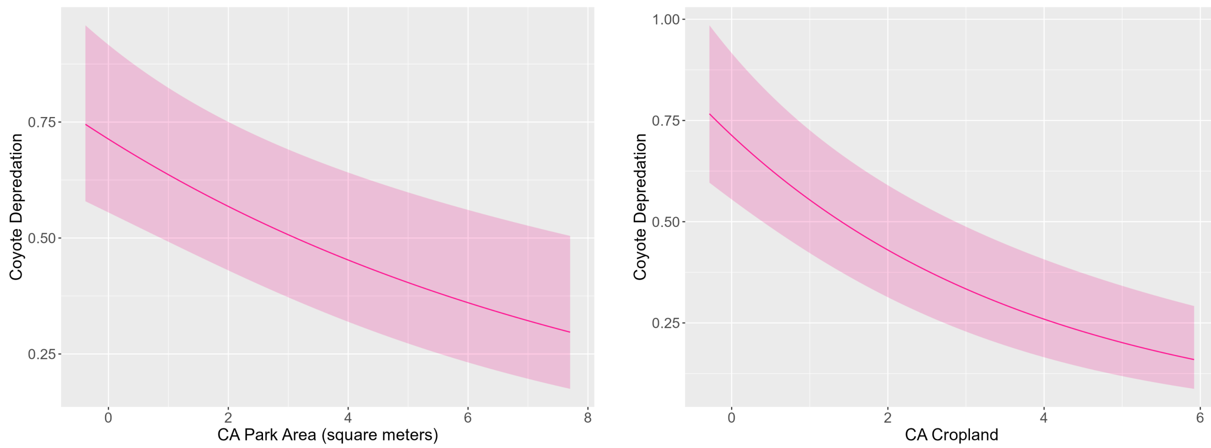

Figure 9: Relationship between abundance of coyote depredation with park area (left) and cropland (right).

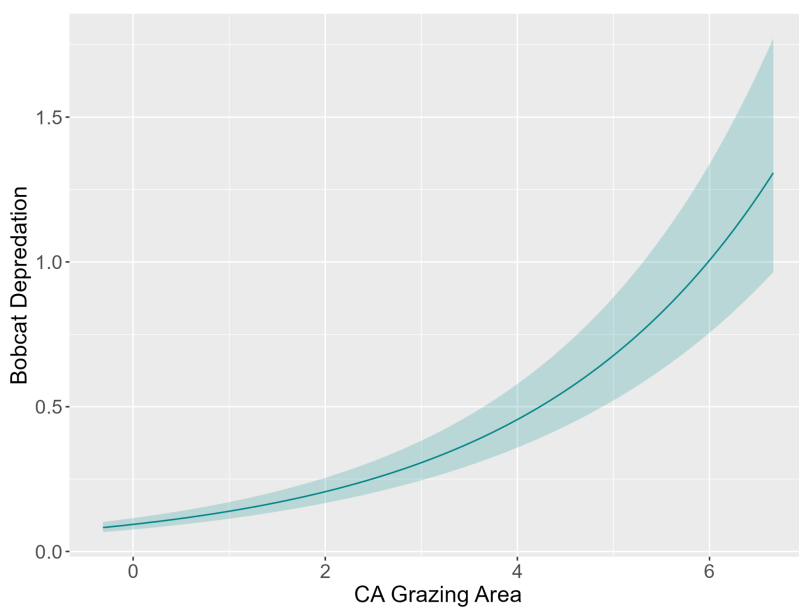

Figure 10: Relationship between abundance of bobcat depredation and grazing.

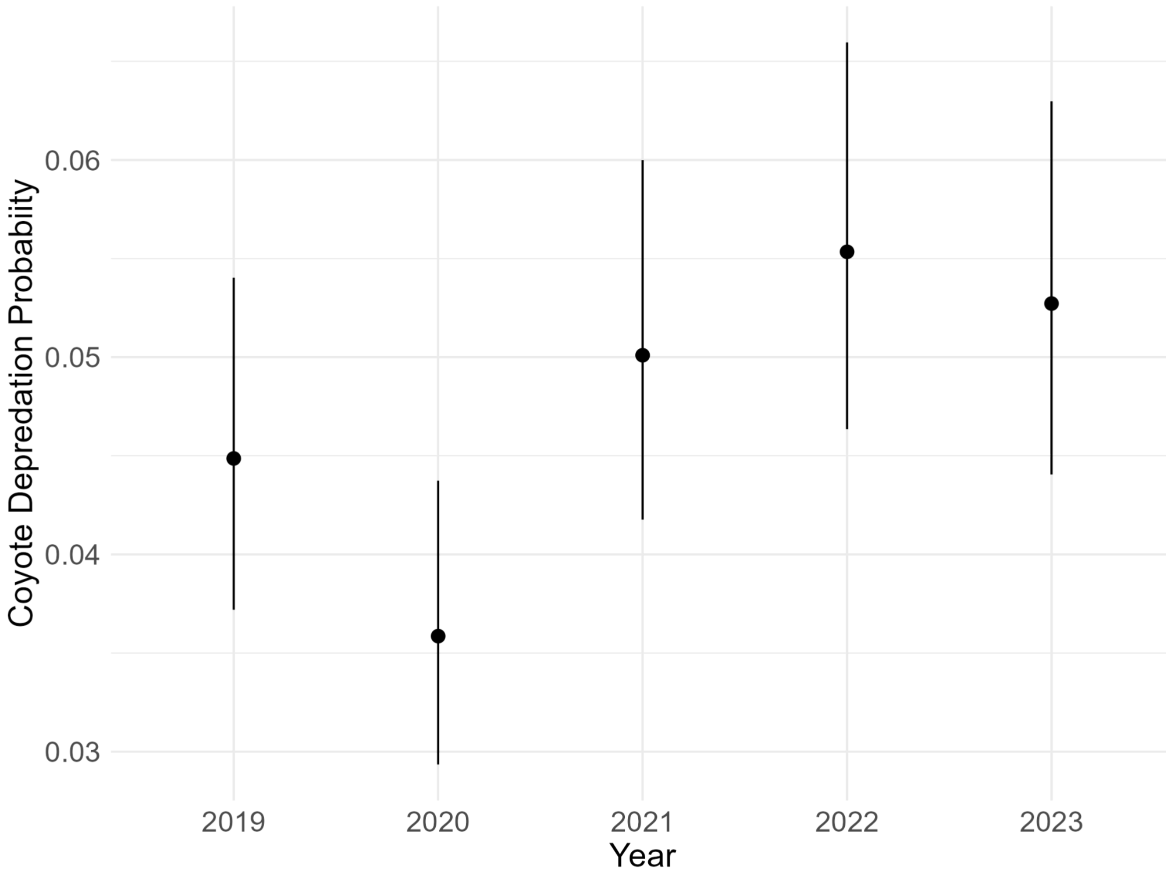

Figure 11: Probability of coyote depredation over the five year period from 2019 to 2023.

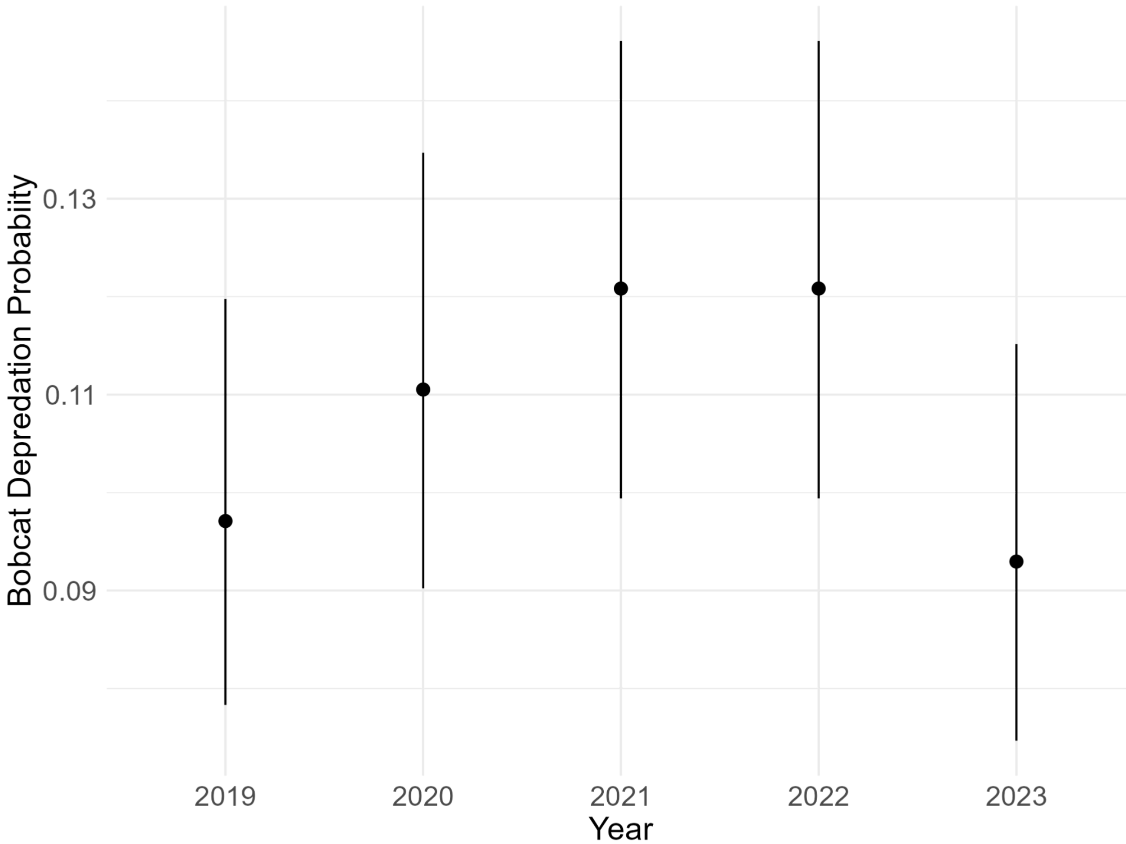

Figure 12: Probability of bobcat depredation over the five year period from 2019 to 2023.

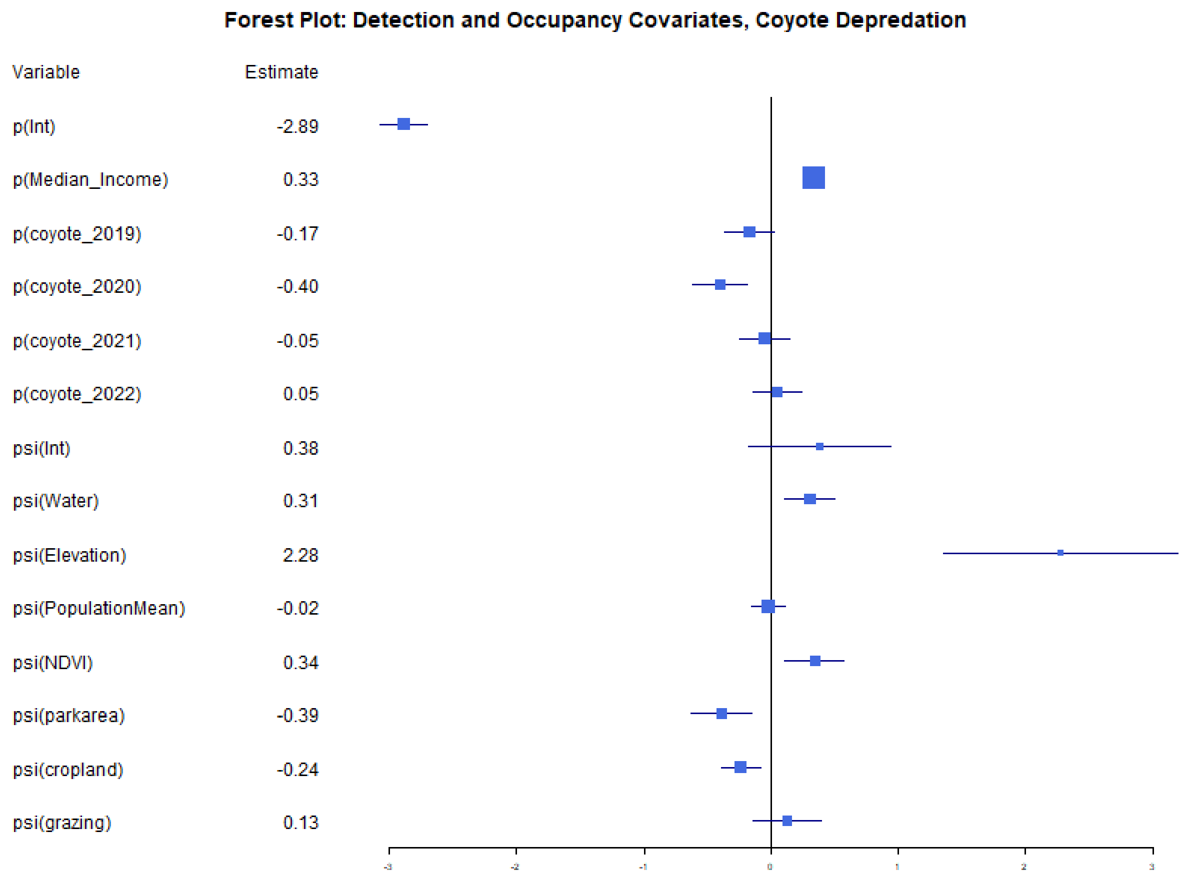

Figure 13: Forest plot of all covariates for the coyote occupancy model with a 95% confidence interval. Observation level covariates are median income and year. Site level covariates are water, elevation, population mean, NDVI, park area, cropland, and grazing.

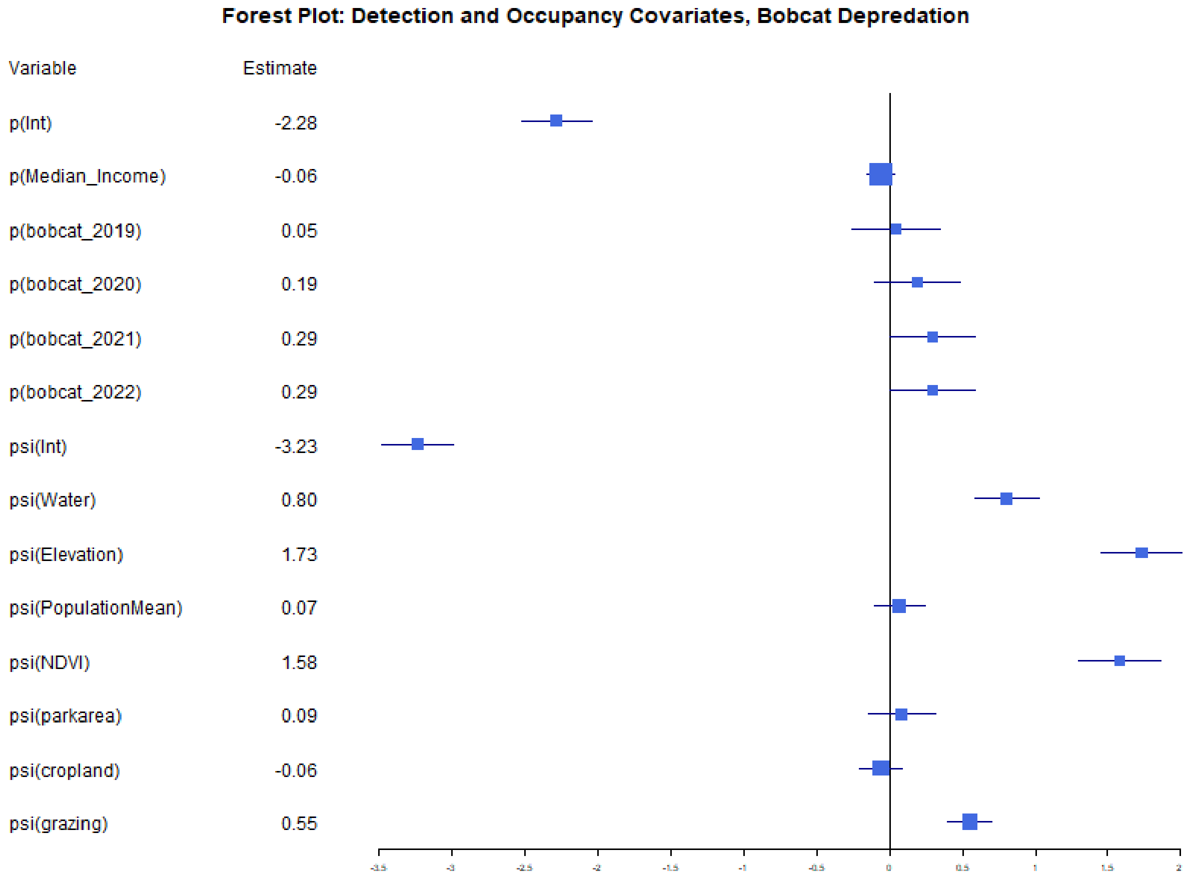

Figure 14: Forest plot of all covariates for the bobcat occupancy model with a 95% confidence interval. Observation level covariates are median income and year. Site level covariates are water, elevation, population mean, NDVI, park area, cropland, and grazing.