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Status of river otter populations across New York State

Summary of population surveys conducted by the NY DEC Bureau of Wildlife and SUNY ESF Roosevelt Wild Life Station

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Executive Summary

This research was undertaken to provide robust information on the status of river otter (*Lontra canadensis*) statewide to provide a foundation for management planning and a means of monitoring population change in the future independent of harvest data. Long-term sign surveys (Region 9) provided information on the recovery of otter over time and incidental sightings of otter across the recovery zone were used to map otter habitat. To assess the contemporary status of otter populations across the recovery zone we considered alternative non-invasive survey methods such as camera trapping, genetic capture-mark-recapture, eDNA, and sign surveys, ultimately settling on winter sign surveys within an occupancy modeling framework as the most efficient and effective means for monitoring otter given the large geographic scope of interest.

From the analysis of historical surveys conducted in DEC Region 9 (1997 to 2015), we observed the recovery of the otter population following their translocation to western NY between 1995-2000. For about a decade following translocations, otter remained rare across the landscape, shifting their distribution without increasing the overall number of sites used. We observed a large increase in otter distributions ~2010, with the estimated probability of site use by otter doubling on average (from 0.14 pre-2010 to 0.33 after). From 2013-2015, site colonization and extinction rates, and an occupancy-estimate of population growth, all pointed to population stability and were consistent with our expectations should otter have saturated the available habitat.

Based on the Region 9 survey successes, a broad-scale survey was designed with field surveys carried out by DEC staff and technicians in every region. The broad-scale survey was first deployed during winter 2016-17, with refinements made to the design for surveys conducted during winter 2017-18. Using the 2017-18 data, we estimated a spatially-explicit probability of occupancy by otter, which, given that we likely did not achieve population closure during our surveys, should be interpreted as the probability that otter used a site at least once during the survey period. The average probability of habitat use across Wildlife Management Units (WMUs) ranged from 0.02-0.31 statewide. The mean prediction across WMU's in the recovery zone (mean = 0.16, SD = 0.03) was not statistically different from the mean predicted across southern zone WMU's that have remained open to harvest (mean = 0.17, SD = 0.03; t = 1.31, P = 0.09).

Using occurrence records collected from sign surveys, road kills, trapper by-catch, and opportunistic sightings (N= 185 records collected 2001-2012), habitat suitability for otter was mapped using logistic regression (and after correcting for large-scale sampling biases and fine-scale road biases). Predicted habitat suitability increased nonlinearly with the amount of shoreline habitat and decreased with increasing percentage slope, percentage agricultural land, and road density. A high degree of correspondence was observed between predicted habitat suitability and locations where otter were observed during the 2016-17 broad-scale surveys (R^2 = 0.90). Ultimately, the model indicated that ~50% of the recovery zone is of intermediate to high habitat quality for otter.

Overall, this study indicated that river otter populations have recovered across central to western NY State, and have effectively saturated the available habitat. However, they still remain relatively uncommon across much of this range given the patchiness of available habitat, with the probability of site use by otter declining as road density increases and where forest cover and available shoreline habitat is low. Continued collection of incidental sightings may be useful for informally monitoring otter populations but will not replace formal population survey data needed to track spatio-temporal changes in populations over relatively short time intervals. As a result, bridge-based sign surveys will likely remain the primary means of monitoring otters in areas closed to harvest, and the current study indicates those data are highly compatible with opportunistic sighting records.

The objective of continued analysis is to design an effective means of monitoring potential change in otter populations in the future independent of harvest data, so as to ensure robust populations of otter across the state.

Contents

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Introduction

Once widely distributed across North America (Melquist et al. 2003), river otter (*Lontra canadensis*) were extirpated by the mid-20th century across much of their historic range due to habitat loss, pollution, and unregulated trapping (Conner 1971, Polechla 1990). By the 1930s, otter were considered functionally extirpated across much of NY State (central to western NY) with harvest moratoriums imposed as early as 1936 (NYSDEC 2018). Otter maintained populations that have supported annual harvests in northern and eastern regions of the state (Figure 1). Within a designated 'recovery zone' (Figure 1), attempts to restore otter populations included releases of otter translocated from their strongholds in the Adirondack and Catskill regions. These efforts appeared successful given documentation of otter throughout the region from both survey and public reports. However, monitoring of otter has been inconsistent across the recovery zone and, as a result, insufficient to provide a statistically valid assessment of population status to effectively inform management action. The research reported herein was undertaken to devise an efficient and effective monitoring plan for otter, provide a robust assessment of the status of the statewide otter population at present, and map the habitat available to otter across the state.

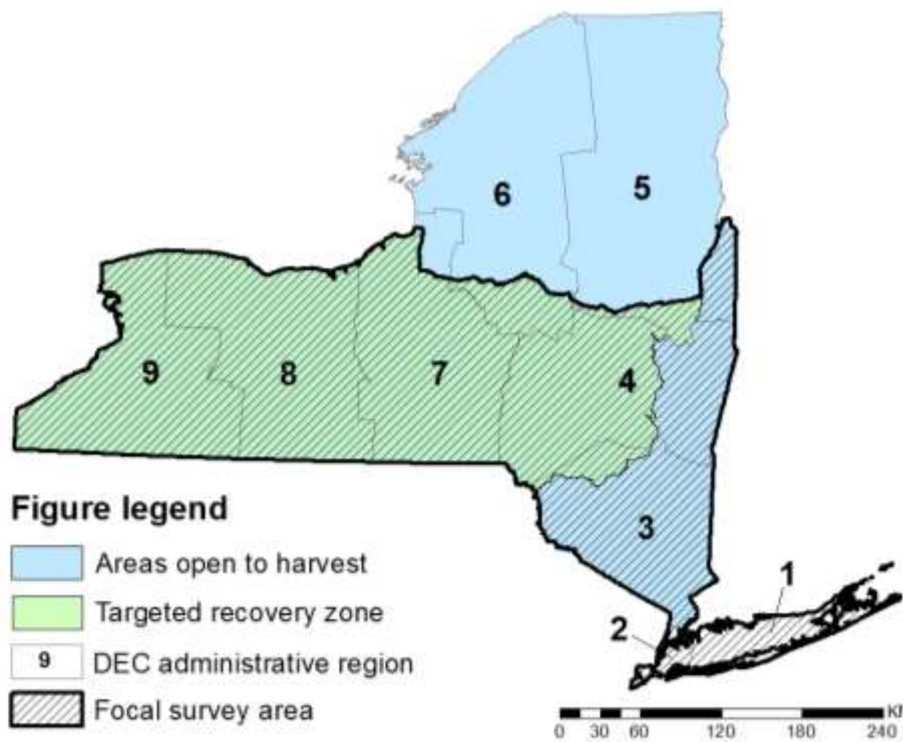

Figure 1. Focal study area for river otter in New York State.

Study objectives

The research objectives summarized in this report were to:

- Examine trends in the river otter population in western New York since 2002.
- Design and implement a robust survey of habitat occupancy by river otter across the focal area to inform contemporary population status.
- Map high quality habitat for otter across the recovery zone.

- Develop a robust protocol for long-term monitoring of river otter in areas closed to harvest.

Additionally, the research team explored the value of alternative methods, namely genetic approaches, camera traps, and incidental sightings as potentially efficient means of monitoring otter distribution and abundance. The results of two of those explorations are available in a M.S. thesis[1], whereas an exploration of eDNA methods in collaboration with Dr. Hyatt Green (SUNY ESF) is ongoing and not covered in this report.

Historic trend in otter populations within the recovery zone

In concert with otter translocations, Bureau of Wildlife staff initiated winter sign surveys for otter in 1997 as a means of monitoring population recovery. Surveys involved a set of road-stream intersections that were each visited once per winter, with 100-m of shoreline searched for otter sign (i.e., tracks or scats). The design of these bridge-based sign surveys preceded modern occupancy modeling approaches. As a result, the repeat survey structure or informative survey covariates required to correct for the probability of otter detection (which certainly varied among sites and over time) was lacking. We explored alternative means of fitting occupancy models to these historic survey data so as to track the progress of otter population recovery over time and provide information on future survey designs.

For this analysis, we focused exclusively on Region 9. Although winter sign surveys were conducted intermittently across the recovery zone, Region 9 staff conducted surveys at 159 sites each year between 1997-1999 and 2002-2015. We limited this analysis to the data from 2002-2015, during which otter were detected at 50 different sites with 2-11 detections per site.

Temporal approach (years as replicate surveys)

To estimate the probability of otter detection, we divided survey years into three different 'periods' spanning 4-5 years each (Figure 2) and used year as a replicate survey within period. Under this design the estimated probability of occupancy (ψ) is correctly

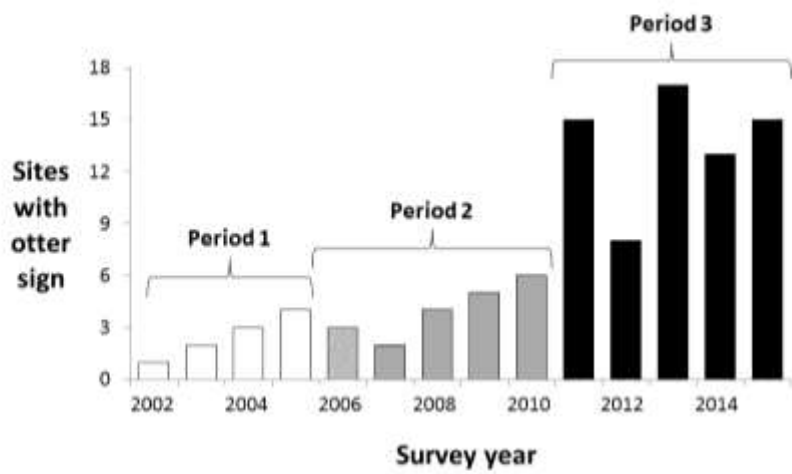

Figure 2. Annual count of survey sites in Region 9 where otter were detected. Periods 1-3 indicate blocks of time within which each annual survey was treated as a replicate survey for each site.

[1] Powers, K. (2018) Monitoring occurrence and habitat use by river otters, *Lontra canadensis*, across New York State. M.S. thesis, State University of New York College of Environmental Science and Forestry, Syracuse, NY.

interpreted as the probability that otter used a given survey site at least once during the survey period. Given that we had 3 survey periods and were interested in population trend, we fit a so-called 'seasonal' occupancy model. Seasonal models estimate the within-period probability of detection ($\hat{p}$) and probability of site occupancy (ψ) as well as between- period probabilities of site colonization (γ) or extinction (ε) and an occupancy-based estimate of population growth (λ).

Table 1. Comparison of alternative multi-season models fit to the Region 9 otter survey sign survey data. For each model, the number of estimated parameters (K), difference in AIC value (ΔAIC) and AIC$_c$ model weight (ω_i) are given.

Model	K	ΔAIC	ω_i
ψ(road5k, shore5k), γ(period), ε(period), $\hat{p}$(period)	9	0.00	0.37
ψ(road1k, shore1k), γ(period), ε(period), $\hat{p}$(period)	9	3.09	0.08
ψ(road5k), γ(period), ε(period), $\hat{p}$(period)	8	3.48	0.07
ψ(shore5k), γ(period), ε(period), $\hat{p}$(period)	8	5.29	0.03
ψ(road10k, shore10k), γ(period), ε(period), $\hat{p}$(period)	9	6.27	0.02
NULL: ψ(.), γ(.), ε(.), $\hat{p}$(.)	4	21.45	0.00

Alternative models were fit to determine whether model parameters varied among periods and, further, the degree to which local landscape conditions affected site occupancy by otter. Site covariates included local elevation, percent slope, and proximity to historic translocation site as well as the percent coverage of agricultural lands or forest, road density, and shoreline density surrounding the site. Shoreline habitat was derived from line features representing rivers, lakes, ponds and open marshes (National Wetlands Inventory data; USFWS 2009) and rivers ≥40-m wide (National Hydrography Data; USGS 2011). These linear features were converted to a 30-m binary raster (shoreline = 1, no shoreline = 0). The proportion of area that contained shoreline within a radius of 1-, 5-, or 10-km centered on each survey site was then calculated. These same radii were also used to quantify percent cover (derived from National Land Cover Data; USGS 2011) and road density variables. Models were fit using Program Presence, and alternative models were compared using Akaike's Information Criterion.

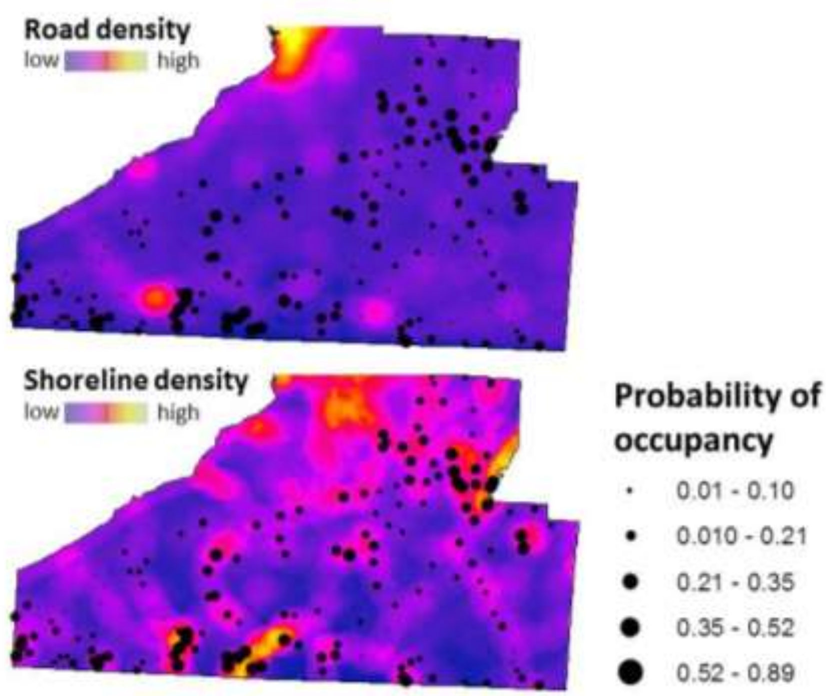

Figure 3. Partial probability of occupancy by river otter as a function of either road density (top) or shoreline density (bottom) in Region 9.

We observed strong evidence that detection, colonization and extinction probabilities varied among periods, and that site occupancy probability varied with the density of shoreline and roads within a 5-km radius of each site (Table 1). The estimated probability of detection increased from 0.22 (95% CI 0.09-0.35) in period 2 to 0.32 (0.23-0.41) in period 3, likely reflecting greater otter abundance across the landscape over time, and consistent with expectations for 200-m long sign surveys for otter in other areas (Jeffress et al. 2011)[2]. We observed a crude occupancy rate (number of sites where otter were detected/159) of only 0.06 during period 1. Low observation of otter in this first period led to a high degree of uncertainty around the estimated occupancy probability during that initial survey period (95% CI 0.04-0.61). *However, as the* population expanded during periods 2 and 3 a sufficient number of otter detections were acquired to achieve informative estimates (crude occupancy rates of 0.14 and 0.25, respectively). The probability of site occupancy declined with increasing road density and increased with increasing shoreline density (Figure 3). Accounting for these spatial differences, the mean predicted probability of occupancy for otter increased from 0.14 (95% CI 0.02-0.26) during period 2 to 0.33 (0.21-0.45) during period 3.

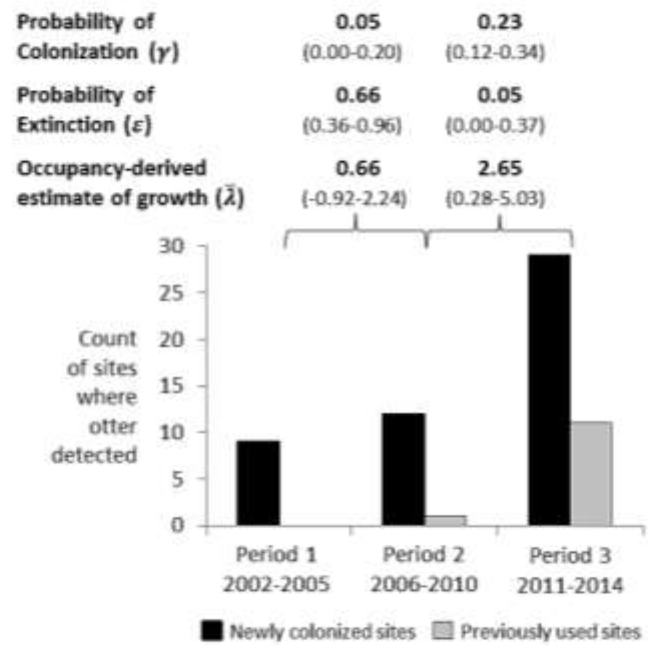

Figure 4. The number of sites where otter were detected for the first time in each period (newly colonized) versus sites where they had been previously detected (previously used). Also shown are the estimated probabilities of site colonization and extinction between periods, and the occupancy-derived estimate of population growth rate between periods (with 95% CI in parenthesis).

Otter remained relatively rare across the landscape through about 2010 (detected at only 9-12 sites in periods 1 and 2). Because roughly the same number of sites was used by otter between periods 1 and 2, we observed negligible population growth ($\bar{\lambda}$ = 0.66, 95% CI -0.92 – 2.24) and a low probability of site colonization (0.05; 95% CI 0.00-0.20). However, otter used different sites in period 2 than they did in period 1 (Figure 4), yielding a high probability of site extinction (0.66; 95% CI 0.36-0.96). These early patterns may have been due to the small population size requiring large movements in search of mates, causing a geographical shift rather than numerical increase in the population through period 2.

In contrast, a high rate of population growth was observed between periods 2 and 3 ($\bar{\lambda}$ = 2.65; 95% CI 0.28-5.03). During period 3 the population seemed to 'settle' (Figure 2), evidenced by resightings of otter at a high number of previously used sites (yielding a low probability of site extinction (0.05; 0.00-0.37; Figure 4). During this time the population also spread into new areas, evidenced by a high

[2] Jeffress, M.R., C. P. Paukert, B.K. Sandercock, and P.S. Gipson. 2011. Factors affecting detectability of river otters during sign surveys. Journal of Wildlife Management, 75:144-150.

number of new sites where otter were detected which yielded a moderate probability of site colonization (0.23; 95% CI 0.12-0.34; Figure 4).

The long-term nature of the sign surveys in Region 9 enabled us to overcome the lack of replicate surveys (using years as replicates) and track growth in the otter population growth following their translocation into western NY. However, expanding surveys to achieve a broader-scale assessment of contemporary status of otter populations required additional exploration of design modifications that would allow estimation of detection probability within a given year, e.g., repeat surveys of a given site or alternative means of estimating detection, e.g., spatial replication.

Spatial approach (sites as replicates within blocks)

We explored spatial replication, i.e., a space-for-time substitution, to estimate occupancy probability using sign survey data from a single year. Under this design, survey sites are grouped within larger sample units, with each additional site serving as a replicate survey to inform both detection probability and occupancy probability of the larger unit.

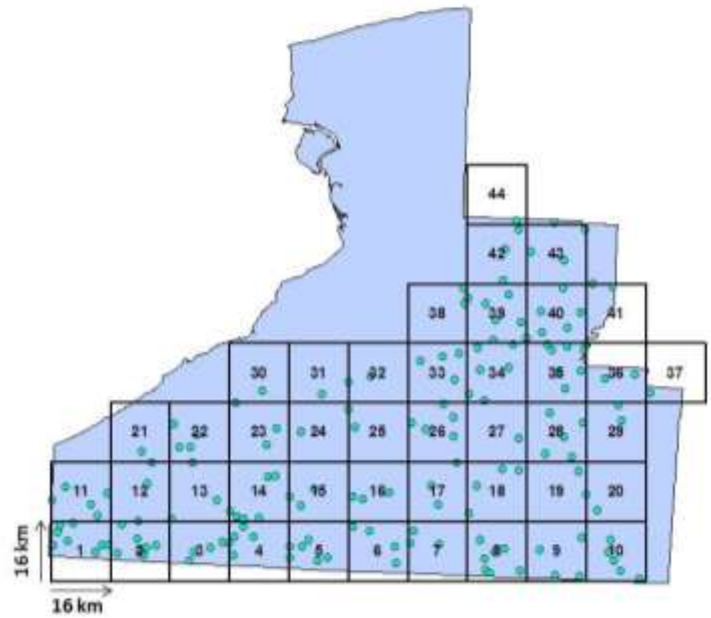

Figure 5. Sample blocks for the spatial replicate design applied to Region 9 surveys. The green dots indicate the survey locations.

To test this approach, we grouped the Region 9 survey sites into 'blocks', 16 x 16 km in size (large enough to encompass the average otter home range). A total of 44 blocks were identified within Region 9, with 1-8 replicate surveys per block (Figure 5). Given the multiple years of survey data available, we applied the spatial replicate approach to each of the last 3 years of surveys (2013, 2014, 2015), and again fit a multi-season model across years, which allowed us to not only estimate detection and occupancy probabilities within each year but also to ascertain whether the contemporary otter population in Region 9 was growing, declining, or stable. We investigated the same site covariates as described previously, but averaged covariate values across survey sites to represent block-level conditions. Models were fit using Program Presence.

Consistent with the temporal replicate model, we observed strong evidence that the probability of otter occupancy at the block level increased with the density of shoreline and decreased with the density of roads (null model ΔAIC ≥ 2.35 compared to top 2 models: Table 2). At the block level, covariates measured over the 5 to 10 km radii were equally informative (ΔAIC = 0.40; whereas the site level analysis indicated 5- and 1-km radii to most informative). There was no indication that colonization, extinction or detection probability varied among our 3 survey years (ΔAIC for best time-varying model = 3.58; Table 5).

Table 2. Comparison of alternative models fit to the spatial replicate surveys for Region 9. For each model, the number of estimated parameters (K), difference in AIC value (ΔAIC) and AIC_c model weight (ω_i) are given.

Model	K	ΔAIC	ω_i
ψ(road5k, shore5k), γ(.), ε(.), $\hat{p}$(.)	5	0.00	0.27
ψ(road10k, shore10k), γ(.), ε(.), $\hat{p}$(.)	5	0.40	0.22
ψ(shore5k), γ(.), ε(.), $\hat{p}$(.)	4	1.31	0.14
ψ(road1k, shore1k), γ(.), ε(.), $\hat{p}$(.)	5	1.78	0.11
ψ(road5k, shore5k, forest5k), γ(.), ε(.), $\hat{p}$(.)	6	1.90	0.10
ψ(.), γ(.), ε(.), $\hat{p}$(.)	4	2.75	0.07
ψ(road5k), γ(.), ε(.), $\hat{p}$(.)	4	3.14	0.06
ψ(road5k, shore5k), γ(year), ε(year), $\hat{p}$(.)	7	3.58	0.04

The estimated probability of detection at the block level was 0.14 (95% CI 0.09-0.19), about half of what we observed at the site level using temporal replicates. This was to be expected given that the probability of occupancy and probability of detection at a site will be to some degree confounded when different sites are visited once in lieu of each site being visited multiple times. Future surveys might increase detection probability by recording informative survey covariates for the detection process (e.g., snow conditions) or increasing the length of shoreline searched (see Jeffress et al. 2011) – considerations we will revisit later.

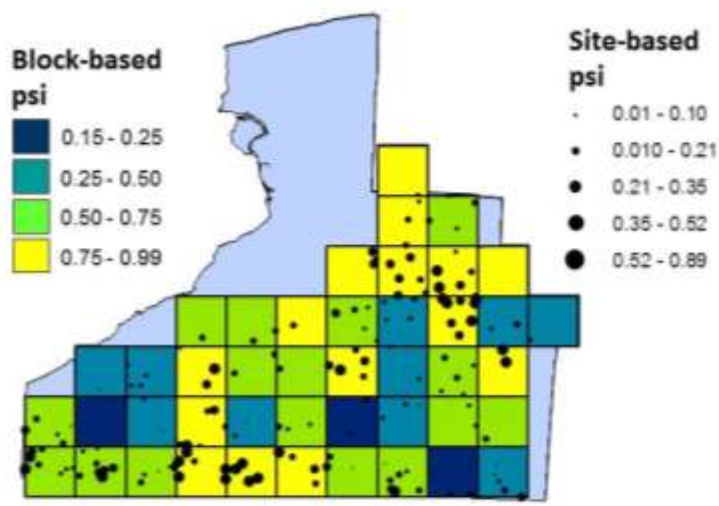

Figure 6. The predicted probability of otter occupancy at the block- and site-level in Region 9.

In any occupancy study, estimates of occupancy probability increase predictably with an increasing sample unit size. So, as anticipated, block-level occupancy predictions were higher ($\bar{\psi}$ = 0.62, 95% CI 0.38-0.84) than the previous site-level analysis ($\bar{\psi}$ = 0.33, 95% CI 0.21-0.45; Figure 6). In other words, whereas 62% of the blocks in Region 9 were predicted to be used at least once by otter within a given survey year, there was a 33% probability that otter used any given site at least once during a longer 5-year survey period (deliberate reference of site 'use' versus 'occupancy' reflects appropriate inference given known violations of population closure assumptions under these survey designs).

Importantly, over the course of these three years, all signs pointed to population stability. The estimated site colonization probability between survey years was 0.00 (95% CI 0.00-0.00), site extinction probability was 0.02 (0.00-0.26), and the occupancy-based estimate of population growth was effectively nill (0.98; 95% CI 0.74-1.22). These results are consistent with a population that has saturated the available habitat.

Given that the spatial replicate approach provided sufficiently precise estimates of detection and occupancy probability from a single year survey, we adopted this approach for broader-scale sampling across the recovery zone.

Broad-scale surveys of otter habitat occupancy

Consideration of alternative approaches

A lack of robust information on population status limits management planning for otter in areas currently closed to harvest across the state (Figure 1). Recent efforts to estimate the abundance of river otter from spraints (using non-invasive genetic sampling and capture-mark-recapture) indicated such approaches to be logistically and financially infeasible given the large-geographic scope of this project[3]. For this reason, we focused on occupancy- rather than abundance-based survey efforts. We further evaluated the efficacy of alternative approaches to detecting site occupancy by otter that included camera trap surveys of aquatic habitat[4] and an ongoing eDNA study.

Camera surveys would enable replicate surveys of a site, with potentially less survey investment than sign-based surveys. Safety considerations limited such surveys to ice-free periods. Even so, surveying aquatic habitats with cameras proved challenging given dynamic water levels and vegetation growth[4]. Ultimately, although camera traps may be useful for determining minimum group sizes and relative otter abundances in local areas of interest, the rate of otter detections in our tests proved too low, and the potential costs too high, to effectively scale this approach up to broad-scale surveys.

Likewise, initial tests of eDNA from water samples at sites known to be occupied by otter failed to detect otter and, as such, was deemed to not be a reasonable means of replacing sign-based surveys. That said, eDNA investigations have continued to look into detection of otter via analysis of soil sediments (where DNA might be concentrated) rather than within the water column. Moreover, eDNA might be useful in combination with snow tracking surveys, not as a means of replacing the effort involved in sign-based surveys (which was our original desire) but as a means of increasing certainty on species detections based on animal sign.

Lacking a more efficacious alternative, we focused on improving the design of winter sign-based surveys for river otter across the focal study area.

Broad-scale survey design

We adapted the spatial replicate (block-based) design used with the Region 9 data into a broad-scale survey covering southern New York State, with a desire for inference from a given single year survey at the level of the Wildlife Management Unit Aggregate (WMUA; Figure 7 top panel). Based on

[3] Burns, E. (2014) Non-invasive techniques for monitoring river otters in the Finger Lakes Region of New York. M.S. thesis, SUNY ESF, Syracuse, NY.
[4] Powers, K. (2018) Monitoring occurrence and habitat use by river otters, *Lontra canadensis*, across New York State. M.S. thesis, SUNY ESF, Syracuse, NY.

the Region 9 survey results, we conducted simulations to help design the most efficient surveys, which involved:

- Quadrupling the amount of effort at a site by increasing the length of the shore searched from 100- to 400-m (expecting to increase the estimated probability of detection[5]).
- Surveying ≥4 sites/block, with sites selected to provide effective spatial coverage of the block (i.e., attempting to survey one suitable location within each quadrant).
- Spreading surveys within a block out in time to ensure independence between snow conditions and occupancy status.
- Surveying each site only once, favoring surveys of additional sites over repeat visits of a given site.
- Employing a removal design such that a given survey site was searched the full 400 m if otter sign was not detected but was terminated at the point where otter sign was detected with a high degree of certainty.

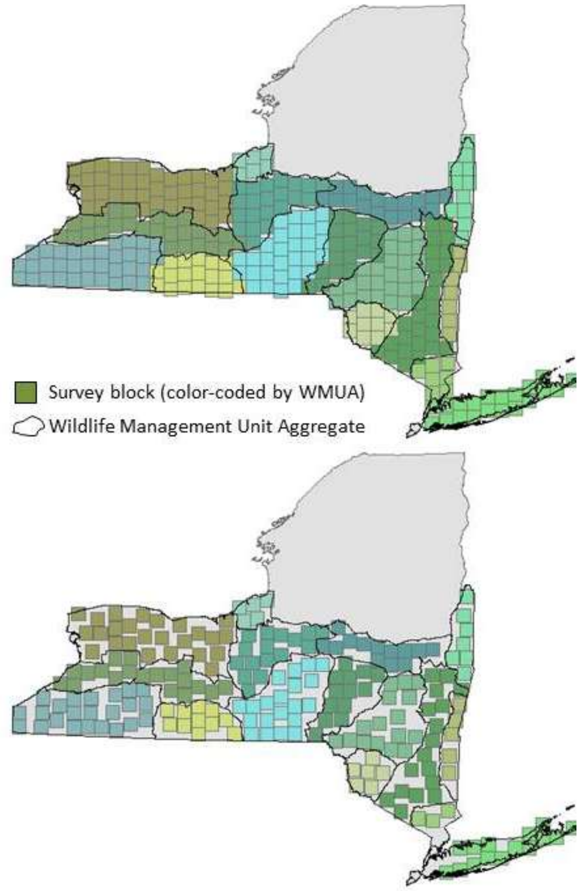

Figure 7. Sign-based surveys to document otter occurrence across New York State during winter 2016-17 and 2017-18.

Further, survey teams recorded survey-specific covariates (e.g., tracking conditions and bank accessibility) to allow the estimated detection probability to vary over space and time, recorded the presence of other species (e.g., beaver whose presence might facilitate otter occurrence), indicated how certain they were with respect to their detection of otter sign (enabling us to choose only the most certain records of otter occurrence for robust data analysis), and took photos of the sign observed (which enabled expert review of their calls).

In the first year (winter 2016-17), field teams surveyed at least one site within the great majority of blocks (90%), but achieved the desired 4+ surveys in less than half of the blocks (48%; Table 3). Importantly, the percentage of blocks within which otter were detected increased steeply as a function of the number of replicate surveys per block (Figure 8), and saturated after 4 surveys were completed. For this reason, in year 2 we reduced the total number of blocks to be surveyed (Figure 7, lower panel) so as to shift effort to repeat surveys within a greater proportion of blocks. We reduced the number of blocks by 34% in year 2 (Figure 7 bottom panel), and shifted the location of blocks to ensure coverage of

[5] Jeffress et al. (2011)

Table 3. Sign survey effort summary by year and DEC region.

	Winter 2016-17 surveys			Winter 2017-18 surveys		
Region	Number of assigned survey blocks	Percent of blocks surveyed at least once (# blocks)	Percent of blocks with ≥4 replicate surveys (# blocks)	Number of assigned survey blocks	Percent of blocks surveyed at least once (# blocks)	Percent of blocks with ≥4 replicate surveys (# blocks)
9	59	92% (54)	59% (32)	37	100% (37)	100% (37)
8	61	100% (61)	84% (51)	41	102% (42)	93% (38)
7	58	88% (51)	10% (5)	38	102% (39)	102% (39)
6	9	133% (12)	83% (10)	9	89% (8)	88% (7)
5	11	--	--	11	100% (11)	100% (11)
4	60	97% (58)	31% (18)	36	100% (36)	97% (35)
3	45	80% (36)	17% (6)	27	78% (21)	5% (1)
1-2	20	90% (18)	89% (16)	15	100% (15)	100% (15)
Totals	323	90% (290)	48% (138)	214	98% (209)	86% (183)
			Percent change over previous year	**–34%**	**+9%**	**+79%**

the entire WMUA while also ensuring that there was at least one accessible survey location within each quadrant of the remaining blocks. In survey year 2 (winter 2017-18), teams surveyed 98% of the blocks at least once and achieved ≥4 surveys within the great majority of blocks (86%; Table 3).

Based on analysis of the first year's survey we further streamlined the record keeping process to increase survey efficiency in year 2 (e.g., recording conditions once for the entire survey rather than every 100-m segment). We continued with the 400-m search effort given that an additional 20% of otter detections were gained with each additional 100-m increment in effort (Figure 9). This pattern of increasing detections with increased survey effort has been consistently observed with otter elsewhere, and importantly, has been shown to be a function of effort only (total area searched) not a bias due to the road-based initiation point of surveys[6].

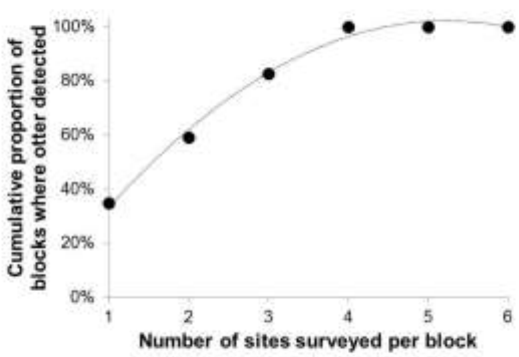

Figure 8. Accumulation curve for the percentage of blocks where otter were detected given effort.

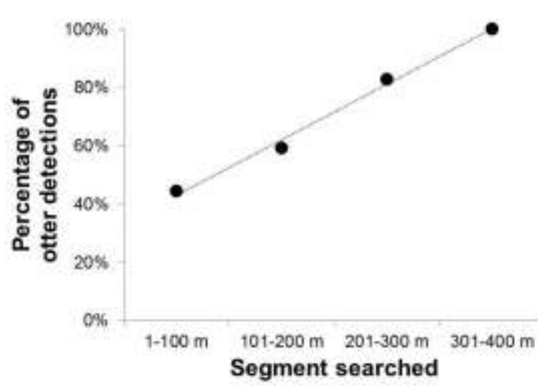

Figure 9. Percentage of otter detections corresponding to each 100-m segment searched.

[6] Jeffress et al. (2011)

In both years, otter sign was widespread across the study region (Figure 10), with otter detected at 8.5 and 12.6% of the sites surveyed in the first and second winters, respectively. Field staff were more experienced in the identification of otter sign in year 2 which, together with potentially better tracking conditions, may account for the ~48% increase in detections between years. Crude occupancy rates (i.e., the number of blocks in which otter were detected ÷ the number of blocks surveyed × 100) were 23.1% and 44.9% in the first and second survey years, respectively. The apparent increase in crude occupancy rate between years likely stems in large part from the greater effort extended per survey block in year 2.

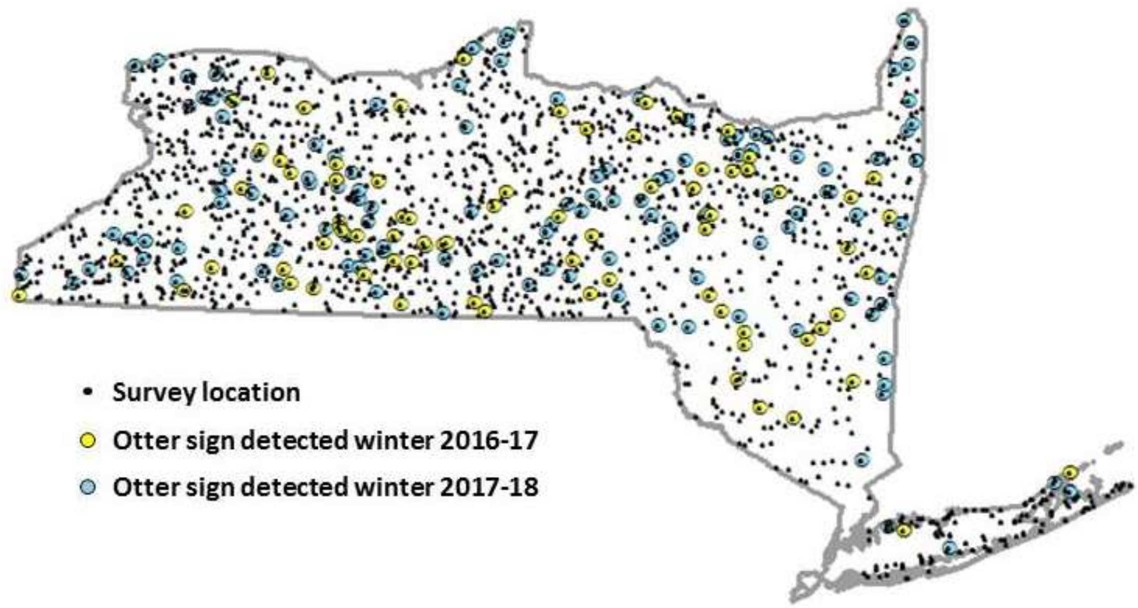

Figure 10. Combined survey locations across the two survey years, with locations where otter sign was detected indicated separately for 2016-17 and 2017-18.

Photo verification of otter detections

Photographic records of putative otter sign were subjected to independent and blind review by 2-3 wildlife experts (A. MacDuff, S. Smith, and M. Clark). Overall, our photo reviewers agreed 76-81% of the time regarding their calls of whether photos documented sign of river otter (Table 4).

Reviewers commented that photos quite often were difficult to draw conclusions from, yet their calls largely corroborated the calls made by field crews (Table 5). Ultimately, where photo evidence was clear, we used the photo call to set the final determination regarding otter detection at a site. However, where reviewers indicated uncertainty in the call or poor photo quality we retained the original field call. For all sites, including those lacking photographs, calls of

Table 4. Percent agreement among expert reviewers on confirmation of otter sign from field photos.

Survey year	# sites with photos	% expert agreement on call
2016-17	74	75.7%
2017-18	218	80.7%

"certain" or "more certain than not" were classified as an otter detection, whereas "doubtful" calls were classified as no detection. Field calls and photo reviewers agreed on these collapsed categories ~78% of the time (Table 5).

Table 5. Percent agreement between field calls and photo review calls regarding detection of otter sign at a site in 2018-19 survey year.

Field crew call regarding otter sign	Photo review call: Otter – yes	Photo review call: Otter - no
Certain	88.6	11.4
More certain than not	59.5	40.5
Doubtful	37.5	62.5
No	16.4	83.6

Collapsed categories	Overall percent agreement
Otter detection	78.5
No detection	77.6

Statistical methods

Given that the spatial replicate approach willingly confounds the detection and occupancy processes, we sought an alternative modeling approach to gain robust inference. Alternatives considered involved the inclusion of informative covariates on the detection process under the spatial replicate approach[7], a multi-scale occupancy approach that would divide surveys into 100-m segments (with each segment considered a spatial replicate at a site)[8], and a time-to-detection approach that estimates detection probability based on the amount of effort (time or, in our case, distance) until the otter detection[9]. Ultimately, we applied the time-to-detection approach with nested random effects to account for the effects of survey design (sites nested within blocks, blocks nested within WMUAs).

Candidate covariates considered to inform detection probability included the number of days since last snowfall, tracking conditions, amount of bank access and detection of either muskrat or beaver (Table 6). Candidate covariates considered to inform the occupancy process included the presence of beaver, site slope and elevation, the percentage of surrounding area (within either 1-, 5-, or 10-km radius buffers) covered by forest, road density within the surrounding area, and the percentage of surrounding area comprised of shoreline (as defined previously in the Region 9 data analysis). As an alternative to the shoreline variable, we also considered the total amount of aquatic habitat defined by rivers and lakes using national hydrography data.

[7] Royle, J.A. and R.M. Dorazio (2008) Hierarchical Modeling and Inference in Ecology: The Analysis of Data from Populations, Metapopulations and Communities. Elsevier Ltd., Burlington, MA
[8] Pavlacky, D.C., Jr., J.A. Blakesley, G.C. White, D.J. Hanni, and P.M. Lukacs (2011) Hierarchical multi-scale occupancy estimation for monitoring wildlife populations. Journal of Wildlife Management, 76(1):154-162.
[9] Kery M, Royle JA (2015) Applied Hierarchical Modeling in Ecology: Analysis of distribution, abundance and species richness in R and BUGS: Volume 1:Prelude and Static Models. Academic Press

Models were fit in a Bayesian framework using non-informative priors. To retain only informative covariates, we conducted Bayesian model selection using an indicator variable approach and retained covariates having a Bayes Factor (BF) > 1.0[10,11]. We conducted model selection for the detection process independent of the occupancy process, then fit the full random effects formulation for both processes simultaneously. Baseline probabilities of occupancy were expected to vary with survey design, so we included random intercepts for blocks nested within WMUA. Moreover, baseline probabilities of detection may depend on the observation team, which varied by DEC region, so we included a random intercept of region in the detection model.

Table 6. Candidate covariates informing detection and occupancy probabilities.

Detection probability	Occupancy probability
Days since last snow (<24 hours, 1-3 days, >3 days)	Habitat type (Lake, pond, marsh, stream, river)
Tracking conditions (poor, fair, excellent)	Beaver detected (1 = yes, 0 = no)
Bank access (<50%, 50-90%, >90%)	Slope (percentage)
Beaver detected (1 = yes, 0 = no)	Elevation (m)
Muskrat detected (1 = yes, 0 = no)	Percentage shoreline[a]
	Area of aquatic habitat[a]
	Percentage forest[a]
	Road density (km/km^2)[a]

[a]Variables measured within 3 different radii: 1-km, 5-km or 10-km.

We gauged that reliable estimates had been achieved given convergence of three independent MCMC estimates, with convergence assessed using the Gelman-Rubin diagnostic ($\hat{R}$)[12]. Generally, we considered a variable to be an important predictor when the 95% credible interval around the estimated parameter did not include zero[12,13]. In practice, we quantified what proportion of a given credible interval had the same sign as the estimated coefficient given that a larger proportional coverage would provide evidence of a trend away from zero.

Model results from the 2018 surveys

Based on our indicator-variable selection process, informative covariates for the process of detecting otter included days since last now and tracking conditions (BF ≥ 2.08). Informative covariates for site occupancy by otter included habitat type, detection of beaver, road density (1-, 5- or 10-km radius), proportion forest (5- or 10-km radius), and proportion shoreline (1-, 5-, or 10-km radius)(BF ≥ 1.02). For the variables measured over multiple scales, we selected the scale having the highest BF for inclusion in the final model.

[10] Kuo L, Mallick B (1998) Variable selection for regression models. Sankhyā Indian J Stat Ser B 1960-2002 60:65–81

[11] Link WA, Barker RJ (2006) Model weights and the foundations of multimodel inference. Ecology 87:2626–2635

[12] Gelman A (2004) Parameterization and Bayesian modeling. J Am Stat Assoc 99:537–545. doi: 10.1198/016214504000000458

The full model successfully converged on parameter estimates (all $\hat{R}$<1.01). The model indicated that the **probability of otter detection** was highest 3+ days following the last snowfall and under excellent tracking conditions (Table 7). Detection of beaver activity at a site increased **the probability of site occupancy** by otter (Table 7). Habitat type was represented as a categorical variable, as such the coefficients should be interpreted relative to the reference category (streams). As a result, with respect to habitat type the probability of site occupancy in rank order from highest to lowest was for ponds, wetlands, streams, rivers, and then lakes. With respect to the larger landscape context surrounding a site, the probability of site occupancy increased with an increasing proportion of shoreline within a 1-km radius, increasing proportion of forest within a 10-km radius, and decreasing density of roads with a 1-km radius.

Table 7. Final model predicting the probability of otter detection and otter occupancy. Shown is the estimated coefficient value ($\bar{\beta}$) for each variable along with the standard deviation (SD), 95% credible interval, and the proportion of the posterior distribution (credible interval) having the same sign as the coefficient (f).

Covariate	$\bar{\beta}$	SD	Posterior credible interval Low (2.5%)	Posterior credible interval High (97.5%)	f
Detection probability					
Intercept	2.095	0.361	1.276	2.711	1.000
Days since last snowfall *(Reference category: >3 days)*					
<24 hours	–1.041	0.355	–1.732	–0.341	0.998
1-3 days	–0.669	0.333	–1.321	–0.011	0.977
Tracking conditions *(Reference category: Excellent)*					
Fair	–0.285	0.335	–0.940	0.395	0.806
Poor	–1.785	0.424	–2.601	–0.934	1.000
Occupancy probability					
Intercept	–2.218	0.546	–3.227	–1.091	1.000
Habitat type *(Reference category: Stream)*					
Wetland	0.692	0.402	–0.088	1.499	0.959
Pond	1.092	0.372	0.379	1.845	0.999
River	–0.238	0.335	–0.905	0.408	0.759
Lake	–0.167	0.579	–1.358	0.919	0.602
Beaver presence	0.393	0.229	–0.056	0.846	0.957
Road density (1-km radius, km/km^2)	–0.230	0.090	–0.418	–0.062	0.997
Proportion shoreline (1-km radius)	18.852	5.353	8.640	29.708	1.000
Proportion forested (10-km radius)	0.658	0.843	–1.153	2.157	0.791

Applying the final model to the landscape indicated, as expected, that the highest probability of otter occurrence occurred within the Adirondack region, Tug Hill Plateau, and Catskill Mountains (Figure 11). Assuming closure, the probability of site occupancy is analogous to the proportion of area occupied by otter. But, given the lack of closure of our sampling design, we interpret these predicted values to reflect the probability that otter used a site at least once during the winter survey period.

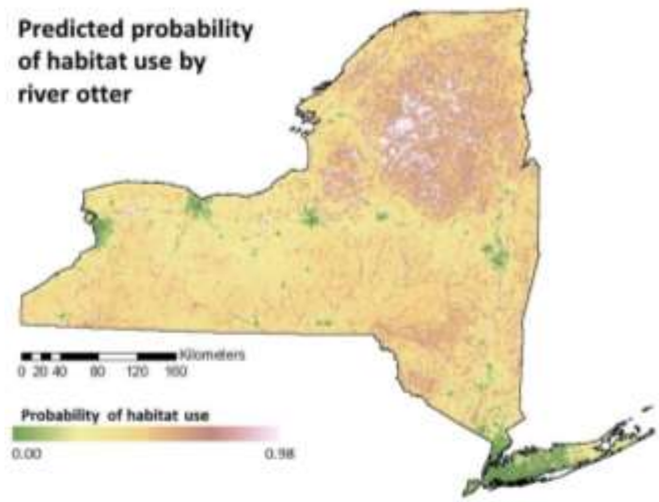

Figure 11. Predicted probability of site occupancy (i.e., habitat use) by otter across NY, 2018.

The mean predicted probability of otter occurrence at the WMU level ranged 0.02-0.31 (Figure 12), and helped differentiate regions where otter probability of use is high (northern harvest zone), intermediate (southern harvest zone and recovery zone), and low (Regions 1 and 2; Figure 12). We detected no statistical differences between the grand mean across the recovery zone versus the southern harvest zone (t = 1.31, df = 73, P = 0.09).

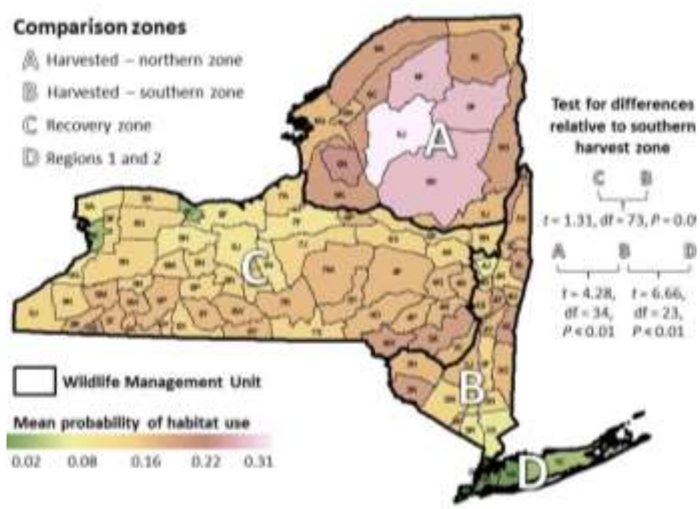

Figure 12. Mean predicted probability of habitat use by otter within each wildlife management unit. Also shown are tests for differences in the grand mean across 4 zones of management interest.

Remaining work

The work remaining to be done involves:

1) Analyzing the 2017 data in the Bayesian model framework, and comparing the 2017 and 2018 results,
2) Using the survey results to design an efficient long-term monitoring plan
3) Continuing exploration of eDNA as a means to improve survey effectiveness

We anticipate completing 1 and 2 above by June 2019, and 3 by December 2019.

Mapping otter habitat

Species Distribution Models (SDMs) are used to detect statistical relationships between locations where species are known to occur and environmental and landscape covariates (Elith & Leathwick 2009). Since 1998, verified records of otter occurrence have been collected across the NY State recovery zone (N = 233 records collected 2001-2012, Figure 13). These data originated from 4 sources: bridge-based sign surveys conducted by DEC staff (46%; surveys involved a single visit to a site/winter with 100 m of shoreline searched/visit), incidental reports from DEC employees (37%), by-catch from trappers verified by DEC staff (13%), and confirmed road kills (4%; A.J. MacDuff, NYSDEC, unpublished data).

A major assumption of SDMs is a constant detection probability over time and space (or that heterogeneity in detection probability is modelled). Standardized surveys typically include a measure of effort (e.g., time spent surveying), local survey covariates known to influence detectability (e.g., proximity of roads, ambient noise levels), or other data related to spatio-temporal variation in detection probability (e.g., number of neighboring blocks in which the species was detected; MacKenzie et al. 2006) as was included in the large-scale sign surveys for otter conducted in recent years. Another important assumption underlying SDMs is that the sample of occurrence records is derived from a random sampling process (Royle et al. 2012), such that each member of target population has a chance of being sampled. With opportunistic records of animal these assumptions are clearly violated, but it does not necessarily follow that such data are not informative with respect to species distributions.

Given that "all models are wrong, but some are useful" (Box and Draper 1987), we conducted ad hoc corrections for obvious sources of bias in incidental occurrence records for river otter across New York, and then applied a rigorous validation approach to evaluate the degree of utility of those bias corrections and model predictions. Two obvious sources of bias were identified: a broad-scale effort bias

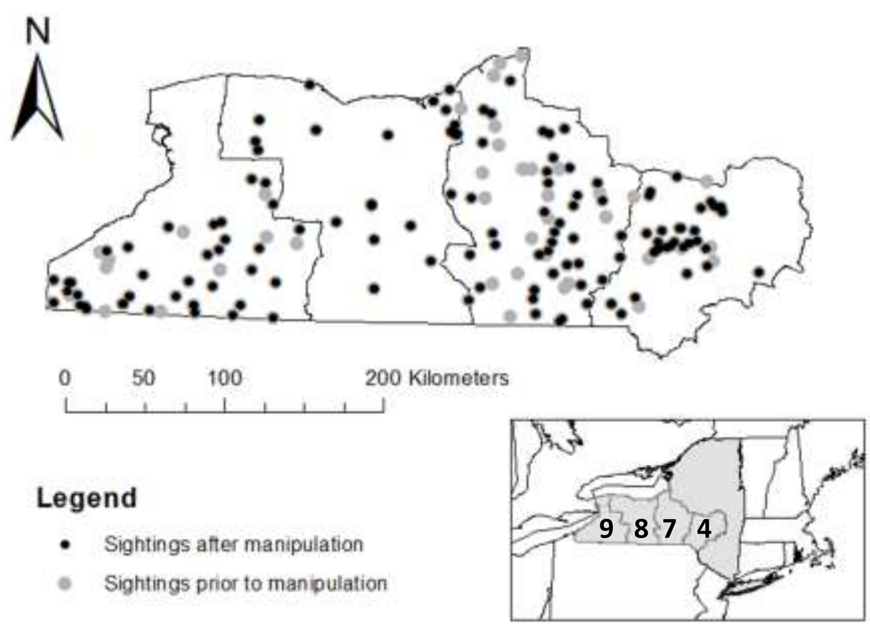

Figure 13. Gray dots indicate 235 verified otter observations prior to effort bias corrections, black dots are the 185 observations after bias correction. Inset map shows DEC regions.

(differences in regional reporting) and fine-scale road bias (with all sightings being tied to areas near roads). To mitigate these biases, we equilibrated observation intensity across regions *a priori* (to 1 sighting/330 km^2; yielding N = 185 observations for modeling) and then restricted inference to readily accessible areas (i.e., ≤700 m from the nearest road, the maximum distance from roads that otter were recorded). We further restricted modeling efforts to winter (November – March), providing the greatest number of records, and for this effort we assumed population closure given that the winter period excluded periods of pup recruitment and the study area was closed to otter harvest. Logistic models were fit to the sightings data using the R package MAXLIKE (Royle et al. 2012) and the covariates described previously. Models were evaluated using Akaike's Information Criterion corrected for small sample sizes (Burnham & Anderson 2002).

Results

Assessment of bias corrections

Refitting the top 10 models to partially- or fully-uncorrected data yielded the same conclusions regarding the set of influential covariates (same top model received >90% of AIC_c model weight in each case), effective covariate form (i.e., nonlinear fit to proportion shoreline detected in all cases), and the direction of coefficient effects (see Powers 2018). However, failing to account for the broad-scale effort bias yielded somewhat greater confidence regarding the top model, likely due to its influence on estimated coefficient values which varied -7.1% to +48.0% after bias correction. In particular, correcting for regional differences in effort substantially modified coefficient values for proportion shoreline. Overall, broad-scale effort bias contributed ~2.5 times more change in observed effect sizes (21.0% on average) as fine-scale road bias (8.4% change on average). Failing to adjust for fine-scale road bias had the greatest effects on degree slope and proportion shoreline, with the least overall effect observed in the road density coefficient.

Important variables influencing otter distribution

Ultimately, the best model received strong support (AIC ω_i = 0.91), with the important

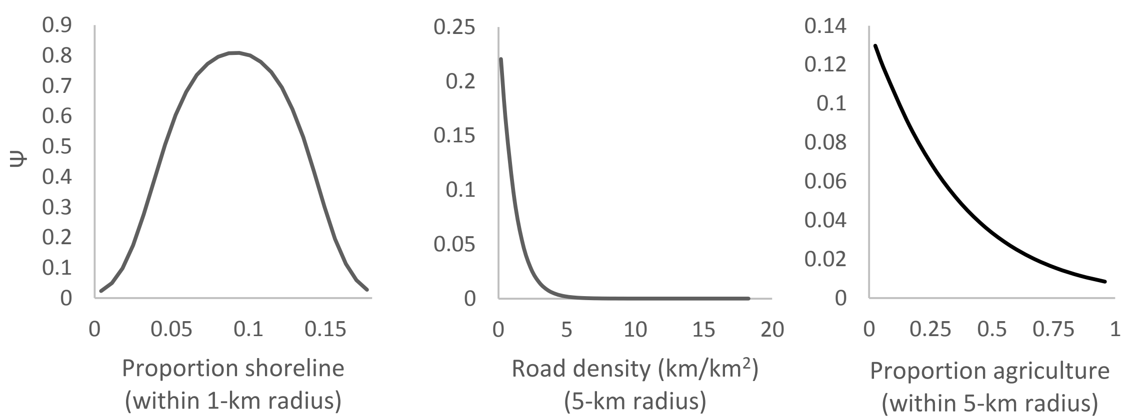

Figure 14. Predicted probability of otter occurrence (ψ; partial slopes) given the covariate indicated.

variables, in declining order of influence, being proportion shoreline (1-km radius), road density (5-km radius), local degree slope, and proportion agricultural land cover (5-km radius). Availability of shoreline habitat was the most influential factor, with a nonlinear response. Holding all other variables at their mean, predicted otter occurrence (ψ) peaked where ~9% of the landscape within a 1-km radius consisted of shoreline habitat. For reference, the great majority (90%) of the landscape included ≤2.8% shoreline, and the maximum amount of shoreline within 1-km radius in the study area was 23%. Collectively, landscapes corresponding with peak ψ included freshwater forest- or shrub-dominated wetlands along the periphery of large lakes and rivers.

Otters avoided areas of high road density as has been observed elsewhere (Robitaille & Laurence 2002, Gorman et al. 2006). Areas with a high proportion of agriculture were also avoided by otters and have similar issues to areas with high road density—e.g., increased runoff, high levels of pollution, and potential eutrophication issues from fertilizer runoff (Wang et al. 1997).

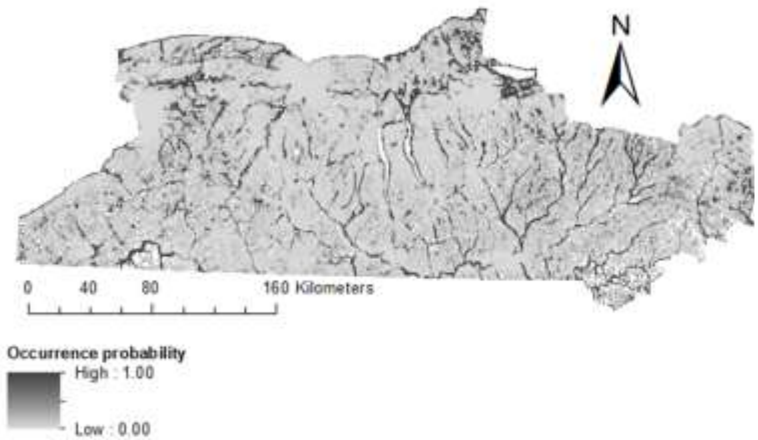

Figure 15. Predicted probability of otter occurrence (ψ) across the recovery zone.

Model validation and classification of otter habitat

Using the most parsimonious model (based on the fully corrected data), ψ was predicted to each 250-m cell across the study area (Figure 15). A set of 57 otter observations were used to validate model predictions following Johnson et al. (2006), with these withheld data having been acquired from the statewide, bridge-based sign survey conducted during winter 2016-17. We observed a high degree of correspondence between expected and observed otter locations (R^2 = 0.90), indicating strong predictive capacity for the model.

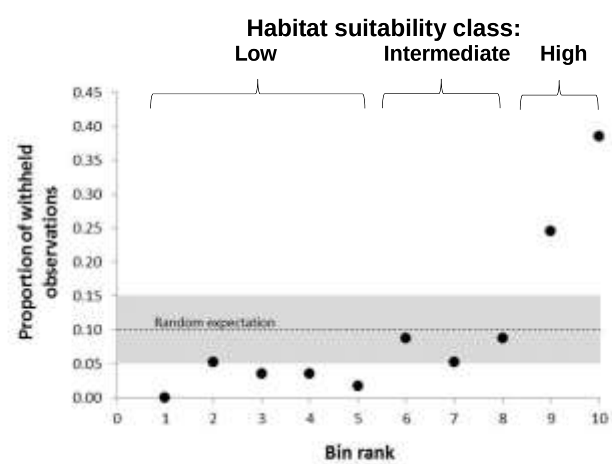

Figure 16. Assignment of bins of predicted ψ into categories of habitat suitability for otter.

Ultimately, predicted ψ was classified into categories representing high, moderate, and low habitat suitability. To identify appropriate cutoffs between categories, I plotted the frequency of withheld otter locations within 10 equal-area bins of predicted ψ such that each bin corresponded to 10% of the areal extent of the study area (following Boyce et al. 2002). Using this convention, by random chance alone one would expect 10% ($p = 0.1$, corresponding to $0.04 < \psi < 0.14$) of withheld otter locations to correspond to each bin (i.e., use ≈ availability). By extension, bins having $p < 0.1$ (i.e., use disproportionately lower than expected) would indicate low habitat suitability (corresponding to $\psi < 0.04$) and bins having $p > 0.1$ (i.e., use disproportionately greater than expected) would correspond to high habitat suitability ($\psi > 0.14$; Figure 16).

The model indicated that ~20% of the targeted recovery zone (~1,000 km^2) is of potentially high suitability for otter, with an additional 30% of the area being moderately suitable (Figure 16). Of course the actual distribution and abundance of otters across this landscape will further depend upon factors not directly modeled in this study such as contaminant levels and prey availability. Importantly, discordance between areas the model predicts as highly suitable and survey returns might be used to identify areas where local site mitigations might be needed to realize otter habitat potential.

Ultimately, the model was extrapolated to map the statewide suitability of habitat for otter (Figures 17,18).

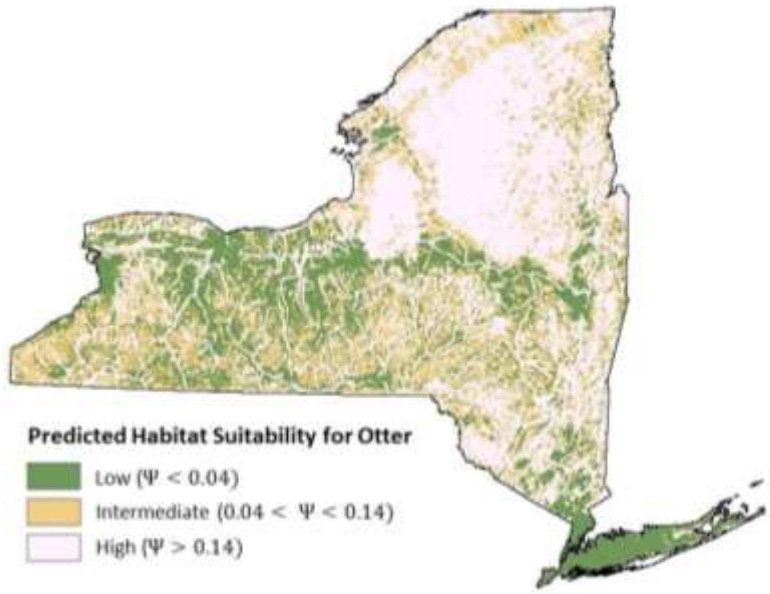

Figure 17. Predicted habitat suitability for river otter.

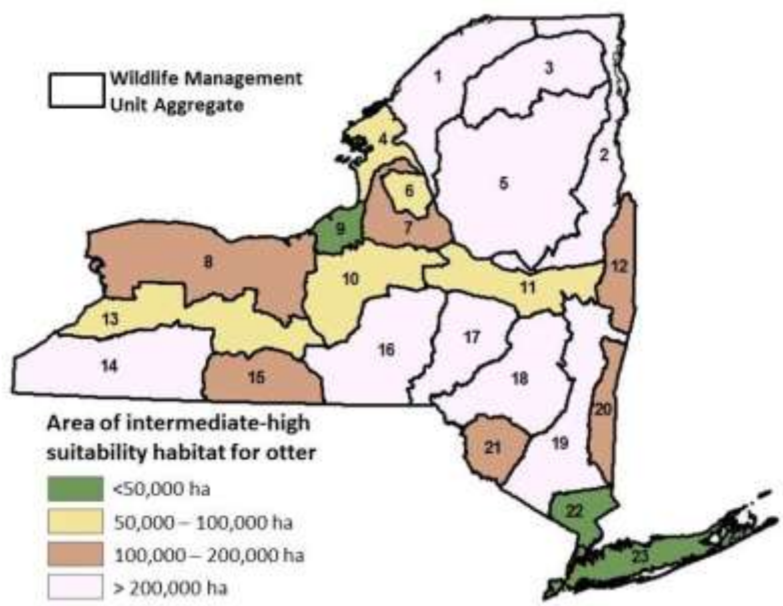

Figure 18. Amount of intermediate-high suitability habitat for otter by Wildlife Management Unit Aggregate.

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Supplementary Information

Raster calculation used to map probability of otter occupancy in ArcGIS.

Exp(- 2.218 + (0.692 * "Logit prediction\wetland") + (1.092 * "Logit prediction\ponds") - (0.238 * "Logit prediction\rivers") - (0.167 * "Logit prediction\lakes") + 0.393 - (0.230 * "Logit prediction\rddens_1k.asc") + (18.852 * "Logit prediction\shore_1k.asc") + (0.658 * "Logit prediction\for_10k.asc")) / (1 + Exp(- 2.218 + (0.692 * "Logit prediction\wetland") + (1.092 * "Logit prediction\ponds") - (0.238 * "Logit prediction\rivers") - (0.167 * "Logit prediction\lakes") + 0.393 - (0.230 * "Logit prediction\rddens_1k.asc") + (18.852 * "Logit prediction\shore_1k.asc") + (0.658 * "Logit prediction\for_10k.asc")))

Distribution of the predicted probability of otter occupancy across NY State, indicating a highly skewed distribution having a mean of 0.18.