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Research article

Housing proximity and vegetation cover affect diel activity patterns of domestic cats (*Felis catus*) in regionally protected shorelines

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Abstract

Free-roaming domestic cats (*Felis catus*) are among the most impactful non-native species globally, causing the extinction of 63 endemic vertebrate species. Their potential ecological impact is especially pronounced in urban areas adjacent to protected spaces where elevated cat densities threaten local wildlife. While cat ecology in human-dominated environments is well-studied, the social-ecological factors influencing cats' spatial and temporal activity are less certain. Examining these factors is crucial for regionally protected landscapes, as increased cat activity can undermine conservation efforts and complicate policy implementation. In this study, we used motion-activated trail cameras across protected shoreline sites in California's East Bay region to analyze cat detection patterns and their temporal activity concerning vegetation greenness (NDVI), human population density, median household income, and housing proximity. Our findings show that cat detections decreased when the distance from residential areas increased, with housing proximity being the only significant predictor among the spatial variables tested. Temporal analysis revealed a strong preference for nocturnality, with the greatest selection for nighttime and twilight periods observed in areas closer to residential housing and vegetation cover. Our results suggest that free-roaming cats alter their activity spatially and temporally to select areas where they can avoid predation from top predators while exploiting food subsidies near housing communities. These results highlight the complex ecological interactions near human infrastructure and how environmental composition contributes to the behavioral patterns of free-roaming cats.

Key words: diel activity, temporal patterns, free-roaming domestic cats, social-ecological, socioeconomics, invasive species, behavioral ecology

Introduction

Non-native speciespose numerous threats to biodiversity in cities due to their ability to exploit human-disturbed environments and infiltrate novel habitats facilitated by human movement (Shocat *et al.* 2010, Doherty *et al.* 2016, Gaertner *et al.* 2017, Padayachee *et al.* 2017). As an example, domestic cats (*Felis catus*) are one of the most common, impactful non-native species worldwide, directly compromising biodiversity and public health (Lepczyk *et al.* 2023, Loss *et al.* 2017, Lepczyk *et al.* 2022). Globally, free-roaming cats are responsible for the extinction of 63 endemic vertebrate species and have been introduced to 5% of all island systems worldwide (Loss *et al.* 2017, Medina *et al.* 2011). In the U.S. alone, free-roaming cats kill 1.3–4.0 billion wild birds and 6.3–22.3 billion wild mammals annually (Loss *et al.* 2013). Furthermore, while domestic cats are primarily known for their direct predation on wildlife, other observations highlight how cats have nonconsumptive indirect impacts on urban wildlife (Loss *et al.* 2017, Loss *et al.* 2013). Observations from Fardell *et al.* 2023 revealed that wildlife in urban environments increased their activity in the absence of cats in the same 24-hour period as a deliberate form of avoidance (Fardell *et al.* 2023, Fardell *et al.* 2022). In addition to their impact on wildlife mortality and behavior, cats can carry several zoonoses including rabies, pneumonic plague, toxoplasmosis, or feline leukemia virus, which have myriad implications for wildlife and human health (Loss *et al.* 2017, Loss *et al.* 2013). With over 90 million domestic cats in the United States, it is an urgent priority to determine how urban conditions affect cat ecology to mitigate the conservation and ecological threats posed by the species (Dabritz *et al.* 2010, Dubey *et al.* 2008, Robertson *et al.* 2008).

Cat abundance and activity are often attenuated by human influence, emphasizing how people are central mediators of their ecology (Herrera *et al.* 2022, Cove *et al.* 2023, Bennett *et al.* 2021,

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Herrera et al. 2022, Vanek et al. 2021, Clyde et al. 2022). Cat abundance increases in high-density residential areas, (Bennett et al. 2021, Clyde et al. 2022, Flockhart et al. 2016) with additional evidence suggesting income negatively correlates with cat occupancy (Cove et al. 2023, Gow et al. 2024). Several other factors, including habitat-to-urban edge ratio, human population densities, and greenspace availability, all positively impact cat detections and occupancy (Cove et al. 2023, Vanek et al. 2021, Flockhart et al. 2016, Crooks and Soule 1999, Barratt 1997, Gehrt et al. 2013). Consequently, ecological factors alone are insufficient in determining cat spatial ecology and thus require an analysis of the societal factors mediating observed spatial patterns. Another dimension of animal behavior that is becoming more important in interpreting the ecology of wildlife in urban environments is the time of day (Gallo et al. 2022). However, less work exists detailing cat temporal activity, which may provide greater insight into how the species uses green spaces within urban systems across time.

Wildlife can adjust their temporal behavior in response to predation risk, competition, food availability, and local environmental conditions (Manlick et al. 2020, Finke and Snyder 2008, Shores et al. 2019). Within urban environments, wildlife utilize avoidance strategies to reduce dangerous encounters with people and navigate complex human-dominated environments (Gallo et al. 2019, Smith et al. 2017). A global meta-analysis from 2018 highlighted this, detailing that mammals become more nocturnal in areas with greater human disturbance (Gaynor et al. 2018). Consideration of this is crucial because, as urbanization increases over time, the availability of habitat patches within urban ecosystems diminishes (Magle et al. 2021). This makes it more difficult for animals to find shelter or optimize temporal niches when confronted with anthropogenic disturbance and/or negative interactions with other species (Manlick and Pauli 2020, Gilbert et al. 2022). As a response, animals may adjust their temporal behavior with greater discretion beyond the spatial constraints they experience in human-dominated environments (Gallo et al. 2022, Gallo et al. 2019). In the same way cities vary in size, human activity, land use, and growth patterns, the response animals have behaviorally to varying environmental characteristics might also be context-specific (Pacione 2009, Fidino et al. 2021). Therefore, examining how free-roaming cats adjust their temporal activity in response to landscape characteristics might explain how cats behave within urban ecosystems with greater detail.

Additionally, another lingering question surrounding the temporal behavior of cats is understanding how socioeconomic variables potentially inform it. Within urban systems, due to systemic frameworks that facilitate socioeconomic disparities and inequality in society (e.g. historical redlining), the material conditions of urban environments can contrast dramatically based on the affluence or economic burden of surrounding areas (Nardone et al. 2021, Leong et al. 2018, Schell et al. 2020, Cushing et al. 2015). As an example, urban areas with a greater distribution of wealth tend to have more biodiversity, larger amounts of greenspace (i.e. NDVI), and experience less anthropogenic disturbance in some instances (Magle et al. 2021, Nardone et al. 2021, Leong et al. 2018). This contrasts with low-income communities that hold less greenspace, reduced biological diversity, have more impervious surface area, and deal with a greater degree of environmental hazards (Schell et al. 2020, Estien et al. 2024, Wood et al. 2024, Jesdale et al. 2013, Casey et al. 2017). Interestingly enough, research findings reveal that urban wildlife can adjust their temporal patterns along a gradient of urbanization in response to these characteristics (Gallo et al. 2022, Gallo et al. 2019). However, for a widespread predator inextricably linked to human-dense environments the information on socioeconomic status and temporality in domestic cats is sparse. As such, socioeconomic status may be a useful and unique proxy for understanding the temporal patterns of free-roaming domestic cats in urban environments.

Here, we used motion-triggered wildlife cameras across regionally protected shoreline parks in the eastern region of the San Francisco Bay Area in California (hereon, referred to as the East Bay) to assess how social-ecological factors corresponded with cat spatial and temporal ecology. Specifically, we asked: (i) How do the social-ecological features of urban landscapes influence domestic cat detections?, and (ii) How do social-ecological features influence the temporal activity patterns of free-roaming cats? Since domestic cats are opportunistic by nature, we hypothesized that cat abundance and activity in parks would be influenced by the proximity of wealthier neighborhoods as a function of resource availability within the surroundings. We also predicted that the distance of houses to natural habitat would be associated with cat detections, as prior literature suggests human population densities positively impact cat occurrence (Bennett et al. 2021, Vanek et al. 2021, Crooks and Soule 1999). For temporal patterns, we predicted that cat nocturnality would increase at shorelines closer to residential areas with greater median income, vegetation cover, and dense human populations (Fig. 1).

Materials and methods

Study area and design

The East Bay region of California (37.849206, −121.998653) is situated within the ancestral and unceded homelands of the Ohlone, Muwekma, and Chochenyo First Nation Peoples. It is also the location of several cities, including Oakland, Berkeley, and Richmond, in the San Francisco Bay Area of California, USA. The East Bay subregion comprises Alameda and Contra Costa counties with around 2.7 million residents (~739.6 people per km^2) (U.S. Census Bureau 2021). The climate resembles Mediterranean conditions, exemplified by mild to cool winters (mean temperature: 40–50°F/4–10°C) and hot, dry summers (mean temperature: 50–70°F/10–21°C) (NOAA 2021, Lionello et al. 2006). The San Francisco Bay Area holds a mosaic of land-cover types including grasslands, oak woodlands, coniferous forests, coastal salt marshes, chaparral, and urban development (Santos et al. 2010).

We deployed 26 motion-triggered camera traps (Model: Bushnell TrophyCam E3) across 10 regional shoreline park locations owned and managed by the East Bay Regional Parks District (Fig. 2). Each sampled shoreline location was equipped with two to five cameras. We selected camera locations with sufficient canopy cover to reduce false triggers via sun exposure and positioned camera traps ≥ 700 m apart within a regional shoreline park to minimize spatial autocorrelation (Herrera et al. 2022, Gallo et al. 2022, Magle et al. 2021). Each camera trap unit was placed approximately ~ 1 m above the ground. Cameras were programmed to take a single photo with a 30-second resting interval between detections. The survey period extended from 5 April 2022 to 11 December 2022, for 250 days and 4911 camera trap nights (Table S7). Each camera was active for at least 30 days before removal. Throughout the study, five cameras were stolen and two were tampered with, but were still operational after retrieval.

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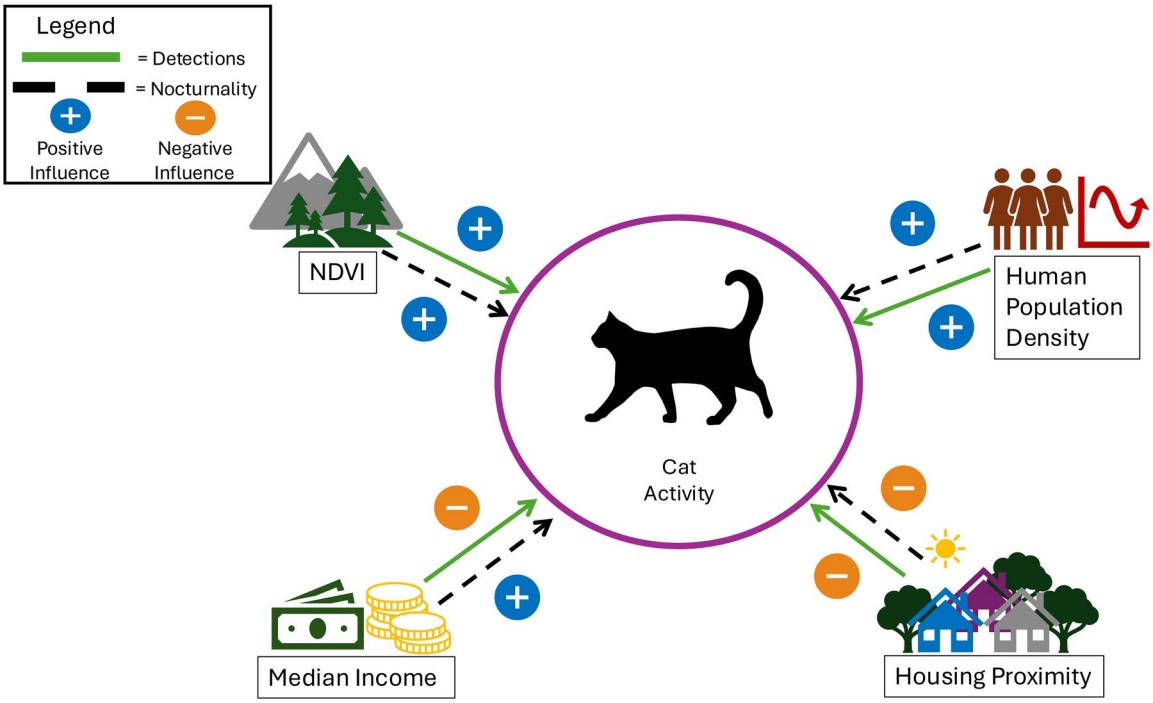

Figure 1. Conceptual graphic illustrating the influence of social-ecological variables on free-roaming cat activity and nocturnality across urban shoreline parks. The figure details specific environmental and social predictors—housing proximity, median household income, NDVI (normalized difference vegetation index), and human population density—and their respective positive or negative associations with cat detections and nocturnal activity. Detection is represented by solid green lines, while nocturnality is dashed black lines. Positive or negative influence is visualized with blue plus signs or orange minus signs. Image created via Microsoft PowerPoint Software. Domestic cat silhouette created by Skye McDavid under a CC0 1.0 Universal Public Domain Dedication License.

Data processing and summary statistics

We used the Wildlife Insights application (https://www.wildlifeinsights.org) to identify free-roaming domestic cats in each image. Before review, Wildlife Insights utilizes an AI computer vision program to identify species. However, uploaded images were still reviewed and manually confirmed by two independent observers. Afterward, we uploaded the CSV file downloaded from Wildlife Insights into R and generated a count estimate for each camera unit across the shoreline parks (Tables 1 and 2). To account for individual detection events, we coded a 30-minute interval to filter image replicates. We then estimated the mean number of domestic cat detections broadly for each shoreline park to showcase the variation in our graphic plot relating to detection events and socio-ecological variables (Fig. 3) (Mills and Harris 2020, Estien *et al.* 2025, Hentati *et al.* 2024). Because each image observation contains a time-date stamp, we utilized circular statistics to determine the mean hour and standard deviation of detection events throughout the shoreline locations (Table S4).

Predictor variables

Covariates included in the analysis were linear distance to the nearest house (hereon referred to as housing distance), normalized difference vegetation index (NDVI), median household income, housing density (per/km^2), and population density (people/km^2). To evaluate NDVI, we generated multispectral image layers with a 30 m^2 resolution through Landsat 8 satellite observations for 2022 for both the 'wet' (November–April) and 'dry' (May–October) seasons to account for seasonal differences in vegetation (USGS 2022, Gorelick *et al.* 2017). After observing high collinearity (Pearson correlation coefficient = 0.864) between the two, we selected the "dry" season as the best fit for the study period. Median household income, population density, and housing density were collected using the *tidycensus* package in R, pulling information from the 2022 U.S. census tract for Contra Costa and Alameda counties (Walker *et al.* 2024). Similarly, domestic cat abundance corresponds positively to human-dense environments; therefore, we selected population density as it connects to our questions appropriately. Housing distance (meters) was calculated using the linear distance tool in ArcGIS by connecting a line to the closest observed residential house for each camera location (Herrera *et al.* 2022, Chamberlain and Hocking 2024). It should be noted that housing density was originally included in this process but omitted after multi-collinearity was found between this variable and population density (correlation = 0.807).

Modeling approach

Generalized linear mixed models

To assess how total cat detections varied with our social-ecological covariates, we used a Poisson-log generalized linear mixed model (Roy 2022, Robins *et al.* 2019, Stark *et al.* 2020, Salek *et al.* 2015). Shoreline Park location was set as our random effect. Sampling effort (i.e. camera survey length) was treated as an offset variable, and the number of detections was our dependent variable. We compiled five candidate univariate models corresponding to our developed hypotheses (Table S1). Model 1 represented our urban model, with housing proximity and population density as the fixed effects; Model 2 represented environmental conditions and included NDVI as a fixed effect; Model 3 represented our socioeconomic model and included median income; Model 4 was our global model and included all the covariates; and lastly, Model 5 was our null model where fixed effects were omitted. Each GLMM was fit in R using the *glmer* function in the

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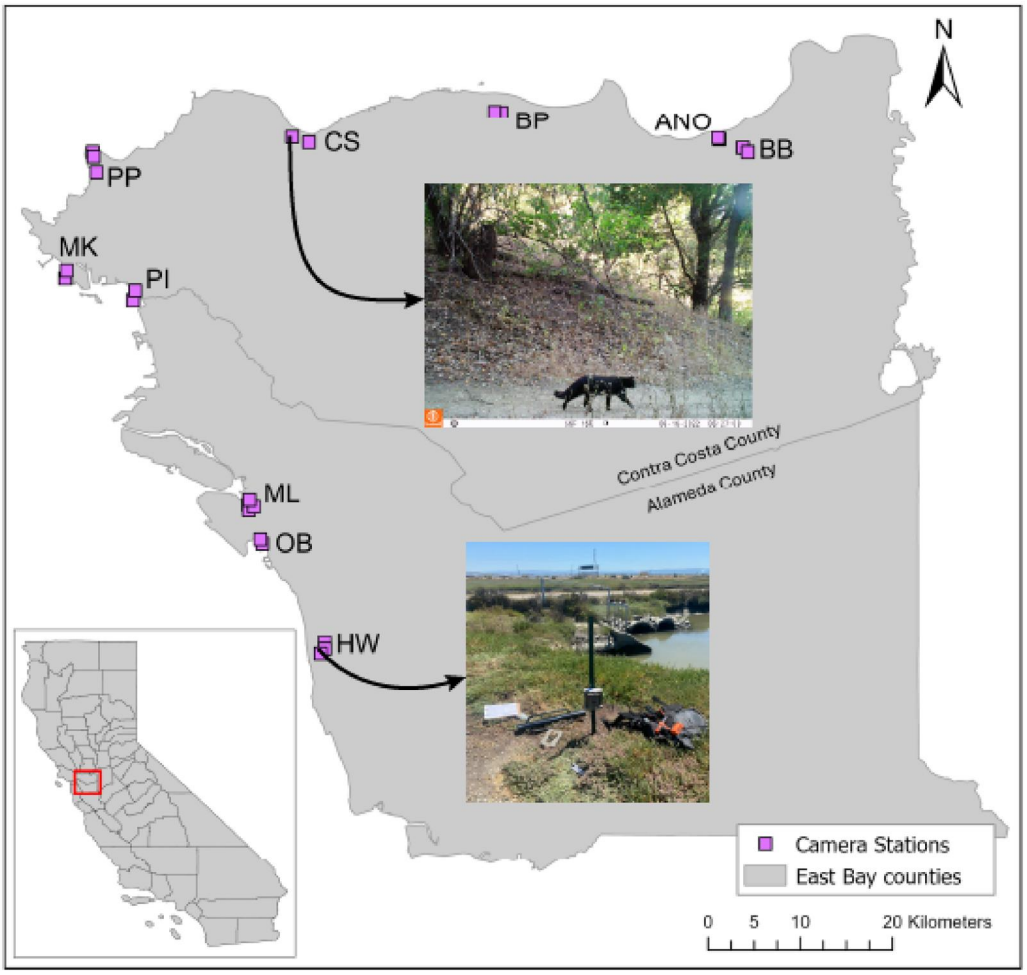

Figure 2. Map of the study site in the East Bay Region of Northern California indicating camera stations ($n = 26$), East Bay counties (northern: Contra Costa County, southern: Alameda County), and labeled shoreline sites ($n = 10$). Shoreline sites included ANO: Antioch/Oakley Regional Shoreline, BP: Bay Point Regional Shoreline, BB: Big Break Regional Shoreline, CS: Carquinez Strait Regional Shoreline, HW: Hayward Regional Shoreline, MK: Miller Knox Regional Shoreline, ML: Martin Luther King, Jr Regional Shoreline, OB: Oyster Bay Regional Shoreline, PI: Point Isabel Regional Shoreline, and PP: Point Pinole Regional Shoreline.

lme4 package (Bates *et al.* 2015). We then reviewed the performance of each model, selecting the best-fit model with the lowest AICc score (Table S1). Model residuals corresponding to detection events and associated covariates were extracted from the best-fit model (Table S2), and covariate effect sizes were plotted for the best-fit model (Ludecke 2023).

Estimating temporal selection patterns

We used the *suncalc* package to partition the sunlight periods into three distinct categories: day, twilight, or night (Benoit and Achraf 2022, R Core Team 2023). Sunlight periods are typically partitioned into several categories such as "dawn," "day," "dusk," "night," and "deep night." However, because of the limited sample size (i.e. ~ 691 observations), we coalesced dawn and dusk to represent twilight (i.e. crepuscular period). We then selected day and night to reduce statistical overdispersion and the number of bins used in the model input. Across the shoreline parks, we observed that twilight had the lowest number of detections (~ 70 observations total) compared to a nighttime total of 449 detections, highlighting the variance of observations (Table 2). Dawn is categorized as the beginning of the morning astronomical twilight (when the sun's center is 18° below the horizon) and ending when the bottom edge of the sun touches the horizon. Dusk is the beginning of evening astronomical twilight until it becomes dark enough for astronomical observations (e.g. constellations and moon phases). Daytime is defined by the temporal period between the astronomical twilight periods of dawn and dusk. Lastly, nighttime is defined as the period between the end of dusk and 1 hour before the sun is at its lowest point (the darkest moment of the night astronomically), and from 1 hour after the sun is at its lowest point to dawn (Gallo *et al.* 2022).

A single fully parameterized Bayesian softmax model was fitted using a Markov Chain Monte Carlo (MCMC) algorithm implemented using the *nimble* package in R (Denwood 2016, Page and Schuyler 2003). All parameters, including the intercepts, were given normal uniform priors (i.e. 0,1) using a logistic regression distribution (Gallo *et al.* 2022, Gelman *et al.* 2008, Northrup *et al.* 2018). Furthermore, because detections are not evenly distributed across a 24-hour cycle, we included a log offset for the number of hours available in each temporal category at the time of detection. The development of this model includes all predictor variables concerning our research assumptions. Four parallel chains were constructed for each parameter, where each chain consisted of 80,000 iterations and a burn-in period of 20,000 iterations. Model convergence was then inspected by visually assessing the trace plot, and by ensuring the Gelman-Rubin statistic

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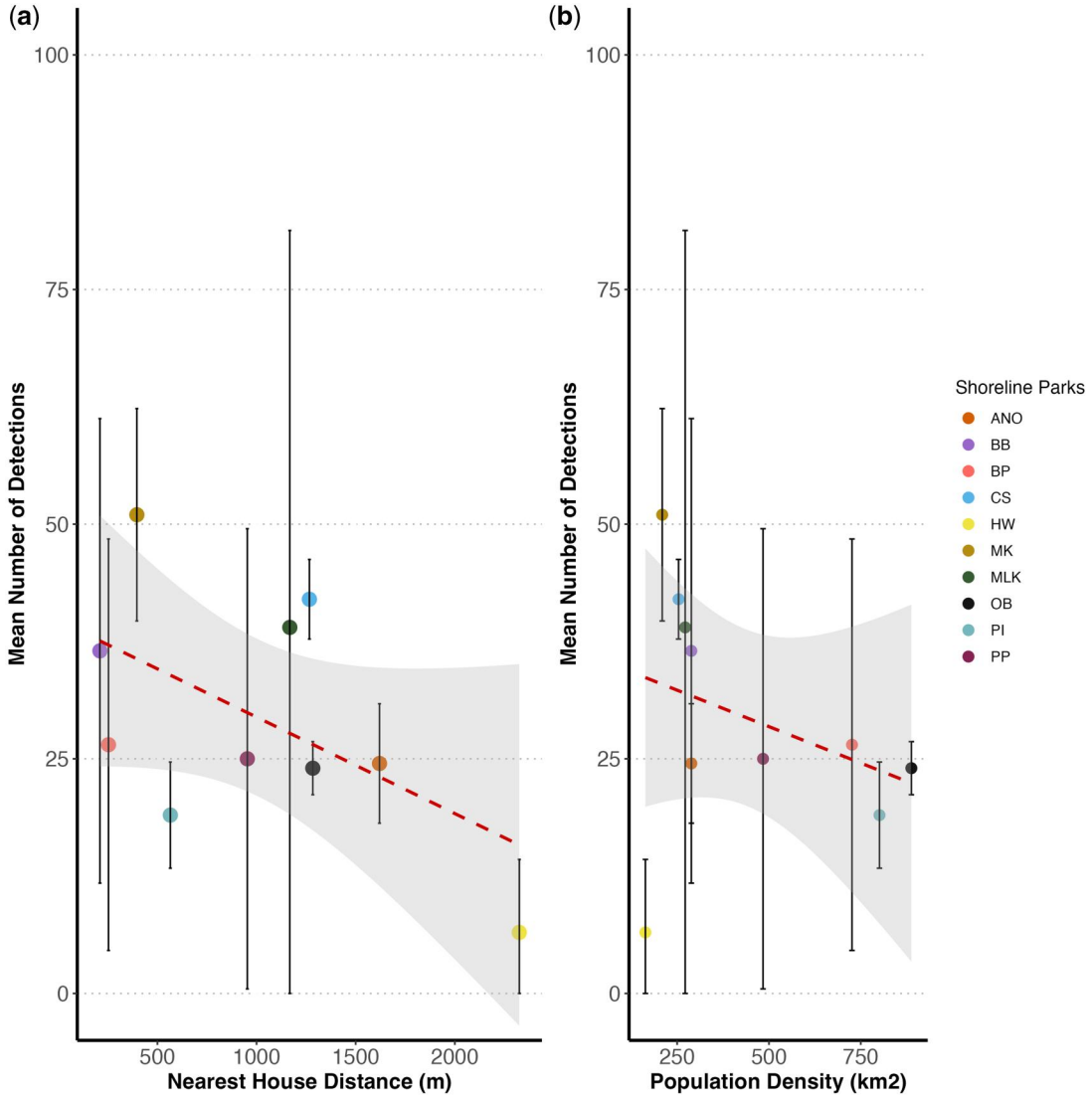

Figure 3. Relationship between (a) housing distance (m) and mean number of cat detections and (b) population density (km^2) and mean number of cat detections with 95% confidence interval (shaded polygon). The red dotted line indicates the trendline highlighting an underlying pattern of individual mean values. The vertical error bars represent the standard deviation for the mean number of detections.

was <= 1.10 (Andrew and Donald 1992, Kruschke 2010). We then confirmed that effective sample sizes for all our samples were at least 10,000 for reasonable estimate stability (Andrew and Donald 1992, Kruschke 2010). Variables were determined to be significant if their 95% credible intervals did not overlap zero. In our model, estimates > 0 on the scale of relative selection indicate preferential selection, and values ≤ 0 suggest avoidance or a stable neutral effect. Summary statistics for each sunlight period and corresponding detection events were calculated for each shoreline location from this process (Table 2).

Results

Summary statistics

There were 4911 trap nights across, with a mean sampling effort of 240.34 days per camera. We captured a total of 691 detections of domestic cats on 23 of our 26 cameras, with a range of 1 to 99 detections per shoreline site (Table 1). The mean hour of detection for domestic cats observed across shoreline parks was 0.39 hour (~12:23 AM), with a median of 0 hour (~12:00 AM), and a circular standard deviation of 5.31 hour (Table S4). The number of cat detections captured throughout the observed sunlight periods also varied among the shoreline parks surveyed (Table 2).

Detection activity in response to social-ecological variables in urban areas

Our urban GLMM model (i.e. Model 1) (i.e. nearest house distance and population density) was the top-ranked model (Table S5). Housing distance ($\beta = -0.31$, 95% CI [−0.45, −0.18], $P < 0.001$) was negatively associated with cat detection (Fig. 3). Population density ($\beta = -0.12$, 95% CI [−0.32, 0.09], $P > 0.05$) was also negatively associated with cat detection. Out of the predictor variables, population density was the only one that was not significant. No other predictor variables were associated with cat detections.

Relative selection for observed diel period categories

Temporal responses to environmental conditions were only significant for housing proximity and vegetation cover (Fig. 4). In areas with greater proximity to houses and vegetation cover, free-roaming domestic cats selected for nocturnal and

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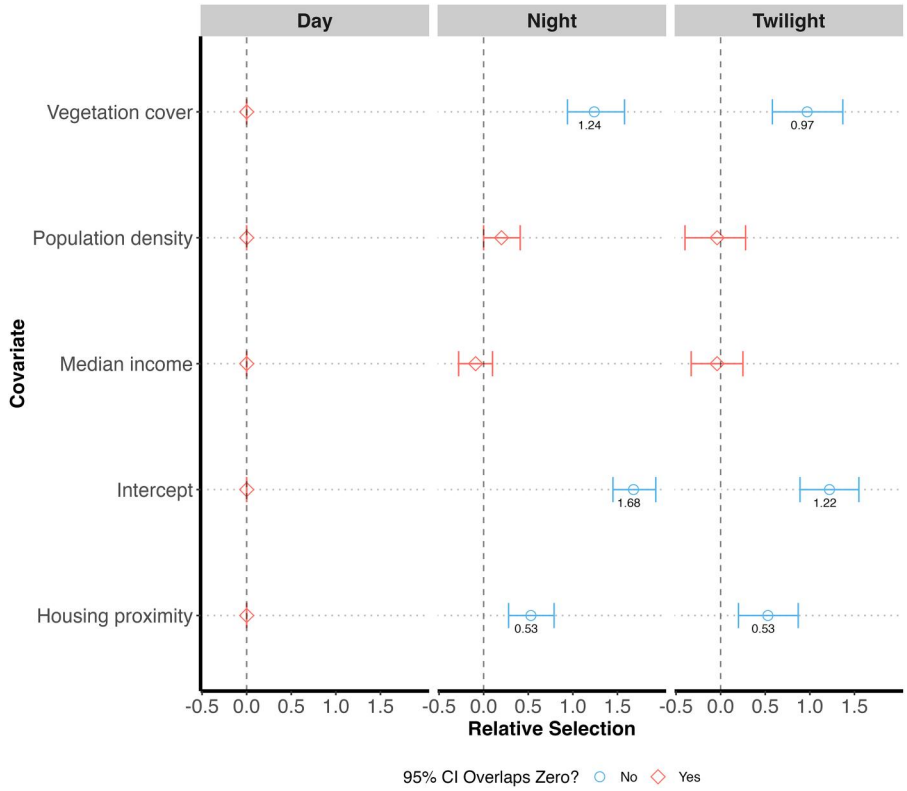

Figure 4. 95% credible intervals for environmental covariates on the temporal selection behavior of domestic cats, categorized across different temporal periods: Day, Night, Twilight. Each point indicates the median estimation (50% quantile) of the effect of the covariate represented as a form of relative selection. Points >0 on the scale of relative selection indicate preferential selection, and values ≤ 0 suggest avoidance or a stable neutral effect.

Table 1. Descriptive statistics for detections of domestic cats observed across 10 shoreline parks (i.e. Sampling Zone) from April 2022 to December 2022.

Shoreline Park	Total detections	Mean +/SD of detections	Min and Max detections
ANO	49	24.5 + 6.36	(20, 29)
BB	73	36.5 + 24.75	(19, 54)
BP	53	26.5 + 21.92	(11, 42)
CS	84	42 + 4.24	(39, 45)
HW	13	6.5 + 7.78	(1, 12)
MK	102	51 + 11.31	(43, 59)
MLK	156	39 + 42.29	(6, 99)
OB	48	24 + 2.83	(22, 26)
PI	38	19 + 5.66	(15, 23)
PP	75	25 + 24.52	(1, 50)

crepuscular hours of activity. The intercept estimate shows a general preference for nocturnal (β = 1.68, 95% CI [1.45, 1.93]) and crepuscular (β = 1.22, 95% CI [0.89, 1.55]) hours of the day. Housing proximity reveals significant responses during the twilight (β = 0.53, 95% CI [0.20, 0.87]) and night (β = 0.53, 95% CI [0.28, 0.79]) categories, with the median estimate equal for the two. Twilight, however, showed a slightly larger posterior distribution, suggesting more variance in relative selection. Vegetation cover also expressed significance during the twilight periods (β = 0.97, 95% CI [0.58, 1.37]) and night (β = 1.24, 95% CI [0.94, 1.58]). No significant responses were observed for other covariates, such as median income and population density, for other diel periods. We found no evidence of selective avoidance by free-roaming domestic cats for certain environmental covariates across the sunlight periods observed (Table S3).

Among shoreline park variation in temporal activity patterns

From our analysis we found that domestic cats, on average, had a higher prospect of being nocturnal (active at night) across most parks except Hayward Regional Shoreline (HW) and Point Isabel Regional Shoreline (PI), where cats were more likely to select for diurnal periods (Fig. 5). While cats predominantly selected for nocturnal activity, we observed that free-roaming cats exhibited considerable variation in diel activity across individual sampling sites. For example, across all shoreline parks, the likelihood of temporal selection of night ranged from as low as 0.15 to 0.89 (Table S6). Overall, we did not observe other significant differences in diel variation for the individual sampling sites.

Discussion

Unpacking how animals act across space and time is essential to understanding how nonhuman organisms respond to their environment. Understanding how animals use time discretely as a complex ecological resource, however, is something researchers are still beginning to unravel (Gaynor *et al.* 2018, Kronfeld-Schor and Dayan 2003). Our findings indicated that domestic cats are temporally reflexive in response to environmental gradients and more selective in their activity across a 24-hour cycle. We found that free-roaming cat detections were negatively associated with the distance of houses near shoreline parks, with fewer detections at locations further away from residential areas. We also observed increased nocturnality across all sites, with greater vegetation cover and housing proximity functioning as the strongest contributors to shaping cat diel patterns. These findings offer

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Table 2. The total number of detections and detections in each time category for domestic cats across 10 shoreline park locations (i.e. Sampling Zone) from April 2022 to December 2022.

Shoreline Park	No. of cameras	Total detections	No. of day detections	No. of twilight detections	No. of night detections
ANO	2	49	8	5	36
BB	2	73	49	8	16
BP	2	53	3	11	39
CS	2	84	10	10	64
HW	3	13	0	1	12
MK	2	102	31	12	59
MLK	4	156	1	8	147
OB	2	48	4	4	40
PI	2	38	5	10	23
PP	5	75	61	1	13
Total	26	691	172	70	449

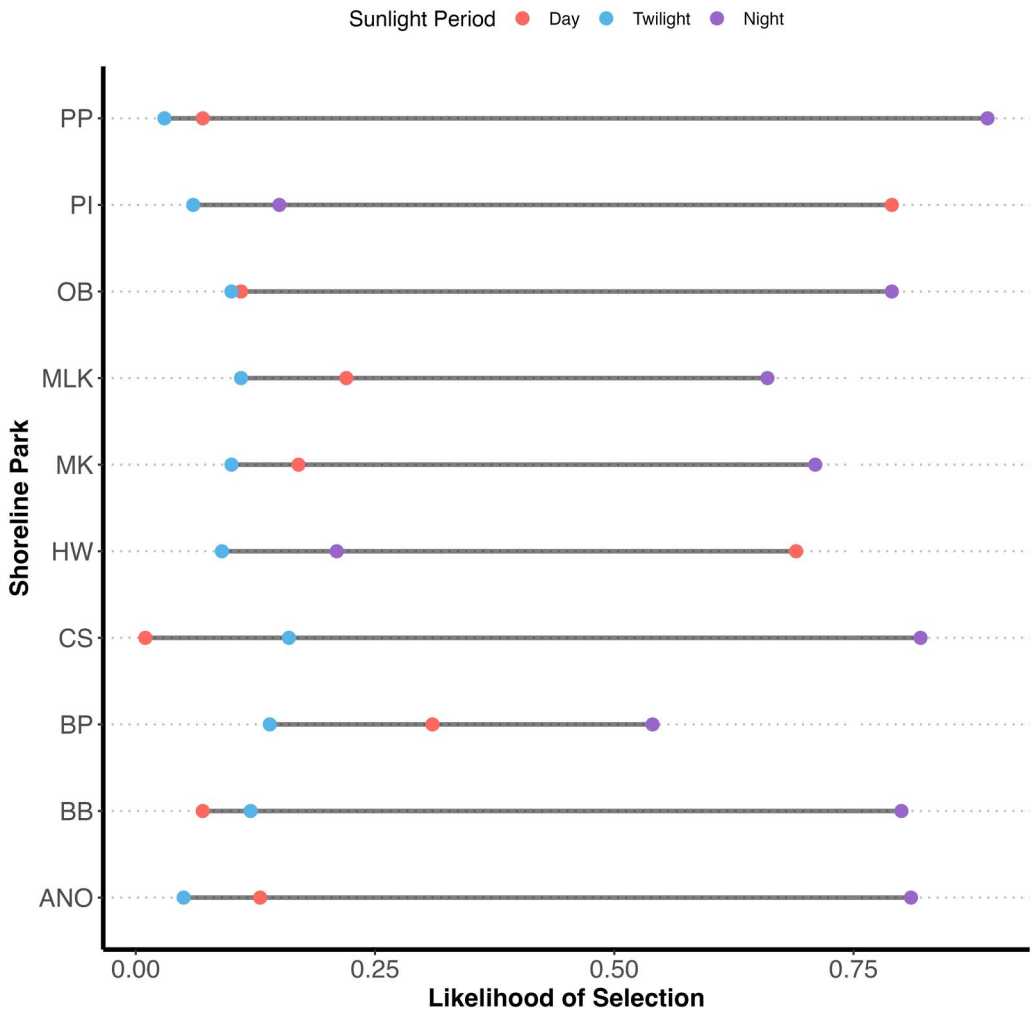

Figure 5. Cleveland plot detailing the likelihood of selection for shoreline parks across different sunlight periods, including day, twilight, and night. Each point denotes the median estimate.

insight into how free-roaming cat diel activity is highly attenuated to the complex interplay of ecological and anthropogenic conditions.

The distance of houses from shoreline parks negatively predicted detections, suggesting the proximity of developed spaces to natural areas facilitates cat presence. Similar studies substantiate this, where cat abundance is greatest in high-density residential areas and responsive to distance from natural areas and residential environments (Cove *et al.* 2023, Bennett *et al.* 2021, Vanek *et al.* 2021, Clyde *et al.* 2022, Flockhart *et al.* 2016). Crooks and Soule (1999) attribute cat population ecology to landscape characteristics, where the proportion of urban edges to habitat patches positively informs abundance (Crooks and Soule 1999). For example, observations in Chicago, IL, found that cat

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occupancy increases with building density, and detectability was highest near preserve boundaries. It should also be understood that cat abundance can be informed by cat owners in these respective areas (Bennett et al. 2021, Vanek et al. 2021). Moreover, the energetic costs of movement alongside environmental barriers like roads may further restrict cat dispersal events into nearby natural habitats (Thomas et al. 2014, Zollner and Lima 2005, Bonte et al. 2012, Carbone et al. 2007). Our observations of cat predation events, all within 700 m of the nearest house, align with previous findings that cats exploit urban-proximate green spaces where human-supplemented resources in developed habitats can artificially sustain dense cat populations (Barratt 1997, Thomas et al. 2014, Horn et al. 2011).

Temporal activity patterns were most affected by vegetation cover and housing proximity. In regional shoreline parks closer to residential houses with greater vegetation cover, we found that cats primarily selected for nocturnal and twilight periods. Our results illustrate that cats use natural areas or parks when people are physically absent. Since people are generally less active at night, cats may select for nocturnal periods in these areas to avoid interactions with pedestrians (Gaynor et al. 2018, Turner and Bateson 2000). This corresponds with observations showing that unowned cats in dense urban settings express greater nocturnality (Bennett et al. 2021). Furthermore, since people supplement food resources to free-roaming cats, cats less wary of human presence may be active near human settlements during crepuscular periods to access food and shelter (Zito et al. 2015). Free-roaming cats are potentially oscillating between twilight and nocturnal periods using human proximity near natural areas as an ecological indicator to maximize access to natural prey items and human food subsidies while shielding themselves from potential predation (Crooks 2002, Kays et al. 2015, Berger 2007). This suggests that residential areas operate as a shield against local threats and facilitate the exploitation of resources in their immediate surroundings (Gehrt et al. 2013, Lowry et al. 2013). Alternatively, while ownership status is difficult to decipher through wildlife cameras, the temporal pattern observed could also be influenced by the fine-scale decision-making of owners deciding when their pets get "outdoor time."

We found no diel activity changes related to human population density and median income, nor a noticeable link between detection events and human density. Additionally, the shoreline sites we sampled are not in the middle of residential spaces, but rather adjacent to them. Therefore, conventional urban ecological research approaches to evaluate population densities cannot be neatly captured in this study because we explicitly surveilled cat activity in areas that lack human settlements. A more nuanced metric would be integrating fine-scale human activity rather than standing variation in population densities, as cats might respond directly to how people move across the landscape (Ellis-Soto et al. 2023). A potential way to incorporate this would be recording the frequency of site visitation in natural areas throughout 24 hour as an indication of human activity patterns. Utilizing game cameras in the same way we monitor wildlife would typically be an effective solution to achieve this, but because our cameras are primarily off-trail, their reliability in capturing human activity would be inconsistent. Future studies might benefit from using human mobility data from cellphone data or hourly visitation data collected by some park systems. Similarly, median household income is nonexistent in protected areas where residential spaces are absent. Therefore, as a proxy for income, we measured the income of residential spaces adjacent to parks, although this metric is not an indication of who visits these spaces. While biodiversity correlates to the wealth of residential areas, regionally protected shorelines typically have state-allocated funds to manage and steward those spaces, separate from the financial investments made within neighboring towns and communities (Leong et al. 2018, Chamberlain et al. 2019). Using median household income in this research application may simply be an ineffective or inappropriate measure of environmental quality.

The study and management of free-roaming domestic cat behavior is a complex, multi-layered issue that requires incorporating diverse data points and public collaboration to generate compelling inferences and develop effective solutions. For example, future research should incorporate habitat quality, diet information, movement patterns, and human mobility data to disentangle the environmental pressures shaping the ecology of free-roaming cats. In addition, targeted conservation strategies are crucial to mitigate the ecological toll from free-roaming cats (Lepczyk et al. 2022). Improved monitoring at urban-wildland interfaces can advance our understanding of movement patterns and behavior in important conservation areas. Habitat management in recovery areas for wildlife that spatially and temporally overlap with free-roaming cats or predator reintroduction efforts could also limit habitat suitability, restricting cats from accessing protected habitats (Crooks and Soule 1999, Kays et al. 2015, Sih et al. 2010, Doherty et al. 2017, Hohnen et al. 2016). Similarly, managing food supplementation (e.g. local ordinances) at an urban-wildland interface could effectively mitigate cat activity near conservation-relevant habitats (Lepczyk et al. 2022, Zito et al. 2015, Doherty et al. 2017, Hernandez et al. 2018). In addition, public education on responsible pet ownership near natural areas and risks from food provisions could bolster the efficacy of conservation efforts (Hernandez et al. 2018, Bevins et al. 2012, Lepczyk et al. 2015, Gaudreault et al. 2020, Carlen et al. 2023, Andrade and Rhodes 2012). Implementing zoning ordinances based on residential proximity to protected areas and community engagement in wildlife stewardship may also help protect vulnerable species from human-mediated cat dispersion (Herrera et al. 2022, Thomas et al. 2014, Hanmer et al. 2017, Metsers et al. 2010).

We highlight that the proximity of housing to natural areas and available vegetation cover influence domestic cat activity substantially. In addition, our study contributes more insight into cat behavior in urban environments in response to social-ecological variables across conservation-relevant habitats. Our results emphasize the need for understanding the complex ecology of domestic cats as a formidable non-endemic predator and how qualities of human society, such as human presence and urban systems, intersect with the behavior of domestic cats, allowing them to disrupt many wildlife communities. Naturally, as humanity continues towards the future, urban environments will continue encroaching upon wildlife habitat (Ma et al. 2024). Therefore, it is crucial to determine the most salient anthropogenic factors affecting cat activity patterns to mitigate the collateral damage cats may have on wildlife and, more broadly, conservation efforts across the globe. By doing so, we will be able to implement more efficient efforts to conserve and protect these wildlife populations while securing the welfare of one of our most beloved companion animals on the planet.

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Author contributions

Tyus Devon Williams (Conceptualization [lead], Data curation [lead], Formal analysis [lead], Investigation [lead], Methodology [lead], Project administration [lead], Visualization [lead], Writing—original draft [lead]), Daniel J. Herrera (Formal analysis [supporting], Sofware [supporting], Resources [supporting], [Writing—review & editing [supporting]), Cesar O. Estien (Data curation [supporting], Investigation [supporting], Resources [supporting], Writing—review & editing [supporting]), Christine Eleanor Wilkinson (Visualization [supporting], Writing—review & editing [supporting]), Justin Brashares (Supervision [supporting], Writing—review & editing [supporting]), and Chris Schell (Funding acquisition [lead], Investigation [supporting], Project administration [supporting], Resources [supporting], Supervision [lead], Writing—review & editing [supporting])

Supplementary data

Supplementary data are available at *JUECOL* online.

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Data availability

All related data and R scripts have been deposited at Dryad: https://doi.org/10.5061/dryad.v6wwpzh6f.

References

Andrade GSM, Rhodes JR. Protected areas and local communities. *Ecol Soc* 2012;**17**:1–16.

Andrew G, Donald B R. Inference from iterative simulation using multiple sequences. *Stat. Sci* 1992;**7**:457–72.

Barratt DG. Home range size, habitat utilisation and movement patterns of suburban and farm cats *Felis catus*. *Ecography* 1997; **20**:271–80.

Bates D, Mächler M, Bolker B *et al.* Fitting linear mixed-effects models using lme4. *J Stat Soft* 2015;**67**:1–48.

Bennett KFP, Evans BS, Clark JA, *et al.* Domestic cat abundance and activity across a residential land use gradient. *Front Ecol Evol* 2021;**9**:643845.

Benoit T, Achraf E. suncalc: Compute Sun Position, Sunlight Phases, Moon Position and Lunar Phase. (2022).

Berger J. Fear, human shields and the redistribution of prey and predators in protected areas. *Biol Lett* 2007;**3**:620–3.

Bevins SN, Carver S, Boydston EE *et al.* Three pathogens in sympatric populations of pumas, bobcats, and domestic cats: implications for infectious disease transmission. *PLoS One* 2012;**7**:e31403.

Bonte D, Van Dyck H, Bullock JM *et al.* Costs of dispersal. *Biol Rev Camb Philos Soc* 2012;**87**:290–312.

Carbone C, Teacher A, Rowcliffe JM. The costs of carnivory. *PLoS Biol* 2007;**5**:e22.

Carlen EJ *et al.* A framework for contextualizing social-ecological biases in participatory science data. *People Nat* 2023;**6**:377–90.

Casey JA, *et al.* Race/ethnicity, socioeconomic status, residential segregation, and spatial variation in noise exposure in the contiguous United States. *Environ Health Perspect* 2017;**125**:ehp898.

Chamberlain DE, Henry DAW, Reynolds C *et al.* The relationship between wealth and biodiversity: a test of the luxury effect on bird species richness in the developing world. *Glob Chang Biol* 2019; **25**:3045–55.

Chamberlain S, Hocking D. rnoaa: "NOAA" Weather Data from R. (2024).

Clyde HE, Norris DR, Lupton E *et al.* Estimating habitat characteristics associated with the abundance of free-roaming domestic cats across the annual cycle. *Wildlife Res* 2022;**49**:583–95.

Cove MV *et al.* Counting the C apital's cats: estimating drivers of abundance of free-roaming cats with a novel hierarchical model. *Ecol. Appl* 2023;**33**:e2790.

Crooks KR, Soulé ME. Mesopredator release and avifaunal extinctions in a fragmented system. *Nature* 1999;**400**:563–6.

Crooks KR. Relative sensitivities of mammalian carnivores to habitat fragmentation. *Conserv. Biol* 2002;**16**:488–502.

Cushing L, Morello-Frosch R, Wander M *et al.* The haves, the have-nots, and the health of everyone: the relationship between social inequality and environmental quality. *Annu Rev Public Health* 2015;**36**:193–209.

Dabritz HA, Conrad PA. Cats and toxoplasma: implications for public health. *Zoonoses Public Health* 2010;**57**:34–52.

Denwood MJ. runjags: An R package providing interface utilities, model templates, parallel computing methods and additional distributions for MCMC models in JAGS. *J Stat Soft* 2016; **71**:1–25.

Doherty TS, Glen AS, Nimmo DG *et al.* Invasive predators and global biodiversity loss. *Proc Natl Acad Sci U S A* 2016;**113**:11261–5.

Doherty TS, Dickman CR, Johnson CN *et al.* Impacts and management of feral cats *Felis catus* in Australia. *Mammal Rev* 2017; **47**:83–97.

Dubey JP, Jones JL. Toxoplasma gondii infection in humans and animals in the United States. *Int J Parasitol* 2008;**38**:1257–78.

Ellis-Soto D, Oliver RY, Brum-Bastos V *et al.* A vision for incorporating human mobility in the study of human–wildlife interactions. *Nat Ecol Evol* 2023;**7**:1362–72.

Estien CO, Wilkinson CE, Morello-Frosch R *et al.* Historical redlining is associated with disparities in environmental quality across California. *Environ Sci Technol Lett* 2024;**11**:54–9.

Estien CO, Stanton LA, Schell CJ. Human densities, not pollution, affect urban coyote boldness and exploration. Preprint at https://doi.org/10.21203/rs.3.rs-5868687/v1 (2025).

Downloaded from academic.oup.com/jue/article/11/1/juaf017/8363193 by guest on 20 September 2026

Fardell LL, Nano CEM, Pavey CR, *et al.* Small prey animal foraging behaviors in landscapes of fear: effects of predator presence and human activity along an urban disturbance gradient. Front Ecol Evol 2022;**10**:805891.

Fardell LL, Pavey CR, Dickman CR. Influences of roaming domestic cats on wildlife activity in patchy urban environments. Front Ecol Evol 2023;**11**:1123355.

Fidino M, Gallo T, Lehrer EW *et al.* Landscape-scale differences among cities alter common species' responses to urbanization. *Ecol Appl* 2021;**31**:e02253.

Finke DL, Snyder WE. Niche partitioning increases resource exploitation by diverse communities. *Science* 2008;**321**:1488–90.

Flockhart DTT, Norris DR, Coe JB. Predicting free-roaming cat population densities in urban areas. *Anim. Conserv* 2016;**19**:472–83.

Gaertner M, Wilson JRU, Cadotte MW *et al.* Non-native species in urban environments: patterns, processes, impacts and challenges. *Biol Invasions* 2017;**19**:3461–9.

Gallo T, Fidino M, Lehrer EW *et al.* Urbanization alters predator-avoidance behaviours. *J Anim Ecol* 2019;**88**:793–803.

Gallo T, Fidino M, Gerber B *et al.* Mammals adjust diel activity across gradients of urbanization. *Elife* 2022;**11**:e74756.

Gaudreault NN, Trujillo JD, Carossino M *et al.* SARS-CoV-2 infection, disease and transmission in domestic cats. *Emerg Microbes Infect* 2020;**9**:2322–32.

Gaynor KM, Hojnowski CE, Carter NH *et al.* The influence of human disturbance on wildlife nocturnality. *Science* 2018;**360**:1232–5.

Gehrt SD, Wilson EC, Brown JL *et al.* Population ecology of free-roaming cats and interference competition by coyotes in urban parks. *PLoS One* 2013;**8**:e75718.

Gelman A, Jakulin A, Pittau MG *et al.* A weakly informative default prior distribution for logistic and other regression models. *Ann Appl Stat* 2008;**2**:1360–83.

Gilbert NA, Stenglein JL, Pauli JN *et al.* Human disturbance compresses the spatiotemporal niche. *Proc Natl Acad Sci U S A* 2022;**119**:e2206339119.

Gow EA, Aubrey B, Cossar L *et al.* Conducting community-led research using trail cameras to develop baseline wandering domestic cat local abundance estimates. *Facets* 2024;**9**:1–14.

Gorelick N, Hancher M, Dixon M *et al.* Google Earth Engine: planetary-scale geospatial analysis for everyone. *Remote Sens. Environ* 2017;**202**:18–27. https://doi.org/10.1016/j.rse.2017.06.031

Hanmer HJ, Thomas RL, Fellowes MDE. Urbanisation influences range size of the domestic cat (*Felis catus*): consequences for conservation. *J. Urban Ecol* 2017;**3**:jux014.

Herrera DJ, Cove MV, McShea WJ *et al.* Prey selection and predation behavior of free-roaming domestic cats (Felis catus) in an urban ecosystem: implications for urban cat management. *Biol. Conserv* 2022;**268**:109503.

Herrera DJ, Cove MV, McShea WJ *et al.* Spatial and temporal overlap of domestic cats (Felis catus) and native urban wildlife. *Front Ecol Evol* 2022;**10**:1048585.

Hernandez SM, Loyd KAT, Newton AN *et al.* The use of point-of-view cameras (Kittycams) to quantify predation by colony cats (*Felis catus*) on wildlife. *Wildl Res* 2018;**45**:357–65.

Hentati Y *et al.* Environmental contamination predicts mammal diversity and mesocarnivore activity in the Seattle-Tacoma metro area. Preprint at https://doi.org/10.22541/au.173153356.63884647/v1 (2024).

Horn JA, Mateus-Pinilla N, Warner RE *et al.* Home range, habitat use, and activity patterns of free-roaming domestic cats. *J Wildl Manag* 2011;**75**:1177–85.

Hohnen R, Tuft K, McGregor HW *et al.* Occupancy of the invasive feral cat varies with habitat complexity. *PLoS One* 2016;**11**:e0152520.

Jesdale BM, Morello-Frosch R, Cushing L. The racial/ethnic distribution of heat risk–related land cover in relation to residential segregation. *Environ Health Perspect* 2013;**121**:811–7.

Kays R, Costello R, Forrester T *et al.* Cats are rare where coyotes roam. *JMAMMAL* 2015;**96**:981–7.

Kronfeld-Schor N, Dayan T. Partitioning of time as an ecological resource. *Annu Rev Ecol Evol Syst* 2003;**34**:153–81.

Kruschke JK. Bayesian data analysis. *Wiley Interdiscip Rev Cogn Sci* 2010;**1**:658–76.

Leong M, Dunn RR, Trautwein MD. Biodiversity and socioeconomics in the city: a review of the luxury effect. *Biol Lett* 2018;**14**:20180082.

Lepczyk CA, Lohr CA, Duffy DC. A review of cat behavior in relation to disease risk and management options. *Appl. Anim. Behav. Sci* 2015;**173**:29–39.

Lepczyk CA, Fantle-Lepczyk JE, Dunham KD *et al.* A global synthesis and assessment of free-ranging domestic cat diet. *Nat Commun* 2023;**14**:7809.

Lepczyk CA, Duffy DC, Bird DM *et al.* A science-based policy for managing free-roaming cats. *Biol Invasions* 2022;**24**:3693–701.

Lionello P *et al.* The Mediterranean climate: an overview of the main characteristics and issues. In Lionello, P., Malanotte-Rizzoli, P. & Boscolo, R. (eds.), *Developments in Earth and Environmental Sciences*. vol. **4**. Elsevier, 2006, 1–26.

Loss SR, Will T, Marra PP. The impact of free-ranging domestic cats on wildlife of the United States. *Nat Commun* 2013;**4**:1396.

Loss SR, Marra PP. Population impacts of free-ranging domestic cats on mainland vertebrates. *Front Ecol Environ* 2017;**15**:502–9.

Loss SR, Boughton B, Cady SM *et al.* Review and synthesis of the global literature on domestic cat impacts on wildlife. *J Anim Ecol* 2022;**91**:1361–72.

Lowry H, Lill A, Wong BBM. Behavioural responses of wildlife to urban environments. *Biol Rev Camb Philos Soc* 2013;**88**:537–49.

Lüdecke D. sjPlot: Data Visualization for Statistics in Social Science. (2023).

Ma D, Abrahms B, Allgeier J *et al.* Global expansion of human-wildlife overlap in the 21st century. *Sci Adv* 2024;**10**:eadp7706.

Manlick PJ, Pauli JN. Human disturbance increases trophic niche overlap in terrestrial carnivore communities. *Proc Natl Acad Sci U S A* 2020;**117**:26842–8.

Magle SB, Fidino M, Sander HA *et al.* Wealth and urbanization shape medium and large terrestrial mammal communities. *Glob Chang Biol* 2021;**27**:5446–59.

Medina FM *et al.* A global review of the impacts of invasive cats on island endangered vertebrates | EndNote Click. https://click.endnote.com/viewer?doi=10.1111%2Fj.1365-2486.2011.02464.x&token=WzMzMDcwNzgsIjEwLjExMTEvai4xMzY1LTI0ODYuMjAxMS4wMjQ2NC54Il0.JewzLjvXpQB1162J2Q-Uzk1CGgk (2011).

Metsers EM, Seddon PJ, van Heezik YM. Cat-exclusion zones in rural and urban-fringe landscapes: how large would they have to be? *Wildl Res* 2010;**37**:47–56.

Mills KL, Harris NC. Humans disrupt access to prey for large African carnivores. *Elife* 2020;**9**:e60690.

Nardone A, Rudolph KE, Morello-Frosch R *et al.* Redlines and greenspace: the relationship between historical redlining and 2010 greenspace across the United States. *Environ Health Perspect* 2021;**129**:17006.

Northrup JM, Gerber BD. A comment on priors for Bayesian occupancy models. *PLoS One* 2018;**13**:e0192819.

Downloaded from academic.oup.com/jue/article/11/1/juaf017/8363193 by guest on 20 September 2026

NOAA. National Oceanic and Atmospheric Administration, 2021.

Pacione M. Urban Geography: A Global Perspective. (2009).

Padayachee AL, Irlich UM, Faulkner KT *et al.* How do invasive species travel to and through urban environments? *Biol Invasions* 2017; **19**:3557–70.

Page DL, Schuyler PA, Dupont WD *et al.* Atypical lobular hyperplasia as a unilateral predictor of breast cancer risk: a retrospective cohort study. *Lancet* 2003;**361**:125–9.

Robertson SA. A review of feral cat control. *J Feline Med Surg* 2008; **10**:366–75.

Roy V. Chapter 7 - MCMC for GLMMs. In Srinivasa Rao, A. S. R., Young, G. A. & Rao, C. R. (eds.), *Handbook of Statistics* vol. **47**: Elsevier, 2022, 135–159.

Robins CW, Kertson BN, Faulkner JR *et al.* Effects of urbanization on cougar foraging ecology along the wildland–urban gradient of western Washington. *Ecosphere* 2019;**10**:e02605.

R Core Team. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing (2023).

Santos MJ, Thorne JH, Christensen J *et al.* An historical land conservation analysis in the San Francisco Bay Area, USA: 1850–2010. *Landsc. Urban Plan* 2014;**127**:114–23.

Šálek M, Drahníková L, Tkadlec E. Changes in home range sizes and population densities of carnivore species along the natural to urban habitat gradient. *Mammal Rev* 2015;**45**:1–14.

Schell CJ, Dyson K, Fuentes TL *et al.* The ecological and evolutionary consequences of systemic racism in urban environments. *Science* 2020;**369**:eaay4497.

Shores CR, Dellinger JA, Newkirk ES *et al.* Mesopredators change temporal activity in response to a recolonizing apex predator. *Behav. Ecol* 2019;**30**:1324–35.

Shochat E, Lerman SB, Anderies JM *et al.* Invasion, competition, and biodiversity loss in urban ecosystems. *BioScience* 2010;**60**:199–208.

Sih A, Bolnick DI, Luttbeg B *et al.* Predator–prey naïveté, antipredator behavior, and the ecology of predator invasions. *Oikos* 2010; **119**:610–21.

Smith JA, Suraci JP, Clinchy M *et al.* Fear of the human "super predator" reduces feeding time in large carnivores. *Proc R Soc B* 2017; **284**:20170433.

Stark JR, Aiello-Lammens M, Grigione MM. The effects of urbanization on carnivores in the New York metropolitan area. *Urban Ecosyst* 2020;**23**:215–25.

Thomas RL, Baker PJ, Fellowes MD. Ranging characteristics of the domestic cat (Felis catus) in an urban environment. *Urban Ecosyst* 2014;**17**:911–21.

Turner DC, Bateson PPG. *The Domestic Cat: The Biology of Its Behaviour*. Cambridge University Press, 2000.

U.S. Census Bureau. Contra Costa County and Alameda County Populations, 2021.

U.S. Geological Survey (USGS). Landsat 8 Collection 2 Level-2, Tier 1 Data. U.S. Geological Survey, 2022.

Vanek JP, Rutter AU, Preuss TS *et al.* Anthropogenic factors influence the occupancy of an invasive carnivore in a suburban preserve system. *Urban Ecosyst* 2021;**24**:113–26.

Walker K, Herman M. tidycensus: Load US Census Boundary and Attribute Data as "tidyverse" and "sf"-Ready Data Frames. (2024).

Wood EM *et al.* Historical racial redlining and contemporary patterns of income inequality negatively affect birds, their habitat, and people in Los Angeles, California. *Ornithol Appl* 2024; **126**:duad044.

Zito S, Vankan D, Bennett P *et al.* Cat ownership perception and caretaking explored in an internet survey of people associated with cats. *PLoS ONE* 2015;**10**:e0133293.

Zollner PA, Lima SL. Behavioral tradeoffs when dispersing across a patchy landscape. *Oikos* 2005;**108**:219–30.

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