Modeling Bobcat *Lynx rufus* Habitat Associations Using Telemetry Locations and Citizen-Scientist Observations: Are the Results Comparable?

Author(s): Derek J. A. Broman, John A. Litvaitis, Mark Ellingwood, Patrick Tate and Gregory C. Reed

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Modeling bobcat *Lynx rufus* habitat associations using telemetry locations and citizen-scientist observations: are the results comparable?

Derek J. A. Broman, John A. Litvaitis, Mark Ellingwood, Patrick Tate and Gregory C. Reed

D. J. A. Broman, J. A. Litvaitis (john@unh.edu) and G. C. Reed, Dept of Natural Resources and the Environment, Univ. of New Hampshire, Durham, NH 03824 USA. – M. Ellingwood and P. Tate, New Hampshire Fish and Game Department, Concord, NH 03301 USA

To understand large scale animal–habitat associations, biologists often rely on intensive home-range based studies, where a large number of locations are obtained from relatively few individuals equipped with radio transmitters and then extrapolate patterns of habitat use to much larger areas. Alternatively, extensive methods (e.g. incidental observations) that provide few observations per individual can be effectively used to sample large areas. Both methods have advantages, limitations, and potential sources of bias. We used these different approaches in an effort to identify habitat features that may be important to expanding populations of bobcats *Lynx rufus* in New Hampshire, USA. Twelve adult bobcats with GPS-equipped transmitters provided detailed summaries of movement patterns within a 2300-km^2 study area. We also solicited incidental observations from citizens throughout the state (24 200 km^2). Using locations from both methods, we developed logistic models based on a comparison of home range composition to study area composition (second-order habitat selection). We also explored an approach to reduce potential bias associated with incidental observations (overrepresentation of human population centers) by applying a weighing factor. The telemetry and uncorrected observation-based models overlapped substantially with eight common covariates. The telemetry-based model indicated that bobcats preferred areas with few roads, limited human development, high stream densities, and steep topography. In contrast, the adjusted (to reduce bias) observation-based model indicated bobcats preferred areas with an abundance of roads and development with few streams and limited topographic variation. Because of these differences, we recommend caution when using sightings to model habitat associations unless biases associated with such information can be identified and overcome. Although public sightings had limited application for describing bobcat habitat, they were useful in documenting a recent range expansion and revealing novel prey use by bobcats.

Understanding wildlife–habitat associations is an essential cornerstone of effective conservation (Morrison 2001). As a result, a variety of approaches have emerged to identify the biotic and abiotic features that affect the distribution and abundance of a specific species (Litvaitis et al. 1992, Pearce and Boyce 2006). Among the factors to consider when selecting an approach to investigate habitat affinities are the spatial scales at which information is gathered and then applied. For example, if the goal of an investigation is to obtain detailed information on demographics and patterns of habitat use within a local study area, live-captures or radio telemetry may be appropriate techniques (Litvaitis et al. 1992). To address issues described at larger spatial scales (e.g. regional patterns of habitat suitability or population expansion), biologists may extrapolate from home-range based studies (Zimmermann and Breitenmoser 2007) or use extensive methods that include incidental observations (Woolf et al. 2002) or structured detection programs that rely on volunteers or citizen scientists (Snäll et al. 2011). These extensive efforts may be the only practical source of information to investigate the distribution or habitat associations of rare or secretive species (Palma et al. 1999).

Regardless of the approach used, it is important to acknowledge the advantages, limitations, and potential biases of the selected method. For example, recent advances in telemetry (in particular the addition of global positioning systems, GPS) have provided biologists with an ability to obtain many locations that can reveal details of habitat use that previously were very difficult to obtain (Johnson et al. 2008, Martin et al. 2009). However, the cost of GPS-equipped telemetry may limit the number of individuals studied and, therefore, may not reveal habitat associations of all segments of a population (Hebblewhite and Haydon 2010). Differential detection rates among available cover types also can affect interpretation of the resulting data sets (Friar et al. 2010). Additionally, telemetry-based investigations are usually conducted at a local or landscape scale, and habitat associations may vary in response to the relative abundance of specific features that can change at larger spatial scales (Mosher et al. 1986, Mysterud and Ims 1998).

As a result, any extrapolation from a single study area to a regional or statewide scale may be compromised. On the other hand, observation-based investigations may be able to sample a large segment of the target population throughout the region of interest (Linde et al. 2010, Cooper et al. 2012). Yet such information may be prone to error or bias because observers may misidentify the target species (McKelvey et al. 2008), observers are not randomly distributed (Clements et al. 2012), and detection rates may vary with covariates that determine the probability of occurrence (Yackulic et al. 2013).

We are interested in understanding bobcat *Lynx rufus* habitat associations in New Hampshire, a region where this species has undergone dramatic changes in abundance during the past 50 years (Litvaitis et al. 2006). In the late 1950s, bobcat populations responded to the abundance of prey associated with large areas of reverting farmlands (Litvaitis et al. 1984). At that time, >400 bobcats year^{-1} were harvested for bounty payment (Litvaitis 1993). Subsequently, shrubland habitats matured into closed-canopy forests and prey populations declined precipitously (Litvaitis 1993). By the mid 1980s, <20 bobcats year^{-1} were harvested during regulated trapping and hunting seasons (Litvaitis et al. 2006). Since 1989, bobcats have been protected in New Hampshire and harvest seasons have been closed. In recent years, incidental sightings and collisions with motor vehicles suggest that bobcats are becoming more abundant in New Hampshire (Litvaitis et al. 2006, Broman 2012), similar to other regions of North America (Roberts and Crimmins 2010).

To understand environmental features that may affect the vitality of bobcats in New Hampshire, we initiated a study to identify important habitat features. Our goal was to develop a statewide map of potential bobcat distribution based on habitat suitability. To achieve this, we explored the utility of two very different approaches: an intensive, telemetry-based investigation within a restricted study area and an extensive effort that relied on incidental bobcat observations by citizens throughout the state. Specifically, our objectives were to generate two very different data sets on bobcat spatial distributions, apply similar analytical techniques, and then compare the resulting suitability models to determine if they revealed consistent patterns of habitat associations.

Material and methods

Habitat model based on telemetry

Study area

Bobcats were captured in an approximately 2300-km^2 region of southwest New Hampshire. This area had the greatest historical harvests and frequent sightings (Litvaitis et al. 2006). Dominant overstory species include eastern hemlock *Tsuga canadenesis*, eastern white pine *Pinus strobus*, American beech *Fagus grandifolia*, yellow birch *Betula alleghaniensis*, paper birch *Betula papyrifera*, northern red oak *Quercus rubra*, red maple *Acer rubrum*, and sugar maple *Acer saccharum*. Topography is moderately rugged with elevation reaching 965 m above sea level at the peak of Mount Monadnock. Average annual snowfall is between 127–178 cm and average annual temperatures are –6°C in the winter and 15°C in the summer (NOAA 2011). Human population density is approximately 42 km^{-2} (Cheshire County, NH; US Census Bureau 2011). Maintained road density within the study area is 1.4 km km^{-2}.

Capture and monitoring

Licensed trappers were contracted by New Hampshire Fish and Game Department from November 2009 to March 2010. Bobcats were captured with baited box traps. Males weighing more than 9.0 kg and females weighing more than 6.5 kg were assumed to be adults and equipped with a numbered ear tag and a radiocollar. Collars included Sirtrack drop-off collars (Internal Release, 220 g, Sirtrack Ltd) and Lotek Wildcell collars (Wildcell, 270 g, Lotek Wireless). All study animals were handled in accordance with Univ. of New Hampshire Institutional Animal Care and Use Committee (protocol no. 081201).

Both collar models had VHF and GPS capabilities, as well as a timed mortality beacon. Sirtrack and Lotek GPS collars obtained a fix every 7 and 5 h, respectively. Locations were downloaded from Sirtrack collars after dropoff (1 September 2010), whereas the Lotek collars sent locations via short message services (SMS messages) to a ground station. A GPS location screening technique consisted of removing two-dimensional (2D) fixes with a dilution of precision greater than 5.0 (Lewis et al. 2007). This technique was selected because it removed inaccurate locations while retaining as much data as possible (Lewis et al. 2007).

Home-range estimation

Home ranges were calculated using a fixed-kernel density estimator with least squares cross-validation (Worton 1989, Seaman and Powell 1996, Millspaugh et al. 2006) using the Animal Movement extension (Hooge and Eichenlaub 1997) for ArcView 3. Home ranges were based on a minimum of 30 locations (Seaman and Powell 1996) and 95% utilization distributions (UD) and core areas (50% UD, Powell 2000, Tucker et al. 2008) were plotted.

Habitat modeling

Habitat selection was based on resource-selection functions (RSF) and a use versus available design fit to logistic-regression functions (Boyce et al. 2002, Manly et al. 2002). Resource selection in this design is defined at the unit of a home range and as using a habitat feature disproportionately to its availability (second-order selection, Johnson 1980). Eleven candidate features were selected to describe bobcat habitat (Table 1) based on reviews of studies conducted in nearby states (McCord 1974, Fox 1990, Donovan et al. 2011) and other northern regions (Koehler and Hornocker 1991, Lovallo and Anderson 1996). Map extent (i.e. grid size) for habitat features was 30×30 m, expect for snowfall data, which was 1×1 km.

Use versus available comparisons followed a sampling design of 1:1. Bobcat GPS locations that fell within the 95% UD were compared to an equal number of randomly generated locations within a minimum convex polygon (MCP) around all bobcat locations (the effective study area). This comparison of home-range habitat selection versus available habitat within the study area habitat is common practice and satisfies RSF assumptions that each bobcat has access to all

Table 1. Variables used to investigate bobcat habitat associations based on telemetry locations of marked animals in southwestern New Hampshire or incidental observations from volunteers collected statewide. For most features, information was obtained at telemetry locations, incidental observations, or random points. However, the method used to describe land cover, roads, and streams differed between telemetry and observation-based assessments.

Habitat measurement	Justification	GIS data source
Elevation (m)	Bobcats prefer areas of low elevation (Lovallo and Anderson 1996)	USGS Digital Elevation Model (DEM)
Slope (degrees)	Bobcats have been found in ledges and areas of high slope (McCord 1974)	DEM Spatial Analyst calculation
Northwest aspect (present/absent)	Aspect influences sun exposure and consequently snow depth and vegetation (Koehler and Hornocker 1991)	DEM Spatial Analyst calculation
Land cover (development, scrubland, forest, and wetland): for the telemetry-based model, this was the land cover associated with individual telemetry or random locations. For the observation-based model, this was the percent coverage of each land cover type within simulated home ranges centered on observations or random locations.	Bobcats prefer certain land cover types (Freeman 2010, Broman 2012)	2006 National Land Cover Dataset (Fry et al. 2011)
Snowfall (mm)	Snowfall has negative impacts on movement and survival (Litvaitis et al. 1986a,b)	Compiled from the NOAA National Weather Service's National Operational Hydrologic Remote Sensing Center's (NOHRSC) Snow Data Assimilation System (SNODAS; NOHRSC 2004) by NHFG
Ruggedness (vector ruggedness measurement)	Bobcats have been found in ledges and rugged terrain (McCord 1974)	VRM Tool calculation (Sappington et al. 2007)
Road density: For the telemetry-based model, this was the density of all roads (km km^{-2}) around each location of marked bobcats or random locations within the telemetry study area. For the observation-based model, this was the total length of roads within simulated home ranges centered on observations or random points in the state.)	Roads have a negative impact on bobcat survival (Litvaitis and Tash 2008)	Spatial Analyst calculation
Stream density: For the telemetry-based model, this was the density of all streams (km km^{-2}) around each location of marked bobcats or random locations within the telemetry study area. For the observation-based model, this was the total length of streams within simulated home ranges centered on observations or random points in the state.)	High stream densities are associated with areas of high historical harvest in New Hampshire (Broman 2012)	Spatial Analyst calculation

available habitats (Manly et al. 2002). Geospatial Modeling Environment (Beyer 2012) in ArcGIS 10.0 were used to generate random locations and derive habitat measurements for each location.

Data evaluation

Prior to model development, a Spearman rank correlation was used to identify collinearity between continuous variables. If $|r| \geq 0.70$, the more practical variable (i.e. easier to recognize on the landscape) was retained (Broman 2012); however, no continuous variables were removed. To address the correlation of GPS data in space and time (Boyce 2006, Dormann et al. 2007), individual bobcats were used as a random intercept in a mixed-effect logistic regression model to allow for spatial autocorrelation between locations and unbalanced numbers of locations (Breslow and Clayton 1993, Gillies et al. 2006). The issue of temporal autocorrelation can be problematic (Dormann et al. 2007, Boyce et al. 2010, Fieberg et al. 2010), but the statistical package used (lmer function in lme4 package, Bates et al. 2011; in R) limited our abilities to address correlations in the model framework. Rather than censor data until statistical independence was met (e.g. destructive sampling, Swihart and Slade 1985), we elected not to account for temporal autocorrelation and contend information derived from large datasets is more valuable than information derived from statistically independent yet substantially smaller datasets.

GPS bias was addressed by weighing locations by the inverse probability of successfully acquiring a GPS fix (Friar et al. 2004, Hebblewhite et al. 2007). Collar test data were generated by D. Mallett (Dept of Wildlife Ecology, Univ. of Maine; pers. comm.) in nearby Maine, enabling us to calculate the probability of acquiring a GPS fix (*Pfix*) for three land cover types (light development, shrub/scrub and forest) using logistic regression to model the probability of a fix attempt being successful (1) or unsuccessful (0). However, addressing GPS bias ultimately had little influence on model fitness and training.

Model training and testing

A multivariate model containing the 11 habitat covariates was fit to the telemetry data. The Akaike information criterion (AIC) value was used to assess model fit. Validation of the model was done using a *k*-fold cross-validation technique that evaluates a model on its ability to predict animal locations (Boyce et al. 2002, Johnson et al. 2006). This technique used a normalized, equal area, moving-window average binning technique (Wiens et al. 2008), and technique products (mean fold Spearman rank correlation coefficient 'r_s', standard deviation, and p-value) were used to identify the model's ability to predict locations (Wiens et al. 2008).

Development of a statewide map of suitable habitats based on telemetry locations

The home range habitat selection RSF model was used to develop a statewide map of bobcat habitat. This approach also seemed appropriate for the analysis of sighting locations. RSF values were normalized (0 to 1) producing a relative probability of use. Map units were resampled to 1×1 km during model development, using the Raster Calculator tool, to reflect the coarsest resolution of the habitat variables.

Habitat model based on incidental observations

Observations of bobcats by citizens throughout the state were solicited from a project-based website (<http://mlitvaitis.unh.edu/Research/BobcatWeb/bobcats.htm>). Observations included incidental sightings of bobcats or coincidental photographs taken by camera traps. Locations of observations from May 2008 through February 2011 were ranked based on the level of precision that the observer recorded, where: 1 = recorded as geographic coordinates, 2 = location described by the observer (e.g. distance and direction from a major road intersection), or 3 = only general vicinity was recorded (e.g. sighted on Route 4 in the town of Concord). Only locations ranked a 1 or 2 were retained for our analysis.

We assumed that each incidental observation was the product of a spatial intersection of human and animal. Although it is possible that some of the observations were of transient bobcats, we assumed that bobcats were selecting immediate or local habitat features within established home ranges. To examine selection patterns, we used the same scale of analysis (second order) as the telemetry-based model. Similar to the methods used by Palma et al. (1999) and Woolf et al. (2002), we buffered each eligible observation with an area equivalent to the home range of a female bobcat (29.7 km^2) and did the same for an equal number of locations that were randomly generated throughout the state using Hawth's Tools (Beyer 2004). For most habitat features, information was obtained at individual telemetry locations, incidental observations, or random points. However, the methods used to describe land cover, road density, and stream density differed between models to enable us to examine the composition of simulated home ranges (Table 1). Essentially, we compared the habitat within 'used home ranges' (polygons centered on observations) to the habitat within 'available home ranges' (polygons centered on random locations). This approach differed from the analysis used with telemetry locations. Because individuals were not identified, we considered our samples to represent selection at a population level with available habitat described statewide.

We suspected that our observation-based locations were biased by the distribution of observers (e.g. more frequently associated with human settlements) and by increased visibility of bobcats in some portions of the environment (e.g. backyards, roadsides and agricultural fields). To address these issues, we attempted to correct for observation bias by developing a weighing factor (modified from Clements et al. 2012). This approach was originally designed for use with the program MaxEnt (Philips et al. 2006), and therefore, some modifications were made to accommodate our analysis. Essentially, a bias layer was generated by weighing each observer-based location in relation to surrounding observer-based locations with a Gaussian kernel. Following recommendations by Clements et al. (2012), a standard deviation equal to the radius of the marked female bobcat (3.1 km) was used. Next, the inverse of these values were taken and scaled with values centered on 1 to avoid inflating the effective sample size. These values were then included in the modeling framework in the same manner as the GPS bias was addressed in the telemetry-based model. This technique is meant to put less weight on sightings that occur in areas with high human densities that often result in higher recorded observations and more weight on those observations that occur away from population centers. As a result, the effect of sampling certain individuals multiple times is reduced while giving additional weight to bobcats that were less likely to be detected.

Variable screening and model development and validation followed procedures for the habitat model based on telemetry locations except that individuals were not identified in the sightings, therefore data was pooled for the population and no random intercept was included.

Development of a habitat suitability map followed similar methods used in the telemetry-based approach, with the exception that percentages of land cover and total length of roads and streams (km) within each buffer were used. We estimated the amount of suitable habitat within the state for each model by first generating mean RSF scores for actual and simulated home ranges. We then used the minimum mean RSF score of transmitter-equipped bobcats to estimate the amount of suitable habitat in New Hampshire and used a similar approach for simulated homes centered on incidental observations.

Results

Twelve adult bobcats (10 M, 2 F) were captured and fitted with GPS collars (Broman 2012). Data were obtained from 11 (10 M, 1 F), with 115–970 locations per individual (54.7% fix success). After screening for error, 4583 locations (86% of original data) collected from November 2009 to December 2010 were used for home range calculation. Mean home range of males was 93.5 km^2, whereas the female home range was 29.7 km^2. Additional details of bobcat movements

Table 2. Fit and predictability of habitat-selection models based on bobcat telemetry locations from southwest New Hampshire (November 2009 to December 2010) and incidental sightings collected statewide (May 2008 to February 2011). The telemetry-based model was developed using a mixed effect logistic regression and the observation-based model was developed using logistic regression; therefore direct comparisons between models are inappropriate. The closer the model mean r_s value is to 1.0, the higher correlation between frequencies of resource selection function values and bin number and thus the higher the model predictability.

			k-fold validation		
Habitat model	n variables	AIC score	Mean r_s	Mean SD	Mean p
Telemetry locations	11	12570	0.981	0.031	<0.001
Incidental observations	11	3034	0.434	0.353	0.182

were summarized by Broman (2012). Removing data points that fell outside the 95% UD left 4,412 locations available for habitat analysis.

Habitat model based on telemetry

The telemetry-based model (second-order selection) predicted well based on *k*-fold outputs (Table 2). Bobcats selected areas with low road densities and limited snow depth, at lower elevations, with high stream densities, and areas with rugged topography (Table 3). Wetlands, scrubland, and forest were favored, whereas development and northwest aspects were used proportionally less than their availability (Table 3). The minimum mean RSF score of all collared bobcat home ranges used in the telemetry-based model was 0.40. Applying this criterion throughout the state yielded 14 010 km^2 (58% of the state) of suitable habitat (Fig. 1).

Habitat model based on incidental observations

A total of 411 sightings were reported from 162 townships, throughout the period of solicitation, and included radio-equipped bobcats. Of these observations, 298 were ranked as category 1 or 2 and used in our analysis. The observation-based model was not a good predictor of habitat use based on *k*-fold outputs (Table 2). Based on the unadjusted version of this model, bobcats selected areas with low snow depth, at lower elevations, more streams and roads, and areas with low slope, but high ruggedness (Table 3). Simulated home ranges centered on observations contained more wetlands and forest but less scrubland and development than home ranges centered on random locations throughout the state (Table 3).

The telemetry-based and unadjusted version of observation-based models differed on coefficient sign (+/–) for slope, scrubland, and road density whereas the telemetry-based and bias adjusted version of the observation-based model differed for slope, development, stream and road densities (Table 3). From those discrepancies, we conclude that the distribution of observers or their detection rates were clearly biased toward human population centers (more development, abundant roadways, and riparian areas) and habitats where bobcats were conspicuous (relatively flat and developed). The apparent preference for anthropogenic features (roads and development) suggests that our efforts to correct observer biases were not sufficient. Using the bias adjusted version, the minimum mean RSF score of simulated home ranges centered on incidental observations was 0.05 and yielded 13 497 km^2 (56% of the state) of suitable habitat (Fig. 1).

Discussion

Our telemetry-based model indicated that bobcats selected areas with an abundance of wetlands at low elevations, with limited heavy development, and few roads. Selection for wetlands (or bogs) by bobcats has been detected in the neighboring states of Maine (Major and Sherburne 1987), Massachusetts (Beredzen 1985), and Vermont (Donovan

Table 3. Variables (coefficients, standard errors, and p-values) associated with habitat-selection models generated from telemetry locations and incidental observations of bobcats in New Hampshire. Values are displayed for the observation-based model with and without a weighing factor to reduce observer bias. All models were created using resource selection functions following a used versus available design.

	Telemetry locations			Incidental observations (bias addressed)			Incidental observations (bias not addressed)		
Variable	Beta	SE	p	Beta	SE	p	Beta	SE	p
Intercept	1.602	0.168	<0.001	−0.518	1.01	0.608	−0.631	1.037	0.543
Elevation	−0.004	<0.001	<0.001	−0.008	<0.001	0.055	−0.002	0.001	0.074
Slope	0.020	0.005	<0.001	−0.003	0.022	0.161	−0.050	0.026	0.056
Snow	−0.003	0.001	<0.001	−0.002	0.001	0.191	−0.004	0.002	0.003
Ruggedness	89.615	15.303	<0.001	143.900	73.400	0.050	93.466	81.533	0.252
Wetland*	1.383	0.114	<0.001	5.377	2.583	0.037	7.206	2.693	0.007
Scrubland*	0.760	0.180	<0.001	0.086	3.560	0.711	−2.328	4.164	0.576
Development*	−0.186	0.123	0.129	0.401	3.736	0.915	−5.720	3.796	0.132
NW aspect	−0.095	0.067	0.155	−0.210	0.260	0.420	−0.336	0.280	0.231
Forest*	0.034	0.080	0.674	1.314	1.155	0.255	1.911	1.215	0.116
Stream density**	0.194	0.019	<0.001	−0.007	0.004	0.114	0.003	0.004	0.538
Roads density**	−0.295	0.026	<0.001	0.010	0.009	0.261	0.021	0.009	0.016

*For the telemetry-based model, land cover was described at individual locations; whereas for the observation-based model, this was the percent coverage of each land cover within simulated home ranges centered on observations or random points.
**For telemetry-based model, road and stream density were measured at bobcat telemetry locations and a comparable number of random points within the telemetry study area (km/km^2). For the observation-based model, we compared total length of roads and streams within simulated homes ranges centered on observations and an equivalent number of random points distributed throughout the state.

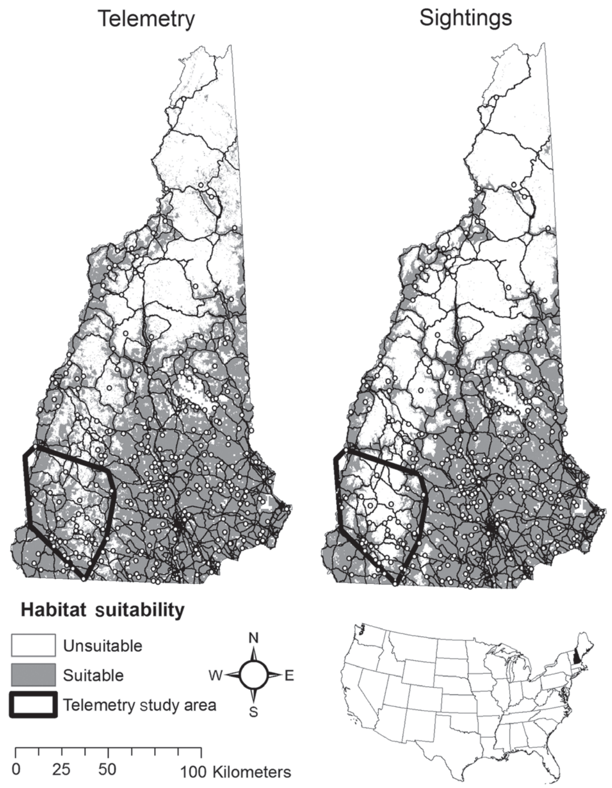

Figure 1. Bobcat habitat-suitability maps based on telemetry locations and incidental observations. The telemetry-based model was developed using locations obtained from transmitter-equipped bobcats in southwest New Hampshire that were monitored from November 2009 to December 2010. The observation-based model was developed using incidental sightings collected by the public-at-large from May 2008 to February 2011. Telemetry locations and observations were analyzed at second order of habitat selection (selection for home ranges). Maps were constructed by calculating a resource-selection function (RSF) value for each 1×1-km map unit. Map units were determined to be suitable if they had scores greater than the minimum mean RSF score for the home ranges of the collared bobcats. The telemetry study area was the area contained by a minimum convex polygon generated around locations of transmitter–equipped animals. Bobcat sightings (white circles) and major roads (black lines) are shown for reference. Map of contiguous United States indicates location of our study (shaded black).

et al. 2011). Other studies have also reported that bobcats prefer low elevations (Koehler and Hornocker 1989, Fox 1990, Lovallo and Anderson 1996). Bobcat avoidance of roads and developed areas is supported by Crooks (2002), Riley et al. (2006), and Donovan et al. (2011). Additionally, Litvaitis and Tash (2008) suggested that the abundance of high-traffic volume roads in southeastern New Hampshire could effectively limit the viability of bobcat populations in that region. Suitability maps generated by both models showed substantial overlap (Fig. 1). However, we suggest that the observation-based model identified productive habitat features (forests and wetlands) but failed to identify detrimental habitat features (roads and development) and therefore, may have included high-risk or sink habitats (based on apparent elevated mortality rates associated with roads and contact with humans in developed areas).

Previous efforts that relied on observation-based data have effectively described carnivore-habitat association at large spatial scales (Carroll et al. 2001), including bobcats in New Hampshire (Litvaitis et al. 2006). In that study, investigators relied on observations and incidental captures of bobcats reported by conservation officers, cooperating amateur naturalists, and licensed trappers from 1990–2004, presumably when bobcats were at densities lower than present-day populations. Using those observations to describe home-range composition (second-order selection), bobcats seemed to select areas with large blocks of forest, less developed land, less annual snowfall, and fewer highways and primary roads in comparison to random locations distributed throughout the state (Litvaitis et al. 2006). Those features are quite similar to those included in our telemetry-based model but differ from our observation-based model (Table 3).

Few studies have compared citizen scientist data to telemetry-based efforts used to identify carnivore-habitat associations. Among those that did, Quinn (1995) found that public observations of coyotes *Canis latrans* were biased toward habitats where people were concentrated and coyotes easily seen, similar to our results. Although there were some differences, the major habitat association of coyotes to woodlands was similar between observation and telemetry-derived locations. Quinn (1995) suggested that observation-based investigations of habitat use may be most effective in regions where habitat patch sizes are relatively small and human accessibility and sighting distances among patches are similar. Even if access or visibility within a patch is low, analyses of animal distribution relative to distance from habitat components can help identify important habitat patches when visibility around these patches is high (Quinn 1995). In our study, habitat patches were large. As a result, observations of bobcats were likely biased toward openings (near developments and roadsides) where detection rates were higher than other portions of the landscape.

Reducing observer bias

Our attempts to correct for observer bias did not reconcile the contradictions between observation and telemetry-based efforts and may have actually increased the discrepancy by changing coefficients to suggest selection for development. We caution that the technique we applied (e.g. inversely weighting observations by their proximity to others) may not be suitable for other situations. Should a concentrated abundance of observations occur as the product of quality habitat (instead of observer density), this technique would penalize those observations by adding a low weighting factor. We suspect that bobcats observed in close proximity to roads are moving between more productive portions of their individual home ranges when they are observed. Citizen reporting rates were likely a function of human population density, road density, and observer motivation (e.g. residents of suburban southern New Hampshire are less familiar with species such as bobcats and hence more likely to report their observations). In reviewing our observation-based locations, we found that 272 of 298 (91%) were within 0.5 km of a road, and 129 of 298 (43%) were within 0.5 km of a major road or highway. As a result, it may be very difficult

Figure 2. Photographs of bobcats in suburban New Hampshire backyards. Top: a bobcat is loafing underneath two bird feeders (credit: B. Quinn). Bottom: a juvenile bobcat has just captured a gray squirrel that was attempting to forage at a bird feeder (credit: H. and A. Swartz).

to substantially reduce the biases associated with these data after they were collected.

One modification that might reduce detection bias is to restrict participants. For example, Linde et al. (2010) and Cooper et al. (2012) relied on observations of archery hunters to model large-scale features of bobcat and gray fox *Urocyon cinereoargenteus* habitats, respectively. Although hunters are not randomly distributed, their detection rates of carnivores may be influenced less by features that facilitate observation (e.g. cleared land or roadsides) and thus, provide a more representative sample of carnivore habitat preferences. Standardizing hunter observations by effort (e.g. observations / 1000 h in the field) may provide additional opportunities to monitor changes in population size (Kindberg et al. 2009). Alternatively, it may be possible to develop a program that incorporates occupancy models. For example, volunteers could be encouraged to report detections of several species of woodland carnivores (including bobcats). Under these circumstances, the essential non-detections of bobcats could be extracted from records of those volunteers that reported detections of other carnivores but did not observe bobcats (van Strien et al. 2013).

Value of incidental observations

Although our application of observations by citizen scientists proved ineffective for modeling habitat, bobcat sightings may still provide useful information for large-scale investigations. For example, public sightings tended to occur in portions of the state with less snow depth than randomly distributed locations (Table 3). This agrees with previous efforts to describe bobcat habitat in New Hampshire (Litvaitis et al. 2006). Snow depth can affect bobcat mobility (McCord 1974, Koehler and Hornocker 1989), prey acquisition (Petraborg and Gunvalson 1962), and survival (Litvaitis et al. 1986b). Yet it is an environmental feature that varies at a relatively large-spatial scale and thus, is less likely affected by observer distribution in comparison to such features as development or road density. Telemetry data collected within the study area is likely insufficient for providing insight on the influence of such features at a statewide scale.

Cataloguing incidental observations may be an efficient method to monitor large-scale changes in the distribution of a low-density species like bobcats. For example, comparing incidental observations collected in New Hampshire during 1990–2004 (Litvaitis et al. 2006) to those used in this study (from 2008 to 2011), we identified an obvious expansion of bobcats into the southeastern portion of the state. Sightings and accompanying photographs also revealed previously unknown prey associations that may affect winter survival, especially in human-dominated landscapes. Specifically, a number of winter sightings occurred at or near bird feeders, where bobcats were photographed ambushing gray squirrels *Sciurus canadensis* and wild turkeys *Meleagris gallopavo* (Fig. 2). Such adaptations to human-facilitated prey may partially explain the increase in bobcat abundance and also the expansion of bobcats into more developed portions of New Hampshire where they were previously absent (Litvaitis et al. 2006).

In conclusion, we recommend that future efforts that rely on public observations to describe animal–habitat associations proceed with caution. Such data are inexpensive to gather and have the added benefit of increasing public awareness. However, investigators should explore potential sources of detection bias that may subsequently confound the patterns that are revealed and consider modifications that may reduce biases (e.g. assign randomly-distributed areas to search for evidence of presence/absence or provide a detailed protocol that avoids conditions that may compromise subsequent analysis). Identifying environmental features that are less prone to detection or observer-distribution bias can also provide opportunities for using observational data to compliment other sources of information (e.g. local telemetry-based studies). In our experience, citizen scientists provided reliable information on regional patterns of bobcat distribution, identified a recent range extension within the state, and revealed a possible explanation for how this species is coping with increasing human populations.

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