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Mismatched spatial scales can limit the utility of citizen science data for estimating wildlife-habitat relationships

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Abstract

While most carnivore populations are declining worldwide, some species are successfully living in human-modified landscapes. For example, coyotes (*Canis latrans*) have expanded their range across North America and into many urban areas making it important to understand factors influencing broad-scale patterns of occurrence. We used citizen science data in the form of coyote observations by archery deer hunters from throughout the state of Illinois to evaluate factors affecting coyote detection and occupancy. Our statewide participant-level occupancy estimate (0.63) was 58% greater than our naïve occupancy estimate (0.40) while detection probability was <0.25, highlighting the importance of using modeling frameworks that account for imperfect detection when modeling occupancy of cryptic species with low detection rates. Time period (AM/PM) had the largest effect on detection of coyotes, with detections greater in the AM. The number of hours hunted (analogous to effort) also impacted coyote detection, with more hours hunted increasing coyote detections. In contrast, none of the landscape covariates examined had strong effects on coyote occupancy. While coyote ubiquity and generalist habitat use may at least partially explain our results, we suspect it also is because the landscape covariates were measured at the county level, as more precise participant location data were unavailable, whereas participants effectively surveyed a much smaller area. Since scale affects the strength and direction of species-habitat relationships, this scale mismatch is likely an important limitation when using many sources of citizen scientist observations to infer species-habitat relationships for widespread generalist species when precise participant location data are unavailable.

KEYWORDS

Canis latrans, citizen science, coyote, occupancy, spatial scale

1 | INTRODUCTION

Carnivores are crucial to structuring ecosystems through predation and competition (Berger, 2013; Estes et al., 2011; Ripple & Beschta, 2004). Carnivores can control prey abundance and promote prey species diversity (Estes, Crooks, & Holt, 2001; Paine, 1966), and affect abiotic ecosystem dynamics such as wildfire, carbon sequestration,

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biogeochemical cycles and water flow through trophic cascades (Beschta & Ripple, 2019; Estes et al., 2011). Carnivores also affect other carnivores, both limiting other species through competition (Levi & Wilmers, 2012; Wang, Allen, & Wilmers, 2015) and provisioning nutrition in the form of carrion for scavenging carnivores (Allen, Elbroch, Wilmers, & Wittmer, 2015; Wilmers, Crabtree, Smith, Murphy, & Getz, 2003). Despite the importance of carnivores to ecological communities, most carnivore populations are declining worldwide (Ripple et al., 2014), although some carnivore species are successfully living in human-altered environments (e.g., Mueller, Drake, & Allen, 2019; Wang et al., 2015).

Coyotes (*Canis latrans*) have been one of the most successful carnivores in both exploiting human-modified landscapes and expanding their range in North America over the last century (Gehrt, Anchor, & White, 2009; Kays, Gompper, & Ray, 2008; Newsome & Ripple, 2015). Historically, coyotes occupied portions of the midwestern and western regions of North America (Hody & Kays, 2018). Since the early to mid-1900s, coyotes' range has expanded eastward following the extirpation of wolves (Levi & Wilmers, 2012; Newsome & Ripple, 2015; Ripple, Wirsing, Wilmers, & Letnic, 2013). In addition to facilitating competitive release through the extirpation of wolves, humans have altered the landscape through deforestation during this time period, creating more open habitat that coyotes prefer (Ripple et al., 2013). As a result, coyotes have become the apex carnivore in many areas without competition from larger carnivores (Gehrt et al., 2009; Gosselink, Deelen, Warner, & Joselyn, 2003; Hody & Kays, 2018). Coyotes are a well-studied species with well-known habitat preferences, but understanding patterns of coyote occurrence within small spatial units (e.g., site-level occupancy) across broad spatial extents (e.g., regions or management units, Green, Pavlacky, & George, 2019) is also important for better understanding their effects on other smaller carnivores (Fedriani, Fuller, Sauvajot, & York, 2000; Gosselink et al., 2003) and the potential for human-coyote conflicts (White & Gehrt, 2009).

Citizen science, where members of the public contribute to scientific research through data collection (Dickinson, Zuckerberg, & Bonter, 2010), has expanded means by which researchers and managers can collect species occurrence data across broad spatial extents (e.g., Mueller et al., 2019; Rafiq et al., 2019). One form of citizen science widely used by management agencies is wildlife observations by hunters, where participating individuals document wildlife species they see while hunting (Crum, Fuller, Sutherland, Cooch, & Hurst, 2017; Roberts & Crimmins, 2010). These surveys provide a potentially economical means to monitor trends in wildlife populations as they require relatively little effort on the agency's part but yield a large amount of data across broad spatial extents (Bonney et al., 2009; Solberg & Saether, 1999). Hunter observations may therefore allow researchers and managers to estimate and monitor the distribution and abundance of wildlife species over broad spatiotemporal extents (Crum et al., 2017; Hansen, Gagen, Budeau, Coggins, & Reishus, 2015; Hochachka et al., 2012) with relatively few logistical and financial costs. These observations also provide opportunities to monitor both game and nongame species, which may not be feasible with other data sources (i.e., harvest data). However, an appropriate application of citizen science data requires addressing assumptions and limitations regarding the data and sampling design, such as the accuracy of species identification and the precision of the geographic locations of observations. Additionally, analyses should account for imperfect detection when possible, yet doing so can be challenging with citizen science data (e.g., Broman, Litvaitis, Ellingwood, Tate, & Reed, 2014; Mahard, Litvaitis, Tate, Reed, & Bromanm, 2016, but see Brommer, Alakoski, Selonen, & Kauhala, 2017). Because hunters often hunt multiple times within a given hunting season, these events can function as repeated site visits provided that hunters hunt within the same general area across visits. Such a sampling design provides a framework for estimating detection, thereby improving estimates of occupancy and abundance. However, studies utilizing hunter observations often do so using observations per unit effort or area without accounting for imperfect detection (e.g., Ueno, Solberg, Iijima, Rolandsen, & Gangsei, 2014 but see Crum et al., 2017 and Rich et al., 2013).

The purpose of this study was to evaluate habitat associations of fine-scale coyote occupancy using citizen science observations provided by archery deer hunters across the state of Illinois, the United States. Within Illinois, the coyote population has apparently increased since the 1970s (Gosselink et al., 2003; Gosselink, Van Deelen, Warner, & Mankin, 2007), which may increase the potential for human-coyote conflicts. Our first objective was to test for the effects of multiple landscape covariates on coyote occupancy. Our second objective was to evaluate the effects of diel and weather conditions on coyote detection. Our third objective was to estimate and compare coyote occupancy across the 10 Wildlife Management Units (WMUs) in Illinois that are used by the Illinois Department of Natural Resources in their development and implementation of wildlife management and conservation programs.

2 | MATERIALS AND METHODS

2.1 | Study area

We used data we collected from across the state of Illinois from October and November 2016 (Figure 1). The land

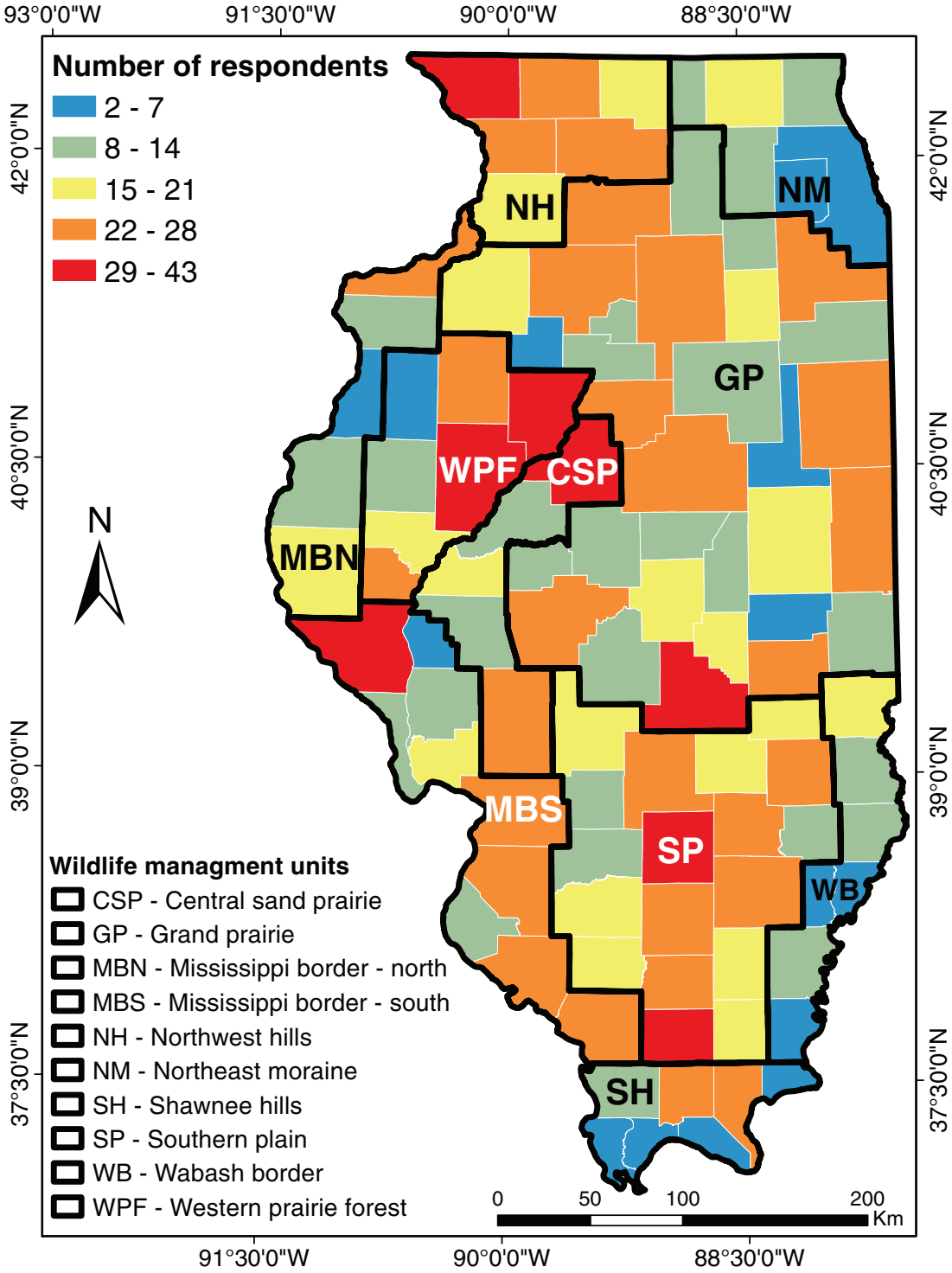

FIGURE 1 Map of Illinois showing number of respondents to the 2016 archery deer hunters survey by county and Wildlife Management Unit [Color figure can be viewed at wileyonlinelibrary.com]

cover of Illinois varied across the state, with high urbanization in the northeastern portion of Illinois (i.e., the Chicago metropolitan area), primarily commercial agriculture in central Illinois and a mosaic of forest and agriculture in the southern part of Illinois. WMUs in Illinois largely reflect regional variation in geology and historical vegetation cover (Table 1). Statewide mean monthly temperature ranged from −2.8°C in January to 24.3°C in August (mean monthly temperature in 2016 was 12.67°C), and monthly precipitation ranged from 2.2 cm in January to 17.5 cm in July (mean monthly precipitation in 2016 was 8.4 cm). Average monthly temperature

TABLE 1 Select land cover proportions and weather data (mean and range) by wildlife management unit (WMU) in Illinois during the 2016 study period (1st October through 14th November)

WMU	Agriculture	Forest	Urban	Wetland	Precipitation (mm)	Min temperature (°C)
Northeast Moraine	0.26	0.08	0.54	0.04	2.53 (0–25.09)	7.32 (−1.33–18.36)
Northwest Hills	0.64	0.12	0.09	0.02	1.76 (0–16.38)	6.18 (−3.76–17.56)
Grand Prairie	0.79	0.06	0.09	0.01	2.01 (0–16.21)	7.57 (−2.12–18.08)
Mississippi border - north	0.60	0.17	0.07	0.03	1.89 (0–22.66)	8.40 (−1.21–19.09)
Western Prairie Forest	0.58	0.24	0.07	0.01	2.38 (0–35.35)	7.65 (−1.8–18.95)
Central Sand Prairie	0.67	0.15	0.07	0.03	1.82 (0–22.59)	6.78 (−2.25–19.4)
Mississippi border - south	0.46	0.25	0.10	0.05	1.75 (0–38.75)	8.65 (−2.35–19.67)
Southern plain	0.56	0.21	0.07	0.03	1.65 (0–38.42)	8.72 (−3.17–19.65)
Wabash border	0.66	0.18	0.06	0.03	1.66 (0–41.01)	7.75 (−4.4–19.42)
Shawnee Hills	0.20	0.47	0.05	0.07	0.49 (0–7.06)	9.71 (−1.92–19.68)

was 15.5°C in October and 8.9°C in November and average monthly precipitation was 6.1 cm in October and 6.6 cm in November (data accessed at https://mrcc.illinois.edu/CLIMATE/ on May 23, 2019). Temperatures during the study period showed an increasing north–south gradient (Table 1).

2.2 | Data collection

We collected observations from participating archery deer hunters (hereafter participants) across all 102 counties in Illinois during the first period of the 2016 archery deer hunting season (October 1st to November 14th, Figure 1). A total of 4,100 surveys were sent to a randomly selected sample of the 90,233 registered archery deer hunters in the state of Illinois before the start of the 2016 archery deer season. Survey materials included a cover letter explaining the purpose of the study, the due date and a stamped return envelope. Participants recorded data each day they hunted, including the date, time period (AM or PM), number of hours hunted per time period, county hunted and number of target species observed, including coyotes. Due to participant privacy concerns, participants provided their locations at the county level rather than at a finer spatial scale. We considered 10 covariates that could affect coyote occupancy and detection based on *a priori* hypotheses (Table 2). We used the 2016 National Land Cover Database (NLCD, 30-m pixels, accessed November 1, 2019 from www.mrlc.gov) and the *ClassStat* function in the package *SDMTools* (v. 1.1–221.2, VanDerWal, Falconi, Januchowski, Shoo, & Storlie, 2019) in program R (v. 3.6.1, R Core Team, 2018) to measure all landscape covariates. Because participant locations were reported by county, we measured all landscape covariates at the county scale. We calculated the proportion of each county that was agriculture (i.e., cultivated crops), forest (deciduous, evergreen and mixed), grassland (grassland/herbaceous and pasture/hay; combined because we assumed these two land covers would be structurally and ecologically equivalent for coyotes [Cherry et al., 2016]), and urban (all developed classes). We also measured forest patch density, mean forest perimeter-area ratio, and mean grassland perimeter-area ratio.

We obtained the daily minimum temperature and precipitation for each day of the study period from NOAA weather stations across Illinois using the *rnoaa* package (v. 0.9.5, Chamberlain, 2019). We created statewide 1-km pixel rasters of interpolated weather values for each day of the 2016 archery hunting season and extracted average pixel value for each county. We used inverse-distance weighting with the *gstat* package (Benedikt, Pebesma, & Heuvelink, 2016; Pebesma, 2004) and used 10-fold cross-validation to select the number of neighbors and distance decay function for each day. We provide the summary statistics for each covariate used in Table S1.

2.3 | Statistical analyses

Due to the hierarchical nature of our sampling design (participants with multiple visits nested within counties), we initially modeled our data using a single-season multi-scale occupancy model, which estimates occupancy at both the sample unit scale (the county level) and at the sample station scale (the participant level) (Nichols et al., 2008). However, coyotes were detected in all but two counties in Illinois and preliminary analyses showed that estimated county-level occupancy was 1.00, making coyotes ubiquitous throughout Illinois at the county

TABLE 2 The name and description (measured at county scale unless otherwise noted) of each covariate used in our models for coyote (*Canis latrans*) participant-level occupancy and detection in Illinois using observations by archery hunters during the 2016 study period (1st October through 14th November)

Covariate	Description	Sign	Hypothesis/reason
Forest patch density	Patch density of forest land cover	+ Occupancy	Coyotes use edge and smaller patches of forest (Lesmeister, Nielsen, Schauber, & Hellgren, 2015; Wait, Ricketts, & Ahlers, 2018) so will be more likely to occupy areas with high patch density.
Forest shape index	Mean perimeter-area-ratio (MPAR) for forest	+ Occupancy	Coyotes use forest edge habitat for easier movement and cursorial hunting and will be more likely to occupy areas with greater forest edge (Kays et al., 2008; Lesmeister et al., 2015; Randa & Yunger, 2006).
Grassland shape index	Mean perimeter-area-ratio (MPAR) for grassland	+ Occupancy	Coyotes prefer open habitat and greater MPAR indicates greater grassland edge with which coyotes may be positively associated (Cherry, Howell, Seagraves, Warren, & Conner, 2016; Lesmeister et al., 2015; Randa & Yunger, 2006).
Agricultural cover	% county that is agriculture	− Occupancy	Coyote abundance is negatively associated with agriculturally-dominated landscapes (Cherry et al., 2016)
Urbanization	% county that is urban environment	− Occupancy	While coyotes can persist near urban areas, they will be less abundant and less likely to occupy these areas (Kays et al., 2008; Leflore, Fuller, Finn, DeStefano, & Organ, 2019; Lesmeister et al., 2015; Randa & Yunger, 2006; Wait et al., 2018; Wang et al., 2015).
Hours	Time spent hunting per record	+ Detection	The number of hours a hunter is active (as a proxy for effort) will increase the probability of detection.
Day of year	Number of days since opening of archery deer season	− Detection	Coyotes will be more wary as hunting season progresses, becoming more difficult to detect with increasing days since opening day.
Time period	AM or PM (binary)	− Detection	Citizen scientists more often detect coyotes in AM than PM time periods (Mueller et al., 2019).
Temperature	Daily minimum temperature	+ Detection	Coyotes will be less active and have lower detection with decreasing temperature (Lesmeister et al., 2015).
Precipitation	Daily precipitation	− Detection	Coyotes will be less active and have lower detection with increasing precipitation.

Note: For each covariate we include the hypothesized effects on occupancy or detection and the reasoning for the hypothetical effects.

level. We therefore modeled coyote occupancy at the participant-level (hunting site locations of participants) using single-season single-scale occupancy models (MacKenzie et al., 2002). We assumed that individual participants visited the same general area in a given county during each day they hunted within that county; a reasonable assumption given the prevalence of stand-based archery hunting. Because of our large sample size (>100 participants per covariate), we drew inferences from a single global model. This approach allowed us to simultaneously model all our a priori selected covariates and estimate effect sizes directly from standardized model coefficients without model averaging across a candidate model set (Cade, 2015; Fieberg & Johnson, 2015). We screened all occupancy and detection covariates for strong collinearity ($r \geq .7$, variance inflation factors [VIF] ≥ 3.0). Strong collinearity was not present among our final covariate set ($|r| \leq .69$, VIF ≤ 2.28) with five detection variables and five occupancy variables (Table 2). We z-score standardized all continuous covariates prior to analyses and fit models using the *unmarked* package (v. 0.13-1, Fiske & Chandler, 2011). Finally, we fit a model where participant-level occupancy was modeled only as a function of WMU as a 10-level categorical covariate. We performed this analysis to determine if coyote occupancy varies spatially across Illinois and across units used in coyote management. We retained our original five detection covariates in this model.

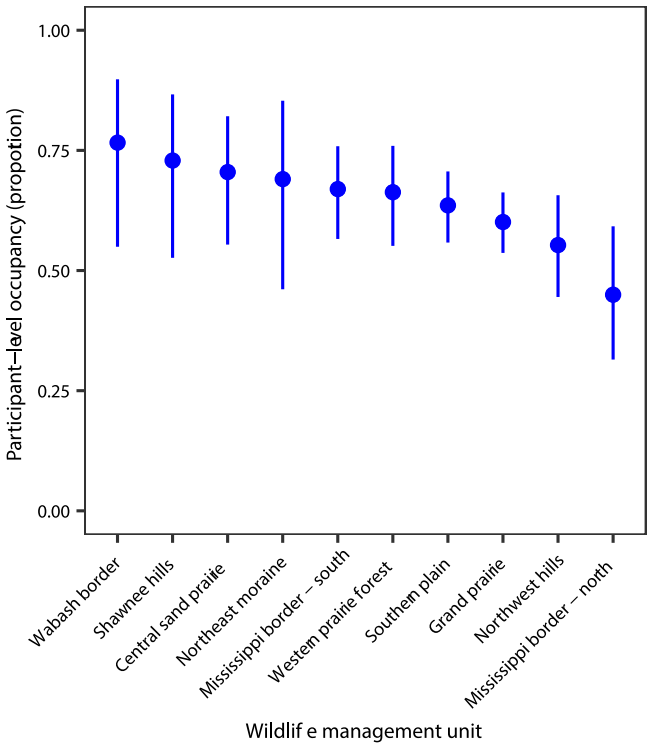

FIGURE 2 Participant-level coyote (*Canis latrans*) occupancy and 95% CI as vertical lines for each Wildlife Management Unit in Illinois during the 2016 study period [Color figure can be viewed at wileyonlinelibrary.com]

3 | RESULTS

We used data from 1,240 study participants (30% response rate), which included 1,749 unique participant-county combinations, from all 102 counties in Illinois. The number of participants per county ranged from 2 to 43 (mean = 17, SD = 9). Days hunted averaged 10 days (range = 1–45 days, SD = 8) during the study period and participants had a mean of 13 time periods per individual (range = 1–81, SD = 11). During each time period

TABLE 3 Coefficient estimates (β), standard errors (*SE*), z statistics and p values for coyote (*Canis latrans*) detection and participant-level occupancy covariates in our global model

	Covariate	β	*SE*	*z*	*p*
Occupancy	Intercept	0.52	0.08	6.75	<.0001
	Forest patch density	0.08	0.11	0.79	.43
	Forest shape index	0.12	0.11	1.08	.28
	Agricultural cover	0.03	0.10	0.32	.75
	Grassland shape index	−0.07	0.11	−0.57	.57
	Urbanization	0.06	0.10	0.56	.58
Detection	Intercept	−1.90	0.04	−48.54	<.0001
	Time period (PM)	−0.43	0.05	−7.78	<.0001
	Day of year	0.05	0.03	1.46	.14
	Hours	0.17	0.03	6.31	<.0001
	Temperature	−0.03	0.04	−0.75	.45
	Precipitation	−0.04	0.03	−1.19	.23

Note: All continuous covariates were z-score standardized.

hunted, participants were in the field for a mean of 3.03 hours ($SD = 0.95$, range = 0.25–7.00).

Naïve participant-level occupancy (i.e., proportion of participants that detected a coyote) for coyotes was 0.40, and participant-level occupancy estimated from our global model when all covariates were held at their mean values was 0.63 (95% CI = 0.59–0.66). Estimated participant-level occupancy for coyotes across each WMU ranged from 0.45 (95% CI = 0.31–0.59) in the Mississippi Border—North WMU to 0.77 (95% CI = 0.55–0.90) in Wabash Border WMU (Figure 2). Correlations were weak between occupancy for each WMU and the WMU-wide proportion of forest, agriculture, urban and wetland ($|r| \leq .39$, Table 1). None of the covariates we tested had significant effects on coyote participant-level occupancy ($p \geq .28$, Table 3).

In our global model, the time period that the participant was in the field had the largest significant effect on participant detection of coyotes ($z = -7.79$, $p < .0001$; Table 3), followed by number of hours hunted ($z = 6.32$, $p < .0001$; Table 3). Probability of detecting a coyote at the mean number of hours hunted (3 hours) was greater in the AM time period (0.13, 95% CI = 0.12–0.14) than the PM time period (0.09, 95% CI = 0.08–0.10, Figure 3). Predicted detection probabilities were < 0.25 across our observed range of number of hours hunted. No other detection covariates that we tested had significant effects ($p \geq .14$, Table 3).

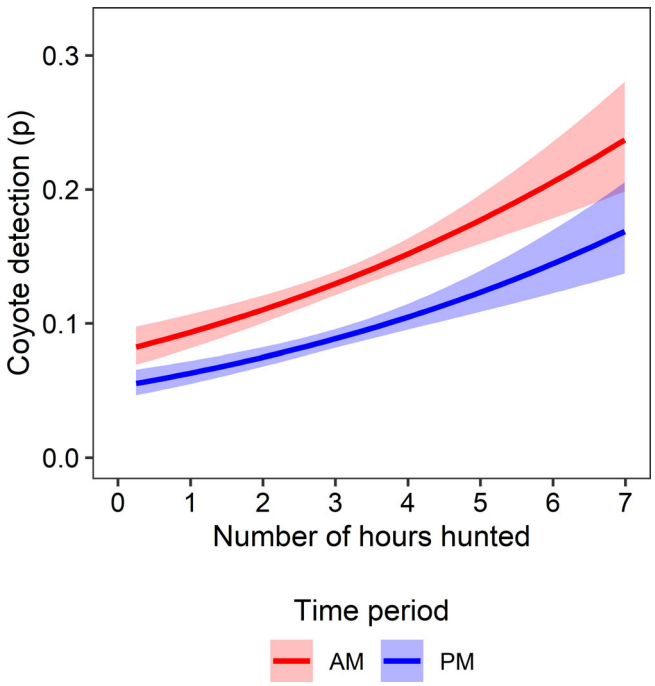

FIGURE 3 Relationships between coyote (*Canis latrans*) detection probability for participating archery deer hunters in Illinois during the 2016 study period with time period and number of hours hunted. Mean occupancy and 95% CI are shown as shaded areas [Color figure can be viewed at wileyonlinelibrary.com]

4 | DISCUSSION

Despite our efforts to identify landscape covariates that would explain participant-level occupancy of coyotes, none of the *a priori* county-level landscape covariates we considered in our analyses were significantly related to participant-level coyote occupancy. We suspect that this may reflect a mismatch between the scale at which we measured landscape covariates (individual counties) and the effective sampling area of participating hunters. The landscape covariates we used represented average conditions across a county which likely masks heterogeneity in landscape conditions at locations where participants actually hunted. Additionally, we found variation in participant-scale occupancy as the naïve participant-level occupancy was 0.40, and the probability of a hunter detecting a coyote during an observation period was not equal to 1, which provides evidence for a mismatch in scale rather than a lack of variation in coyote occupancy. Scale influences the strength and direction of species-habitat relationships (Bowyer & Kie, 2006; Levin, 1992; Moraga, Martin, & Fahrig, 2019) and this scale mismatch may limit our ability to detect species-habitat relationships. Furthermore, participants likely selected sites non-randomly with regards to county-level landscape conditions (e.g., preferentially selecting woodlands), leading to further deviations in participant-level and county-wide landscape characteristics. Coyotes are also widespread within Illinois (ubiquitous at the county level, the scale at which we measured landscape covariates) and occupy a diversity of habitats (Gosselink et al., 2003; Lesmeister et al., 2015; Randa & Yunger, 2006). Consequently, participant-level occupancy of widespread generalist species may show a relatively weak response to landscape covariates measured at broader spatial extents. It is possible that species with more specialized habitat associations (e.g., forest obligates) may show a stronger association with landscape features measured at scales larger than the sampling unit but additional data are needed to test this hypothesis. These considerations highlight important limitations when using observations with imprecise locations from citizen scientists to infer species-habitat relationships and the need to consider the species' habitat ecology and distribution.

Despite the lack of significant covariates for participant-level occupancy, estimates of participant-level occupancy varied across Wildlife Management Units, demonstrating spatial variation in coyote occupancy when measured at finer scales. However, the 95% CI around the

occupancy estimates for each WMU overlapped, making it difficult to ascertain the factors responsible for geographic variation in participant-level occupancy. Our participant-level occupancy estimates are similar to those reported for coyotes elsewhere in the midwestern USA using camera traps (Berry, Schooley, & Ward, 2017; Lesmeister et al., 2015; Wait et al., 2018). We suggest that analyzing observational data from citizen scientists within a hierarchical modeling framework that accounts for imperfect detection is a better option for modeling the distribution of cryptic wildlife species compared to estimates of observation per unit effort or area sampled. Indices that fail to account for imperfect detection may lead to misleading inferences, particularly for species with low detection rates (e.g., Kéry et al., 2009; Rota, Fletcher, Evans, & Hutto, 2011). For example, our overall participant-level occupancy estimate was approximately 58% greater than our naïve estimate across the state, indicating a substantial increase in accuracy. However, more statistically robust methods for estimating abundance or density (e.g., mark-recapture or radio telemetry) are difficult to implement long term at spatial scales as broad as the state of Illinois. Citizen scientist observations can be more easily accommodated within a hierarchical modeling framework than other common approaches for monitoring carnivores and other wildlife species (e.g., spotlight surveys, harvest data) and may have potential for estimating broad-scale geographic variation in occupancy or long-term trends.

We found that two covariates had strong effects on coyote detection; hunting during AM time periods and hunting for a greater number of hours both significantly increased the probability of detecting coyotes, as predicted. Higher detection during AM periods is consistent with other citizen science studies of coyotes (Mueller et al., 2019). Coyotes are largely crepuscular or nocturnal (Lesmeister et al., 2015) and are generally more active during AM daylight periods than PM daylight periods (Mueller et al., 2019), which is probably why we found higher detection during AM time periods. Increased detection with increasing number of hours hunted is analogous to increased detection with increased effort. Our detections were low compared to camera trap detections in forested landscapes in southern Illinois (0.31–0.52, Lesmeister et al., 2015), which is the habitat most deer hunters prefer to hunt. However, our detection rates were similar to those estimated from camera trapping at grassland restoration sites in central Illinois (0.12–0.25, Berry et al., 2017). Participant level detection may only account for a portion of coyote diel activity as Illinois regulations allow for hunting from a half-hour before sunrise to a half-hour after sunset (Illinois Department of Natural Resources, 2016). This highlights an important consideration when using citizen science data as humans and wildlife are often active at the different times of day. Natural history of a species should therefore be considered when designing a citizen science study or analyzing citizen science data.

Many management agencies collect citizen science data, such as sightings of rare wildlife (Olson, Van Deelen, Clare, & Allen, 2020) or observations of game species by hunters (Crum et al., 2017; Roberts & Crimmins, 2010; Ueno et al., 2014), and these surveys may be an efficient and low-cost tool to inform management and conservation of wildlife (Mueller et al., 2019; Rafiq et al., 2019). Archery deer hunter surveys are sometimes considered one of the most accurate data available to management agencies (Crum et al., 2017; Mahard et al., 2016). We suggest that the utility of archery deer hunter observations is best when participant observations are analyzed within a hierarchical modeling framework that accounts for factors influencing variation in detection rates. Collecting data that could help better model variation in detection (e.g., weather conditions, vegetation cover) increases the accuracy of the occupancy estimates (Dickinson et al., 2010). While we think our assumption that participants repeatedly hunt within the same general area is reasonable within our study system, deviations from this assumption should not bias our results provided that the occupancy status of a species does not change within the area actually hunted by a given participant.

Our results also illustrate the limitations of citizen science data when modeling occupancy as a function of landscape features when precise participant locations are unknown. Participants only reported the county in which they hunted, meaning landscape covariates must be measured at the county level, yet an individual participant's observations represent a small effective sampling area of unknown location within a specific county (Cooper, Nielsen, & McDonald, 2012). We also assumed that participants hunted in the same location across repeated visits and violations of this assumption should be assessed in future studies. Measuring landscape features across spatial extents much larger than the effective sampling area may limit inference regarding finer-scale species landscape relationships (e.g., Cooper et al., 2012). The data we collected are not unlike those collected by other state agencies with regards to the spatial scale of participant locations. Agencies should consider possible mismatches between the scale of their covariates and effective sampling areas when evaluating drivers of occupancy across management-level scales (e.g., states or regions). We recommend that managers collect precise location data from citizen scientists when possible to maximize the utility of their occupancy estimates.

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