Animal Conservation

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Integrated Species Distribution Model Using Historical Data Shows Decline in a Common Semi-Aquatic Mammal

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ABSTRACT

Effective conservation requires an understanding of drivers of a species' distribution as well as long-term changes in their distribution. In recent decades, advances in data collection and analysis have allowed researchers to integrate a wide range of information to model species distributions, particularly by allowing presence-only data and detection-nondetection data to be formally combined in integrated species distribution models (ISDMs). However, these models are rarely used to investigate long-term trends, which are important in evaluating a species' status. Here, we use historical presence-only data of river otters (*Lontra canadensis*; 366 latrine locations from 1999 to 2007 and 105 locations of road-killed individuals recorded from 1999 to 2020) and 919 detection-nondetection surveys from 230 sites between 2021 and 2023 to understand the current distribution of river otters in Rhode Island, USA, as well as the changes in river otter distribution over the past two decades. We found that river otters were strongly associated with key habitat features such as streams and water, positively associated with urban areas, and tolerant of some contaminants, such as lead. Furthermore, despite uncertainties in historical river otter occurrence, we found clear supporting evidence that river otter intensity of use had declined from 1999 to 2023. This decline occurred despite being protected from harvest and in contrast to range expansions in other parts of the northeastern USA throughout the second half of the 20th century. Our results suggest the utility of this approach to detect declines in species for which historical data are available and a need for better understanding the cause of river otter declines. Where monitoring consists of opportunistically collected data, species conservation could benefit by continuing to collect these data as well as introducing designed surveys, as this would allow better integration of data types, improving trend estimation and reducing the amount of (typically more expensive) designed surveys needed.

1 | Introduction

Animal conservation relies on accurate information about a species' distribution and population dynamics. This provides information to wildlife and land managers on where to target interventions to support species occurrence and to understand when habitat or population interventions may be required (Elith and Leathwick 2009). In recent decades, advances in data collection (e.g., remote camera trapping, widespread citizen science programs, passive audio recording) and methodology (e.g., occupancy modeling (MacKenzie et al. 2002), species distribution models (SDMs; Elith and Leathwick 2009), and integrated species distribution models (ISDMs; Dorazio 2014)) have allowed more rigorous evaluations of the relationship between the locations in which species are found and remotely mapped landscape features. In particular, the ability to use ISDMs to combine presence-only data from disparate sources with detection-nondetection data allows researchers to leverage the wider coverage in both time and space typical of opportunistically collected data (which are typically presence-only) and the greater confidence in the results from designed studies (Dorazio 2014; Koshkina et al. 2017; Fletcher Jr. et al. 2019; Miller et al. 2019).

To date, most ISDMs have leveraged large data sets from a short time span, allowing inference to be a static snapshot of a species' distribution (Miller et al. 2019; Fletcher Jr. et al. 2019; Emmet et al. 2023), or have used historical data and assumed that the species distribution is constant over time (e.g., Schank et al. 2017; Landau et al. 2022; but see e.g., Twining et al. 2024; Strebel et al. 2022 for examples with year included as a random effect). Historical data are often widely available through museum records and online databases; less available, but just as abundant, are data on species presence, opportunistically collected by individuals or by wildlife agencies. Typically, each of these types of opportunistically collected data has a sampling bias (such as towards area more frequently included in checklists) that must be corrected for to avoid biased estimators of species distribution (Rota et al. 2011; Dorazio 2014; Fletcher Jr. et al. 2019). Combining historical records and designed studies can improve the precision of SDMs by better accounting for imperfect detection in the historical data (Miller et al. 2019); however, if the species' distribution has changed over the time period in which the different data sets were collected, the assumption of a static distribution may lead to inaccurate or imprecise estimates. Additionally, changes in a species distribution are of interest in themselves; declines in species' area of occupancy or extent of occurrence are criteria for listing on the IUCN Red List (IUCN 2001) and changes in the response of the species to landscape features may reflect important changes in the species' ecology that are relevant to its conservation. Dynamic occupancy models (MacKenzie et al. 2003) require systematic sampling done repeatedly over time, which can be expensive and often do not occur over long time periods (e.g., decades). However, many managers have access to historical records that are less systematically collected and have or could obtain records from designed surveys over shorter time periods; this provides an opportunity for managers to combine these sources of information to estimate trends for many species whose conservation status is not well understood. Although rarely used for this purpose, ISDMs can be effective at analyzing changes in the distributions of species with long time series of spatial data but which lack repeated, standardized surveys across time (Grattarola et al. 2023).

We focus here on applying an ISDM to river otters (*Lontra canadensis*) in Rhode Island, USA. River otters are a common, semi-aquatic mustelid found across much of North America (Melquist et al. 2003). Although river otters are primarily aquatic, they are able to cross land barriers between water bodies and watersheds and consume large amounts of fish, bivalves, and other aquatic prey, traits which make them important predators within freshwater aquatic habitats (Melquist et al. 2003; Cote et al. 2008). Across much of their distribution throughout North America, river otters are trapped for their fur, which contributed to declines in parts of their native range into the mid-twentieth century (Melquist et al. 2003; Roberts et al. 2020). More recently, river otter populations have rebounded in many parts of their range and expanded into areas they were previously extirpated from, such as the southwest U.S. (Melquist et al. 2003; Polechla et al. 2004; Converse et al. 2014), Midwest U.S. (Raesly 2001; Melquist et al. 2003; Ellington et al. 2018), and Long Island, New York (Bottini 2019). River otters are typically found in wetland habitats, are cryptic, and often occur at low densities (Day et al. 2016). As such, they are unlikely to be detected in line transect or camera trapping studies intended to capture a wide range of species if these studies are not designed to include wetland areas.

In the state of Rhode Island, river otters are widespread, but their population status is unknown. The intentional harvest of otters was banned in the state in 1971, which has allowed the population to be relatively unimpacted by trapping but has also made the river otter population more difficult to monitor since it limits the availability of harvest data, the primary data source available for many furbearers in the state. However, since 1999, state biologists have kept opportunistic records of two types of river otter data: latrine locations and roadkill locations. Here, we combine these historical data sources with detection-nondetection surveys conducted in 2021–2023 to model the relationship between river otter occupancy and landcover covariates and to estimate changes in otter occupancy over two decades. Our objectives were to aid river otter conservation by identifying areas of the state, landcover classes, and attributes of water bodies that were strongly associated with otter presence and by evaluating river otter occurrence trends in Rhode Island, which may inform managers' conservation decisions.

2 | Methods

2.1 | Site Selection

We sampled sites for semi-aquatic mammals (river otters, beavers (*Castor canadensis*), and muskrats (*Ondatra zibethicus*)) throughout Rhode Island's contiguous terrestrial landscape, including all parts of the state draining into Block Island Sound (excluding Block Island) and Narragansett Bay via the Blackstone River or streams to its west and south (Figure 1). We established a grid covering the sampling area with each grid cell being square with sides of 0.5 km in length, which roughly corresponded to the home range size for beavers and muskrats (Allen 1982; Ahlers et al. 2010; McClintic et al. 2014; Ganoe et al. 2021; Matykiewicz et al. 2021). Sites (i.e., cells from this grid) were available for selection if they had at least 5% of their area covered by wetland or water and less than 95% of their area covered by water. Due to concerns about excluding streams, which are used by all three species, we also included sites that did not meet these criteria but had at least a second-order stream present. Because river otters have large home ranges (Gorman et al. 2006; Crowley et al. 2017) relative to the other species we sampled for, we also imposed a larger grid on the sampling area, with sides of 1 km in length, and used this larger grid in our analysis of otter data (i.e., surveys from all four

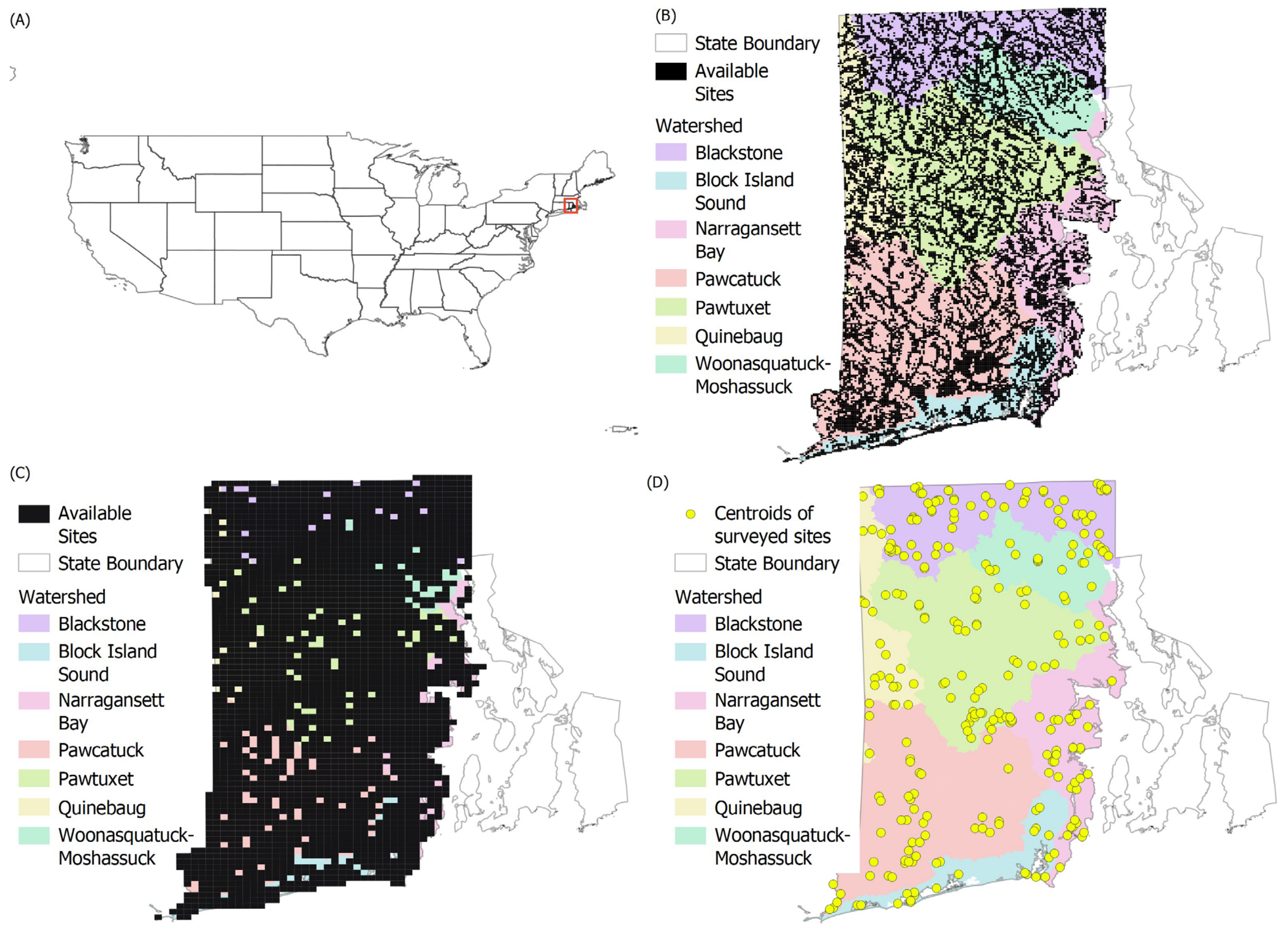

FIGURE 1 | Maps of the study area within Rhode Island, USA. (A) shows the location of Rhode Island within the continental USA (within the red rectangle). (B) shows the 0.25 km^2 sites available for detection-nondetection sampling of river otters, (C) shows the km^2 sites used in the integrated species distribution model, and (D) shows the locations of centroids of 0.25 km^2 sites surveyed.

small sites that comprised a larger site were counted as detections or nondetections of the larger site), resulting in 2301 larger sites.

2.2 | Landscape Covariates

We initially defined the sampling frame by calculating the proportion of each site covered by each landcover class in the Land Use and Landcover (2011) dataset available from RIGIS (RIGIS 2014). To understand the relationship between otter occupancy and landcover, we used the National Land Cover Database (NLCD; USGS 2003; Dewitz 2021). The NLCD has landcover classifications for several years between 2001 and 2019 using similar methodologies and classifications, which allows valid comparisons between different time frames (Dewitz 2021). We reclassified the NLCD data from each available year into 5 classes: open water, open wetland, forested wetland, urban (any "developed" classification in the original data), and other. We then calculated the proportion of each of the 2301 larger sites covered by each landcover class in each year for which NLCD data exist using the exactextractr (version 0.10.0) package (Baston 2023) in R version 4.2.1 (R Core Team 2022). Since otters are wetland obligates, we hypothesized that there would be a positive relationship between otter presence and the proportion of the site covered in water and wetlands. Although otters can tolerate urban areas (Mech 2003; Gallant et al. 2009; DeNeve Weeks 2020; Nixon et al. 2024), urban areas present a variety of threats to otters (e.g., vehicle strikes) and urban streams may have fewer prey species available (e.g., Johnson et al. 2013; Monteiro Pierce et al. 2020; but see Meng et al. 2002); these threats may not be adequately captured by other variables in our model, so we expected a negative relationship between otter presence and the proportion of a site classified as urban.

River otters use both fresh and salt-water areas, but salt-water areas of Rhode Island are often very different in both their abiotic (i.e., many areas have high salinity or significant wave action) and biotic features, so river otter use may be different between salt and freshwater areas. Because the NLCD does not distinguish between fresh and salt water, we used the RIGIS 2011 data to create an indicator variable that was equal to 1 for sites that contained salt water, intertidal rivers and creeks, salt marsh, or intertidal areas, and 0 otherwise. Additionally, we included an indicator of whether the site contained a second-order or greater stream, which we expected would be used by river otters as a corridor for movement but which was not always large enough for a pixel in the NLCD raster to be classified as water or wetland. To understand patterns of river otter intensity of use that may not be apparent from landcover associations, we also included an effect of watershed; although many of the differences between watersheds in Rhode Island are evident in the landcover classifications, other patterns of high or low river otter use may help focus conservation efforts or future research.

River otters may respond to aspects of habitat quality that are not captured by landcover covariates, such as water quality and prey availability. The state of Rhode Island monitors for water quality in many ponds and streams throughout the state, and records of the results of this monitoring are available in the RIGIS Rivers and Streams (RIGIS 2023b) and RIGIS Lakes and Ponds (RIGIS 2023a) datasets. These data include the designated use for each water body (e.g., fish and wildlife habitat, drinking water supply) and list any impairments that prevent the water body from achieving the standards required for its designated use. We used these listed impairments to generate water quality variables reflecting whether the site contained a water body that did not meet water quality standards due to the presence of elevated levels of lead (Pb), mercury (Hg), other metals (i.e., aluminum, iron, copper, zinc, and cadmium), polychlorinated biphenyls (PCBs), or non-native plants; due to low levels of dissolved oxygen (DO_2) or benthic invertebrates; or due to the presence of fecal indicator bacteria (coliform bacteria or *Enterococcus* spp). We also included an indicator of whether the site contained a water body that had been stocked with hatchery-raised trout. We expected that river otters would respond negatively to the presence of elevated levels of metals and PCBs because many of these contaminants bioaccumulate and can reach concentrations at which they are likely to be harmful in aquatic predators (Kimber and Kollias 2000; Sleeman et al. 2010; Peterson and Schulte 2016; Crowley et al. 2018; Huang et al. 2018; Wainstein et al. 2022). We expected lower river otter intensity of use at sites with low DO_2 and few benthic invertebrates because these can impact populations of fish and shellfish that otters rely on as prey; similarly, we expected higher river otter intensity of use at sites that contained water bodies stocked with trout since these fish could represent a food subsidy. We expected higher river otter intensity of use at sites with elevated fecal indicator bacteria; although otter presence cannot be reliably inferred by fecal indicator bacteria (Oliveira et al. 2017), areas with elevated fecal indicator bacteria may indicate areas near point sources of sewage discharge or persistence of indicator bacteria in the intestines of fish (Devane et al. 2020). High concentrations of fish would likely indicate good habitat for otters, and the point-source discharges may come with other nutrient inputs (Carey and Migliaccio 2009), which may serve to concentrate fish in a small area (McCallum et al. 2019). We expected that river otter intensity of use would be lower at sites with water bodies that contained non-native plants, as these may lead to lower levels of native prey species to which river otters are adapted; however, the data contained no indication of the type of non-native plants present.

2.3 | Data Collection

2.3.1 | Detection-Nondetection Surveys

We stratified our sampling by watershed and randomly selected 150 sites within each watershed and surveyed as many as we could access. We surveyed the Pawcatuck River, Block Island Sound, and Quinebaug River watersheds in 2021, Pawtuxet River and Narragansett Bay watersheds in 2022, and Blackstone River, Woonasquatucket River, and Moshassuck River watersheds in 2023. Each year, we selected 150 sites in each watershed. Sites were surveyed once in winter (January–April) and once again in summer (June–August) to increase the number of independent surveys of each site.

We surveyed for river otters on foot and kayak by searching for otter sign along wetland areas of each site. Two observers were present on each survey, in which they recorded the time and sign type of each river otter sign encountered (i.e., scat, latrines, chewed fish or shells, or slides). Surveys continued until the observers had covered all the accessible wetland areas in the site. We used these data to generate detection-nondetection records for each survey.

We expected that river otter detection would be more difficult in sites surveyed by kayak since latrines were often high enough on the banks to make them hard to see from a kayak. We also considered the influence of weather on river otter detection; weather variables were obtained using the openmeteo package (version 0.2.4) in R (Pisel 2023) to access the Open-Meteo API (Zippenfenig 2023). We used the first recorded location of an observer in a site as the time and location for the openmeteo query and obtained the temperature and cloud cover at the start of the survey (rounded to the nearest hour) as well as the total precipitation in the previous 24 h. We expected lower detection after heavy precipitation and on cloudy days since precipitation could either cover up (in the case of snow) or wash away (in the case of rain) river otter signs, and cloud cover may reduce visibility. If detection was dramatically different in summer or winter, or if detection was lower on particularly cold days, we would expect temperature at the start of the survey to be related to detection. We matched the GPS locations of each observer, taken once per minute, to the RIGIS land use and landcover (2020) dataset to calculate the proportion of time the observer spent in wetlands, water, or urban areas (RIGIS 2022). We expected that areas with high hypothesized river otter occupancy might have larger populations and thus more sign available for detection, so we expected higher detection in wetlands and water and lower detection in urban areas (i.e., impervious surfaces).

2.3.2 | Roadkill Data

Roadkill data consisted of locations and dates of otters found dead along roads from 1999 to 2020. Data were reported to state biologists by other Rhode Island Department of Environmental Management (DEM) employees and law enforcement on an opportunistic basis when they found roadkilled river otters. We assigned each location to its corresponding site and treated the number of roadkilled otters in a site and year within the ISDM (described in full below) as the result of a binomial thinning of the intensity of otter use in that site and year.

Roadkill is necessarily restricted to roads, and may be more likely to occur on larger roads. Road segments were calculated by splitting the road centerlines in the RIDOT Roads (RIGIS 2016) dataset available in RIGIS where those segments intersected the boundaries of our sites. Because speed limits in rural areas of

Rhode Island are often high enough for roadkill to be a threat even on small roads, we considered any road with a Federal Highway Administration Functional Classification system classification of less than 7 (local) to be a major road. As well as the density of major roads, we included the effects of the presence of arterial roads and of freeways, as these are likely to have more daily traffic and higher speeds than the other roads in our set.

2.3.3 | Latrine Locations

State biologists recorded locations of river otter latrines in Rhode Island from 1999 to 2008. Latrines are areas used for defecation, rolling, and grooming, and are visited repeatedly by otters, whether individually or in groups (Rostain et al. 2004; Green et al. 2015); since otter latrines are easily identified by the presence of large amounts of scat, researchers have used latrines as indications of otter presence for decades (Greer 1955; Melquist and Hornocker 1983; Dubuc et al. 1990; Newman and Griffin 1994; Ben-David et al. 1998; Swimley et al. 1998; Jeffress, Paukert, Sandercock, and Gipson 2011; Crowley et al. 2012; Holland et al. 2019). Researchers initially recorded latrines during surveys for beaver presence, while later additions included latrines found during other field work or reported by trappers. Most latrines were recorded while biologists were kayaking along rivers or streams, so we expected latrine detection to be higher in areas with second-order or greater streams. We also calculated the distance from the center point of each site to the nearest boat launch because we expected observers to be more likely to record latrines in locations they could easily access. Because many latrines were detected during beaver surveys, we included an indicator of whether the watershed in which the site is located was surveyed for beaver in a given year in the model of latrine detection.

The original intent when recording latrine locations was to resurvey them periodically, but only some latrines were re-visited. We treated each resurveyed latrine as a single-visit detection-nondetection survey with a constant probability of detection. Latrines were counted as redetected if researchers found fresh river otter sign at the same latrine site in a different year and were considered nondetected if the latrine could not be found or if the sign there was estimated to be older than a year.

2.4 | Data Analysis

We developed an ISDM in which the distribution of river otters across the landscape in a given year was given by an inhomogeneous Poisson point process (Fletcher Jr. et al. 2019). ISDMs link the intensity of use (λ) of a species at a site to two different detection processes: presence-only data and detection-nondetection data. The number of presence-only points in a site follows a Poisson distribution with a mean of b * λ (Koshkina et al. 2017), where b is the probability of detecting the species in presence-only datasets. Detection-nondetection data require conversion from intensity of use to presence or absence (Z) of the species at the site, which follows a Bernoulli distribution with the probability of $(1 - e^{-\lambda})$. Detection or nondetection of the species then follows a Bernoulli distribution with probability Z*p, where p is the detection probability. In our model, the basic ISDM described above is extended to incorporate multiple data types and to allow the intensity of use at a site to change between years.

In this model, the intensity of river otter use at site i and year w follows a Poisson distribution with an expectation of λ where $\log(\lambda_{i,w}) = \beta \times x_{i,w}$, where $x_{i,w}$ is a vector of site and year variables associated with the coefficients β. Site and year variables included the proportion of the site covered by water, by wetlands, and by urban areas, the presence of water bodies with impairments such as metals, whether the site contained a water body stocked for trout, the presence of a second order or larger stream, the presence of salt water, watershed, and a time trend (Tables 1 and 2). We included a linear time trend for intensity of use because a trend in λ is an important indication of conservation status but many years had relatively few observations, such that we considered more complex time effects unlikely to be estimable. This intensity of river otter use was then multiplied by $b^L_{i,w}$, the probability of latrine detection, and $b^R_{i,w}$, the probability of detecting roadkill, to obtain the expected number of each type of point; e.g., the expected number of roadkill in a site and year is $\lambda_{i,w}\ x\ b^R_{i,w}$. We linked these probabilities to logit-linear models, as $\text{logit}\left(b^L_{i,w}\right) = \alpha^L \times x^L_{i,w}$ and $\text{logit}\left(b^R_{i,w}\right) = \alpha^R \times x^R_{i,w}$, such that they are dependent on site and year variables in the design matrix x, which are associated with the vector of coefficients α^L and α^R. Variables in the latrine model included distance to a public boat launch, presence of second order or larger streams, the presence of salt water, whether a beaver survey was conducted in that watershed and year, and a time trend; variables in the roadkill model included the density of roads, the presence of freeways, the presence of arterial roads, and a time trend (Table 3). We included a time trend for detection in both presence-only datasets because sampling effort was higher in earlier years in the dataset. In each year, a site was either used by river otters or not, given by $Z_{i,w} \sim \text{Bernoulli}\left(1 - e^{-\lambda_{i,w}}\right)$. At sites used by river otters in a year, the probability of detecting them in the detection-nondetection surveys was given by $y_{i,w} \sim \text{Bernoulli}\left(p_{i,w}\right)$ where $\text{logit}\left(p_{i,w}\right) = \alpha^D \times x^D_{i,w}$, such that the probability of detection is dependent on site, year, and survey-specific variables (Table 3). Variables in the detection-nondetection submodel included observer, the time that the observer spent in water, in wetland, and in urban areas, the temperature at the start of the survey, the cloud cover at the start of the survey, the total precipitation in the 24 h prior to the start of the survey, and whether the survey was done on foot or by kayak (Table 3). Note that we included observer effects in $x^D_{i,w}$ using effect coding, such that we estimate a grand mean across all observers with observer effects as a difference from the grand mean. Given that a site was used by river otters in a year and that an attempt was made to relocate a previously detected latrine, the probability of detecting it was given by $y^r_{i,w} \sim \text{Bernoulli}\left(p^r_{i,w}\right)$ where $\text{logit}\left(p^r_{i,w}\right) = \alpha^{rD}$.

Our model allows river otter occupancy to change across years through the linear time trend and by way of the land-cover variables hypothesized to impact river otter occupancy changing. Although the actual relationship between time and river otter intensity of use may be more complex than a trend, this allowed us to include an effect of time while introducing relatively little complexity. Our presence-absence data were collected in two seasons (summer and winter), but we did not retain the seasonal structure in our analysis because the other

TABLE 1 | Site-level covariates on river otter intensity of use in Rhode Island, USA, between 1999 and 2023, predicted effects of these covariates, probability of support for predictions, and the 95% highest posterior density interval (HDPI) of the coefficient for each covariate. Estimates are on the log scale and from an integrated species distribution model.

Site-level covariate	Description	Predicted effect on otter use	Probability of support[a]	95% HPDI
Water	Proportion of site covered by water in NLCD data[b]	Positive	0.969	(−0.00186, 0.236)
2nd order stream	Presence of a second-order or larger stream in RIGIS freshwater rivers and streams data	Positive	1.00	(0.477, 0.979)
Urban areas	Proportion of site covered by urban areas in NLCD data[b]	Negative	0.00	(0.206, 0.421)
Salt water	Presence of salt water, estuaries, or tidal rivers and streams in RIGIS[c] 2011 data	Negative	0.548	(−0.540, 0.490)
Wetland	Proportion of site covered by open wetlands or forested wetlands in NLCD data[b]	Positive	1.00	(0.197, 0.371)
Non-native plants	Presence of a waterbody with a water quality impairment for presence of non-native plants	Negative	0.00	(0.240, 0.799)
Benthic invertebrates	Presence of a waterbody with a water quality impairment for lack of benthic invertebrates	Negative	1.00	(−1.50, −0.462)
Trout	Presence of a waterbody that is stocked with trout	Positive	0.953	(−0.0475, 0.706)
Dissolved oxygen	Presence of a waterbody with a water quality impairment for low levels of dissolved oxygen	Negative	0.476	(−0.540, 0.545)
Lead	Presence of a waterbody with a water quality impairment for elevated lead	Negative	0.003	(0.143, 0.782)
Mercury	Presence of a waterbody with a water quality impairment for elevated mercury	Negative	0.542	(−0.323, 0.290)
Other metals	Presence of a waterbody with a water quality impairment for elevated levels of other metals (Cadmium, aluminum, zinc, copper, and iron)	Negative	0.989	(−0.931, −0.0559)
PCBs	Presence of a waterbody with a water quality impairment for presence of PCBs	Negative	0.607	(−0.902, 0.680)
Fecal indicator bacteria	Presence of a waterbody with a water quality impairment for presence of *Enterococcus* or coliform bacteria	Positive	0.999	(0.104, 0.506)
Time trend	A linear time trend	None	NA	(−0.118, −0.0312)

[a]Calculated as the proportion of posterior samples in which the coefficient was estimated in the same direction as the prediction.
[b]National Land Cover Database (NLCD) data was taken from the closest year to the date of the survey or the presence-only data point's collection.
[c]Rhode Island Geographic Information Systems.

data sources were not structured in the same way and because attempting to split the years into seasons would have further reduced the available data to estimate intensity of use in each season. Our model therefore assumes that the site is closed to changes in river otter intensity of use within a year but can change between years. Further, we assume there is a static relationship in the response of river otters to the landcover variables (i.e., temporal stationarity). We see this as reasonable because our variables are available at a relatively coarse scale and the expected responses (e.g., a positive response to open water) are related to fundamental characteristics of river otter ecology (Melquist et al. 2003). Furthermore, given the sparse presence-only data, this assumption was necessary to ensure parameter estimation convergence. NLCD data were not available for every year, so it is possible that changes in landcover between years could drive changes in river otter intensity of use before the landcover changes were detected, but overall landcover change was small, so we expect such errors to be minimal.

We implemented this model in a Bayesian context using prior distributions intended to be relatively uninformative (Northrup and Gerber 2018). We used normal priors on each β and logistic priors on each $\boldsymbol{\alpha}$. For logistic priors, the location

TABLE 2 | Estimated coefficients on river otter use associated with each watershed in the study in Rhode Island, USA, between 1999 and 2023. Effects represent differences from the grand mean, which had a median of 0.276 with a highest posterior density interval (HPDI) of (−0.474, 1.07). Estimates are on the log scale and from an integrated species distribution model. Median refers to the posterior median for each coefficient.

Watershed	Median	95% HPDI
Block Island Sound	−0.157	(−0.404, 0.0788)
Blackstone	0.0584	(−0.308, 0.409)
Narragansett	−0.284	(−0.573, −0.00286)
Pawcatuck	−0.352	(−0.586, −0.129)
Pawtuxet	0.656	(0.477, 0.829)
Quinebaug	0.901	(0.637, 1.17)
Woonasquatucket-Moshassuck	−1.10	(−2.01, −0.235)

parameter was 0 and the scale parameter 1. Most normal priors had a mean of 0 and a variance of 1; exceptions were the intercept for river otter intensity of use, β_0, which had a mean of −0.367 (corresponding to a probability of occupancy of 0.5) and a variance of 0.25 and the time trend for intensity of use, which had a mean of 0 and a variance of 1/25 (thus, when the effect of the time trend is largest at the end of the study period, the prior is the same as the prior for other effects on intensity of use). We fit models with Markov chain Monte Carlo (MCMC) methods in JAGS (version 4.3.1; Plummer 2003) via the runjags (version 2.2.2-4; Denwood 2016) package in R (version 4.4.0). We report coefficient estimates as posterior medians (e.g., β) with 95% highest posterior density intervals (HPDI) and we estimated the probability of support for each prediction by calculating the proportion of posterior samples in which the coefficient was estimated in the same direction as the prediction; a probability of > 0.90 indicates strong statistical support and > 0.70 but less than 0.90 indicates moderate support, and a probability > 0.50 but less than 0.70 indicates weak support. Probabilities of support less than 0.5 indicate no support for the predicted effect. All effects in the model are reported in the tables, but only moderate and strong effects are reported in the text.

3 | Results

3.1 | Detection-Nondetection Surveys

We surveyed 274 0.25 km^2 sites in 230 larger (1 km^2) sites across 3 years, resulting in 919 surveys. The number of surveys per site varied; some 1 km^2 sites were visited only once, and one site was surveyed 11 times, with an average of 4 surveys per site. River otters were detected on 70 surveys across 46 sites.

We found that detection in these surveys varied widely by observer (and variation among observers was larger than differences due to landscape or weather variables); $\alpha^D_{\mathrm{observer}}$ for the observer least likely to detect otters was estimated at −1.04 (difference from grand-mean across observers; HPDI = (−2.61, 0.295)), while $\alpha^D_{observer}$ for the observer most likely to detect river otters was estimated at 1.84 (HPDI = (0.998, 2.69)). The estimated effects of landcover on detection were smaller but were estimated more precisely than observer effects; river otter detection was higher when the observer spent more time in wetland ($\alpha^D_{wetland}$ = 0.280, HPDI = (−0.0858, 0.652)), water (α^D_{water} = 0.195, HPDI = (−0.223, 0.614)), or urban ($\alpha^{\mathrm{D}}_{\mathrm{urban}}$ = 0.163, HPDI = (−0.165, 0.471)) areas (Figure 2). Our predictions of higher river otter detection when observers spent more time in water and wetlands were supported (moderate support for water; strong support for wetlands) but our prediction of lower detection in urban areas was not (Table 3). We found that river otter detection was higher during surveys with more cloud cover (α^D_{cloud} = 0.327, HPDI = (−0.0221, 0.667)), and higher temperatures (α^D_{temp} = 0.112, HPDI = (−0.217, 0.443)); detection was lower when the survey was done by kayak (α^D_{kayak} = −0.248, HPDI = (−1.00, 0.497)).

3.2 | Roadkill Surveys

Within our study area, 105 roadkilled river otters were detected in 92 sites, with at least one detection in every year from 1999 to 2020. Roadkill detections were more frequent earlier in the dataset (Figure 3). We found limited evidence for higher roadkill detection in areas with higher road density ($\alpha^R_{density}$ = 1.02, HPDI = (–1.77, 4.27)), and no evidence that roadkill detections were higher in sites with freeways or arterial roads (Table 3 and Figure 4a). Roadkill detection decreased over time (α^R_{trend} = −0.196, HPDI = (−0.679, 0.327); Figure 4a). Parameter uncertainty (e.g., HPDIs) associated with roadkill detection was much larger than those associated with detection in the detection-nondetection surveys (Table 3).

3.3 | Latrine Surveys

Within our study area, 366 river otter latrines were detected in 253 sites, with most detections occurring between 1999 and 2007 (Figure 3). Latrines were more likely to be detected in areas with second order or greater streams (α^L_{stream} = 1.21, HPDI = (–1.99, 4.73)); (Table 3 and Figure 4b). We found limited support for higher detection in areas closer to public boat launches ($\alpha^L_{launchdistance}$ = −0.371, HPDI = (−2.38, 2.17)) and in watersheds and years in which beaver surveys occurred (α^L_{beaver} = 0.506, HPDI = (−2.63, 3.89)). Latrine detection decreased over time (α^L_{trend} = −0.262, HPDI = (−0.713, 0.241)). As with roadkill detection, there was more parameter uncertainty (e.g., wider HPDIs) for latrine detection than those for detection in the detection-nondetection surveys.

In total, 73 latrine locations were re-surveyed in a subsequent year, and latrines were located and still in use at 53 of these. Most resurveys occurred in 2003 (38 resurveys) or 2007 (21 resurveys). The naïve probability of redetecting latrines was 0.726 (53 redetected latrines out of 73 attempted redetections), while the estimated probability of redetecting latrines (p^r) was 0.774 (HPDI = (0.650, 0.872)), suggesting that some sites at which a redetection was attempted were no longer predicted to support river otter occupancy.

TABLE 3 | Site- and survey-level covariates used to model river otter detection in Rhode Island, USA, between 1999 and 2023, predicted effects of these covariates, probability of support for predictions, and the 95% highest posterior density interval (HPDI) of the coefficient for each covariate. Estimates are on the logit scale and from an integrated species distribution model.

Covariate	Description	Predicted effect on otter detection	Submodel	Probability of support[a]	95% HPDI
Urban	Proportion of time the observer spent in urban areas	Negative	Detection-nondetection	0.158	(−0.165, 0.471)
Water	Proportion of time the observer spent in water	Positive	Detection-nondetection	0.817	(−0.223, 0.614)
Wetland	Proportion of time the observer spent in wetlands	Positive	Detection-nondetection	0.932	(−0.0858, 0.652)
Temperature	Temperature in Celsius at the start of the survey	Positive	Detection-nondetection	0.749	(−0.217, 0.443)
Cloud cover	Proportion of the sky covered by clouds at the start of the survey	Negative	Detection-nondetection	0.033	(−0.0221, 0.667)
Precipitation	Total precipitation in the previous 24 h	Negative	Detection-nondetection	0.439	(−0.364, 0.450)
Kayak	Whether the survey was done by kayak	Negative	Detection-nondetection	0.744	(−1.00, 0.497)
Observer	Random effect of observer	Variable	Detection-nondetection	Varied[b]	
Distance to launch	Distance from point to nearest public boat launch	Negative	Latrine points	0.619	(−2.38, 2.17)
Stream	Presence of a second-order or larger stream	Positive	Latrine points	0.793	(−1.99, 4.73)
Beaver Survey	Whether beaver surveys occurred in the watershed that year	Positive	Latrine points	0.636	(−2.63, 3.89)
Salt	Presence of salt water, estuaries, or tidal rivers and streams in RIGIS 2011 data	Negative	Latrine points	0.440	(−3.15, 3.65)
Freeway presence	Presence of freeways in site	Positive	Roadkill points	0.625	(−2.67, 3.84)
Arterial presence	Presence of arterial roads in site	Positive	Roadkill points	0.678	(−2.47, 3.92)
Road Density	Density of all road segments in site	Positive	Roadkill points	0.764	(−1.77, 4.27)

[a]Calculated as the proportion of posterior samples in which the coefficient was estimated in the same direction as the prediction.
[b]See Table S1.

3.4 | River Otter Intensity of Use

River otter use was higher in areas with a second order or greater stream (β_{stream} 0.720, HPDI = (0.477, 0.979)), with more wetland ($\beta_{\text{wetland}} = 0.285$, HPDI = (0.197, 0.371)), water ($\beta_{\text{water}} = 0.118$, HPDI = (−0.00186, 0.236)), or urban ($\beta_{\text{urban}} = 0.312$, HPDI = (0.206, 0.421)) land cover, at sites containing waterbodies with impairments due to non-native plants ($\beta_{\text{NNP}} = 0.519$, HPDI = (0.240, 0.799)), lead ($\beta_{\text{Pb}} = 0.463$, HPDI = (0.143, 0.782)), or fecal indicator bacteria ($\beta_{\text{FIB}} = 0.309$, HPDI = (0.104, 0.506))

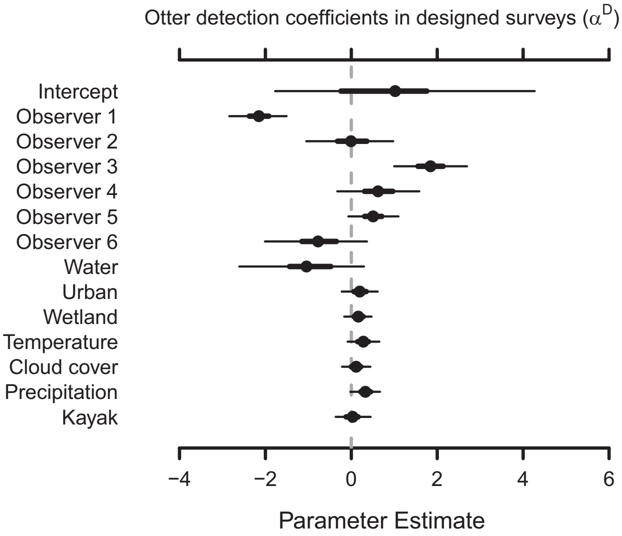

FIGURE 2 | Posterior estimates of coefficients ($\boldsymbol{\alpha}^{\mathrm{D}}$) on detection ($p$) in detection/nondetection surveys from the integrated species distribution model of river otters in Rhode Island, USA. The circles indicate the posterior median, while the thin lines show the 95% highest posterior density intervals (HPDI) and the thick lines the 50% HPDI. Coefficients are on the logit scale; positive numbers indicate a higher probability of detection. Landcover effects (water, urban, and wetland) are effects of the amount of time the observer spent in each landcover category during their survey. Observer effects are the difference between an individual observer and the grand mean of all observers; observer six is several observers with very few observations pooled together. Temperature refers to the temperature at the site at the start of the survey, cloud cover to the proportion of the sky covered by clouds at the start of the survey, and precipitation to the total water equivalent of all precipitation in the 24 h preceding the start of the survey. Landcover and weather variables were scaled to have a mean of 0 and a standard deviation of 1. Kayak is an indicator variable equal to one if the survey was conducted by kayak and zero if by foot.

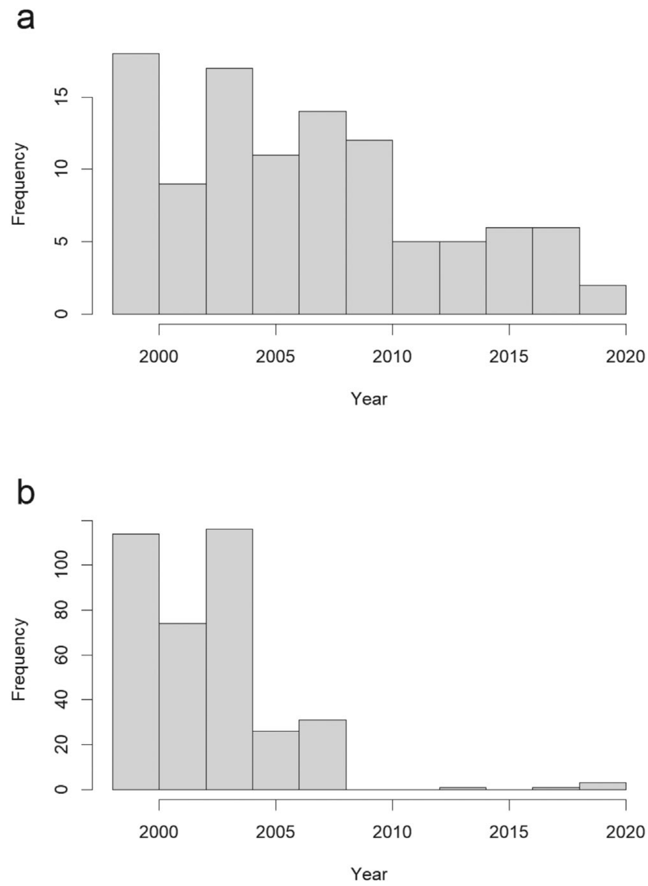

FIGURE 3 | Histogram of river otter roadkill (a) and latrine (b) location detections by year in Rhode Island, USA, from 1999 to 2020. Note that the y-axis limits differ between subplots.

and at sites containing water bodies that were stocked with trout ($\beta_{\mathrm{trout}} = 0.332$, HPDI = (−0.0475, 0.706)). River otter intensity of use was lower in sites with impairments due to lack of benthic invertebrates ($\beta_{\mathrm{benthic}} = -0.974$, HPDI = (−1.50, −0.462)), or presence of other metals ($\beta_{\mathrm{othermet}} = -0.488$, HPDI = (−0.931–0.0559)). We found no support or limited support for effects of impairments due to low dissolved oxygen, presence of mercury, or presence of PCBs, and in sites with salt water (Table 1 and Figure 5). We also found that intensity of use varied widely by watershed (Table 2). Our predictions of higher river otter occupancy in areas with more water and wetlands or containing water bodies with elevated levels of fecal indicator bacteria were strongly supported, as was our prediction of lower occupancy in areas with high concentrations of other metals and with low levels of benthic invertebrates, but our prediction of lower river otter occupancy in urban areas, areas with high concentrations of lead, and areas with non-native plants were not supported (Table 1). We found that predicted river otter occupancy decreased over time (β_{trend} −0.0750, HPDI = (−0.118, −0.0312); Figure 5). There was uncertainty in the magnitude of decline (Figure 6), but the estimated trend was negative in all but 26 of the 40,000 posterior samples, providing unambiguous support for the direction of the trend.

4 | Discussion

Landcover and human pressure on ecosystems have changed considerably in the last several decades, including in our study area, where urbanization has continued (Novak and Wang 2004) and human impacts dramatically change local aquatic communities through increased nutrient loads (e.g., Vadeboncoeur et al. 2010; Hollister et al. 2021, but see Savoie et al. 2017). Rhode Island continues to experience shifts away from industrial and agricultural land use and towards forested and residential land use. The resulting impacts on water quality and landscape features are complex; with some sources of contaminants (e.g., heavy metals from industrial processes) reduced and others (e.g., fecal indicator bacteria from wastewater; nitrogen from fertilizers on residential lawns) increasing or mixed. Our results show that river otter responses to these changes are also complex, but that the combined impact is a negative trend in river otter occupancy in our study area (Figures 6 and 7). We found that river otter occupancy has declined in Rhode Island over the past two decades despite the protected status of the species in the state. A site with mean level of each landcover covariate, no salt water or streams, and no impairments or fish stocking would have seen a decline in predicted occupancy from 0.736 in 1999 to 0.198 in 2023. Although the magnitude of decline is uncertain, the negative trend was unambiguous, providing clear evidence that the occurrence of river otters has declined between 1999 and 2023.

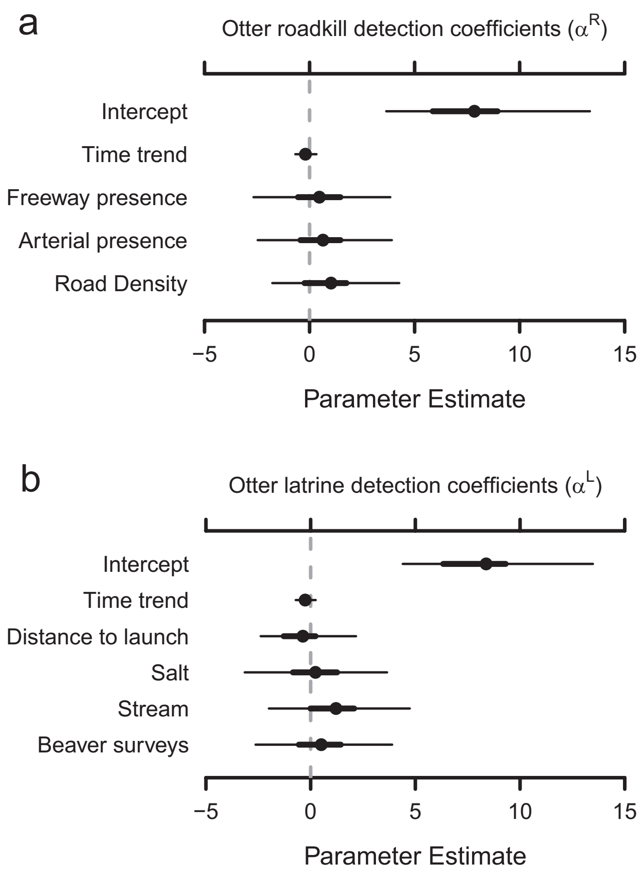

FIGURE 4 | Posterior estimates of coefficients ($\boldsymbol{\alpha}$) on detection for otter roadkill (b^R, subplot a) and latrines (b^L, subplot b) from the integrated species distribution model of river otters in Rhode Island, USA. The circles indicate the posterior median, while the thin lines show the 95% highest posterior density intervals (HPDI) and the thick lines the 50% HPDI. Coefficients are on the logit scale; positive numbers indicate a higher probability of detection. Salt is a categorical variable equal to 1 if the site contained salt water in the RIGIS 2020 landcover dataset and 0 otherwise; stream is a categorical variable equal to 1 if the site had a ssecond-orderor greater stream; beaver surveys is a categorical variable equal to 1 if researchers surveyed for beaver colonies in the watershed the site was located in during the year the latrine was found; pthe resence of roads is a categorical variable equal to 1 if roads were present. Road density is the total length of road segments of the respective type in a site, and distance to launch is the distance from the center point of a site to the nearest public boat launch; these variables were scaled to have a mean of 0 and a standard deviation of 1. The time trend is the yearly change in detection probability.

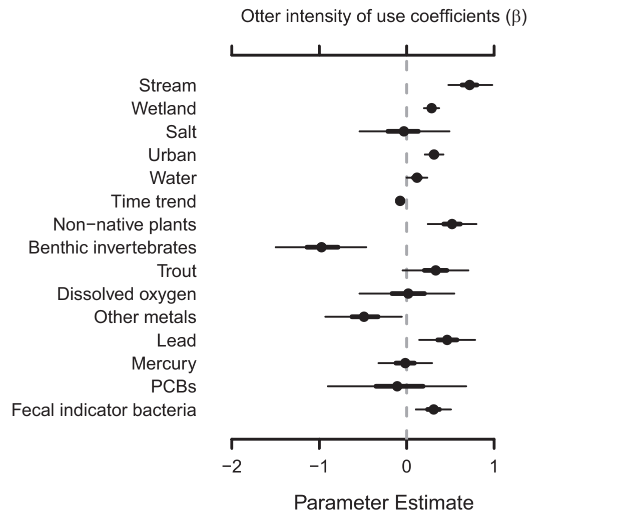

FIGURE 5 | Posterior estimates of coefficients (β) on site-level otter intensity of use (λ) from the integrated species distribution model of river otters in Rhode Island, USA. The circles indicate the posterior median, while the thin lines show the 95% highest posterior density intervals (HPDI) and the thick lines the 50% HPDI. Coefficients are on the log scale; positive numbers indicate higher intensity of use. Salt is a categorical variable equal to 1 if the site contained salt water in the RIGIS 2020 landcover dataset and 0 otherwise; stream is a categorical variable equal to 1 if the site had a second order or greater stream. Wetland, urban, and water covariates are the proportion of the site covered by the corresponding landcover class. The time trend is the yearly change in intensity of otter use. Lead, mercury, other metals, PCB, non-native plants, and fecal indicator bacteria covariates are indicators equal to 1 if the site contained a waterbody with an impairment due to the presence of those features (fecal indicator bacteria were *Enterococcus* and coliform bacteria; other metals were cadmium, aluminum, copper, iron, and zinc). Benthic invertebrates and dissolved oxygen covariates are equal to 1 if the site contains a waterbody with an impairment due to low levels of benthic invertebrates and dissolved oxygen, respectively.

Past declines in otter abundance have been linked to water quality, changes in aquatic communities, and trapping (Melquist et al. 2003); none of these causes seems likely to drive the declines we observed as harvest of river otters is illegal in Rhode Island, water quality in our study area has not declined dramatically (Briggs and Feiffer 1986; Nimiroski et al. 2008; Savoie et al. 2017; Hollister et al. 2021), and fish biomass in coastal waters has increased during our study period (Innes-Gold et al. 2020). Some aspects of poor water quality in our study area, such as the presence of elevated lead levels and fecal indicator bacteria, were positively associated with river otter intensity of use, suggesting that, at the levels measured in our data sources, these do not limit river otter use. The presence of fecal indicator bacteria could reflect inputs from wastewater treatment facilities, which may have other impacts on local ecosystems, such as nitrogen inputs and seasonally stable temperatures, that increase productivity and benefit otter prey species (McCallum et al. 2019). Lead is toxic to river otters, and the mechanism that would lead to higher otter use in areas with elevated lead levels is unclear. We found that river otter intensity of use is higher in sites stocked with trout and lower in sites that contain water bodies that are impaired by a lack of benthic invertebrates, reflecting that intensity of use is related to prey availability. Our results suggest that river otters are tolerant of a range of water quality conditions provided prey availability remains high; we were unable to find any research to suggest a decline in overall prey availability in our study area. Evaluating prey abundance may be an important focus for river otter conservation in Rhode Island.

River otter occurrence was driven by landcover patterns as well as water quality. River otter intensity of use was higher in areas with second-order or greater streams and in sites with more water and more wetland landcover, an expected pattern given the species' reliance on aquatic habitats (e.g., Gallant et al. 2009; Jeffress, Paukert, Sandercock, and Gipson 2011; Hanrahan

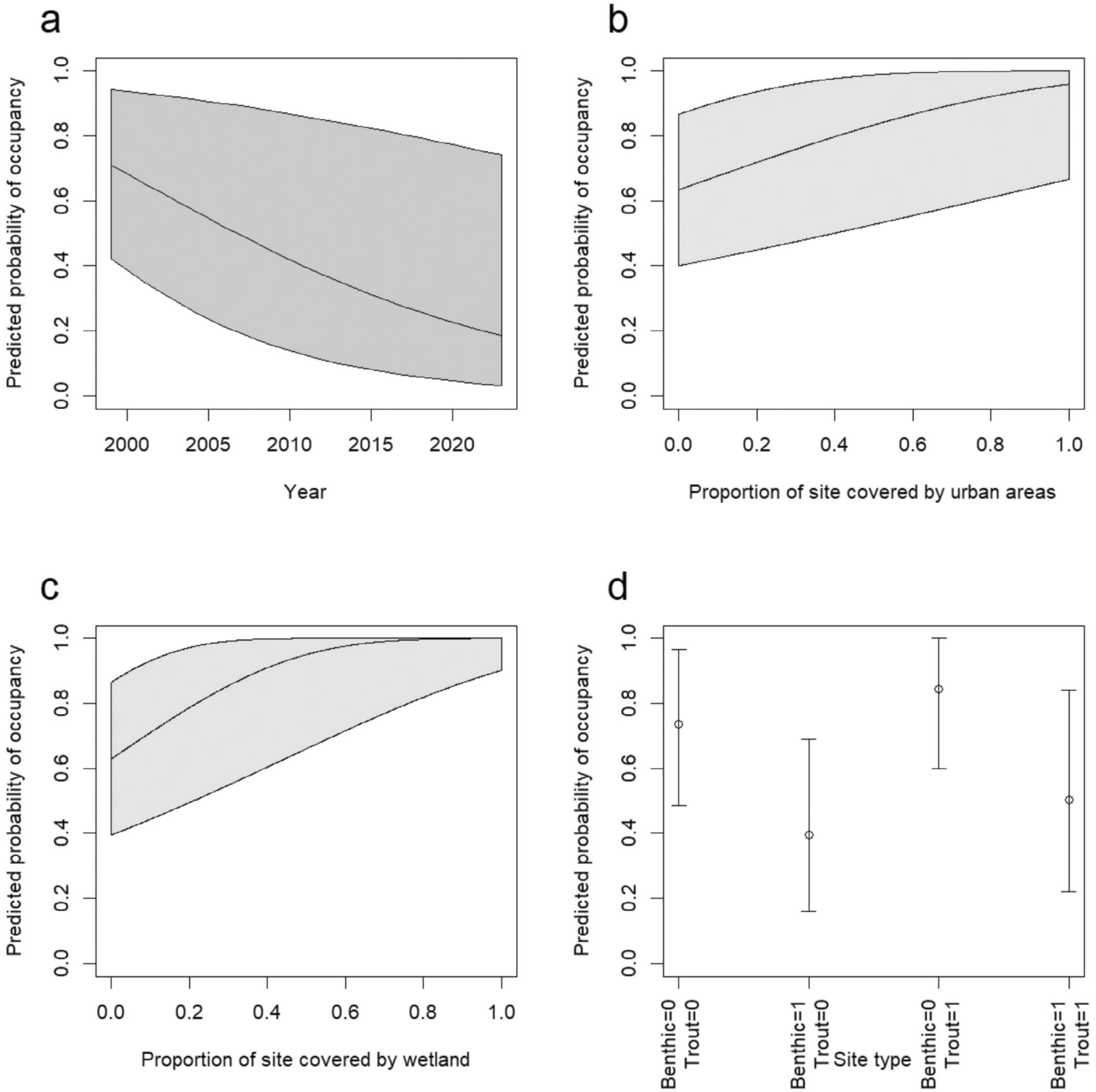

FIGURE 6 | Predicted river otter occupancy (a) by year at a site with mean values for all landcover covariates, no impairments, no salt, and no stream present; (b) by the proportion of the site covered by urban areas at a site with mean values for all other landcover covariates, no impairments, no salt, and no stream present in 1999; (c) by the proportion of the site covered by wetlands at a site with mean values for all other landcover covariates, no impairments, no salt, and no stream present in 1999; (d) by site type for sites with and without waterbodies stocked with trout and impairments due to lack of benthic invertebrates, at sites with mean values for landcover covariates, no stream present, no salt water, and no other impairments. The solid center line of plots (a–c) represents the posterior median while the shaded areas indicate 95% from the integrated species distribution model of river otters in Rhode Island, USA. The circles indicate the posterior median, while the thin lines show the 95% highest posterior density intervals (HPDI). The central circle in plot (d) represents the posterior median while the error bars represent 95% HPDI.

et al. 2019; Holland et al. 2019; Powers et al. 2021). We predicted lower occurrence in sites with more urban areas, as previous studies have shown that otters avoid areas of high road density (Robitaille and Laurence 2002; Powers et al. 2021), avoid developed areas (Hanrahan et al. 2019; Holland et al. 2019), or are not responsive to road density (Jeffress, Paukert, Sandercock, and Gipson 2011), but in our study, river otters were more likely to occur at sites with more developed land. A pattern of higher occurrence near areas of high human activity is typical in species distribution models that do not account for imperfect detection (e.g., Fithian et al. 2015); however, this pattern exists in our study despite including covariates in all detection submodels intended to account for this, suggesting that the bias towards urban areas is not an artifact of a mis-specified detection model.

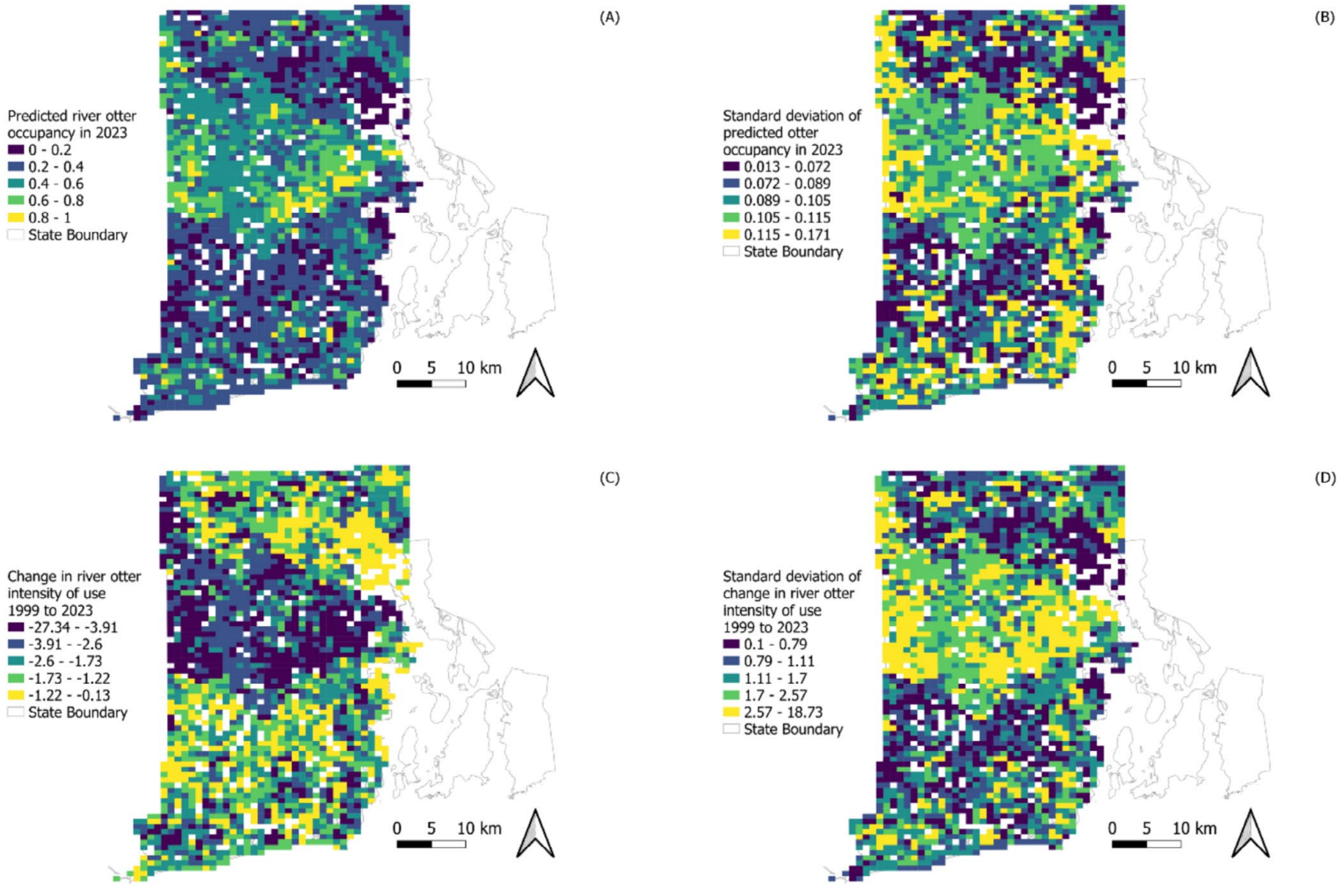

FIGURE 7 | Predicted probability of river otter occupancy (ψ) in 2023 (A), standard deviation of predicted river otter occupancy in 2023 (B), change in the intensity of river otter use from 1999 to 2023 (C), and the standard deviation of change in the intensity of river otter use from 1999 to 2023 (D) across the study area in Rhode Island, USA from the integrated species distribution model. Probability of river otter occupancy (A) is shown as the median posterior estimate of probability of occupancy, with yellow shading indicating areas of higher predicted occupancy and blue areas of lower predicted occupancy. Intensity of river otter use (λ) is unbounded and therefore exhibits more variation than river otter occupancy (ψ); areas of yellow shading in (B) represent locations with higher standard deviations in intensity of use among posterior samples. Change in river otter intensity of use (c) is shown as the posterior median of the difference between intensity of use in 2023 and 1999 with yellow shading indicating areas where otter use declined the least over the time period of the study and blue shading indicating areas where use declined the most. Unshaded areas were not included in the study.

Although river otters were more likely to use sites with more urban landcover, their fitness may be lower in urban areas (i.e., these areas may serve as an ecological trap for river otters), particularly given the large size of the roadkill dataset used in this study. Roadkill is a significant source of mortality for many mammals (Moore et al. 2023), including otters (Hauer et al. 2002; Jancke and Giere 2011), and as urban areas expand, river otters in Rhode Island may encounter more roads and more cars on existing roads, making movement hazardous.

As Rhode Island is the 2nd most densely populated state in the United States, river otters in our study area may not be able to avoid human development as easily as river otters in midwestern states (Jeffress, Paukert, Sandercock, and Gipson 2011; Hanrahan et al. 2019; Holland et al. 2019) or western New York (Powers et al. 2021). Many of the urban areas in Rhode Island are coastal, and river otter preference for urban sites could reflect higher prey availability in estuaries and brackish or salt water; although we included a salt water effect in the model, it may not fully reflect the ecological differences between inland streams that are cut off from the ocean by dams and rivers and streams that are connected to the ocean. Notably, detection was also higher in urban areas for the detection-nondetection surveys as well. This suggests that river otter sign is particularly easy to find in urban landscapes, perhaps because the wetlands in urban areas are condensed into smaller areas with better defined boundaries, whereas rural wetlands (and especially coastal wetlands) are expansive, with fewer obvious places to check for sign; it may also suggest that river otter populations are higher in urban areas and sign is more common.

Our work demonstrates the utility of ISDMs in incorporating multiple sources of data of varying quality, which allows us to leverage historical data to reveal declines in a protected species. However, it also demonstrates some of the challenges. Many of the coefficients associated with the detection of latrines or roadkill were estimated with large uncertainty, which makes meaningful inference on those variables difficult. This issue could be mitigated by collecting better information on survey effort for presence-only data. The covariates we included in the models of latrine and roadkill detection were based on variables we predicted to be important, but none of them were collected at the same time as the presence-only records. Complete records of how many attempts to find otter latrines were made in a given season could help correct temporal biases, and better records of the roadkill reporting process and of traffic volumes could help correct both temporal and spatial biases.

Another source of uncertainty in this study is the lack of temporal overlap between presence-only and detection-nondetection data. Although the submodels still share information through the landcover and water quality covariates, our power to discriminate between detection and occurrence would be increased if there were years in which both types of sampling were done. If managers intersperse detection-nondetection surveys at regular intervals (e.g., every 3 or 4 years) along with collecting presence-only data, their power to estimate trends in occurrence will increase. Previous studies (e.g., Jeffress, Paukert, Whittier, et al. 2011; Powers et al. 2021) have demonstrated the effectiveness of sign surveys focused on bridges and other obvious points where river otters cross roads; these features are typically easy to sample and are a natural area of focus for detection-nondetection surveys. Alternatively, managers could record when and where they are actively searching for latrines, allowing a subset of latrine locations to be converted into detection points and generating some points where latrines were sought but not found. Either approach would be inexpensive and effective at generating data on a comparable scale to the detection-nondetection data used here (i.e., ten surveys a year would result in as many detection-nondetection sites as we surveyed).

Effective conservation of a species requires an understanding of its distribution. Detecting changes in distribution can be very important both in alerting practitioners to a conservation need and in accurately assessing where to direct resources. Here, we demonstrate the utility of combining historical presence-only data and data from designed studies in an integrated model, revealing declining occupancy in river otters in Rhode Island. These models may be applicable to many other species for which historical data exist and could significantly advance managers' understanding of the conservation needs of wildlife in their area.

Author Contributions

C.B. and B.D.G. conceived of the project; C.B. collected and organized the presence-only data; J.G.C. collected the detection-nondetection data; J.G.C. and B.D.G. analyzed the data and led the writing of the manuscript.

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Data Availability Statement

Data and analysis code are publicly available for reference at https://doi.org/10.5281/zenodo.14827223.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Table S1:** Observer effects on detection probability in detection-nondetection surveys. Effects represent differences from the grand mean, which had a median of −2.15 with a highest posterior density interval (HPDI) of (−2.84, −1.51). Estimates are on the logit scale and from an integrated species distribution model.