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Original Research Article

Predicting wildlife distribution patterns in New England USA with expert elicitation techniques

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A B S T R A C T

Understanding the impacts of landscape change on species distributions can help inform decision-making and conservation planning. Unfortunately, empirical data that span large spatial extents across multiple taxa are limited. In this study, we used expert elicitation techniques to develop species distribution models (SDMs) for harvested wildlife species (n = 10) in the New England region of the northeastern United States. We administered an online survey that elicited opinions from wildlife experts on the probability of species occurrence throughout the study region. We collected 3396 probability of occurrence estimates from 46 experts, and used linear mixed-effects methods and landcover variables at multiple spatial extents to develop SDMs. The models were in general agreement with the literature and provided effect sizes for variables that shape species occurrence. With the exception of gray fox, models performed well when validated against crowdsourced empirical data. We applied models to rasters (30 × 30 m cells) of the New England region to map each species' distribution. Average regional occurrence probability was highest for coyote (0.92) and white-tailed deer (0.89) and lowest for gray fox (0.42) and moose (0.52). We then stacked distribution maps of each species to estimate and map focal species richness. Species richness (s) varied across New England, with highest average richness in the least developed states of Vermont ($s = 7.47$) and Maine ($s = 7.32$), and lowest average richness in the most developed states of Rhode Island ($s = 6.13$) and Massachusetts ($s = 6.61$). Our expert-based approach provided relatively inexpensive, comprehensive information that would have otherwise been difficult to obtain given the spatial extent and range of species being assessed. The results provide valuable information about the current distribution of wildlife species and offer a means of exploring how climate and land-use change may impact wildlife in the future.

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1. Introduction

Changes in land cover (the ecological characteristics of the land), land use (how land is utilized), and climate patterns can alter the ecology and biological diversity of an area (Brown and Laband, 2006; Foley et al., 2005; Lindenmayer and Franklin, 2002; Vitousek et al., 1997). The New England region in the northeastern United States encompasses the states of Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont (186,458 km^2; Fig. 1), and has a long history of profound social, economic, and ecological changes (Dupigny-Giroux et al., 2018; Jeon et al., 2014; Thompson et al., 2013). New England is currently the most forested and densely populated region in the country. However, this economically and ecologically important region (Dupigny-Giroux et al., 2018; Foster et al., 2010) is undergoing relatively rapid changes in land cover composition, land use intensities, and climatic conditions (Foster, 1992; Olofsson et al., 2016; Rustad et al., 2012; Thompson et al., 2013). With modern pressures of a human population that has more than doubled over the last century (~107% increase; U.S. Census Bureau, 2019), forests throughout the region are in decline (Olofsson et al., 2016). Moreover, the New England region has experienced a 10 mm/decade increase in average annual precipitation and a ~1 °C increase in average temperature over the last century (Hayhoe et al., 2007; Huntington et al., 2009; Rogers and Young, 2014). In New England, these changes

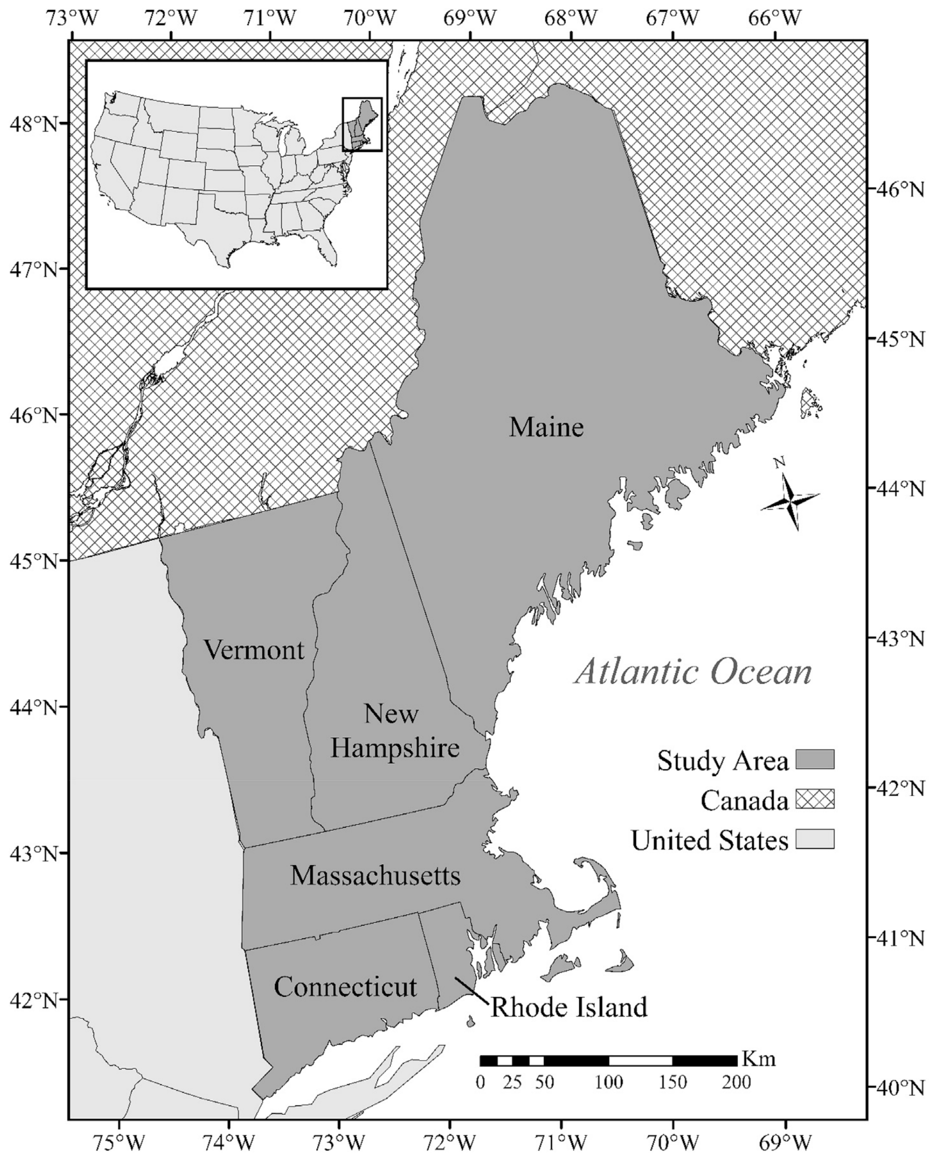

Fig. 1. The study area (dark gray) within the northeastern United States (light gray). The study area included the full extent of the six New England states (Rhode Island, Connecticut, Massachusetts, Vermont, New Hampshire, and Maine).

have significantly impacted the diversity, distribution, and abundance of wildlife (DeGraaf and Yamasaki, 2001; Rustad et al., 2012; Thompson et al., 2013).

Limited funding and resources preclude management of all wildlife species, highlighting the need for focal species strategies. A focal species strategy identifies and directs attention to key wildlife species, making it easier to track management and conservation success (U.S. Fish and Wildlife Service, 2015). In New England, game species typically attract public attention, help generate funding for agencies, and can trigger management activities on the landscape (Lueck, 2005). With diverse life histories and habitat requirements, game species can act as surrogates for the protection of non-game wildlife and overall biodiversity (Caro, 2010). For example, game species with large home ranges, such as the bobcat (*Lynx rufus*), often act as umbrella species benefiting other non-target species through their protection and management (Simberloff, 1998). Other game species such as moose (*Alces alces*) may act as indicator species signaling the effects of environmental changes (Caro, 2010). Because annual harvest is often tracked through time and space (typically at the town level or within wildlife management units), localized monitoring programs are already in place for game species. Thus, using game species as focal species may alleviate monitoring demands and help facilitate the conservation of a broader range of taxa.

When developing a regional conservation effort, species distribution models (SDMs) – or models that describe how a species is distributed across an area of interest – can provide important information and predictive insight (Guisan and Thuiller, 2005; Pearce et al., 2001; Rustad et al., 2012; Turner and Gardner, 2015). Unfortunately, even for highly monitored game species, regional species distribution models for New England wildlife are lacking. Given that management is regulated at the state level, studies of harvested species are typically focused on single species and concentrated on local extents or on a state-by-state basis (Organ et al., 2012). Localized studies may fail to capture a geographic region's complex and variable environmental conditions and often overlook important landscape level influences (Murray et al., 2008; Turner and Gardner, 2015). Broad scale distribution data are needed to better capture the influence of climate and land-use change on regional population dynamics and inform priority conservation and management activities across the region (James et al., 2010; Murray et al., 2008; Pearce et al., 2001). Inadequate assessments of species distributions may contribute to 1) inefficient, expensive, and unsustainable conservation and management practices, 2) declines in biodiversity, and 3) the loss of ecologically, economically, and culturally important species (Franklin, 2010).

To address these issues, we used expert elicitation methods to collect species probability of occurrence data for a set of managed wildlife species in New England. Our objectives were to: 1) Develop a regional, multi-species survey that collects species-specific probability of occurrence data at numerous sites across New England; 2) Conduct the survey with expert elicitation methods, in which experts were asked to report the probability of occurrence of target species at a subset of study sites; 3) Analyze results to develop SDMs with generalized linear mixed-effect and stepwise modeling approaches; and 4) Map wildlife species regional distributions and identify areas of multispecies conservation interest. This approach allowed for quick and effective data collection and the generation of geographically consistent and ecologically relevant SDMs for wildlife species in New England. The SDMs provide insight into the factors that shape species' distributions and a means of better assessing the effects of management actions and landscape change on wildlife in the region. Our approach can be applied to other species, regions, and spatial extents, and is especially relevant to species of high management or conservation value and contexts in which little empirical data exist.

2. Methods

2.1. Study area

The study area included the six New England states (Connecticut, Rhode Island, Massachusetts, Vermont, New Hampshire, and Maine) in the northeastern United States (Fig. 1). This region covers 186,458 km^2 with topography ranging from coastal plains to mountain peaks nearly 2000 m above sea level. Climatic conditions vary by season and geographic location throughout the region. Long-term climate records indicate an average annual precipitation of 104 cm and monthly temperature ranging from 6 °C (Jan) to 19 °C (Jul) (Huntington et al., 2009).

The region supports a growing human population (ca. 14, 735, 000 in the 2016 U.S. Census) with three-quarters of the population concentrated in the major metropolitan areas of southern New England (U.S. Census Bureau, 2018). This uneven population distribution contributes to regional variability in land use patterns and intensities. Approximately 80% of the region is covered in forest (Foster et al., 2010). Forested regions are ecologically diverse with areas dominated by northern hardwood, spruce-fir, oak-hickory, and pine-oak forest types (Brooks et al., 1992; Duveneck et al., 2015). Development (9.3% of the region), agriculture (5.9% of the region) and water (12.3% of the region) constitute the majority of the non-forested landscape (Homer et al., 2015).

2.2. Focal species

We elicited information and developed models for 10 commonly harvested species in New England (Table 1). The focal group included seven species in the Carnivora order (American black bear, bobcat, coyote, gray fox, raccoon, red fox, and striped skunk), two species in the Artiodactyla order (moose and white-tailed deer), and one species in the Galliformes order (wild turkey). We selected these species because they are frequently the target of wildlife management programs in New England.

Table 1
List of wildlife species in the New England region of the northeastern United States included in expert elicitation and model development. Sample size ranged between 188 and 535 and indicates the number of occurrence estimates collected for each species through an expert elicitation survey. Species models were validated using iNaturalist datasets that included between 106 and 1771 occurrence records. Generalized home range scales (500m, 3km, and 5km) indicate the secondary analysis scale(s) used for each species during model development.

Common name	Genus	Species	Sample size	Home range scale	iNaturalist sample size
American black bear	*Ursus*	*americanus*	423	5km	249
Bobcat	*Lynx*	*rufus*	373	3km	424
Coyote	*Canis*	*latrans*	355	3km	338
Gray fox	*Urocyon*	*cinereoargenteus*	188	3km	106
Moose	*Alces*	*alces*	459	5km	280
Raccoon	*Procyon*	*lotor*	233	500m	556
Red fox	*Vulpes*	*vulpes*	253	3km	443
Striped skunk	*Mephitis*	*mephitis*	198	500m	193
White-tailed deer	*Odocoileus*	*virginianus*	535	3km	1771
Wild turkey	*Meleagris*	*gallopavo*	379	500m, 3km	1652

2.3. Objective 1 — Develop wildlife survey

We developed a survey to capture expert opinions of the probability of occurrence of each species. The survey asked experts to evaluate a set of sites and provide an occurrence estimate for target species at each site (see below). Development of the survey involved: 1) identifying survey sites, 2) estimating site characteristics, and 3) selecting appropriate experts.

2.3.1. Survey sites

Survey sites were U.S. Department of Agriculture (USDA) Forest Service Forest Inventory and Analysis (FIA) plot locations (see Bechtold and Patterson, 2005). Forest inventory plots occur in all forested lands in the United States and are spatially distributed across a national base grid (hexagonal grid with a plot randomly located within each 6000-acre hexagon; Bechtold and Patterson, 2005). The New England region included 6930 plots. Our sites were uniform circles, 3.14 km^2 in area (1-km radius), centered on the perturbed coordinates (see McRoberts et al., 2005) of all of these FIA plots. We used a 1-km radius in an effort to include diverse land cover within sites while also keeping the site small enough for survey participants (i.e., wildlife experts; see below) to accurately estimate occurrence.

2.3.2. Site covariates

We compiled a comprehensive covariate list that incorporated all potentially important drivers of distribution based on a literature review of each species' behavior and ecology. Site-specific information for a total of 54 covariates was provided to experts during the elicitation survey (see below). These covariates included 47 land cover variables (32 associated with forest species and 5 associated with forest age), 3 topographic variables, and 4 climate variables (Table A1). Covariate data were extracted and summarized for each site using the statistical computing language R (R Core Team, 2019) and the Geographic Information System, ArcGIS 10 (ESRI, Redlands, California, USA).

2.3.3. Experts

Wildlife experts were selected based on experience and qualifications. Baseline qualifications required experts to have a background in wildlife management, conservation, or related field, and strong knowledge of one or more of the focal species in the New England region. Experts were identified predominantly by their current and past research contributions, academic contributions, and work experience related to wildlife management and conservation. Professional wildlife biologists were recruited by contacting state and federal agencies. Additional experts — including experienced hunters and trappers — were identified according to their field-based knowledge and through expert nomination. All participation was voluntary; survey protocols were approved by the University of Vermont Institutional Research Board (IRB 17—0417).

2.4. Objective 2 — Conduct wildlife survey

2.4.1. New England Wildlife Survey

Expert opinion data were collected through a web-based survey interface developed by the Vermont Cooperative Fish and Wildlife Research Unit called AMSurvey (https://code.usgs.gov/vtcfwru/amsurvey). The survey tool was inspired by the 'Elicitator' framework developed by James et al. (2010) and consisted of three main sections, as described below.

2.4.1.1. Section 1. This section provided introductory information and a pre-survey questionnaire. Each expert was provided with written instructions, reference materials and a video tutorial to guide them through the elicitation process (see https://code.usgs.gov/vtcfwru/amsurvey/wiki for example materials). Experts were asked to identify their area of expertise (six possible regions, separated by state boundaries; multiple regions could be selected) and their target species of expertise (more than one species could be selected). Experts also completed a short pre-survey questionnaire, which focused on demographic information and the nature of their expertise (Appendix A).

2.4.1.2. Section 2. This section was the elicitation survey itself. A subset of the FIA sites (n = 30) were selected for each expert through a k-means clustering approach (Likas et al., 2003). Sites within the user's spatial area of expertise were clustered into 30 groups based on site covariate values. Then, we randomly sampled one site within each of the 30 groups to create an expert-specific subset of study sites. This approach ensured that an expert's sites were spatially and compositionally diverse in multivariate space.

The survey presented sites in random order one by one, and experts were asked to estimate the probability of occurrence for each of their selected target species during the breeding season at each site. Experts could complete less than 30 sites (e.g., skipping sites in which they were unfamiliar) and could elect to complete an additional 30 sites. Site-specific covariate data (Table A1) were displayed in a window containing an interactive satellite image, pie charts depicting land cover, forest species and forest age composition, and a list of relevant site characteristics (Fig. 2). The interactive satellite image (Google Maps, Google, Inc., Mountain View, California USA) was featured in the left portion of the browser window with an imbedded boundary circle to indicate the survey site location and extent (Fig. 2A). Experts could adjust the view of the satellite image (e.g., zoom or drag) to aid in site evaluation. Above the map image were two tabs ("Land Cover" and "Forest Composition"; Fig. 2B) that experts could select to view pie charts with percent cover information for site variables. An additional table of site characteristics related to climate, topography/geography, and road cover was displayed below the satellite image (Fig. 2C). The right portion of the browser window displayed an output graph of the expert's response (Fig. 2D). The title of this graph included the expert's target species, with the active selection designated by bolded text. Below the graph were two sliding scale bars ("Probability of Occurrence" and "Confidence in this Estimate") that experts were able to manipulate to provide an estimate of species occurrence within the site.

Experts were asked to estimate occurrence on a probability scale ranging from "low" (0 probability of occurrence or absent) to "high" (equal to a probability of 1.0, or 100%), and then indicate their confidence in each estimate on a scale from "low" (confidence value of 0) to "high" (confidence value of 1.0). Confidence measures were used to generate what the experts believed was the "true range" of probability of occurrence (e.g., an estimate with low confidence would have a large range of possible values). The manipulation of these estimate measures instantaneously altered the output graph, providing experts with visual feedback of their estimations.

2.4.1.3. Section 3. This section involved a covariate importance ranking exercise and a brief post survey questionnaire. Experts were able to define additional variables they believed influence species distribution; these variables were combined with the covariates presented in the site surveys during model development. Experts then allocated directionality (positive, negative, or neutral) to each variable and ranked them in their perceived order of importance (Fig. A1). The post survey questionnaire collected information about the survey experience and allowed experts to provide feedback on the elicitation process (Appendix A).

2.5. Objective 3 − Develop species distribution models

2.5.1. Data

Expert survey responses were downloaded into a comprehensive dataset that provided expert opinion data in the form of occurrence probabilities and measures of uncertainty (ranging from 0 to 1), as well as site data and site-specific covariate information. The dataset contained site level information for 74 different covariates; these covariates included the site variables used in the elicitation survey (n = 54; Table A1); however, additional expert-identified variables (n = 6), forest classification variables (n = 9), and climate variables (n = 5) were also included, as described later.

2.5.2. Model covariate reduction

For each species, the full covariate list was reduced to a "working" covariate list by three criteria: 1) Variables from the comprehensive list that demonstrated a strong linear correlation ($r \geq 0.6$) with the probability of occurrence data were included in the species' working covariate list; 2) The top ranked variables identified in the survey's covariate ranking exercise were included in the working covariate list. An importance score was calculated for each of the top ranked variables (i.e., variables ranked 1−5) by dividing the variables average rank by the number of times the variable appeared in the top five. Variables with an importance score less than or equal to 1 were identified as expert covariates and were included in the working covariate list; and 3) Any variables that were not specified by covariate rank or expert response criteria, yet were commonly identified in the literature, were also included in the working covariate list. Ultimately, the "working" covariate list was reduced to a simplified "final" covariate set (Table 2) to be used in species-specific distribution modeling.

We considered each variable in the working list at two spatial scales: A uniform site scale (1-km radius) was used for all species as well as a secondary species-specific landscape scale, which roughly corresponded to the species' home range size (500m, 3km, or 5km radius; Table 1). Scaled working covariates were compared using single variable models; the better performing scale for each variable was retained in the working list. Finally, we examined correlations within the working

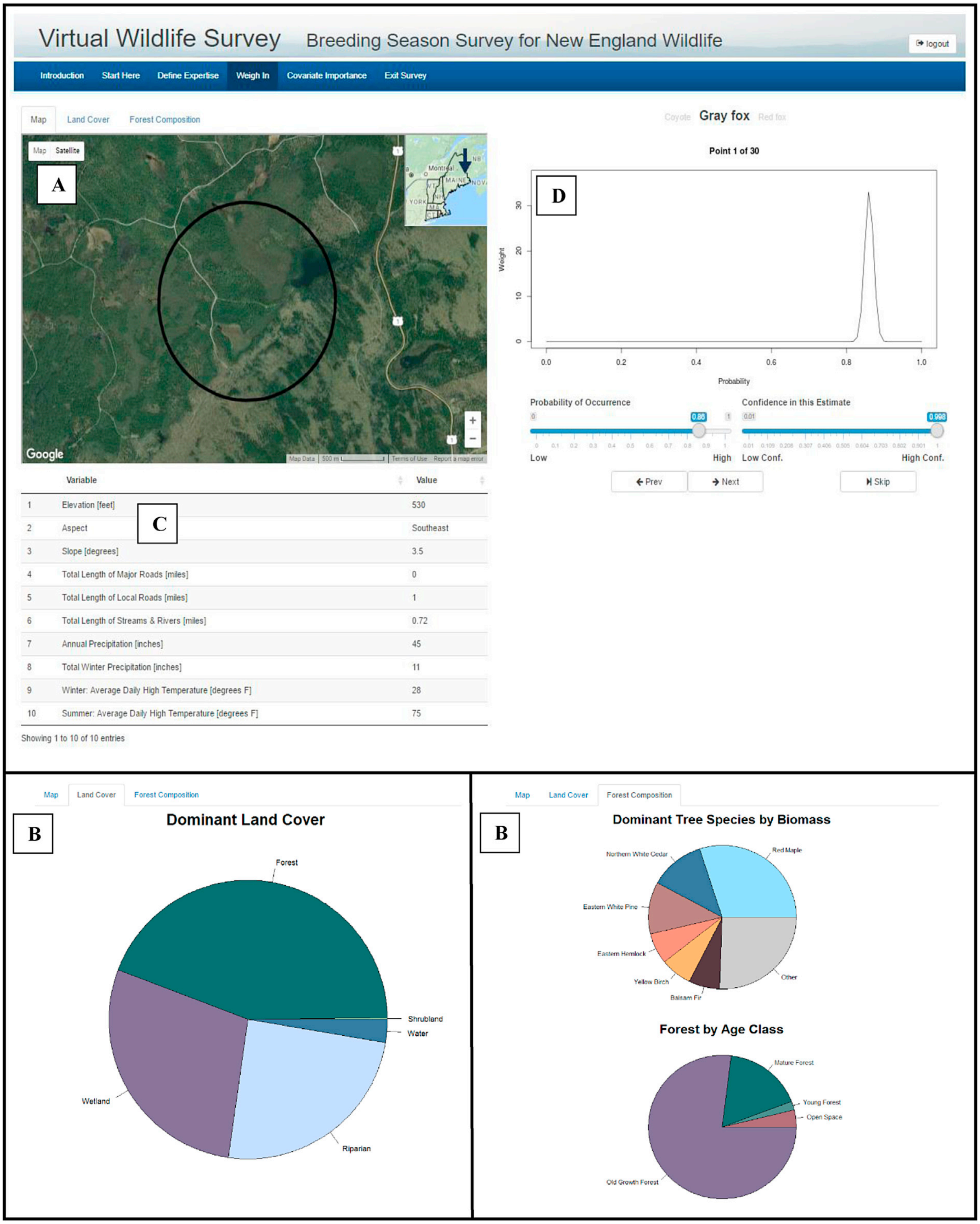

Fig. 2. Expert elicitation survey interface: A) interactive satellite map; B) additional images tabs (found to the right of the Map tab, above the satellite image) displaying Land Cover and Forest Composition pie charts; C) table of covariates and corresponding site values; and D) expert response sliders and linked output graph.

Table 2
Final covariates used in step-wise model selection for each species. Each species' covariate list was simplified from 74 variables assessed at the standard site scale (1km) and a species-specific landscape scale (500m, 3km, or 5km). Standardized step-based methods were used to identify the 6 to 13 most influential (scaled) variables believed to impact species occurrence throughout the New England region.

Covariates	Species (scale)									
	American black bear	Bobcat	Coyote	Gray fox	Moose	Raccoon	Red fox	Striped skunk	White-tailed deer	Wild turkey
mean_annual_precip_mm	5km	–	–	–	–	–	–	–	–	–
mean_DEM_km	–	–	–	1km	–	500m	–	500m	–	–
mean_fall_tmax_degC	–	–	–	–	1km	–	–	–	–	–
mean_winter_precip_mm	–	3km	1km	–	–	–	3km	–	3km	–
prop_agriculture	5km	1km	–	3km	–	500m	1km	500m	1km	–
prop_all_roads	1km	–	–	–	–	–	–	–	–	–
prop_conif_forest	–	–	–	–	5km	–	3km	–	3km	–
prop_decid_forest	–	–	–	–	–	500m	–	–	–	1km
prop_developed	–	1km	–	–	1km	500m	–	–	–	–
prop_early_succession	1km	3km	–	–	5k	–	3km	–	3km	3km
prop_fagugran	5km	–	–	–	–	–	–	–	3km	1km
prop_forest	5km	–	–	–	5km	–	3km	–	–	–
prop_forest_edge	–	1km	1km	1km	–	–	–	500m	–	1km
prop_grassland	–	–	1km	–	–	–	–	500m	–	3km
prop_hemlock_tamarack_cedar	–	–	–	–	–	–	–	–	3km	–
prop_high_dev	–	–	–	–	–	–	1km	–	1km	500m
prop_major_roads	–	–	3km	–	–	–	–	–	–	–
prop_mature_forest	1km	–	–	–	–	500m	–	500m	1km	500m
prop_oak	5km	–	–	–	–	500m	–	500m	–	3km
prop_old_forest	–	–	–	–	–	–	–	–	–	3km
prop_riparian	–	–	–	1km	5km	1km	3km	–	1km	1km
prop_rock	–	–	–	–	–	–	–	500m	–	–
prop_shrubland	–	3km	3km	3km	1km	500m	3km	1km	3km	3km
prop_waterbodies	–	–	1km	–	–	1km	–	–	–	–
prop_wetland	5km	–	3km	–	–	–	–	1km	–	–
prop_young_forest	–	–	–	1km	1km	–	1km	–	3km	3km

covariate list to eliminate redundant variables, providing a "final" covariate set for species-specific distribution modeling. Variables that did not exhibit correlation were retained in the final covariate list. Variables that exhibited correlation were compared using preliminary single variable models. Within a correlated set, only the top performing variable was retained and the remaining variables were removed from the covariate list.

2.5.3. Model selection

We used generalized linear mixed modeling approaches to develop SDMs from expert elicited probability of occurrence data. Species-specific models were analyzed in the R package lme4 (Bates et al., 2014) with stepwise modeling methods (described below). We used a glmer weighted approach (from the lmer4 package) to weight each expert's occurrence estimate by the expert's corresponding confidence estimate at a given site. This allowed us to account for expert identified uncertainty during model selection, giving higher influence to site elicitations in which experts were confident and lower influence to potentially less accurate estimates. For all models the response variable was probability of occurrence; expert, site, eco-region and state terms were specified as random-effects and covariates from the species' final covariate list were considered fixed-effects. Null models only contained random-effect variables for site and expert (these random-effects were included in all models).

Our stepwise model development incorporated forward and backward model selection and tested every variable combination to determine the best-fit model. Beginning with forward selection, a species' null model was run with glmer (from the lmer4 package) to create a logistic start model, and covariates were added sequentially based on the model's p-value criterion (0.05). Backward selection followed a similar approach with the glmer function (lmer4 package), beginning with the comprehensive model and dropping covariates from the model during each step of selection based on the p-value. To ensure that the best combination of variables was identified during stepwise selection, a secondary check was run to test all combinations of the variables retained during forward and backward selection. All combination models were ranked according to Akaike's Information Criterion (AIC; Burnham and Anderson, 2002) and the top performing model was selected. The top performing variable combination – typically consistent with the model identified by forward and backward selection – represented the final "best-fit" model.

2.5.4. Model validation

We used research grade species occurrence data (presence-only) from the crowdsourced biodiversity application, iNaturalist (iNaturalist, 2019) to test the performance of each species' top ranked model. For each species, we extracted occurrence data for sightings reported in the New England region between 2010 and 2018 (breeding season only). We trimmed datasets to help ensure that records were both confirmed (i.e., records included photo or audio evidence and an accurate species identification) and unique observations (i.e., records were distinct through time and space; Table 1). To test model performance, sighting (i.e., presence) locations were buffered (100m radius) and then superimposed on the species regional distribution map. Model estimated occurrence was calculated for each iNaturalist sighting. Predicted occurrences were then binned from 0 to 1 in increments of 0.1, and then plotted in a histogram to display how well the model predicted occurrence at these sites. Histograms that were skewed to the right (toward 1) indicated that the model estimated high occurrence likelihoods for many of the iNaturalist sites, suggesting that the model performed well against empirical data.

2.6. Objective 4 – Map species distributions

2.6.1. Mapping

We developed distribution maps for each species across New England using the raster package in R (Hijmans, 2016). For each species, we multiplied the parameter coefficients from the top model to each corresponding covariate value in a given cell (30 × 30 m) in raster maps of the study area. These values were then summed to obtain a logit score for each cell. Any SDM with significant random-effects (such as state or ecoregion random-effects) were added at this time. Logits were then transformed to occurrence probabilities with the logit link function. This process generated a set of spatially uniform maps that depicted the distributions of focal species throughout the New England region. The resulting distribution maps were also stacked and then cell values summed across all species to create an aggregate occurrence map. This community-aggregated map provided a measure of species richness for the focal group (Sauer et al., 2013). Richness values potentially ranged from 0 (no species present) to 10 (all species present).

3. Results

3.1. Objectives 1 & 2 – Multispecies expert opinion survey

A total of 46 wildlife experts participated in the New England Wildlife Survey and completed surveys from August to November 2017. Expert participants were primarily scientists, state agency personnel, and hunters/trappers. Experts contributed to site surveys in Connecticut ($n = 4$), Maine ($n = 11$), Massachusetts ($n = 6$), New Hampshire ($n = 20$), Rhode Island ($n = 4$), and Vermont ($n = 25$). A total of 3396 occurrence estimates were collected at 1258 different survey sites. Occurrence estimates were collected for American black bear ($n = 423$), bobcat ($n = 373$), coyote ($n = 355$), gray fox ($n = 188$), moose ($n = 459$), raccoon ($n = 233$), red fox ($n = 253$), striped skunk ($n = 198$), white-tailed deer ($n = 535$) and wild turkey ($n = 379$; Table 1).

3.2. Objective 3 – Species distribution models

Species-specific “final” covariate lists contained between six and thirteen probable drivers of distribution (Tables 2 and 3). The final lists contained variables identified by expert opinion, literature review and correlation with species occurrence, and were specified as fixed-effects during species distribution modeling. Random-effects for state and eco-region were included in 4 of 10 SDMs (Table 4) and shifted the model intercept within the corresponding regions (Table 5). Proportion agriculture was included in the majority (7 of 10) of the SDMs; forest variables were included in 9 of 10 SDMs, and climate variables were included in 6 of 10 SDMs.

Across species, top-ranking models contained two to six fixed-effect covariates and two or three random-effect covariates (Table 4). All fixed-effect model covariates exhibited individual effects significantly different from zero (Table 5, Fig. A2). All models had normally distributed residuals (mean = 0), and adhered to the assumptions of probabilistic likelihood models (Fig. A3).

Final SDMs converged and performed well when tested against crowdsourced empirical data. Seven of the 10 SDMs estimated high occurrence probabilities (mean ≥ 0.6) for greater than 75% of the iNaturalist sites (Fig. 3). Two of the remaining SDMs performed with moderate success – i.e., high occurrence probabilities were estimated for 67% (bobcat) and 65% (wild turkey) of the iNaturalist sites. One species' model (gray fox) exhibited low performance – i.e., high occurrence probabilities were estimated at only 33% of the iNaturalist sites.

3.3. Objective 4 – Species distribution maps

Distribution maps provided fine scale species-specific probability of occurrence estimates throughout New England (Fig. 4). ***American black bear*** occurrence was relatively high (average probability of occurrence, $\mu_p = 0.80$; Table 6), with greatest occurrence likelihoods in central regions of Vermont, New Hampshire, and Maine (Fig. 4A). ***Bobcat*** occurrence likelihoods were moderate throughout New England ($\mu_p = 0.67$; Table 6), with higher likelihoods in the less developed northern regions (Fig. 4B). ***Coyote*** occurrence was high throughout the region ($\mu_p = 0.92$; Table 6), with lower probability of occurrence in the highly developed regions of Massachusetts, Rhode Island, and Connecticut (Fig. 4C). ***Gray Fox*** occurrence was low throughout New England ($\mu_p = 0.42$; Table 6), with moderate occurrence likelihoods in central regions of Vermont

Table 3
Covariates used in model development for 10 wildlife species in the New England region of the northeastern United States. A total of 26 fixed-effect variables and 4 random-effect variables were included in model development. The fixed-effects included 22 land cover variables, 1 topographic variable, and 3 climate variables. The random-effects included 2 variables (site and expert) that were included in all models and 2 candidate variables (state and eco-region). Fixed-effect variables were included at the site scale (1km) or a generalized home range scale (500m, 3km, or 5km).

Variable	Covariate name	Description	Source
Agriculture	prop_agriculture	Area where land cover is classified as pasture, hay and cultivated crops.	National Land Cover Database 2011 (NLCD 2011; U.S. Geological Survey, 2014)
All Roads	prop_all_roads	Area where land cover is classified as major roads (controlled access highways, secondary highways or major connecting roads, ramps) or local roads (local roads, 4WD roads, private driveways).	National Transportation Database (NTD, 2016; U.S. Geological Survey, 2016)
American Beech	prop_fagugran	Forested land that is occupied by American Beech (*Fagus grandifolia*).	Duveneck et al. (2015)
Annual Precipitation	mean_annual_precip_mm	Average annual precipitation during the years 2010, 2011 and 2012.	Duveneck and Thompson, 2017; Stoner et al., 2013
Barren Land	prop_rock	Area where land cover is classified as barren land (i.e. rock, sand, or clay).	NLCD 2011
Conifer Forest	prop_conif_forest	Area where land cover is classified as evergreen forest.	NLCD 2011
Deciduous Forest	prop_decid_forest	Area where land cover is classified as deciduous forest.	NLCD 2011
Developed	prop_developed	Area where land cover is classified as developed open space, low intensity, medium intensity and high intensity development.	NLCD 2011
Early Successional Forest	prop_early_succession	Forested land that is classified by tree cohorts between 2 and 19 years old.	Duveneck & Thompson 2017
Eco-Region	EcoRegion	Area classified by terrestrial Eco Regions.	The Nature Conservancy (2009)
Elevation	mean_DEM_km	Height above sea level in kilometers.	Digital Elevation Model (DEM 2017; U.S. Geological Survey, 2017)
Fall: Average Daily High Temperature	mean_fall_tmax_degC	Average daily high temperature observed during the months of September, October and November during 2010–2012.	Duveneck & Thompson 2017; Stoner et al. 2013
Forest	prop_forest	Area where land cover is classified as deciduous, evergreen & mixed forest.	NLCD 2011
Forest Edge	prop_forest_edge	Area classified as forest that is within 300m of non-forest land cover.	NLCD 2011
Grassland	prop_grassland	Area where land cover is classified as grassland, herbaceous, pasture or hay.	NLCD 2011
Hemlock-Tamarack-Cedar Forest	prop_hemlock_tamarack_cedar	Forested land where AGB (above ground biomass) is dominated by Eastern Hemlock (*Tsuga canadensis*), native Tamarak (*Larix laricina*) and Northern White Cedar (*Thuja occidentalis*).	Duveneck & Thompson 2017
High Development	prop_high_dev	Area where land cover is classified as medium or high intensity development.	NLCD 2011
Late Successional Forest	prop_old_forest	Forested land that is classified by tree cohorts older than 100 years.	Duveneck & Thompson 2017
Major Roads	prop_major_roads	Area where land cover is classified as a major road (i.e. controlled access highways, secondary highways or major connecting roads, ramps).	NTD 2016
Mature Forest	prop_mature_forest	Forested land that is classified by tree cohorts between 40 and 100 years old.	Duveneck & Thompson 2017
Oak Forest	prop_oak	Forested land where AGB is dominated by White Oak (*Quercus alba*), Scarlet Oak (*Quercus coccinea*), Chestnut Oak (*Quercus prinus*), Northern Red Oak (*Quercus rubra*) and Black Oak (*Quercus velutina*).	Duveneck & Thompson 2017
Riparian	prop_riparian	Area where vegetation is classified as riparian.	U.S. Department of the Interior et al., 2012
Shrubland	prop_shrubland	Area where land cover is classified as shrub/scrub.	NLCD 2011
State	State	Area classified by USA state boundaries.	MassGIS, 2018
Total Winter Precipitation	mean_winter_precip_mm	Average cumulative winter (December–February) precipitation during the years 2010–2012. Note: This measure includes all types of precipitation, not just snowfall.	Duveneck & Thompson 2017; Stoner et al. 2013
Water	prop_waterbodies	Area occupied by waterbodies; lakes, ponds, reservoirs, estuaries, swamps and marshes.	NLCD 2011
Wetland	prop_wetland	Area classified as woody wetlands or emergent herbaceous wetlands.	NLCD 2011
Young Forest	prop_young_forest	Forested land that is classified by tree cohorts between 20 and 39 years old.	Duveneck & Thompson 2017

Table 4
Final distribution models for estimating species occurrence throughout the New England region of the northeastern United States. Models were developed using expert opinion data and generalized linear mixed modeling. Expert and site specific random-effects and fixed-effects were included during model fitting.

Species	Model formula
American black bear	Mean ~ prop_mature_forest + prop_all_roads + prop_forest_5k + mean_annual_precip_mm_5k + prop_fagugran_5k + (1 | State) + (1 | Expert) + (1 | Site)
Bobcat	Mean ~ prop_developed + prop_forest_edge + prop_agriculture + (1 | Expert) + (1 | Site)
Coyote	Mean ~ prop_waterbodies + prop_forest_edge + prop_major_roads_3k + prop_wetland_3k + prop_agriculture + (1 | Expert) + (1 | Site)
Gray fox	Mean ~ prop_forest_edge + prop_agriculture_3k + mean_DEM_km + (1 | State) + (1 | Expert) + (1 | Site)
Moose	Mean ~ prop_young_forest + prop_developed + prop_shrubland +mean_fall_tmax_degC + prop_forest_5k + (1 | Expert) + (1 | Site)
Raccoon	Mean ~ prop_agriculture_500m + prop_mature_forest_500m + mean_DEM_km_500m + prop_oak_500m + prop_developed_500m + (1 | Expert) + (1 | Site)
Red fox	Mean ~ prop_agriculture + prop_high_dev +mean_winter_precip_mm_3k + prop_shrubland_3k + (1 | Expert) + (1 | Site)
Striped skunk	Mean ~mean_DEM_km_500m + prop_mature_forest_500m + prop_agriculture_500m + prop_forest_edge_500m + (1 | Expert) + (1 | Site)
White-tailed deer	Mean ~ prop_agriculture + prop_high_dev + prop_mature_forest + prop_hemlock_tamarack_cedar_3k + (1 | EcoRegion) + (1 | Expert) + (1 | Site)
Wild turkey	Mean ~ prop_decid_forest + prop_forest_edge + prop_riparian + prop_grassland_3k + (1 | EcoRegion) + (1 | Expert) + (1 | Site)

and New Hampshire (Fig. 4D), and distinctly higher mean occurrence observed in the less developed western regions of Massachusetts ($\mu_{p\ \mathrm{Massachusetts}} = 0.69$; Table 6). ***Moose*** occurrence varied considerably between northern and southern New England (Fig. 4E), leading to moderate regional occurrence ($\mu_p = 0.52$; Table 6). ***Raccoon*** occurrence was high throughout much of New England ($\mu_p = 0.87$; Table 6), with lower occurrence probabilities moving north into the mountainous regions of Vermont, New Hampshire, and Maine (Fig. 4F). ***Red Fox*** occurrence was moderate throughout the region (μ_p p = 0.64; Table 6), with highest likelihoods in regions of northwestern Vermont and northeastern Maine (Fig. 4G). ***Striped skunk*** occurrence was moderate-high throughout much of New England ($\mu_p = 0.75$; Table 6), with higher likelihoods in the southern states and lower elevation regions of Vermont, New Hampshire, and Maine (Fig. 4H). ***White-tailed deer*** occurrence was high throughout the region ($\mu_p = 0.89$; Table 6), except in the highly developed areas of Massachusetts, Rhode Island and Connecticut (Fig. 4I). ***Wild turkey*** occurrence was moderate throughout much of the region ($\mu_p = 0.68$; Table 6) with highest occurrence likelihoods in the less developed areas of Connecticut, Vermont, Rhode Island, and Massachusetts (Fig. 4J).

Overall, 5 focal species (American black bear, coyote, raccoon, striped skunk, and white-tailed deer) exhibited high regional occurrence ($\mu_p > 0.75$), 4 species (bobcat, moose, red fox, and wild turkey) exhibited moderately high regional occurrence ($0.50 < \mu_p \leq 0.75$) and 1 species (gray fox) exhibited moderately low regional occurrence ($0.25 < \mu_p \leq 0.50$). State-based statistics for each species show considerable variability in occurrence likelihoods across state-boundaries (Table 6).

Species richness estimates (s) ranged from 2.42 to 8.72, with a regional average of 7.16 (Fig. 5, Table 7). Occurrence across all species was highest in the lower elevation regions of Maine, New Hampshire, and Vermont, and lowest in the most developed regions of Massachusetts, Connecticut, and Rhode Island. The largest connected area with high focal species richness ($s \geq 8.0$) was along the Connecticut River Valley in northern Massachusetts through Vermont and New Hampshire and north into the Western Foothills of Maine. At the state level, focal species richness was highest in Vermont (average species richness, $\mu_s = 7.47$) and Maine ($\mu_s = 7.32$) and lowest in Rhode Island ($\mu_s = 6.13$) and Massachusetts ($\mu_s = 6.61$; Table 7).

4. Discussion

Species distribution models capture the influence of landscape conditions on wildlife occurrence and can help inform and prioritize conservation and management activities (Elith and Leathwick, 2009). We demonstrated that expert elicitation techniques combined with stepwise mixed-effect modeling methods can be used to develop spatially compatible SDMs for wildlife species. Our SDMs for 10 harvested species performed well at predicting species occurrence throughout the New England region, offering new information on factors that shape distributions. This set of spatially compatible and regionally applicable models offer probabilistic insight that can help inform conservation and management decisions.

4.1. Expert elicitation

Expert elicitation is used in many fields to gain information when empirical data are limited, unavailable, or difficult to obtain (James et al., 2010). To overcome the limitations and challenges of observational studies, expert opinion data have been used by numerous studies to model habitat quality and predict wildlife distributions (Aylward et al., 2018; Murray et al., 2009; Pearce et al., 2001; Yamada et al., 2003), identify habitat linkages (Clevenger et al., 2002), and estimate species movement corridors (Aylward et al., 2018). Elicitation offers a relatively quick and inexpensive approach to data collection that can be particularly valuable to large-scale studies of rare or poorly documented species. Collecting an ample amount of occurrence

Table 5
Fixed-effect parameter estimates with standard error, upper and lower 95% confidence intervals (CI), and p-values for covariates in 10 species models. Random-effects associated with state or eco-region are included when significant, noted in parentheses. Models estimate species-specific occurrence in the New England region of the northeastern United States.

Species	Covariate	Estimate	Standard error	Lower CI	Upper CI	P-value
American black bear	(Intercept)	25.64	11.34	3.42	47.86	0.0237
	prop_mature_forest	3.27	0.86	1.59	4.95	0.0001
	prop_all_roads	−12.47	2.15	−16.68	−8.26	0.0000
	prop_forest_5k	6.16	0.88	4.43	7.90	0.0000
	mean_annual_precip_mm_5k	−21.90	8.50	−38.57	−5.24	0.0100
	prop_fagugran_5k	2.40	1.01	0.42	4.38	0.0174
	(Connecticut)	1.90	–	–	–	–
	(Maine)	0.48	–	–	–	–
	(Massachusetts)	−0.44	–	–	–	–
	(New Hampshire)	−0.77	–	–	–	–
	(Rhode Island)	0.14	–	–	–	–
	(Vermont)	−1.41	–	–	–	–
Bobcat	(Intercept)	0.22	0.36	−0.48	0.93	0.5322
	prop_developed	−2.6	0.50	−3.58	−1.62	0.0000
	prop_forest_edge	1.02	0.42	0.19	1.85	0.0155
	prop_agriculture	1.42	0.52	0.40	2.44	0.0064
Coyote	(Intercept)	1.42	0.72	0.01	2.82	0.0481
	prop_waterbodies	−4.08	0.97	−5.99	−2.18	0.0000
	prop_forest_edge	2.79	0.54	1.73	3.86	0.0000
	prop_major_roads_3k	−32.05	9.94	−51.54	−12.56	0.0013
	prop_wetland_3k	2.85	1.34	0.21	5.48	0.0341
	prop_agriculture	1.31	0.71	−0.07	2.70	0.0636
Gray fox	(Intercept)	−3.53	0.76	−5.02	−2.03	0.0000
	prop_forest_edge	5.57	0.74	4.12	7.02	0.0000
	prop_agriculture_3k	3.31	1.15	1.06	5.56	0.0039
	mean_DEM_km	−1.82	0.89	−3.57	−0.08	0.0408
	(Connecticut)	−0.84	–	–	–	–
	(Maine)	−0.80	–	–	–	–
	(Massachusetts)	1.99	–	–	–	–
	(New Hampshire)	−0.29	–	–	–	–
	(Rhode Island)	0.16	–	–	–	–
	(Vermont)	0.49	–	–	–	–
Moose	(Intercept)	8.13	1.61	4.97	11.29	0.0000
	prop_young_forest	7.02	2.93	1.27	12.76	0.0167
	prop_developed	−4.59	0.78	−6.11	−3.06	0.0000
	prop_shrubland	5.11	1.37	2.43	7.79	0.0002
	mean_fall_tmax_degC	−73.71	8.98	−91.32	−56.1	0.0000
	prop_forest_5k	3.52	0.65	2.25	4.79	0.0000
Raccoon	(Intercept)	1.65	0.71	0.27	3.04	0.0194
	prop_agriculture_500m	3.04	0.75	1.58	4.51	0.0000
	prop_mature_forest_500m	1.21	0.54	0.15	2.27	0.0248
	mean_DEM_km_500m	−2.09	0.66	−3.37	−0.80	0.0015
	prop_oak_500m	1.66	0.83	0.03	3.3	0.0466
	prop_developed_500m	2.26	0.60	1.07	3.44	0.0002
Red fox	(Intercept)	−3.16	1.77	−6.63	0.3	0.0735
	prop_agriculture	3.28	0.61	2.09	4.47	0.0000
	prop_high_dev	−3.23	1.21	−5.60	−0.86	0.0076
	mean_winter_precip_mm_3k	12.65	6.30	0.31	24.99	0.0445
	prop_shrubland_3k	3.50	2.10	−0.63	7.62	0.0966
Striped skunk	(Intercept)	1.91	0.79	0.36	3.45	0.0158
	mean_DEM_km_500m	−6.25	0.60	−7.44	−5.07	0.0000
	prop_mature_forest_500m	0.91	0.58	−0.23	2.06	0.1182
	prop_agriculture_500m	3.40	0.76	1.91	4.88	0.0000
	prop_forest_edge_500m	0.74	0.49	−0.22	1.70	0.1288
White-tailed deer	(Intercept)	1.17	0.68	−0.17	2.50	0.0872
	prop_agriculture	4.22	0.83	2.60	5.84	0.0000
	prop_high_dev	−10.52	0.84	−12.17	−8.88	0.0000
	prop_mature_forest	1.47	0.62	0.27	2.68	0.0168
	prop_hemlock_tamarack_cedar_3k	10.50	1.69	7.18	13.82	0.0000
	(Lower New England/Northern Piedmont)	0.33	–	–	–	–
	(North Atlantic Coast)	0.06	–	–	–	–
	(Northern Appalachian/Acadian)	−0.09	–	–	–	–
	(St. Lawrence - Champlain Valley)	−0.41	–	–	–	–
Wild turkey	(Intercept)	−1.83	0.69	−3.18	−0.48	0.0080
	prop_decid_forest	1.33	0.58	0.20	2.47	0.0214
	prop_forest_edge	1.95	0.59	0.81	3.10	0.0008
	prop_riparian	2.97	1.17	0.67	5.26	0.0112
	prop_grassland_3k	16.76	2.52	11.81	21.70	0.0000

(*continued on next page*)

Table 5 (*continued*)

Species	Covariate	Estimate	Standard error	Lower CI	Upper CI	P-value
	(Lower New England/Northern Piedmont)	0.35	–	–	–	–
	(North Atlantic Coast)	0.82	–	–	–	–
	(Northern Appalachian/Acadian)	−0.05	–	–	–	–
	(St. Lawrence - Champlain Valley)	−1.49	–	–	–	–

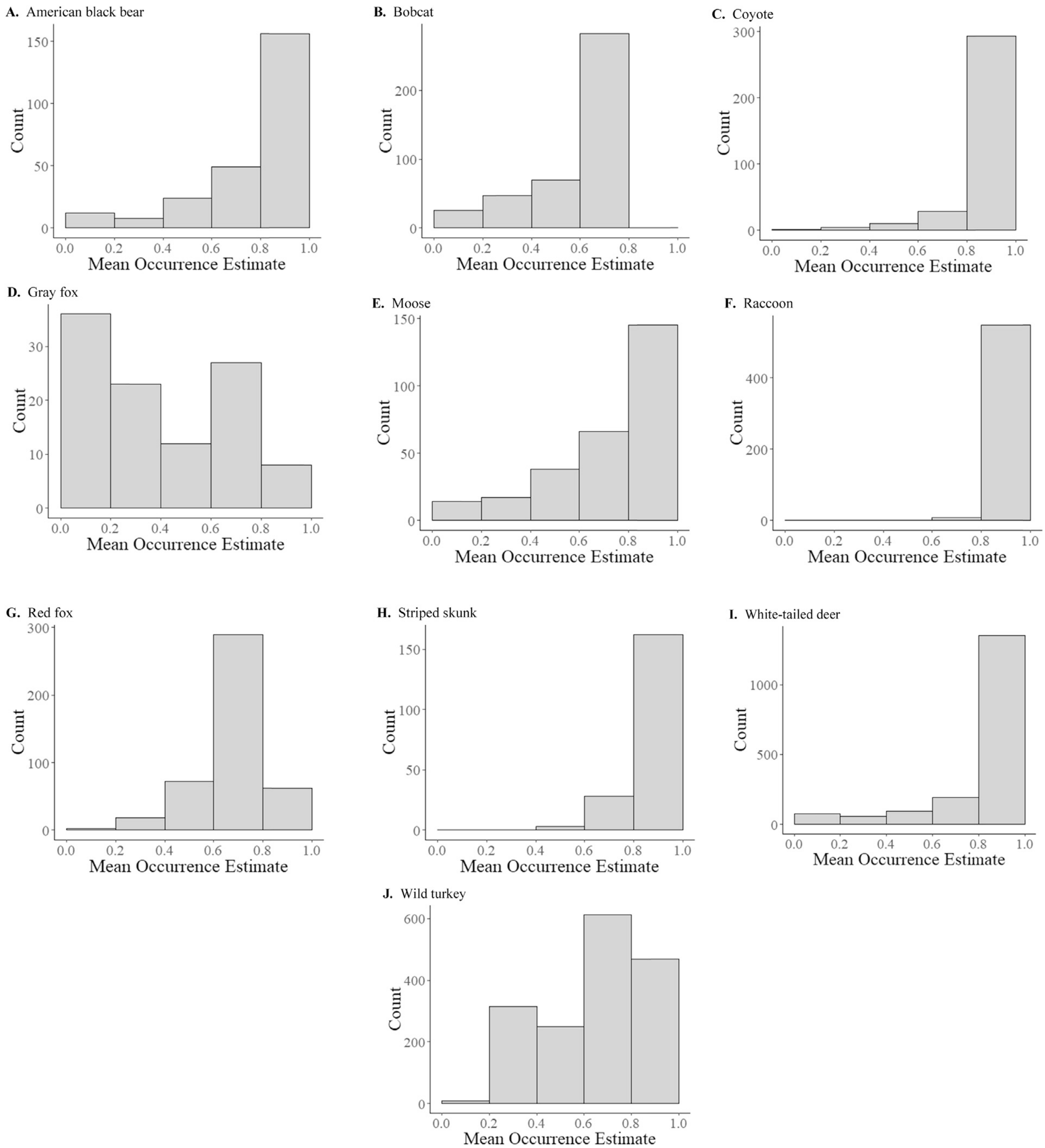

Fig. 3. Distribution of model estimated mean occurrence at sites with positive occurrence records (i.e., presence data). Species presence data were sourced from iNaturalist and included community-sourced occurrence records for all focal species throughout the New England region of the northeastern United States. Presence locations were buffered (circular; 100m radius) and model estimated mean occurrence was calculated for each site. Histograms show the distribution of mean occurrence estimates. Note that the y-axis scale is different among species. The majority of the species models estimated high occurrence at >70% of the presence locations indicating that that models have strong predictive ability.

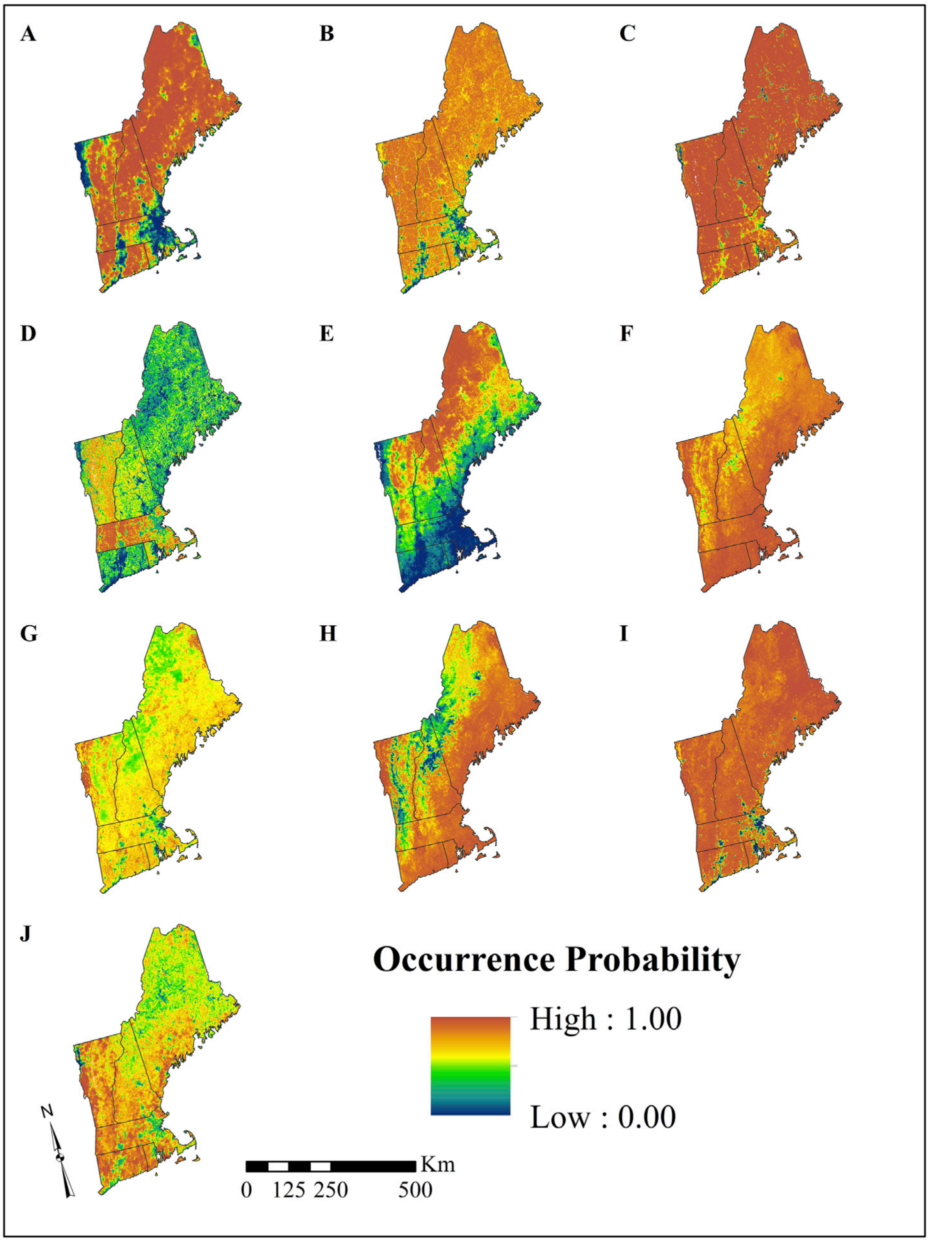

Fig. 4. Estimated occurrence of 10 focal wildlife species (A–J) in the New England region of the northeastern United States. Occurrence estimates were based on species-specific distribution models fit using expert opinion data and generalized linear mixed modeling. Species models incorporated site and expert associated random intercept effects and fixed habitat effects. Distribution maps correspond with the following species: A) American black bear, B) Bobcat, C) Coyote, D) Gray fox, E) Moose, F) Raccoon, G) Red fox, H) Striped skunk, I) White-tailed deer, and J) Wild turkey. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

data for 10 different wildlife species at the New England regional extent would be difficult and costly without the use of expert elicitation techniques.

While expert elicitation generates valuable information and overcomes many challenges of observational studies, opinion-based studies introduce their own challenges. Using opinion-based data can create room for personal biases, and the possible introduction of inaccurate information (Low Choy et al., 2009). Additionally, if an elicitation platform is challenging to use, difficult to understand, or provides ambiguous instructions, experts may misinterpret how best to provide opinions, which could lead to low quality data (James et al., 2010; Low Choy et al., 2009). We addressed these concerns by designing a survey application that was user-friendly, provided clear and concise instructions, and offered an engaging and interactive experience (https://code.usgs.gov/vtcfwru/amsurvey/wiki). The survey was tested on several volunteers beforehand to ensure ease

Table 6
Regional and state-level mean occurrence estimates for 10 wildlife species in the New England region of the northeastern United States. Occurrence estimates were based on species-specific distribution models fit using expert opinion data and generalized linear mixed modeling. Species models incorporated site and expert associated random intercept effects and fixed habitat effects.

Species	Region	Minimum	Maximum	Mean	Standard Deviation
American black bear	Connecticut	0.00	1.00	0.73	0.31
	Maine	0.00	1.00	0.91	0.15
	Massachusetts	0.00	1.00	0.46	0.37
	New Hampshire	0.00	1.00	0.84	0.23
	Rhode Island	0.00	0.97	0.42	0.32
	Vermont	0.00	1.00	0.74	0.31
	New England	0.00	1.00	0.80	0.29
Bobcat	Connecticut	0.09	0.81	0.57	0.20
	Maine	0.09	0.84	0.70	0.07
	Massachusetts	0.09	0.80	0.55	0.20
	New Hampshire	0.09	0.80	0.69	0.11
	Rhode Island	0.09	0.77	0.52	0.21
	Vermont	0.09	0.84	0.72	0.07
	New England	0.09	0.84	0.67	0.13
Coyote	Connecticut	0.07	0.99	0.89	0.13
	Maine	0.03	0.99	0.94	0.13
	Massachusetts	0.02	0.99	0.87	0.16
	New Hampshire	0.04	0.99	0.94	0.11
	Rhode Island	0.03	0.99	0.83	0.20
	Vermont	0.04	0.99	0.93	0.14
	New England	0.02	1.00	0.92	0.14
Gray fox	Connecticut	0.01	0.81	0.27	0.17
	Maine	0.00	0.82	0.31	0.16
	Massachusetts	0.12	0.99	0.69	0.25
	New Hampshire	0.00	0.87	0.45	0.18
	Rhode Island	0.03	0.88	0.36	0.25
	Vermont	0.01	0.98	0.61	0.20
	New England	0.00	0.99	0.42	0.24
Moose	Connecticut	0.00	0.80	0.09	0.09
	Maine	0.00	1.00	0.67	0.28
	Massachusetts	0.00	0.87	0.15	0.18
	New Hampshire	0.00	1.00	0.54	0.30
	Rhode Island	0.00	0.66	0.06	0.08
	Vermont	0.00	1.00	0.59	0.27
	New England	0.00	1.00	0.52	0.34
Raccoon	Connecticut	0.67	1.00	0.95	0.03
	Maine	0.19	1.00	0.86	0.08
	Massachusetts	0.49	1.00	0.93	0.06
	New Hampshire	0.12	1.00	0.86	0.10
	Rhode Island	0.81	1.00	0.96	0.03
	Vermont	0.33	0.99	0.85	0.10
	New England	0.12	1.00	0.87	0.09
Red fox	Connecticut	0.08	0.97	0.68	0.12
	Maine	0.11	0.98	0.63	0.08
	Massachusetts	0.07	0.97	0.63	0.13
	New Hampshire	0.07	0.95	0.62	0.08
	Rhode Island	0.08	0.95	0.62	0.17
	Vermont	0.10	0.98	0.67	0.11
	New England	0.07	0.98	0.64	0.10
Striped skunk	Connecticut	0.20	0.99	0.87	0.08
	Maine	0.00	0.99	0.76	0.20
	Massachusetts	0.03	1.00	0.82	0.16
	New Hampshire	0.00	0.99	0.66	0.27
	Rhode Island	0.71	0.99	0.90	0.03
	Vermont	0.01	0.99	0.64	0.26
	New England	0.00	1.00	0.75	0.22
White-tailed deer	Connecticut	0.00	1.00	0.83	0.23
	Maine	0.00	1.00	0.93	0.07
	Massachusetts	0.00	1.00	0.79	0.26
	New Hampshire	0.00	1.00	0.90	0.11
	Rhode Island	0.00	0.99	0.70	0.32
	Vermont	0.00	1.00	0.91	0.08
	New England	0.00	1.00	0.89	0.15
Wild turkey	Connecticut	0.19	1.00	0.79	0.19
	Maine	0.13	1.00	0.61	0.14
	Massachusetts	0.19	1.00	0.73	0.19
	New Hampshire	0.13	0.99	0.70	0.13
	Rhode Island	0.22	1.00	0.74	0.19

Table 6 (*continued*)

Species	Region	Minimum	Maximum	Mean	Standard Deviation
	Vermont	0.04	1.00	0.77	0.17
	New England	0.04	1.00	0.68	0.17

of use and clarity. We also recruited a large cohort (n = 46) of experts from management agencies and research institutions throughout New England, and had experts provide responses only for the species and regions in which they had self-identified expertise. Contribution from numerous wildlife experts helped to reduce individual bias and collect regionally representative data.

We developed models of distribution during the breeding season, which is often the focus of species and population level management. However, because the actual timing of the breeding season varied among species in the focal group, the seasonal accuracy of expert's responses may have diminished when experts provided feedback for multiple species. This could have led to more generalized occurrence data and may explain why variables in some of the SDMs were not breeding season specific (e.g., the inclusion of grassland in the wild turkey model). Expert elicitation modeling could be improved by reducing seasonal ambiguity (e.g., survey species with a common breeding season) or conducting more specific assessments (e.g., survey a single species).

There are also several potential benefits of using expert elicitation to create SDMs. First, the approach incorporates information from expert knowledge and experience, as well as the literature. The elicitation process required experts to assign occurrence probabilities along with their certainty, effectively aggregating the expert's opinion as an informed prior probability distribution for each site. In setting this distribution, experts are using knowledge of the species, which is presumably based on an amalgamation of their experiences with the species and the landscape. These educated responses provide a level of information not necessarily obtainable from an empirical study (Kynn, 2005; Murray et al., 2009). Second, including experts in data collection may promote expert buy-in and user confidence in the data and resulting products (i.e., maps), potentially leading to more proactive and collaborative conservation and management decisions (Reed, 2008). Third, the trends observed in our SDMs were consistent with the literature and provide covariate effect sizes that allowed us to estimate species occurrence throughout the study region.

4.2. SDM performance

We validated our models with observational data (presence records) from the crowd-source platform, iNaturalist. While other sources of data were available for some of our focal species such as radio-collar and harvest data, these records were often concentrated at small spatial scales or lacked a reasonable spatial resolution (e.g., harvest locations recorded at the town or wildlife management unit scale), were inconsistent across space and time, or were collected in time periods that did not coincide with our landcover data. We used iNaturalist data because they provided a consistent source of region-wide occurrence data for all 10 focal species. The iNaturalist records were validated and classified as 'research grade', and allowed us to test model performance with separate data, obtained through alternative methods − i.e., community observation rather than expert opinion.

Our SDMs generally fit the iNaturalist data well, suggesting that they reflected the effects of landscape conditions on occurrence for all species in the focal group, except one, the gray fox. There are several possible explanations for the lower performance of the gray fox model, including: 1) the sample size of expert opinion values may not have been adequate enough to describe occurrence (samples size for this species was considerably less than for other species; Table 1); 2) experts may have had less certainty about estimating occurrence for the species, which is poorly studied in the region; and 3) the available validation data may have been biased and less representative for the species. Using community-sourced occurrence data for validation purposes presents challenges (Sardà-Palomera et al., 2012; Tulloch and Szabo, 2012). While measures were taken to reduce bias and maximize data accuracy, community-sourced data is inherently skewed towards areas most accessible to the human observer (i.e., developed and/or open land types) and is restricted by the voluntary nature in which it is collected (Tulloch et al., 2013; Tulloch and Szabo, 2012). Testing the gray fox model against other independent data sets would help assess the accuracy of the model. Despite the challenges of model development and validation, our SDMs provide novel information about the effect size of important variables and can be used to estimate species occurrence in new locations or changing landscapes.

4.3. Distribution models and maps

Many studies have been conducted to identify important habitats for wildlife species. However, few studies have quantified the effects that habitat variables have on multiple wildlife species or large regional extents. Our approach generated accessible expert informed models for multiple wildlife species, allowing us to determine species-specific effects and compare effects across species in the focal group. Generally, most SDMs included variables at both site scale and the species-specific landscape scale, emphasizing the importance of assessing variables at multiple spatial scales as certain variables may be more or less influential at different scales.

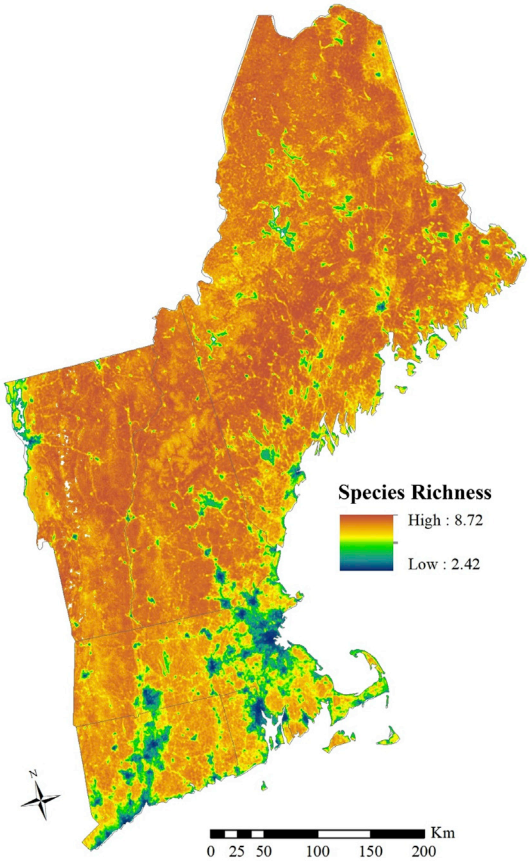

Fig. 5. Species richness based on probability of occurrence estimates for 10 focal wildlife species in the New England region of the northeastern United States. Each value represents the sum of occurrence values across all species at a given site.

Table 7
State-based species richness information for 10 wildlife species in the New England region of the northeastern United States. Species richness was calculated using aggregate occurrence estimates from species-specific distribution models for 10 wildlife species. Species models were fit using expert opinion data and generalized linear mixed modeling.

Region	Minimum	Maximum	Mean	Standard deviation
Connecticut	2.50	8.35	6.68	1.24
Maine	2.52	8.58	7.32	0.64
Massachusetts	2.59	8.72	6.61	1.41
New Hampshire	2.42	8.41	7.19	0.81
Rhode Island	2.51	8.30	6.13	1.55
Vermont	2.69	8.68	7.47	0.73
New England	2.42	8.72	7.16	0.94

Focal species occurrence was generally highest in structurally diverse forested areas and lowest in highly developed areas. These relationships are not surprising as many of the focal species are forest obligates. All SDMs included at least one forest variable. The two forest variables that appeared in SDMs most commonly were mature forest and forest edge; however, six other forest composition and forest structure variables appeared across all SDMs. The inclusion of these forest variables emphasizes the importance of habitat structure and habitat configuration for the wildlife species we included in the study, and the need to effectively conserve forested lands in the face of human development and land-use change. Because forest use activities can alter these variables on the ground, it is important to have models (and maps) that capture the influence of any changes and can be continually improved or updated as new information becomes available (i.e., forming the basis of adaptive management; Williams, 2011).

Observing lower occurrence probabilities in developed areas is also not surprising. While many species utilize urbanized landscapes, the presence of development often reduces the availability and accessibility of important habitat (Fischer and Lindenmayer, 2007). We found that high disturbance development variables, including roads and developed areas, exhibited negative relationships with occurrence in six of the SDMs. However, human-associated variables such as forest edge and agriculture appeared in eight of our SDMs and exhibited positive relationships with occurrence. These differences indicate that varied levels of human disturbance impact wildlife in different ways and suggest that certain levels of anthropogenic influence can produce favorable habitat conditions within a landscape (Fahrig et al., 2011; Hunter and Schmiegelow, 2011; Tews et al., 2004).

We were also able to quantify relationships between climate variables and species occurrence. Three species models (American black bear, moose, and red fox) included climate variables as fixed-effects. Isolating climate variables as direct influencers of distribution can provide insight on how shifts in climate directly impact wildlife species. While several studies have identified climate change as a threat to wildlife (Chapin et al., 2000; Pacifici et al., 2017; Thomas et al., 2004), little is known about the effects of climate variables on individual species. Our modeling approach allowed us to quantify relationships between species occurrence and important climate variables, offering a quantitative basis for assessing the consequences of climate and land-use change. This information may be particularly important as changes in climate and land-use are projected to increase in the future and will likely have considerable impacts on species distributions and overall species richness (Chapin et al., 2000; Díaz et al., 2019; Rustad et al., 2012).

Through expert elicitation and mixed modeling methods, we were able to develop a collection of SDMs and distribution maps that offer valuable information about wildlife occurrence in New England. These versatile modeling tools provide regionally applicable and spatially compatible information for multiple wildlife species and provide a means for future scenario-based assessments. These forecasted assessments can help inform proactive decision-making and benefit long-term management and conservation planning throughout the New England region.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gecco.2019.e00853.

References

Aylward, C.M., Murdoch, J.D., Donovan, T.M., Kilpatrick, C.W., Bernier, C., Katz, J., 2018. Estimating distribution and connectivity of recolonizing American marten in the northeastern United States using expert elicitation techniques. Anim. Conserv. https://doi.org/10.1111/acv.12417.

Bates, D., Mächler, M., Bolker, B., Walker, S., 2014. Fitting linear mixed-effects models using lme4. J. Stat. Softw. 67, 1–48. https://doi.org/10.18637/jss.v067.i01.

Bechtold, W.A., Patterson, P.L., 2005. The enhanced forest inventory and analysis program — national sampling design and estimation procedures. USDA Gen. Tech. Rep. SRS 80, 85.

Brooks, R.T., Frieswyk, T.S., Griffith, D.M., Cooter, E., Smith, L., 1992. The New England Forest. Baseline for New England Forest Health Monitoring.

Brown, R.M., Laband, D.N., 2006. Species imperilment and spatial patterns of development in the United States. Conserv. Biol. 20, 239–244. https://doi.org/10.1111/j.1523-1739.2005.00294.x.

Burnham, K.P., Anderson, D., 2002. Model Selection and Multimodel Inference: a Practical Information-Theoretic Approach. https://doi.org/10.1007/b97636.

Caro, T.M., 2010. Conservation by Proxy: Indicator, Umbrella, Keystone, Flagship, and Other Surrogate Species, second ed. Island Press, Washington.

Chapin, F.S., Zavaleta, E.S., Eviner, V.T., Naylor, R.L., Vitousek, P.M., Reynolds, H.L., Hooper, D.U., Lavorel, S., Sala, O.E., Hobbie, S.E., Mack, M.C., Díaz, S., 2000. Consequences of changing biodiversity. Nature 405, 234–242. https://doi.org/10.1038/35012241.

Clevenger, A.P., Wierzchowski, J., Chruszcz, B., Gunson, K., 2002. GIS-generated, expert-based models for identifying wildlife habitat linkages and planning mitigation passages. Conserv. Biol. 16, 503–514.

DeGraaf, R.M., Yamasaki, M., 2001. New England Wildlife: Habitat, Natural History, and Distribution. U. S. Department of Agriculture, Forest Service, Northeastern Forest Experimental Station. University Press of New England, Hanover, NH.

Díaz, S., Settele, J., Brondízio, E., Ngo, H.T., Guèze, M., Agard Trinidad, J., Arneth, A., Balvanera, P., Brauman, K., Watson, R.T., Baste, I.A., Larigauderie, A., Leadley, P., Pascual, U., Baptiste, B., Demissew, S., Dziba, L., Erpul, G., Fazel, A., Fischer, M., María Hernández, A., Karki, M., Mathur, V., Pataridze, T., Sousa Pinto, I., Stenseke, M., Török, K., Vilá, B., Carneiro da Cunha, M., Mace, G.M., Mooney, H., 2019. Summary for Policymakers of the Global Assessment Report on Biodiversity and Ecosystem Services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services.

Dupigny-Giroux, L.-A., Mecray, E., Lemcke-Stampone, M., Hodgkins, G.A., Lentz, E.E., Mills, K.E., Lane, E.D., Miller, R., Hollinger, D., Solecki, W.D., Wellenius, G. A., Sheffield, P.E., MacDonald, A.B., Caldwell, C., 2018. Chapter 18 : Northeast. Impacts, Risks, and Adaptation in the United States: the Fourth National Climate Assessment, Volume II. U.S. Global Change Research Program, Washington, DC. https://doi.org/10.7930/NCA4.2018.CH18.

Duveneck, M.J., Thompson, J.R., 2017. Climate change imposes phenological trade-offs on forest net primary productivity. J. Geophys. Res. Biogeosciences. https://doi.org/10.1002/2017JG004025.

Duveneck, M.J., Thompson, J.R., Wilson, B.T., 2015. An imputed forest composition map for New England screened by species range boundaries. For. Ecol. Manag. 347, 107–115. https://doi.org/10.1016/j.foreco.2015.03.016.
Elith, J., Leathwick, J.R., 2009. Species distribution models: ecological explanation and prediction across space and time. Annu. Rev. Ecol. Evol. Syst. 40, 677–697. https://doi.org/10.1146/annurev.ecolsys.110308.120159.
Fahrig, L., Baudry, J., Brotons, L., Burel, F.G., Crist, T.O., Fuller, R.J., Sirami, C., Siriwardena, G.M., Martin, J.L., 2011. Functional landscape heterogeneity and animal biodiversity in agricultural landscapes. Ecol. Lett. 14, 101–112. https://doi.org/10.1111/j.1461-0248.2010.01559.x.
Fischer, J., Lindenmayer, D.B., 2007. Landscape modification and habitat fragmentation: a synthesis. Glob. Ecol. Biogeogr. https://doi.org/10.1111/j.1466-8238.2007.00287.x.
Foley, J.A., DeFries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Stuart Chapin, F., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A., Kucharik, C.J., Monfreda, C., Patz, J.A., Colin Prentice, I., Ramankutty, N., Snyder, P.K., 2005. Global consequences of land use. Science 309, 570–574. https://doi.org/10.1126/science.1111772.
Foster, D.R., 1992. Land-use history (1730-1990) and vegetation dynamics in central New England, USA. J. Ecol. 80, 753–771.
Foster, D.R., Donahue, B.M., Kittredge, D.B., Lambert, K.F., Hunter, M.L., Hall, B.R., Irland, L.C., Lilieholm, R.J., Orwig, D.A., D'Amato, A.W., Colburn, E.A., Thompson, J.R., Levitt, J.N., Ellison, A.M., Keeton, W.S., Aber, J.D., Cogbill, C.V., Driscoll, C.T., Fahey, T.J., Hart, C.M., 2010. Wildlands and Woodlands: A Vision for the New England Landscape. Cambridge, MA.
Franklin, J., 2010. Mapping Species Distributions: Spatial Inference and Prediction. Cambridge University Press. https://doi.org/10.1017/s0030605310001201.
Guisan, A., Thuiller, W., 2005. Predicting species distribution: offering more than simple habitat models. Ecol. Lett. https://doi.org/10.1111/j.1461-0248.2005.00792.x.
Hayhoe, K., Wake, C.P., Huntington, T.G., Luo, L., Schwartz, M.D., Sheffield, J., Wood, E., Anderson, B., Bradbury, J., DeGaetano, A., Troy, T.J., Wolfe, D., 2007. Past and future changes in climate and hydrological indicators in the US Northeast. Clim. Dyn. 28, 381–407. https://doi.org/10.1007/s00382-006-0187-8.
Hijmans, R.J., 2016. Raster: Geographic Data Analysis and Modeling.
Homer, C., Dewitz, J., Yang, L., Jin, S., Danielson, P., Xian, G., Coulston, J., Herold, N., Wickham, J., Megown, K., 2015. Completion of the 2011 national land cover database for the conterminous United States – representing a decade of land cover change information. Photogramm. Eng. Remote Sens. 81, 345–354. https://doi.org/10.14358/PERS.81.5.345.
Hunter, M., Schmiegelow, F., 2011. Wildlife, forests and forestry: principles of managing forests for biological diversity. J. Wildl. Manag. https://doi.org/10.1002/jwmg.209.
Huntington, T.G., Richardson, A.D., McGuire, K.J., Hayhoe, K., 2009. Climate and hydrological changes in the northeastern United States: recent trends and implications for forested and aquatic ecosystems. Can. J. For. Res. 39, 199–212. https://doi.org/10.1139/X08-116.
iNaturalist, 2019. iNaturalist research-grade observations. Available from. https://www.inaturalist.org. https://doi.org/10.15468/AB3S5X.
James, A., Choy, S.L., Mengersen, K., 2010. Elicitator: an expert elicitation tool for regression in ecology. Environ. Model. Softw. https://doi.org/10.1016/j.envsoft.2009.07.003.
Jeon, S.B., Olofsson, P., Woodcock, C.E., 2014. Land use change in New England: a reversal of the forest transition. J. Land Use Sci. 9, 105–130. https://doi.org/10.1080/1747423X.2012.754962.
Kynn, M., 2005. Eliciting expert knowledge for Bayesian logistic regression in species habitat modelling. Fac. Sci. Technol. Qld. Univ. Technol.
Likas, A., Vlassis, N., Verbeek, J., 2003. The global k-means clustering algorithm. Pattern Recognit. 36, 451–461. https://doi.org/10.1016/S0031-3203(02)00060-2.
Lindenmayer, D.B., Franklin, J.F., 2002. Conserving Forest Biodiversity: a Comprehensive Multiscale Approach. Island Press.
Low Choy, S., O'Leary, R., Mengersen, K., 2009. Elicitation by design in ecology: using expert opinion to inform priors for Bayesian statistical models. Ecology 90, 265–277. https://doi.org/10.1890/07-1886.1.
Lueck, D., 2005. An Economic Guide to State Wildlife Management, PERC Research Study RS. Political Economy Research Center.
MassGIS, 2018. Data: New England Boundaries. Mass Bur. Geogr. Inf. https://docs.digital.mass.gov/dataset/massgis-data-new-england-boundaries (accessed 5.31.19).
McRoberts, R., Holden, G., Nelson, M.D., Liknes, G.C., Moser, W.K., Lister, A.J., King, S.L., Lapoint, E., Coulston, J.W., Smith, W.B., Reams, G.A., 2005. Estimating and circumventing the effects of perturbing and swapping inventory plot locations. J. For. 275–279.
Murray, J.V., Goldizen, A.W., O'Leary, R.A., McAlpine, C.A., Possingham, H.P., Choy, S.L., 2009. How useful is expert opinion for predicting the distribution of a species within and beyond the region of expertise? A case study using brush-tailed rock-wallabies Petrogale penicillata. J. Appl. Ecol. 46, 842–851. https://doi.org/10.1111/j.1365-2664.2009.01671.x.
Murray, J.V., Low Choy, S., McAlpine, C.A., Possingham, H.P., Goldizen, A.W., 2008. The importance of ecological scale for wildlife conservation in naturally fragmented environments: a case study of the brush-tailed rock-wallaby (Petrogale penicillata). Biol. Conserv. 141, 7–22. https://doi.org/10.1016/j.biocon.2007.07.020.
Olofsson, P., Holden, C.E., Bullock, E.L., Woodcock, C.E., 2016. Time series analysis of satellite data reveals continuous deforestation of New England since the 1980s. Environ. Res. Lett. 11, 064002 https://doi.org/10.1088/1748-9326/11/6/064002.
Organ, J.F., Geist, V., Mahoney, S.P., Williams, S., Krausman, P.R., Batcheller, G.R., Decker, T.A., Carmichael, R., Nanjappa, P., Regan, R., Medellin, R.A., Cantu, R., Mccabe, R.E., Craven, S., Vecellio, G.M., Decker, D.J., Bookhout, T.A., Rentz, T., 2012. The North American Model of Wildlife Conservation. Bethesda.
Pacifici, M., Visconti, P., Butchart, S.H.M., Watson, J.E.M., Cassola, F.M., Rondinini, C., 2017. Species' traits influenced their response to recent climate change. Nat. Clim. Chang. 7, 205–208. https://doi.org/10.1038/nclimate3223.
Pearce, J.L., Cherry, K., Drielsma, M., Ferrier, S., Whish, G., 2001. Incorporating expert opinion and fine-scale vegetation mapping into statistical models of faunal distribution. J. Appl. Ecol. 38, 412–424. https://doi.org/10.1046/j.1365-2664.2001.00608.x.
R Core Team, 2019. R: A language and environment for statistical computing. R Found. Stat. Comput. https://doi.org/10.1017/CBO9781107415324.004.
Reed, M.S., 2008. Stakeholder participation for environmental management: a literature review. Biol. Conserv. https://doi.org/10.1016/j.biocon.2008.07.014.
Rogers, L., Young, S., 2014. Temperature change in new England: 1895-2012. Int. J. Undergrad. Res. Creativ. Act. 6, 3. https://doi.org/10.7710/2168-0620.1024.
Rustad, L., Campbell, J., Dukes, J.S., Huntington, T., Lambert, K.F., Mohan, J., Rodenhouse, N., 2012. Changing Climate , Changing Forests : the Impacts of Climate Change on Forests of the Northeastern United States and Eastern Canada, vol. 56. U.S.Forest Serv.
Sardà-Palomera, F., Brotons, L., Villero, D., Sierdsema, H., Newson, S.E., Jiguet, F., 2012. Mapping from heterogeneous biodiversity monitoring data sources. Biodivers. Conserv. 21, 2927–2948. https://doi.org/10.1007/s10531-012-0347-6.
Sauer, J.R., Blank, P.J., Zipkin, E.F., Fallon, J.E., Fallon, F.W., 2013. Using multi-species occupancy models in structured decision making on managed lands. J. Wildl. Manag. 77, 117–127. https://doi.org/10.1002/jwmg.442.
Simberloff, D., 1998. Flagships, umbrellas, and keystones: is single-species management passe in the landscape era? Biological Conservation, pp. 247–257. https://doi.org/10.1016/S0006-3207(97)00081-5.
Stoner, A.M.K., Hayhoe, K., Yang, X., Wuebbles, D.J., 2013. An asynchronous regional regression model for statistical downscaling of daily climate variables. Int. J. Climatol. https://doi.org/10.1002/joc.3603.
Tews, J., Brose, U., Grimm, V., Tielbörger, K., Wichmann, M.C., Schwager, M., Jeltsch, F., 2004. Animal species diversity driven by habitat heterogeneity/diversity: the importance of keystone structures. J. Biogeogr. https://doi.org/10.1046/j.0305-0270.2003.00994.x.
The Nature Conservancy, 2009. TNC Terrestrial Ecoregions. http://maps.tnc.org/ (accessed 6.24.19).
Thomas, C.D., Cameron, A., Green, R.E., Bakkenes, M., Beaumont, L.J., Collingham, Y.C., Erasmus, B.F.N., De Siqueira, M.F., Grainger, A., Hannah, L., Hughes, L., Huntley, B., Van Jaarsveld, A.S., Midgley, G.F., Miles, L., Ortega-Huerta, M.A., Peterson, a T., Phillips, O.L., Williams, S.E., 2004. Extinction risk from climate change. Nature 427, 145–148. https://doi.org/10.1038/nature02121.

Thompson, J.R., Carpenter, D.N., Cogbill, C.V., Foster, D.R., 2013. Four centuries of change in northeastern United States forests. PLoS One 8. https://doi.org/10.1371/journal.pone.0072540.
Tulloch, A.I.T., Mustin, K., Possingham, H.P., Szabo, J.K., Wilson, K.A., 2013. To boldly go where no volunteer has gone before: predicting volunteer activity to prioritize surveys at the landscape scale. Divers. Distrib. 19, 465–480. https://doi.org/10.1111/j.1472-4642.2012.00947.x.
Tulloch, A.I.T., Szabo, J.K., 2012. A behavioural ecology approach to understand volunteer surveying for citizen science datasets. Emu 112, 313–325. https://doi.org/10.1071/MU12009.
Turner, M.G., Gardner, R.H., 2015. Landscape Ecology in Theory and Practice. Springer, New York, New York, NY. https://doi.org/10.1007/978-1-4939-2794-4.
U.S. Census Bureau, 2019. Resident Population in the New England Census Division. Retrieved from FRED. Fed. Reserv, Bank St. Louis. https://fred.stlouisfed.org/series/CNEWPOP (accessed 9.30.19).
U.S. Census Bureau, P.D, 2018. Annual Estimates of the Resident Population for the United States, Regions, States, and Puerto Rico: April 1, 2010 to July 1, 2018. https://www.census.gov/data/tables/time-series/demo/popest/2010s-state-total.html (accessed 7.19.19).
U.S. Department of the Interior, U.S.G.S, 2012. Existing Vegetation Type Layer, LANDFIRE 1.3.0. LANDFIRE. https://www.landfire.gov/vegetation.php (accessed 12.6.19).
U.S. Fish, Wildlife Service, 2015. Migratory Bird Program - Conserving America's Birds. https://www.fws.gov/birds/management/managed-species/focal-species.php (accessed 5.2.19).
U.S. Geological Survey, 2017. 1 Meter Digital Elevation Models (DEMs) - USGS National Map 3DEP Downloadable Data Collection. U.S. Geological Survey. https://www.sciencebase.gov/catalog/item/543e6b86e4b0fd76af69cf4c (accessed 11.6.19).
U.S. Geological Survey, 2016. USGS national transportation dataset (NTD). ftp://rockyftp.cr.usgs.gov/vdelivery/Datasets/Staged/Tran/GDB (accessed 11.6.19).
U.S. Geological Survey, 2014. NLCD 2011 Land Cover (2011 Edition, Amended 2014) - National Geospatial Data Asset (NGDA) Land Use Land Cover. U.S. Geological Survey. https://www.sciencebase.gov/catalog/item/581d050ce4b08da350d52363 (accessed 11.6.19).
Vitousek, P.M., Mooney, H. a, Lubchenco, J., Melillo, J.M., 1997. Human domination of earth' s ecosystems. Science 277, 494–499. https://doi.org/10.1126/science.277.5325.494.
Williams, B.K., 2011. Adaptive management of natural resources-framework and issues. J. Environ. Manag. https://doi.org/10.1016/j.jenvman.2010.10.041.
Yamada, K., Elith, J., McCarthy, M., Zerger, A., 2003. Eliciting and integrating expert knowledge for wildlife habitat modelling. Ecol. Model. 165, 251–264. https://doi.org/10.1016/S0304-3800(03)00077-2.