Occupancy of Semi-Aquatic Mammals in an Urban Landscape

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Abstract

Throughout midwestern North American ecosystems, semi-aquatic mammals including beaver (*Castor canadensis*), mink (*Neovision vision*), muskrat (*Ondatra zibethicus*), and river otter (*Lontra canadensis*) co-exist in wetlands. These species are ecologically important through their manipulation of habitats and interactions with other species present. Although natural resource managers in urban ecosystems are interested in semi-aquatic mammals and factors affecting their ecology, few such studies exist in the literature. We studied impacts of restoration practices and other environmental covariates on detection and occupancy of the 4 aforementioned focal species on forest preserves managed by the Lake County Forest Preserve District (Lake County, Illinois, USA). Sign surveys were conducted during December-April in 2018-19 and 2019-20. We quantified 12 variables representing bank measurements, temperature, precipitation, soil type, and survey replicate to inform the detection process and quantified 12 variables representing forest cover measurements, aquatic plant measurements, dominant landcover, restoration practices, and anthropogenic disturbances for the occupancy process. Single species, multi-season occupancy models were run in RStudio using the package *unmarked*. Detection probabilities ranged from 0.10 ± 0.07 for river otters to 0.60 ± 0.03 for muskrats; occupancy probabilities ranged from 0.28 ± 0.18 for river otters to 0.90 ± 0.05 for muskrats. Detection and occupancy were influenced by similar environmental factors (bank measurements, precipitation, and survey replicate for detection; and stream measurements and food availability for occupancy) compared to more rural locations. We provide further evidence that muskrats are urban adapters and document the initial stages of river otter recolonization in the Chicago Metropolitan Area.

Introduction

Wetlands are among the most important and vulnerable ecosystems globally (Williams and Dodd 1978; Mitsch and Gosselink 1993). These ecosystems are critical to the survival of native species, communities, and biodiversity, but threatened by increasing human populations and urban expansion (Alig et al. 2004; Stubbs et al. 2020). Although wetlands are crucial to wildlife, many have been degraded or destroyed for housing, agriculture, roads, and grazing areas, resulting in many becoming fragmented and isolated, particularly in the wildland-urban interface (Williams and Dodd 1978; Stubbs et al. 2020). This isolation can cause wildlife populations to decline or become extirpated (Allan and Flecker 1993) because of decreased dispersal abilities (Ahlers et al. 2016), reduced suitable habitat (Kozaliewicz 1993), or direct mortality. Wetlands also provide subsistence and production materials which can advance social and economic development for humans (Lin et al. 2015). Wetland preservation in urban areas is of increased interest given wetlands' role as buffers against stormwater runoff and for filtration of toxic industrial waste (Lin et al. 2015).

Throughout midwestern North American ecosystems, semi-aquatic mammals such as beaver (*Castor canadensis*), mink (*Neovision vision*), muskrat (*Ondatra zibethicus*), and river otter (*Lontra canadensis*) co-exist in wetlands (Kadlec et al. 2007; Mowry et al. 2011; Ahlers et al. 2016; Holland et al. 2018). These species are important components of wetland ecosystems since they utilize both aquatic

and terrestrial environments (Danell 1996; Snodgrass and Meffe 1998; Bonesi and Macdonald 2004). Therefore, these mammals bridge the gap between both ecosystems and assist in moving nutrients between them (Naiman et al. 1988). Semi-aquatic mammals directly and indirectly manipulate the structure of ecosystems they inhabit through their use of prey, woody species, and forbs (Danell 1996; Simberloff 1998; Holland et al. 2019a). This behavior can alter the biodiversity and richness of plant species (Danell 1996) and restructure wetlands (Snodgrass and Meffe 1998; Law et al. 2019) resulting in landscape modifications which are generally beneficial to biodiversity (Danell 1996; Rosell et al. 2005; Law et al. 2019).

Semi-aquatic mammals play an important role within their habitats but may be negatively affected by the isolation and fragmentation that occurs in urban landscapes (Allan and Flecker 1993; Bonesi and Macdonald 2004; Stubbs et al. 2020). Muskrat use of aquatic and herbaceous plants for food and building material can increase the diversity and abundance of aquatic vegetation (Danell 1996; Larreur et al. 2020). Unlike other semi-aquatic mammalian species, muskrats are not as sensitive to changing habitats and are capable of feeding on invasive species, allowing them to react positively to increased human presence (Cotner and Schooley 2011). Beavers manipulate wetlands to create their own habitats (Simberloff 1998; Snodgrass and Meffe 1998) often resulting in an increase in plant richness and biodiversity, thereby creating suitable habitat for other species (Snodgrass and Meffe 1998; Russell et al. 1999; Holland et al. 2019a; Law et al. 2019). A beaver-impounded pond provides suitable habitat for fish, waterfowl, and herptiles by slowing the water, causing an increase in aquatic plants (Snodgrass and Meffe 1998; Russell et al. 1999; Schlosser and Kallemeyn 2000; Law et al. 2019). Mink are generalists that feed on terrestrial and aquatic prey species (Bonesi and Macdonald 2004; Wolff et al. 2015) and are considered a sub-ordinate competitor, and occasionally prey, to river otters (Sargeant et al. 1973; Bonesi and Macdonald 2004). In rural landscapes, urban areas are often avoided because mink can be sensitive to anthropogenic disturbance and road presence (Ahlers et al. 2016; Holland et al. 2019b). River otters are the apex predator of aquatic ecosystems in much of North America and are strongly affected by the presence of other semi-aquatic species (Bonesi and Macdonald 2004; Feltrop et al. 2016; Holland et al. 2018). Beaver-impounded areas provide favorable habitat for river otter prey (e.g. fish and crustaceans) (Snodgrass and Meffe 1998; Schlosser and Kallemeyn 2000; Holland et al. 2018; Hanrahan et al. 2019), whereas muskrats and beavers create useable den sites (Melquist and Hornocker 1983). Although river otters are resilient to low levels of anthropogenic disturbance and road presence, they are negatively affected as anthropogenic disturbance increases (Robitaille and Laurence 2002; Jeffress et al. 2011; Hanrahan et al. 2019; Holland et al. 2019b).

The Lake County Forest Preserve District (hereafter LCFPD) is a special purpose unit of government in the Chicago Metropolitan Area of Illinois, USA (Glowacki and Preuss 2015; Lake County Forest Preserves 2019) that is interested in conservation of semi-aquatic mammals. The LCFPD is active in restoration of forest preserves, conducting prescribed burns, chemical and mechanical invasive plant removal, and reforestation practices, and is interested in how restoration efforts and other environmental variables affect species' occupancy. Although the benefits of restoration practices such as prescribed burns and invasive species removal have been demonstrated (DeGoliér et al. 2015; Kernan 2015), we are unaware of

any studies of the impacts of these practices on semi-aquatic mammals. Further, most studies of semi-aquatic mammals focus on rural areas (Jeffress et al. 2011; Holland et al. 2018) or smaller urban areas with urban buffers (Stearns and Serfass 2010; Cotner and Schooley 2011; Wolff et al. 2015), unlike Lake County, Illinois. Urban sprawl often results in the fragmentation and destruction of native wildlife habitats while degrading the quality of the remaining habitat through increased nonnative species (Kernan 2015; Linders et al. 2018; Stubbs et al. 2020).

Our goal was to understand how environmental variables, including the implementation of habitat restoration practices, affected semi-aquatic mammal occupancy (MacKenzie et al. 2017) on lands managed by the LCFPD. We hypothesized muskrat occupancy would not differ between restored and unrestored sites (Cotner and Schooley 2011) but occupancy would be higher at smaller wetland sites close to anthropogenic disturbance with more ground cover and aquatic plants (Lacki et al. 1990; Cotner and Schooley 2011; Holland et al. 2019a; Larreur et al. 2020). We predicted beaver occupancy would be higher at sites with greater numbers of saplings, herbaceous cover, aquatic plants, and forested cover (Raffel et al. 2009; McClintic et al. 2014; Holland et al. 2019a; Wang et al. 2019). We also believed beaver occupancy would be higher in larger wetlands with greater stream density (Snodgrass and Meffe 1998). We predicted mink occupancy to be higher in restored sites (Robitaille and Laurence 2002; Jeffress et al. 2011; Haan and Halbrook 2014; Ahlers et al. 2016); sites in areas with lotic water further from anthropogenic disturbance with greater shoreline cover; and areas with relatively high ground cover, forested cover, and stream density (Haan and Halbrook 2014; Holland et al. 2018; Ahlers et al. 2016; Crego et al. 2018; Holland et al. 2019b). We predicted higher occupancy for river otters in restored sites (Robitaille and Laurence 2002; Jeffress et al. 2011; Haan and Halbrook 2014; Ahlers et al. 2016), larger forested wetlands, and areas with lower stream density farther from anthropogenic disturbance (Robitaille and Laurence 2002; Jeffress et al. 2011; Holland et al. 2018; Holland et al. 2019b).

Study Area

Surveys were conducted on properties owned by the LCFPD (Figure 1). Lake County is a highly urbanized environment with a human population of 703,520 (density 613 people/km²), the third-most populous county in Illinois (United States Census Bureau 2018). Lake County has a mean road density of 4.4 km roads/km² and an elevation of 164-260 m. Mean annual precipitation during our study period (Dec-Apr) is 37.0 mm with the high 54.0 mm during March and the low 25.0 mm during February (United States Climate Data 2018). Mean low temperature is -7.7°C and mean high temperature is 6.5°C (United States Climate Data 2018).

The LCFPD owns and manages 62 preserves (126 km²) throughout Lake County (Lake County Forest Preserves 2019). Preserves are a key division of the Chicago Wilderness and are important to native wildlife (Chicago Region Biodiversity Council 1999). Dominant landcover of preserves varies but overall consists of forests and woodlands (34%), wetlands (24%), grasslands (17%), prairies (11%), croplands (9%), and shrublands (3%); other cover types comprise 2% (ESRI 2011). Preserves undergo restoration

practices to restore them to native vegetation communities and create suitable habitat for wildlife (Chicago Region Biodiversity Council 1999; Glowacki and Preuss 2015).

Methods

Survey Site Selection

Survey sites were chosen randomly using ArcGIS (ESRI 2011) based on restoration practices (i.e. prescribed burns, chemical or mechanical invasive removal, reforestation, or combination) implemented within the previous 3 years and their proximity to a water body. Forty-nine sites (24 restored and 25 unrestored) were sampled in 2018-19 and 48 sites (25 restored and 23 unrestored) were sampled in 2019-20. Restored sites had ≥ 1 of the aforementioned restoration activities occurring; it was impossible to separate restoration practices into their own categories given limited locations undergoing these practices on the study area. This number of sampling sites balanced logistical concerns, including availability of restored sites, with statistical power to garner acceptable results (MacKenzie et al. 2017). Half of the sample sites were located in or near lotic areas and the other half in or near lentic areas, as we wished to assess whether this variable affected species' occupancy (Naiman et al. 1988; Kadlec et al. 2007; Jeffress et al. 2011; Ahlers et al. 2016). To maintain independence among sites, all were separated by > 3.5 km; this represents the second largest diameter home range found among our focal species (i.e., river otter) (Gorman et al. 2006) and a meaningful scale for occupancy analysis.

Sign Surveys

Two surveyors visited each survey site 5 times during December-April 2018-19 and 2019-20 with 2 weeks between survey replicates. Surveys occurred during these months due to increased visibility of sign given vegetation was sparse on the landscape (Jeffress et al. 2011). Each site consisted of a 400-m transect with each observer surveying 200 m for each site (Jeffress et al. 2011). Each surveyor walked along the bank and sandbars and looked for sign of muskrat, beaver, mink, and river otter (i.e., tracks, scat, lodging of mammals, and evidence of foraging) (Jeffress et al. 2011; Lesmeister and Nielsen 2011); sign was used as a basis for presence/absence designations of sites for occupancy modeling. For beavers, floating forage items (i.e., a floating piece of foraged-upon vegetation) were not considered given possible origin elsewhere. Surveyors identified all fresh mammal tracks located and determined substrate type (i.e., sand, silt, and clay) to the nearest 10% for track imprints (Jeffress et al. 2011; Lesmeister and Nielsen 2011; Holland et al. 2018). Transects that had measurable precipitation (>1 cm) within the previous 2 days were not surveyed to avoid sign degradation (Cotner and Schooley 2011; Jeffress et al. 2011).

Survey and Habitat Covariates

We measured 12 covariates likely to affect detection of focal species (Table 1) to estimate detection probability (MacKenzie et al. 2017). Detection covariates were associated with temperature, precipitation,

bank measurements, and tracking substrate, where the percentage of substrate for all tracks was measured to the nearest 10%.

We measured 12 covariates likely to affect occupancy of focal species (Table 1) for occupancy modeling (MacKenzie et al. 2017). For aquatic habitat, we estimated channel width (m) in field, and through ArcGIS we measured the area of lakes (ha), density of streams (km of streams/km²) ≤ 50 m from the water's edge along the mainstream channel ≤ 1 km of the surveyed segment, and whether the wetland was lotic or lentic (ESRI 2011; Holland et al 2018). Once per season, we took 5 samples of submerged and emergent aquatic plants 5 m apart at every 100 m interval using a 20 x 50 cm Daubenmire square (Cotner and Schooley 2011; Barela et al. 2016). For terrestrial habitat, we determined the dominant land cover at 500 m and percentage forest cover ≤ 50 m of the water's edge along the mainstream channel ≤ 1 km of the surveyed segment using ArcGIS (ESRI 2011; Holland et al. 2018). Once per season, we sampled the number of saplings with a diameter of 2-10 cm within a 20 m arc from the waters' edge and estimated percentage of ground cover every 100 m (Roberts and Arner 1984; Raffel et al. 2009; Cotner and Schooley 2011; Haan and Halbrook 2014). Five samples of ground cover were estimated using a 20 x 50 cm Daubenmire square held 1 m above ground (Barela et al. 2016) at each location with the midpoint 5 m from the waters' edge and 4 more locations 5 m from the midpoint, including 1 at the waters' edge. To measure the effects of anthropogenic disturbance, we estimated the percentage of developed area ≤ 1 km, road density ≤ 50 m of the water's edge along the mainstream channel ≤ 1 km of the surveyed segment, and distance to the nearest population center of $\geq 2,500$ people (Holland et al. 2018) using ArcGIS (ESRI 2011).

We conducted standard variable reduction procedures to minimize the inclusion of correlated covariates in occupancy analysis. Since covariate data were not normally distributed, we calculated Spearman's Rank Correlation Coefficients (Fowler and Cohen 1995) to assess possible correlation among 5 sets of covariates (waterbody, terrestrial ground cover, aquatic plant vegetation, landscape land cover, and anthropogenic effects) representing 25 total covariates. If pairs of covariates were correlated ($r \geq 0.60$) (MacKenzie et al. 2017; Holland et al. 2019a) the most informative covariate was retained for analysis (Fowler and Cohen 1995; Anile et al. 2020).

Occupancy Modeling

Detection probability (MacKenzie et al. 2017) was estimated for each site, replicate, and species. We also calculated naïve occupancy for each species per study year by dividing the number of sites with detection by the number of sites surveyed (Holland et al. 2019b). Due to restoration completed on sites between study years, some sites were only sampled for 1 season resulting in 44 sites used in modeling. Multi-season occupancy models were conducted in RStudio using package unmarked (RStudio Team 2020). These models estimate detection (p), initial occupancy (ψ), colonization (γ), and extinction (ϵ) probability for each species (MacKenzie et al. 2017). A multi-stage sequential approach was used; first to determine the top model for detection; second to fit the top-ranked model from the detection process to determine the top occupancy model, and then continuing to determine best-fit models for colonization and

extinction (Lesmeister et al. 2015; MacKenzie et al. 2017; Cassel et al. 2020). Top models were assessed for appropriate data dispersion using a MacKenzie and Bailey Goodness of Fit test, using a parametric bootstrap with 1,000 replicates (MacKenzie et al. 2017; Holland et al. 2019b).

Detection models were first run by holding occupancy, colonization, and extinction covariates constant. Detection covariates consisted of 6 data sets (i.e. bank measurements, temperature, last precipitation, 2-week precipitation, observers, and time) totaling 10 covariates. Covariates were run first as single-covariate models and then as multi-covariate in *a priori* models with up to 5 covariates per model (MacKenzie et al. 2017; Anile et al. 2020). Models were ranked using Akaike's Information Criterion (AIC), with the top model based on the lowest value and any model $\leq 2 \Delta AIC$ considered significant (Burnham and Anderson 2004). Where required, models were run as qAIC to correct for overdispersion of data (MacKenzie et al. 2017).

Once the top detection model was determined, occupancy models were run for each species, with the previous top-ranked detection model used as detection covariate, which was kept constant among models, and colonization and extinction kept constant among models (MacKenzie et al. 2017). Occupancy covariates consisted of 5 data categories (i.e., waterbody, terrestrial habitat, aquatic habitat, dominant landcover, and anthropogenic disturbance) totaling 29 covariates. Covariates used within the models varied by species based on *a priori* hypotheses with muskrats using 10 covariates, 8 for beavers, 9 for mink, and 6 for river otters. All covariates were run as *a priori* single-covariate models first, then run as multi-covariate models (MacKenzie et al. 2017; Anile et al. 2020). Overall, 18 models were run for muskrats, 18 for beavers, 16 for mink, and 6 for river otters (fewer models converged for river otters).

Once the top initial occupancy model was determined, colonization models were run for each species, with the previous top-ranked model covariates used for detection and initial occupancy covariates, and extinction kept constant among models (MacKenzie et al. 2017). The same routine was implemented for extinction, using the previous top-ranked model for colonization.

All models were then ranked using AIC and number of parameters within the model to develop parsimonious models (MacKenzie et al. 2017; Campbell et al. 2019). AIC weights for each covariate were summed to determine the covariate or combination of covariates that had the strongest support for occupancy (MacKenzie et al. 2017; Campbell et al. 2019). Parameters with a 95% confidence interval that did not overlap 0 were considered highly significant, those with 85% confidence interval not overlapping 0 were significant, and those overlapping 0 were considered non-significant (MacKenzie et al. 2017; Campbell et al. 2019; Holland et al. 2019b). A goodness-of-fit test ($\alpha = 0.05$) with a parametric bootstrap of 1,000 iterations was conducted on the top model for each species to determine the reasonable chance of the observed detection histories occurring (Campbell et al. 2019; Holland et al. 2019b; Anile et al. 2020). Once the top models were determined for each species, we ran simulations to predict the occupancy and detection probability for each covariate within our competitive models (MacKenzie et al. 2017; Holland et al. 2019b).

Results

Muskrats were detected at 88 of 97 sites and naïve occupancy was apparently similar between study years (Table 2). Muskrats were detected in 256 of 473 surveys, primarily through scat (174 of 256 detections). Beavers were detected at 55 sites; naïve occupancy was slightly lower in 2018-19 than 2019-20 (Table 2). Beavers were detected in 201 surveys, primarily through forage (185 of 201 detections). Mink were detected at 47 sites; naïve occupancy was slightly lower in 2018-19 than 2019-20 (Table 2). Mink were detected in 76 surveys, primarily through tracks (54 of 76 detections). River otters were detected at 10 sites; naïve occupancy was apparently similar between study years (Table 2). River otters were detected in 12 surveys, mainly through tracks (7 of 12 detections). Modeled detection rates ranged from 0.10 ± 0.07 for river otters to 0.60 ± 0.03 for muskrats (Table 2). Modeled occupancy rates ranged from 0.28 ± 0.18 for river otters to 0.90 ± 0.05 for muskrats (Table 2).

Muskrats

Four supported models, including 3 covariates, best described the detection process in muskrats (Supplemental Information). The top model ($qAIC = 368.44$) indicated detection probability had a positive relationship with survey replicate, and a negative relationship with both last precipitation being snow and bank angle (Tables 3 and 4). When snow was present, replicate 5 had the highest detection probability (0.77) with the lowest (0.52) during replicate 3 (Figure 2A). When snow was not present, replicate 3 had the highest detection probability (0.65) with the lowest (0.38) during replicate 1 (Figure 2B). When snow was present, detection probability (0.50-0.39) was highest when bank angle was between 30 and 67 degrees (Figure 2C). When snow was not present, bank angle effect on detection probability (0.73-0.63) was highest between 0 and 30 degrees (Figure 2D). The other 3 competitive models consisted of survey replicate and last snow ($\Delta qAIC = 0.37$), survey replicate and bank angle ($\Delta qAIC = 0.86$), and survey replicate ($\Delta qAIC = 1.82$) (Tables 3 and 4). Muskrat occupancy (Supplemental Information), colonization, and extinction were not affected by any covariates (Tables 3 and 4) and top model had reasonably adequate fit ($P = 0.066$).

Beavers

Three supported models above the null model, including 3 covariates, best described the detection process in beavers (Supplemental Information). The top model ($qAIC = 161.45$) indicated detection probability had a positive relationship with survey replicate (Tables 3 and 5). Replicate 5 had the highest detection probability (0.87) with the lowest (0.64) during replicate 1 (Figure 3A). The second-best model ($\Delta qAIC = 0.52$) indicated detection probability had a positive relationship with survey replicate and a negative relationship with bank angle (Tables 3 and 5). Bank angle effect on detection probability (0.89-0.79) was highest between 0 and 25 degrees (Figure 3B). The third-best model ($\Delta qAIC = 0.75$) indicated detection probability had a positive relationship with both survey replicate and amount of rainfall within the previous 2 weeks (Tables 3 and 5). The 2-week precipitation effect on detection probability (0.78-0.88) was highest between 10 and 17 cm of precipitation (Figure 3C).

Two supported models, including 2 covariates, best described the occupancy process in beavers (Supplemental Information). The top model ($\Delta qAIC = 157.48$) indicated occupancy probability had a positive relationship with stream density (Tables 3 and 5). Stream density effect on occupancy probability (0.82-0.99) was highest between 3 and 6 km of streams/km² (Figure 4A). The second-best model ($\Delta qAIC = 1.92$) indicated occupancy probability had a positive relationship with both stream density and number of saplings (Tables 3 and 5). The effect of the number of saplings on occupancy probability (0.83-0.94) was highest between 200 and 370 trees (Figure 4B). Beaver colonization and extinction were not affected by any covariates (Tables 3 and 5) and top model had reasonably adequate fit ($P = 0.008$).

Mink

Three supported models, including 3 covariates, best supported the detection process in mink (Supplemental Information). The top model ($qAIC = 218.04$) indicated detection probability had a positive relationship with survey replicate and a negative relationship with previous total precipitation (Tables 3 and 6). Replicate 5 had the highest detection (0.39) with the lowest (0.13) during replicate 1 (Figure 5A). Total previous precipitation effect on detection probability (0.39-0.30) was highest between 0 and 3 cm (Figure 5B). The second-best model ($\Delta qAIC = 1.02$) indicated detection probability had a positive relationship with survey replicate (Tables 3 and 6). The third-best model ($\Delta qAIC = 1.46$) indicated detection probability had a positive relationship with survey replicate and negative relationship with the amount of precipitation within previous 2 weeks (Tables 3 and 6). The 2-week precipitation effect on detection probability (0.48-0.33) was highest between 0 and 7 cm (Figure 5C).

Two supported models, including 2 covariates, best described the occupancy process in mink (Supplemental Information). The top model ($qAIC = 212.78$) indicated occupancy probability had a positive relationship with stream density (Tables 3 and 6). Stream density effect on occupancy probability (0.98-1.00) was highest between 3 and 6 km of streams/km² (Figure 6). The second-best model ($\Delta qAIC = 1.77$) indicated occupancy probability had a positive relationship with both stream density and herbaceous cover (Tables 3 and 6). However, because the standard error for herbaceous cover overlapped 0 for both 95% and 80% confidence intervals, this covariate was considered nonsignificant (Table 3). Mink colonization and extinction were not affected by any covariates (Tables 3 and 6) and top model had reasonably adequate fit ($P = 0.073$).

River Otters

In the top model for river otter detection, occupancy, colonization, and extinction (Supplemental Information) were not affected by any covariates (Tables 3 and 7). The top model had reasonably adequate fit ($P = 0.033$).

Discussion

Cross-species themes

Detection and occupancy of semi-aquatic mammals in urbanized Lake County, Illinois, were influenced by similar environmental factors as compared to more rural locations. Detection probabilities were affected by bank measurements and survey replicate. Survey replicates (i.e., for muskrat, beaver, and mink) sampled later in the season had higher detection rates as waterways were unfrozen, allowing individuals to move to terrestrial areas and be detected (Brietzke 2015; Hodder et al. 2016). Although bank measurements generally do not affect detection of muskrats and beavers due to their habit of burrowing in steep banks (Cotner and Schooley 2011; Holland et al. 2019a), we presumed that areas with steeper banks and less substrate availability for burrowing did not retain much sign. This was because sign may degrade more easily on steeper banks or animals will forgo steeper banks for those more easily traversed. Previous studies have shown substrate impacting detection rates of semi-aquatic mammals (Jeffress et al. 2011; Holland et al. 2019b), however the presence of frozen ground precluded the utility of this covariate during our study.

Occupancy patterns of beavers and mink were primarily affected by covariates directly associated with stream measurements, such that sites with greater stream density had higher occupancy. These results coincided with our predictions and other studies (Raffel et al. 2009; Haan and Halbrook 2014; Holland et al. 2019a; Holland et al. 2019b). Higher stream densities allow greater movement between suitable fragmented habitats in urban areas (Williams and Dodd 1978; McClintic et al. 2014; Stubbs et al. 2020) and give the most access to terrestrial and aquatic systems which allows mink to conduct their hunting and avoidance behaviors safely (Bonesi and Macdonald 2004; Haan and Halbrook 2014; Crego et al. 2019).

Restoration did not affect occupancy of focal species. We provide 2 possible explanations for this finding. First, due to our sampling strategy and the general limitation of restored sites on the study area (A. Rutter, Lake County Forest Preserve District, unpublished data), it was necessary to combine several restoration practices into one category of restored sites, as opposed to several categories, to maintain adequate sample sizes of unrestored vs. restored sites for analysis. This combination of differing restoration practices may have precluded a clear signal of the impacts of restoration on semi-aquatic mammals. Second, given the resilience of focal species (perhaps with the exception of river otters, who are in the early stages of recolonizing the region (Bluett et al. 1999, Bluett et al. 2004), it is entirely possible that restoration practices simply had no effect on species occupancy whatsoever. Recent research has indicated semi-aquatic mammals are capable of thriving in habitats once thought prohibitive (Cotner and Schooley 2006; Johnson et al. 2007; Hodder et al. 2018). Even river otters, once thought to be extremely sensitive sentinels of environmental degradation, have shown the ability to recolonize the midwestern United States where habitat was once thought unsuitable (Bluett et al. 2004; Johnson et al. 2007; Nielsen 2016). Although both of these reasons, likely acting concurrently, may have precluded our ability to detect an effect of restoration on focal species, we can conclude that restoration did not negatively impact species' occupancy. Our research here is exploratory; given the dearth of research on how restoration practices affect semi-aquatic mammals, we recommend further work in this area with more tightly controlled experimentation, such as monitoring response of individual animals (e.g., via radiotelemetry) to restoration activities before and after those activities occur.

Environmental covariates did not affect colonization and extinction of any focal species, likely due to having too few survey years during our study. Multi-season occupancy models work best when there are more surveys years, or longer periods between surveys, which allows enough data or time to determine a difference in site presence or absence (MacKenzie et al. 2017). Although multi-season models are not conducive to obtaining colonization and extinction results when surveys are few, we employed them in our analysis because they can improve results for detection and occupancy probability (MacKenzie et al. 2017).

Species-specific themes

Muskrats

Muskrat detection probability in our study ($\hat{p} = 0.60 \pm 0.03$) was slightly lower than other studies (0.78 ± 0.04 , Cotner and Schooley 2011). Detection of muskrats was affected by the last precipitation being snow. Snowfall on lower bank angles caused a decrease in detection, as these areas tend to have the thickest layer of snow which distorts tracks (Jeffress et al. 2011). When coupled with high bank angle, detection probability drastically decreased as less snow accumulated in such areas. Snow also coincided with survey replicate, as earlier replicates with more snowfall had a lower detection rate due to both greater snowfall distorting tracks and frozen wetlands stopping individuals from leaving water ways.

Muskrat occupancy probability in our study ($= 0.90 \pm 0.05$) was considerably higher than other studies (0.59 ± 0.09 , Cotner and Schooley 2011). Occupancy rates can give insight into the abundance of individuals within an area (Stanley and Royle 2005; MacKenzie et al. 2017; Gnanaolivu et al. 2020). Since muskrat occupancy and detection were high on our study area, their abundance was likely also high; resulting in individuals being detected more often (Stanley and Royle 2005; MacKenzie et al. 2017; Gnanaolivu et al. 2020). This likely high abundance of muskrats was also supported during surveys, such that muskrat sign was often found throughout entire transects, whereas sign was found more sporadically for other focal species.

No covariates affected occupancy of muskrats, perhaps due to their nearly ubiquitous presence across the study area. Although models did not support our prediction of muskrats occupying sites closer to urban areas, their high occupancy rate suggests the study area is of the proper habitat for muskrats to flourish. Cotner and Schooley (2011) believed muskrats are urban adapters, which allows them to survive in environments with high human-induced stress (Ditchkoff et al. 2006). Unlike other semi-aquatic mammalian species, muskrats are not sensitive to most changing habitats and are capable of feeding on invasive species, allowing them to react positively to increased human presence (Cotner and Schooley 2011).

Beavers

Beaver detection probability in our study ($\hat{p} = 0.76 \pm 0.03$) was slightly higher than other studies (0.61 , Breck et al. 2012). Detection of beavers was also affected by 2-week precipitation amount, with higher

amounts causing an increase in beaver detection. This increase in precipitation caused flooding to occur at many sites, allowing easier movement and access to trees for forage that were previously ignored or unavailable (Naiman et al. 1988; Holland et al. 2019a). Once flooded, terrestrial systems that were previously unused by beavers due to being too far from water (McClintic et al. 2014), became available as new food sources. This caused an increase in forage sign, even though tracks and scat decreased.

Beaver occupancy probability in our study ($= 0.57 \pm 0.07$) was slightly lower than other studies (0.74 ± 0.06 , Breck et al. 2012). Our prediction that beaver occupancy would be higher in areas with relatively more saplings within the site was supported by the data. Beavers typically favor saplings as a food source over large trees, as they are more easily accessible during winter than herbaceous plant matter (Raffel et al. 2009; McClintic et al. 2014). Although we found numerous trees foraged by beavers, occupancy was not higher in forested areas as predicted. McClintic et al. (2014) found beavers increased home range sizes in fragmented habitats; beavers in our urban study area were probably utilizing both forested and non-forested areas for movement, using the latter to forage for green biomass (McClintic et al. 2014). However, we were unable to model the effects of herbaceous ground cover due to poor model convergence. Although we predicted sites with greater amounts of submerged vegetation to have higher beaver occupancy, we were unable to assess this prediction because water iced up too early during surveys.

Mink

Mink detection probability in our study ($\hat{p} = 0.26 \pm 0.04$) was lower than other studies (0.72 ± 0.03 , Schooley et al. 2012; 0.69 ± 0.02 , Ahlers et al. 2016). Mink detection was also affected by last precipitation amount and amount of precipitation within the previous 2 weeks, with higher amounts of precipitation decreasing mink detection. Even though surveys were not conducted 2 days after precipitation >1 cm, higher previous precipitation may have raised water levels high enough to hide or degrade sign (Schooley et al. 2012). Precipitation over the previous 2-weeks had a similar effect.

Mink occupancy probability in our study ($= 0.57 \pm 0.10$) was lower than other studies (0.93 ± 0.03 , Schooley et al. 2012). Although our prediction that mink occupancy would be higher at sites with relatively high stream densities was supported by our data, prediction that sites with greater ground cover would be occupied at higher rates was not. Even though herbaceous material was included in top models, the covariate itself was not considered significant. Since herbaceous material was widespread throughout our study area, there may not have been a large enough difference between occupied and non-occupied sites to be significant. Although other studies suggested other ground cover types such as boulders, woody debris, and shoreline cover influence mink (Haan and Halbrook 2014), these covariates were insignificant in our analysis, likely due to poor representation on our study area. Shoreline cover made detection highly difficult due to thick ground cover, resulting in poor detection within certain areas. Our predictions that sites with greater forest cover and further from anthropogenic disturbance would have higher occupancy, were also rejected. Although Holland et al. (2019b) found mink preferred forested areas in southern Illinois, this was not the case in our study area. Although forests provide ample resting

and hiding spots via fallen logs (Haan and Halbrook 2014), grasslands within our study area likely provided as much cover. Unlike Ahlers et al. (2016), we did not find covariates related to anthropogenic disturbance to affect mink. Although mink may be negatively impacted by anthropogenic disturbance, our study area was likely too uniformly urbanized to detect this relationship.

River Otters

River otter detection probability in our study ($\hat{p} = 0.10 \pm 0.07$) was lower than other studies (Jeffress et al. 2011, 0.33 ± 0.05) but occupancy probability ($= 0.28 \pm 0.18$) was similar (Jeffress et al. 2011, 0.34 ± 0.03). Since river otter occupancy and detection was exceedingly low, their abundance was likely also low, given that smaller populations will result in individuals being detected less often (Stanley and Royle 2005; MacKenzie et al. 2017; Gnanaolivu et al. 2020). River otter detection was also low for surveys at individual sites, such that sign was only detected once throughout entire transects. These likely rates of detection and occupancy (and thus abundance) also made it likely that no environmental covariates affected occupancy of these species (MacKenzie et al. 2017) as only the null model was supported for occupancy analysis. River otters only recently recolonized the study area (A. Rutter, Lake County Forest Preserve District, personal communication) and therefore were not abundant in our urban landscape (Robitaille and Laurence 2002; Holland et al. 2019b). In fact, the few river otter signs found were within less-urbanized sites where less anthropogenic disturbance occurred (Stubbs et al. 2020). River otters are also notorious for leaving behind little sign, owing to the tendency for numerous individuals to defecate in a single, small area and their tendency to move long distances without coming ashore, lowering their detection rates (Reid et al. 1994; Jeffress et al. 2011).

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Tables

Table 1. Variables used to model detection and occupancy of semi-aquatic furbearers in Lake County, Illinois, USA 2018-2020.

Probability of:	Variable	Class	Source
Detection	Observer: 1	Observer	
Observer			

	Observer: 2		Observer	
Observer	Bank height (m)		Soil	Observer
	Bank width (m)		Soil	
Observer	Bank angle (%)		Soil	Observer
	Maximum temperature (°C)		Temperature	Weather
Underground ^a	Average temperature (°C)	Temperature	Weather	Underground ^a
	Minimum temperature (°C)	Temperature		Weather Underground ^a
	Last precipitation type		Rainfall	Weather
Underground ^a	Rain			
	Snow			
	Last precipitation amount (cm)	Rainfall		Weather Underground ^a
	Last precipitation date		Rainfall	Weather
Underground ^a	2-week precipitation amount (cm)		Rainfall	Weather
Underground ^a	2-week precipitation type		Rainfall	Weather
Underground ^a	Rain			
	Snow			
	Mix			
	Survey replicate		Day	
Observer	Restoration practices	Management	GIS; Modified from	
Occupancy				
LCFPD Restoration Practices ^b	Ground cover (%)	Local	Observer	
	Herbaceous			
	Grass			
	Exposed roots			
	Shrubs			
	Woody debris and boulders			
	Bare ground			
	Shoreline			
	Number of saplings	Local	Observer	
	Dominant landcover	Landscape	GIS; Modified from Lake County	
Landcover Data ^b				
	Grassland			
	Urban			
	Forest			
	Cropland			
	Prairie			

	Shrubland		
	Wetland		
	Percent forest (%)	Landscape	GIS; Modified
	from Lake County Landcover Data ^b		
	Wetland type	Landscape	GIS Interpolation ^b
	Channel width (m)	Landscape	Observer
	Area of lake (acres)	Landscape	GIS
Interpolation ^b			
	Stream density (km of streams/km ²)	Landscape	GIS; %
Streams ^b			
	Aquatic vegetation (%)	Local	Observer
	Emergent		
	Submerged		
	No plants		
	Developed area (%)	Landscape	GIS; Modified
from Lake County Landcover Data ^b			
	Road density (km of roads/km ²)	Landscape	GIS; %
Road ^b			
	Distance to urban area (km)	Landscape	GIS; Lake County
Population Data >2,500 ^b			

^a Weather Underground 2019

^b ESRI 2011

Table 2. Modeled detection and occupancy rates, primary sign (%) found, and naïve occupancy rates (i.e., number of sites where detected/number of sites surveyed) for semi-aquatic furbearers in Lake County, Illinois, USA, 2018-2020.

Species	Detection	Primary Sign	Occupancy		Total	Modeled
	Modeled		2018-19	2019-20		
Muskrat	0.60 ± 0.03	Scat – 65.2	89.8	91.7	90.7	0.90 ± 0.05
Beaver	0.76 ± 0.03	Forage – 92.0	53.1	60.4	56.7	0.57 ± 0.07
Mink	0.26 ± 0.04	Tracks – 71.0	42.9	54.2	48.4	0.57 ± 0.10
River otter	0.10 ± 0.07	Tracks – 58.3	10.2	10.4	10.3	0.28 ± 0.18

Table 3. Results of final models for multi-season occupancy of semi-aquatic mammals in Lake County, Illinois, USA, 2018-2020.

Species	CI does not overlap 0		Variable	β
	Probability of			
SE	95%	80%		
Muskrats	Detection		Survey replicate	0.568
0.093	*			
			Last precipitation: snow	-0.670
0.286	*			
			Bank angle	-0.252
0.115	*			
	Initial occupancy		Null	2.180
0.526	*			

1.170	Colonization	Null	1.280
0.620	Extinction	Null	-2.530
Beavers Detection	*	Survey replicate	0.326
0.110	*	Bank angle	-0.375
0.156	*	2-week precipitation amount	0.364
0.160	*	Stream density	1.893
0.664	*	Saplings	0.723
0.453	*		
0.537	Colonization	Null	-1.070
0.738	Extinction	Null	-2.450
Mink	Detection	Survey replicate	0.374
0.109	*	Last precipitation amount	-0.421
0.171	*	2-week precipitation amount	-0.325
0.164	*	Stream density	4.560
1.910	*	Herbaceous	1.100
1.160	Colonization	Null	-1.270
0.896	Extinction	Null	-3.390
3.840	Detection	Null	-0.966
River otters	Initial occupancy	Null	-2.160
0.910	*		
0.707			

Table 4. Top competitive ($\Delta\text{qAIC} \leq 2$) model results for probability of detection (p), initial occupancy (Ψ), colonization (γ), and extinction (ε) of muskrats in Lake County, Illinois, USA, 2018-2020. Models were ranked based on the lowest Akaike's Information Criterion (qAIC) where $\Delta\text{qAIC} = \text{qAIC}_i - \text{minimum qAIC}$, K = number of parameters, w =qAIC weight, and LL = log likelihood. The variables in the top model for each parameter were represented as (top) in the next modeling step.

Parameter	Model	K	qAIC
ΔqAIC	w LL		

Detection	$\Psi(.) \gamma(.) \varepsilon(.) p(\text{survey replicate} + \text{last snow} + \text{bank angle})$	8	368.44
	0.00 0.28 -174.16		
	$\Psi(.) \gamma(.) \varepsilon(.) p(\text{survey replicate} + \text{last snow})$	7	368.81
0.37	0.23 -175.85		
	$\Psi(.) \gamma(.) \varepsilon(.) p(\text{survey replicate} + \text{bank angle})$	7	369.30
	0.86 0.18 -176.09		
	$\Psi(.) \gamma(.) \varepsilon(.) p(\text{survey replicate})$	6	370.26
1.82	0.11 -177.99		
Initial Occupancy	$\Psi(.) \gamma(.) \varepsilon(.) p(\text{top})$	8	368.44
0.00	0.22 -174.16		
Colonization	$\Psi(\text{top}) \gamma(.) \varepsilon(.) p(\text{top})$	8	368.44
0.00	0.22 -174.16		
Extinction	$\Psi(\text{top}) \gamma(\text{top}) \varepsilon(.) p(\text{top})$	8	368.44
0.00	0.22 -174.16		

Table 5. Top competitive ($\Delta\text{AIC} \leq 2$) model results for probability of detection (p), initial occupancy (Ψ), colonization (γ), and extinction (ε) of beavers in Lake County, Illinois, USA, 2018-2020. Models were ranked based on the lowest Akaike's Information Criterion (qAIC) where $\Delta\text{qAIC} = \text{qAIC}_i - \text{minimum qAIC}$, K= number of parameters, w=qAIC weight, and LL= log likelihood. The variables in the top model for each parameter were represented as (top) in the next modeling step.

Parameter	Model	K	qAIC
ΔqAIC	w LL		
Detection	$\Psi(.) \gamma(.) \varepsilon(.) p(\text{survey replicate})$	6	161.45
0.00	0.14 -73.59		
	$\Psi(.) \gamma(.) \varepsilon(.) p(\text{survey replicate} + \text{bank angle})$	7	161.97
0.52	0.11 -72.43		
	$\Psi(.) \gamma(.) \varepsilon(.) p(\text{survey replicate} + \text{2-week amount})$	7	162.20
0.75	0.10 -72.54		
Initial Occupancy	$\Psi(\text{stream density}) \gamma(.) \varepsilon(.) p(\text{top})$	7	157.48
0.00	0.33 -70.18		
	$\Psi(\text{stream density} + \text{saplings}) \gamma(.) \varepsilon(.) p(\text{top})$	8	159.40
1.92	0.13 -69.64		
Colonization	$\Psi(\text{top}) \gamma(.) \varepsilon(.) p(\text{top})$	7	157.48
0.00	0.33 -70.18		
Extinction	$\Psi(\text{top}) \gamma(\text{top}) \varepsilon(.) p(\text{top})$	7	157.48
0.00	0.33 -70.18		

Table 6. Top competitive ($\Delta\text{AIC} \leq 2$) model results for probability of detection (p), initial occupancy (Ψ), colonization (γ), and extinction (ε) of mink in Lake County, Illinois, USA, 2018-2020. Models were ranked based on the lowest Akaike's Information Criterion (qAIC) where $\Delta\text{qAIC} = \text{qAIC}_i - \text{minimum qAIC}$, K= number of parameters, w=qAIC weight, and LL= log likelihood. The variables in the top model for each parameter were represented as (top) in the next modeling step.

Parameter	Model	K	qAIC
ΔqAIC	w LL		

Detection	$\Psi(.)$	$\gamma(.)$	$\varepsilon(.)$	$p(\text{survey replicate} + \text{precipitation amount})$	7	218.04
	0.00		0.36	-100.47		
	$\Psi(.)$	$\gamma(.)$	$\varepsilon(.)$	$p(\text{survey replicate})$	6	219.07
	1.02		0.21	-102.40		
	$\Psi(.)$	$\gamma(.)$	$\varepsilon(.)$	$p(\text{survey replicate} + 2\text{-week amount})$	7	219.50
	1.46		0.17	-101.19		
Initial Occupancy	$\Psi(\text{stream density})$	$\gamma(.)$	$\varepsilon(.)$	$p(\text{top})$	8	212.78
	0.00		0.34	-96.33		
	$\Psi(\text{stream density} + \text{herbaceous})$	$\gamma(.)$	$\varepsilon(.)$	$p(\text{top})$	9	214.55
	1.77		0.14	-95.63		
Colonization	$\Psi(\text{top})$	$\gamma(\text{top})$	$\varepsilon(.)$	$p(\text{top})$	8	212.78
	0.00		0.34	-96.33		
Extinction	$\Psi(\text{top})$	$\gamma(\text{top})$	$\varepsilon(.)$	$p(\text{top})$	8	212.78
	0.00		0.34	-96.33		

Table 7. Top competitive ($\Delta\text{AIC} \leq 2$) model results for probability of detection (p) and initial occupancy (Ψ) of river otters in Lake County, Illinois, USA, 2018-2020. Models were ranked based on the lowest Akaike's Information Criterion (qAIC) where $\Delta\text{qAIC} = \text{qAIC}_i - \text{minimum qAIC}$, K = number of parameters, w =qAIC weight, and LL = log likelihood. The variables in the top model for each parameter were represented as (top) in the next modeling step.

Parameter	Model	K	qAIC
ΔqAIC	w LL		
Detection	$\Psi(.)$ $p(.)$	5	42.83
0.00	0.26 -15.63		
Occupancy	$\Psi(.)$ $p(\text{top})$	5	42.83
0.00	0.37 -15.63		
Colonization	$\Psi(\text{top})$ $\gamma(\text{top})$ $\varepsilon(.)$ $p(\text{top})$	5	42.83
0.00	0.37 -15.63		
Extinction	$\Psi(\text{top})$ $\gamma(\text{top})$ $\varepsilon(.)$ $p(\text{top})$	5	42.83
0.00	0.37 -15.63		

Figures

Figure 1

Study area, showing location of Lake County, the sites surveyed, and restored and unrestored forest preserves in Lake County, Illinois, USA, 2018-2020.

Figure 2

Relationships between the 3 most supported variables and muskrat detection probability in Lake County, Illinois, USA, 2018-2020. The top competitive models incorporated survey replicate, bank angle, and last precipitation being snow. Dotted lines are 95% confidence intervals.

Figure 3

Relationships between the 3 most supported variables and beaver detection probability in Lake County, Illinois, USA, 2018-2020. The top competitive models incorporated survey replicate, bank angle, and previous 2-week precipitation amount. Dotted lines are 95% confidence intervals.

Figure 4

Relationships between the 2 most supported variables and beaver occupancy probability in Lake County, Illinois, USA, 2018-2020. The top competitive models incorporated stream density (km of streams/km²) and the number of saplings. Dotted lines are 95% confidence intervals for stream density and 80% for number of saplings.

Figure 5

Relationships between the 3 most supported variables and mink detection probability in Lake County, Illinois, USA, 2018-2020. The top competitive models incorporated survey replicate, last precipitation amount, and previous 2-week precipitation amount. Dotted lines are 95% confidence intervals.

Figure 6

Relationships between the most supported variable and mink occupancy probability in Lake County, Illinois, USA, 2018-2020. The top competitive model incorporated stream density (km of streams/km²). Dotted lines are 95% confidence intervals.

Supplementary Files

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- [SupplementalInformation.docx](#)