Effects of landcover on mesocarnivore density and detection rate along an urban to rural gradient

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ARTICLE INFO

ABSTRACT

Human development has major implications for wildlife populations. Urban-exploiter species can benefit from human subsidized resources, whereas urban-avoider species can vanish from wildlife communities in highly developed areas. Therefore, understanding how the density of different species varies in response to landcover changes associated with human development can provide important insight into how wildlife communities are likely to change and provide a starting point for predicting the consequences of those changes. Here, we estimated the population density of five common mesocarnivore species (coyote (*Canis latrans*), bobcat (*Lynx rufus*), red fox (*Vulpes vulpes*), raccoon (*Procyon lotor*), and Virginia opossum (*Didelphis virginiana*)) at 12 study sites along an urban to rural gradient in the greater Fayetteville Area, Northwest Arkansas, USA between November 2021, and March 2022. At each study site, we applied the Random Encounter Model (REM) to data from camera traps to calculate the density of five focal species. Coyote density ranged from 0.5 to 0.93 individuals/km^2. Raccoon density ranged from 0.19 to 20.25 individuals/km^2. Bobcat density ranged from 0 to 1.06 individuals/km^2. Opossum density ranged from 0 to 3.43 individuals/km^2. Red fox density ranged from 0 to 0.10 individuals/km^2. Coyote and raccoon density showed a positive relationship with anthropogenic noise. Opossum density increased with HUD. Red Fox and bobcat density showed a negative relationship with forest area and a positive relationship with distance to water respectively, however confidence intervals for both species overlapped zero. The density estimates we report based on camera trap data of unmarked animals were consistent with reports from the literature for these same species derived from traditional methods, providing additional support to the REM as a viable, non-invasive method to calculate density of unmarked species. Our second analysis consisted of taking camera level density estimates and treating them as detection rates corrected for camera viewshed and animal movement. Coyote and raccoon detection rate showed a positive relationship with anthropogenic noise. Red Fox detection rate was positively related to developed open space, and negatively related to distance to water. Similarly to red fox, opossums detection rate was higher in areas with more developed open space. We found no evidence that bobcat density or detection rate varied with any of the landcover or anthropogenic variables we measured.

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1. Introduction

Human development has major effects on wildlife communities. As the human footprint expands, greenspace and nature reserves become fragmented, isolated, and the amount of forest edge increases (De Chant et al., 2010; Soifer et al., 2021). Wildlife species can respond to this expansion in different ways, with some species capable of exploiting anthropogenic subsidies (e.g., food, shelter, etc.) and living in close proximity to humans (Ordeñana et al., 2010). These species are often referred to as urban exploiters and can persist and thrive in urban areas and in urban greenspaces (Greenspan et al., 2018). Other species, referred to as urban exploiters, may be driven out of developed areas due to food specialization, conflict with domestic animals, or lower tolerance to disturbance (Blair, 1996; Lowry et al., 2013; Łopucki et al., 2019).

Mesocarnivores, small and medium-sized mammalian predators (Roemer et al., 2009), are a group of animals that are particularly adaptable and often reside in urban areas. Northern raccoons (*Procyon lotor,* hereafter, raccoon), red fox (*Vulpes vulpes*), coyote (*Canis latrans*), and Virginia opossum (*Didelphis virginiana,* hereafter, opossum) are highly adaptable to urban environments and the densities of these species can be higher in human-dominated areas than more natural sites (Greenspan et al., 2018; Tucker et al., 2021). These species have been shown to benefit from urban environments by taking advantage of human-subsidized food resources (waste food, compost, bird seed: (Contesse et al., 2004, Bozek et al., 2007, Handler et al., 2020, Larson et al., 2020)). These species can also benefit by using refuges associated with human infrastructure that provide either predator-free space, thermal refugia, or safe space to rear young (Shannon et al., 2014; Herr et al., 2010; Sarkar and Bhadra, 2022). Some species may simply benefit and occur in higher densities because their primary predators are less likely to persist in these smaller, isolated greenspaces near humans (Atickem et al., 2014; Moll et al., 2018; Gámez and Harris, 2021). Developed open landcover such as residential lawns, cemeteries, golf courses and parks can serve as novel habitat where other mammals (including predators of smaller mammals and mesocarnivores) may have difficulty persisting, therefore serving as spatial refugia for some species (Imhoff et al., 2000; Gallo et al., 2017).

In contrast to urban-adapters, urban-avoiders are species that may be pushed out of developed areas or occur in lower densities relative to undisturbed areas (Blair, 1996). These more sensitive species, such as bobcats (*Lynx rufus*) and gray foxes (*Urocyon cinereoargenteus*), are often rare or absent from areas with higher levels of development (Parsons et al., 2018) and are associated with
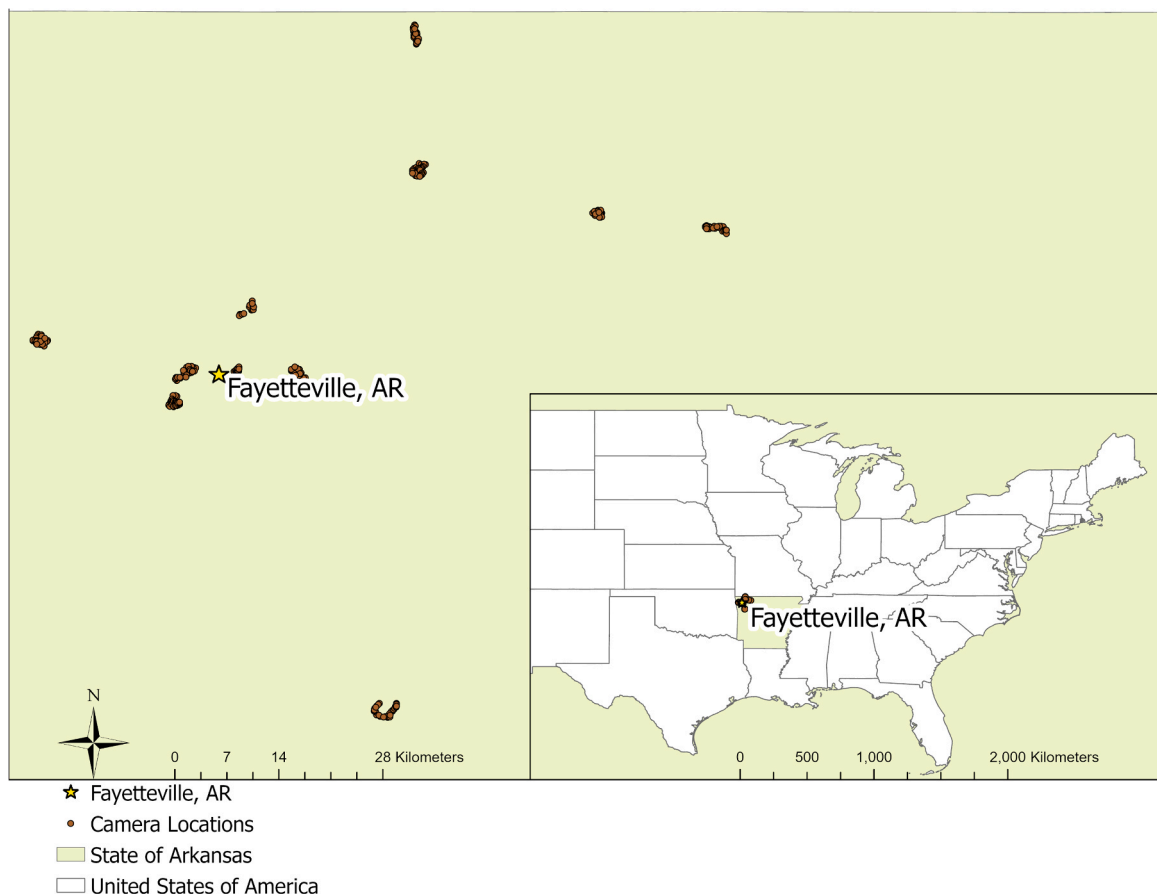

Fig. 1. Locations of camera traps used to study the density and detection rates of mammalian mesocarnivores in Northwest Arkansas, USA. Sites were chosen to represent a continuum of human activity and development. All sites were of similar habitat and elevation to account for behavioral changes based on habitat. Sites were sampled between November 2021 and March 2022.

greater forest cover (Rodriguez et al., 2021). There is also evidence that larger canids such as coyote and domestic dog (*Canis familiaris*) can competitively exclude gray fox in urban areas (Morin et al., 2022). Some species may persist in developed areas but experience lower fitness or a reduced realized niche (Smith et al., 2018).

While numerous studies have evaluated the occurrence and community composition of mesocarnivores in natural and urbanized greenspaces (Prange & Gehrt 2004; Fidino et al., 2016; Greenspan et al., 2018), we often lack information about the density of animals in these locations. Estimates of density are critical for managers seeking to predict and proactively manage mesocarnivore populations (Wright and Hubbell, 1983). Currently, several approaches for generating density of unmarked animals through the use of camera traps exist (Loonam et al., 2021, Ausband et al., 2022, Young et al., 2019, Moeller et al., 2018). These approaches have the advantage of being less expensive and less invasive than traditional methods that rely on capture and marking of animals (Thomas et al., 2011; Meek et al., 2019). One such approach is the Random Encounter Model (hereafter, REM) that was first developed by Rowcliffe et al. (2008) and uses the field of view of a motion-triggered camera combined with movement parameters of focal species to estimate density. This method has been successfully validated in trials with known population sizes (Rowcliffe et al., 2008; Cusack et al., 2015; Kavčić et al., 2021) and applied to other studies successfully (Manzo et al., 2012; Zero et al., 2013, Palencia et al., 2021). Given that many of the common mesocarnivores in the United States have been intensively studied and we often know the space use and movement parameters of these species, the REM is a promising approach for rapidly estimating the density of mesocarnivores across a number of sites.

Here, we aim to explore variation in the density and detection rate of five common mesocarnivores (red fox, coyote, bobcat, raccoon, and opossum) at 12 study sites along an urban to rural gradient in the Ozark Mountains Ecoregion of Arkansas, USA (Fig. 1). Northwest Arkansas is an optimal area for our study as it has been experiencing dramatic growth over the past 30 years, with the current human population of 546,725 expected to nearly double by the year 2045 (Northwest Arkansas Regional Planning Committee, 2021). We expected that the density and detection rate (an indicator of space and habitat use) of each of our focal species would vary widely between study sites based on the degree of human activity and development. Specifically, we predicted that red fox, raccoon, and opossum would occur at the highest population densities and have the greatest detection rates at the most urban sites and the lowest densities and detection rates at the most natural, undeveloped sites. We predicted that coyotes would have higher densities and detection rates at sites with intermediate levels of development and that their densities and detection rates would be more strongly correlated with landscape cover (habitat heterogeneity, proximity to water, etc.) than strict measures of human development (Rodriguez et al., 2021; Poessel et al., 2013). Finally, we predicted that bobcats would occur at their highest population densities and have the greatest detection rates at more natural sites and would be absent or occur at very low densities with low detection rates at the most developed sites.

2. Methods

2.1. Study Sites

Our study took place within the Ozark Mountain Ecoregion in the greater Fayetteville metropolitan area in Northwest Arkansas, USA. The Fayetteville metropolitan area covers 8321.7 km^2, and the current human population of 546,725 is predicted to double by the year 2045 (Northwest Arkansas Regional Planning Committee, 2021). To account for variation in the wildlife community associated with habitat, we chose only study sites that were dominated by mature oak-hickory forests and located between 220 and 554 m in elevation. Study sites ranged in size from 39 to 42,169 ha.

We chose sites to represent the continuum of human development representative of the area with sites ranging from 2 to 58 km from downtown Fayetteville (36.06162, −94.16114). Our study sites consisted of Arkansas Natural Heritage Commission (ANHC) natural areas, National Forests, Arkansas State Parks, City of Fayetteville parks, and private properties (Table 1).

Table 1
Natural areas located in Northwest Arkansas USA where the densities of five mesocarnivores were estimated using motion-triggered camera traps from Nov 2021 – Mar 2022. Sites were chosen to represent a continuum of human development from urban to rural sites as measured by distance from each site to downtown Fayetteville, AR. Number of cameras present at each site was determined by the size of the site. Sites with fewer cameras were active longer to ensure a minimum of 600 trap nights.

Site	No. of Cameras	Dates Active	Total Trap Nights	Distance to Downtown Fayetteville (km)
Mt. Sequoyah Woods	13	Nov 6 – Jan 8	806	2.10
Markham Hill	25	Nov 1 – Dec 6	853	3.00
Centennial Park/Millsaps Mountain	12	Jan 16 – Mar 21	747	4.30
Lake Fayetteville Park	12	Jan 15 – Mar 22	682	9.60
Kessler Mountain Park	28	Feb 16 – Mar 23	996	5.70
Lake Sequoyah Park	15	Nov 3 – Jan 9	1005	9.60
Ozark National Forest, Weddington	30	Dec 8 – Jan 12	1025	20.00
Hobbs State Park	29	Jan 14 – Feb 8	1015	34.70
Bear Hollow Natural Area	28	Dec 9 – Jan 13	1131	46.40
Ozark National Forest, White Rock	29	Feb 20 – Mar 24	923	49.60
Devils Eyebrow Natural Area	30	Jan 10 – Feb 14	997	50.60
Ninestone Land Trust	30	Nov 2 – Dec 7	1086	58.10

2.2. Camera Placement and Settings

At each study site, we deployed between 12 and 30 Spypoint Force Dark (Spypoint Inc, Victoriaville, Quebec, Canada) and Browning Strikeforce XD cameras (Browning, Morgan, Utah, USA) during the winter/leaf off season in Arkansas (November 2021 to March 2022), allowing us to control for seasonal variation in mammal communities. At each site, we used the recreational trail systems to facilitate efficient random camera deployment. We used ArcGIS Pro (ArcGIS Pro 2.8.3, 2021; Esri Inc, Redlands, CA) and OnX Hunt Map (OnXMaps 2023, Missoula, MT) to manually delineate available trails at each study site and then created a 150 m buffer on each side of all trails. Given the high density of trails at most of our study sites, the buffers created for each trail system used for camera deployment encompassed most of the study sites. We generated random points for camera deployment that lay between 20 and 150 m away from the trail using the Create Random Point tool in ArcGIS Pro. Each camera location was a minimum of 150 m away from the next nearest camera. We deployed cameras within a 50 m buffer around the randomly selected point to ensure suitable topography and a clear field of view devoid of dense vegetation that would reduce our ability to detect animals and result in false triggers. However, we specifically did not place cameras in locations that would have maximized animal detections (such as game trails, water sources, etc.) because this can bias density estimates (Rowcliffe et al., 2016; Kavčić et al., 2021). We deployed cameras between study sites at either 5 or 10 week intervals. Sites with more than 25 cameras were surveyed for 5 consecutive weeks while sites with fewer than 25 cameras remained active for 10 weeks (Supplemental Table 1). Due to camera malfunction and theft the number of trap nights at each site varied but we ensured that sampling effort exceeded 600 trap nights at each site which is above the minimum number of trap nights needed to conclude that undetected species are absent from the area surveyed (Carbone et al., 2001). The difference in deployment lengths across this study allowed a high sampling effort at all sites.

We placed cameras on trees 50 cm above ground. All cameras were set to take bursts of three photos at each motion-trigger. We set the delay between bursts to the minimum possible for each camera - 0 s for Spypoint cameras, and 1 s for Browning cameras, allowing a near continuous capture when the camera was triggered. We sorted all photos using the Timelapse 2.0 software, developed by Greenberg et al. (2019). We grouped all photos of a single species within a span of 5 min into a single "episode" to avoid double counting individuals. A 5-minute episode is a conservative delineation to avoid over-counting, as studies have shown that even shorter episode lengths are sufficient to reduce double-counting bias (Meek et al., 2014). We recorded the species and number of individuals present in each episode.

2.3. Density Estimation

We used the REM approach (Rowcliffe et al., 2008) to estimate density of each focal species at each camera location. The REM has three major assumptions: that animals move randomly throughout their environment (cameras are not baited or set on environmental features that would impact detection probability like downed logs, water bodies, or burrows), detection events represent individual animals, and that the population is closed (Rowcliffe et al., 2008). While some of our sites were in close proximity to one another, there were often barriers such as freeways or large roads between sites that would limit movement. We restricted the survey period to the winter months to minimize violations of a closed population (e.g., no births and minimal deaths).

To estimate the density (*D*) of our five focal species from camera trap detections, we applied the REM equation:

$$D = \frac{y}{t} \times \frac{\pi}{Vr(2 + \theta)}$$

Where *y* refers to the total detections of each animal per camera and *t* is the total trap nights in hours (measure of trapping effort). *V* is the day range of each species, referring to how far an animal travels in a 24-hour period. We used published day range estimates for each species and used the median day range value for each species from all reported estimates to parameterize our models (Supplemental Table 1). We chose to use the median value of literature-reported day ranges to avoid the influence of extreme values because the REM is more sensitive to day range than other variables, such as detection angle (Cusack et al., 2015). Values for the detection radius (r), and detection angle (*θ*) were collected for each camera in the field through walk tests. A walk test entailed walking directly towards each camera to calculate detection radius and from each side at 5 m from the camera to calculate detection angle in degrees. Detection was determined by whether or not the detection light was triggered on the camera during each walk test. The detection angle was later converted to radians for density calculations (Rowcliffe et al., 2008; Caravaggi et al., 2016). We were not able to collect the detection radius and detection angle for 14 cameras due to camera malfunction (no detection light during walk test) so we applied the average detection angle for the given camera model (Schaus et al., 2020). We used the REM equations modeled in Microsoft Excel (Microsoft Corporation) to calculate the density of each focal species at each camera. However, because REM density estimates rely upon the collective viewshed of cameras at a study site, we then averaged all camera-level density estimates to calculate overall estimated density at each study site.

2.4. Detection Rates

In addition to analyzing site-level density estimates, we used the camera-level density estimate values as a response variable in additional analyses. Detection rate is a frequently used metric to evaluate the relative abundance, space use, and habitat use of wildlife (Royle and Nichols, 2003; O'Brien, 2011; McCarthy et al., 2013). Detection rate is typically defined as the number of a focal species detected divided by the number of trap nights surveyed (O'Brien, 2011). The REM density estimates calculated at each camera trap are

a detection rate that take into account both the viewshed of the individual camera as well as the day range movement distance of each focal species. Thus, these camera-level REM estimates function as corrected detection rates (hereafter referred to as CDR).

2.5. Variable Selection and Statistical Analysis

We used two sets of analyses to relate both density and detection rate to anthropogenic and environmental landcover variables. To calculate the anthropogenic and environmental landcover variables to use in analysis, we used ArcGIS Pro (ArcGIS Pro 2.8.3, 2021; Esri Inc, Redlands, CA) to extract six a-priori identified predictor variables from 500 m buffers created around each camera. We used a 500 m buffer around each camera, as this spatial scale has been shown to be biologically meaningful for the focal species (Fidino et al., 2016; Magle et al., 2015; Gallo et al., 2017). We extracted maximum Housing Unit Density (HUD) using the SILVIS housing layer (Hammer et al., 2004, Table 2). As SILVIS uses polygons with housing unit values to catalog the data, we took the maximum value of housing units within the 500 m buffer radius. We extracted anthropogenic noise from the layer created by Mennitt and Fristrup (2016); Buxton et al., 2017, Table 2) and used the "L50" anthropogenic sound level estimate, which was calculated by taking the difference between predicted environmental noise and the calculated noise level. Therefore, we assume that higher levels of L50 sound corresponded to higher human presence and activity, as prominent features projected by the estimated anthropogenic noise value reflect major U.S. cities and their surrounding transportation networks, reflecting human activity with areas having high noise values having high levels of human activity (voices, vehicles, and other sources of anthropogenic noise; Mennitt and Fristrup, 2016; Buxton et al., 2017). For each camera location we extracted the maximum L50 value. Metrics for developed open landcover, forest area, and distance to forest edge were all derived from the 2019 National Land Cover Database (NLDC, Dewitz, 2021, Table 2). Developed open landcover refers to open spaces with less than 20% impervious surface such as residential lawns, cemeteries, golf courses, and parks and has been shown to be important for mesocarnivores (Poessel et al. (2013); Gallo et al. (2017)). Forest area was calculated by combining all forest types within the NLDC layer (deciduous forest, mixed forest, coniferous forest), and summarizing the total area (m^2) within the 500 m buffer. Distance to forest edge was derived by creating a 30 m buffer on each side of all forest boundaries and calculating the distance from each camera to the nearest forest edge. Distance to water was created by combining the waterbody and flowline features in the National Hydrography Dataset (U.S. Geological Survey) for the state of Arkansas to capture both permanent and ephemeral water sources that may be important to wildlife. Distance to water and distance to forest edge were calculated using the geoprocessing tool "near" in ArcGIS Pro which calculates the distance between a point and the nearest feature. We used a search radius of 50 km when using the "near" tool to ensure features were not missed. Average Daily Traffic (ADT) was extracted from the Arkansas Department of Transportation database (Arkansas GIS Office). The maximum value for ADT was calculated using the Summarize Within tool in ArcGIS Pro. Distance to Downtown was calculated from each camera to downtown Fayetteville, AR (36.06162, −94.16114) using the "measure" tool in ArcGIS Pro.

We tested for correlation between covariates with a Spearmen correlation matrix and removed any variable with correlation greater than |0.6|. Correlation coefficients between ADT and HUD and between distance to forest edge and forest area were both greater than |0.6|; therefore, we dropped ADT and distance to forest edge from analyses as we predicted that HUD and forest area would have larger biological impacts on our focal species (Kretser et al., 2008). Variables were scaled prior to running each model.

2.5.1. Site-level density analysis
To assess which landcover variables most influenced the density of each focal species, we used a General Linear Model (GLM) analysis using r programming and the "lme4" and "AICcmodavg" packages. Because our sample size was small (N = 12 sites), we ranked a limited number of a-priori models consisting of single variables. We explored models for housing unit density (HUD), anthropogenic noise, distance to water, forest area, developed open, and distance to downtown Fayetteville. We then used Akaike Information Criteria for small sample sizes (AICc) selection criteria with an a priori cutoff of two for the ΔAIC delta value.

2.5.2. Corrected detection rate analysis
To assess which landcover variables most influenced the detection rate of each focal species, we assembled 49 Generalized Linear Mixed Models (GLMMs) with additive effects (all two way pairs and individual variables)_ using r programming and the "lme4" and "AICcmodavg" packages for six predictor variables: housing unit density (HUD), noise, distance to water, and developed open, and

Table 2
Summary statistics for landcover variables used for evaluating density of five commonly occurring mesocarnivores estimated with the Random Encounter Model on an urban to rural gradient in Northwest Arkansas, USA. Values are derived from each camera location, and then averaged across each of the twelve study sites. Camera trap locations used in this study. dB = decibels.

Landcover Variable	Mean	SE
Forest Area (m2)	61.24	4.35
Distance to Water(m)	172.76	26.20
Noise (dB)	5.11	1.40
HUD (units/km2)	394.11	191.08
Developed Open Space (2)	2.91	0.87
Distance to downtown (km)	24.48	6.07

distance to downtown Fayetteville, including a global model (all variables) and a null model (no variables). We then used Akaike Information Criteria for small sample sizes (AICc) selection criteria with an a priori cutoff of two for the ΔAIC delta value. Top models were considered those within 2 ΔAICc. When there were multiple competing models within 2 ΔAICc that included the same term (e.g., forest cover), we derived a parameter estimate of that term using model averaging (Burnham and Anderson, 2002).

3. Results

From the 287 cameras we deployed, we accumulated 28,249 total independent wildlife detections over 11,236 trap nights. Raccoons were the most common species detected with 3392 individual detections, followed by coyotes (533 detections), opossum (506 detections), bobcats (103 detections), and red fox (20 detections). We detected raccoons, coyotes, and opossum at all 12 study sites, bobcats at 92% of sites (11 of 12), and red fox only at 42% of study sites (5 of 12).

3.1. Density

We were able to use the REM to estimate densities for all species (Fig. 2). Raccoon density ranged from 0.19 to 20.25 individuals/ km^2 with the lowest densities occurring at Weddington, and the highest densities occurring at Millsaps. The density of coyotes ranged from 0.05 to 0.93 individuals/km^2, with the lowest densities occurring at Hobbs State Park and the highest densities of coyotes occurring at Mt. Sequoyah. Opossum ranged in density from 0 to 3.43 individuals/km^2, with the lowest densities occurring at White Rock and the highest Densities occurring at Lake Fayetteville. The density of bobcats ranged from 0 to 1.06 individuals/km^2, with the lowest density occurring in Markham Hill, and the highest density occurring at Lake Fayetteville. Red fox density ranged from 0 to 0.10 individuals/km^2. Red fox were detected only at 5 out of 12 sites, and densities were highest at Millsaps. Density of our focal species varied between sites (Fig. 2), though pairwise comparisons for bobcats revealed the only significant difference between sites occurred between Markham Hill, which recorded no bobcats, and sites that did have detections of bobcats.

For coyotes and raccoons, anthropogenic noise was the best predictors of density (Coyote: β = 0.06, 95% confidence interval (CI) = 0.02–0.25; Raccoon: β = 1.37, 95% confidence interval (CI) = 2.77–8.15, Table 3). Opossum density was best predicted by HUD (β = −0.28, 95% confidence interval (CI) = 0.32–1.43; Table 3). While distance to water and forest area were the top models for bobcats and red fox respectfully, beta values overlapped zero for both species (Bobcat: β = 0.10, 95% confidence interval (CI) = −0.33 to − 0.07); Red fox: β = −0.02, 95% confidence interval (CI) = −0.04 to − 0.0; Table 3).

3.2. Detection Rates

For coyotes, anthropogenic noise was the best predictor for coyote CDR and was included in the top three models (Table 4). No
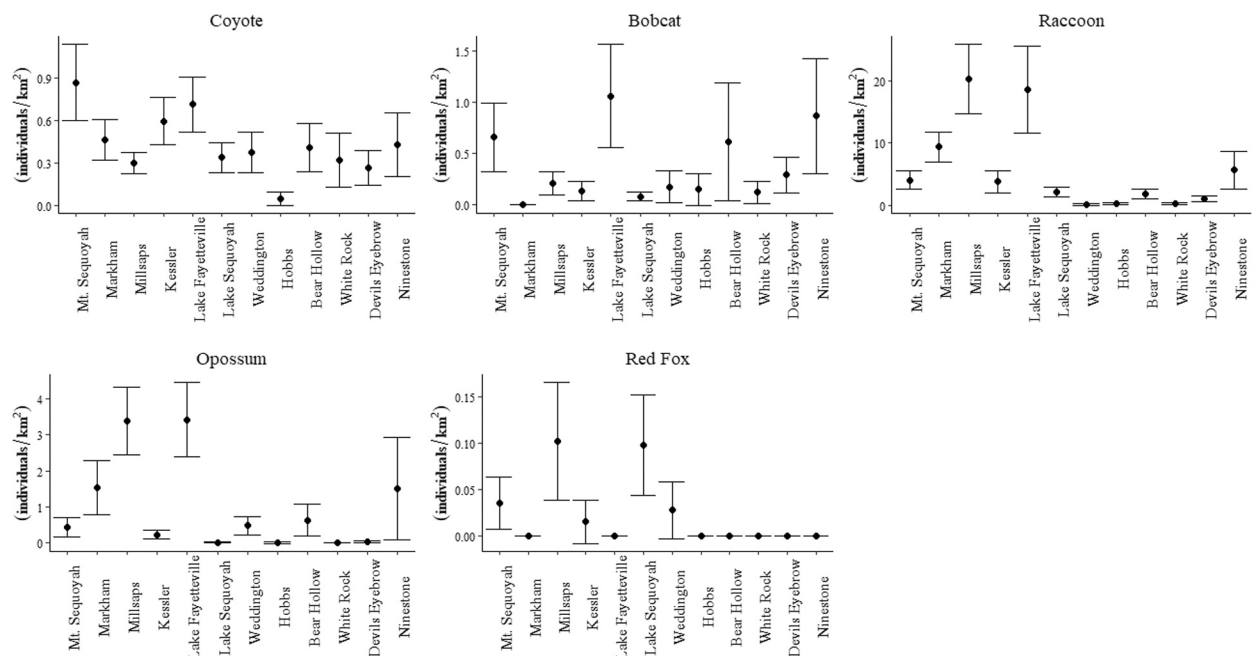

Fig. 2. Mean density (± SE) of five mesocarnivores estimated at twelve study sites throughout the Ozark Mountain Ecoregion in Northwest Arkansas, USA. Density estimates were derived from motion triggered camera traps deployed from Nov 2021 – Mar 2022 and estimated using the Random Encounter Model (Rowcliffe et al., 2008). Sites are arranged on the x-axis from the most urban to the most rural.

Table 3

Model selection statistics for mesocarnivore density and anthropogenic and environmental variables. Density is derived from motion-activated camera trap data and the REM and then averaged across each site. Models were ranked using Akaike's Information Criteria for small sample size (AICc) and includes the number of parameters (K), difference from the top model (ΔAICc), model weight (AICcWt), and cumulative weight included for each model. Table displays the top models with ΔAICc values within an apriori cut off of two.

Models	K	AICc	ΔAICc	AICcWt	LL	Cum.Wt
Coyote						
Noise	3	1.34	0.00	0.48	3.83	0.48
Developed Open Space	3	1.97	0.64	0.35	3.51	0.83
Forest Area	3	5.63	4.30	0.06	1.68	0.88
Distance to Downtown	3	6.20	4.86	0.04	1.40	0.92
HUD	3	6.29	4.96	0.04	1.35	0.96
Distance to Water	3	6.48	5.15	0.04	1.26	1.00
Raccoon						
Noise	3	77.20	0.00	0.50	-34.10	0.50
HUD	3	77.34	0.13	0.47	-34.17	0.98
Forest Area	3	83.99	6.78	0.02	-37.49	0.99
Developed Open Space	3	87.81	10.61	0.00	-39.40	1.00
Distance to Downtown	3	88.58	11.37	0.00	-39.79	1.00
Distance to Water	3	88.60	11.40	0.00	-39.80	1.00
Red Fox						
Forest Area	3	-41.67	0.00	0.49	25.34	0.49
HUD	3	-40.03	1.64	0.21	24.51	0.70
Developed Open Space	3	-38.68	2.99	0.11	23.84	0.81
Noise	3	-38.08	3.60	0.08	23.54	0.89
Distance to Water	3	-37.77	3.90	0.07	23.39	0.96
Distance to Downtown	3	-36.65	5.03	0.04	22.82	1.00
Bobcat						
Distance to Water	3	15.11	0.00	0.31	-3.05	0.31
Forest Area	3	16.57	1.46	0.15	-3.78	0.46
HUD	3	16.68	1.57	0.14	-3.84	0.60
Developed Open Space	3	16.72	1.61	0.14	-3.86	0.73
Noise	3	16.78	1.67	0.13	-3.89	0.87
Distance to Downtown	3	16.81	1.70	0.13	-3.91	1.00
Opossum						
HUD	3	39.34	0.00	0.56	-15.17	0.56
Noise	3	40.27	0.93	0.35	-15.63	0.92
Forest Area	3	44.15	4.81	0.05	-17.58	0.97
Developed Open Space	3	47.15	7.81	0.01	-19.07	0.98
Distance to Downtown	3	47.40	8.06	0.01	-19.20	0.99
Distance to Water	3	47.40	8.06	0.01	-19.20	1.00

models without noise had an ΔAICc value less than two. In all models, noise had a positive relationship with coyote CDR (model averaged β = 0.36, 95% CI = 0.06–0.67), indicating coyotes occurred at higher CDRs in areas with high levels of human activity (Fig. 3).

As with coyotes, the CDR for raccoons was best predicted by anthropogenic noise. Noise occurred in all 5 models with ΔAICc values less than 2 (Table 4). In all models, noise was positively related to raccoon CDR (β = 0.95, 95% CI = 0.41–1.48), indicating that raccoons are more likely to have higher CDRs in areas with high levels of human activity (Fig. 4).

Red fox CDR was best predicted by developed open space (β = 0.35, 95% CI = 0.19–0.51, Fig. 5(A)) and distance to water (β = −0.13, 95% CI = −0.26 to −0.01, Fig. 5(B)). These variables were included in each of the top five models. (Table 5). In all models, developed open space had a positive relationship with red fox CDR (Fig. 5 (A)) indicating red fox may gravitate toward anthropogenic habitat within developed areas. Additionally, all models showed a negative relationship between red fox CDR and distance to water (Fig. 5(B)).

For bobcats, the top model in the AICc model selection was the null model (Table 4). No other model held consistent support for any of the selected variables. While all variables were included in the top 6 models, all were nonsignificant and did not show any clear trends in covariate effects on bobcat density. The null model included only the random effect of site.

Opossum CDR was best predicted by developed open space. In all top models, developed open space had a positive relationship with opossum detection rate. Similarly to red fox, this may indicate opossum are able to take advantage of anthropogenic habitat within developed areas (model averaged β = 0.72, 95% CI = 0.38–0.1.06, Fig. 6).

4. Discussion

We found that trends in densities of coyote, opossum, and raccoon were consistent with the expectation for urban exploiters. Coyote

Table 4

Model selection statistics for mesocarnivore detection rate estimates and anthropogenic and environmental variables. The corrected detection rate (CDR) is derived from camera traps and camera level density estimates from the REM. Models were ranked using Akaike's Information Criteria for small sample size (AICc) and includes the number of parameters (K), difference from the top model (ΔAICc), model weight (AICcWt), and cumulative weight included for each model. Table displays the top models with ΔAICc values within an apriori cut off of two. Complete AICc tables are available in supplementary materials (Supplemental Table 2–6). HUD = housing density unit.

| Models	K	AICc	ΔAICc	AICc Wt	LL	Cum.Wt
Coyote						
Noise	4	-103.54	0.00	0.14	55.84	0.14
HUD + Noise	5	-102.69	0.85	0.09	56.45	0.23
Noise + Distance to Downtown	5	-102.61	0.93	0.09	56.41	0.31
Noise + Forest Area	5	-102.52	1.02	0.08	56.36	0.39
Raccoon						
Noise	4	607.80	0.00	0.15	-299.83	0.15
Noise + Forest	5	608.86	1.06	0.09	-299.32	0.24
Noise + Distance to Downtown	5	608.97	1.17	0.08	-299.38	0.32
Noise + Distance to Water	5	609.09	1.29	0.08	-299.44	0.40
Noise + Developed Open Space	5	609.18	1.37	0.08	-299.48	0.48
HUD + Noise	5	609.68	1.88	0.06	-299.73	0.54
Red Fox						
Distance to Water + Developed Open Space	5	-1732.49	0.00	0.19	871.35	0.19
HUD + Distance to Water + Developed Open Space	6	-1732.05	0.45	0.15	872.17	0.35
Noise + Distance to Water + Developed Open Space	6	-1730.93	1.56	0.09	871.62	0.43
Distance to Water + Forest + Developed Open Space	6	-1730.53	1.96	0.07	871.42	0.51
Distance to Water + Developed Open Space + Distance to Downtown	6	-1730.50	1.99	0.07	871.40	0.58
Bobcat						
null	3	-678.56	0.00	0.13	342.32	0.13
Distance to Water	4	-677.37	1.19	0.07	342.75	0.20
HUD	4	-677.14	1.42	0.06	342.64	0.26
Noise	4	-676.80	1.76	0.05	342.47	0.31
Developed Open Space	4	-676.72	1.84	0.05	342.43	0.36
Distance to Downtown	4	-676.55	2.01	0.05	342.35	0.41
Forest Area	4	-676.50	2.06	0.05	342.32	0.45
Opossum						
HUD + Distance to Water + Developed Open Space	6	-418.20	0.00	0.13	215.25	0.13
Distance to Water + Developed Open Space	5	-417.94	0.26	0.11	214.08	0.24
HUD + Developed Open Space	5	-417.82	0.38	0.10	214.02	0.34
Distance to Water + Forest Area + Developed Open Space	6	-417.62	0.58	0.09	214.96	0.43
HUD + Forest Area + Developed Open Space	6	-417.31	0.90	0.08	214.80	0.51
HUD + Noise + Distance to Water + Forest Area + Developed Open Space	8	-417.09	1.11	0.07	216.80	0.59
HUD + Distance to Water + Forest Area + Developed Open Space + Distance to Downtown	8	-416.97	1.23	0.07	216.74	0.65
Developed Open Space	4	-416.53	1.67	0.05	212.34	0.71
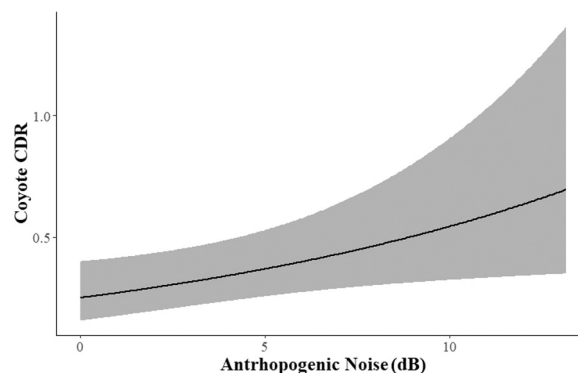
Fig. 3. Model averaged relationship between anthropogenic noise and coyote corrected detection rate (CDR, *Canis latrans*) estimated through trail cameras and the Random Encounter Model (Rowcliffe et al., 2008) at 12 study sites in northwest Arkansas, USA. The displayed relationship was derived from model averaging the top three models (Table 2) from AICc prediction of the effects of anthropogenic and environmental variables on coyote CDR.
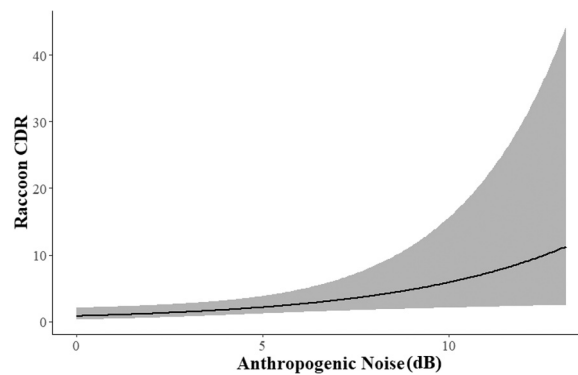
Fig. 4. Model averaged relationship between anthropogenic noise and Northern raccoon (*Procyon lotor*) corrected detection rate (CDR) estimated through trail cameras and the Random Encounter Model (Rowcliffe et al., 2008) at 12 study sites in northwest Arkansas, USA. The displayed relationship was derived from model averaging the top five models (Table 4) from AICc prediction of the effects of anthropogenic and environmental variables on raccoon CDR.
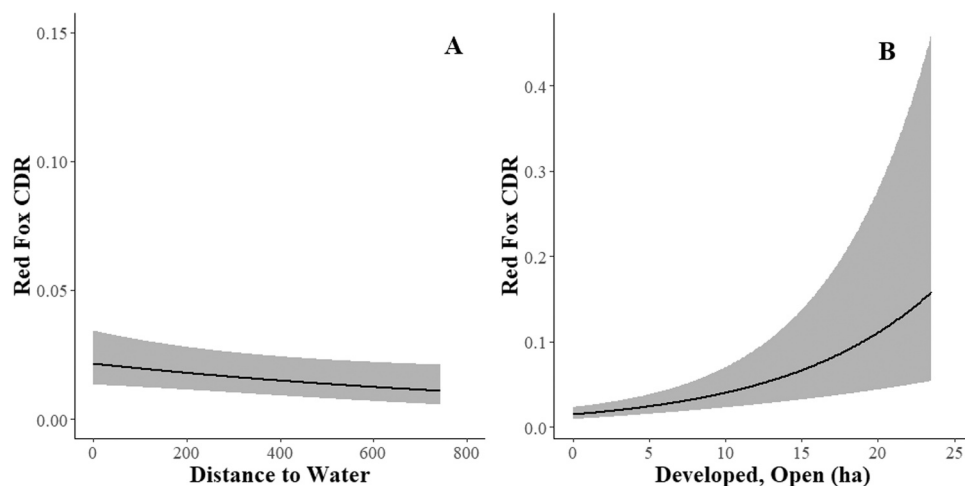

Fig. 5. Model averaged relationship between red fox corrected detection rate and both distance to water (A) and developed open space (B). Density was estimated through trail cameras and the Random Encounter Model (Rowcliffe et al., 2008). Derived from model averaging the top five models (Table 4) from AICc prediction for effects of anthropogenic and environmental variables on red fox density.

Table 5

Literature-derived density estimates for five focal mesocarnivores: raccoon (*Procyon lotor*), red fox (*Vulpes vulpus*), coyote (*Canis latrans*), Virginia opossum (*Didelphis virginiana*), and bobcat (*Lynx rufus*). These estimated are compared to density estimates from our study conducted in Northwest Arkansas, USA. Density estimates for our study area were calculated through the Random Encounter Model (REM, Rowcliffe et al., 2008).

| Citation	Raccoon (ind/km^2)	Red Fox (ind/km^2)	Coyote (ind/km^2)	Opossum (ind/km^2)	Bobcat (ind/km^2)
Kasparian et al. (2004)	-	-	-	2.35	-
Wolcott (2011)	-	-	-	0.07	-
Bernasconi (2020)	-	-	-	0.26	-
Morin et al. (2018)	-	-	-	-	0.38
Stoddart et al. (2001)	-	-	0.75	-	-
Morin et al. (2016)	-	-	0.067	-	-
Webbon et al. (2004)	-	1.22	-	-	-
Sarmento et al. (2009)	-	0.83	-	-	-
Goszczyński (1989)	-	0.71	-	-	-
Rosatte et al. (2010)	5.66	-	-	-	-
Pandolfi et al. (1997)	-	5.74	-	-	-
Wrangham et al. (1993)	-	2	0.90	-	0.30
Fenton (2019)	1.28	-	0.73	2.05	0.21
Species Average	3.47	2.28	0.37	0.44	0.31
Study Area Average	5.66	0.02	0.43	0.97	0.36
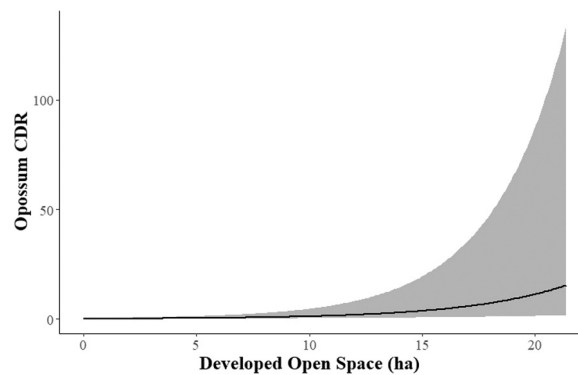
Fig. 6. Model averaged relationship between developed open space against opossum corrected detection rate estimates. Corrected detection rate estimates were derived from camera traps in Northwest Arkansas, USA, and density estimates calculated through the Random Encounter Model (Rowcliffe et al., 2008).

and raccoon density were positively correlated with anthropogenic noise, and opossum showed a positive relationship with HUD. Red fox density showed a negative relationship with forest area, though confidence intervals overlapped zero. Bobcat similarly showed a positive correlation with distance to water, yet confidence intervals overlapped zero.

When looking at CDRs, four out of the five focal species showed relationships between CDR and our predictor variables. Coyote and raccoon CDR increased as anthropogenic noise levels increased. Red fox CDR was negatively correlated with distance to water, and positively associated with developed open space. Similarly, opossum CDR was positively correlated with developed open space. We found no evidence that bobcat CDR corresponded consistently with the definition of an urban-avoider or an urban-exploiter and showed no correlation to any landcover variables.

Contrary to our predictions, we found that both coyote density and CDR increased in areas with high human activity as measured by estimated anthropogenic noise. This likely reflects the ability of coyotes to co-exist with humans (Tigas et al., 2002; Bateman and Fleming, 2012) and likely a benefit to coyotes for exploiting human-subsidized resources (Morey et al., 2007; Fedriani et al., 2001). Coyotes have been shown to be highly adaptable to urban settings and are adept at exploiting human-subsidized resources (Prange et al., 2003; Gross et al., 2012; Bateman and Fleming, 2012; Breck et al., 2019), though they are often perceived as a threat to human safety and are frequently blamed for depredating pets (Loven, 1995; Alexander and Quinn, 2011), and they can carry diseases that are transmittable to domestic dogs (rabies, canine heartworm disease etc.; Pluemer et al., 2019). Thus, high densities and detection of coyotes in areas of high human activity can lead to both real and perceived conflicts. While coyotes are adept at co-existing with humans, there are both social and ecological reasons why a high density of coyotes in urban areas and neighboring natural areas could be problematic, as conflict increases with higher density of coyotes (Poessel et al., 2017). Coyotes, as an extremely adaptable species, are known to take advantage of anthropogenic food sources (Morey et al., 2007), and are able to prey on species associated with humans such as rodents, cottontails (*Sylvilagus floridanus*), and outdoor pets such as cats, dogs, and chickens (Fox, 2006). Since our study sites are all in forested areas that are within or adjacent to the urban matrix of northwest Arkansas, it would make sense that noise be the top predictor explaining coyotes' affinity for urban areas.

While we did not find a significant relationship between red fox density and any of our predictor variables, they showed a negative relationship between CDR and distance to water, but a positive relationship between CDR and developed open space. Because they were only detected in 5 study sites, all of which were our more urban study sites, this suggests that foxes are able to take advantage of anthropogenic resources that increase as developed open space does, including food and shelter. In Melbourne, Australia, a study conducted on urban foxes indicated that 61% of natal dens occurred in residential, public park, or industrial lands (Marks and Bloomfield, 2006). However, foxes are also known to forage in open areas, which could explain their affinity for developed open space (Goldyn et al., 2003).

We saw an increase between density and noise for raccoons as well as positive correlations between raccoon CDR and noise. Access to subsidized resources has been shown to decrease winter weight loss in raccoons (Mech et al., 1968; Hoffmann, 1979; Rosatte et al., 1991; Riley et al., 1998). Higher densities of raccoons can also create a greater risk of ecological and social conflicts, increasing the risk of disease outbreaks (such as canine distemper) within their populations as well as the potential for these diseases to spread to pets (Prange et al., 2004; Schell et al., 2021). High densities of raccoons in areas of high human activity not only increases the risk of conflict associated with zoonotic disease spread (Schell et al., 2021), but also of conflict between raccoons and pets or between raccoons and humans (raiding trash cans, etc.).

Opossum density increased with HUD, and we say an increase between opossum CDR and developed open space. Opossums in urban areas have been shown to occupy smaller home ranges and obtain higher body mass in urban areas (Wright et al., 2012). Similarly to red fox, developed open space could provide opossums with increased foraging opportunity (such as trash, birdseed and other anthropogenic food sources (Bozek et al., 2007; Johansson and DeGregorio, 2023) and reduced competition and predation by larger more dominant mesocarnivores (Gámez and Harris, 2021).

While bobcats were widespread (detected at 11 of 12 study sites) we found little support for landscape variables correlating with bobcat density or CDR. The only differences between sites occurred with Markham Hill. Since Markham Hill was the only site where

bobcats were not detected, there may not be enough variance in bobcat density across cameras to measure variables influencing density. It is possible that because bobcats in Arkansas have large home ranges (64.2 km^2 for adult males, 24.5 km^2 for adult females; Rucker et al., 1989) and show territoriality, the density of the species at most sites is fairly uniform with only a small number of resident individuals being able to be supported in these relatively small natural areas. Because bobcat density tends to be low (Wrangham et al., 1993; Morin et al., 2018; Fenton, 2019) detecting differences in density between sites likely needs to be evaluated on a larger spatial scale.

By using only motion-triggered camera traps, we successfully calculated the density of five focal species at twelve different study sites using the REM. The density estimates we calculated were comparable to estimates from the literature (Table 5). The REM relies upon knowledge of how far each focal species travels in a 24-hour period and has been shown to be highly influenced by this movement parameter (Cusack et al., 2015). For this study, we used literature values for each species to parameterize our models. This reliance on previously published movement parameters is one of the reasons we chose well-studied and common mesocarnivores as our focal species. Practitioners focusing on rare or understudied species may not be able parameterize their models with published estimates and may have to rely on concurrent radiotelemetry to generate their own movement parameters. Cusack et al. (2021) describe the movement parameter to be the most important when accurately estimating density through the REM. Therefore, if we had chosen incorrect values for our movement parameter, we could have seen much different estimates in density. Fortunately, we found a close alignment between our density estimates and estimates from the literature (Table 5) using traditional approaches, which gave us confidence in our choice of parameters. Additionally, because our comparisons among sites used the same movement parameters, any bias would have been consistent among sites. Gilbert et al. (2020) also notes this as a disadvantage to the REM. While we were able to use literature derived values, measurements were taken from many different habitats and regions. Additionally, because our research spanned different levels of urbanization, there is a chance that using literature-derived day ranges could be problematic due to differences in behavior across the urban-rural gradient and across habitats and geographical regions for our focal species. For example, it has been documented that many species have smaller home ranges in urban environments (Prange et al., 2004; Wright et al., 2012; Šálek et al., 2015). Since the overall goal of our study was to use density estimates to evaluate how species density correlates to environmental and anthropogenic variables, and not explicitly state the number of species per km^2 for each site, we believe our approach still has value for exploring changes in density over a large special scale. We attempted to control for possible changes in movement behavior by sampling within intact patches of hardwood forests that were larger than 39 ha.

In general, our density estimates for four of our five focal species aligned with reports from the literature (Table 5), which is encouraging and shows the robustness of the REM approach. However, our density estimates for red fox (0.1 individuals/km^2) were lower than what appeared in reports from the literature (Table 5), though this is likely due to red fox only being detected at 5 of the 12 sites and having a small number of detections (N = 20). Our application of REM may not be as reliable for rarely encountered species as it was for more common species.

Through the use of widely available camera traps and an established model for density estimation (Rowcliffe et al., 2008), we were able to calculate reliable density estimates for five cryptic, primarily nocturnal, mesocarnivore species. Furthermore, we were able to correlate their density, as well as a CDR to landcover variables. This approach provides valuable insight into how different species respond to landcover change and may be useful in predicting where potential social or ecological conflicts may arise as a result of these changing densities. We were also able to assess the potential impacts of environmental and anthropogenic variables on variation in mesocarnivore density. However, we should acknowledge that our density estimates were made for only a single year and undoubtedly these population levels fluctuate based on diseases, resources, and environmental factors. We believe there is still value in even short duration studies of this nature. Because the continued spread of urbanization is inevitable, understanding how mammal communities and species respond to different anthropogenic influences is crucial. Remotely sensed datasets, such as anthropogenic noise (Buxton et al., 2017), NLDC (Dewitz, 2021), and HUD (Hammer et al., 2004), continue to improve, allowing us to gain better understandings of specific effects of urbanization on wildlife. Lastly, the REM continues to gain support as a reliable, non-invasive, and cost-effective method for density estimations which could aid and improve traditional methods of population monitoring. While the REM is certainly not the only available method of estimating density from unmarked animals using camera traps (such as time to event or space to event models) these types of models rely on timelapse data rather than motion-triggered detections and movement parameters. (Moeller et al., 2019). We found the REM to be an appropriate choice for our study system, as movement parameters of these heavily studied species were available from the literature, and timelapse requires additional batteries, storage, and frequent downloads. We found estimation of density to be relatively straightforward so long as all components of the model are collected properly and assumptions are met, which could allow it to be adapted by a wide range of stakeholders for species monitoring.

Declaration of Competing Interest

Data Availability

Data has been published through Dryad (McTigue 2023) and is publically available.

Acknowledgements

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.gecco.2023.e02716.

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