Estimating Occupancy Probability of Moose Using Hunter Survey Data

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ABSTRACT Monitoring rare species can be difficult, especially across large spatial extents, making conventional methods of population monitoring costly and logistically challenging. Citizen science has the potential to produce observational data across large areas that can be used to monitor wildlife distributions using occupancy models. We used citizen science (i.e., hunter surveys) to facilitate monitoring of moose (*Alces alces*) populations, an especially important endeavor because of their recent apparent declines in the northeastern and upper midwestern regions of the United States. To better understand patterns of occurrence of moose in New York, we used data collected through an annual survey of approximately 11,000 hunters between 2012 and 2014 that recorded detection–non-detection data of moose and other species. We estimated patterns of occurrence of moose in relation to land cover characteristics, climate effects, and interspecific interactions using occupancy models to analyze spatially referenced moose observations. Coniferous and deciduous forest with low prevalence of white-tailed deer (*Odocoileus virginianus*) had the highest probability of moose occurrence. This study highlights the potential of data collected using citizen science for understanding the spatial distribution of low-density species across large spatial extents and providing key information regarding where and when future research and management activities should be focused. © 2016 The Wildlife Society.

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Monitoring species that occur at low densities can be difficult, especially across large regions, making conventional methods of population monitoring costly and logistically challenging. Occupancy models are an effective method for monitoring the spatial distribution of wildlife populations when only detection–non-detection data are available (MacKenzie et al. 2006). Such monitoring can aid wildlife management and conservation by detecting and understanding changes in the distributions of wildlife populations (Gibbs et al. 1999). The recent integration of citizen science data and advances in occupancy modeling techniques have allowed for the monitoring of difficult to detect wildlife species such as gray wolves (*Canis lupus*; Miller et al. 2011,

2013; Rich et al. 2013; Ausband et al. 2014), American black bears (*Ursus americanus*), bobcats (*Lynx rufus*; Erb et al. 2012), leopards (*Panthera pardus*), and golden cats (*Caracal aurata*; Martinez-Marti et al. 2016).

Moose (*Alces alces*) are a valued species for wildlife viewing and tourism promotion in New York; however, the current size and distribution of the moose population are poorly understood. Following a 100-year absence in much of the northeastern United States, which resulted from land conversion and unregulated hunting associated with European colonization, moose re-colonized New York around 1980 during an expansion of moose range (Fig. 1; Wattles and DeStefano 2011). New Hampshire, Vermont, and Massachusetts were re-colonized by moose prior to New York and these states observed rapid moose population growth, reaching population sizes as large as 6,000 moose in New Hampshire, with population sizes stabilizing and declining within the past decade (Wattles and Destefano 2011). The population of moose in New York appears to have grown much more slowly than populations in adjacent states based on trends in

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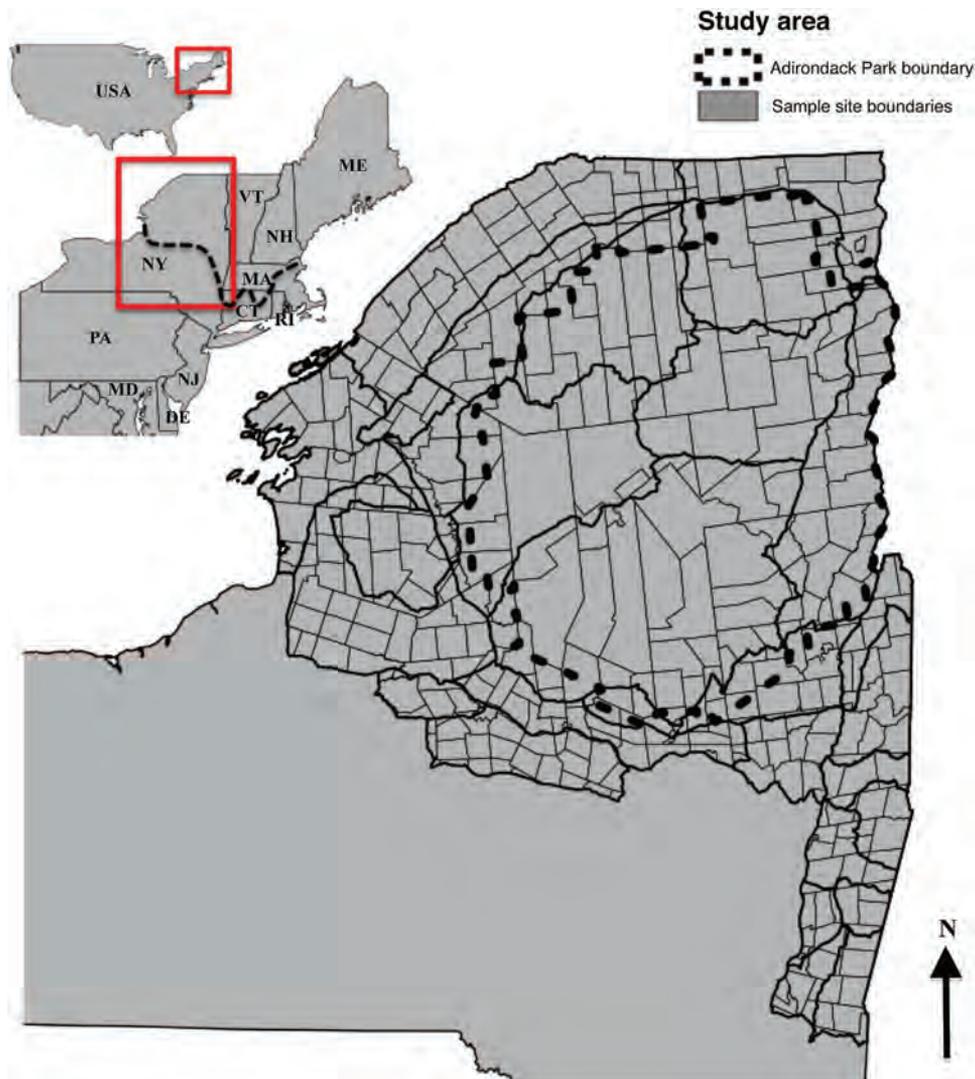
Figure 1. The study area contained 581 sample sites, delineated based on the borders of 328 towns (thin lines) and 27 wildlife management units (thick lines) in northern New York, USA. Additionally, the Adirondack Park, outlined in the thick dashed line, represents approximately 48% of the study area. The dashed line in the inset of the northeastern United States depicts the southern extent of the current moose range.

moose-vehicle-collision records and moose sighting reports (Wattles and DeStefano 2011). Additionally, there is uncertainty associated with the range of the moose population size (i.e., $n = 500–800$ individuals) estimated by the New York State Department of Environmental Conservation (NYSDEC). Recent declines in moose populations across the upper midwest and northeast regions of the United States motivated research investigating the effects of parasitism, habitat availability, and climate on populations across the southern extent of the moose range across these regions (Murray et al. 2006; Lenarz et al. 2009, 2010, 2012; Musante et al. 2010; DelGiudice et al. 2011; Mech and Fieberg 2014; Street et al. 2016). Monitoring could help elucidate uncertainties associated with the distribution of the moose population in New York and factors influencing their distribution, and inform future research, and management and conservation decisions concerning moose in New York.

Estimating the abundance or density of moose in New York as a function of covariates hypothesized to influence these characteristics could resolve uncertainties associated with the population size and distribution of moose in New York. However, estimating the abundance of a low-density species such as moose is often costly and potentially imprecise, especially if detection rates are low or it is difficult to capture and mark individuals, even at smaller spatial scales (MacKenzie et al. 2005). A viable alternative to estimating the abundance of low-density populations is to estimate patterns associated with the distribution of a species. Traditionally, species distribution modeling has been a popular tool used to monitor and predict species' distributions (Guisan and Zimmermann 2000, Austin 2007, Elith and Leathwick 2009). Species distribution models generally use presence-absence or presence-only data that describe where a species occurs to evaluate species-environment relationships (Guisan and Zimmerman 2000, Austin 2007). However, statistical methods used in species distribution modeling do not explicitly incorporate detection error (i.e., the possibility that the species of interest is not observed when present or mistakenly reported

as present when it is actually absent), which can bias model results (MacKenzie et al. 2006, Elith and Leathwick 2009).

Occupancy models explicitly model the detection process and the underlying ecological state of a system and perform better than models that do not explicitly model the detection process (Rota et al. 2011). Specifically, occupancy models use detection–non-detection data to estimate probabilities of site occupancy (i.e., probability that ≥1 individual is present at a site) across a study area (MacKenzie et al. 2005, 2006) by accounting for the possibility that when a species is present at a site it may go undetected (MacKenzie et al. 2006). Without accounting for such imperfect detection, estimated occurrence of a species can be biased low, leading to the conclusion that a species occupies fewer sites across a landscape than it actually does (MacKenzie et al. 2006). Moreover, occupancy modeling allows for occupancy probability to be modeled as a function of site-specific characteristics, and detection probability to be modeled as a function of site-specific and survey-specific characteristics (MacKenzie et al. 2006).

Therefore, the occupancy modeling framework facilitates a formal evaluation of how patch characteristics influence moose occupancy, thereby providing insight into potential mechanisms that may be restricting the distribution of moose in New York. However, collecting the data necessary to estimate moose occupancy across New York could be difficult and costly because moose occur at low densities (1 moose/ 64–102 km^2) across a large area of the state (~51,000 km^2). At such a low density, moose would likely be difficult to detect, so sample sites would have to be visited many times to achieve a precise estimate of occupancy (MacKenzie and Royle 2005). Moreover, because the hypothesized moose range covers a large area of New York (~36%), many sample sites would need to be visited to representatively sample the area. If such a study were carried out, collecting data would be time-intensive and financially costly, even if only a small set of sample sites were surveyed. Using citizen scientists, non-professional individuals collaborating with scientists in research ventures to collect data (Dickinson et al. 2012), is a feasible alternative that can reduce costs and time investment. For instance, Rich et al. (2013) used data from annual public surveys of between 50,000 and 80,000 deer and elk (*Cervus canadensis*) hunters across Montana regarding their observations of wolves to develop estimates of wolf pack occupancy across the state.

In New York, there are over 500,000 white-tailed deer hunters who, collectively, spend millions of hours in the field each year, representing a large and valuable data collection resource (NYSDEC 2011). The NYSDEC conducts big game hunter surveys to collect detection–non-detection data for moose and other species of interest (Appendix A). Hunter surveys can provide data that could be sufficient to provide estimates of moose occupancy across New York. However, data collected using citizen scientists can sometimes produce false positive detections, (Royle and Link 2006, Miller et al. 2011, Sutherland et al. 2013), which is assumed not to occur for a traditional occupancy analysis (MacKenzie et al. 2006). For instance, hunters could misidentify deer tracks or pellets as that of moose if they are not well informed in identification of

moose and deer sign. Recent advances in occupancy modeling effectively deal with this issue by re-parameterizing the detection component of the occupancy model, allowing for estimation of the probability of making a false positive detection (Miller et al. 2011).

We used a false positive occupancy modeling framework to analyze moose detection–non-detection data collected from NYSDEC hunter surveys from 2012 to 2014 to estimate the spatial distribution of moose across northern New York, assess hypotheses concerning influences that could affect moose occupancy and detection, and evaluate the effectiveness of monitoring the distribution of the moose population in New York using occupancy modeling and hunter survey data.

STUDY AREA

We estimated occupancy of moose across the southern and western extent of the current estimated range of moose in the northeastern United States (Fig. 1). Our study area corresponds with 27 NYSDEC wildlife management units (~51,000 km^2), located in northern New York (Fig. 1). Elevations ranged from 1 m above sea level in the Hudson River Valley to >1,600 m in the High Peaks of the Adirondacks. Mean summer high temperatures ranged from 28°C at lower elevations to 23°C at higher elevations, and mean winter low temperatures ranged from −7°C at lower elevations to −16°C at higher elevations. Mean annual snowfall ranged from 1 m to 5 m, whereas mean annual rainfall ranged from 75 cm to 170 cm, with the highest snow and rainfall totals occurring across the southwestern portion of the study area. Common fauna of the study area include white-tailed deer, American black bear, Eastern coyote (*Canis latrans*), and American beaver (*Castor canadensis*). Over 70% of this area was forested, with dominant tree species including American beech (*Fagus grandifolia*), sugar maple (*Acer saccharum*), and yellow birch (*Betula alleghaniensis*) at lower elevations and red spruce (*Picea rubens*) and balsam fir (*Abies balsamea*) at higher elevations. Agriculture and other human development constituted <20% of the study area, whereas open water covered nearly 5% of the area. Density of public roads across the study area was 1.09 km/km^2.

METHODS

Hunter Surveys

The NYSDEC distributed surveys to approximately 11,000 white-tailed deer and American black bear hunters across New York annually (2012–2014; Appendix A). Surveys were distributed to hunters that had reported successfully harvesting a deer or bear in New York during the previous year. The hunting season lasted 44 days each year (20 Oct–2 Dec 2012, 26 Oct–8 Dec 2013, 25 Oct–7 Dec 2014). Surveys were distributed in November of 2012 (i.e., during the hunting season), and in October, before the regular deer season, of 2013 and 2014. Surveys requested that hunters record the date and duration of each hunt and the county, wildlife management unit, and town within which each hunt occurred, which we used to identify the sample site of the survey. Additionally, surveys requested that hunters record

observations of any moose sign (i.e., scat, tracks) and of any male, female, or calf moose observed. If the hunter was unable to identify the sex or age class of an observed moose, they could report the observation as an unknown moose. Surveys also requested that hunters record the number of deer and bear observed during each hunt.

Occupancy Modeling

We analyzed the 2012–2014 hunter survey data using the single season occupancy model described by Miller et al. (2011), which allow for detections of different states (i.e., moose and moose sign). We were primarily interested in spatial patterns of moose occurrence rather than patterns in turnover rates between years (i.e., colonization and extinction rates) and therefore adopted a single season approach in which site occupancy is assumed to be independent between years, conditional upon the covariates for each site used to model occupancy (Fuller et al. 2016).

Occupancy models simultaneously estimated detectability (p), the probability that a hunter detects a moose or tracks or sign, and occupancy (ψ), the probability that a site is occupied by ≥1 moose. Additionally, the model described in Miller et al. (2011) allows for multiple detection states in which a subset of detections can be false positive detections. This results in 3 parameters related to detectability being estimated: 1) the probability of making a certain or uncertain detection, given that ≥1 moose is present (p); 2) the probability of making an uncertain detection, given that moose are absent (i.e., a false positive detection [p_{10}]); and 3) the probability that, given a detection occurred, the state of the detection is certain, thus confirming the presence of moose (b). We treated observations of moose sign as uncertain (i.e, misidentification could result from hunters inability to distinguish similar size moose and deer sign). Additionally, it is possible that moose sign may have been produced prior to and persisted through the hunting season; thus, occupancy is estimated for a period of time before the hunting season (i.e., during summer) to the end of the hunting season. Given there are no other wild mammals in New York of similar size or appearance, we assumed that observations of moose could be treated as certain. We also assumed that hunters correctly recalled when and where they observed moose, which was most likely to have been violated during the first few weeks of the 2012 hunting season, prior to when surveys were distributed in November.

We defined these sample sites with a spatial scale that would produce estimates of moose occupancy that would be meaningful biologically and to management. We overlaid the boundaries of 27 wildlife management units and 328 towns located within the study area (Fig. 1). This resulted in 581 sites, each associated with a unique town-wildlife management unit combination. Sample sites ranged from <1 km² to 993 km² with a mean size of 88.5 ± 111.3 (SD) km². Because nearly all of the sample sites are larger than the typical autumn moose home range (∼15 km² and 5 km² for M and F, respectively; Cederlund and Sand 1994), the risk of violating the assumption that sample site state was constant within each season, which could lead to overestimating occupancy, is negligible in all but the smallest sample sites (74 <5 km² and 124 <15 km²).

We defined the sampling occasion as a single visit to a sample site by an individual hunter to incorporate all detections and non-detections of moose and moose sign. This allows for >1 sampling visit to occur at a sample site during a day (∼30% of visits occur at the same site and on the same day as another visit). In so doing, we assumed that detections were independent (i.e., we did not receive survey responses from hunters who had hunted together).

We used a likelihood-based framework to derive estimates of occupancy (i.e., probability that ≥1 moose or moose sign is present in a sample site) and detection (i.e., probability of an individual hunter observing a moose or moose sign on a given day, given that a moose or moose sign is present in the sample site).

Hypotheses and Model Covariates

We developed a set of *a priori* hypotheses regarding factors that could affect occupancy and detection of moose in northern New York (Tables 1 and 2). We hypothesized that the year, sample-site area, climate, land cover characteristics, and white-tailed deer prevalence (i.e., index of relative abundance) could influence moose occupancy (Table 1), and that the year, sampling effort (i.e., hours hunted during a visit to a sample unit), and time of year (i.e., ordinal date) of sampling occasions could influence the detection probability of moose (Table 2).

Moose in New York occupy the southern extent of their current range, where temperatures regularly exceed their thermoneutral zone (Renecker and Hudson 1986, McCann et al. 2013). Although moose have a number of behavioral responses to mitigate heat stress, summer temperatures across the study area can be >10°C warmer than temperatures that McCann et al. (2013) reported to be thermally stressful for moose in Minnesota. Therefore, we expected that moose occupancy would be negatively associated with the daily maximum temperatures during summer prior to each year's hunting season. To test this hypothesis, we calculated the average daily maximum temperature during July and August (PRISM Climate Group, http://prism.oregonstate.edu, accessed 04 May 2015) for each year for each sample site and used those values as covariates on occupancy.

Land cover characteristics could also influence the occurrence of moose (Table 1). Moose commonly forage in early successional forest and wetlands, and select mature forest for cover, so we expected moose occupancy to be positively associated with these land cover types (Dussault et al. 2005; Bjorneraas et al. 2011, 2012; van Beest et al. 2012). We expected that moose occupancy would be negatively associated with human development, because moose tend to avoid road networks and urbanized areas (Laurian et al. 2008, Jiang et al. 2009, Grosman et al. 2011, Beyer et al. 2013). To test these hypotheses, we calculated the proportion of 7 land cover types (Table 1) within each sample site according to the 30-m National Land Cover Database 2011 (Jin et al. 2013) and used those values as covariates on occupancy.

Table 1. Within our static, false positive occupancy modeling framework, we modeled occupancy probability of moose in New York, USA, 2012–2014, as a function of all possible combinations of covariates describing sample site area, climate, land cover, and white-tailed deer prevalence.

Occupancy covariate	Sample-unit-specific measurement	Mean	Range	Rationale
Sample site area	$\log_{10}$ (sample site area [m^2])	7.94	3.3–8.9	As size of sample site increases, the probability that a moose occurs within it should also increase.
Climate	Mean summer daily maximum temperature (°C)	27.13	22.1–31.3	Moose become thermally stressed when temperature exceeds 17°C, which is often exceeded in northern New York (Renecker and Hudson 1986, McCann et al. 2013).
Land cover	Proportion of scrubland	0.05	0–0.31	Moose preferentially forage in high productivity scrubland-early successional forest (Dussault et al. 2005; Bjorneraas et al. 2011, 2012; van Beest et al. 2012).
	Proportion of coniferous forest	0.16	0–1	Moose prefer mature conifer stands for thermal cover and winter foraging (Dussault et al. 2005; Bjorneraas et al. 2011, 2012; van Beest et al. 2012).
	Proportion of deciduous forest	0.40	0–1	Moose use mature deciduous stands for thermal cover and foraging, especially during the summer (Bjorneraas et al. 2011).
	Proportion of mixed forest	0.07	0–1	Moose prefer mature stands, especially those with a conifer component, for thermal cover (Bjorneraas et al. 2011).
	Proportion of wetland	0.10	0–1	Moose prefer wetlands for foraging on aquatic plants and for thermal stress relief (Bjorneraas et al. 2012).
	Proportion of agriculture	0.19	0–1	Moose tend to avoid open areas but may use agricultural areas to forage (Bjorneraas et al. 2011).
	Proportion of developed land	0.07	0–1	Moose avoid roads, urbanized areas, and non-vegetated land (Laurian et al. 2008, Jiang et al. 2009, Grosman et al. 2011, Beyer et al. 2013).
White-tailed deer	No. white-tailed deer observed/hour	0.55	0–6	White-tailed deer host a number of parasites that can be lethal to moose (Lankester 2002, 2011; Murray et al. 2006).

White-tailed deer are a host to many parasite species that can be transmitted to moose with detrimental and sometimes lethal effects on moose (Lankester 2002, Murray et al. 2006, Lankester 2011). Therefore, we predicted that occupancy of moose would be negatively associated with white-tailed deer prevalence (Table 1). We calculated the average number of deer observed/hour by hunters in each sample site (i.e., an index of relative abundance) from hunter surveys and used those values as a covariate on occupancy.

We expected detection probability to be positively associated with sampling effort, because the more time a hunter spends at a site on a given day, the more likely they are to observe a moose if it is present. We also expected the time of year to influence detection probability. Moose activity changes throughout the year, especially during autumn when hunter observations were recorded. During the rut, which typically occurs in October, males become more active, dramatically increasing their movement rate, and all adults become more social, resulting in individuals congregating (Bubenik 1987). This increased movement and group size could lead to increased detectability early in the hunting season. Conversely, tree phenology could influence visibility of moose, making it easier for hunters to observe moose once trees have shed their leaves late in the hunting season.

Estimation of Moose Occupancy

Considering all possible model parameterizations for every combination of covariates would result in a prohibitively large number of possible candidate models ($n = 30{,}670{,}848$), we adopted a step-wise approach to compare competing models on the different structural components, Ψ, p, p_{10}, and b (Miller et al. 2011, Doherty et al. 2012). We tested 2 successive sets of candidate models, using program PRESENCE v 7.8 (Hines 2006), to test for the effects of the aforementioned covariates on occupancy and detection probability. In the initial model set, we tested all combinations of covariates for each parameter independently (Ψ: $n = 4{,}096$, p: $n = 24$, p_{10}: $n = 13$, and b: $n = 24$) while using the full parameterization for other parameters. Additionally, to test for the presence of false positive detections in the hunter survey data, we compared each model to an equivalently parameterized model where we assumed false positive detections did not to occur ($p_{10} = 0$ [i.e., detections of moose sign were assumed not to occur at unoccupied sites]). We also used a data cloning approach, including 25 copies of the encounter history, to determine whether p_{10} was extrinsically non-identifiable (Lele et al. 2010). Using our cloned encounter history, we compared 2 fully parameterized models, one that estimated p_{10} and the

Table 2. Within our static, false positive occupancy modeling framework for moose in New York, USA, 2012–2014, we modeled detection probability (p), false positive detection probability (p_{10}), and the probability that a detection was that of a moose (b) as a function of all combinations of our sampling effort and date covariates.

Detection covariate	Survey-specific measurement	Rationale
Sampling effort	Hours hunted	Increased time in the field should lead to increased probability of detection.
Time of yr	Date	Tree phenology influences hunters' visibility. Moose activity and sociality change throughout the yr (Bubenik 1987).
	Date^2	Elevated moose activity early in the hunting season, and trees shedding their leaves late in the hunting season could lead to increased detection probability at the beginning and end of the hunting season.

other that fixed $p_{10} = 0$. We used Akaike's Information Criterion (AIC) to select supported parameterizations (ΔAIC $\leq$ 7) of each parameter (Burnham and Anderson 2002). Then, in the final model set, we tested all combinations of all supported parameterizations from the initial model set. Doherty et al. (2012) compared step-wise approaches similar to the approach we employed to test all possible models and reported that step-wise approaches produce similar model rankings and parameter estimates and that estimates were improved by model averaging in all model selection approaches. Therefore, we model averaged over all supported models in this final model set to produce estimates of moose occupancy across the ranges of covariate values occurring across the study area.

We estimated unconditional occupancy (i.e., the probability that a sample site is occupied based upon estimates of covariate effects and site-specific covariate values) across the entire study area by model averaging occupancy estimates from all supported models. Because sample sites were not equivalently sized, we constructed a grid of equivalently sized, 10 km by 10 km, sample sites across the study area. This grid contained roughly the same number of sample sites that the original study area delineation contained (576 units within the grid vs. 581 units within the original delineation). We predicted unconditional occupancy across this grid in the same manner as with the original study area delineation to visualize patterns of unconditional occupancy across the study area irrespective of sample-site area.

We evaluated the power of our occupancy modeling approach to detect changes in occupancy between years following the methods of Guillera-Arroita and Lahoz-Monfort (2012). We calculated the proportional change in occupancy that could be detected with 80% power and 95% confidence using sampling effort ranging from 10–30 sample visits/site and 200–450 sample sites visited for a system with probabilities of occupancy and detection of 0.1.

RESULTS

The hunter response rate was 11–14% across all of New York during the years 2012–2014 (Table 3). The response rate was highest in 2012 (14.3%) when surveys were distributed in November after the hunting season began (Table 3). From 2012 to 2014, 729, 347, and 525 hunters provided responses from within the study area, respectively. These survey responses contained information on 67,258 hours of hunting from 15,820 sampling visits (Table 3). Sample sites that were visited at least once in a given year were visited on average 19.2 times during that year. Additionally, between 35,000 km^2 and

45,000 km^2 were surveyed within the study area each year. Naïve estimates of occupancy across the study area were 0.141, 0.083, and 0.109 during 2012, 2013, and 2014, respectively.

In the initial model set, parameterizations that assumed no false positive detections (i.e., $p_{10} = 0$) received overwhelming support when compared to models that estimated the false positive detection probability. When testing for parameterizations of p_{10}, the only model to receive support was the parameterization that fixed $p_{10} = 0$. Additionally, when testing for supported parameterizations of p, b, and Ψ, only parameterizations tested alongside $p_{10} = 0$ were supported. Three parameterizations of p were supported in the initial model set: the fully parameterized detection model; a parameterization containing the effects of year, sampling effort, and date; and a parameterization containing the effects of year and sampling effort. Two parameterizations of b were supported in the initial model set: the fully parameterized model and a parameterization containing the effects of year, date, and date^2. Additionally, 181 parameterizations of Ψ were supported in the initial model set.

In the final model set, which combined the supported parameterizations of p, b, and Ψ, 290 of 1,086 parameterizations received some support (ΔAIC $\leq$ 7). Moose occupancy was associated with year; parameterizations on occupancy including a year effect received considerable support (cumulative AIC weight = 0.937) in our final model set. A sample site with average covariate values from across the study area was estimated to have an occupancy probability of 0.150 (95% CI = 0.076–0.276) in 2012, 0.069 (95% CI = 0.045–0.103) in 2013, and 0.081 (95% CI = 0.041–0.153) in 2014. However, the average probability of moose occupancy for visited sample sites was 0.201 (95% CI = 0.182–0.219) in 2012, 0.122 (95% CI = 0.106–0.137) in 2013, and 0.138 (95% CI = 0.122–0.155) in 2014. Moose occupancy was positively associated with log-transformed sample site area and the proportion of a sample site composed of coniferous forest (Fig. 2). Additionally, moose occupancy was positively associated with the proportion of a sample site composed of deciduous forest, not associated with the proportion of a sample site composed of early successional forest or scrubland, and negatively associated with the number of deer observed/hour by hunters, average summer high temperature, and the proportions of a sample site composed of agriculture, development, mixed forest, and wetlands (Fig. 2).

Detection probability was associated with year; parameterizations on detection that included a year effect received considerable support (cumulative AIC weight = 1) in the final model set. Detection probabilities were highest in 2013

Table 3. The New York State Department of Environmental Conservation surveyed white-tailed deer and black bear hunters across the state of New York, USA, about their observations of moose and moose sign, hunting effort, and sample sites visited while hunting within our study area during the 2012–2014 hunting seasons (20 Oct–2 Dec 2012, 26 Oct–8 Dec 2013, and 25 Oct–7 Dec 2014).

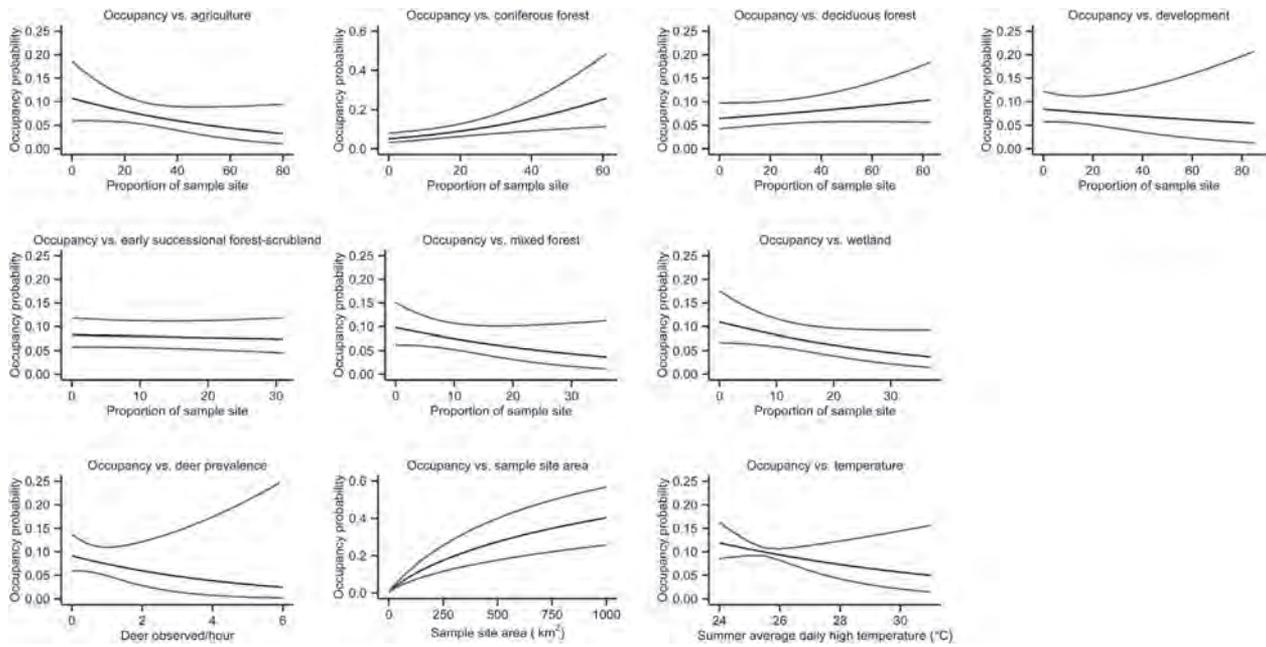| Yr	Surveys distributed	Surveys returned	Return rate	Number of visits	Hours hunted	Sample sites visited	Sites with only sign detected	Sites with only moose detected	Sites with sign and moose detected
2012	11,000	1,569	0.143	7,020	30,519	333	39	3	5
2013	11,004	1,194	0.109	3,166	12,960	242	5	10	5
2014	11,000	1,313	0.119	5,634	23,779	294	22	6	4

Figure 2. Model-averaged estimates of moose occupancy (in black) and 95% confidence interval (in gray) across the ranges of occupancy covariates occurring across the study area in northern New York, USA, 2012–2014. We calculated estimates by model averaging real predictions of unconditional moose occupancy from supported models from our final model set. We constructed the 95% confidence intervals from the model-averaged unconditional real variance estimates, which we calculated using the delta method.

(0.157, 95% CI = 0.142–0.173) and similar in 2012 (0.073, 95% CI = 0.068–0.77) and 2014 (0.072, 95% CI = 0.056–0.092). Detection probability was positively associated with sampling effort (Fig. 3). Detection probability and the probability of a detection being that of a moose were both negatively associated with date and date[2], indicating that the probability of detecting a moose was highest early in the hunting season and declined through the season (Fig. 3).

Occupancy probabilities were highest within the Adirondack Park in northern New York, whereas occupancy probabilities were lowest around developed areas associated with Lake Ontario and the heavily developed I-90 corridor in the western and southern portions of the study area, respectively. Occupancy probabilities were also relatively high in the southwestern portion of the study area, which corresponds to the relatively undeveloped Tug Hill Plateau (Fig. 4).
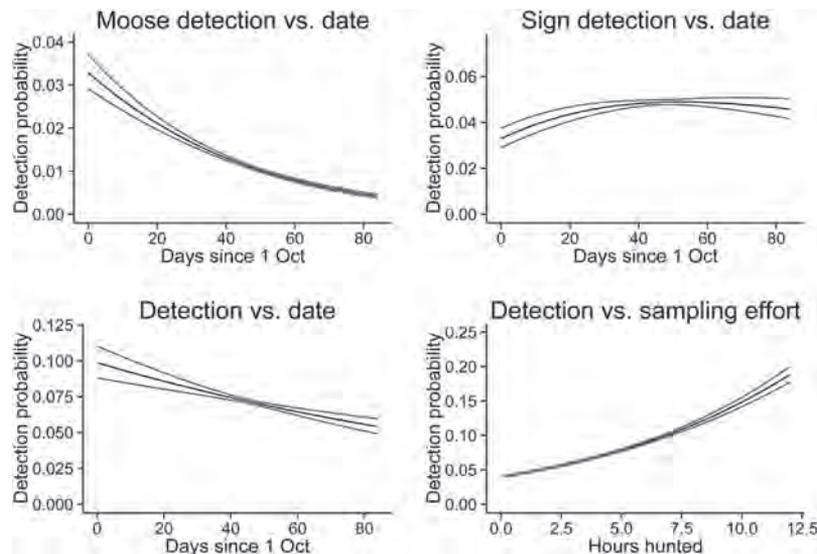

Figure 3. Model-averaged estimates of the probability of detecting moose depending on date (A), the probability of detecting moose sign depending on date (B), the probability of detecting either moose or moose sign depending on date (C), and the probability of detecting either moose or moose sign depending on sampling effort (D) in northern New York, USA, 2012–2014. Estimates of detection probability are in black and their 95% confidence intervals are in gray. We calculated estimates by model averaging real predictions of unconditional moose occupancy from supported models from our final model set. We constructed the 95% confidence intervals from the model-averaged unconditional real variance estimates, which we calculated using the delta method.

The sampling effort from the 2012 hunter surveys (333 visited sample sites and a mean of 22 visits/sites) would have been able to detect the smallest proportional change in occupancy (0.59), followed by the sampling effort of 2014 (294 visited sample sites, a mean of 19 visits/site, and a 0.65 proportional change in occupancy detected), whereas the 2013 sampling effort (242 visited sample sites and a mean of 13 visits/site) would only be able to detect a proportional change in occupancy of 0.76 (Fig. 5). Increasing the number of sample sites visited and the number of visits per sample site increased the ability of occupancy modeling to detect smaller changes in occupancy between years (Fig. 5). However, there were diminishing returns regarding the ability of occupancy models to detect changes in occupancy from increasing the number of sampling visits/site (Fig. 5).

DISCUSSION

This study highlights the potential of data collected using citizen science, namely hunter surveys, for understanding the spatial distribution of low-density species across large spatial extents. Because of the sheer quantity of data collected and the large spatial extent over which it was collected, conducting this occupancy study without citizen science would have been prohibitively expensive and logistically unmanageable.

Data collected by citizen scientists can, however, include errors (i.e., false positive detections) that may produce biased results in occupancy studies (Miller et al. 2011). Our false positive occupancy modeling framework allowed us to account for the possible presence of false negative and false positive detection errors in the big game hunter survey dataset, which is critical for accurately estimating occupancy when the species of interest is not always detected when present, and when other species are sometimes misidentified as the species of interest (MacKenzie et al. 2006, Miller et al. 2011). Without formally accounting for detection errors, we would have underestimated occupancy at visited sample sites by 29.7% in 2012, 31.8% in 2013, and 21.2% in 2014,
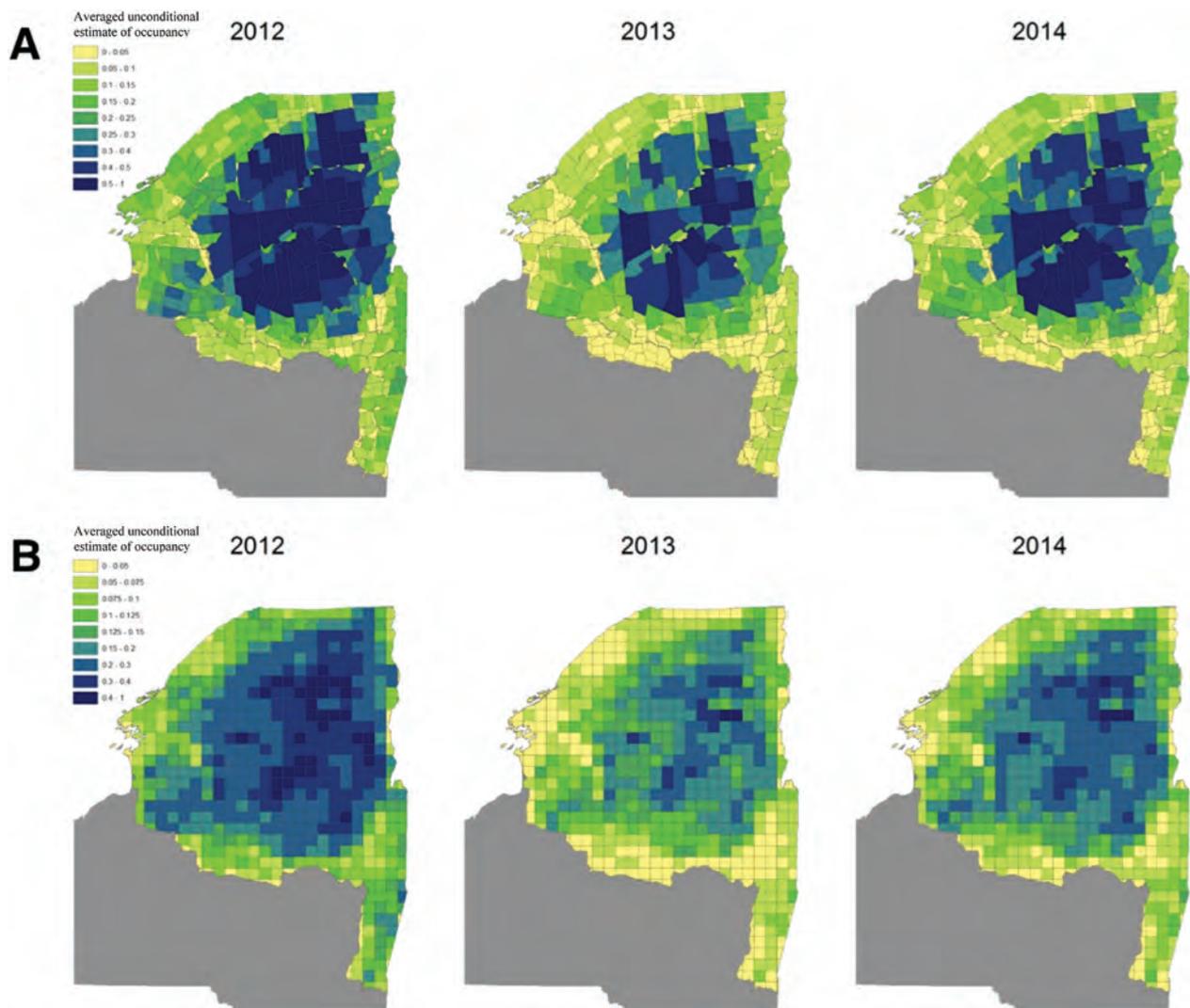

Figure 4. Model-averaged unconditional estimates of moose occupancy (2012–2014) across the study area in northern New York, USA. We present estimates of moose occupancy for sample sites at the spatial scale over which hunters collected data on moose detections and non-detections (A) and predictions of moose occupancy for arbitrarily defined sample sites of equivalent size to illustrate patterns of moose occupancy irrespective of sample site size (B).
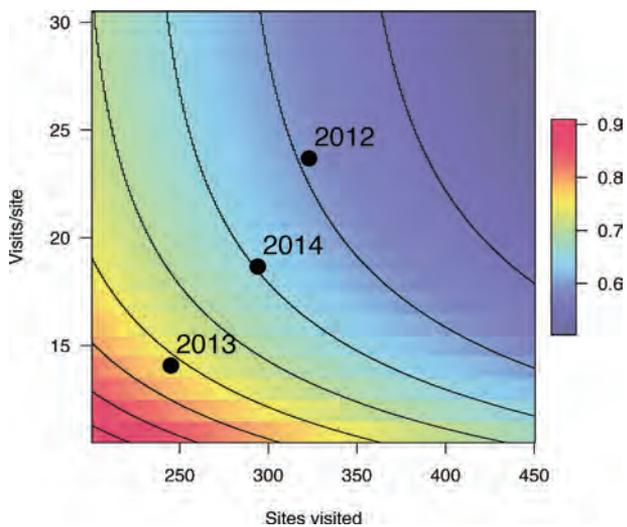
Figure 5. We calculated the proportional change in occupancy that could be detected between years using various sampling efforts, ranging from 10–30 sample visits/site and 200–450 sample sites, which included the sampling efforts from the 2012–2014 New York State Department of Environmental Conservation big hunter survey used to estimate occupancy of moose in northern New York, USA. We calculated what proportional change in occupancy could be detected with 80% power and 95% confidence when the detection probability is 0.1 and the initial probability of occupancy is 0.1 according to Guillera-Arroita and Lahoz-Monfort (2012).

highlighting the importance of accounting for the detection process in understanding a species distribution. However, without accounting for detection errors, we would have overestimated moose occupancy across the entire study area in at least 2013 and 2014, when our naïve estimates of occupancy, 0.083 and 0.109 respectively, were larger than our estimates of occupancy, 0.078 and 0.081. This discrepancy is likely due to hunters preferentially visiting sample sites that are larger in area and therefore have a higher probability of being occupied. This is a consequence of the coarse spatial scale over which data were collected. Ideally all sample sites would be the size of a moose home range during autumn to avoid this issue. To address this sampling bias under the current spatial scale, additional hunter surveys could be distributed to targeted areas along the edges of the study area where sample sites are smallest.

Hunters did not make detections of moose sign at sample sites where moose were estimated to be absent, as indicated by our supported models being those where the false positive detection probability was fixed to zero. Given that false positive rates have been found to occur in other applications of citizen science, we are surprised by this lack of support (Miller et al. 2013, Pillay et al. 2013, Rich et al. 2013, Ausband et al. 2014). This may indicate that hunters are more capable of distinguishing moose sign from that of other species, specifically white-tailed deer. More broadly, this result provides evidence that hunters can generate a vast amount of valuable data on species distribution patterns that are useful for scientific inquiry and wildlife management. The ability to test for the presence of such detection errors is valuable, though, because false positive detections can bias

occupancy estimates, especially when occupancy probabilities are low (Miller et al. 2011).

We estimate that 7–17% of sample sites across our study area, in northern New York, were occupied by moose during 2012–2014, with the highest probabilities of occupancy being in the center of the Adirondack Park. Additionally, by analyzing the detection–non-detection data collected via hunter surveys using occupancy modeling, we were able to explicitly estimate associations between moose occupancy and different land cover types, climate, and white-tailed deer prevalence (Fig. 2). Understanding these associations can provide needed insight regarding the moose distribution along the southern extent of their range and in New York, where little is known about their status. Moose occupancy was positively associated with the proportion of mature forests and negatively associated with the proportion agriculture within a site (Fig. 2), which is consistent with previous work that has demonstrated that moose select mature forest for both cover and forage (Bjorneraas et al. 2011, 2012; van Beest et al. 2012) while avoiding agriculture and other areas associated with human influences (Herfindal et al. 2009). We confirmed that in terms of occurrence and spatial distribution, many moose habitat associations at their southern range extent appear to match those in other parts of their range.

However, we found that the proportion of early successional forest or scrubland, mixed forest, and wetlands within a site, which are all typically considered to be preferred land cover types for moose (Bjorneraas et al. 2011, 2012), were not associated with moose occupancy in our study (Fig. 2). Moose habitat selection can be dependent on a matrix of preferred land cover types (Osko et al. 2004, Dussault et al. 2005), and therefore, the lack of association with these land cover types may be a result of matrix composition within our study area. Early successional forest or scrubland, mixed forest, and wetlands are 3 of the 4 least common land cover types, with the fourth being development, across the study area, and none occur most frequently within the Adirondack Park where moose occupancy is highest. Early successional forest or scrubland most commonly occurs in the southwestern portion of the study area, and mixed forest occurs most commonly along the eastern edge of the Adirondack Park along Lake Champlain, whereas wetlands occur most commonly along the St. Lawrence and Hudson Rivers outside of the Adirondacks. Sample sites in each of these areas are outside or on the periphery of the Adirondack Park and contain higher frequencies of development and agriculture. Additionally, the land cover data used from the National Land Cover Database does not distinguish between high productivity early successional forest, which we would expect moose to prefer, and low productivity scrubland, which we would expect moose not to prefer. Therefore, our results may reflect the paucity of these land cover types within the core of the moose range within New York and our inability to distinguish between early successional forest and scrubland, rather than indicating that moose occupancy is not influenced by early successional forest, mixed forest, and wetlands.

Although summer temperatures across our study area regularly exceed the thermoneutral zone of moose, moose occupancy was only weakly negatively associated with summer high temperatures. Moose are capable of behaviorally mediating heat stress by seeking thermal cover in closed canopy forest or wetlands (McCann et al. 2013), which may have compensated for the high summer temperatures moose experience in New York. Although not analyzed in our study, winter temperature may also be important in determining moose occupancy at large spatial scales because short, warm winters may increase winter tick (*Dermacentor albipictus*) survival, which has been hypothesized to increase the mortality rate of moose in subsequent years (Musante et al. 2010). This dynamic could lead to lower probabilities of moose occupancy in areas with warmer winters than areas with cooler winters.

Parasite-mediated competition with white-tailed deer (Schmitz and Nudds 1994) could have influenced the negative association of moose occupancy with our index of relative abundance of white-tailed deer. Brainworm (*Parelaphostrongylus tenuis*) is thought to play a role in moose mortality where moose and white-tailed deer range overlap, whereas giant liver flukes (*Fascioloides magna*) can lead to sub-lethal effects and less frequently mortality among infected moose (Schmitz and Nudds 1994, Murray et al. 2006). Nevertheless, our results indicate that this relationship between white-tailed deer and moose may be occurring across northern New York. Future work could help elucidate the impacts of parasite-mediated competition between white-tailed deer and moose by examining multi-species occupancy dynamics at a smaller spatial scale than this study, and by studying cause-specific mortality of moose across New York.

We observed differences in moose occupancy probabilities among years; however, our static occupancy modeling framework was unable to suggest the influences of these changes. We did attempt to estimate colonization and extinction rates using a dynamic occupancy modeling framework to better understand these inter-year differences in occupancy, but the dynamic framework was unable to provide precise and meaningful estimates of colonization and extinction rates using the big game hunter survey data set. This issue was likely caused by the low initial occupancy and insufficient temporal replication, and could potentially be ameliorated with additional years of hunter survey data (MacKenzie et al. 2003).

Detection probabilities were low across all 3 years, and as expected, detection probability increased when hunters spent more time hunting. Additionally, the detection probability and the probability that a detection was that of a moose decreased throughout the hunting season. This may suggest that increased moose movement associated with the rut early in the hunting season leads to an increased probability of detections as we hypothesized. Because moose were easiest to detect early in the hunting season (i.e., during late Sep and early Oct) we recommend that future research regarding moose focuses sampling effort during this time. For instance, distributing surveys to hunters who are expected to hunt during the bow or muzzleloader seasons, which occur before the regular hunting season, could increase detection probability. By doing so, future work can minimize the sampling effort required to reach a desired precision in its estimates.

Our study demonstrates the power and effectiveness of using citizen science to estimate and monitor the distribution of wildlife species across large spatial extents. We propose using hunter survey data to cover large spatial extents with large sampling effort to estimate patterns and rates of species occurrence about which inference would be logistically and financially challenging otherwise.

MANAGEMENT IMPLICATIONS

Occupancy analyses can be used to direct future research, conservation, and management actions, providing spatial reference over large areas regarding species occurrence. These analyses allow for future work to more effectively spatially stratify sampling effort, so that undue effort is not spent where the species of interest is not present. Future research regarding moose in New York should focus efforts primarily in and around forests with a conifer component to maximize data collection on this species. Additionally, our power analysis demonstrated that, despite the low detection probability achieved from hunter surveys and moose occupying few sites across New York, hunter surveys are a viable method to monitor the distribution of moose in New York. The power analysis also indicated that it might be more beneficial to prioritize increasing the number of sample sites visited rather than increasing the number of visits per sample site. This suggests that distributing surveys to hunters that are likely to hunt at different sample sites, or even supplementing the hunter survey data by the NYSDEC sampling sites that are not likely to be visited by hunters, could increase the ability to detect changes in moose occupancy across New York.

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Appendix A. New York State Department of Environmental Conservation Big Game Hunter Survey.

NEW YORK STATE DEPARTMENT OF ENVIRONMENTAL CONSERVATION

Big Game Regular Season Log and Observation Survey

Instructions

Please use this form during the Regular (Gun) Deer and Bear Seasons only. Record your: 1) deer hunting activity, 2) deer, bear and moose sightings, and 3) deer or bear harvests. This information will help DEC track the amount of effort expended by hunters each year and changes in deer, bear and moose populations.

Hunt Locations: identify each county, town and WMU where you hunt. If either the town or WMU is different, record it as a separate site number.

Hunting Log and Observations: fill in the date, site and hours hunted for each day you hunt during the Regular Deer/Bear Season, even if you did not see any big game that day. Leave sighting cells blank if you did not see any big game that day.

- If you hunt multiple sites on the same day, record the information for each site separately using a new line for each site.
- Deer Sightings: if you cannot see whether the deer you observe has antlers or not, include them in the "unknown" category. Antlerless deer includes adult does, all fawns, and spike bucks with antlers less than 3 inches long.
- Bear Sightings: if you cannot identify whether a bear is an adult or a cub, include it in the "unknown" category.
- Moose Sightings: if you cannot identify whether a moose is a bull, cow or calf, include it in the "unknown" category. Mark "Sign" for observations of tracks, scat, etc.

Deer and Bear Harvest: record information about any deer or bear you took during the Regular Season only. Do not include information about deer or bear you took during other seasons. Include the date, site #, age and sex of the animal. For antlerless deer, write the number you took during the Regular Season in the box provided. You must also report all harvests via DEC's online or phone reporting system.

Keep this form clean: do not take it in the field. Leave the form in your vehicle or home where you can fill it out each day after hunting.

Need more sheets? If you need additional log sheets to list more sites or days of hunting activity, call 518-402-8883 for assistance.

Return your Hunting Log and Observation Survey in the postage-paid envelope by December 20. You may make a copy, but return the original. Send the form to:

NYSDEC Game Management, 625 Broadway, Albany, NY 12233-4754

EXAMPLE

Did you hunt during the 2013 Regular Firearms Season?
- Yes; continue.
- No; return survey as described above.

Hunt Locations

Site #	County (first 4 letters)	Town (first 7 letters)	WMU	Nearest Village
1				
2				
3				
4				
5				
6				

Thank you for participating!

Return survey by December 20.

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Big Game Regular Season Hunting Log and Observation Survey

Hunting Activity (Record all days that you hunt)				# Deer Sightings			# Bear Sightings (Leave blank if no deer, bear or moose are seen)			# Moose Sightings				
Month	Day	Site #	# Hours Hunted	Buck	Antlerless	Unknown	Adult	Cub	Unknown	Bull	Cow	Calf	Unknown	Sign
		1 2 3 4 5 6												○
		1 2 3 4 5 6												○
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		1 2 3 4 5 6												○

Regular Season Deer and Bear Harvest
(Only include harvest of deer or bear taken during the Regular Firearms Seasons)

Deer Take

Did you take a deer during the regular season?
○ No   ○ Yes; provide information below

Month	Day	Site #	# Antlerless	Antlered
	/	1 2 3 4 5 6		○
	/	1 2 3 4 5 6		○
	/	1 2 3 4 5 6		○
	/	1 2 3 4 5 6		○
	/	1 2 3 4 5 6		○

Bear Take

Did you take a bear during the regular season?
○ No   ○ Yes; provide information below

Month	Day	Site #
	/	1 2 3 4 5 6

○ Adult   ○ Male
○ Cub   ○ Female
○ Unknown   ○ Unknown

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