Neighborhood Ethnicity is Related to Occupancy of Mammals Across a Diverse Metropolitan Area

by

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ABSTRACT

More people live in cities or metropolitan areas than ever before, which encompass many types of urbanization. These areas are culturally diverse and densely populated heterogeneous landscapes that are shaped by socio-ecological patterns. Cities support human and wildlife populations that are influenced indirectly and directly by human decisions. This process can result in unequal access to environmental services and accessible green spaces. Additionally, biodiversity distribution is influenced by human decisions. Although neighborhood income can drive biodiversity in metropolitan areas (i.e., the 'luxury effect'), other socio-cultural factors may also influence the presence and abundance of wildlife beyond simple measures of wealth. To understand how additional social factors shape distributions of wildlife, I ask, are patterns of wildlife distribution associated with neighborhood ethnicity, in addition to income and ecological landscape characteristics within metropolitan areas? Utilizing data from 38 wildlife cameras deployed in neighborhood public parks and non-built spaces in metro Phoenix, AZ (USA), I estimated occupancy and activity patterns of coyotes (*Canis latrans*), desert cottontail rabbits (*Sylvilagus audubonii*), and domestic cats (*Felis catus*) across gradients of median household income and neighborhood ethnicity, estimated by the proportion of Latinx residents. Neighborhood ethnicity appeared in the top models for all species, and neighborhood % of Latinx residents was inversely associated with presence of native Sonoran Desert animals (coyotes and cottontail rabbits). Furthermore, daily activity patterns of coyotes differed in neighborhoods with higher vs. lower proportion of Latinx residents. My results suggest that socio-cultural variables beyond income are associated with wildlife distributions, and that factors associated with neighborhood ethnicity may be an informative correlate of city-wide ecological patterns. In this research, I unraveled predictive social variables and differentiated wildlife

distribution across neighborhood gradients of income and ethnic composition, bringing attention to the potentially unequal distribution of mammals in cities.

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INTRODUCTION

More than half of the global human population now lives in metropolitan areas, and it is projected that this trend will continue in the coming years (United Nations 2018). Urbanization is characterized by rapid and widespread land use and land cover change that fragments wildlife habitat into distinct heterogenous landscapes, threatening biodiversity conservation and ecosystem service provisioning (Alberti & Marzluff 2004; Aronson et al. 2016; Cincotta et al. 2000; Grimm et al. 2008; Moll et al. 2019; Scalenghe & Marsan 2009). Historical and systemic forces, such as racism and classism, have also separated people geographically across metropolitan areas, resulting in unequal access to ecosystem services, tree cover and green spaces, and weakens resident connections with nature (Locke et al. 2021; Turner et al. 2004). Although distributions of wildlife populations are shaped by the degree of urbanization (Aronson et al. 2014; Lepczyk et al. 2017; Lerman et al. 2021; McKinney 2008), it is less clear how wildlife distributions in metro areas are influenced by social factors such as income and race. When metropolitan areas support biodiversity and positive human connections, they enhance sustainability and wellbeing, and thus better ensure a just and biodiverse future (Apfelbeck et al. 2020; Carter et al. 2014; McPhearson et al. 2016; Pickett et al. 2016). Despite habitat loss within metropolitan areas, residential properties and greenspaces – particularly moderately developed suburban areas – can support diverse wildlife communities, especially of species that have adapted to utilize residential properties (Lerman & Warren 2011; McKinney 2002).

Residential landscapes are social-ecological systems that include neighborhoods of people with diverse lifestyles and values, as well as vegetation, wildlife, and other geographic and biophysical elements that shape wildlife habitat and resident experiences with nature (Cook et al. 2012; Larson et al. 2010; Roman et al. 2018). Across metropolitan areas, population density and impervious surfaces (e.g., roads, buildings) are strongly associated with habitat availability and wildlife distribution across levels of urbanization (Shochat et al. 2010). Within residential areas with similar levels of urbanization, social factors affect the quality of habitat for many wildlife species, which can shape wildlife distributions (Hope et al. 2006; Loss et al. 2009; Luck et al. 2013; Magle et al. 2016). For example, the wealth of residents is often positively related to tree cover (Clarke et al. 2013) and biodiversity across many taxa (Ackley et al. 2015; Chamberlain et al. 2019; Davis et al. 2012; Leong et al. 2018; Li et al. 2019), and has been termed "the luxury effect" (Hope et al. 2003). The richness of medium to large-bodied mammals across cities also increases with wealth to various extents across US cities, while diversity strongly decreases with urban intensity (Magle et al. 2021), suggesting that other social variables are likely important for predicting mammal distributions. Mechanistic explanations are not always apparent for the luxury effect, and this pattern may be related to wealthier residents' ability to control landscaping or move to areas with more vegetation, homeowner preferences for vegetation and certain plant traits, and cultural legacies of landscape choices (Larsen & Harlan 2006; Larson et al. 2010; Locke & Baine 2015; Martin et al. 2004; Mennis 2006). As wealth is an informative predictor of tree cover and wildlife distributions, it appears to be more important in some ecosystems than others, such as in drylands where biota is dependent on water provisioning (Chamberlain et al. 2020). The composition of vegetation and thus wildlife habitat influences wildlife species in neighborhoods (Belaire et al. 2014). Notably, "luxury" is not a universal term, and having more vegetation and wildlife in a neighborhood is not always perceived as positive by residents, and the term does not describe the relationship with wealth for all species.

Although the luxury effect can help researchers understand wildlife distributions across residential landscapes, wealth alone is insufficient to explain the social drivers of wildlife distribution where other social forces in addition to income, such as culture and segregation, shape neighborhood structure and function (Kuras et al. 2020; Schell et al. 2020). While income often positively correlates to metrics of biodiversity, such as species richness, other measurements of biodiversity and study design highly influence the presence of a relationship (Kuras et al. 2020). Complex and systemic human patterns, such as systemic racism and classism result in inequities in the heterogeneous landscapes of neighborhoods, leading to ecological consequences for humans and wildlife (Schell et al. 2020). Often the inequities of the landscape results in environmental injustices for minority residents (Schell et al. 2020). The relationship between ethnicity and ecological patterns is a timely topic, as racial segregation is still prevalent across the United States. Significant levels of segregation of white and minority residents (mostly Black, Hispanic/Latinx, Asian) is widespread, and white residents tend to live in majority white neighborhoods (Frey 2021a). Notably, racial segregation of neighborhoods prevails even when similar levels of income are present across ethnic groups (Reardon et al. 2015). For example, middle-class Latinx and Black residents typically live in poorer neighborhoods (census tracts with lower than the median household yearly income) than white residents of the same income level (Reardon et al. 2015). And poor white residents live in neighborhoods with higher average incomes (Reardon et al. 2015). The reasons for this are linked to preferences of residents and remnants of unequal housing practices (Reardon et al. 2015), such as the discriminatory practice of redlining. This is the historical practice of denying residents of neighborhoods housing loans based upon their perceived risk of investment, centered around the race of residents (Jesdale et al. 2013). Regarding ecological patterns and ethnicity in cities, people of color often experience unequal access to ecosystem services and more frequent disservices. For example, minoritized neighborhoods often have less tree cover (Locke et al. 2019; Watkins & Gerrish 2018), are more exposed to air and water pollutants (Grineski et al. 2007; Tessum et al. 2019), often have less access to safe (risk to hazards and crime) greenspaces (Rigolon 2016; Rigolon & Németh 2021), and experience more intense urban heat island effects (Hoffman et al. 2020; Hsu et al. 2021; Jesdale et al. 2013; Wilson 2020). Notably, cities in the Southwest United States show some of the largest heat differences in redlined neighborhoods (Hoffman et al. 2020). The quality and type of wildlife habitat is likely impacted by these systemic differences in neighborhoods related to the ethnic composition of residents.

Ethnicity in neighborhoods is a social variable that relates to socio-ecological relationships regarding wildlife distributions. For example, low income and Latinx neighborhoods are associated with fewer native bird and plant species (Kinzig et al. 2005), while higher income and lower levels of Latinx residents are related to desert adapted vegetation and xeric style landscaping types (Warren et al. 2019). Residential landscapes function as wildlife habitat, and are maintained by residents with preferences that are dependent on social factors such as culture, education, and time spent living in a region (Arreola 2012; Larsen & Harlan 2006; Larson et al. 2009; Martin 2015; Zhou et al. 2009). Although minority and low-income neighborhoods often have a negative relationship with bird and plant species, it is not known if similar patterns are seen in taxa like mammals. Additionally, ethnicity is closely related to income, making the disentanglement of ethnicity difficult. Including ethnicity in ecological models in addition to income may provide informative predictions of urban mammal ecological patterns. By integrating human social patterns that have not been explored, it may improve predictive models and inform management of mammal populations in urban landscapes.

Similar to many taxa, global mammal populations are in a decline and mammal diversity is often negatively associated with increased levels of urbanization; however, neighborhoods still support mammal biodiversity (Ceballos & Ehrlich 2002; McCleery 2010). Several groups of native and non-native mammals have developed strategies to adapt to habitats in neighborhoods throughout the United States. Those adaptions vary depending on factors such as the life history, behavior, and ecology of the species (Santini et al. 2019). For example, some medium-bodied mammals have been able to exploit the resources within heterogeneous neighborhoods by adapting their diets and shifting their activities to smaller home ranges and different times of day to avoid human conflict (Gallo et al. 2022; Gehrt et al. 2009). While changes in daily activity of species is dictated by environmental and innate forces, typically species exhibit a shift from their natural activity patterns (nocturnal, crepuscular, diurnal) to increased nocturnality in human disturbed landscapes (Gaynor et al. 2018). Native North American mammal species, and taxa like coyote (*Canis latrans*) and rabbits (*Sylvilagus* spp.) may occur at moderate levels of urbanization, emphasizing the importance of urban greenspaces (areas with vegetation; Fidino et al. 2021; Gallo et al. 2017; Parsons et al. 2018) and therefore the impacts of social factors that influence the features of the greenspaces. Rabbit species tend to rely on vegetation and cover for food and avoidance of native and non-native predators in neighborhoods (Chapman & Willner 1978; Paul & Friend 2020). Coyotes often utilize neighborhoods, but tend to avoid spaces with high levels of impervious surfaces and will use corridors, such as washes and small patches of green space within their large home ranges (Atwood et al. 2004; Gehrt et al. 2009; Gese et al. 2012, 2012; Grubbs & Krausman 2009). Along with native mammals, the presence of non-native free-ranging domestic cats is driven by humans in residential landscapes. Domestic cats impact wildlife communities through direct predation and injury, disease transmission, native species extinctions, the death of billions of wild animals, and indirectly create an 'ecology of fear' or fear of predation in other species such as lagomorphs (Elizondo & Loss 2016; Loss et al. 2013; Loyd et al. 2017). Mammal species have relationships at the regional scale, and decreasing diversity is common across gradients of increasing urbanization. While regional patterns are informative, mammal species in neighborhoods of similar urbanization levels may be impacted by social patterns other than income that influence their spatial distributions and activity patterns.

In this research, my objective was to investigate the relationship between ethnicity and mammal species' spatial distributions and daily activity within neighborhoods, independent of income levels. I investigated the relationship between the ethnicity of residents and the occupancy and daily activity patterns of mammals within neighborhoods in the semi-arid Phoenix metropolitan area (Arizona, USA). I hypothesized that social variables other than income relate to mammal ecological patterns, and that ethnicity is an informative predictor of mammal occupancy and activity within neighborhoods. To test these hypotheses, I utilized an array of motion triggered wildlife cameras in neighborhood parks and greenspaces across gradients of median neighborhood household income and the proportion of residents who identified as Latinx in the Phoenix metro area. I conducted single-season-single-species occupancy models and evaluated the effect and importance of 2 social covariates (neighborhood median household income and % of Latinx residents) and 3 landscape covariates (impervious surfaces, normalized difference vegetation index or NDVI, and presence of water). Additionally, I investigated potential shifts in daily activity patterns between higher and lower income and Latinx levels of neighborhoods. Studying mammals in the Phoenix metro area can offer much needed insight to socio-ecological patterns in neighborhoods.

METHODS

Study Area

I tested my hypotheses in community parks and open spaces in, or adjacent to, moderate-density residential neighborhoods where most residents live within the Phoenix metropolitan area and within the boundaries of the Central-Arizona Phoenix Long Term Ecological Research area (CAP LTER). These sites are in Maricopa County of Arizona, United States within the lower Colorado River Basin of the Sonoran Desert. The landscape of the metro area comprises residential and industrial/commercial areas, transportation corridors, crop lands, desert parks, hundreds of public community parks, and >1,400 artificial water bodies that sustain a desert "oasis" by irrigation from the Colorado, Verde, and Salt rivers (Bradley & Colodner 2020; Larson et al. 2009). Neighborhood parks and greenspaces typically contain grassy sports fields or playgrounds in addition to grass, trees, and other shrubs that support storm runoff (Lara-Valencia & Garcia-Perez 2018). These urban greenspaces are used by residents for recreation and are also expected to be used by wildlife seeking cover and resources (Haight et al. in preparation 2022, Gallo et al. 2017).

The study area comprises highly populated sprawling cities, and population trends have surpassed the growth of any other US city in the past decade (Hing 2020; Keys et al. 2007). Of this growing population, many residents identify as Hispanic or Latinx, and like other US cities, Latinx-majority neighborhoods are common (Arreola 2012; Lara 2012). Wealth disparities exist throughout the area as well with a median household income of $67,799 (US Census 2021). The metro Phoenix was also the first area that the luxury effect was observed (Hope et al.

2003). The racial/ethnic composition of the metro area includes 53.4% white residents, 32.0% Hispanic, 6.7% Black or African American, 4.8% Asian, and 3.3% two or more races, 2.9% American Indian and Alaska Native, 0.3% Native Hawaiian and other Pacific islander (US Census Bureau 2021). The Latinx community within metro Phoenix is diverse but dominated by people of Mexican (89%) or Puerto Rican (1.9%) heritage (Pew Research Center 2016). Like in other metropolitan areas in the US, neighborhoods within metro Phoenix have a history of segregation driven by redlining and other discriminatory policies that led to settlement of non-white residents (commonly Black and Latinx) into less desirable, more industrial landscapes than white residents (Bolin et al. 2005; Mapping Inequality 2022). Although understudied in this region, the social-ecological legacies of such actions may be long lasting (Grove et al. 2018). Varying from national patterns, access to public parks in metro Phoenix neighborhoods is relatively equitable, with similar density of parks in Latinx and lower income neighborhoods compared to dominantly White and upper income neighborhoods (Lara-Valencia & Garcia-Perez 2018; Wen et al. 2013). However, parks in Latinx neighborhoods tend to have less tree-cover and natural features, and more features such as grills, sports facilities etc., while non-Latinx neighborhoods tend to have more natural features (Lara-Valencia & Garcia-Perez 2018).

Site Selection

I estimated the occupancy and activity patterns of wildlife during June-September 2019 and 2021 in public parks and greenspaces within or adjacent to residential neighborhoods that spanned a gradient of income (median household income) and ethnic (% Latinx) composition in the Phoenix metro area (Figure 1). To focus on wildlife populations that may utilize or pass-through built landscapes within neighborhoods, I selected sites from the pool of publicly funded parks (2021 sites).

To sample sites with similar urbanization levels (impervious surfaces) I selected sites in community parks or other greenspaces that were located > 2-km from a desert park preserve. This resulted in sites being located >0.85km to an open desert area that is not designated as a preserve. Then, using the 2017 American Community Survey and within ArcMap, I evaluated the average median household income and average racial/ethnic composition of residents within a 1-km radius of the site (defined in this study as a 'neighborhood') as well as around camera sites that were deployed previously in 2019 (Lewis & Haight 2022). Due to the prevalence of people who identify as white or Latinx in the study area, I focused on sites within neighborhoods where these ethnic/racial groups dominate. I aimed to sample across the gradient of ethnic composition and income levels throughout the metro area. As income and ethnicity are often highly correlated across the metro area, I aimed to reduce the correlation between the two variables. To reduce correlation between income and ethnicity data, I considered inclusion of a site in this study if the neighborhood median household income and proportion of Latinx residents were within the top or bottom quartile of each category, or if a site's inclusion reduced the correlation between the two variables. To aid in the interpretation of results, I also aimed to sample neighborhoods that had similar proportions of non-Latinx communities of color by considering sites where the neighborhood proportion of non-white, non-Latinx residents were within one standard deviation of the metro-wide mean value. I used a final set of 38 sites from 2019 (10 camera sites) and 2021 (28 camera sites).

Camera Methods

I aimed to sample medium to large-bodied wildlife species that occupy the study area. To do so, I placed a non-baited, motion-activated wildlife camera (Cuddeback black flash in 2019 and 2021; Bushnell Core low-glow in 2021) at a location I believed would maximize the potential to capture the presence of wildlife (signs of a natural pathway, scat, or tracks; Kays et al. 2020; Lewis et al. 2021). Based on similar camera placement methods between survey years and similar trigger speeds of cameras, wildlife detection was similar between years (Rovero et al. 2013). Each camera was secured to a tree at approximately knee height, and perpendicular to the expected wildlife path. Once triggered, cameras were programmed to capture three photos with a 30-s quiet period between triggers (2019 cameras) or two photos with a 2-min quiet period (2021 cameras). Each photo was identified to the species level by two independent observers and an expert third observer to resolve any discrepancies.

Social Covariates

I utilized the average median household income and percent of Latinx resident values within a 1-km radius of each camera site (see site selection section) as two continuous social covariates. The values for my sites ranged from 4% to 86% of residents who identify as Latinx (median = 21%), and 7% to 88% who identify as White (median = 68%). While income ranged from $27,069 to $130,221 (median = $69,497). I evaluated collinearity between income and ethnicity using Pearson's correlation and used a threshold of $r < 0.7$ (Goad et al. 2014; Millar & Fox 2003). The correlation between neighborhood median household income and ethnicity of $r = -0.64$ (Appendix, Table A1).

Landscape Covariates

For landscape covariates, I estimated normalized difference vegetation index (NDVI), the extent of impervious surfaces (% impervious cover), the presence of a water feature (artificial or natural body of water, such as a pond, canal, or river), and the distance to a water feature. I averaged continuous NDVI and impervious surface values across multiple buffer sizes around each site (125 m, 250 m, 500 m, 750 m, 1000 m, 1500 m, and 2000-m radii). I estimated mean impervious surface cover in ArcMap with the national land cover data percent imperviousness layer (Dewitz 2021). I calculated NDVI utilizing the derived values from the CAP LTER NDVI layer (Sabu & Frazier 2022) in ArcMap. I measured the closest distance to a water feature in Google Earth. Then I determined the categorical presence of a water feature within multiple buffer zones around each site using Google Earth (125 m, 250 m, 500 m, 750 m, 1000 m, 1500 m, and 2000-m radii). Next, I evaluated the most supported buffer size for each species in occupancy models by comparing univariate models of each buffer and covariate using Akaike information criterion value (AICc; Appendix, Table A2, A3; Burnham & Anderson 2004). I took a similar approach to determine the most supported measurement type (categorical presence vs distance to) for water by comparing univariate occupancy models of the most supported buffer size (categorical presence) and the distance to water (Appendix, Table A2, A3). This resulted in support for categorical presence of water features over distance to water for all species and one buffer size per covariate used per species (Appendix, Table A4, A5, A6). I evaluated collinearity between the continuous covariates using Pearson's correlation and retained variables with $r < 0.7$ (Appendix, Table A1; Goad et al. 2014; Millar & Fox 2003). I also evaluated the individual correlations with ethnicity and income to park size (for sites that were within a park) and found no correlation between the variables (Appendix, Figures A1, A2).

Occupancy Modeling Approach

I conducted single-species-single-season occupancy models on species that were commonly detected at my sites. I included native Sonoran Desert species coyote (*Canis latrans*) and desert cottontail rabbit (*Sylvilagus audubonii*) and non-native domestic cats (*Felis catus*) in my analyses. To estimate occupancy probability (psi) and detection probability (p) based on their association with social (average neighborhood income and Latinx) and landscape covariates (MacKenzie et al. 2018). I evaluated detection (1) and non-detection (0) data for the metro Phoenix summer months (June 3rd-September 30th) with ten, 12-day occasions (MacKenzie et al. 2018; Sollmann 2018). Occupancy analyses were executed in program R version 4.1.3 (Core Development Team 2013) using the "RMark" package (Laake & Rexstad 2022). To determine if detection probability was influenced by detection related covariates, I evaluated the time varying option in RMark (detection probabilities across occasions), effort days (number of sample days per camera), the intercept-only (dot) model, and all combinations of these covariates using AICc model selection. Of these, the dot model was most supported for detection probability of all species (Appendix, Table A7), and was thus used in all subsequent model runs for occupancy. All continuous covariate values were standardized by subtracting the mean value and dividing by the standard deviation (Schielzeth 2010). I ran all possible combinations of the social and landscape covariate combinations on psi, resulting in 32 models per species. I then used lowest AICc model selection to determine the most supported models per species. I considered models to be informative if they performed better than the dot model and resulted in a delta AICc value < 2 (Burnham and Anderson 2004, Lewis et al. 2021). Additionally, to provide further insight on each covariate's relationship to species occupancy, I calculated the variable importance values (VIV) by summing the Akaike weights for each covariate across all models (Anderson 2008).

Daily Activity Patterns Approach

I evaluated how daily activity patterns of coyotes, desert cottontail rabbits, and domestic cats overlapped between categories of income and ethnicity. I divided neighborhoods by their 1-km averaged median household income (higher-income vs.

lower-income) and % Latinx residents (higher-Latinx vs. lower-Latinx; Appendix, Table A8). I used the package "overlap" in R to calculate the coefficient of activity overlap (0 = no overlap; 1 = total overlap) and 95% confidence intervals (Ridout & Linkie 2009). I optimized the coefficient estimate and confidence intervals by using 10,000 bootstrap simulations and created overlap density plots using the von Mises kernel approach for circular data that corresponds to the time of day (Ridout & Linkie 2009). I followed small sample recommendations when there were less than 50 detections in either category (Ridout & Linkie 2009). To ensure independent animal detections, I only included photos that were greater than 30 minutes apart (Sollmann 2018). Each of the species evaluated had at least 20 detections and at least 5 sites in each category, and visual inspection of results indicated sufficient sample sizes to estimate activity patterns (Lewis et al. 2021). I concluded that daily activity patterns of a species shifted in the higher vs. lower income or Latinx neighborhoods if the upper limit of the 95% confidence interval of overlap was < 0.90 (Lewis et al. 2021).

RESULTS

Occupancy of Wildlife and Domestic Animals Across Neighborhoods

I detected 28 species total across all taxa and 13 mammal species from 49,360 photos over 122 sample days across my 38 camera sites from June-September. My dataset for the target species included 208, 2744, and 2549 detections of coyotes, desert cottontail rabbits, and domestic cats respectively. Occupancy and detection probabilities and (95% confidence intervals) of 0.54 (0.35, 0.67) and 0.34 (0.28, 0.42) for coyotes, 0.21 (0.11, 0.37) and 0.74 (0.62, 0.82) for cottontails, and 0.71 (0.55, 0.83) and 0.69 (0.63, 0.74) for cats were also found (Table 1.). Along with landscape covariates, both median household income and % of Latinx residents in neighborhoods surrounding the sites were significantly associated with the occupancy of coyotes and cottontails. Latinx appeared in both species' top models (Figure 2.) and both appeared in the top model for coyotes (lowest AICc; Appendix, Tables A9a-c, A10a-c, Figure 2.). For domestic cats, neither of the social covariates appeared in the top model (Appendix, Table A11a-c). Combining the weights of all models, neighborhood ethnicity was more important (VIV) for occupancy of both native mammals and domestic cats. Coyote's (VIV) values were 0.95 (Latinx) and 0.67 (income), and cottontail rabbit's (VIV) values were 0.99 (Latinx) and 0.24 (income) while domestic cat's values were 0.47 (Latinx) and 0.26 (income; Anderson 2008; Figure 3.). Notably, the highest VIV for domestic cats was for impervious surfaces at 0.95 (Anderson 2008; Figure 3.).

The direction and significance of covariates vary for native and domestic mammal occupancy across the range of residential neighborhoods in this study. Native coyotes in metro Phoenix had negative (negative beta estimate) and significant (95% confidence interval does not overlap zero) relationships with both social covariates and landscape variables of impervious surfaces and presence of water. But had a positive relationship (positive beta estimate) with NDVI (Appendix, Tables A9a-c). Similarly, native desert cottontail rabbits had negative relationships (negative betas estimates) with both social covariates of income and ethnicity (significant) and landscape variable impervious surfaces. However, cottontails had a positive relationship with NDVI and presence of water (Appendix, Tables A10a-c). In contrast, invasive domestic cats had a negative relationship with social covariate income, but a positive relationship with Latinx and a significant positive relationship with all landscape covariates (impervious surfaces, NDVI, and presence of water; Appendix, Tables A11a-c, Figure 3.). The top models including covariates for all three species were more supported than the dot models (intercept-only model), signifying that the models explain the data (Appendix, Tables A9a-c, A10a-c, A11a-c).

However, the sign of the beta estimates switched for income and NDVI depending on the presence of other covariates, suggesting collinearity may be present for these two variables (Appendix, Tables A9a-c, A10a-c, A11a-c). Specifically, income switched from negative values in models that include Latinx to positive values in some models that did not include Latinx for all three species (Appendix, Tables A9a-c, A10a-c, A11a-c). NDVI switched from positive to negative for domestic cats in three models when associated with multiple other variables (Latinx, water, income; Appendix, A11c).

Daily Activity Patterns in Neighborhood Categories

None of the species shifted between income levels, and desert cottontail rabbits were not included in analyses for lack of sufficient sample size (Appendix, Table A8). Daily activity of coyotes shifted between levels of Latinx residents (Figure 4.). In the higher-Latinx neighborhoods, coyotes started their activity later in the evening and remained more active into the early morning than in lower-Latinx neighborhoods (overlap estimate of 0.72 and a 95% confidence interval of 0.55-0.88; Appendix, Table A12, Figure 4.). In contrast, daily activity patterns of domestic cats did not appear to be associated with neighborhood income or ethnicity (overlap estimate 0.87 with a 95% confidence interval of 0.81-0.92 and 0.89 with a 95% confidence interval of 0.84-0.95, respectively; Appendix, Table A12, Figure 4.).

DISCUSSION

By integrating social variables into ecological models, my study provides insights into socio-ecological patterns that shape wildlife distributions (Des Roches et al. 2021). Specifically, I provide insights into socio-ecological patterns and the relationship with mammals that may not be fully captured by evaluating income alone. As expected, I found evidence that the percent of Latinx residents in a neighborhood was related to occupancy probability of native and non-native mammals. My conclusions are supported by the findings of a consistent pattern of Latinx appearing in the top models for all species. Not only did Latinx appear in the top models, but it was the most important variable (highest VIV value) for coyotes and cottontail rabbits, and even more important than income for all three species (higher VIV value than income). Income was informative for coyotes and cottontails and appeared in top models but was less supported than Latinx. This study adds to the knowledge that social variables are related to mammal spatial patterns and introduces ethnicity as a new variable. Other research has found Mesopredator mammal species (e.g. coyote) distribution is related to socioeconomic (housing density, vacancy rates, per capita income) and habitat availability (Magle et al. 2016), and a combination of environmental and social factors (building density, household income, occupation) relate to coyote distribution to varying extents (Wine et al. 2015). My results are similar, as a combination of social and environmental variables were supported in my results. Additionally, my study compliments research that found that the effects of systemic racism influences wildlife populations, where neighborhoods with more minority residents have wildlife populations with less genetic diversity (Schmidt & Garroway 2022).

Consistent with my predictions, occupancy of native mammals (coyotes and cottontail rabbits) decreased with an increasing percent of Latinx residents in neighborhoods. Although these patterns have not been observed in mammals, these results are consistent with patterns seen when evaluating tree cover and urban heat, in that minority neighborhoods experience less ecosystem services (Dialesandro et al. 2021; Grove et al. 2014; Hsu et al. 2021) and potentially less or lower quality wildlife habitat. Also consistent with previous studies, environmental variables of impervious cover, NDVI, and water were important for these species, as these are all variables associated with the level of urbanization as well as the availability of cover and resources (Mckinney 2002). Further, the level of urbanization is negatively associated with many mammal species, but the amount of greenspace and housing density of regions can be positively (greenspace) and negatively (housing density) associated with species at varying thresholds (Fidino et al. 2021). Coyotes had a negative relationship with impervious surfaces and presence of water, and positive with NDVI. This is consistent with coyote distribution patterns, as coyotes tend to frequent moderately dense neighborhoods even within the urban matrix (Grubbs & Krausman 2009), and artificial water features in the area may not be substantial water sources for coyotes. Cottontails had a negative association with impervious surfaces and then positive with water features and NDVI. This is also consistent with cottontail patterns as these species have smaller home ranges that heavily rely on vegetation for food and cover to hide from predation (Chapman & Willner 1978). Species may be present due to historical ranges or previous land use histories and shifting demographics of neighborhoods (Fukasawa & Akasaka 2019; Lowry et al. 2012; Roman et al. 2018). Redlining and discriminatory housing practices were prevalent in the Phoenix metro area in the 1930s, in which racial segregation was common in Phoenix's early development (Bolin et al. 2005). These practices resulted in fragmented uses of land and environmental inequity, zones of dis-amenities, and fewer ecosystem services that were targeted toward low-income and minority neighborhoods, common with national trends (Tessum et al. 2019; Wen et al. 2013; York et al. 2014). The combined environmental features of the study area such as urbanization levels, fragmented land use history, and the explicit link of ethnic minority neighborhoods to environmental inequities may contribute to my findings. Wildlife historical ranges and quality of habitat may be related to spatial distributions of native species.

In addition to historical practices, the neighborhoods I studied were primarily Latinx or white dominated, in which residents' ethnicities are direct drivers of decisions at the household level (Grove et al. 2006; Larsen & Harlan 2006) that may impact mammal occupancy. Although these are not direct links to mammal patterns, presumably, varied access to yards for anthropogenic food sources, or predator-prey dynamics between domestic and wild species is impacted by the presence of a physical barrier, such as fencing (Hansen et al. 2020; Kays 2014; Mella-Méndez et al. 2019; Murray & St. Clair 2017; Van Helden et al. 2020). The presence of vegetative cover in yards may influence mammal activity as it can provide habitat connectivity and protection for mammal species (Grade et al. 2022). Neighborhood scale decisions that impact wildlife habitat are likely impacting the habitat for mammal species. Often homeowner associations (HOA) control aspects of the landscape and pest control, which may influence the presence of these species (Hadidian 2015; Lerman et al. 2012). And neighborhoods with HOAs can have greater and more diverse native bird and plant species than non-HOA neighborhoods (Lerman et al. 2012). Individual decisions about yard use, landscaping, and domestic pet ownership patterns combined with the historical legacies of the landscape may all have a relationship to my results, in which Latinx neighborhoods have a negative relationship with the occupancy of the native species I evaluated and positive with domestic cats.

Domestic cats were common across the Phoenix metro area, and Latinx was positively related to cat occupancy and within top models. I expected Latinx to relate to domestic cat occupancy, but my results suggest impervious surfaces is the better predictor for cat presence in neighborhoods. Impervious surfaces (highest VIV) were more important for domestic cats overall, consistent with patterns of domestic cats persisting in small home ranges close to their homes and therefore impervious surfaces (Kays et al. 2020). The ability to confirm free-ranging cat ownership is beyond the scope of this study, but it is likely that many of the cats I detected are feral. Like global patterns, it is likely that feral cats are abundant in my study area in addition to owned free-ranging cats, and humans are facilitating the persistence of these populations (Elizondo & Loss 2016; Loss et al. 2013, 2022). These results are concerning, since pet and feral cats contribute greatly to the loss of native species and prey upon billions of mammals and birds a year (Kays et al. 2020; McGregor et al. 2020; Molsher et al. 1999). It is also known that pet cats tend to stay near their homes and the urban intensity of their neighborhoods influence their activity (Bennett et al. 2021; Horn et al. 2011). The relationship between cats and human facilitation in urbanized landscapes is likely why the landscape variables have a positive relationship with cat occupancy. Additionally, pet ownership and ownership practices can be linked to ethnicity, in which those who identify as white are more likely to own a pet, while Latinx residents are less likely to have cats (Risley-Curtiss et al. 2006). Similarly, in the CAP LTER study area, residents who participated in the Phoenix Area Social Survey who are Latinx reported to be more likely to have a dog than a cat, and if they have a pet, they report that their pet spends more time outside (Larson & Andrade 2017). The spatial relationship between cats and humans combined with pet ownership practices are likely why I see such a strong relationship with impervious surfaces, but still have support for ethnicity.

I found negative relationships with income and occupancy for all species, which is contradictory to the positive association of wealth and biodiversity. While wealth is associated with increased mammal richness in Phoenix metro (Magle et al. 2021), it is likely that the differences are due to the use of single-species models in this research. Single-species occupancy models differ than species richness, as in urbanized metropolitan areas, mammal richness is typically lower than natural habitats (McCleery 2010). This suggest that this research observed similar patterns with wealth, in which the luxury effect is observed across taxa and regions, but varies considerably based upon study design and measurements of wildlife populations (Kuras et al. 2020). This study offers insight to distributions of an already filtered species pool within the more urbanized zone of the natural to urban gradient (Aronson et al. 2016) and may not capture patterns seen when sampling across the full gradient of urbanization. Further, the results for income appear to be influenced by the other covariates within the models, particularly when associated with Latinx, income will sometimes shift from negative to positive. This suggest that while I have support for Latinx (consistently in the top models, direction of betas consistent), the results for income are less reliable. Notably, beta estimates within models are always dependent on the other variables in the models. Although all the variables I evaluated were below the threshold of 0.70, it appears they may be correlated and influencing one another.

Like the significant relationship with Latinx in the occupancy model results, activity pattern analyses showed shifts in daily activity only for coyotes between Latinx neighborhoods. Counter to my predictions, cats did not shift their activity between any categories. Although I only observed shifts for coyotes between Latinx levels, I expected shifts because mammals can change their daily activity patterns to adapt to human disturbed environments, and often increase nocturnal hours (Gallo et al. 2022; Gaynor et al. 2018; Lewis et al. 2015; Łopucki & Kiersztyn 2020). Coyotes in particular have been observed to decrease crepuscular activity to avoid humans, and coyotes in urbanized areas often have larger home ranges to do so (Gese et al. 2012). Changes in activity are likely attributed to the avoidance of humans and the conflicts that may arise (Suraci et al. 2019). Coyotes will exploit human food sources in neighborhoods (Murray & St. Clair 2017). The time of day these food sources are available within neighborhoods may be a source of change in the daily activities of coyotes (Fedriani et al. 2001; Hansen et al. 2020; Kays 2014). Although not measured in this study, wild mammals will avoid fenced yards with dogs (Kays 2014) and the time-of-day pets are outside may be influencing the activity of coyotes in neighborhoods. While coyotes were estimated to occur in approximately half of the sites (psi = 0.51), they were detected in only six high-Latinx sites, and the shift in activity may be biased by sample size. Additionally, I selected sites based on income and Latinx levels on a continuous scale rather than the broad categories used for the activity analyses, giving less power to interpret the results of activity patterns.

While I found that the ethnicity of residents is a good predictor of mammal species occupancy and a better predictor than income in the study area, there are limitations of this study. I evaluated three species; however, species such as gray fox, racoons, javelinas, several species of squirrels, and ground dwelling bird photos were captured. Additionally, species may be interacting in predator-prey dynamics that were not measured in this study. Future research could evaluate interactions among all three species, as other studies have found that cats and coyotes display avoidance in urban areas, and that domestic cats directly prey on lagomorph species (Kays et al. 2015; McGregor et al. 2020; Paul & Friend 2020). I placed my cameras in locations to avoid human detections; however, I captured photos of humans at all locations, and activity of people within the sites could be influencing animal activity (Gámez & Harris 2021; Li et al. 2020). Additional environmental variables may also influence animal occupancy and activity patterns, such as habitat connecting corridors like washes (Beier & Noss 1998). I evaluated a single summer season and the evaluation of mammal occupancy and daily activity across multiple seasons may reveal shifts in activity and spatial distributions temporally. Lastly, the inclusion of the characteristics of the parks, greenspaces, and private yards of residents can be incorporated. Latinx residents often use their yards as cultural landscapes to enhance the aesthetics and cultural expression within neighborhoods (Arreola 2012). The biophysical features and activity within yards may be influencing wildlife patterns, as well as the parks. Parks in Latinx neighborhoods of the Phoenix metro have fewer natural features (vegetation), and more facilities for sports and group events (sports facilities, grills; Lara-Valencia & Garcia-Perez 2018). The use and experiences residents have with the greenspaces of their neighborhoods are related to the ethnic composition of their neighborhoods. Further research into the use and quality of these greenspaces should be explored to better inform the mechanistic processes driving mammal patterns. Additionally, the diverse experiences and connections to nature, or the value of nature, residents of varying cultural backgrounds may have should be investigated.

My study provides novel insight to socio-ecological systems within a major metropolitan area. My results show a consistent relationship with the ethnicity of residents for two native and one non-native species within neighborhoods. I found that Latinx neighborhoods experienced negative relationships with two native species and positive with one non-native domestic species, complimenting research that investigated social variables in wildlife populations (Magle et al. 2016, 2021; Schmidt & Garroway 2022; Wine et al. 2015). However, this research differentiates the relationship between wealth and ethnicity and provides nuanced insight beyond simple measurements of wealth. Further, these findings may be transferable to other metropolitan areas. The United States is becoming more ethnically diverse (Frey 2021b), and more people live in metropolitan areas (United Nations 2018), thus social factors will continue to influence the landscape and wildlife patterns. Discerning patterns between ethnicity and wildlife distributions will become increasingly important for better understanding and predicting wildlife patterns as the globe continues to urbanize, threatening biodiversity and weakening human connection to nature and wildlife (Soga & Gaston 2016). Urban ecological research should aim to improve sustainability and the well-being of residents in cities.

Table 1. Number of detections, occupancy (psi), and detection probabilities (p), of the intercept-only (dot models) for three mammal species across the 38 sites in metro Phoenix from June-September 2019 and 2021.

Species	Number of detections	Number of sites (n=38)	(psi) Dot model		(p) Dot model	
			Estimate	95% CI	Estimate	95% CI
Coyote	208	19	0.51	(0.35, 0.67)	0.34	(0.28, 0.42)
Desert cottontail rabbit	2744	9	0.21	(0.11, 0.37)	0.74	(0.62, 0.82)
Domestic cat	2549	29	0.71	(0.55, 0.83)	0.69	(0.63, 0.74)

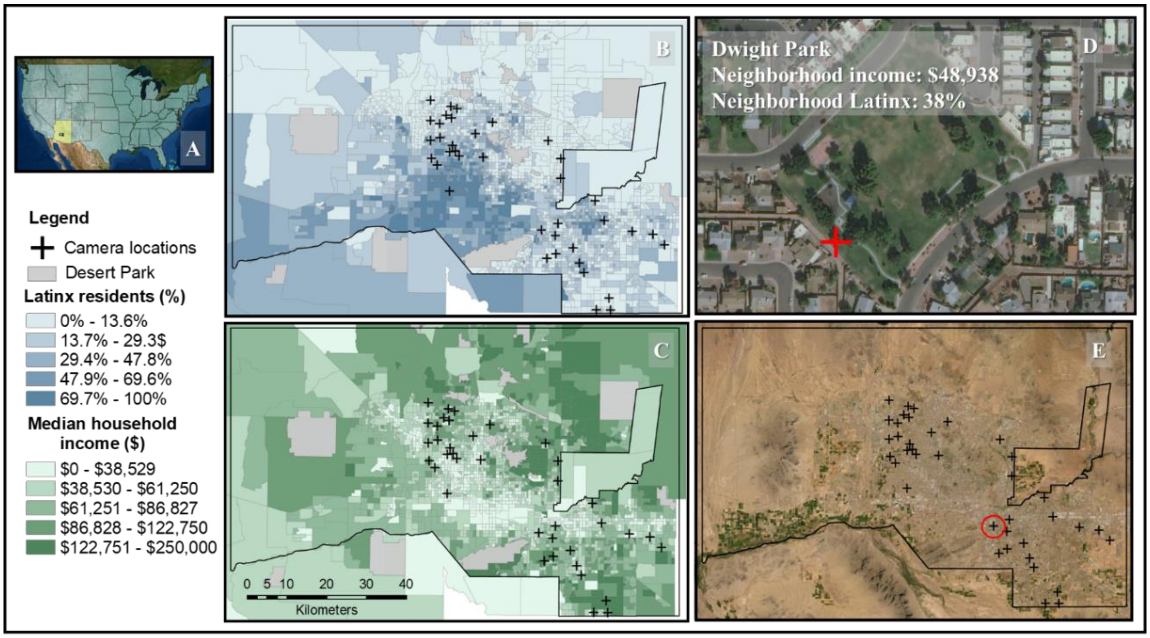

Figure 1. Map of sites used in this study, located within the Central Arizona-Phoenix Long Term Ecological Research area (CAP LTER) in Maricopa County, AZ shown in (A) as a black polygon within AZ (yellow state). Colors indicate sociodemographic data from census blocks, focusing on the proportion of residents who identify as Latinx (B) and median household income (C) (American Community Survey 2017, Brown et al. 2021). Plus symbols are camera locations. Red circle indicates (D) Dwight Park, an example study site shown in (E), and where a camera was placed within the greenspace.

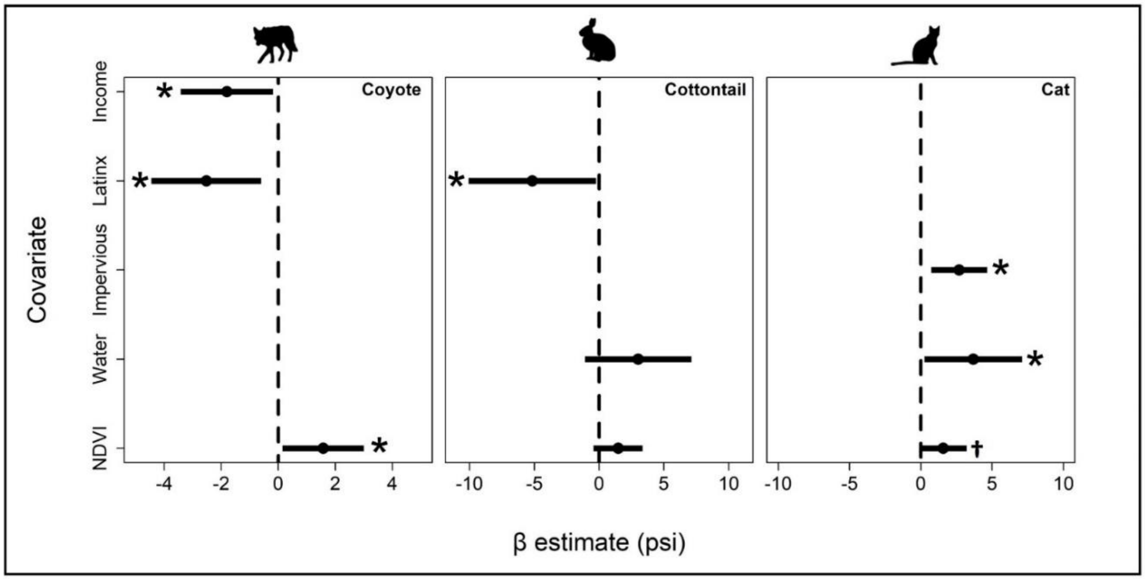

Figure 2. Beta estimates and 95% confidence intervals for the top model (lowest AICc) for coyotes, desert cottontail rabbits, and domestic cats within the CAP LTER boundary in AZ. Asterisks (*) denote that the 95% confidence interval of the estimate does not overlap zero. (†) indicates that the at the 90% confidence level does not overlap 0.

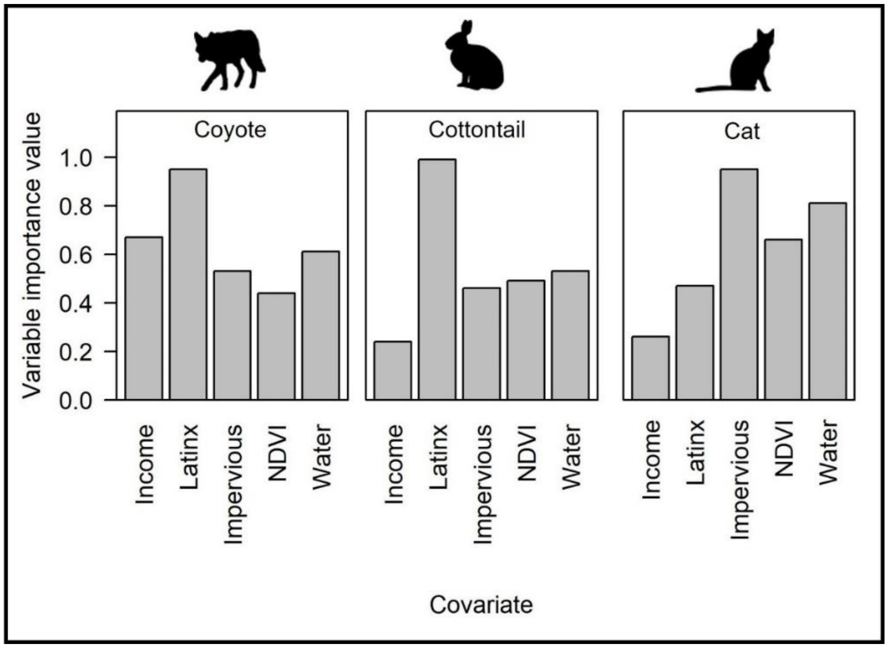

Figure 3. Variable importance values (VIV) for native species (coyote and desert cottontail rabbit) and non-native domestic cat within the CAP LTER boundary in AZ.

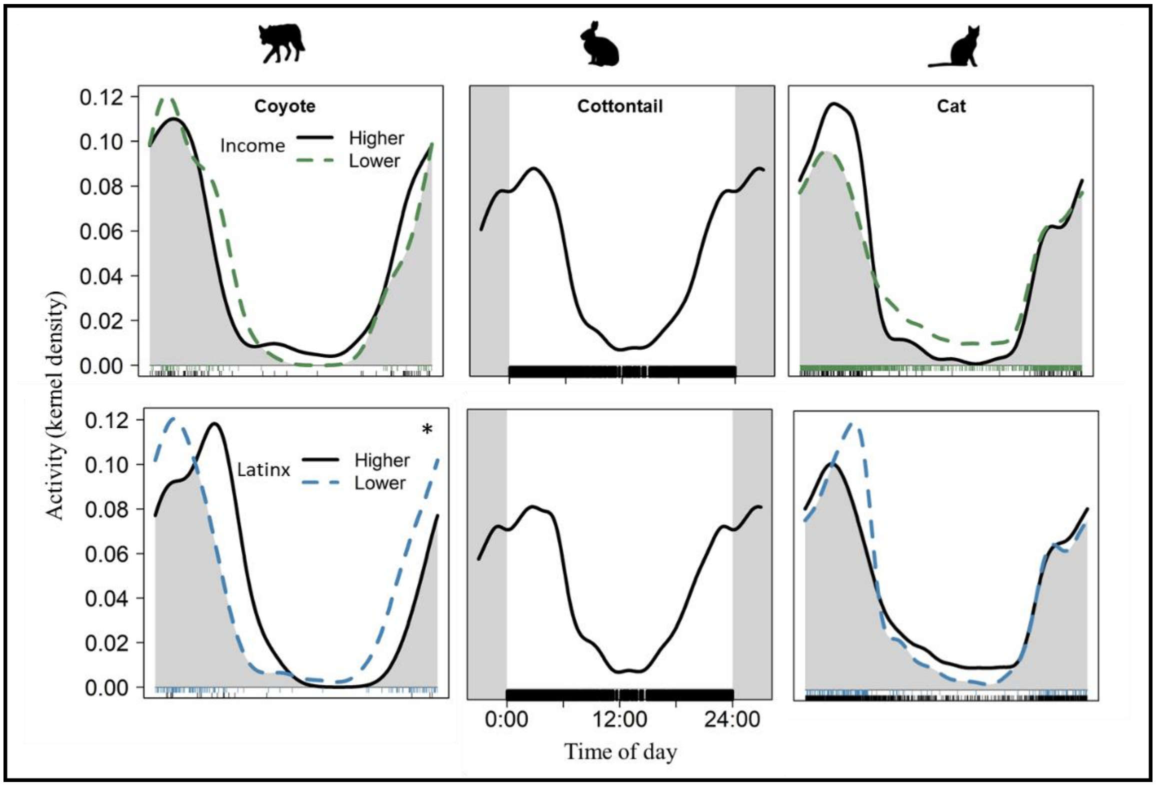

Figure 4. Daily activity patterns of coyotes, desert cottontail rabbits, and domestic cats, across categories neighborhood income and neighborhood proportion of Latinx residents within the CAP LTER boundary in AZ. Solid lines are activity in higher-income or higher-Latinx neighborhoods, and dotted lines are activity in lower-income or lower-Latinx neighborhoods. Percent values in the lower right corner of panels are the overlap estimate (0-100%). Asterisk (*) in the upper right corner of the panel denotes that daily activity was shifted in lower vs. higher income/ethnicity categories (upper 95% CI < 0.90).

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APPENDIX A

RESULTS FOR OCCUPANCY AND DAILY ACTIVITY PATTERN ANALYSES

Table A1: Pearson's correlations (r) between continuous covariates across a range of geographic buffer sizes. I used an r value > 0.7 (bolded) as the threshold for collinearity between model predictor variables.

	Pearson's correlation																
	Income	Latinx	Impervious							Distance (water)	NDVI						
	1 (km)	1 (km)	2000 (m)	1500 (m)	1000 (m)	750 (m)	500 (m)	250 (m)	125 (m)	(m)	2000 (m)	1500 (m)	1000 (m)	750 (m)	500 (m)	250 (m)	125 (m)
Income (1km)	1.00	-0.64	-0.62	-0.64	-0.61	-0.49	-0.35	-0.25	-0.24	-0.19	0.46	0.46	0.42	0.32	0.16	0.10	0.15
Latinx (1km)		1.00	0.38	0.37	0.31	0.20	0.11	0.06	0.06	0.05	-0.23	-0.23	-0.20	-0.13	-0.01	0.07	0.12
Impervious (2000m)			1.00	**0.97**	**0.88**	**0.78**	**0.70**	0.54	0.39	0.24	**-0.73**	-0.67	-0.57	-0.50	-0.40	-0.20	-0.14
Impervious 1500(m)				1.00	**0.96**	**0.87**	**0.79**	0.62	0.47	0.24	**-0.73**	-0.72	-0.64	-0.58	-0.46	-0.21	-0.14
Impervious 1000(m)					1.00	**0.97**	**0.91**	**0.73**	0.57	0.26	-0.66	-0.70	-0.67	-0.63	-0.51	-0.24	-0.16
Impervious 750(m)						1.00	**0.97**	**0.80**	0.61	0.28	-0.61	-0.65	-0.65	-0.64	-0.54	-0.26	-0.17
Impervious (500m)							1.00	**0.88**	0.68	0.25	-0.56	-0.60	-0.62	-0.63	-0.60	-0.36	-0.23
Impervious (250m)								1.00	**0.90**	0.15	-0.53	-0.60	-0.65	-0.69	**-0.73**	-0.63	-0.50
Impervious (125m)									1.00	0.06	-0.45	-0.55	-0.62	-0.65	-0.67	-0.65	-0.65
Distance (water) (m)										1.00	-0.20	-0.19	-0.22	-0.24	-0.20	-0.04	-0.06
NDVI 2000 (m)											1.00	**0.95**	**0.89**	**0.84**	**0.75**	0.57	0.50
NDVI 1500 (m)												1.00	**0.97**	**0.93**	**0.83**	0.61	0.54
NDVI 1000 (m)													1.00	**0.97**	**0.89**	0.68	0.61
NDVI 750 (m)														1.00	**0.95**	0.69	0.60
NDVI 500 (m)															1.00	**0.83**	0.69
NDVI 250 (m)																1.00	**0.92**
NDVI 125 (m)																	1.00

Table A2: AICc model selection results using non-correlated geographic buffer sizes and categorial vs. continuous estimates of water availability. The lowest AICc ranking variables from this modeling exercise were included to estimate occupancy of each species.

Coyote (Impervious)				
Model	AICc	DeltaAICc	Weight	Deviance
psi(250m) p(.)	284.83	0.00	0.28	278.13
psi(125m) p(.)	285.09	0.26	0.25	278.39
psi(500m) p(.)	286.44	1.61	0.13	279.73
psi(1500m) p(.)	286.73	1.89	0.11	280.02
psi(1000m) p(.)	287.16	2.33	0.09	280.46
psi(2000m) p(.)	287.43	2.60	0.08	280.72
psi(750m) p(.)	287.44	2.61	0.08	280.74

Domestic cat (Impervious)				
Model	AICc	DeltaAICc	Weight	Deviance
psi(750m) p(.)	368.06	0.00	0.23	361.35
psi(500m) p(.)	368.38	0.32	0.20	361.67
psi(250m) p(.)	368.50	0.45	0.19	361.80
psi(1000m) p(.)	368.76	0.70	0.16	362.05
psi(125m) p(.)	369.17	1.11	0.13	362.47
psi(1500m) p(.)	370.96	2.90	0.05	364.25
psi(2000m) p(.)	372.33	4.28	0.03	365.63

Desert cottontail rabbit (Impervious)				
Model	AICc	DeltaAICc	Weight	Deviance
psi(125m) p(.)	124.36	0.00	0.32	117.66
psi(250m) p(.)	124.87	0.50	0.25	118.16
psi(750m) p(.)	126.55	2.18	0.11	119.84
psi(500m) p(.)	126.94	2.57	0.09	120.23
psi(2000m) p(.)	127.00	2.64	0.08	120.30
psi(1000m) p(.)	127.06	2.70	0.08	120.36
psi(1500m) p(.)	127.29	2.93	0.07	120.59

Coyote (NDVI)				
Model	AICc	DeltaAICc	Weight	Deviance
psi(1500m) p(.)	284.88	0.00	0.29	278.18
psi(750m) p(.)	285.39	0.50	0.23	278.68
psi(1000m) p(.)	285.98	1.10	0.17	279.28
psi(500m) p(.)	286.00	1.12	0.17	279.30
psi(2000m) p(.)	287.24	2.36	0.09	280.54
psi(250m) p(.)	288.95	4.06	0.04	282.24
psi(125m) p(.)	290.31	5.42	0.02	283.60

Domestic cat (NDVI)				
Model	AICc	DeltaAICc	Weight	Deviance
psi(1500m) p(.)	374.59	0.00	0.16	367.89
psi(1000m) p(.)	374.65	0.06	0.15	367.95
psi(2000m) p(.)	374.78	0.19	0.14	368.08
psi(250m) p(.)	374.79	0.20	0.14	368.09
psi(750m) p(.)	374.80	0.21	0.14	368.09
psi(125m) p(.)	374.83	0.24	0.14	368.13
psi(500m) p(.)	374.91	0.31	0.13	368.20

Desert cottontail rabbit (NDVI)				
Model	AICc	DeltaAICc	Weight	Deviance
psi(750m) p(.)	125.48	0.00	0.19	118.77
psi(2000m) p(.)	125.54	0.06	0.18	118.83
psi(1500m) p(.)	125.84	0.36	0.16	119.13
psi(1000m) p(.)	125.94	0.46	0.15	119.24
psi(500m) p(.)	126.05	0.57	0.14	119.34
psi(250m) p(.)	126.41	0.93	0.12	119.71
psi(125m) p(.)	127.78	2.30	0.06	121.07

Coyote (Water categorical)				
Model	AICc	DeltaAICc	Weight	Deviance
psi(1500m) p(.)	288.86	0.00	0.23	113.07
psi(125m) p(.)	289.46	0.60	0.17	98.56
psi(2000m) p(.)	289.59	0.74	0.16	113.06
psi(1000m) p(.)	290.15	1.29	0.12	110.03
psi(250m) p(.)	290.36	1.50	0.11	99.20
psi(750m) p(.)	290.45	1.59	0.10	106.03
psi(500m) p(.)	290.56	1.70	0.10	99.89

Domestic cat (Water categorical)				
Model	AICc	DeltaAICc	Weight	Deviance
psi(750m) p(.)	372.90	0.00	0.27	158.39
psi(1000m) p(.)	373.61	0.71	0.19	163.85
psi(500m) p(.)	374.41	1.51	0.13	153.68
psi(250m) p(.)	374.74	1.84	0.11	150.45
psi(1500m) p(.)	374.91	2.01	0.10	165.66
psi(2000m) p(.)	374.92	2.02	0.10	165.29
psi(125m) p(.)	374.95	2.05	0.10	152.04

Desert cottontail rabbit (Water categorical)				
Model	AICc	DeltaAICc	Weight	Deviance
psi(125m) p(.)	122.70	0.00	0.55	12.12
psi(250m) p(.)	124.61	1.91	0.21	12.59
psi(500m) p(.)	125.86	3.16	0.11	13.08
psi(750m) p(.)	127.92	5.23	0.04	14.69
psi(1000m) p(.)	128.76	6.06	0.03	16.56
psi(1500m) p(.)	128.83	6.13	0.03	20.11
psi(2000m) p(.)	128.90	6.20	0.02	20.29

Coyote (Water categorical vs distance to)				
Model	AICc	DeltaAICc	Weight	Deviance
psi(1500m) p(.)	288.86	0.00	0.68	113.07
psi(distance km) p(.)	290.39	1.53	0.32	283.69

Domestic cat (Water categorical vs distance to)				
Model	AICc	DeltaAICc	Weight	Deviance
psi(750m) p(.)	372.90	0.00	0.74	158.39
psi(distance km) p(.)	374.97	2.07	0.26	368.26

Desert cottontail rabbit (Water categorical vs distance to)				
Model	AICc	DeltaAICc	Weight	Deviance
psi(125m) p(.)	122.70	0.00	0.96	12.12
psi(distance km) p(.)	128.86	6.17	0.04	122.16

Table A3: Results of AICc model selection to determine the most supported buffer sizes for each covariate per species.

Species	Covariate	Buffer size (radius, in m)
Coyote	Income	1000
	Latinx	1000
	Impervious	250
	NDVI	1500
	Water (categorical)	1500
Desert cottontail rabbit	Income	1000
	Latinx	1000
	Impervious	125
	NDVI	750
	Water (categorical)	125
Domestic cat	Income	1000
	Latinx	1000
	Impervious	750
	NDVI	1500
	Water (categorical)	750

Table A4: Covariates used in occupancy analyses for coyote and the size of parks for cameras that were sited within a park.

Site	Income $ (1km)	Latinx % (1km)	Impervious % (250m)	Water (Yes/No) (1500 m)	NDVI (1500 m)	Park size (acre)
Tarrington Ranch	27069.63	0.36	36.03	No	0.06	4.20
S14	38374.73	0.39	44.18	No	0.02	6.60
T14	38673.52	0.38	51.74	No	0.00	0.00
Desert West	42020.58	0.86	28.11	Yes	0.01	100.71
AB18	43525.02	0.40	71.97	No	-0.09	0.00
Navarrete	43550.82	0.53	46.67	No	-0.04	3.94
AC19	44601.38	0.22	34.41	Yes	0.05	0.00
Westown	47832.73	0.30	58.98	Yes	-0.01	4.12
Butler	48656.16	0.37	45.67	No	0.02	5.00
Sahuaro Ranch	48936.76	0.32	33.42	Yes	0.02	73.00
Dwight	48938.01	0.38	52.61	Yes	-0.11	4.00
Selleh	49573.79	0.18	49.58	Yes	-0.06	6.30
Braewood	51889.71	0.38	46.23	No	-0.01	7.09
AE19	52037.57	0.22	32.29	No	-0.02	0.00
Discovery	65167.75	0.46	35.74	Yes	0.07	9.50
Folley Memorial	67045.02	0.40	47.69	Yes	-0.03	0.00
R13	67800.57	0.28	59.93	Yes	0.01	0.00
AA17	67908.85	0.15	32.00	Yes	0.04	0.00
Desert Rose	69103.39	0.15	45.02	No	0.00	7.00
Y19	69891.00	0.24	72.86	Yes	-0.08	0.00
Chesnutt	72042.09	0.16	41.88	Yes	-0.03	5.00
Arrowhead Shores	74099.05	0.09	45.71	Yes	-0.02	8.91
Comanche	75159.69	0.10	43.56	Yes	0.00	11.00
Z20	76003.84	0.21	52.99	No	-0.05	0.00
Foothills	80362.77	0.16	33.95	Yes	0.02	29.00
AF19	83629.63	0.21	24.76	No	0.04	0.00
Mescal	84155.21	0.04	33.20	No	0.00	10.00
Dos Lagos	84725.58	0.11	50.95	Yes	0.05	5.70

Greenbriar	88252.36	0.11	58.78	No	0.03	3.00
Sycamore Grove	89353.04	0.29	43.85	Yes	0.07	4.80
La Paloma	91203.41	0.13	41.37	Yes	0.04	14.86
Deer Villlage	92515.00	0.11	41.10	No	0.04	8.67
Moon Valley	98768.50	0.17	37.90	No	0.04	10.56
Paseo Verde	102723.92	0.14	39.01	No	0.10	12.00
Chuckwalla	107804.82	0.15	47.29	Yes	0.04	4.46
Estrada	117153.30	0.12	57.64	Yes	0.02	8.00
Hanger	129048.95	0.13	23.87	Yes	0.02	15.00
Veterans Oasis	130221.44	0.11	16.13	Yes	0.12	113.00

Table A5: Covariates used in occupancy analyses for cottontail rabbits.

Site	Income ($) (1km)	Latinx (%) (1km)	Impervious (%) (125m)	Water (Yes/No) (1500 m)	NDVI (750 m)
Tarrington Ranch	27069.63	0.36	33.02	No	0.08
S14	38374.73	0.39	21.28	No	0.02
T14	38673.52	0.38	52.48	No	-0.01
Desert West	42020.58	0.86	24.22	No	0.05
AB18	43525.02	0.40	68.26	No	-0.11
Navarette	43550.82	0.53	33.71	No	-0.06
AC19	44601.38	0.22	32.19	No	0.08
Westown	47832.73	0.30	49.91	No	0.01
Butler	48656.16	0.37	30.00	No	0.02
Sahuaro Ranch	48936.76	0.32	31.02	No	0.06
Dwight	48938.01	0.38	41.63	No	-0.08
Selleh	49573.79	0.18	40.66	Yes	-0.05
Braewood	51889.71	0.38	34.73	No	-0.02
AE19	52037.57	0.22	28.91	No	-0.01
Discovery	65167.75	0.46	21.55	No	0.07
Folley Memorial	67045.02	0.40	41.69	No	-0.03
R13	67800.57	0.28	59.00	No	-0.01
AA17	67908.85	0.15	26.65	Yes	0.03
Desert Rose	69103.39	0.15	36.42	No	0.00
Y19	69891.00	0.24	75.07	No	-0.10
Chesnutt	72042.09	0.16	28.44	No	-0.01
Arrowhead Shores	74099.05	0.09	38.90	No	0.00
Comanche	75159.69	0.10	30.74	No	0.00
Z20	76003.84	0.21	49.70	No	-0.06
Foothills	80362.77	0.16	22.13	No	0.04
AF19	83629.63	0.21	21.17	No	0.04
Mescal	84155.21	0.04	30.73	No	-0.01
Dos Lagos	84725.58	0.11	37.13	Yes	0.06

Greenbriar	88252.36	0.11	44.89	No	-0.01
Sycamore Grove	89353.04	0.29	41.57	No	0.09
La Paloma	91203.41	0.13	39.89	No	0.00
Deer Village	92515.00	0.11	23.86	No	0.05
Moon Valley	98768.50	0.17	27.76	No	0.05
Paseo Verde	102723.92	0.14	31.30	No	0.10
Chuckwalla	107804.82	0.15	38.62	No	0.00
Estrada	117153.30	0.12	47.15	No	0.01
Hanger	129048.95	0.13	11.60	No	0.04
Veterans Oasis	130221.44	0.11	17.00	Yes	0.10

Table A6: Covariates used in occupancy analyses for domestic cats.

Site	Income ($) (1km)	Latinx (%) (1km)	Impervious (%) (250m)	Water (Yes/No) (1500 m)	NDVI (1500 m)
Tarrington Ranch	27069.63	0.36	53.67	No	0.06
S14	38374.73	0.39	60.00	No	0.02
T14	38673.52	0.38	64.14	No	0.00
Desert West	42020.58	0.86	48.25	Yes	0.01
AB18	43525.02	0.40	73.01	No	-0.09
Navarette	43550.82	0.53	58.76	No	-0.04
AC19	44601.38	0.22	36.16	Yes	0.05
Westown	47832.73	0.30	64.46	No	-0.01
Butler	48656.16	0.37	62.11	No	0.02
Sahuaro Ranch	48936.76	0.32	51.47	Yes	0.02
Dwight	48938.01	0.38	61.42	Yes	-0.11
Selleh	49573.79	0.18	64.36	Yes	-0.06
Braewood	51889.71	0.38	61.18	No	-0.01
AE19	52037.57	0.22	35.26	No	-0.02
Discovery	65167.75	0.46	39.33	No	0.07
Folley Memorial	67045.02	0.40	54.52	No	-0.03
R13	67800.57	0.28	59.28	No	0.01
AA17	67908.85	0.15	36.38	Yes	0.04
Desert Rose	69103.39	0.15	58.87	No	0.00
Y19	69891.00	0.24	64.40	Yes	-0.08
Chesnutt	72042.09	0.16	57.07	No	-0.03
Arrowhead Shores	74099.05	0.09	55.65	No	-0.02
Comanche	75159.69	0.10	60.11	No	0.00
Z20	76003.84	0.21	56.99	No	-0.05
Foothills	80362.77	0.16	48.79	No	0.02
AF19	83629.63	0.21	28.80	No	0.04
Mescal	84155.21	0.04	45.41	No	0.00
Dos Lagos	84725.58	0.11	61.09	Yes	0.05
Greenbriar	88252.36	0.11	61.95	No	0.03

Sycamore Grove	89353.04	0.29	36.81	No	0.07
La Paloma	91203.41	0.13	50.30	No	0.04
Deer Village	92515.00	0.11	51.11	No	0.04
Moon Valley	98768.50	0.17	53.58	No	0.04
Paseo Verde	102723.92	0.14	44.62	No	0.10
Chuckwalla	107804.82	0.15	48.24	No	0.04
Estrada	117153.30	0.12	46.98	No	0.02
Hanger	129048.95	0.13	39.20	No	0.02
Veterans Oasis	130221.44	0.11	16.35	Yes	0.12

Figure A1: Plot of the park size surrounding cameras sites, and the proportion of Latinx residents in the 1-km buffer surrounding the sites r = 0.31.

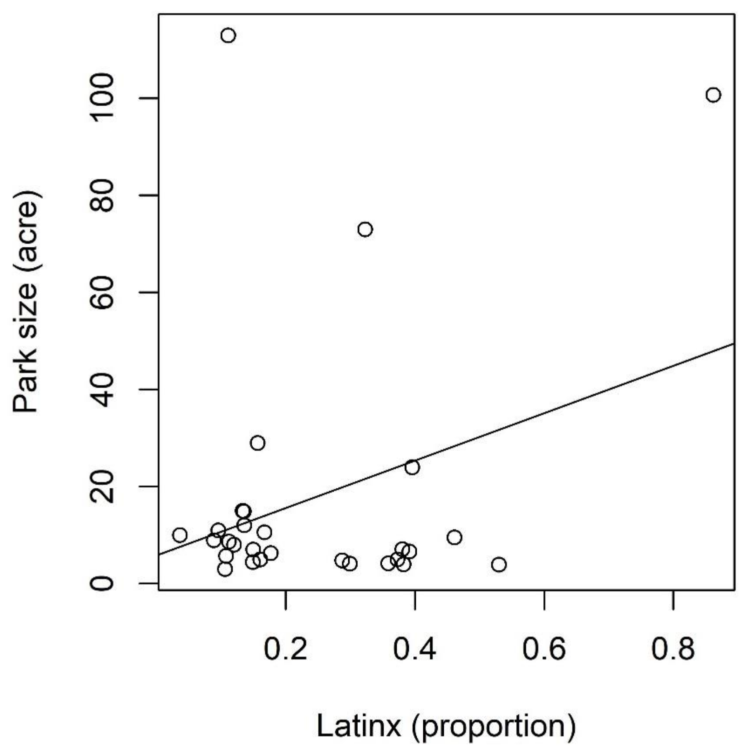

Figure A2: Plot of the park size surrounding cameras sites, and the median household income of residents in the 1-km buffer surrounding the sites r = 0.10.

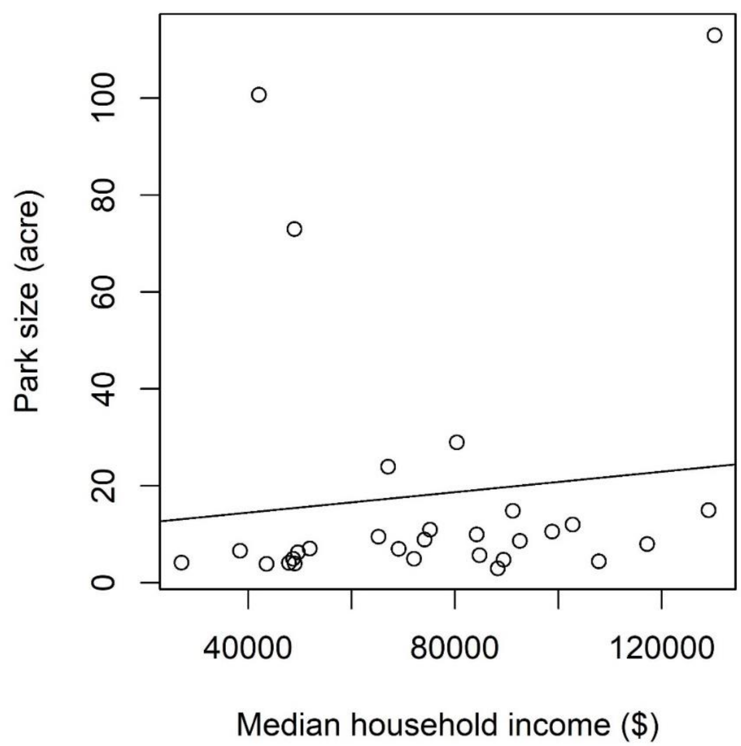

Table A7: Model selection results for detection probability (p) for coyote, desert cottontail rabbit, and domestic cat.

	Model	AICc	Delta AICc	Weight	Deviance
Coyote	psi(.) p(.)	288.25	0.00	0.65	81.35
	psi(.) p(Effort)	289.51	1.25	0.35	282.80
	psi(.) p(Time varying)	309.65	21.40	0.00	74.94
	psi(.) p(Time varying + Effort)	312.51	24.25	0.00	276.03
Desert cottontail rabbit	psi(.) p(.)	126.56	0.00	0.75	1.08
	psi(.) p(Effort)	128.74	2.18	0.25	122.03
	psi(.) p(Time varying)	145.66	19.10	0.00	-7.63
	psi(.) p(Time varying + Effort)	149.86	23.30	0.00	113.38
Domestic cat	psi(.) p(.)	373.43	0.00	0.54	131.41
	psi(.) p(Effort)	373.78	0.35	0.46	367.07
	psi(.) p(Time varying)	389.41	15.98	0.00	119.58
	psi(.) p(Time varying + Effort)	392.04	18.61	0.00	355.56

Table A8: Independent detections (>30 min apart) of coyote, desert cottontail rabbits, and domestic cats within four categories of neighborhood income and proportion of Latinx residents, split at the median of each category (19 neighborhoods per category). The percent of sites are the number of sites within the category divided by the total number of sites (38). Also shown are mean and standard deviations of the number of detections of each species across sites within each category. (H) and (L) represent the higher and lower categories of each variable.

Statistic	Coyote				Desert cottontail rabbit				Domestic cat			
	Income		Latinx		Income		Latinx		Income		Latinx	
	H	L	H	L	H	L	H	L	H	L	H	L
Total detections (#)	77	66	20	123	948	112	0	1060	150	1197	1180	167
Number of sites	12	7	6	13	7	1	0	8	12	17	16	13
Percent of sites	32	18	16	34	18	3	0	21	32	45	42	34
Mean detections	6.42	9.43	3.33	9.46	135.43	-	-	132.50	12.50	74.81	78.67	12.85
Standard deviation	5.32	16.42	3.39	12.10	200.43	-	-	185.74	11.45	109.79	112.33	13.08

Table A9a: Single season occupancy model results for coyote. All combinations (32) on occupancy probability (psi) were modeled and detection probability was held constant as the intercept-only (dot) model, p(.) and I = income, L = Latinx, Im = Impervious, N = NDVI, and W = Water.

Coyote model selection				
Model	AICc	Delta AICc	Weight	Deviance
psi(I + L + N) p(.)	278.49	0.00	0.19	266.62
psi(I + L + W + N) p(.)	279.34	0.85	0.13	264.63
psi(I + N+ Im + L) p(.)	279.77	1.28	0.10	265.06
psi(I + L + Im) p(.)	280.12	1.63	0.08	268.25
psi(L + W + Im) p(.)	280.31	1.81	0.08	268.43
psi(L + Im) p(.)	280.45	1.96	0.07	271.24
psi(I + L + W + Im) p(.)	280.54	2.04	0.07	265.83
psi(I + L + W + Im + N) p(.)	280.99	2.49	0.06	263.25
psi(L + W + N) p(.)	282.09	3.59	0.03	270.21
psi(L + N) p(.)	282.64	4.14	0.02	273.42
psi(L + Im + N) p(.)	282.70	4.21	0.02	270.83
psi(L + W + Im + N) p(.)	282.72	4.23	0.02	268.01
psi(L + W) p(.)	282.75	4.26	0.02	273.54
psi(I + L + W) p(.)	283.53	5.03	0.02	271.65
psi(L) p(.)	283.53	5.04	0.02	276.82
psi(I + L) p(.)	283.66	5.16	0.01	274.44
psi(Im) p(.)	284.83	6.34	0.01	278.13
psi(N)p(.)	284.88	6.39	0.01	278.18
psi(W + N) p.()	285.26	6.76	0.01	276.04
psi(W + Im) p(.)	285.36	6.87	0.01	276.15

psi(Im + N) p(.)	285.72	7.23	0.01	276.51
psi(W + Im + N) p(.)	286.29	7.80	0.00	274.42
psi(I + Im) p(.)	287.07	8.58	0.00	277.86
psi(I + N) p(.)	287.29	8.79	0.00	278.08
psi(I + W + Im) p(.)	287.46	8.96	0.00	275.58
psi(I + W + N) p (.)	287.92	9.42	0.00	276.04
psi(.) p(.)	288.20	9.71	0.00	81.29
psi(I + N + Im) p(.)	288.36	9.87	0.00	276.49
psi(W) p (.)	288.86	10.36	0.00	113.07
psi(I + W + Im + N) p (.)	289.11	10.62	0.00	274.40
psi(I) p(.)	289.91	11.42	0.00	283.21
psi(I + W) p(.)	290.17	11.67	0.00	280.96

Table A9b: Single season occupancy model results for coyote. All combinations (32) on occupancy probability (psi) were modeled and detection probability was held constant as the intercept-only (dot) model, p(.). Confidence intervals that do not overlap zero are considered significant and are bolded. The most strongly supported covariate buffer size follows the covariate name. I = income, L = Latinx, Im = Impervious, N = NDVI, and W = Water.

Coyote beta estimates (psi) social covariates								
Model	I (1km)				L (1km)			
	Estimate	SE	95%	90%	Estimate	SE	95%	CI 90 %
psi(I + L + N) p(.)	-1.80	0.83	**(-3.42, -0.19)**	**(-3.16, -0.44)**	-2.52	0.98	**(-4.45, -0.60)**	**(-4.13, -0.91)**
psi(I + L + W + N) p(.)	-1.67	0.83	**(-3.30, -0.04)**	**(-3.03, -0.31)**	-2.65	1.04	**(-4.70, -0.61)**	**(-4.36, -0.94)**
psi(I + N + Im + L) p(.)	-1.76	0.82	**(-3.36, -0.16)**	**(-3.10, -0.42)**	-2.37	0.95	**(-4.24, -0.51**	**(-3.93, -0.81)**
psi(I + L + Im) p(.)	-1.13	0.66	(-2.42, 0.17)	**(-2.21, -0.05)**	-1.96	0.85	**(-3.63, -0.28)**	**(-3.35, -0.57)**
psi(L + W + Im) p(.)					-1.26	0.58	**(-2.40, -0.12)**	**(-2.21, -0.31)**
psi(L + Im) p(.)					-1.08	0.49	**(-2.04, -0.11)**	**(-1.88, -0.28)**
psi(I + L + W + Im) p(.)	-1.08	0.68	(-2.41, 0.25)	(-2.20, 0.04)	-2.16	0.93	**(-4.00, -0.33)**	**(-3.69, -0.63)**
psi(I + L + W + Im + N) p(.)	-1.62	0.82	**(-3.23, -0.01)**	**(-2.96, -0.28)**	-2.48	1.00	**(-4.44, -0.52)**	**(-4.12, -0.84)**
psi(L + W + N) p(.)					-1.21	0.60	**(-2.38, -0.04)**	**(-2.19, -0.23)**
psi(L + N) p(.)					-0.96	0.51	(-1.97, 0.04)	**(-1.80, -0.12)**
psi(L + Im + N) p(.)					-1.02	0.50	**(-2.00, -0.03)**	**(-1.84, -0.20)**
psi(L + W + Im + N) p(.)					-1.20	0.59	**(-2.35, -0.05)**	**(-2.17, -0.23)**
psi(L + W) p(.)					-1.43	0.60	**(-2.60, -0.25)**	**(-2.41, -0.45)**
psi(I + L + W) p(.)	-0.76	0.58	(-1.89, 0.37)	(-1.71, 0.19)	-2.22	0.93	**(-4.06, -0.39)**	**(-3.75, -0.69)**
psi(L) p(.)					-1.13	0.50	**(-2.12, -0.14)**	**(-1.95, -0.31)**
psi(I + L) p(.)	-0.84	0.56	(-1.94, 0.27)	(-1.76, 0.08)	-1.97	0.84	**(-3.62, -0.31)**	**(-3.35, -0.84)**
psi(Im) p(.)								
psi(N)p(.)								

psi(W + N) p.()				
psi(W + Im) p(.)				
psi(Im + N) p(.)				
psi(W + Im + N) p(.)				
psi(I + Im) p(.)	0.23	0.45	(-0.66, 1.12)	(-0.97, 0.51)
psi(I + N) p(.)	-0.14	0.42	(-0.96, 0.69)	(-0.83, 0.55)
psi(I + W + Im) p(.)	0.35	0.48	(-0.60, 1.29)	(-0.44, 1.14)
psi(I + W + N) p (.)	-0.02	0.44	(-0.87, 0.84)	(-0.74, 0.70)
psi(.) p(.)				
psi(I + N + Im) p(.)	-0.07	0.47	(-1.00, 0.86)	(-0.84, 0.70)
psi(W) p (.)				
psi(I + W + Im + N) p (.)	0.06	0.49	(-0.89, 1.02)	(-0.74, 0.86)
psi(I) p(.)	0.29	0.36	(-0.43, 1.00)	(-0.30, 0.88)
psi(I + W) p(.)	0.40	0.38	(-0.34, 1.13)	(-0.22, 1.02)

Table A9c: Single season occupancy model results for coyote. All combinations (32) on occupancy probability (psi) were modeled and detection probability was held constant as the intercept-only (dot) model, p(.). Confidence intervals that do not overlap zero are considered significant and are bolded. The most strongly supported covariate buffer size follows the covariate name. I = income, L = Latinx, Im = Impervious, N = NDVI, and W = Water.

Coyote beta estimates (psi) environmental covariates												
Model	Im (250m)				N (1500m)				W (1500m)			
	Estimate	SE	95%	90%	Estimate	SE	95%	90%	Estimate	SE	95%	90%
psi(I + L + N) p(.)					1.58	0.73	**(0.15, 3.00)**	**(0.38, 2.78)**				
psi(I + L + W + N) p(.)					1.55	0.73	**(0.13, 2.98)**	**(0.35, 2.75)**	-1.32	0.99	(-3.27, 0.62)	(-2.94, 0.30)
psi(I + N + Im + L) p(.)	-0.71	0.59	(-1.87, 0.44)	(-1.68, 0.26)	1.22	0.77	(-0.29, 2.73)	(-0.04, 2.48)				
psi(I + L + Im) p(.)	-1.11	0.52	**(-2.12, -0.10)**	**(-1.96, -0.26)**								
psi(L + W + Im) p(.)	-1.20	0.67	(-2.51, 0.12)	**(-2.30, -0.10)**					-1.50	0.96	(-3.38, 0.38)	(-3.07, 0.07)
psi(L + Im) p(.)	-1.17	0.61	(-2.36, 0.01)	**(-2.17, -0.17)**								
psi(I + L + W + Im) p(.)	-1.16	0.56	**(-2.25, -0.06)**	**(-2.08, -0.24)**					-1.45	1.00	(-3.40, 0.50)	(-3.09, 0.19)
psi(I + L + W + Im + N) p(.)	-0.74	0.65	(-2.01, 0.53)	(-1.81, 0.33)	1.15	0.78	(-0.38, 2.67)	(-0.13, 2.43)	-1.29	1.01	(-3.27, 0.69)	(-2.95, 0.37)
psi(L + W + N) p(.)					0.83	0.50	(-0.15, 1.82)	**(0.01, 1.65)**	-1.54	0.92	(-3.35, 0.27)	**(-3.05, -0.03)**
psi(L + N) p(.)					0.77	0.46	(-0.12, 1.67)	**(0.02, 1.52)**				
psi(L + Im + N) p(.)	-0.97	0.67	(-2.28, 0.34)	(-2.07, 0.13)	0.35	0.55	(-0.72, 1.42)	(-0.55, 1.25)				
psi(L + W + Im + N) p(.)	-0.96	0.74	(-2.41, 0.48)	(-2.17, 0.25)	0.39	0.61	(-0.80, 1.58)	(-0.61, 1.39)	-1.50	0.95	(-3.36, 0.37)	(-3.06, 0.06)
psi(L + W) p(.)									-1.52	0.92	(-3.32, 0.28)	**(-3.03, -0.01)**
psi(I + L + W) p(.)									-1.46	0.95	(-3.33, 0.41)	(-3.02, 0.10)
psi(L) p(.)												
psi(I + L) p(.)												
psi(Im) p(.)	-0.95	0.47	**(-1.86, -0.03)**	**(-1.72, -0.18)**								
psi(N)p(.)					0.90	0.43	**(0.06, 1.75)**	**(0.19, 1.61)**				

psi(W + N) p.()					0.98	0.46	**(0.08, 1.87)**	**(0.23, 1.73)**	-1.09	0.77	(-2.60, 0.41)	(-2.35, 0.17)
psi(W + Im) p(.)	-0.96	0.46	**(-1.86, -0.07)**	**(-1.71, -0.21)**					-1.05	0.76	(-2.55, 0.45)	(-2.30, 0.20)
psi(Im + N) p(.)	-0.63	0.52	(-1.65, 0.38)	(-1.48, 0.22)	0.61	0.50	(-0.37, 1.58)	(-0.21, 1.43)				
psi(W + Im + N) p(.)	-0.63	0.51	(-1.63, 0.38)	(-1.47, 0.21)	0.66	0.53	(-0.37, 1.70)	(-0.21, 1.53)	-1.11	0.78	(-2.65, 0.43)	(-2.39, 0.17)
psi(I + Im) p(.)	-0.97	0.50	(-1.94, 0.01)	**(-1.79, -0.15)**								
psi(I + N) p(.)					0.96	0.48	**(0.03, 1.90)**	**(0.17, 1.75)**				
psi(I + W + Im) p(.)	-0.99	0.51	(-1.99, 0.02)	**(-1.83, -0.15)**					-1.17	0.80	(-2.73, 0.40)	(-2.48, 0.14)
psi(I + W + N) p (.)					0.98	0.50	**(0.01, 1.95)**	**(0.16, 1.80)**	-1.09	0.78	(-2.62, 0.45)	(-2.37, 0.19)
psi(.) p(.)												
psi(I + N + Im) p(.)	-0.62	0.52	(-1.64, 0.41)	(-1.47, 0.23)	0.64	0.56	(-0.45, 1.74)	(-0.28, 1.56)				
psi(W) p (.)									-0.90	0.70	(-2.26, 0.47)	(-2.05, 0.25)
psi(I + W + Im + N) p (.)	-0.64	0.53	(-1.69, 0.41)	(-1.51, 0.23)	0.63	0.59	(-0.52, 1.78)	(-0.34, 1.60)	-1.13	0.80	(-2.70, 0.44)	(-2.44, 0.18)
psi(I) p(.)												
psi(I + W) p(.)									-1.07	0.73	(-2.51, 0.37)	(-2.27, 0.13)

Table A10a: Single season occupancy model results for desert cottontail rabbits. All combinations (32) on occupancy probability (psi) were modeled and detection probability was held constant as the intercept-only (dot) model, p(.) and I = income, L = Latinx, Im = Impervious, N = NDVI, and W = Water.

Desert cottontail rabbit model selection				
Model	AICc	Delta AICc	Weight	Deviance
psi(L + W + N) p(.)	112.46	0.00	0.12	100.58
psi(L + W + Im) p(.)	112.47	0.01	0.12	100.59
psi(L + N) p(.)	112.68	0.22	0.11	103.47
psi(L + W) p(.)	112.96	0.50	0.10	103.75
psi(L + Im) p(.)	113.01	0.56	0.09	103.80
psi(L) p(.)	113.80	1.34	0.06	107.10
psi(I + L + N) p(.)	113.96	1.51	0.06	102.90
psi(L + W + Im + N) p(.)	114.21	1.75	0.05	99.50
psi(L + Im + N) p(.)	114.27	1.81	0.05	102.39
psi(I + L + W + N) p(.)	114.65	2.19	0.04	99.94
psi(I + L + Im) p(.)	114.67	2.21	0.04	102.79
psi(I + L + W + Im) p(.)	114.85	2.40	0.04	100.14
psi(I + N + Im + L) p(.)	114.99	2.53	0.03	100.28
psi(I + L + W) p(.)	115.62	3.16	0.03	103.74
psi(I + L + W + Im + N) p(.)	116.00	3.54	0.02	98.27
psi(I + L) p(.)	116.26	3.80	0.02	107.05
psi(I + W) p(.)	121.10	8.64	0.00	111.88
psi(W + Im) p(.)	121.40	8.94	0.00	112.19
psi(I + W+ Im) p(.)	121.58	9.12	0.00	109.71
psi(W) p(.)	122.70	10.24	0.00	12.12

psi(W + N) p(.)	122.77	10.31	0.00	113.55
psi(I + W + N) p(.)	122.84	10.38	0.00	110.96
psi(W + Im + N) p(.)	123.63	11.17	0.00	111.75
psi(I + Im) p(.)	123.98	11.52	0.00	114.77
psi(I) p(.)	124.02	11.56	0.00	117.32
psi(I + W + Im + N) p(.)	124.33	11.87	0.00	109.62
psi(Im) p(.)	124.36	11.90	0.00	117.66
psi(I + N) p(.)	125.10	12.64	0.00	115.89
psi(N) p(.)	125.48	13.02	0.00	118.77
psi(Im + N) p(.)	126.12	13.70	0.00	116.95
psi(I + N + Im) p(.)	126.33	13.98	0.00	114.57
psi(.) p(.)	126.56	14.10	0.00	108.00

Table A10b: Single season occupancy model results for desert cottontail rabbits. All combinations (32) on occupancy probability (psi) were modeled and detection probability was held constant as the intercept-only (dot) model, p(.). Confidence intervals that do not overlap zero are considered significant and are bolded. The most strongly supported covariate buffer size follows the covariate name. I = income, L = Latinx, Im = Impervious, N = NDVI, and W = Water.

Desert cottontail rabbit beta estimates (psi) social covariates								
Model	I (1km)				L (1km)			
	Estimate	SE	95%	90%	Estimate	SE	95%	CI 90 %
psi(L + W + N) p(.)					-5.16	2.51	**(-10.08, -0.24)**	**(-9.28, -1.04)**
psi(L + W + Im) p(.)					-5.16	2.71	(-10.46, 0.14)	**(-9.60, -0.72)**
psi(L + N) p(.)					-5.08	2.30	**(-9.59, -0.56)**	**(-8.85, -1.31)**
psi(L + W) p(.)					-4.86	2.44	**(-9.65, -0.07)**	**(-8.86, -0.86)**
psi(L + Im) p(.)					-5.03	2.55	**(-10.03, -0.02)**	**(-9.21, -0.85)**
psi(L) p(.)					-4.47	2.09	**(-8.57, -0.37)**	**(-7.90, -1.04)**
psi(I + L + N) p(.)	-0.76	0.74	(-2.22, 0.69)	(-1.97, 0.45)	-5.16	2.25	**(-9.57, -0.75)**	**(-8.85, -1.47)**
psi(L + W + Im + N) p(.)					-5.16	2.62	**(-10.30, -0.02)**	**(-9.46, -0.86)**
psi(L + Im + N) p(.)					-5.16	2.48	**(-10.01, -0.30)**	**(-9.23, -1.09)**
psi(I + L + W + N) p(.)	-0.62	0.84	(-2.26, 1.02)	(-2.00, 0.76)	-5.16	2.40	**(-9.87, -0.45)**	**(-9.10, -1.22)**
psi(I + L + Im) p(.)	-0.72	0.83	(-2.35, 0.91)	(-2.08, 0.64)	-5.16	2.62	**(-10.29, -0.03)**	**(-9.46, -0.86)**
psi(I + L + W + Im) p(.)	-0.59	0.96	(-2.47, 1.30)	(-2.16, 0.98)	-5.16	2.70	(-10.45, 0.13)	**(-9.59, -0.73)**
psi(I + N + Im + L) p(.)	-1.06	0.91	(-2.84, 0.73)	(-2.55, 0.43)	-5.16	2.43	**(-9.92, -0.40)**	**(-9.15, -1.17)**
psi(I + L + W) p(.)	0.06	0.70	(-1.32, 1.44)	(-1.09, 1.21)	-4.81	2.50	(-9.71, 0.08)	**(-8.91, -0.71)**
psi(I + L + W + Im + N) p(.)	-0.96	1.02	(-2.96, 1.04)	(-2.63, 0.71)	-5.16	2.54	**(-10.14, -0.18)**	**(-9.33, -0.99)**
psi(I + L) p(.)	-0.14	0.62	(-1.35, 1.08)	(-1.16, 0.88)	-4.63	2.23	**(-9.00, -0.27)**	**(-8.29, -0.97)**
psi(I + W) p(.)	0.97	0.52	(-0.06, 1.99)	**(0.12, 1.82)**				
psi(W + Im) p(.)								

psi(I + W+ Im) p(.)	0.82	0.56	(-0.28, 1.92)	(-0.10, 1.74)
psi(W) p(.)				
psi(W + N) p(.)				
psi(I + W + N) p(.)	0.79	0.53	(-0.25, 1.83)	(-0.08, 1.66)
psi(W + Im + N) p(.)				
psi(I + Im) p(.)	0.75	0.47	(-0.17, 1.68)	(-0.02, 1.52)
psi(I) p(.)	0.91	0.44	**(0.04, 1.78)**	**(0.19, 1.63)**
psi(I + W + Im + N) p(.)	0.77	0.57	(-0.35, 1.89)	(-0.16, 1.70)
psi(Im) p(.)				
psi(I + N) p(.)	0.72	0.45	(-0.17, 1.60)	(-0.02, 1.46)
psi(N) p(.)				
psi(Im + N) p(.)				
psi(I + N + Im) p(.)	0.69	0.48	(-0.25, 1.63)	(-0.10, 1.48)
psi(.) p(.)				

Table A10c: Single season occupancy model results for desert cottontail rabbits. All combinations (32) on occupancy probability (psi) were modeled and detection probability was held constant as the intercept-only (dot) model, p(.). Confidence intervals that do not overlap zero are considered significant and are bolded. The most strongly supported covariate buffer size follows the covariate name. I = income, L = Latinx, Im = Impervious, N = NDVI, and W = Water.

Desert cottontail beta estimates (psi) environmental covariates												
Model	Im (250m)				N (1500m)				W (1500m)			
	Estimate	SE	95%	90%	Estimate	SE	95%	90%	Estimate	SE	95%	90%
psi(L + W + N) p(.)					1.47	0.96	(-0.43, 3.36)	(-0.10, 3.04)	3.01	2.10	(-1.10, 7.12)	(-0.43, 6.45)
psi(L + W + Im) p(.)	-1.45	0.93	(-3.28, 0.38)	(-2.98, 0.08)					2.64	1.66	(-0.61, 5.90)	**(0.08, 5.36)**
psi(L + N) p(.)					1.53	0.96	(-0.36, 3.41)	(-0.04, 3.10)				
psi(L + W) p(.)									2.38	1.42	(-0.41, 5.17)	**(0.05, 4.71)**
psi(L + Im) p(.)	-1.36	0.86	(-3.04, 0.32)	(-2.28, 0.05)								
psi(L) p(.)												
psi(I + L + N) p(.)					1.74	0.94	(-0.09, 3.57)	(-0.20, 3.28)				
psi(L + W + Im + N) p(.)	-0.99	1.00	(-2.94, 0.96)	(-2.63, 0.65)	1.00	1.00	(-0.97, 2.96)	(-0.64, 2.64)	2.98	2.10	(-1.13, 7.09)	(-0.46, 6.42)
psi(L + Im + N) p(.)	-0.91	0.93	(-2.73, 0.91)	(-2.43, 0.62)	1.10	1.00	(-0.86, 3.06)	(-0.54, 2.74)				
psi(I + L + W + N) p(.)					1.64	0.97	(-0.26, 3.53)	**(0.05, 3.23)**	2.48	1.94	(-1.32, 6.27)	(-0.70, 5.66)
psi(I + L + Im) p(.)	-1.67	1.00	(-3.64, 0.29)	**(-9.46, -0.86)**								
psi(I + L + W + Im) p(.)	-1.73	1.13	(-3.94, 0.48)	(-3.58, 0.12)					2.29	1.57	(-0.80, 5.37)	(-0.28, 4.86)
psi(I + N + Im + L) p(.)	-1.29	1.09	(-3.44, 0.85)	(-3.08, 0.50)	1.34	0.93	(-0.49, 3.16)	(-0.19, 2.87)				
psi(I + L + W) p(.)									2.42	1.51	(-0.54, 5.38)	(-0.06, 4.90)
psi(I + L + W + Im + N) p(.)	-1.38	1.21	(-3.76, 1.00)	(-3.36, 0.60)	1.23	0.96	(-0.65, 3.12)	(-0.34, 2.80)	2.38	1.92	(-1.39, 6.15)	(-0.77, 5.53)
psi(I + L) p(.)												
psi(I + W) p(.)									2.95	1.38	**(0.25, 5.66)**	**(0.69, 5.21)**
psi(W + Im) p(.)	-1.18	0.71	(-2.57, 0.21)	**(-2.34, -0.02)**					2.87	1.34	**(0.23, 5.51)**	**(0.67, 5.07)**

psi(I + W+ Im) p(.)	-0.95	0.73	(-2.38, 0.47)	(-2.15, 0.25)					3.00	1.45	**(0.15, 5.84)**	**(0.62, 5.38)**
psi(W) p(.)									2.86	1.25	**(0.40, 5.31)**	**(0.81, 4.91)**
psi(W + N) p(.)					0.78	0.53	(-0.27, 1.82)	(-0.09, 1.65)	2.80	1.34	**(0.17, 5.43)**	**(0.60, 5.00)**
psi(I + W + N) p(.)					0.57	0.60	(-0.62, 1.75)	(-0.41, 1.55)	3.00	1.48	**(0.09, 5.90)**	**(0.57, 5.43)**
psi(W + Im + N) p(.)	-0.97	0.77	(-2.49, 0.55)	(-2.23, 0.29)	0.42	0.64	(-0.83, 1.68)	(-0.63, 1.47)	2.89	1.40	**(0.15, 5.63)**	**(0.59, 5.19)**
psi(I + Im) p(.)	-0.89	0.63	(-2.13, 0.34)	(-1.92, 0.14)								
psi(I) p(.)												
psi(I + W + Im + N) p(.)	-0.85	0.79	(-2.40, 0.70)	(-2.15, 0.45)	0.22	0.72	(-1.19, 1.63)	(-0.96, 1.40)	3.02	1.49	**(0.11, 5.93)**	**(0.58, 5.46)**
psi(Im) p(.)	-1.11	0.61	(-2.30, 0.08)	**(-2.11, -0.11)**								
psi(I + N) p(.)					0.63	0.55	(-0.45, 1.71)	(-0.27, 1.53)				
psi(N) p(.)					0.84	0.50	(-0.13, 1.81)	**(0.02, 1.66)**				
psi(Im + N) p(.)	-0.85	0.67	(-2.17, 0.46)	(-1.95, 0.25)	0.49	0.59	(-0.66, 1.64)	(-0.48, 1.46)				
psi(I + N + Im) p(.)	-0.75	0.69	(-2.12, 0.61)	(-1.88, 0.38)	0.29	0.66	(-0.99, 1.58)	(-0.79, 1.37)				
psi(.) p(.)												

Table A11a: Single season occupancy model results for domestic cats. All combinations (32) on occupancy probability (psi) were modeled and detection probability was held constant as the intercept-only (dot) model, p(.) and I = income, L = Latinx, Im = Impervious, N = NDVI, and W = Water.

Domestic cat model selection				
Model	AICc	Delta AICc	Weight	Deviance
psi(W + Im + N) p(.)	363.51	0.00	0.22	351.64
psi(L + W + Im + N) p(.)	363.53	0.02	0.22	348.82
psi(W + Im) p(.)	365.32	1.80	0.09	356.10
psi(L + W + Im) p(.)	365.50	1.99	0.08	353.63
psi(I + W + Im + N) p(.)	365.96	2.45	0.06	351.25
psi(I + L + W + Im + N) p(.)	366.00	2.49	0.06	348.27
psi(L + Im + N) p (.)	366.99	3.48	0.04	355.12
psi(I + L + W + Im) p(.)	367.25	3.74	0.03	352.54
psi(L + Im) p(.)	367.42	3.91	0.03	358.21
psi(I + W + Im) p(.)	367.89	4.38	0.02	356.02
psi(Im) p(.)	368.06	4.55	0.02	361.35
psi(Im + N) p(.)	368.22	4.71	0.02	359.01
psi(I + N + Im) p(.)	368.39	4.88	0.02	356.52
psi(I + Im) p(.)	369.40	5.89	0.01	360.19
psi(I + N + Im + L) p(.)	369.55	6.04	0.01	354.84
psi(L) p(.)	369.90	6.39	0.01	363.20
psi(I + L + Im) p(.)	370.08	6.57	0.01	358.21
psi(L + W_ p(.)	370.39	6.88	0.01	361.18
psi(I) p(.)	370.49	6.98	0.01	363.79
psi(I + W) p(.)	371.35	7.84	0.00	362.14

psi(I + L) p(.)	371.74	8.23	0.00	362.53
psi(L + N) p(.)	372.41	8.90	0.00	363.20
psi(.) p(.)	372.62	9.11	0.00	131.00
psi(I + L + W) p(.)	372.63	9.12	0.00	360.76
psi(I + N) p(.)	372.70	9.19	0.00	363.49
psi(W) p(.)	372.90	9.39	0.00	158.39
psi(L + W + N) p(.)	373.05	9.54	0.00	361.17
psi(I + W + N) p(.)	373.78	10.27	0.00	361.90
psi(I + L + N) p(.)	374.22	10.70	0.00	362.34
psi(N) p(.)	374.59	11.08	0.00	367.89
psi(W + N) p (.)	375.03	11.52	0.00	365.82
psi(I + L + W + N) p (.)	375.39	11.87	0.00	360.68

Table A11b: Single season occupancy model results for domestic cats. All combinations (32) on occupancy probability (psi) were modeled and detection probability was held constant as the intercept-only (dot) model, p(.). Confidence intervals that do not overlap zero are considered significant and are bolded. The most strongly supported covariate buffer size follows the covariate name. I = income, L = Latinx, Im = Impervious, N = NDVI, and W = Water.

Domestic cat beta estimates (psi) social covariates								
Model	I (1km)				L (1km)			
	Estimate	SE	95%	90%	Estimate	SE	95%	90%
psi(W + Im + N) p(.)								
psi(L + W + Im + N) p(.)					1.06	0.72	(-0.34, 2.46)	(-0.12, 2.24)
psi(W + Im) p(.)								
psi(L + W + Im) p(.)					0.95	0.66	(-0.35, 2.25)	(-0.13, 2.03)
psi(I + W + Im + N) p(.)	-0.40	0.66	(-1.70, 0.90)	(-1.48, 0.68)				
psi(I + L + W + Im + N) p(.)	0.73	1.01	(-1.24, 2.70)	(-0.93, 2.39)	1.55	1.04	(-0.48, 3.58)	(-0.16, 3.26)
psi(L + Im + N) p (.)					1.14	0.73	(-0.29, 2.56)	(-0.06, 2.34)
psi(I + L + W + Im) p(.)	0.76	0.76	(-0.74, 2.25)	(-0.49, 2.01)	1.60	0.99	(-0.33, 3.54)	(-0.02, 3.22)
psi(L + Im) p(.)					0.94	0.63	(-0.30, 2.18)	(-0.09, 1.97)
psi(I + W + Im) p(.)	-0.14	0.49	(-1.11, 0.82)	(-0.94, 0.66)				
psi(Im) p(.)								
psi(Im + N) p(.)								
psi(I + N + Im) p(.)	-0.81	0.56	(-1.91, 0.29)	(-1.73, 0.11)				
psi(I + Im) p(.)	-0.46	0.44	(-1.33, 0.40)	(-1.18, 0.26)				
psi(I + N + Im + L) p(.)	-0.34	0.66	(-1.63, 0.95)	(-1.43, 0.74)	0.93	0.82	(-0.67, 2.53)	(-0.41, 2.27)
psi(L) p(.)					1.13	0.60	(-0.04, 2.29)	**(0.15, 2.11)**
psi(I + L + Im) p(.)	0.02	0.56	(-1.08, 1.13)	(-0.90, 0.94)	0.96	0.78	(-0.57, 2.48)	(-0.32, 2.24)
psi(L + W) p(.)					1.16	0.60	(-0.01, 2.33)	**(0.18, 2.14)**

psi(I) p(.)	-0.79	0.40	**(-1.57, -0.01)**	**(-1.45, -0.13)**				
psi(I + W) p(.)	-0.77	0.40	(-1.57, 0.02)	**(-1.43, -0.11)**				
psi(I + L) p(.)	-0.42	0.51	(-1.42, 0.59)	(-1.26, 0.42)	0.75	0.73	(-0.68, 2.18)	(-0.45, 1.95)
psi(L + N) p(.)					1.13	0.62	(-0.09, 2.34)	**(0.11, 2.15)**
psi(.) p(.)								
psi(I + L + W) p(.)	-0.35	0.54	(-1.41, 0.71)	(-1.24, 0.54)	0.84	0.76	(-0.65, 2.33)	(-0.41, 2.09)
psi(I + N) p(.)	-0.93	0.50	(-1.91, 0.04)	**(-1.75, -0.11)**				
psi(W) p(.)								
psi(L + W + N) p(.)					1.15	0.61	(-0.05, 2.34)	**(0.15, 2.15)**
psi(I + W + N) p(.)	-0.91	0.52	(-1.92, 0.10)	**(-1.76, -0.06)**				
psi(I + L + N) p(.)	-0.54	0.60	(-1.73, 0.64)	(-1.52, 0.44)	0.73	0.73	(-0.71, 2.16)	(-0.47, 1.93)
psi(N) p(.)								
psi(W + N) p (.)								
psi(I + L + W + N) p (.)	-0.45	0.65	(-1.72, 0.82)	(-1.52, 0.62)	0.80	0.77	(-0.70, 2.30)	(-0.46, 2.06)

Table A11c: Single season occupancy model results for domestic cats. All combinations (32) on occupancy probability (psi) were modeled and detection probability was held constant as the intercept-only (dot) model, p(.). Confidence intervals that do not overlap zero are considered significant and are bolded. The most strongly supported covariate buffer size follows the covariate name. I = income, L = Latinx, Im = Impervious, N = NDVI, and W = Water.

Domestic cat beta estimates (psi) environmental covariates												
Model	Im (250m)				N (1500m)				W (1500m)			
	Estimate	SE	95%	90%	Estimate	SE	95%	90%	Estimate	SE	95%	90%
psi(W + Im + N) p(.)	2.69	1.00	**(0.73, 4.64)**	**(1.05, 4.33)**	1.57	0.84	(-0.07, 3.21)	**(0.19, 2.95)**	3.68	1.75	**(0.25, 7.11)**	**(0.81, 6.55)**
psi(L + W + Im + N) p(.)	2.69	1.11	**(0.52, 4.85)**	**(0.87, 4.51)**	1.77	0.94	(-0.07, 3.61)	**(0.23, 3.31)**	3.75	1.95	(-0.07, 7.58)	**(0.55, 6.95)**
psi(W + Im) p(.)	1.44	0.54	**(0.37, 2.50)**	**(0.55, 2.33)**					3.10	1.72	(-0.28, 6.47)	**(0.28, 5.92)**
psi(L + W + Im) p(.)	1.33	0.57	**(0.22, 2.44)**	**(0.40, 2.26)**					3.12	1.83	(-0.48, 6.71)	**(0.12, 6.12)**
psi(I + W + Im + N) p(.)	2.43	1.04	**(0.40, 4.46)**	**(0.72, 4.14)**	1.62	0.84	(-0.02, 3.26)	**(0.24, 3.00)**	3.35	1.81	(-0.20, 6.90)	**(0.38, 6. 32)**
psi(I + L + W + Im + N) p(.)	3.27	1.52	**(0.28, 6.26)**	**(0.78, 5.76)**	1.80	0.99	(-0.14, 3.74)	**(0.18, 3.42)**	4.76	2.66	(-0.46, 9.98)	**(0.40, 9.12)**
psi(L + Im + N) p (.)	1.57	0.65	**(0.29, 2.85)**	**(0.50, 2.64)**	1.04	0.62	(-0.18, 2.26)	**(0.02, 2.06)**				
psi(I + L + W + Im) p(.)	1.82	0.86	**(0.14, 3.50)**	**(0.41, 3.23)**					3.98	2.14	(-0.22, 8.19)	**(0.47, 7.49)**
psi(L + Im) p(.)	0.93	0.46	**(0.03, 1.83)**	**(0.18, 1.68)**								
psi(I + W + Im) p(.)	1.34	0.63	**(0.11, 2.57)**	**(0.31, 2.37)**					2.97	1.78	(-0.52, 6.46)	**(0.05, 5.89)**
psi(Im) p(.)	1.01	0.43	**(0.16, 1.86)**	**(0.30, 1.72)**								
psi(Im + N) p(.)	1.59	0.63	**(0.36, 2.82)**	**(0.56, 2.62)**	0.85	0.58	(-0.28, 1.98)	(-0.10, 1.80)				
psi(I + N + Im) p(.)	1.51	0.66	**(0.23, 2.80)**	**(0.43, 2.59)**	1.13	0.62	(-0.09, 2.36)	**(0.11, 2.15)**				
psi(I + Im) p(.)	0.85	0.47	(-0.07, 1.77)	**(0.08, 1.62)**								
psi(I + N + Im + L) p(.)	1.55	0.66	**(0.26, 2.84)**	**(0.47, 2.63)**	1.14	0.65	(-0.14, 2.41)	**(0.07, 2.21)**				
psi(L) p(.)												
psi(I + L + Im) p(.)	0.94	0.48	(-0.00, 1.87)	**(0.15, 1.73)**								
psi(L + W) p(.)									1.49	1.17	(-0.81, 3.78)	(-0.43, 3.41)

psi(I) p(.)								
psi(I + W) p(.)					1.39	1.21	(-0.97, 3.76)	(-0.59, 3.37)
psi(I + L) p(.)								
psi(L + N) p(.)	0.00	0.41	(-0.81, 0.80)	(-0.67, 0.67)				
psi(.) p(.)								
psi(I + L + W) p(.)					1.43	1.19	(-0.90, 3.77)	(-0.52, 3.38)
psi(I + N) p(.)	0.25	0.46	(-0.65, 1.15)	(-0.50, 1.00)				
psi(W) p(.)					1.44	1.13	(-0.78, 3.65)	(-0.41, 3.29)
psi(L + W + N) p(.)	-0.04	0.46	(-0.95, 0.87)	(-0.79, 0.71)	1.49	1.18	(-0.81, 3.80)	(-0.45, 3.43)
psi(I + W + N) p(.)	0.14	0.50	(-0.74, 1.22)	(-0.68, 0.96)	1.35	1.19	(-0.98, 3.68)	(-0.60, 3.30)
psi(I + L + N) p(.)	0.21	0.47	(-0.72, 1.14)	(-0.56, 0.98)				
psi(N) p(.)	-0.23	0.37	(-0.95, 0.50)	(-0.84, 0.38)				
psi(W + N) p (.)	-0.25	0.42	(-1.07, 0.56)	(-0.94, 0.44)	1.45	1.14	(-0.79, 3.68)	(-0.42, 3.32)
psi(I + L + W + N) p (.)	0.15	0.53	(-0.89, 1.19)	(-0.72, 1.02)	1.39	1.19	(-0.94, 3.72)	(-0.56, 3.34)

Table A12: Overlap estimates and 95% confidence intervals of each species within each covariate category (income or Latinx). Values range from 0 to 1. An asterisk (*) denotes that daily activity was shifted (upper 95% CI < 0.9).

Species	Category	Overlap estimate	95 % CI lower	95% CI upper
Coyote	Income	0.85	0.78	0.95
Coyote	Latinx	0.72*	0.55	0.88
Cottontail	Income	Not available	Not available	Not available
Cottontail	Latinx	Not available	Not available	Not available
Cat	Income	0.87	0.81	0.92
Cat	Latinx	0.89	0.84	0.95