Landscape and Urban Planning 189 (2019) 362–371

Contents lists available at ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Research Paper

Using citizen science to inform urban canid management

Marcus A. Mueller[a], David Drake[b,*], Maximilian L. Allen[c]

[a] University of Wisconsin-Madison, 1630 Linden Drive, Madison, WI 53706, USA
[b] University of Wisconsin, 1630 Linden Drive, Madison, WI 53706, USA
[c] Illinois Natural History Survey, 1816 S. Oak Street, Champaign, IL 61820, USA

ARTICLE INFO

Keywords:
Canis latrans
Citizen science
Coyote
INaturalist
Red fox
Vulpes vulpes

ABSTRACT

Urban wildlife populations present different scenarios for managers compared to rural populations, partly because of greater diversity in stakeholder attitudes and opinions regarding urban wildlife. Wild urban canids—especially coyotes (*Canis latrans*)—have been of increasing interest throughout North America in recent years. Our objective was to evaluate the potential of using iNaturalist-generated observations of urban red foxes and coyotes for cost-effective, customizable data collection to inform urban canid management. Our research is important on two fronts; first, it is a way to engage the public to make them more aware of urban canids, and secondly, it is an attempt to empirically test if we can more efficiently and effectively track coyotes and red foxes in urban areas. We used iNaturalist to collect over 800 community-generated locations for red foxes (*Vulpes vulpes*) and coyotes in Madison, WI from 2015 and 2016. We concurrently placed radio-collars on 11 red foxes and 11 coyotes to determine areas used in this urban ecosystem. We compared iNaturalist to radio-telemetry locations to identify factors that led to a positive relationship between these two inherently different spatial data sets. Greatest overlap between iNaturalist and telemetry data for both red foxes and coyotes occurred in areas with moderate human development and there was minimal overlap in natural areas. The overlap between iNaturalist and telemetry locations was comparable for both species, but the underlying mechanism differed by species-specific habitat use. iNaturalist reports appeared to show where and when humans most often interacted with red foxes and coyotes, rather than their true spatiotemporal distribution. Understanding the relationship between community-generated reports and local canid distribution may inform how iNaturalist can be used as a management tool and allow managers to proactively monitor and manage human-wildlife interactions with urban wildlife.

1. Introduction

Urban land acreage in the continental USA has quadrupled since 1945, and as of 2014 88% of Americans lived in urban areas (Nickerson, Ebel, Borchers, & Carriazo, 2017). Urban ecosystems are inherently different than their rural counterparts, primarily due to human presence, but also because of increased habitat fragmentation, increased movement barriers (i.e., roads, development), and anthropogenic sources of food and mortality (Bateman & Fleming, 2012). Human activities are often an important driver of the distribution, abundance, and dynamics of wildlife in urban ecosystems (Warren et al., 2010). For example, species richness generally decreases with urbanization, but species density increases because urban ecosystems provide resources that allow synanthropic species to persist, adapt, or thrive (McKinney 2002, 2006, McCleery, Mooreman, & Peterson, 2014).

Urban carnivores are examples of synanthropic species that present wildlife managers with unique and challenging scenarios due to the close proximity and interactions between carnivores and humans and their domestic pets (Gehrt, Riley, & Cypher, 2010). The degree of urbanization in an area determines which carnivore species exist on the landscape as well as interspecific interactions with other sympatric carnivores (Wang, Allen, & Wilmers, 2015, Mueller, Drake, & Allen, 2018). Carnivores can be an important and positive addition to the urban landscape in that they will predate pest or overabundant wildlife species, and their presence adds to the local biodiversity (Hundenko et al., 2010). However, these and other positive effects are often overlooked because of perceived or real human-carnivore conflicts (Soulsbury & White, 2015). Furthermore, the opportunity for human-carnivore interactions in urban ecosystems increases because of the increased human density. Human-carnivore interactions often shape stakeholder (those people whom are affected by wildlife management

* Corresponding author at: 1630 Linden Dr., Madison, WI 53593, USA.
E-mail addresses: ddrake2@wisc.edu (D. Drake), maxallen@illinois.edu (M.L. Allen).

https://doi.org/10.1016/j.landurbplan.2019.04.023
Received 10 May 2018; Received in revised form 28 February 2019; Accepted 25 April 2019

actions) perception and experience (Curtis & Hadidian, 2010, Hundenko, Siemer, & Decker, 2010) and in turn stakeholders often inform management objectives (Hundenko et al., 2010). The social impacts resulting from positive or negative human-wildlife interactions can be a catalyst for public action and can have management implications that directly affect wildlife populations (Hundenko et al., 2010). Public perspective and action is especially true for red foxes (*Vulpes vulpes*) and coyotes (*Canis latrans*), two charismatic urban-adapted canids that can elicit positive and negative responses from stakeholders interacting with them.

As habitat generalists, red foxes and coyotes have expanded their ranges in North America over the last century and are present in many major metropolitan areas (Bekoff & Gese, 2003, Cypher, 2003, Bateman & Fleming, 2012). Foxes are often viewed favorably, but can cause property damage through denning and are potential disease vectors (Soulsbury, Baker, Iossa, & Harris, 2010). Coyotes are generally viewed less favorably, and concern for the health and safety of humans and domestic pets often dictates the public's response to urban coyotes (Soulsbury & White, 2015). Management of urban coyote populations is primarily focused on minimizing human-coyote conflict, despite the relatively low number of coyote attacks on humans and domestic animals (Gehrt, Anchor, & White, 2009, Gehrt & Riley, 2010).

Citizen science, where members of the public contribute to scientific research by assisting with data collection (Dickinson, Zuckerberg, & Bonter, 2010), can be a cost-effective tool to address many of the challenges of studying and managing urban wildlife populations (Connelly, Seimer, & Decker, 2012). Citizen science can also provide an avenue for the public to have a direct and positive experience, so they become invested in the issue at hand. A large number of stakeholders living in close proximity to wildlife is an ideal situation for the use of citizen science, but the full potential of citizen science is just beginning to be understood (Bonney et al., 2009). A major benefit of citizen science—especially using the internet—is that it allows for the collection of data across large spatial and temporal scales considered prohibitive using traditional methods because of cost, logistics, and other barriers (Hochachka et al., 2012; Lepczyk et al., 2009). Major drawbacks and challenges of using citizen science data include error due to variation in observer quality and sampling bias. These shortcomings can potentially be remedied proactively by training participants and using standardized protocols or reactively during data analyses (Dickinson et al., 2010; Hochachka et al., 2012). Citizen science participation by landowners also facilitates data collection on private lands, a frequent logistical hurdle for urban wildlife researchers and managers (Dickinson et al., 2010). Finally, citizen science can be used to engage stakeholders by incorporating data into management actions, especially for conservation efforts in residential areas (Cooper, Dickinson, Phillips, & Bonney, 2007).

Access to community-generated data is becoming easier for researchers through web-based platforms like iNaturalist (www.inaturalist.org). iNaturalist is an online social network designed to allow community scientists to record and share observational data of the biotic community. Over 550,000 users have recorded observations of over 210,000 species worldwide since its launch in 2008 (www.inaturalist.org). Users share their individual observations and interact with members of the online community. iNaturalist also allows researchers to create project-specific pages focused on collecting data with specific goals.

As part of an ongoing research project live trapping and radio-collaring red foxes and coyotes, we developed a project-specific iNaturalist page where community scientists could record reports of red foxes and coyotes. Live trapping and radio-collaring and tracking urban coyotes and red foxes is labor-intensive and costly. Using the public to identify and report urban canid locations could be a more cost-efficient way to track coyotes and red foxes throughout urban areas, may improve management of human-carnivore interactions, and is a way to engage the public in order to potentially raise awareness and tolerance for wildlife sharing the urban landscape with humans. Our objective was to evaluate the potential of using iNaturalist-generated observations of urban red foxes and coyotes for cost-effective, customizable data collection to inform urban canid management. Specifically, our research aimed to answer the following questions:

1. What are the characteristics of iNaturalist-generated observations of urban canids? We hypothesized that most iNaturalist reports of red foxes and coyotes would be in relatively close proximity to high densities of humans and roads and during diurnal hours (Mueller et al., 2018).
2. How accurately do iNaturalist-generated observations of red fox and coyote distribution overlay with radio-collar location data? We hypothesized that the overlay of iNaturalist-generated observations with radio-collar location data would be greater for red foxes than coyotes because red foxes are more closely associated with human presence than coyotes (Mueller et al., 2018).
3. How do landscape and other factors differ in areas with high to low overlap of iNaturalist-generated and radio-collar location data for red foxes and coyotes? We hypothesized that iNaturalist-generated reports would increase in overlap with radio-collar location data in more open landscape that increase an observer's ability to see red foxes and coyotes (Ruette, Stahl, & Albaret, 2003; Lurracea, Brussard, Jaeger, & Barrett, 2007).

2. Methods

2.1. Study area

Our study area was located in Madison, WI, an urban area in Dane County (Fig. 1). Madison is the second largest city in Wisconsin, with a population of 245,000 people. Mean temperatures ranged from 10.4 °C in winter to 20.6 °C in summer with mean yearly precipitation of 87.38 cm (http://www.aos.wisc.edu/~sco/clim-history/state/4700-climo.html). Our 6120 ha study area was defined by a major highway (the beltline highway) and roads for the south and west boundaries, the west shoreline of Lake Monona and the isthmus canal for the eastern boundary, and the south shore of Lake Mendota and a major road for the northern boundary. Our study area encompassed the University of Wisconsin-Madison (UW) campus, along with a mosaic of residential, commercial, and semi-isolated natural areas bounded by developed roads and neighborhoods. Our study area also encompassed several public natural areas, including the UW Lakeshore Nature Preserve, UW Arboretum, and Owen Conservation Park, part of the Madison Parks system. Habitats consisted of upland broadleaf deciduous forests, restored tallgrass prairie, oak savanna, human-planted coniferous forests, and various wetland complexes.

2.2. Capture and monitoring

We live-captured adult red foxes and coyotes, using cable restraints, from November to April during 2015 and 2016. We also opportunistically trapped outside of these seasons to replace collared animals lost due to mortality or collar failure. For full capture details see Mueller et al. (2018). We followed all ethical capture procedures and methods for cable restraints, and our animal handling methods were approved by the University of Wisconsin Animal Care Use Committee (Protocol A01559), and the Wisconsin Department of Natural Resources (WDNR) (Permit # SCP-SOD-001-2014). We fitted each animal with ear tags and a very high frequency (VHF) radio collar (Advanced Telemetry Systems, Isanti, MN; Model # M1950 for red fox and M2220B for coyote) or Global Positioning System (GPS) collar (Lotek Wireless Fish & Wildlife Monitoring, Newmarket, ON; Model #G5C175C).

Once an animal was released wearing a radio-collar, we located it 2–3 times within the first 5 days to ensure it was moving and alive. Following the initial five-day period, we attempted to locate each VHF-

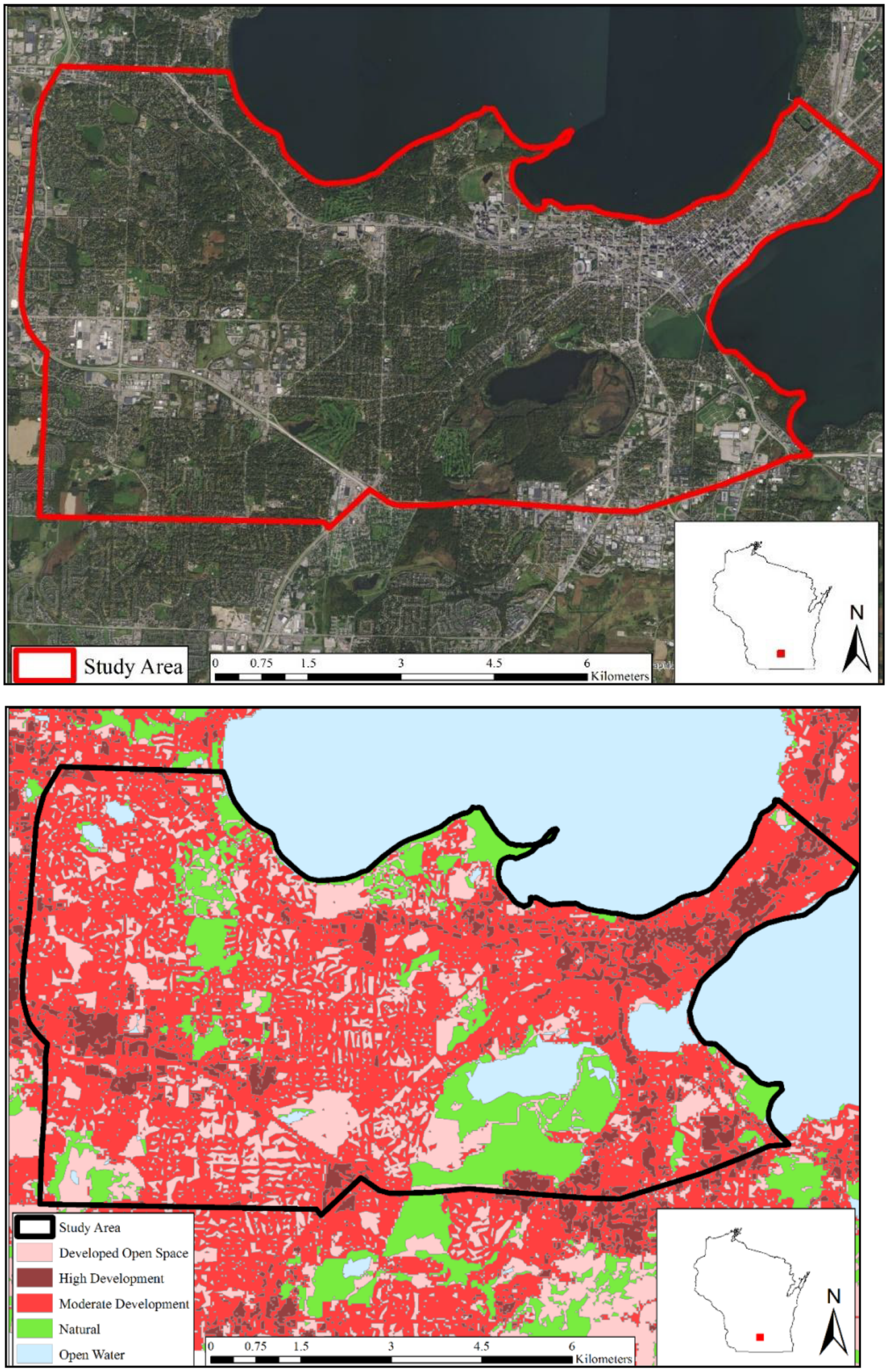


Fig. 1. The top image is the study area (outlined in red) in Madison, WI. The bottom image depicts land cover classifications within our study area based on human development in Madison, WI, 2015–2016. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

collared animal via radio receiver at least once per week for the entire duration that the radio collar functioned or the animal remained alive. We triangulated each location based on the intersection of ≥ 3 telemetry bearings taken within a maximum of 15 min of each other to reduce error based on animal movement (Schmutz & White, 1990). We also located animals using GPS readings if individuals were visually observed. To ensure the accuracy of triangulations, we plotted the telemetry bearings and estimated the location of the animal on a laptop computer to proof locations in the field (unpublished data, Radio-Tracker, John Cary, University of Wisconsin, Madison, WI). We discarded some observations based on the error ellipse, but didn't have a hard cutoff. Triangulations were all field-proofed in real time and if the error calculation didn't work out or had an error ellipse too large to confidently pin an animal to a certain residential block, patch of woods, etc., it was omitted on the spot. During the weekly location of each animal, we tracked them for a 5-hour period, where we located the focal animal once per hour during that period. Weekly tracking periods were systematically rotated around the 24-hour clock to ensure that temporal variation in activity was captured. All GPS-collars were programmed to collect hourly locations on the same rotating schedule.

2.3. Community-generated locations

We used iNaturalist (www.inaturalist.org) to collect community-generated location data for red foxes and coyotes in our study area from May 2015 to December 2016. We created a custom iNaturalist project (http://www.inaturalist.org/projects/uw-urban-canid-project) by specifying our target geographic location (Madison, WI, USA) and species of interest (red fox and coyote). We promoted the project through the UW Urban Canid Project Facebook Page (https://www.facebook.com/uwurbancanidproject/), website (http://uwurbancanidproject.weebly.com/reporting-an-observation.html), and local media. Each community-generated observation had information about each unique sighting, including the species observed, time, location, and 10 optional and brief questions about the observation. A detailed description of how we created the iNaturalist project can be found in Supplementary Material 1.

We omitted any observations from the same user that occurred within 12 h of the previous observation to attempt to reduce the effects of observers making repeated observations of the same animal. We did not have the ability to verify that an iNaturalist-reported red fox or coyote was truly a red fox or coyote. However, we are relatively confident that all iNaturalist reports were accurate for a number of reasons. First, we screened all iNaturalist observations at least weekly and in some instances asked for, and received, additional information from an iNaturalist user to verify the observation. Second, many iNaturalist users uploaded pictures of their observation, and all of the uploaded pictures matched their reported observation. Third, in many areas where iNaturalist reports where located we were also able to document presence of a radio-collared red fox or coyote in the same area.

2.4. Data variables

We used a Geographic Information System (GIS; ESRI. ArcGIS Desktop: Release 10.4. Redlands, CA: Environmental Systems Research Institute) to create a habitat map of our study area based on National Land Cover Database (NLCD) from 2011 (30×30 m resolution; Albers Conical Equal Area projection; 1983 North American datum), especially pertaining to human development. Using Gosselink, Van Deelen, Warner, and Joselyn (2003) for guidance, we omitted or combined the original 20 land cover classifications in the 2011 NLCD to arrive at the 5 land cover categories used in our analysis: developed open space (turf fields, non-forested parks, cemeteries; hereafter OPEN), moderate-intensity development (20–79% impervious surface, residential neighborhoods; hereafter MODR), high-intensity development (> 80% impervious surface, industrial and commercial land; hereafter HIGH), non-developed (natural areas, including forest, grassland, emergent wetlands; hereafter NATR), and water (open bodies of water) (Fig. 1). We used only 5 classes for ease of interpretation if wildlife managers or others wanted to apply our NLCD analysis to another urban area. We obtained local population density (humans/km^2; hereafter HUMN) data from the National Historical Geographic Information System (NHGIS). Estimates were based geographically on 2011 U.S. Census blocks using the most current available data. We calculated road density using local road data (Dane County Land Information Office, 2007; hereafter ROAD). We categorized seasons based on biologically meaningful periods of life for each species: breeding (red fox = November-February, coyote = December-March), pup-rearing (red fox = March-June, coyote = April-July), and non-breeding (red fox = July-October, coyote = August-November) (Cypher, 2003, Bekoff & Gese, 2003).

2.5. Statistical analyses

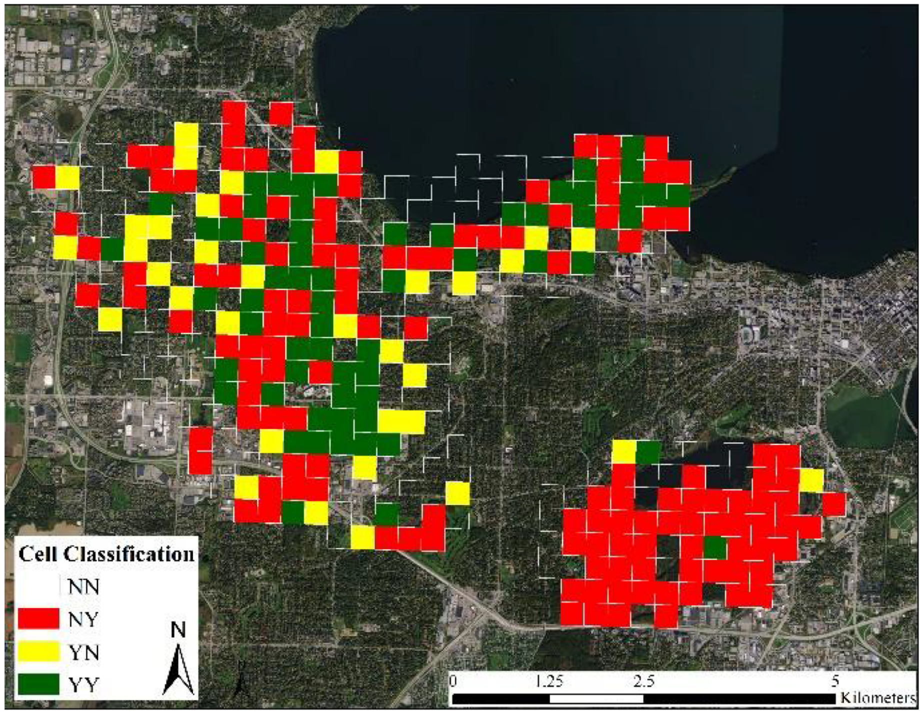
To test for variation in the time of reports between red foxes and coyotes, we converted the time of each report to radians and plotted its kernel density distribution using the *overlap* package (Ridout & Linkie, 2009) in the R statistical program (version 2.11.1; R Foundation for Statistical Computing, Vienna, Austria). We used the *overlapEst* function to test if citizen reporting activity varied between red fox and coyote observations, where we considered $\Delta_4 > 0.80$ to be strong overlap (Lynam et al., 2013). We used a Chi-square test to evaluate the proportion of iNaturalist reports in each land cover category, a Tukey HSD test to evaluate the number of iNaturalist reports by season, and a Welch 2-sample *t*-test to evaluate the estimated distance between the observer and a coyote or red fox. All results were considered significant at the $P < 0.05$ level

To create a focus area for our statistical analyses, we constructed 100% Minimum Convex Polygons (MCPs) using the *adehabitatHR* package (Calenge, 2011) for each radio-collared red fox and coyote, and merged these polygons together for each species. We only included radio locations that overlapped with the sighting data in the same time period from our iNaturalist page (May 2015 to December 2016). The primary reason we chose to use the MCP estimator is because it seems to be the least affected by relatively small sample sizes compared to other home range estimators (Millspaugh et al., 2012). In addition, although MCP is limited for understanding fine-scale use and behavior, we merged all of the individual home ranges for coyotes and red foxes into one home range for each species because we were interested in broader spatial use of our study area by coyotes and red foxes. There was nominal visual difference between our 95% and 100% MCPs home ranges for each radio-collared coyote and red fox that we used to create the merged home ranges, so we included all points in each animal's MCP to maximize our sample sizes.

Using ArcMap (ESRI. ArcGIS Desktop: Release 10.4. Redlands, CA: Environmental Systems Research Institute) we overlaid a 420 m by 420 m grid over each species' merged 100% MCPs. We chose this size because it was approximately the size of 2–3 city blocks (depending on neighborhood) and determined it to be an appropriate resolution to provide a practical, repeatable application for wildlife managers. We classified these cells into four different groups based on the telemetry locations and iNaturalist observations that fell within the cell; in essence, cell classifications indicated where the two data sets overlapped (or not) spatially. The four groups were as follows: YY, or cells that included both iNaturalist and telemetry locations, YN, or cells that included iNaturalist locations but no telemetry locations, NY, or cells that included no iNaturalist locations but included telemetry locations, and NN, or cells that had no iNaturalist or telemetry locations (Fig. 2).

To compare the location of iNaturalist observations to our radio-telemetry locations, we calculated the similarity, sensitivity, and specificity of the iNaturalist data (Nagy, Weckel, Toomey, Burns, & Peltz, 2012). Similarity (matching classifications/total number of cells) considered a "matching classification" to be a cell where the iNaturalist and telemetry classifications matched (i.e., YY or NN) (Nagy et al., 2012). We calculated the sensitivity (cells containing both iNaturalist and telemetry locations/all cells containing iNaturalist locations) to determine the percentage of "true positives", or the probability that a member of the public observed and reported a red fox or coyote (based on if red foxes or coyotes were observed in the cell via radio-telemetry) (Nagy et al., 2012). Finally, we calculated the specificity (cells containing no iNaturalist or telemetry locations/all cells lacking iNaturalist locations) to determine the percentage of "true negatives", or the probability that a member of the public did not observe a red fox or coyote (based on if red foxes or coyotes were not observed in the cell via radio-telemetry) (Nagy et al., 2012).

We analyzed the factors that drove each individual cell's classification using a suite of variables (human density, road density, percent of our five habitat types) in an AIC modeling framework with 8 *a-priori* models (Table 1). We tested for collinearity and correlation using a Pearson's test at the $p < 0.05$ level to determine that no independent variables were significantly correlated. We fit a binomial model using cell classification as our dependent variable. For example, in our first analysis, we compared all cells classified as YY to all cells not classified as YY (i.e., YN, NY, NN). We analyzed each cell classification



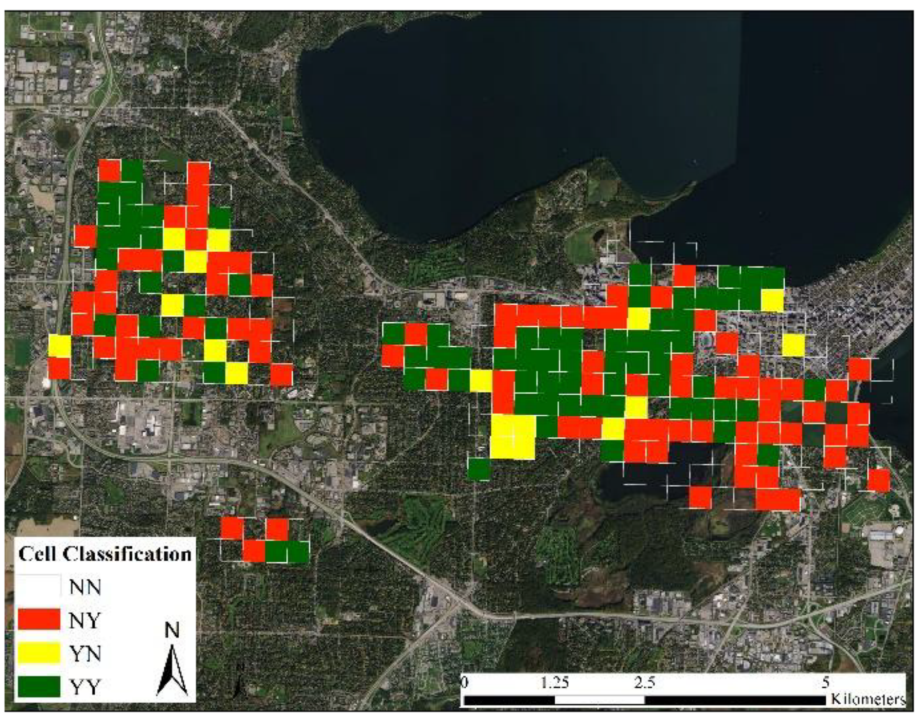


Fig. 2. Grid encompassing coyote (top) and red fox (bottom) 100% MCP's in Madison, WI, 2015–2016. Grid cells were classified based on the presence (or lack) of iNaturalist reports and radio-telemetry locations within each cell. YY indicates cells that contain both iNaturalist and telemetry locations, YN contain only iNaturalist locations, NY contain only telemetry locations, and NN contain neither iNaturalist nor telemetry locations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

individually, resulting in 8 separate statistical analyses (4 tests for each species). We considered the top models to be those within < 0.90 of the cumulative on AICc weights (*w*) (Burnham & Anderson, 2003). In the event there clearly was not one top model, we used model averaging across our top candidate models (Arnold, 2010). We evaluated the explanatory power of our independent variables based on the 90% confidence interval for each variable.

3. Results

3.1. Radio-telemetry data

We captured, marked, and radio-tracked 11 red foxes ($n_{male} = 7$, $n_{female} = 4$) and 11 coyotes ($n_{male} = 7$, $n_{female} = 4$) from May 2015 to December 2016. We collected 1312 total locations (all from VHF

Table 1
A-priori models based on authors' knowledge and observations of study area and study species explaining whether a red fox or coyote was observed in a 420 m by 420 m grid cell using radio telemetry, citizen science observations, both, or neither in Madison, WI, 2015–2016.

Name	Variables	Description
Human Density	HUMN	Cell classification will be driven by where residential human density is the highest because more humans result in more potential observers.
Human Habitat	MODR + HIGH	Cell classification will be driven by habitat on the landscape that is developed by humans because there are more humans present to report canids.
Roads	ROAD	Cell classification will be driven by road density because roads may increase a reporter's ability to observe canids.
Human Use	ROAD + HUMN	Cell classification will be driven by areas that humans use the most, including areas they occupy and travel.
Red Fox Habitat	MODR + OPEN	Cell classification for red foxes will be driven by the amount of preferred fox habitat within a cell because foxes will use these cells at differential rates.
Coyote Habitat	NATR	Cell classification for coyotes will be driven by the amount of preferred coyote habitat within a cell because coyotes will use these cells at differential rates.
Human and Red Fox Habitat	MODR + HIGH + OPEN	Cell classification for foxes will be driven by the amount of human and fox habitat within each cell because the amount of each habitat may alter how frequently humans and foxes use the cell.
Human and Coyote Habitat	NATR + MODR + HIGH	Cell classification for coyotes will be driven by the amount of human and coyote habitat within each cell because the amount of each habitat may alter how frequently humans and coyotes use the cell.

collars) for red foxes ($\bar{x}$ = 131.2 per individual, range = 2–458), and 4382 total locations (2071 VHF and 2311 GPS locations) and for coyotes ($\bar{x}$ = 393.2. range = 36 – 2311). Mean time on air for individual red foxes was 243.6 (± 71.6 SE) days, and for individual coyotes was 282.3 (± 60.7 SE) days. We excluded 3 foxes ($n_{male} = 2$, $n_{female} = 1$) and 1 male coyote from further analyses because of small sample size due to mortality or collar failure.

3.2. iNaturalist responses

We collected 513 community-generated observations of red foxes and 348 community-generated observations of coyotes by 544 unique iNaturalist users. Of the 861 locations, 392 (45.5%) fell within the 100% MCP focus areas (225 red fox, 167 coyote). The proportion of iNaturalist reports occurring in each of the 5 NLCD land use types varied for both coyotes ($X_4^2 = 129.08$, $p < 0.001$) and red foxes ($X_4^2 = 396.98$, $p < 0.001$) (Supplementary Material 2a).

The number of reports varied seasonally for coyotes ($F_{2,16} = 4.851$, $p = 0.023$) but not for red foxes ($F_{2,16} = 2.388$, $p = 0.124$) (Supplementary Material 2b). We collected significantly fewer reports of coyotes during the pup-rearing season compared to the breeding season (p = 0.018). iNaturalist reporting activity appeared to be largely diurnal, with peaks for both species occurring at morning crepuscular hours. Red fox and coyote reports showed strong temporal overlap ($\Delta_4 = 0.805$) (Fig. 3). On average, observers estimated and reported coyotes ($\bar{x}$ = 22.99 m ± 1.43 SE) at significantly farther distances than red foxes ($\bar{x}$=17.86 m ± 0.94 SE) ($t_{606} = 3.14$, $p = 0.002$)

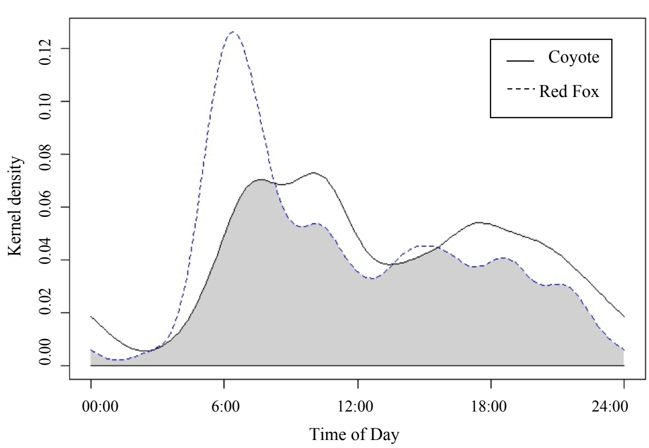


Fig. 3. Kernel density of reports by time of day of red foxes and coyotes via iNaturalist in Madison, WI, 2015–2016 ($\Delta_4 = 0.805$). Grey area refers to temporal overlap between red fox and coyote observations.

Table 2
Results of cell classification for red fox and coyote target areas based on iNaturalist and radio-telemetry locations within 420 m by 420 m grid cells in Madison, WI, 2015–2016. YY indicates cells that contain both iNaturalist and telemetry locations, YN contain only iNaturalist locations, NY contain only telemetry locations, and NN do not contain either iNaturalist or telemetry locations.

	YY (%)	YN (%)	NY (%)	NN (%)	Total
Red Fox	75 (28)	17 (6)	85 (32)	92 (34)	269
Coyote	62 (16)	34 (9)	134 (35)	153 (40)	383

(Supplementary Material 2c).

3.3. Comparison of radio-telemetry to iNaturalist data

In our target areas for each canid species, we classified individual cells based on the number of iNaturalist and telemetry points that fell within a particular cell (red fox = 269, coyote = 383) (Table 2, Fig. 2). The similarity value (matching classifications/total number of cells) was higher for red foxes (0.651) than coyotes (0.561). Sensitivity (cells containing both iNaturalist and telemetry locations/all cells containing iNaturalist locations) was higher for red foxes (0.815) than coyotes (0.646). Specificity (cells containing no iNaturalist or telemetry locations/all cells lacking iNaturalist locations) was higher for coyotes (0.531) than red foxes (0.520).

3.4. Red fox comparison

For our models determining factors driving YY cells for red foxes, the model human and red fox habitat (*w* = 0.68) had over twice as much explanatory power as the next closest model (red fox habitat, *w* = 0.30) (Table 3). After averaging models and calculating unconditional parameter estimates, MODR and OPEN had substantial positive effects on the number of YY cells (Table 4).

When determining the factors driving YN cells, our top three models were human and red fox habitat (*w* = 0.40), human habitat (*w* = 0.27), and red fox habitat (*w* = 0.26) (Table 3). Using model averages and unconditional parameter estimates, none of our modeled effects were substantial based on 90% confidence intervals.

When determining the factors driving NY cells, our top models were human density (*w* = 0.46) and human use (*w* = 0.30) (Table 3). Using model averaging and unconditional parameter estimates, no effects were deemed substantial using 90% confidence intervals.

When determining the factors driving NN cells, our top models were human and red fox habitat (*w* = 0.88) and red fox habitat (*w* = 0.12) (Table 3). After model averaging and calculating unconditional

Table 3
Results of *a-priori* modeling explaining whether a red fox was observed in a 420 m by 420 m grid cell using radio telemetry, citizen science observations, both, or neither in Madison, WI, 2015–2016. YY indicates cells that contain both iNaturalist and telemetry locations, YN contain only iNaturalist locations, NY contain only telemetry locations, and NN do not contain either iNaturalist or telemetry locations.

	YY				
Model	K	AICc	ΔAIC	*w*	Σ*w*
Human and red fox habitat	3	301.53	0.00	0.68	0.68
Red fox habitat	2	303.21	1.68	0.30	0.98
Human habitat	2	308.37	6.84	0.02	1.00
Human use	2	319.24	17.71	0.00	1.00
Null	0	320.42	18.89	0.00	1.00
Road density	1	320.70	19.18	0.00	1.00
Human density	1	320.82	19.29	0.00	1.00
	YN				
Model	K	AICc	ΔAIC	*w*	Σ*w*
Human and red fox habitat	3	120.97	0.00	0.40	0.40
Human habitat	2	121.79	0.81	0.27	0.67
Red fox habitat	2	121.80	0.82	0.26	0.93
Road density	1	125.14	4.17	0.05	0.98
Human use	2	127.11	6.14	0.02	1.00
Null	0	128.81	7.83	0.00	1.00
Human density	1	129.86	8.89	0.00	1.00
	NY				
Model	K	AICc	ΔAIC	*w*	Σ*w*
Human density	1	335.76	0.00	0.46	0.46
Human use	2	336.62	0.87	0.30	0.76
Null	0	337.62	1.86	0.15	0.91
Human habitat	2	339.33	3.58	0.08	0.99
Road density	1	339.57	3.81	0.07	1.00
Red fox habitat	2	339.75	3.99	0.06	1.00
Human and red fox habitat	3	340.58	4.82	0.03	1.00
	NN				
Model	K	AICc	ΔAIC	*w*	Σ*w*
Human and red fox habitat	3	310.76	0.00	0.88	0.88
Red fox habitat	2	314.73	3.97	0.12	1.00
Human habitat	2	322.11	11.35	0.00	1.00
Human use	2	332.49	21.74	0.00	1.00
Road density	1	342.24	31.48	0.00	1.00
Human density	1	344.42	33.66	0.00	1.00
Null	0	347.60	36.84	0.00	1.00

Table 5
Results of *a-priori* modeling explaining whether a coyote was observed in a 420 m by 420 m grid cell using radio telemetry, citizen science observations, both, or neither in Madison, WI, 2015–2016. YY indicates cells that contain both iNaturalist and telemetry locations, YN contain only iNaturalist locations, NY contain only telemetry locations, and NN do not contain either iNaturalist or telemetry locations.

	YY				
Model	K	AICc	ΔAIC	*w*	Σ*w*
Human and coyote habitat	3	358.51	0.00	0.94	0.94
Coyote habitat	2	364.40	5.89	0.05	0.99
Human habitat	2	368.74	10.24	0.01	1.00
Null	0	378.82	20.31	0.00	1.00
Human density	1	379.81	21.30	0.00	1.00
Road density	1	380.82	22.31	0.00	1.00
Human use	2	381.77	23.26	0.00	1.00
	YN				
Model	K	AICc	ΔAIC	*w*	Σ*w*
Road density	1	242.83	0.00	0.62	0.62
Human use	2	244.80	1.96	0.23	0.85
Human habitat	2	246.65	3.82	0.09	0.94
Human and coyote habitat	3	247.87	5.04	0.05	0.99
Coyote habitat	2	251.92	9.09	0.01	1.00
Null	0	254.62	11.79	0.00	1.00
Human density	1	254.94	12.10	0.00	1.00
	NY				
Model	K	AICc	ΔAIC	*w*	Σ*w*
Human and coyote habitat	3	510.86	0.00	1.00	1.00
Coyote habitat	2	530.74	19.88	0.00	1.00
Human habitat	2	538.17	27.31	0.00	1.00
Road density	1	567.10	56.24	0.00	1.00
Human use	2	568.77	57.91	0.00	1.00
Null	0	584.69	73.83	0.00	1.00
Human density	1	584.75	73.89	0.00	1.00
	NN				
Model	K	AICc	ΔAIC	*w*	Σ*w*
Human and coyote habitat	3	568.31	0.00	1.00	1.00
Coyote habitat	2	605.95	37.65	0.00	1.00
Human habitat	2	625.25	56.94	0.00	1.00
Road density	1	682.78	114.48	0.00	1.00
Human use	2	683.34	115.04	0.00	1.00
Null	0	684.38	116.07	0.00	1.00
Human density	1	686.28	117.97	0.00	1.00

Table 4
Variables that had a substantial effect on locating red foxes and coyotes in Madison, WI, 2015–2016. YY indicates cells that contain both iNaturalist and telemetry locations, YN contain only iNaturalist locations, NY contain only telemetry locations, and NN do not contain either iNaturalist or telemetry locations.

	Substantial Effects (Effect Direction and Value)	
Cell Classification	Red Foxes	Coyotes
YY	MODR (1.7) OPEN (2.88)	NATR (0.001) HIGH (−0.008)
YN	No substantial effects	ROAD (0.001)
NY	No substantial effects	NATR (0.009) MODR (−0.02) HIGH (−0.007)
NN	MODR (−1.79) OPEN (−3.75) HIGH (2.52)	NATR (−0.01) HIGH (0.01)

parameter estimates, both MODR and OPEN had negative effects on the number of NN cells, while HIGH had a positive effect (Table 4).

3.5. Coyote comparison

For coyotes, the model human and coyote habitat ($w = 0.94$) was the only model with substantial support when fitted to cells determining the factors driving YY cells (Table 5). In this model, NATR had a substantial positive effect on the number of YY cells and HIGH had a substantial negative effect (Table 4) based on 90% confidence intervals.

When determining the factors driving YN cells, our top model, road density ($w = 0.62$), had nearly three times the explanatory value of our next closest model (human use, $w = 0.23$) (Table 5). After model averaging and calculating unconditional parameter estimates, ROAD had a substantial positive effect on the response variable (Table 4).

When determining the factors driving NY cells, our model human and coyote habitat ($w = 1.0$) was the only model that had substantial support (Table 5). In this model, NATR had a substantial positive effect on the number of NY cells, while MODR and HIGH had substantial negative effects (Table 4) based on 90% confidence intervals.

When determining the factors driving NN cells, human and coyote habitat ($w = 1.00$) again was the only model with substantial support (Table 5). In this model, NATR had a substantial negative effect on the number of NN cells, while HIGH had a substantial positive effect (Table 4).

4. Discussion

We compared locations of urban coyotes and red foxes collected via telemetry to sightings reported by community scientists via iNaturalist to evaluate the potential of using citizen science as a management tool. We found robust similarity rates (YY and NN) for both foxes (65%) and coyotes (56%) between the datasets, suggesting that using citizen science may be a cost-effective method for collecting data on the distribution of urban wildlife. Citizen science allows for the collection of data across large spatial and temporal scales (Hochachka et al., 2012; Lepczyk et al., 2009), but applications and programs such as iNaturalist also allow managers and researchers to collect data for specific areas or species as well. By using social media we were able to alert community scientists to our interest in their sightings of urban canids in Madison, WI and collect over 800 confirmed sightings in less than two years. The experience of many urban stakeholders is shaped by human-wildlife conflicts (Curtis & Hadidian, 2010, Hundenko et al., 2010), but participation in citizen science programs can create positive experiences (Dickinson et al., 2010), while also collecting data that can be used by managers and researchers (e.g., Connelly et al., 2012). The findings from our study suggest value in using citizen science data for managers and researchers, but further research is needed. For example, it is important to understand where citizen science reports are common and where they are lacking so methodology can be changed and tested to improve reporting data, or at the very least understand sampling biases.

There appeared to be variability in how well iNaturalist reports reflected the areas frequently used by red foxes and coyotes determined via radio telemetry. Our hypothesis that most iNaturalist reports would come from areas with increased human and road density and during diurnal hours was only partially supported. Most iNaturalist reports for both red foxes (about 90%) and coyotes (about 80%) occurred in developed open and moderately developed areas, but not high developed areas. Red fox and coyotes seemed to avoid high developed areas, or areas with increased human and road density (Mueller et al., 2018). Our hypothesis that most iNaturalist reports would occur during diurnal hours was supported, and the temporal overlap of sightings for foxes and coyotes was high.

Our hypothesis that iNaturalist-generated observations of red foxes would have greater overlay with radio-collar location data than for coyotes was supported by our data. Similarity rates (YY and NN) for foxes occurred 65% of the time and 56% of the time for coyotes. Sensitivity—the rate at which community-generated observations matched up with known canid locations—was higher for red foxes, suggesting that community scientists see and report the presence of red foxes more than coyotes. Selectivity—the rate at which community-generated locations match up with areas with little to no use by canids—was similar for coyotes and foxes, suggesting that even though coyotes and foxes used different areas within the urban ecosystem, reports from iNaturalist users assess areas of little to no use by both species at similar rates. Similarity, sensitivity and selectivity appeared to be reflective of human development and driven by the selection of land cover types used by both canid species, as most reports of coyotes and red foxes occurred in moderately developed areas. Red foxes in Madison, WI selected for developed landscapes more so than coyotes (Mueller et al., 2018) and may have more opportunities to be observed. Coyotes, on the other hand, are known to spatiotemporally avoid humans in urban ecosystems (Gehrt, Brown, & Anchor, 2011), possibly limiting the potential for the public to observe and report them. This may suggest that community-scientist portals like iNaturalist could be more effective at recording species that frequently share the same areas with humans.

The factors driving similarity rates (YY and NN cells) were stronger for coyotes than for red foxes. For coyotes, our top performing model for YY cells had a higher proportion of preferred coyote habitat (NATR) and a lower proportion of highly developed areas within the cell. Classification of NN cells were driven by the same factors as YY cells, but the direction of their effects was inversed. The trends for red foxes were more equivocal than coyotes. For YY cells, the top performing model suggested that the proportion of preferred land cover (MODR) had the most substantial effect on the variation in cell classification. NN cells was also driven by the amount of preferred land cover within the cell, but similar to coyotes, the direction of the effect was inversed. The inverse correlation between YY and NN classifications for both coyotes and foxes suggests that species-specific land cover selection and use of developed land covers primarily drives the accuracy of these classifications.

For YN cells (containing iNaturalist reports of coyotes, but no telemetry locations), we hypothesized that categorization would be driven by a potential increase in the ability of an observer to see urban canids, even if they did not frequently use the area. The top performing model for coyotes suggested that road density best explained the variation in these data. Roads may allow more people access to a given area, thereby increasing the number of potential observers, or roads may simply have better lines of sight and increase a coyote's chances of being observed in an area. Conversely, in NY cells the proportion of natural area within the cell was the only factor with a substantial positive effect on classification for coyotes. The classification of YN and NY cells were again more equivocal for red foxes. Previous analyses of red fox habitat selection suggested that red foxes displayed a high degree of individual variation in habitat selection in our study area (Mueller et al., 2018). If cell classification is in part driven by land cover selection, this variation may limit our ability to detect substantial effects of our model variables. We did not specifically investigate the variation in detectability by land cover type, but more accurate assessments of the variability in natural land covers (i.e., forest vs. grassland) may provide more information on what factors drive the observations of urban coyotes among different land use types. It is also important to note that YN cells may be confounded by urban canids that were not wearing collars being seen and reported by community scientists. This is more likely for foxes, as we had collared individuals from each of the coyote packs in the study and individuals tend to use the same areas.

All citizen science data have certain limitations, and iNaturalist is no exception. For example, we experienced uneven sampling—both spatially and temporally—and it is important to understand the limitations of this data collection method and how they may be affected by the life history of a target species. In our case, the spatial sampling bias towards developed areas did not appear to negatively impact red fox reports in the same way it affected coyote reports. To account for the sampling bias, citizen-science monitoring using defined transects (Burnham, Anderson, & Laake, 1980, Anderson, Marques, Shoo, & Williams, 2015) or camera traps (Foster & Harmsen, 2012, Allen, Wittmer, Setiawan, Jaffe, & Marshall, 2016, Rich, Miller, Robinson, McNutt, & Kelly, 2017) in otherwise poorly-sampled areas could be used to augment the data. For more cryptic species, correction factors or lures could be implemented in different habitats and conditions to potentially offset poor detection.

One of the keys to our success in obtaining a large amount of iNaturalist observations was public outreach. When promoting iNaturalist to potential users, researchers and managers may want to focus on user rewards and incentives to increase interest and participation. This can help compensate for a general contribution to science often not being enough to motivate participation (Sullivan et al., 2009, Hochachka et al., 2012). For example, eBird uses healthy competition between birders to motivate data collection and saw marked increases in participation since shifting its focus in this manner (Sullivan et al., 2009). It is also important to maintain interest over time, which could allow researchers and managers to potentially observe trends in counts/abundance of urban wildlife, incidents of human-wildlife conflicts, and changes in the local distribution of species.

5. Conclusions

Stakeholder engagement—incorporating those affected by management actions into the management decision making process—is critical for successful wildlife management (Lauber, Decker, Leong, Chase, & Schulsler, 2012, Conover & Dinkins, 2012), and becomes increasingly complicated in urban areas with more people due to the increased stakeholder interest in local wildlife management (McCleery, Moorman, Wallace, & Drake, 2012). Citizen science opportunities provided through portals like iNaturalist have the potential to provide a valuable tool for wildlife managers in urban ecosystems to collect information for proactive management in a cost-effective manner. Involving stakeholders in data collection also provides an avenue to educate and engage stakeholders so they are informed and vested in the management issue at hand, and thereby in better position to support management actions (McCleery et al., 2012).

The findings from our study suggest value in using citizen science data for managers and researchers, but further research is needed to understand sampling biases. For example, it is important to understand where citizen science reports are common and where they are lacking. Methodology may need to be changed and tested to improve reporting data, or at the very least, those using citizen science data need an understanding about how sampling biases may affect management recommendations.

Acknowledgements

We thank the University of Wisconsin-Madison Graduate School and Department of Forest and Wildlife Ecology, and Milwaukee County Parks for funding our research. We thank K. Lindau, H. Hovanec, M. Torkelson, and the many other students and members of the public who assisted with trapping and field work.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2019.04.023.

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