

# Estimates of wildlife species richness, occupancy, and habitat preference in a human-impacted landscape in New York State

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## Research Article

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# Abstract

Despite the widespread adoption of motion-triggered cameras, studies using camera-traps to characterize wildlife communities in human-impacted, residential areas in North America are limited. To fill this data gap, we placed camera traps over three seasons in 22 residential neighborhoods within Dutchess County, NY. To account for imperfect detection, we applied individual-level and community-level Bayesian site-occupancy models to these data. Overall, we captured 280,686 images over 17,820 camera-trap days. We detected 17–22 mammal and non-passerine bird species in each of the seasons of data collection, with our full-community models estimating an actual diversity of 24–33 species in each season. Small, cryptic species were not accurately detected, limiting our ability to model their occupancy. Our models did not indicate any geographic trends. We identified five species, raccoons (*Procyon lotor*), eastern gray squirrels (*Sciurus carolinensis*), red foxes (*Vulpes vulpes*), Virginia opossums (*Didelphis virginiana*), and white-tailed deer (*Odocoileus virginianus*) found in all neighborhoods. The most common variable included in our final occupancy models was the percent of area within each neighborhood that was not habitat, which positively affected occupancy for some species, and negatively affected occupancy for others. The amount of forest, the second most common variable in our final models, negatively affected occupancy for all species. Our estimates characterize a baseline for quantifying species richness and composition in residential areas of Dutchess County, NY and surrounding regions, and offer a comparison to similar studies in natural areas. Overall, the results improve understanding of how human use of landscapes affects individual species and communities.

# Introduction

Wildlife provide important ecosystem services to people. For example, wildlife disperse seeds, control pests, and enrich human recreation. Wildlife can also be sources of conflict with humans, for example when they damage vegetation, collide with motor vehicles, or transmit pathogens. As humans continue to encroach on wildlife habitat worldwide (Venter et al. 2016; Williams et al. 2020), understanding the diversity and species composition of wildlife communities, particularly in human-impacted ecosystems, can inform wildlife and landscape management. But many wildlife species are difficult to detect, particularly if they are cryptic, nocturnal, or highly mobile.

One approach to detecting elusive species is to use cameras, an approach that has rapidly grown in popularity. The annual number of published studies of wildlife species or communities using camera traps has increased 5.2-fold in the past decade and 81-fold since 1994 (Delisle et al. 2021). In part, this widespread adoption is likely attributable to the utility and ease of camera-trapping technology. Infrared, motion-triggered camera traps are cost-effective and accurate tools that allow researchers to study species richness, occupancy, distribution, and relative abundance (Wearn and Glover-Kapfer 2019). Since camera traps remain in the field for extensive periods of time, they allow researchers to capture images of rare species not easily detected by other techniques. Camera-traps have been found to be significantly more effective than live traps at detecting certain wildlife (Wearn and Glover-Kapfer 2019) and, unlike live traps, offer a passive method of detection that does not disturb study animals.

Importantly, since camera traps yield repeated observations from a single location, camera data are well suited for fitting site-occupancy models. Site-occupancy models (Mackenzie et al. 2002) account for imperfect detection (i.e., not detecting a species within a certain area does not necessarily mean the species is absent) by modeling the occupancy process and the detection process separately. This can effectively resolve whether a species is absent because it was not detected, or because it was not present. Failing to resolve the ambiguity of species absence can cause incorrect interpretation of data. For example, when the probability of detecting a species is  $< 1$ , failing to account for imperfect detection leads to underestimates of species distributions and estimates of covariate relationships that are biased toward zero. Additionally, factors that affect our ability to detect a species may erroneously be included in models of species occurrence (Kery 2010). Differentiating occupancy and detection allows both covariates to be included in site-occupancy models, providing a more robust statistical framework to study habitat associations of individual species.

Despite a recent wealth of camera-trap studies, the vast majority of the studies in North America documenting biodiversity have focused completely (Cloyd et al. 2018; Haverland and Veech, 2017; Kays et al. 2017; Kowalski et al. 2015; Parsons et al. 2016; Stark et al. 2020), or partially (Farr et al. 2017; Fidino et al. 2020; Goad et al. 2014; Linske et al. 2018; Moll et al. 2020; Parsons et al. 2018a; Parsons et al. 2019) on natural or protected areas. Although systematically monitoring protected areas with camera-traps is an important element of studying global biodiversity, human-impacted, non-protected landscapes are also critical, especially given the projected expansion of urban areas (Lawler et al. 2014; Liu et al. 2020). Species with low population densities and large spatial requirements are particularly affected by human presence (Crooks 2002). Studies have also shown that certain mammal species fare surprisingly well in urban landscapes (Bateman and Fleming 2012; LaPoint et al. 2013), and that species richness along wild-urban gradients can exhibit a variety of patterns (McDonnell and Hahs 2008).

To better understand the effects of human development on biodiversity, and potentially inform management of habitats and wildlife populations, large-scale studies describing wildlife communities in human-impacted landscapes are essential. To our knowledge, only four studies in North America (Cove et al. 2012; Eakin et al. 2018; Hansen et al. 2020; Kays and Parsons 2014) have utilized camera traps exclusively within non-protected areas to document and examine biodiversity, and only four studies (Hansen et al. 2020; Kays and Parsons 2014; Linske et al. 2018; Parsons et al. 2018b [and derivative works]) have deployed camera traps directly on residential properties. To address this data gap, specifically in the US Northeast, we collected camera-trap data over three seasons in residential neighborhoods within Dutchess County, NY, a predominantly rural-suburban area, with a population of roughly 300,000, and an average housing density of 51 houses / km<sup>2</sup>. We applied Bayesian site-occupancy models to these data to distinguish detection and occurrence. A first goal of the study was to describe the wildlife community within this human-impacted landscape, which can serve as a baseline for biodiversity in residential areas of the Northeast. To achieve this goal, we estimated the full species richness of mammal and non-passerine bird species, as well as the geographic distributions of individual species, while accounting for imperfect detection. A second goal was to explore how anthropogenic

features may affect biodiversity by identifying which species are most and least present in human-impacted environments, and which covariates related to human disturbance increase and decrease individual species occupancy.

## Methods

### Study area

The study area was in Dutchess County, NY, located midway between New York City and Albany, and included residential neighborhoods (average area:  $0.28 \text{ km}^2$ , S.E.:  $0.01 \text{ km}^2$ ) that were selected for inclusion in The Tick Project (Keesing and Ostfeld 2018; Keesing et al. 2021 [in review]). Of the 24 neighborhoods included in The Tick Project, we included data from 22 for the present study. The minimum distance between a camera in one neighborhood and the next closest neighborhood was 1 km (mean: 3.31 km; range: 1.06 km – 17.68 km). Previous studies (Kelly et al. 2008; Moruzzi et al. 2002) have suggested that this distance satisfies the necessary assumption of independence of site-occupancy models.

Forest cover of our study neighborhoods ranged from 18% – 63% of the total area (median = 46.3%), and non-habitat cover ranged from 17% – 42% of the total area (median = 24.2%). Features considered as nonhabitat include buildings, sidewalks, parking lots, pools, trampolines, roads (paved and unpaved), and bodies of water. Neighborhoods contained residential lawns and garden areas comprising 19% – 48% of the total area (median = 30.3%) (Table 1). Neighborhood clumpiness, which measures how aggregated or disaggregated forest patches are ranged from 0.93–0.96 (median = 0.95). Values less than 0 indicate less aggregation than would be expected randomly, while values greater than 0 indicate more aggregation than random. The upper bound of discrete forest patches per neighborhood ranged from 14–60 (median = 33) (Table 1). We report an upper bound because our artificial neighborhood boundaries caused forest patches connected outside of the neighborhood boundary to be interpreted as multiple, separate forest patches.

Table 1

Descriptive statistics of landcover in each of our 22 study neighborhoods, summarizing the percent of the neighborhood's landcover that is non-habitat, forested, and herbaceous, as well as metrics related to forest connectedness. UB = upper-bound. See Methods for full descriptions of each metric

Neighborhood Index	% Non-habitat	% Forested	% Herbaceous	Discrete Patches (UB)	Clumpiness
1	28.9	37.2	33.9	44	0.94
2	24.2	28.3	47.5	45	0.94
3	29.1	47.9	23.0	36	0.95
4	33.7	18.2	48.1	33	0.94
5	24.3	49.5	26.2	30	0.95
6	30.8	38.0	31.2	27	0.96
7	22.0	58.5	19.5	26	0.95
8	17.9	57.0	25.1	42	0.95
9	42.4	26.9	30.7	33	0.94
10	40.4	29.4	30.2	31	0.95
11	42.3	32.7	25.0	32	0.93
12	24.0	42.0	34.0	37	0.96
13	17.4	63.1	19.5	14	0.95
14	19.9	48.9	31.2	40	0.96
15	22.3	53.3	24.4	22	0.95
16	25.4	46.1	28.6	28	0.96
17	33.5	36.1	30.4	28	0.95
18	25.0	37.4	37.6	48	0.94
19	18.9	46.6	34.5	55	0.95
20	22.8	48.5	28.6	60	0.94
21	21.4	57.3	21.3	27	0.95
22	21.4	47.4	31.2	37	0.95

## Camera trapping and data storage

We deployed three un-baited cameras on three unique properties within each neighborhood for roughly three months of autumn-winter camera-trapping in each year 2016–2018 (Table 1) Unless a property

dropped-out of the study, the camera was placed on the same three properties in each neighborhood each season. Similarly, unless a tree was downed, cameras were placed at the same location on the property each season. Both events happened infrequently (< 10%). Each property that hosted a wildlife camera contained forest cover and was selected based on aerial imagery (Parcel Access in ArcMap 10.3, [https://gis.dutchessny.gov/parcelaccess/parcelaccess\\_map.htm](https://gis.dutchessny.gov/parcelaccess/parcelaccess_map.htm)) and in-person observation. We used Bushnell No-Glow Aggressor (model #119776C) cameras set to take three photos, each two seconds apart, when activated by motion. Prior to camera deployment, we identified optimal camera settings (Table S1) to capture images roughly 5 m away. As predator species and other larger mammals, such as deer, may preferentially use game trails for movement, we attempted to limit our placement of cameras along observed game trails to one per neighborhood to avoid bias in our detection. In some neighborhoods, we opted to place more than one camera along a game trail when at these locations, game trails co-occurred with brush or dense vegetation within the view of the camera. We reasoned these areas would provide refuge for meso-mammals that do not typically use game trails. We placed cameras at approximately 45-degree angles to game trails to best detect wildlife moving along the trail. We placed cameras in relatively open areas under the canopy to maximize our detection rate and to avoid having moving vegetation trigger the camera. We mounted cameras on trees that were at least 15 cm in diameter at breast height (DBH). The height at which we placed the camera on the tree depended on the conditions present (e.g., slope, brush cover, downed logs, debris) but, in general, we placed cameras about 0.5 m above the base of the tree.

After the initial 2016–2017 camera trapping season, we created species accumulation curves as a function of trap days to determine the appropriate length of time for cameras to be deployed (Figure S1). In each season, we checked cameras monthly after deployment to replace batteries and SD cards. After a minimum of 90 days of deployment for each camera, we removed all cameras and materials from the field.

We used Camelot (Camelot-Project) software on a secure network to identify species and store the data. Images of a particular species from a single camera were considered independent if they were taken at least 20 minutes apart, this assumption prevented us from recounting the same individual multiple times if they stood in the camera's view for an extended period.

Table 2  
Start and end dates of camera trapping for each camera-trap season

<b>Year</b>	<b>Start of Camera Trapping</b>	<b>End of Camera Trapping</b>	<b>Total images captured</b>
2016	11/22/2016	3/13/2017	74,108
2017	9/25/2017	1/10/2018	104,059
2018	10/1/2018	1/9/2019	102,519

## Statistics

Since cameras were placed to optimally capture images from 5 m away, we did not include any passerine bird species in our results because small birds have a very low probability of detection from this distance (Randler and Kalb 2018). Instead, our results include mammal and non-passerine bird species.

The Relative Abundance Index (RAI) for each year was calculated as the number of independent observations divided by the number of camera-trap days, all multiplied by 100 to convert this ratio to a percentage. Camera-trap days were calculated as the number of cameras times the number of days they were deployed.

To evaluate factors that could affect occupancy, we included the following covariates in our model: the percent of the neighborhood that was not habitat, including roads or structures (referred to as nonhab in model outputs), the percent of the habitat area within the neighborhood that was forest (forest), the average distance between each of the three cameras in the neighborhood and the nearest road (DTR), and the average distance between each of the three cameras in the neighborhood and the nearest house (DTH). Similar to (Eaken et al. 2018), we considered area of non-habitat to represent the intensity of human impact because it includes buildings and pavement and is therefore linked to traffic, urbanization, light, and noise pollution. We expected increased areas of non-habitat within a neighborhood to decrease the probability that each species would be present in that neighborhood (McKinney 2008). We considered the percent of habitat in the neighborhood that was forest to serve as a proxy for forest connectivity and expected that a species would be more likely to be present in neighborhoods with higher percentages of forest (Baguette and van Dyck 2007; Kindlmann and Burel 2008). We used the camera distance to the nearest household to serve as a proxy for human presence, and thus expected the presence of humans to decrease the presence of wildlife, which has been demonstrated for white-tailed deer (*Odocoileus virginianus*) (Keim et al. 2019). Finally, we expected occupancy probability to be negatively correlated with a camera's distance to the nearest road (Fahrig and Rytwinski 2009), given the potential for roads to inhibit movement.

To account for potential detection bias, we included two additional covariates: game trail (gt) and fencing (fence). The game trail variable describes the number of cameras within the neighborhood that were placed on a game trail (0, 1, 2, or 3). Fencing on each property was classified as a (1, 2, or 3) where 1 represents complete, or nearly complete fencing near the perimeter of the property on which the camera was placed, such that > 0.75 of the property is enclosed, 2 represents complete, or nearly complete fencing that encloses between half and three-quarters of the property, and 3 represents smaller or less continuous fenced areas than (1) or (2), including yards with no fencing. We then took the mean of this value for the three properties per neighborhood to calculate an average fencing variable. Although neither of these variables are expected to directly affect a species' occupancy within a neighborhood, they are expected to affect our ability to detect each species, with game trails increasing our ability to detect certain wildlife (Cusak et al. 2015; Kolowski and Forrester 2017) and fenced properties decreasing our ability to detect certain wildlife.

To estimate percent habitat and non-habitat within each neighborhood, we used publicly available statewide digital orthoimagery of Dutchess County (<http://gis.ny.gov/gateway/mg/2016/dutchess/>) taken in the spring of 2016 to classify every pixel in each neighborhood as either habitat (forest, field, lawn, shrub/garden) or non-habitat (e.g. house, shed, driveway, road) using the maximum likelihood classification tool in ArcMap software (version 10.4). To estimate forest habitat in our neighborhoods, we used a GIS layer developed in 2017 by Robert S. Wills, Senior GIS Project Coordinator with New York's Dutchess County Department of Planning and Development. Wills used 6" resolution digital orthoimagery, LiDAR-derived 5' resolution digital elevation model (DEM), and a 5' resolution surface model (SEM) to estimate forest cover in Dutchess County. He subtracted DEM base elevation from the SEM, which resulted in a surface of vegetation and structure heights above ground. He identified structures using a county layer of building blueprints. After including a buffer of 7.6 m around building blueprints, he used the Subtract function of the Raster Math tool to remove non-vegetative height pixels, resulting in vegetative height remaining (i.e. forest cover). We clipped this layer to our neighborhood boundaries to achieve neighborhood estimates of forest cover. We estimated error rates for pixel classifications by selecting a random subset of 10% of the properties in each neighborhood and manually reviewing the output of the classification of the pixels on that property. For habitat/non-habitat, the mean error rate of the maximum likelihood classification was 2.7%. All covariates were checked for multicollinearity and transformed based on a 0–1 max-min transformation.

*Species richness model.* To estimate species richness while accounting for imperfect detection, we implemented the model introduced in Dorazio et al. (2006), a Bayesian methodology that utilizes community-level attributes and species-specific random intercepts to resolve the ambiguity between species absence and species non-detection. We fit a model for each camera-trapping season in WinBUGS (Thomas 1994) using the R package R2WinBugs (Sturtz et al. 2005) in R software (version 4.0.1) (R Core Team 2020). Our simulations included four Markov chains, 55,000 iterations, a burn-in period of 5000 iterations and a thinning rate of 50.

*Individual species site-occupancy models.* To determine which mammal and non-passerine bird species occupied each neighborhood while accounting for imperfect detection, we modeled species-specific detection probabilities ( $p$ ) and occupancy probabilities ( $\psi$ ), using single-species occupancy models (MacKenzie et al. 2002) based on a Bayesian model of inference. Within these models, each day constituted a survey, allowing for repeated observations that enabled us to distinguish between a lack of detection and a true lack of occupancy. Our models assume that occupancy comes from a Bernoulli distribution, and our observation data come from a Bernoulli process with a success rate of  $(\psi * p)$ . Covariates ( $\beta_i$ ) were modeled into occurrence and detection models using the logit function. Due to minimum data requirements, we only fit site-occupancy models for species with naive occupancies  $> 0.10$ .

To select the best subset of covariates for our site-occupancy models for each species, we first separately ranked both the covariates expected to affect occupancy and the covariates expected to affect detection based on their *a priori* expected influence on that species' occupancy and detection probabilities,

respectively. We then used a top-down approach, starting with the full model and removing a single covariate, sequentially, to form each candidate model.

For model evaluation, we performed a 70 – 30, stratified, train-test split on our 2018–2019 presence data using the R function “partition” in the package *splitTools* (Mayer, 2020). Using our train data, we fit site-occupancy models for each candidate subset of covariates. For these models, we ran 3 Markov chains with non-informative, uniform priors for 12,000 iterations, with a burn in rate of 2000, and a thinning rate of 5. Although utilizing AIC values for model comparison is standard when fitting maximum-likelihood site-occupancy models, AIC is not recommended for Bayesian, hierarchical models due to the model’s latent parameters (Broms et al. 2016; Gelman and Vehtari 2013). Instead, to assess model performance and select an optimal candidate model for each species, we took 1000 draws from the posterior distributions of our hyperparameters within our estimated occupancy models to calculate expected occurrence and detection probabilities at each site. We then retained the maximum value from n stochastic, Bernoulli simulations for each of our 1000 draws, where n represents the number of surveys (days) in our test data, to estimate observed occupancy (presence/absence) from our test data. In order to choose the most parsimonious model for each species, we calculated the accuracy of each model as the average number of correct predictions divided by the total number of predictions over the 1000 simulations. Due to its out-of-sample design, this methodology naturally penalizes extra parameters, which would lead to over-fitting of the training data and poor fit among the test data.

Once we determined the most parsimonious subset of variables for our site-occupancy model for each species, we constructed site-occupancy models for 2016–2017 and 2017–2018. We again ran 3 chains with 12,000 iterations, a burn-in rate of 2000, and a thinning rate of 5. Instead of uniform, uninformative priors, we used informed priors based on the posterior distributions for each hyperparameter from the results of the model fit on our 2018–2019 data. To assess goodness of fit, we calculated Bayesian p-values for each model. If our Bayesian p-value determined adequate model fit, we then calculated true occupancy for that species when accounting for imperfect detection.

*Neighborhood biodiversity estimates.* We estimated the number of mammal and non-passerine bird species with naïve occupancies > 0.10 that were present in each of our study neighborhoods when accounting for imperfect detection. Estimates of the actual number of species present are given in Eq. 1, where  $I_{ji}$  is the indicator function that evaluates to 1 if species j is present in neighborhood i and evaluates to 0 otherwise and  $\psi_{ji}$  is the occupancy probability of species j in neighborhood i, and [ ] denotes the standard rounding function.

$$\text{eqn1f}(i) = \sum_j \max(I_{ji}, [\psi_{ji}])$$

For convenience, this model makes the simplifying assumption that each species occupying a neighborhood is independent of each other species occupying the neighborhood.

## Results

Over three years and from 66 cameras, we accumulated 17,820 camera-trap days (5,940 per season) and captured 280,686 images (Table 1) of 24 mammal and non-passerine bird species (17 in 2016–2017, 18 in 2017–2018, and 22 in 2018–2019) (Table 2). Based on our species accumulation curve from 2016–2017 data, the number of mammal and non-passerine bird species detected plateaued around 3600 camera trap days (Figure S1), indicating that the camera deployments were of sufficient duration each season to capture detectable species.

Table 3

Number of independent observations (IOs) and relative abundance indices (RAI), calculated as the product of annual independent observations and 100, divided by the annual camera-trap days, for each detected mammal and non- passerine bird species captured and each camera-trap season, grouped by season

Species (common name)	Species (scientific name)	# IOs (16/17)	RAI (16/17)	# IOs (17/18)	RAI (17/18)	# IOs (18/19)	RAI (18/19)
American black bear	<i>Ursus americanus</i>	1	0.02	0	0	0	0
Black rat	<i>Rattus rattus</i>	0	0	0	0	2	0.03
Bobcat	<i>Lynx rufus</i>	4	0.07	1	0.02	3	0.05
Coyote	<i>Canis latrans</i>	50	0.84	126	2.12	103	1.73
Eastern chipmunk	<i>Tamias striatus</i>	0	0	69	1.16	31	0.52
Eastern cottontail	<i>Sylvilagus floridanus</i>	378	6.36	133	2.24	202	3.40
Eastern gray squirrel	<i>Sciurus carolinensis</i>	2946	49.60	5921	99.68	6381	107.42
Fisher	<i>Martes pennanti</i>	0	0	1	0.02	1	0.02
Gray fox	<i>Urocyon cinereoargenteus</i>	37	0.62	123	2.07	105	1.77
Great blue heron	<i>Ardea herodias</i>	0	0	0	0	2	0.03
Mourning dove	<i>Zenaida macroura</i>	3	0.05	6	0.10	2	0.03
Pileated woodpecker	<i>Dryocopus pileatus</i>	3	0.05	0	0	0	0
Raccoon	<i>Procyon lotor</i>	720	12.12	1164	19.60	1282	21.58
Red fox	<i>Vulpes vulpes</i>	388	6.53	390	6.57	385	6.48
Red squirrel	<i>Tamiasciurus hudsonicus</i>	5	0.08	28	0.47	84	1.41
Red-bellied woodpecker	<i>Melanerpes carolinus</i>	0	0	0	0	1	0.02
Ruffed grouse	<i>Bonasa umbellus</i>	0	0	1	0.02	1	0.02
Southern flying squirrel	<i>Glaucomys volans</i>	0	0	0	0	7	0.12

Species (common name)	Species (scientific name)	# IOs (16/17)	RAI (16/17)	# IOs (17/18)	RAI (17/18)	# IOs (18/19)	RAI (18/19)
Striped skunk	<i>Mephitis mephitis</i>	157	2.64	117	1.97	167	2.81
Virginia opossum	<i>Didelphis virginiana</i>	204	3.43	700	11.79	1028	17.31
White-footed mouse	<i>Peromyscus leucopus</i>	3	0.05	1	0.02	62	1.04
White-tailed deer	<i>Odocoileus virginianus</i>	4157	69.98	6670	112.29	5896	99.26
Wild turkey	<i>Meleagris gallopavo</i>	47	0.79	175	2.95	206	3.47
Woodchuck	<i>Marmota monax</i>	14	0.24	35	0.59	75	1.26

The average number of mammal and non-passerine bird species detected per neighborhood was 12 (range 9–16). Based on our uncorrected observations, i.e. not corrected for imperfect detection, five species were detected in every neighborhood: raccoons (*Procyon lotor*), eastern gray squirrels (*Sciurus carolinensis*), red foxes (*Vulpes vulpes*), Virginia opossums (*Didelphis virginiana*), and white-tailed deer (*Odocoileus virginianus*).

**Species richness models.** Our full community model estimated a mean of 24 (SE: 0.086) mammal and non-passerine bird species in the 2016–2017 season, 25 (SE: 0.092) in the 2017–2018 season, and 33 (SE: 0.138) in the 2018–2019 season (Fig. 3a-c). Species accumulation curves derived from the annual community model indicate the need for upwards of 150 independent camera trap locations throughout the county to capture full species richness (Fig. 3d-f), which is ~7x larger than the number we deployed.

**Individual species site-occupancy models.** Thirteen species had naïve occupancies greater than 0.10, allowing us to fit annual occupancy models for them. Eleven species had naïve occupancies < 0.10 – white-footed mice (*Peromyscus leucopus*), bobcats (*Lynx rufus*), mourning doves (*Zenaida macroura*), ruffed grouse (*Bonasa umbellus*), fishers (*Martes pennanti*), pileated woodpeckers (*Dryocopus pileatus*), red-bellied woodpeckers (*Melanerpes carolinus*), great blue herons (*Ardea herodias*), southern flying squirrels (*Glaucomys volans*), black rats (*Rattus rattus*), and American black bears (*Ursus americanus*). For these species, we did not fit annual occupancy models.

All site-occupancy models had adequate fit as demonstrated by their Bayesian p-values between 0.05 and 0.95 (Table S2). Of the species for which we could create occupancy models, wild turkeys (*Meleagris gallopavo*) were the rarest when accounting for imperfect detection, with an estimated true occupancy of 0.09 in 2016–2017, 0.29 in 2017–2018, and 0.030 in 2018–2019 (Fig. 4). Eastern chipmunks (*Tamias striatus*) and woodchucks (*Marmota monax*) were the most difficult species to detect as demonstrated by

the relatively large discrepancies between their naïve occupancies and model-predicted occupancies each year when accounting for imperfect detection (Fig. 4).

Table 4

Best subset of occupancy | detection covariates for site-occupancy models based on comparison between train and test data from 2018–2019 camera trapping season and corresponding accuracy values for all species with a naïve occupancy  $> 0.10$ . *Nonhab* is the percent of the neighborhood that was not habitat, including roads or structures; *forest* is the percent of the habitat area within the neighborhood that was forest; *DTR* is the average distance between each of the three cameras in the neighborhood and the nearest road; *DTH* is the average distance between each of the three cameras in the neighborhood and the nearest house; *gt* is the number of cameras in a neighborhood that were placed along a game trail; *fencing* is an index characterizing how much of the property was fenced (see Methods for details)

Species (common name)	Species (scientific name)	Site-occupancy covariates	Accuracy
Coyote	<i>Canis latrans</i>	forest, nonhab, DTH	0.64
Eastern chipmunk	<i>Tamias striatus</i>	nonhab, forest, DTR   gt	0.68
Eastern cottontail	<i>Sylvilagus floridanus</i>	nonhab, forest, DTR, DTH   gt, fencing	0.64
Eastern gray squirrel	<i>Sciurus carolinensis</i>	null	1.0
Gray fox	<i>Urocyon cinereoargenteus</i>	forest, nonhab, DTH, DTR	0.66
Raccoon	<i>Procyon lotor</i>	null	1.0
Red fox	<i>Vulpes vulpes</i>	null	1.0
Red squirrel	<i>Sciurus vulgaris</i>	nonhab   gt	0.76
Striped skunk	<i>Mephitis mephitis</i>	nonhab, forest, DTR, DTH   gt	0.75
Virginia Opossum	<i>Didelphis virginiana</i>	null	1.0
White-tailed deer	<i>Odocoileus virginianus</i>	null	1.0
Wild turkey	<i>Meleagris gallopavo</i>	forest, nonhab, DTH, DTR   gt, fencing	0.72
Woodchuck	<i>Marmota monax</i>	nonhab, forest, DTH, DTR   gt, fencing	0.75

Overall, the percent of nonhabitat within a neighborhood was the most common occupancy covariate in our site-occupancy models, ultimately included in the final models for 8 of the 13 species (Table 3). The percent of forested habitat was the second covariate, included for 7 out of the 13 species (Table 3).

For all species for which forest was included as a covariate in the final model, the relationship was negative, meaning that occupancy declined as the percent of habitat that is forest in a neighborhood increased (Table 4). For four species – eastern cottontails (*Sylvilagus floridanus*), gray foxes (*Urocyon*

*cinereoargenteus*), red squirrels (*Sciurus vulgaris*), and striped skunks (*Mephitis mephitis*) – occupancy increased as the area of nonhabitat increased. In contrast, for coyotes (*Canis latrans*), eastern chipmunks (*Tamias striatus*), woodchucks (*Marmota monax*), and wild turkeys (*Meleagris gallopavo*), occupancy decreased as nonhabitat area increased (Table 4).

The average distance between the cameras within a neighborhood and the nearest house, and the average distance between cameras in the neighborhood and the nearest road, were both included in final models for 6 of 13 species. Occupancy increased with distance from the nearest house for eastern cottontails, gray foxes, woodchucks, and striped skunks, and decreased with distance from the nearest house for coyotes and wild turkeys (Table 4). As the average distance to the nearest road increased, occupancy increased for eastern chipmunks, woodchucks, striped skunks, and wild turkeys, while occupancy decreased for eastern cottontails and gray foxes (Table 4).

Of our detection covariates, whether or not cameras were placed on game trails was ultimately included in final models for 6 out of the 13 species (Table 3). For all species for which game trail was included as a covariate in the model, detection decreased as the percent of cameras within the neighborhood located on a game trail increased (Table 4). Fence was only included in the final models for 3 out of 13 species (Table 3). Fenced properties decreased detection for woodchucks and wild turkeys but increased detection for eastern cottontails (Table 4).

Table 5

Estimated parameters ( $\beta$ ) and standard errors (S.E.) for occupancy ( $\psi$ ) and detection (p) parameters for all non-null individual species site-occupancy models

Species	Parameter	Variable	$\beta$	S.E.
Coyote	$\psi$	DTH	-7.2	0.04
	$\psi$	forest	-3.8	0.05
	$\psi$	nonhab	-6.5	0.05
Eastern chipmunk	$\psi$	DTR	5.3	0.09
	$\psi$	forest	-6.4	0.27
	$\psi$	nonhab	-8	0.31
	p	gt	-1.1	0.02
Eastern cottontail	$\psi$	DTH	3.1	0.10
	$\psi$	DTR	-1.9	0.05
	$\psi$	forest	-5.8	0.10
	$\psi$	nonhab	1.7	0.09
	p	fence	0.2	0.01
	p	gt	-0.5	0.02
Gray fox	$\psi$	DTH	11.1	0.04
	$\psi$	DTR	-3.3	0.10
	$\psi$	forest	-7.5	0.08
	$\psi$	nonhab	1.3	0.05
	p	gt	-6.4	0.02
Red squirrel	$\psi$	nonhab	5.9	0.09
	p	gt	-10.3	0.03
Striped skunk	$\psi$	DTH	4.1	0.06
	$\psi$	DTR	6.6	0.05
	$\psi$	forest	-9.2	0.16
	$\psi$	nonhab	10.1	0.05
	p	gt	-0.1	0.01
Wild turkey	$\psi$	DTH	-5.3	0.05

Species	Parameter	Variable	$\beta$	S.E.
	$\psi$	DTR	3.7	0.11
	$\psi$	forest	-0.1	0.05
	$\psi$	nonhab	-1.6	0.08
	p	fence	-4.4	0.01
	p	gt	-3.7	0.02
Woodchuck	$\psi$	DTH	7.6	0.21
	$\psi$	DTR	8.4	0.22
	$\psi$	forest	-7.5	0.22
	$\psi$	nonhab	-1.1	0.14
	p	fence	-0.8	0.02
	p	gt	-6.4	0.02

**Neighborhood biodiversity estimates.** Considering only those species for which we were able to create occupancy models, the average number of estimated species in each of our 22 neighborhoods was 11.9 (range: 10–13, Figure S2), when accounting for imperfect detection. The average difference between the number of species detected and the number of species expected to be present based on our models was 1.4 (range: 0–4, Figure S2). We did not detect any geographic patterns.

## Discussion

Our study utilized 66 motion-triggered cameras deployed annually for three-month periods, for three consecutive years, to study the wildlife community within residential properties of a human-impacted landscape in New York state. Three-month deployment periods allowed detection of both transient and resident individuals, although we could not distinguish between these categories. Passerine birds and some small mammals (e.g. shrews, voles) known to be present in the properties were not readily detectable and excluded from analyses. Other small mammals, such as white-footed mice, known to be ubiquitous in this region (LoGiudice et al. 2003) were infrequently detected and thus not fully modeled for occupancy.

From our imagery alone, we identified 18 mammal and 6 non-passerine bird species. A 2018 study by Linske et al. (2018) that utilized camera traps to measure biodiversity in residential Connecticut yards, identified 12 (non-domestic) mammal species as well as wild turkey and birds of prey. Our cameras captured all mammal species identified in Linske et al. (2018), as well as black rats, fishers, gray foxes, woodchucks, red squirrels, southern flying squirrels and white-footed mice. We detected additional species likely due to our longer duration of camera deployment (17,820 camera trap days compared to

2,240 camera trap days). A 2019 study by Stark et al. (2019), which used camera traps to study predator communities, identified six carnivore and one marsupial species (raccoons, coyotes, black bears, red foxes, striped skunks, bobcats, and opossums) in four preserves in Westchester County, NY and Morris County, NJ. Based on detection and reported relative abundance indices (RAIs), gray foxes, raccoons, red foxes, opossums, and striped skunks were more abundant in our study, while American black bears and coyotes were more abundant in preserves. However, our cameras were deployed between late September and early March, corresponding with the American black bear's hibernation period. Bobcat RAIs between the two studies were comparable. The detection and higher RAIs for most species found in our study provides evidence that moderately developed landscapes (i.e., residential yards) can contain a higher abundance of mammals than natural areas. Results from additional studies (Linkse et al. 2018; Hansen et al. 2020), which utilized camera-traps in residential and natural areas, have found similar results, suggesting that there might be features of residential landscapes that benefit some wildlife species.

Our full species-richness model estimated a maximum of 33 species present, based on our 2018–2019 data. The difference between the number of species estimated by our species-richness model and the number of species directly detected by our cameras highlights the importance of accounting for imperfect detection when using motion-triggered cameras to study biodiversity. We did not detect any strong spatial patterns when modeling estimated distributions of species with naïve occupancies  $> 0.10$ , which may reflect homogeneity between our camera clusters at broader spatial scales ( $\sim 1 \text{ km}$ ).

Eight species that meet the basic requirements for detection by our cameras (body weight  $> 100\text{g}$ , ground-dwelling) and have been identified in Dutchess County, NY (Ueda K, 2021) were not captured by our cameras: muskrats (*Ondatra zibethicus*), American beavers (*Castor canadensis*), North American river otters (*Lontra canadensis*) North American porcupines (*Erethizon dorsatum*), American minks (*Neovison vison*) long-tailed weasels (*Mustela frenata*) snowshoe hares (*Lepus americanus*), and short-tailed weasels (*Mustela erminea*). These species might occur at densities low enough that we failed to detect them with our cameras, or they might not be present in residential communities, owing to habitat specialization. For example, muskrats, beavers, otters, and minks require aquatic habitat.

A second goal of our study was to examine how individual species respond to anthropogenic landscape features. White-tailed deer, Virginia opossums, red foxes, eastern gray squirrels, and raccoons were detected in every one of our study neighborhoods. Their presence at all study locations prevented us from using covariates within site-occupancy models to understand the varying influences of anthropogenic landscape features. These species may thrive in human-impacted areas due to human-subsidized resources, or lower predation/hunting risk. While both ground-dwelling and large enough to be captured by cameras, bobcats and fishers were rarely detected in our neighborhoods. Two additional studies that utilized cameras in residential yards and natural locations in North Carolina (Kays and Parsons 2014; Hansen et al. 2020), also failed to detect bobcats in residential yards, only finding them in less human-impacted locations. Infrequent detection of bobcats in residential areas suggests they may be unable to thrive in such fragmented landscapes. Additionally, as obligate carnivores, due to their diet, bobcats may

be unable to exploit supplemental food resources (Anderson and Lovallo 2003) found in residential yards.

We were able to create site-occupancy models for 13 species. Based on our results, gray foxes, red squirrels, striped skunks, and eastern cottontails were more likely to be present in neighborhoods with more structures and road coverage. Similar results for gray foxes were found in Kays and Parsons (2014). Conversely, Kays and Parsons (2014) found a negative relationship between eastern cottontail occupancy and nonhabitat. Coyotes, woodchucks, wild turkeys, and chipmunks are more likely to be present in neighborhoods with less coverage by structures and roads. Previous studies have found that coyotes have adapted to urban and suburban conditions in some areas (Gehrt et al. 2011, Parsons et al. 2018a) but are relatively rare in others (Kays and Parsons, 2014). While woodchucks are generally considered adaptable to urban habitats (Lehrer et al. 2012), the timing of our camera deployment, corresponding with woodchuck's hibernation, could have influenced our results. Our models for chipmunks might have low accuracy because their small body size and torpor period. Indeed, another small mammal, the white-footed mouse, was detected so infrequently that occupancy models could not be constructed, although this species is among the most widespread and abundant of all vertebrates in such landscapes (LoGiudice et al. 2003, 2008).

Surprisingly, neighborhoods with more habitat that is forest had lower occupancy for coyotes, eastern chipmunks, eastern cottontails, gray foxes, woodchucks, striped skunks, and wild turkeys. These species might be avoiding residential yards when more forested habitat outside of yards is available. Alternatively, these species might be attracted to supplemental food in yards that have less forest.

The average distance between cameras and the nearest house positively affected occupancy for eastern cottontails, woodchucks, striped skunks, and gray foxes, potentially suggesting aversion to humans. Similarly, Gallo et al. (2019) hypothesized that eastern cottontails limit their activity patterns to early and late hours to avoid human activity. Additionally, Lehrer et al. (2012) concluded that woodchucks were not strongly habituated to humans. Occupancy was negatively related to the average distance between the cameras and the nearest house for wild turkeys and coyotes, indicating these species are less human-averse. In the Chicago Metropolitan Area, human-exploited resources, such as garbage, can comprise up to 25% of coyote's diet during seasons with less prey availability (Morey et al. 2007), which may explain why coyotes were more likely to occupy areas close to human homes. Finally, occupancy was positively related to the average distance between the camera and the nearest road for chipmunks, woodchucks, striped skunks, and wild turkeys, indicating road avoidance. Occupancy of eastern cottontails and gray foxes, however, was negatively related to the average distance to the nearest road.

Chipmunks, eastern cottontails, woodchucks, red squirrels, striped skunks, and wild turkeys were all less likely to be detected when more cameras were located along game trails. These species might avoid game trails to limit detection by predators. Finally, fencing negatively influenced detection for wild turkeys and woodchucks, indicating we were less likely to detect each species in properties with more fencing. Fencing, however, had a positive relationship with detection for eastern cottontails, which was also found

in Kays and Parsons (2014). Fenced yards potentially create a safer environment for eastern cottontails by excluding predators.

Interpretations of species occupancy and diversity patterns in residential areas should consider the broader landscape context encompassing the study sites. The regions of Dutchess County, NY in which we conducted our study are largely forested (median 46.3% of the land area), with medians of 30.3% and 24.2% in herbaceous vegetation (including lawns and agriculture) and non-habitat, respectively. Forest connectivity was high (median clumpiness = 0.95), and discrete forest patches were uncommon (median upper bound of discrete patches = 33) (Table 1). Prior research in this region, focusing on changes in vertebrate community structure as the size of forest patches varied, found that small mammals and deer occupied all size ranges of forest patches but other mammal species were more likely to be detected in larger patches (LoGiudice et al. 2003; LoGiudice et al. 2008). Hence, population responses to land use change, particularly abundance and presence/absence may depend on local landscape structure. (Jackson and Fahrig 2014, Moll 2020).

Together, these results allow us to describe a biodiversity baseline for residential properties in the US Northeast and contribute to understanding how anthropogenic landscape features affect biodiversity. Understanding biodiversity in residential areas is particularly important because the rate at which natural landscapes are changing (Venter er al., 2016; Williams et al. 2020). Of course, our findings are based only on data collected within Dutchess County, NY and the response of species occupancy could vary in different geographic areas. Additionally, our cameras were deployed over autumn and winter, so our results may not generalize over all seasons, especially for species that hibernate or undergo periods of torpor during colder months. Finally, as is true of all camera trap studies, motion-triggered cameras are not able to detect small and volant animals. In the future it could be useful to combine camera trapping data with other methods to detect small and non-ground dwelling species to get a more complete picture of overall biodiversity. As landscapes continue to change, it will be important to continue to use camera traps to document biodiversity changes in residential areas.

## Declarations

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## Figures

### Figure 1

Percent of neighborhoods in which we detected each species at least once over all three seasons (2016/2017, 2017/2018, 2018/2019) of camera trapping

## Figure 2

Posterior distributions of species richness from 2016-2017 (**a**), 2017-2018 (**b**) and 2018-2019 (**c**) and corresponding species accumulation curves with standard error bars (below, **d-f**) as a function of total camera trap locations (study neighborhoods), based on methods developed in Dorazio, 2006. The estimated median values of species richness for each year are 23 (2016-2017), 23 (2017-2018), and 33 (2018-2019)

## Figure 3

Observed (darker gray) and estimated (lighter gray) occupancy for 13 species detected with naïve occupancies  $> 0.10$  in (**a**) 2016-2017, (**b**) 2017-2018, and (**c**) 2018-2019 according to individual species site-occupancy models

## Supplementary Files

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