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Integrated species distribution models reveal spatiotemporal patterns of human–wildlife conflict

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Abstract

To mitigate human–wildlife conflict it is imperative to know where and when conflict occurs. However, standard methods used to predict the occurrence of human–wildlife conflict often fail to recognize how a species distribution likely limits where and when conflict may happen. As such, methods that predict human–wildlife conflict could be improved if they could identify where conflict will occur relative to species' underlying distribution. To this end, we used an integrated species distribution model that combined presence-only wildlife complaints with data from a systematic camera trapping survey throughout Chicago, Illinois. This model draws upon both data sources to estimate a latent distribution of species; in addition, the model can estimate where conflict is most likely to occur within that distribution. We modeled the occupancy and conflict potential of coyote (*Canis latrans*), Virginia opossum (*Didelphis virginiana*), and raccoon (*Procyon lotor*) as a function of urban intensity, per capita income, and home vacancy rates throughout Chicago. Overall, the distribution of each species constrained the spatiotemporal patterns of conflict throughout the city of Chicago. Within each species distribution, we found that human–wildlife conflict was most likely to occur where humans and wildlife habitat overlap (e.g., featuring higher-than-average canopy cover and housing density). Furthermore, human–wildlife conflict was most likely to occur in high-income neighborhoods for Virginia opossum and raccoon, despite the fact that those two species have higher occupancy in low-income neighborhoods. As such, knowing where species are distributed can inform guidelines on where wildlife management should be focused, especially if it overlaps with human habitats. Finally, because this integrated model can incorporate data that have already been collected by wildlife managers or city officials, this approach could be used to develop stronger collaborations with wildlife management agencies and conduct applied research that will inform landscape-scale wildlife management.

KEYWORDS
human–wildlife conflict, integrated model, mammals, occupancy model, urban ecology

INTRODUCTION

Human–wildlife interactions are part of the human experience for many people worldwide (Nyhus, 2016). While most human–wildlife interactions are benign or positive in nature (Soulsbury & White, 2015), negative interactions between humans and wildlife (hereafter human–wildlife conflict) do occur, which can have adverse outcomes for both parties. Not only has human–wildlife conflict led to species extinctions (Woodroffe et al., 2005), it is also responsible for considerable loss of human life, livestock depredation, and property damage (Conover, 2002). Finding ways to mitigate human–wildlife conflict is therefore imperative for both humans and wildlife. As a result, research on human–wildlife conflict mitigation has increased at close to an exponential rate since the year 2000 (Nyhus, 2016).

An essential first step in mitigating human–wildlife conflict is to understand where and when conflict occurs. Because predictable systems are easier to manage (Dietze, 2017), identifying the spatial or temporal correlates of human–wildlife conflict hotspots can focus wildlife management efforts and thereby reduce conflict (e.g., Abade et al., 2014; Goswami et al., 2015). Common approaches to identifying such hotspots are to take presence-only conflict locations and compare them to the landscape at large, either through maximum entropy modeling (Sharma et al., 2020) or by generating pseudo-absences and using logistic regression (Miller et al., 2016). While useful, these approaches ignore how a species distribution likely varies within the modeled region and therefore may amplify or limit a species' potential for conflict (Figure 1). Simply put, if a species does not occupy a portion of the landscape, conflict cannot occur at that location. Therefore, models that predict conflict hotspots could be improved by identifying where conflict occurs relative to a species' underlying distribution (Kuiper et al., 2021).

To estimate species' conflict potential relative to their distribution, we used an integrated model developed by Koshkina et al. (2017) that combines presence-only data from opportunistic surveys with systematically collected wildlife survey data. By using both data sources this model can improve the accuracy and precision of species distribution estimates and compartmentalize the bias associated with the presence-only data into its own submodel (Koshkina et al., 2017). Partitioning this bias can be important when the presence-only data lack standardized sampling protocols. Yet, the estimated bias from this model does not have to be a nuisance variable—it depends on what data are supplied. For example, if presence-only human–wildlife conflict data are used in conjunction with wildlife survey data, the estimated "bias" instead represents where conflict is more or less likely to occur relative to the wildlife survey data. Therefore, this modeling approach (Koshkina et al., 2017) could be used to determine the extent to which species presence on the landscape informs where human–wildlife conflict may occur (Figure 1).

However, a species' distribution is not the only determinant of human–wildlife conflict; it is also driven by human behavior. As such, both social and ecological factors must be considered to understand where and when human–wildlife conflict occurs (Carter & Linnell, 2016; Nyhus, 2016). Thus, the goal of this study was to estimate the relative influence of various social–ecological

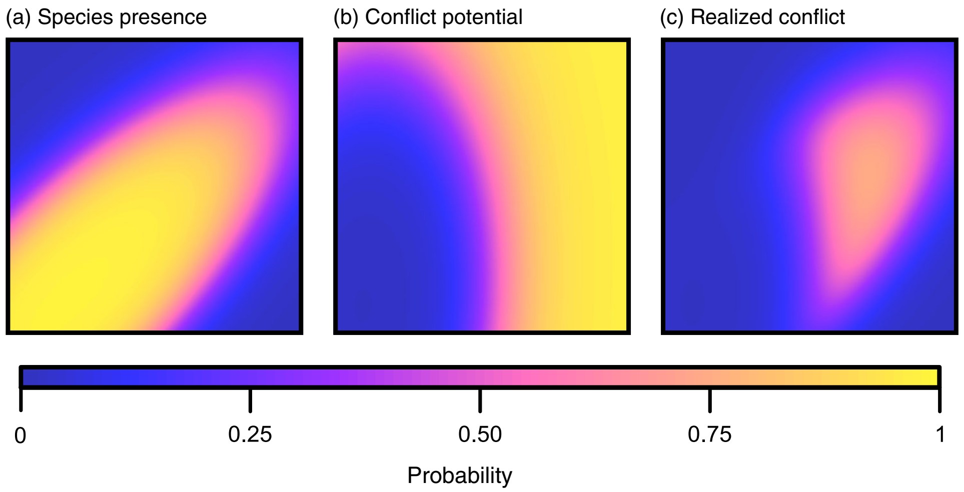

FIGURE 1 (a) Species distribution in landscape, (b) where the species has the greatest likelihood of coming into conflict with humans given their presence across the entire landscape, and (c) the expected distribution of where conflict actually occurs on the landscape, which is the product of where the species is (a) and where conflict is most likely to occur (b).

gradients on the distribution and conflict potential of coyote (*Canis latrans*), Virginia opossum (*Didelphis virginiana*, hereafter opossum), and raccoon (*Procyon lotor*) throughout Chicago, Illinois, a city that receives over 40,000 nuisance wildlife reports per year (City of Chicago, 2021). As three common urban wildlife species throughout North America, coyote, opossum, and raccoon can come into conflict with people through disease transmission, property damage, attacks on humans or their pets, or animal–vehicle collisions. To estimate each species' distribution and conflict potential throughout Chicago, we used the Koshkina et al. (2017) model and combined presence-only nuisance wildlife calls made to the City of Chicago with data from a large-scale, long-term camera trap survey (Magle et al., 2019).

We selected three social–ecological gradients we hypothesized would be associated with these species' distributions or conflict potential throughout Chicago: urban intensity, per capita income, and home vacancy rates. We had four predictions for these variables: first, that urban intensity would be the strongest determinant of these species distributions, with all three species being less likely to occur at higher levels of urban intensity (Magle et al., 2021); second, that conflict would most likely occur in areas where humans and wildlife habitat overlap; third, because income inequality and an individual's perception of wealth are respectively positively and negatively correlated to a person's trust in local government (Rahn & Rudolph, 2005), human–wildlife conflicts reported to the City would be positively correlated with per capita income; and fourth, because opossum (Kanda et al., 2009) and raccoon (Larivière, 2004) readily use anthropogenic structures as denning sites, we predicted that the conflict potential for these two species would be higher in areas with more vacant buildings. By combining readily available data from the city of Chicago with our own biodiversity monitoring efforts, we show how this modeling framework can simultaneously generate salient and actionable predictions of where human–wildlife conflict is most likely within a species distribution.

MATERIALS AND METHODS

This study took place within the city limits of Chicago, Illinois. The third largest city in the United States, Chicago is 606 km^2 and has a human population of around 2.7 million (U.S. Census Bureau, 2019). Located in the Midwestern United States along Lake Michigan, Chicago has a mean annual precipitation of 93.70 cm and experiences cold winters (mean $= -3.11^\circ\text{C}$), moderate springs (mean $= 9.22^\circ\text{C}$), warm summers (mean $= 22.11^\circ\text{C}$), and moderate autumns (mean $= 11.39^\circ\text{C}$) (NOAA, 2021).

Presence-only human–wildlife conflict data

We requested all of the coyote, opossum, and raccoon wildlife complaint data made to Chicago City Services (i.e., calling the nonemergency service line at 311) between 1 January 2011 and 31 December 2013 via the Freedom of Information Act. We asked for this date range at the time of the request because it aligned with the date range of our wildlife survey data that had been classified to the species level by trained experts. Fielded by Chicago Animal Care & Control, wildlife complaints made to the City were related to reports of injured or nuisance animals, animals perceived to be aggressive, requests for assistance from the Chicago Police Department, animal sightings, and animal bites, which were rare. These data included the date and city block where the complaint occurred and a general description of the complaint. These descriptions often contained the species related to the complaint (e.g., "Raccoon – Caller states that there may be three raccoons in her attic"). Sometimes there was uncertainty about which species prompted the complaint. For example, descriptions included terms such as "unknown animal," "coyote or dog," or "opossum or raccoon." These uncertain complaints were removed from the final data set. The remaining complaints were spatially referenced to the block level with the Google geolocation API via the ggmap package in R version 4.0.3 (R Core Team, 2020). This block-level referencing means there is a small amount of uncertainty about the exact location of a wildlife complaint. This should not, however, influence our analysis because we aggregated data at a larger spatial scale (500 m^2) than the size of a Chicago city block (100×200 m) to fit the integrated model. Finally, we grouped the complaint data into four discrete time periods per year to make the 12 months of complaint data match up with the wildlife survey data, which are collected 4 months per year (i.e., January, April, July, and October). To increase the complaint data sample size, we incorporated complaints from the month before and after a given wildlife survey (e.g., April 2012 complaint data also included March and May 2012).

Finally, because these opportunistic data are nuisance reports from city residents, they inherently include a mixture of calls that trigger management intervention (e.g., an animal trapped in an attic) and those that do not trigger management intervention (e.g., people calling to report the presence of a particular species in their neighborhood). Regardless of the management outcome, it is important to recognize that each report represents human conflict from the perspective of the resident, who decided to file a report to the City of Chicago and that the City uses these data to inform wildlife management efforts (Murray et al., 2018).

Wildlife survey data

Coyote, opossum, and raccoon detection/nondetection data came from a large-scale, long-term camera trap survey throughout the Chicago Metropolitan Area (Magle et al., 2019). To collect these data, we sampled 123 urban greenspaces along three 50-km transects that followed a gradient of urban intensity and spanned roughly 4500 km^2. Transects began in downtown Chicago and extended to the northwest, west, and southwest. Camera trap locations (hereafter sites) were separated by at least 1 km. Starting in spring 2011, sites were sampled four times a year in January, April, July, and October for 28 days per sampling period. At each site we secured one Bushnell camera trap roughly 1.5 m up a tree (see Appendix S1: Table S1 for camera settings). Following this, we angled the camera downward to center the field of view at a synthetic fatty acid scent lure (USDA Wildlife Services, Pocatello, Idaho). These lures were used to possibly increase mammal detectability, though later research revealed it barely works (Fidino et al., 2020). Thus, we do not expect lure presence to influence our analysis. Camera trap images were identified to the species level by trained experts. For each sampling period (e.g., July 2012) we calculated (1) the number of days each species was detected at each site and (2) the total number of days a camera was active. To ensure the wildlife survey data were comparable with the wildlife conflict data, we only used sites within Chicago city limits. This resulted in a total of 43 sites and 12 sampling periods between January 2011 and October 2013.

Spatial variables

We compiled six spatial variables to test our predictions: canopy cover (%) (CMAP, 2018), grass cover (%) (CMAP, 2018), impervious cover (%) (CMAP, 2018), housing density (unit: km^{-2}) (Hammer et al., 2004), median income per capita by census tract (US$) (U.S. Census Bureau, 2017), and vacant building reports made to Chicago City Services between January 2011 and December 2013 (reports km^{-2}) (Chicago Data Portal, 2021), which served as a proxy for vacant buildings. We converted these spatial variables to individual rasters with a spatial resolution of 500 m^2. This aggregation step was necessary to evaluate the likelihood function of our integrated model, which required spatial data at all locations within a sampled area (i.e., the entire city of Chicago). We chose a resolution of 500 m^2, which resulted in 2417 unique cells within the city of Chicago, for two reasons. First, the Koshkina et al. (2017) model is scale-invariant, and so the interpretation of model parameters is not dependent on this choice (Dorazio, 2014). Second, finer scales were computationally burdensome for modeling. Because urbanization is a multidimensional process that simultaneously modifies multiple land-cover types (Moll et al., 2019; Padilla & Sutherland, 2021), we applied principal component analysis (PCA) to the canopy cover, grass cover, impervious cover, and housing density layers to create a composite urban intensity metric. We retained the first two PCA components, which explained 75% of the variation in these data. We selected canopy and grass cover for this metric to serve as a habitat proxy, given that these variables would capture local natural areas and greenspace, whereas impervious cover and housing density were chosen to represent the built environment or, in other words, the absence of habitat. The loadings of the first metric, URB1, were canopy (−0.28), grass (−0.58), impervious (0.67), and housing density (0.39). Thus, this metric represented a gradient of urban intensity. Negative values of URB1 represented portions of the Chicago landscape high in canopy and grass cover, whereas positive values were areas with high levels of impervious cover and housing density. The loadings of the second metric, URB2, were canopy (0.82), grass (−0.29), impervious (−0.18), and housing density (0.46). As such, URB2 separated areas of grass or impervious cover when negative from areas with tree cover and houses when positive. After the PCA we had four spatial variables: the two urban intensity metrics (URB1 and URB2), per capita income, and building vacancy. For a map of the two urban intensity metrics, as well as the variables used to create them, see Appendix S1: Figure S1.

Statistical analysis

The integrated model we used, which was an inhomogeneous Poisson point process, was composed of one latent state submodel and two data or observation submodels and was described previously by Koshkina et al. (2017). Thus, we explain the submodels here, all of which can include covariates, but leave the detailed model formulation to Koshkina et al. (2017). The latent state submodel represented the occupancy probability across the entire landscape (ψ), was jointly informed by the presence-only human–wildlife conflict data and wildlife survey data, and was modeled as a Bernoulli trial on the complementary log–log scale for each 500-m^2 cell of Chicago (Koshkina et al., 2017). As such, ψ estimated a species' distribution throughout Chicago. As a reminder, this submodel was scale-invariant, and so the estimated parameters do not depend on the 500-m^2 spatial scaling (Dorazio, 2014). The first data submodel, which was also scale-invariant, represented the spatiotemporal bias associated with the presence-only wildlife conflict data (η) and was modeled as a thinned Poisson process (Koshkina et al., 2017).

In our application of this model, the bias estimated here is not a nuisance parameter. Instead, it represented a species' conflict potential conditional on its presence throughout the environment. As such, assuming the species occupied the entire landscape, η can be used to identify which locations throughout Chicago are more or less likely to generate nuisance wildlife reports relative to where the species was observed in the wildlife survey data (Figure 1b). The second data submodel accounted for the probability that a species was detected given its presence at a camera trap site (ρ) and was modeled as a binomial process on the logit scale. Unlike the first two submodels, the ρ submodel was scale-dependent (Koshkina et al., 2017). Though there is substantial uncertainty about the spatial scale on which mammals respond to urbanization (Moll et al., 2020), a 500-m^2 scale is likely ecologically relevant given that it captured the average home range of both opossum and raccoon, though it is smaller than the average home range for coyote (Magle et al., 2016). However, given this scaling, the coyote camera trap detection submodel likely captured variation in detectability at a more local scale than the opossum or raccoon camera trap detection submodels. Though all three submodels were crucial to the model, the first two housed the most biologically relevant information to address the predictions we made for our spatial variables. For example, because $\Pr(\psi)$ represented a species occupancy probability and $\Pr(\eta)$ was a species conflict potential, their product, $\Pr(\psi) \times \Pr(\eta)$, represented areas within a species distribution that conflict was most likely to occur based on their distribution. Likewise, $\Pr(\psi) \times (1 - \Pr(\eta))$ represented areas within a species distribution that conflict was least likely to occur.

As a departure from Koshkina et al. (2017) and to accommodate t in 1, ..., T primary sampling periods, we added a smoothing term to the linear predictor for ψ that controlled for spatiotemporal autocorrelation in a species distribution (Rushing et al., 2019). Thus, for c in 1, ..., C 500 m^2 landscape cells throughout Chicago (C = 2417), the latent occupancy linear predictor was $\text{cloglog}(\Psi_{c,t}) = f_t(\text{lat}_c, \text{lon}_c) + \boldsymbol{a} \cdot \boldsymbol{r_c} + \nu$, which had three terms: a spatial smoothing function ($f_t(\text{lat}_c, \text{lon}_c)$), a vector of slope parameters ($\boldsymbol{a}$) and their associated covariates ($\boldsymbol{r_c}$), and an offset term (ν) that was the logged area of each cell (km^2). The spatial smoothing term consisted of g_k basis functions and their associated regression coefficients, $\pi_{k,t}$, such that $f_t(\text{lat}_c, \text{lon}_c) = \sum_{k=1}^{K} g_k\ (\text{lat}_c, \text{lon}_c)\pi_{k,t}$. We used a thinned-plate regression spline as our basis function for the latitude (lat_c) and longitude (lon_c) of each cell and set $K = 10$ since the initial tests indicated that this number was sufficient to approximate the smoothing term for each species. To let spatial autocorrelation in one sampling period inform the next sampling period, we parameterized $\pi_{k,t}$ as temporally correlated random effects (Rushing et al., 2019). Thus, for the first primary sampling period, $\pi_{k,t=1}$, we used a standard Bayesian penalization approach and specified multivariate normal priors with a precision matrix proportional to a smoothing penalty term, λ (Wood, 2017). For $\pi_{k,t>1}$, we used first-order autoregressive priors such that $\pi_{k,t} \sim \text{Normal}\left(\pi_{k,t-1}, \sigma^2_\psi\right)$, where $\sigma^2_\psi \sim \text{Inv}-\text{Gamma}(1,1)$. The ψ linear predictor only contained three of the four spatial covariates in the design matrix $\boldsymbol{R}$ (URB1, income, and vacancy), and all slope terms had Normal(0, 1.33) priors. We excluded URB2 in this level of the model for two reasons. First, the ψ and η linear predictors must each have one unique covariate to be identifiable. Second, we were interested in quantifying whether these mammals were more likely to come into conflict when their habitat and people interacted (i.e., our second study prediction). Because positive values of URB2 indicated areas of high canopy cover and housing density, it was the ideal choice to include in η.

We assumed that spatiotemporal autocorrelation occurred due to a distribution of species within Chicago, not from their conflicts. Thus, we used a simpler parameterization for η. For j in 1, ..., J human–wildlife conflicts the linear predictor was $\text{logit}\left(\eta_j\right) = \beta_{t[j]} + \boldsymbol{b} \cdot \boldsymbol{w}_{c[j]}$, where $t_{[j]}$ and $c_{[j]}$ respectively indicate the sampling period and landscape cell of the jth human–wildlife conflict. The first term was a temporally varying intercept, where $\beta_t \sim \text{Normal}\left(\overline{\beta}, \sigma^2_\eta\right)$, $\overline{\beta} \sim \text{Normal}(0, 1.33)$, and $\sigma^2_\eta \sim \text{Inv}-\text{Gamma}(1,1)$. The second term includes a vector of slope parameters ($\boldsymbol{b}$) and covariates ($\boldsymbol{w}_c$) where $\boldsymbol{b} \sim \text{Normal}(0,\ 1.33)$. As with ψ, η contained three spatial covariates in the design matrix $\boldsymbol{W}$: URB2, income, and vacancy.

We used a similar linear predictor for camera trap detection probability, ρ. For s in 1, ..., 43 sites the linear predictor was $\text{logit}\left(\rho_{s,t}\right) = \delta_t + \boldsymbol{d} \cdot \boldsymbol{x}_s$. The first term was a temporally varying intercept such that $\delta_t \sim \text{Normal}\left(\overline{\delta}, \sigma^2_\delta\right)$, $\overline{\delta} \sim \text{Normal}(0, 1.33)$, and $\sigma^2_\delta \sim \text{Inv}-\text{Gamma}(1,1)$. The second term contained a vector of slope parameters, $\boldsymbol{d}$, and their associated covariates ($\boldsymbol{x}_s$). We included both the URB1 and URB2 spatial covariates in this level of the model, and all slope terms within $\boldsymbol{d}$ had Normal(0, 1.33) priors. These variables were included because the local abundance of these species likely varies as a function of urban intensity, which influences species detectability (McCarthy et al., 2013). As a reminder, species were detectable at a survey site only if they were present, which is how we link the latent state model to this detection model. Thus, if $z_{c,t}$ denotes the presence ($z_{c,t} = 1$) or absence ($z_{c,t} = 0$) of the species in cell c and sampling period t, then $y_{s,t}$ Binomial($n_{s,t}$, $\rho_{s,t} z_{c[s],t}$), where $y_{s,t}$ was the number of days a species was observed at the wildlife survey site, $n_{s,t}$ was the number of days sampled, and $c[s]$ denoted the cth cell that site s resided.

Model fit

To fit our Bayesian model, we used JAGS version 4.3.0 (Plummer, 2003) via the runjags package in R version 4.0.3 (R Core Team, 2020). We used 4 chains, a 1000-step adaptation phase, and a 100,000-step burnin and then sampled the posterior 25,000 times on each chain. Chains were thinned by 4 for a total of 25,000 posterior samples. We assessed model convergence of each parameter by visually inspecting traceplots and ensuring Gelman-Rubin diagnostics were <1.10 (Gelman et al., 2013). We provided evidence of an effect by calculating 95% credible intervals (CIs) for each parameter and determined whether they overlapped zero. See Fidino (2022) for all data and code to recreate this analysis.

Model validation

Though the goal of this study was to explore the relationship between social–ecological gradients and human–wildlife conflict, we also contend that model predictions could be used to inform wildlife management. However, for model predictions to be actionable, they should be compared to out-of-sample data. To generate out-of-sample data and validate our models, we fit them one additional time but reduced the presence-only sampling window for each sampling period by 1 month per species. For example, the July 2011 sampling period originally included nuisance wildlife reports between June and August 2011. Thus, we fit the model to nuisance wildlife reports from the month before and during a camera trap deployment (e.g., June and July 2011) and used the August 2011 data for validation. Data were held out in this pattern for all 12 sampling periods to create one out-of-sample data set per species.

After fitting the model to the training data, we calculated the area under the receiver operating characteristic curve (AUC) with the validation data. This metric evaluates how well forecasted probabilities match a binary outcome (i.e., the presence of human–wildlife conflict; Hosmer & Lemeshow, 2000). AUC scores range from 0 to 1. Scores between 0.7 and 0.8 indicate an acceptable fit, between 0.8 and 0.9 a great fit, and greater than 0.9 an exceptional fit. We do acknowledge, however, that AUC has certain qualities that may not make it the most ideal model validation metric in all circumstances. For example, AUC does not provide spatial information about model errors and weights the omission and commission of errors equally (Lobo et al., 2008). See Appendix S2 for further information about AUC and model validation.

RESULTS

Over the 12 sampling periods between 2011 and 2013, coyote, opossum, and raccoon respectively had 2839, 1634, and 2592 conflicts reported to Chicago City Services. The mean number of conflicts per 3-month sampling period was 236.58 for coyote (min = 141, max = 392), 136.17 for opossum (min = 85, max = 171), and 260.00 for raccoon (min = 105, max = 355). We collected 9744 camera trap days out of a possible 14,448 days of camera trap sampling (43 survey sites × 12 sampling periods × 28 days). The mean number of operational survey sites per sampling period was 32.92 (min = 30, max = 39). Coyote, opossum, and raccoon were respectively detected on 200, 352, and 408 camera trap days.

Averaged across primary sampling periods, coyote, opossum, and raccoon were respectively most likely to occupy the northeast (Figure 2a), south (Figure 2b), and southwest (Figure 2c) areas of Chicago. Among-season variability in occupancy was relatively low, and as such, changes in a species spatial autocorrelation from one sampling period to the next was minimal (Appendix S1: Figures S2–S4). Overall, average occupancy across Chicago was 0.26 for coyote (95% CI = 0.12, 0.54), 0.23 for opossum (95% CI = 0.14, 0.37), and 0.29 for raccoon (95% CI = 0.18, 0.47).

The occurrence of all three species showed only weak associations with the modeled covariates (Figure 3a). Both opossum ($a_{\mathrm{URB1,opossum}} = 0.22$, 95% CI = 0.17, 0.27) and raccoon ($a_{\mathrm{URB1,raccoon}} = 0.09$, 95% CI = 0.05, 0.13) had a slightly higher occupancy probability with increasing URB1, which represented a gradient of increasing urban intensity (Figure 3). For example, with a one-unit increase in URB1 from an average location throughout Chicago, opossum occupancy increased by 0.04 (95% CI = 0.02, 0.06), whereas raccoon occupancy increased by 0.02 (95% CI = 0.01, 0.02). All three species' occupancies were associated with Chicago's income gradient (Figure 3a). Coyote occupancy was higher as income increased ($a_{\mathrm{income,coyote}} = 0.14$, 95% CI = 0.09, 0.19), whereas opossum ($a_{\mathrm{income,opossum}} = -0.17$, 95%CI = −0.27, −0.07) and raccoon ($a_{\mathrm{income,raccoon}} = -0.08$, 95% CI = −0.16, −0.01)

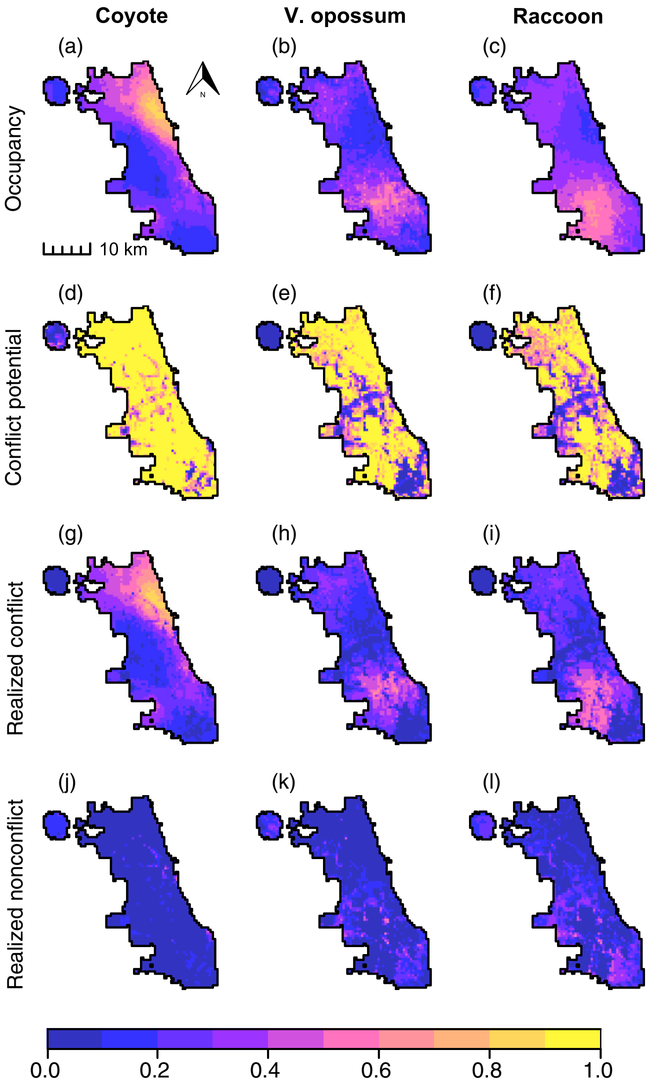

FIGURE 2 Where coyote, opossum, and raccoon most likely occur throughout Chicago, Illinois, and where they are most and least likely to come into conflict with humans. The various subplots indicate the average probability of occupancy (first row), conditional conflict potential (second row), where conflict is most likely to be reported based on their distribution (third row), and where conflict is least likely to be reported based on their distribution (fourth row). These estimates were made with an integrated occupancy model that combined an average of ~2300 wildlife-complaint calls per species that were made to the City of Chicago between 2013 and 2015 with 395 camera trap deployments at 43 unique sites over 12 primary sampling periods during the same time period.

occupancy was lower with increasing income. Finally, coyote occupancy was negatively associated with vacant building reports ($a_{\text{vacancy,coyote}} = -0.16$, 95% CI = −0.23, −0.10), and we failed to detect a relationship with vacancy reports and opossum or raccoon occupancy.

The second submodel represented the probability a Chicago resident would make a nuisance wildlife complaint given that the species occupies that area and is observed. Spatial variation in conflict potential for coyote was strongly and positively associated with URB2 ($b_{\text{URB2,coyote}} = 2.86$, 95% CI = 2.09, 3.63) (Figure 4a), which represented a gradient of either grass or impervious cover when negative to forested areas with higher housing density when positive. We failed to detect a relationship between coyote conflicts and income or vacancy gradients (Figure 3). Opossum and raccoon conflicts were positively associated with URB2, vacancy, and income gradients (Figures 3 and 4). Overall, this resulted in a nearly uniform and high conflict potential across Chicago for coyote (Figure 2d), whereas opossum and raccoon did exhibit some variation in conflict potential based on the three aforementioned gradients (Figure 2e–f). Given the relatively high conflict potential of all three species, the areas where conflict was estimated to be most likely to occur was mostly driven by their respective distributions throughout Chicago (Figure 2g–i). There were, however, some locations throughout Chicago where opossum and raccoon occupancy was high but their conflict potential was low, which were mostly located in small pockets on the South Side of Chicago (Figure 2j–l).

Daily average detection probability via camera trapping varied among species. Coyote had the lowest daily detection probability (0.04, 95% CI = 0.03, 0.07), opossum had the highest (0.13, 95% CI = 0.08, 0.20), and raccoon detectability (0.06, 95% CI = 0.03, 0.10) was slightly higher than coyote. See Fidino (2022) for a summary of all parameter coefficients.

Overall, the model did an acceptable job predicting out-of-sample data for all three species. AUC scores for coyote, opossum, and raccoon were respectively 0.75 (95% CI = 0.66, 0.79), 0.72 (95% CI = 0.68, 0.76), and 0.71 (95% CI = 0.68, 0.78). For a breakdown of the predictive accuracy for each sampling period, see Appendix S2.

DISCUSSION

By combining opportunistic nuisance wildlife reports with systematically collected wildlife survey data, we found that a species' distribution strongly informed where reported human–wildlife conflict was most likely to occur for three common North American mammals throughout Chicago, Illinois (i.e., a species occupancy pattern largely reflects their pattern of realized conflict; Figure 2). However, we did notice that reported conflicts for opossum and raccoon were greatest in high-income areas of Chicago, even though their occupancy probability was low in these locations. Therefore, knowing where species are distributed within a city means, for the most

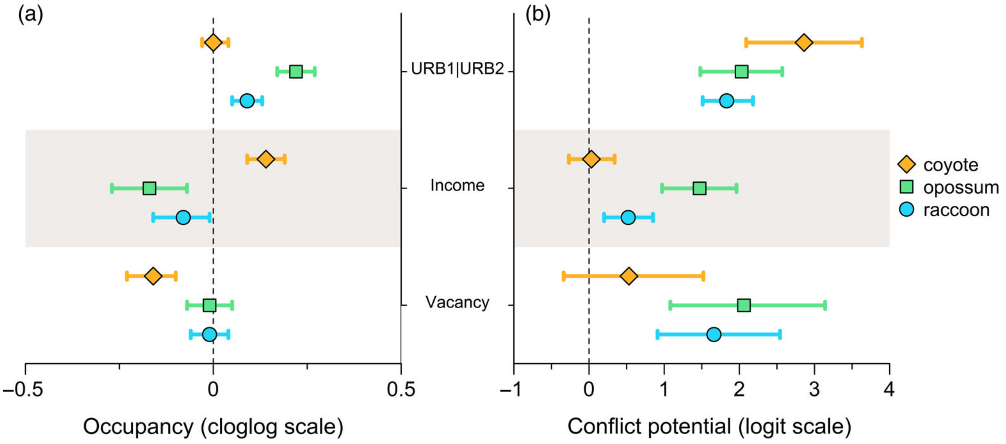

FIGURE 3 Occupancy and conflict potential regression coefficients estimated by the integrated occupancy model for coyote, opossum, and raccoon. The URB1 gradient represented areas of high canopy cover or grass cover when negative to areas of high impervious cover and housing density when positive. The URB2 gradient represented areas of open bare space when negative to areas of high canopy cover and housing density when positive. Income was calculated as median per capita income per square kilometer, whereas vacancy was calculated as the reported vacant building calls to Chicago City Services.

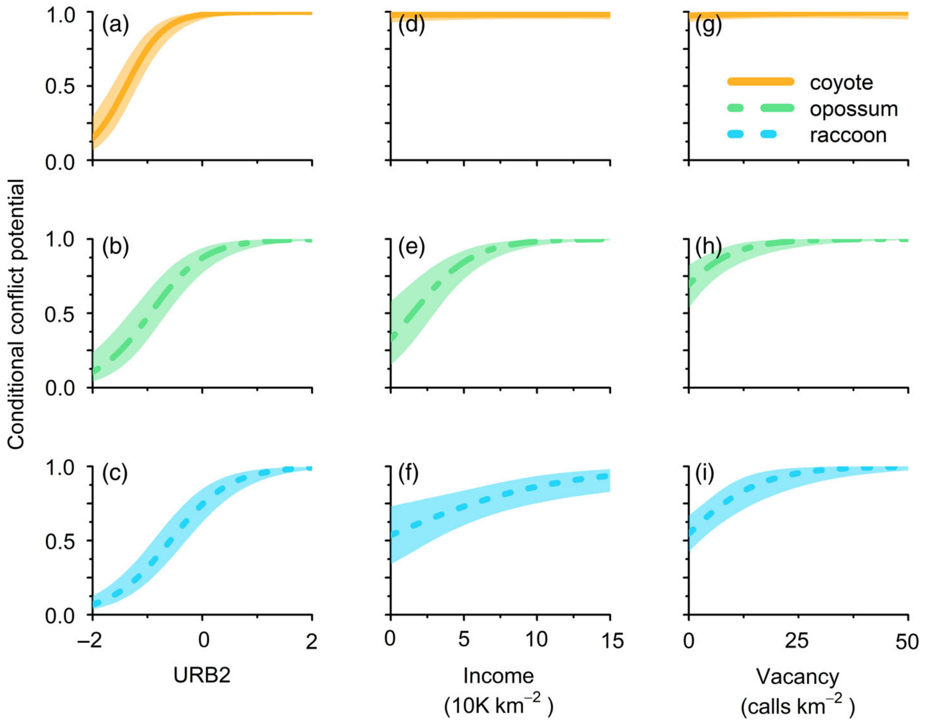

FIGURE 4 (a, d, f) Estimated conditional conflict potential of coyote, (b, e, h) opossum, and (c, f, g) raccoon along three social-ecological gradients. Conditional on their presence, coyote, opossum, and raccoon conflicts were highest in areas of high canopy cover and housing density (i.e., URB2, a–c). Opossum and raccoon were more likely to be reported to Chicago City Services in (e, f) wealthier neighborhoods and (h, i) areas with more vacant building reports.

part, knowing where wildlife management should be focused, though there may be some variability in this relationship along socioeconomic gradients. Just as wildlife research often informs wildlife management at the state or federal level, our results demonstrate the benefits that could be gained when ecologists work with city wildlife management agencies and their data.

We made four predictions related to the social–ecological gradients in our model. Our first prediction was that urban intensity would be the strongest negative determinant of these species' distributions. We did not find this to be true. In fact, we failed to detect a relationship between our urban intensity gradient (URB1) and coyote occupancy, whereas opossum and raccoon occupancy had a small but positive association with URB1. Our previous research showed that the occupancy of these mammals decreased with increasing urban intensity at the scale of the entire Chicago Metropolitan Area (Fidino et al., 2021; Magle et al., 2021). However, we do not believe the current results disagree with our previous findings but instead are indicative of the city-scale focus of this research. Urban intensity is more variable at the scale of the Chicago Metropolitan Area, making it possible to estimate the negative association between species occupancy and urban intensity. However, at the scale of Chicago itself, urban intensity is less variable and greater than the surrounding region. As such, it is likely that these species uniformly respond to the pervasive and heavily built environment within Chicago and increase in occupancy outside of the city. Thus, it is important to consider how landscape-scale features of a study region could influence where species are distributed or how they may respond to varying social-environmental gradients (Fidino et al., 2021).

Our second prediction was that human–wildlife conflict would most likely occur in areas where human and wildlife habitat overlap. Our results support this prediction in that we found strong positive associations between each species' conflict potential and URB2 (i.e., a gradient of increasing canopy cover and housing density). Previous research also found higher levels of conflict when human and wildlife habitats overlapped. For example, human–coyote conflicts were more frequent in suburban areas near greenspace in Denver, Colorado (Poessel et al., 2013), human–black bear (*Ursus americanus*) conflicts were more frequent in areas where people live closer to forests or rivers in Missoula, Montana (Merkle et al., 2011), and human–wildlife conflicts in general were more frequent in suburban and exurban areas throughout a 13-county area of northern New York (Kretser et al., 2008). Though it should not be surprising that the rate of human–wildlife conflict is higher when human and wildlife habitats overlap, the observed similar patterns across a wide variety of urban environments likely indicates that this is a general rule. When human and wildlife habitats do overlap, changing human behavior may be the best course of action to reduce human–wildlife conflict, which could be done through education and local ordinances that outlaw certain behaviors (e.g., feeding wildlife, reducing attractants in yards).

Our third prediction was that reported human–wildlife conflicts in Chicago would be positively related to income, which we observed for opossum and raccoon, even though the occupancy of these two species was lower in high-income areas (Figure 3). Though our model cannot uncover the underlying causes of this pattern, it does point to future areas of research. For example, because income is positively correlated with trust in local government (Rahn & Rudolph, 2005), the positive correlation we observed between nuisance wildlife complaints and income could be an artifact of this relationship (i.e., human–wildlife conflict is underreported in low-income areas). Since the city of Chicago focuses wildlife management on parts of the city with more nuisance wildlife complaints per capita (Murray et al., 2018), wildlife management may be inequitably distributed. One way to investigate this issue would be to survey residents about human–wildlife interactions across an income gradient to determine the willingness of residents to file reports with the City, whether they deal with human–wildlife conflict on their own and regardless of what types of animal behaviors constitute conflict. Not only could such data provide useful qualitative information about whether reported nuisance wildlife complaints track human–wildlife conflict on the landscape, they could also be incorporated into this integrated model to correct for underreported conflicts.

Our fourth prediction was that opossum and raccoon conflicts would be positively associated with the vacant building gradient throughout Chicago. Our results agree with this prediction (Figure 3). Because these species readily use anthropogenic structures as denning sites (Kanda et al., 2009; Larivière, 2004), it may be that vacant properties provide shelter for these species. Living in vacant buildings also puts these species in closer proximity to humans, which could increase human–wildlife conflict. Yet, as we used reported vacant building complaints as a proxy for vacant buildings across Chicago, it may also be that people who were more willing to report vacant buildings are also more willing to report nuisance wildlife. If that were the case, however, we would also expect coyote conflict to be positively associated with vacant building reports, which we did not observe. Nevertheless, though vacant land in urban environments provides a wealth of ecosystem services (Anderson & Minor, 2017), the presence of buildings on vacant land may increase the potential for human–wildlife conflict for some species.

Although nuisance wildlife reports were an abundant and readily available data source, these data have their own limitations. For example, because individual tolerances for wildlife vary (Brenner & Metcalf, 2020), nuisance wildlife reports represent a spectrum of interactions ranging from direct conflict (e.g., property damage) to observational conflict (e.g., a person seeing a species in their neighborhood and reporting it to the city). This spectrum of conflict influences model interpretation, as the estimated conflict potential instead represents a person's willingness to make a nuisance wildlife report irrespective of conflict intensity. A further limitation was that, even with the removal of uncertain species identifications, species misidentification must still be present in these data. One way to address these issues would be to work with city officials and make suggestions on additional types of data to gather when nuisance wildlife reports are filed. For example, asking what the animal was doing that prompted a call or the certainty of the caller's species identification could help subset the data. Doing so could make it possible to generate confirmed cases of human–wildlife conflict, making it possible to use a variety of statistical techniques that could account for false positives (e.g., Clare et al., 2021). Another way to circumvent these issues would be to use a different data source entirely, such as data from commercial wildlife removal services. However, such data may also be subject to their own sets of biases. For example, a company may not service the entire modeled landscape or may not be accessible to low-income residents. Since this model could be extended to incorporate multiple sources of presence-only data, one promising research avenue would be to use multiple sources of presence-only human–wildlife data to estimate where conflict occurs in a landscape.

We demonstrated here how nuisance wildlife reports could be combined with biodiversity monitoring data to estimate where human–wildlife conflict occurs within a species distribution. We believe that this integrated modeling approach can help mitigate human–wildlife conflict for three reasons. First, knowing where to focus wildlife management efforts allows for the strategic use of different management approaches. For example, in areas with a low probability of conflict, it may only be necessary to use educational programs to increase awareness of living with urban wildlife, whereas in areas with a high probability of conflict, educational programs could be used in conjunction with local ordinances to reduce attractants for wildlife (Merkle et al., 2011). Second, this model can be parameterized with the type of data that a city or land manager may already collect, making it easier for ecologists to collaborate with wildlife managers. Finally, because this model must be evaluated across the entire study area, all of the data are already in place to develop spatial predictions of a species distribution and likelihood of conflict (Figure 2). While this latter point may seem minor, maps are a key decision-support tool for wildlife management (Swihart et al., 2020), though their predictive accuracy should be assessed. Thus, we strongly encourage the use of this modeling framework to develop stronger collaborations with wildlife management agencies and conduct research that could mitigate human–wildlife conflict.

AUTHOR CONTRIBUTIONS

Mason Fidino conceived the idea for this manuscript, analyzed the data, and wrote the first draft. Mason Fidino, Elizabeth W. Lehrer, and Seth B. Magle collected the data. All authors contributed substantial revisions to the first manuscript draft.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

All data and code (Fidino, 2022) are available on Zenodo at https://doi.org/10.5281/zenodo.6354467

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