

## RESEARCH ARTICLE

# Leveraging hunters as citizen scientists for monitoring non-target species

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**Funding information**

Montana Codes Annotated, Grant/Award  
Number: 87-2-724; Federal Aid in Wildlife  
Restoration, Grant/Award Number:  
W-157-R7

**Handling Editor:** Mark O'Connell

**Abstract**

1. Hunter populations can provide a tremendous workforce of citizen scientists afield when queried for data. Soliciting incidental observations of non-target species from hunters may be a relatively important but untapped population monitoring resource in systems where hunter effort is common and widespread.
2. During 2012–2016, we queried hunters of deer and elk for observations of a non-target species, moose, across their statewide distribution in Montana. We analysed data in an abundance-detection framework with n-mixture models and evaluated the effects of covariates such as hunter effort, survey response totals, weekly session and forest cover on detection probability before using models to predict moose abundance.
3. We collected an average of 3409 moose observations per year and our best n-mixture model included effects of week, year (number of responses), site (proportionate forest cover) and site-year (hunter effort) on detection probability, as well as an effect of site (area of forest and shrub habitat) on abundance. Density estimates averaged 0.099 (range 0.002–0.439) moose/km<sup>2</sup> across sites or 0.200 (range 0.017–0.799) moose/km<sup>2</sup> when limited to density within shrub and forest cover specifically. Statewide abundance totals across the 5-year study period averaged 10,755 (range 9925–11,620). Goodness-of-fit tests showed that models were identifiable and overdispersion of the data was low, yet some caution is still warranted when extrapolating these data to abundance estimates.
4. Querying a sample of deer-elk hunters for observations of a non-target species yielded thousands of spatially georeferenced detections per year and analysis in a temporally structured framework yielded estimates of both detection probability and abundance. Abundance estimates at this scale are unprecedented for moose in Montana and are encouraging for long-term monitoring over space and time.

**KEYWORDS**

*Alces alces*, citizen science, hunter observations, monitoring, moose, n-mixture model, occupancy, sightings

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## 1 | INTRODUCTION

Science-based monitoring of population abundance and trend is fundamental to conservation and management of wildlife. For many species, such monitoring includes components of citizen science, wherein public citizens are recruited as collectors of data (Brown & Williams, 2019). Long-standing examples of wildlife monitoring founded upon citizen science include volunteer surveys such as the U.S. Christmas Bird count (Dunn et al., 2005), road-side amphibian surveys (Sterrett et al., 2019) or other efforts of organised public involvement towards a given data need. Compared to this active investment of effort, other more passive examples of citizen science include the annual solicitation of harvest and observation data from hunters across many jurisdictions globally (Cretois et al., 2020; LaBonte & Kilpatrick, 2017). Hunter populations can provide a tremendous workforce of citizen scientists afield when queried for data. Furthermore, hunter observations of wildlife have been used to monitor species targeted by hunters (Haskell, 2011; Tallian et al., 2021; Ueno et al., 2014) as well as other species encountered incidentally while hunting (Mahard et al., 2016; Rich et al., 2013).

Through their cumulative numbers and time spent afield, hunters represent an impressive workforce of observers deployed to the natural landscapes occupied by wildlife. A review of hunting statistics within the contiguous United States estimated that deer (*Odocoileus* spp.) hunters alone spend nearly 168 million hunter-days afield each year (QDMA [Quality Deer Management Association], 2019). Spread evenly across the 7.7 million km<sup>2</sup> land area of the contiguous U. S. this translates to an average of almost 22 hunter-days per km<sup>2</sup> of land. Because hunters are not evenly distributed across the country, some regions, states, and areas certainly have even denser hunter effort. Hunting effort is also typically concentrated within specific administratively mandated seasons, which has advantages when seeking to sample closed populations of non-target species.

Low costs and high quantities of data can be enticing benefits of citizen science, yet careful attention to elements of design and sampling are required to minimise effects of bias upon statistical analyses and interpretations (Brown & Williams, 2019; Isaac et al., 2014; Steger et al., 2017). Such biases can occur where sampling (i.e. the detection process) is uneven over space or time or among taxa, which is very often the case with opportunistic data (Geldmann et al., 2016; Steger et al., 2017), including data collected by hunters (Bauder et al., 2021; Mysterud et al., 2020). Fortunately, occupancy-detection methods of design and analysis offer one solution to such variation by explicitly modelling the detection process (Isaac et al., 2014). Where replicates of data collection are possible within a period of closure, these approaches have been successfully applied for monitoring of presence-absence or distribution with citizen science data (Crum et al., 2017; van Strien et al., 2013). Abundance-detection extensions of this approach, such as the n-mixture model for count data (Royle, 2004), offer further potential for monitoring of abundance while accounting for heterogeneity in the detection process common to citizen science data (Belt & Krausman, 2012; Brommer et al., 2017).

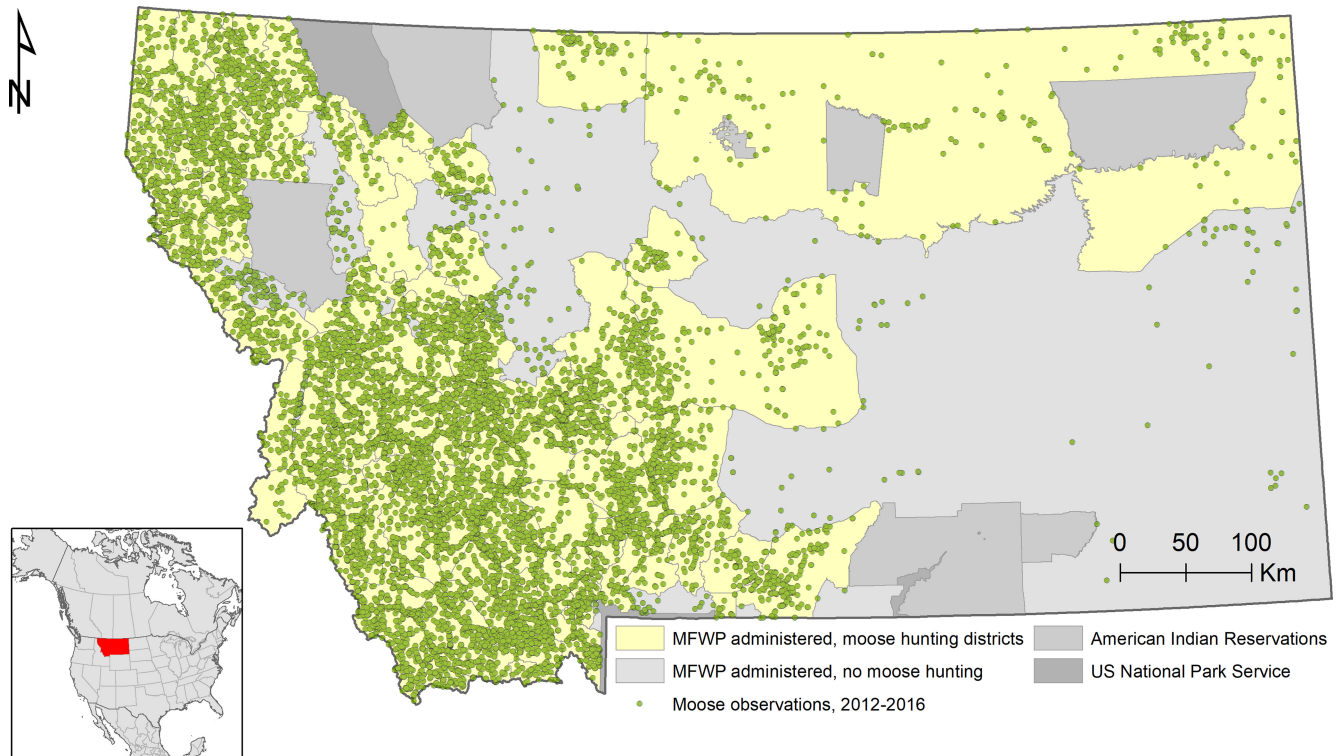
Large or charismatic species may be particularly amenable to citizen science approaches (Steger et al., 2017). For example, moose (*Alces alces*) have been a common target of such monitoring across the boreal forests of their Holarctic range. A review of North American jurisdictions showed 80% (12 of 15) of states and provinces incorporated visual observations of moose by hunters into monitoring programs (Crichton, 1993). Similarly, hunter observations are a foundational component of moose monitoring in some European countries, including Norway (Solberg & Sæther, 1999; Ueno et al., 2014) and Sweden (Ericsson & Wallin, 1999; Tallian et al., 2021). However in many southern jurisdictions, moose hunting opportunity is limited or non-existent, and data from hunters specifically targeting moose are sparse (DeCesare et al., 2016). In these scenarios, moose are a non-target species that may be incidentally observed by a larger workforce of hunters targeting more common species such as deer (Crum et al., 2017). Thus, despite being commonly targeted by hunters in some jurisdictions where they are more numerous (Ueno et al., 2014), moose in lower density populations provide a useful case study for monitoring non-target species via opportunistic observations from hunters.

We applied abundance-detection methods to hunter observation data collected for moose in Montana. Traditional ungulate monitoring in Montana occurs via aerial surveys and hunter harvest statistics (e.g. Paterson et al., 2019). Moose in this environment are widespread but locally occur at low densities with very limited hunter opportunity, do not aggregate to a high degree in this environment and often occupy habitats obscured from above by dense vegetation, which collectively cause monitoring via aerial survey or harvest statistics to be untenable and unsatisfactory (DeCesare et al., 2016). While there were only 365 licensed moose hunters annually in Montana during our study period on average, there were an average of 150,959 and 109,111 hunters of deer and elk, respectively, totaling over two million hunter-days per year. Thus, we targeted this larger pool of deer and elk hunters for observations of moose, a non-target species, during weekly sessions for each of 5 years and analysed data with n-mixture models. We evaluated the effects of hunter effort, survey responses, survey week and forest cover on detection probability and the effect of habitat area on abundance. Lastly, we made predictions of abundance both per site and scaled up to statewide abundance to evaluate the efficacy of this approach for broad-scale monitoring.

## 2 | MATERIALS AND METHODS

### 2.1 | Study area

We collected moose observation data across the entire state of Montana where state-administered deer and elk hunting occurred. We then restricted our analyses to observation data collected within 79 state administered moose hunting districts (HDs), which represented 202,474 km<sup>2</sup> (53%) of Montana's land area (Figure 1). Ecoregions in Montana include the North and South Central



**FIGURE 1** The Montana study area boundary, as delineated by 79 moose hunting districts administered by Montana Fish, Wildlife and Parks, other lands outside of moose hunting districts and hunter observations of moose collected during the five-year study period, 2012–2016.

Rockies Forests where the Rocky Mountains span the western portion of the state, the Montana Valley and Foothill Grasslands along valley floors between mountain ranges, and the Northern Short Grasslands across the central and eastern portions of the state (Olson et al., 2001). Elevation in the study area ranged from 554–3882m and annual precipitation from 16 to 253cm. Mean January temperatures ranged from  $-14^{\circ}\text{C}$  to  $-2^{\circ}\text{C}$  and mean July temperatures from 6 to  $23^{\circ}\text{C}$ .

White-tailed deer (*Odocoileus virginianus*), mule deer (*O. hemionus*) and elk (*Cervus canadensis*) are more abundant than moose in this study area. State-administered hunting of deer and elk during the study period occurred during a 5-week general season across most of the state. Specifically, this season began in late October of each year (start date range: 20 October–26 October), lasted for 37 days and ended in late November or early December (end date range: 25 November–1 December). A general deer hunting licence was available over the counter to residents and allowed rifle hunting of white-tailed deer in 97% of hunting districts and of mule deer in 79% of districts in 2016. A separate general elk licence was also available over the counter to residents and allowed rifle hunting of elk in 85% of districts in 2016. General licence hunting opportunities yielded 79% of deer harvest and 68% of elk harvest in 2016. In addition to general licences, additional hunting opportunity in many areas was available through lottery of permits (conferring additional permitted uses of general licences) and antlerless licences via special drawings.

## 2.2 | Data collection

### 2.2.1 | Moose observation data

Following methods first established for monitoring wolves within Montana (Rich et al., 2013), we used annual phone surveys to query hunters for observations of moose following five hunting seasons of 2012–2016. During these years there were an average of 165,594 (range 161,394–171,604) resident hunters with deer and/or elk licences. For this survey we drew a random sample of licence holders, averaging 50,512 (31%) hunters per year, to target for observations of moose. We added questions to an existing phone survey effort designed for estimating statewide deer and elk hunter harvest in Montana to collect ancillary information regarding moose observations while hunting these more abundant species (Lukacs et al., 2011). We asked a sampled deer and elk hunters: (a) whether or not they saw any moose while deer or elk hunting, (b) if yes, in what district and location (relative to landmarks, property ownership, or names of topographic or hydrologic features), (c) during which week of the 5-week season and (d) how many animals were seen in that location. Distinct observations, as denoted by different locations or time periods, were entered separately but a single observation could include more than one moose. We then digitised the locations of moose observations using information provided and tallied them by week within the boundaries of 79 moose-specific HDs. While data were collected by deer and elk hunters whose hunting behaviour was regulated within deer and elk hunting districts,

we later summarised these observations with respect to moose hunting districts because they are spatial units ultimately of interest for moose population monitoring and management. Public hunting of deer and elk was regulated under the auspices of legal hunting and trapping seasons defined by the Montana Fish and Wildlife Commission, under the authority granted to them in statute MCA 87-1-301.

Hunter observations may suffer from a problematic lack of independence when multiple observations can be collected across hunters for the same individual animal. We expected such repeated counts were present in our dataset, and we used a sequence of spatial analyses to consolidate observations that overlapped in space and time. First, we used global positioning system (GPS) telemetry data collected from 93 adult female moose in three Montana study areas during 2014–2020 to assess the weekly space use of moose during the autumn study period. For these analyses, we assumed movement data collected from adult female moose would adequately describe weekly space use for both males and females. Details of animal capture and handling for those studies are presented in Newby and DeCesare (2020). We subsampled GPS data to daily locations during each 5-week hunting season and estimated the pairwise Euclidean distance between daily locations within each of 1016 moose-weeks. We then divided pairwise distances in half to approximate circular radii extending from each location and used a histogram of the maximum pairwise radii per moose-week to estimate the weekly distribution of potential moose space use surrounding a given location. This distribution of weekly space use was then applied to convert point locations of observations into probability density functions. We buffered observations with concentric circles corresponding in radii to the breaks of the distance histogram, with probability density calculated according to the proportion of locations within each interval and the corresponding concentric circle area. For each observation, the sum of density\*area values across all surrounding buffers equaled 1. We then consolidated each set of buffers surrounding observations within the same year and week into a raster layer. Areas where probability density buffers overlapped represented places where observations may have occurred within the space use of the same moose. In those overlapping areas, we used a single value of the maximum probability density value across all buffers to characterise the density per raster pixel. This consolidated sets of overlapping observations relative to the degree of overlap, such that completely overlapping observations were reduced to be equivalent to a single one, whereas completely non-overlapping observations remained independent. We then summed density buffers per raster within each hunting district to estimate a single count of spatially independent moose observations per week and year of sampling.

### 2.2.2 | Environmental predictors of detection and abundance

We were interested in monitoring moose abundance per HD while accounting for spatio-temporal heterogeneity in detection probability.

We evaluated how detection probability varied according to four covariates, with one covariate hypothesised to vary by each category of site (i.e. HD), year, site-year and week. The site covariate with hypothesised effects on detection was the proportionate forest cover of sites (using Montana Land Cover Framework; MNHP [Montana Natural Heritage Program], 2017). We hypothesised yearly effects on detection according to the number of respondents to questions about moose observations during yearly hunter phone surveys, 2012–2016. The site-year covariate with hypothesised effects on detection was the estimated hunter effort of deer and elk hunters during the general, 5-week rifle season, in hunter-days per km<sup>2</sup>. Hunter effort was estimated distinctly for deer hunters and elk hunters for each site-year according to the mean relationships between hunter harvest (estimated by phone survey every year) and hunter effort (estimated by phone survey in alternating years) per site. Because the proportions of hunters queried for moose observations varied between deer and elk hunters by year, we calculated total effort estimates per site by log-transforming the combined effort of both deer and elk hunters weighted by the proportion of respondents queried for moose observations each year. The week-level covariate was simply the effect of week itself on detection, treated as categorical variables for hunting season weeks 1–5. We treated week as a categorical variable to account for heterogeneity in the amount of hunting effort spent in the field each week, as dictated by weekly variation in weather and hunter behaviour.

We evaluated the effect of area on abundance within each site, including log-transformed metrics of total area, shrub area and forest area. Habitats used by moose in Montana include a variety of forest and shrubland vegetative communities (DeCesare et al., 2014). We simplified land cover data to include binary representations of forest habitats and shrubland habitats and evaluated the log-transformed area of each to inform models of moose abundance.

## 2.3 | Statistical analysis

We analysed counts of moose per site using n-mixture models to simultaneously estimate functions of detection probability and abundance (Royle, 2004). We used a stacked data structure, wherein detection histories for each site-year were recorded independently, and we included a random intercept,  $\gamma_{0,i}$ , for sites  $i$  to account for this dependence in the variance structure (Kéry & Royle, 2021). Steps of analysis included comparison of Poisson, zero-inflated Poisson, and negative binomial mixtures for abundance with Akaike information criteria (AIC) following Kéry and Royle (2021), from which the negative binomial distribution was selected. We also used AIC to conduct model selection and evaluate different covariates for detection and abundance, beginning with univariate analyses to assess strength and relationship of covariates, each centered and standardised, before building multivariable models in a manual forward stepping fashion. When nested models that differed by only a single parameter were within  $\leq 2 \Delta AIC$  units, we additionally screened to exclude models with uninformative parameters following Arnold (2010). We

conducted analysis in R (v. 4.1.2; R Core Team, 2021) following code and model-fitting procedures provided by (Kéry & Royle, 2021), with the exception that we used an updated version of the package unmarked with capability to accommodate our random effect structure (v. 1.2.3; Fiske & Chandler, 2011).

We evaluated model fit by first refitting our final model with increasing values of  $K$ , the maximum value of  $N$  used in computing marginal likelihoods, to ensure model maximum likelihood estimates (MLEs) were identifiable inside rather than on the boundary of the parameter space for abundance and detection (Kéry, 2018). Second, because overdispersion can cause violation of assumptions and inflated predictions from n-mixture models, we evaluated marginal,  $\hat{c}_m$ , and site-sum,  $\hat{c}_s$ , scalar indicators of overdispersion based on Pearson residuals as well as quantile-quantile (qq) plots of randomised quantile residuals against fitted values using the package nmixgof (Knape et al., 2018).

We used the final model to make predictions of detection probability by site, year and week, as well as to estimate abundance at each site. Individual moose were not counted independently in our data, and instead observations of one or more moose together represented the unit of modelled abundance. Thus, we adjusted our predictions to total moose abundance by multiplying by the mean estimate of observation group size, estimated distinctly per administrative region using counts of moose at each observation. To minimise the influence of outlier values on average group sizes reported by hunters, we capped the maximum group size at the 95th percentile value of six moose per group when estimating mean values, in accordance with reported group sizes for Shiras moose (Anderson Jr. & Lindzey, 1996; Peek et al., 1974).

To estimate the total abundance of moose per year across all sites within our study area (excluding areas outside of moose hunting districts), we generated 10,000 Monte Carlo simulations of site-year abundance estimates drawing from random distributions according to model-estimated mean and standard deviation per site-year. We then used the mean and standard deviation of these estimates to

predict statewide totals for each year. We then used two post-hoc analyses to evaluate the evidence for a trend in moose abundance over time. First, we re-estimated our final n-mixture model with a covariate for year in the abundance term to assess the annual trend in average abundance per site (Kéry & Royle, 2021) and second, we conducted a log-linear regression of annual estimates by year to evaluate evidence for a temporal trend at the statewide scale.

### 3 | RESULTS

An average of 31,511 (range 26,390–40,578) deer and elk hunters annually responded to our phone surveys, or 59%–64% of those sampled from the total population. From this sample, we collected an average of 3409 (range 2338–4675) spatially mapped moose observations per year specific to the 5-week general rifle season (Figure 1). Mean group size per observation across sites was 1.99 moose/observation (SD=0.54). Translating these observations to independent weekly count data yielded a mean of 6.4 moose observations (range 0–37) counted per site-week across 79 sites (moose HDs).

Our best n-mixture model included effects of week, year (number of responses), site (proportionate forest cover), and site-year (hunter effort) on detection probability, as well as an effect of site (area of forest and shrub habitat) on abundance (Table 1). Specifically, detection probability was highest during weeks 1–3 of the season and lowest during weeks 4 and 5 (Table 2; Figure 2). Detection probability also increased in years with more survey responses and in site-years with more hunter effort (Table 2; Figure 2). Lastly, detection probability decreased in sites with higher proportionate forest cover (Table 2; Figure 2). The abundance of moose increased with the total area of forest and shrub cover at each site (Table 2).

Model MLEs were not on the boundary of the parameter space as determined by the effects of increasing  $K$  on model AIC and parameter estimates. Estimates were slightly truncated at  $K=200$  but

**TABLE 1** N-mixture models, wherein variation in abundance is described by a negative binomial distribution with mean  $\lambda$  and variation in observed counts is described by a conditional binomial distribution with detection probability,  $p$ , and including covariates for  $p$  and  $\lambda$ , random intercepts,  $\gamma_0$ , per site,  $i$ , Akaike information criteria (AIC) and difference in AIC from the best model,  $\Delta$ AIC, for moose count data in Montana, 2012–2016.

Detection and abundance models			
$p$	$\lambda$	AIC	$\Delta$ AIC
Intercept-only	$\gamma_{0,i}$	9187.4	500.7
Responses	$\gamma_{0,i}$	9086.3	399.6
Week	$\gamma_{0,i}$	8843.2	156.5
Effort	$\gamma_{0,i}$	9183.1	496.4
Forest	$\gamma_{0,i}$	9178.6	491.9
Week + responses	$\gamma_{0,i}$	8741.7	55.0
Week + responses + forest	$\gamma_{0,i}$	8733.7	47.0
Week + responses + forest + effort	$\gamma_{0,i}$	8712.6	25.9
Week + responses + forest + effort	$\gamma_{0,i} + \text{area}_{\text{shrub}}$	8698.4	11.7
Week + responses + forest + effort	$\gamma_{0,i} + \text{area}_{\text{forest}}$	8691.1	4.4
Week + responses + forest + effort	$\gamma_{0,i} + \text{area}_{\text{shrub,forest}}$	8686.7	0.0
Week + responses + forest + effort	$\gamma_{0,i} + \text{area}_{\text{shrub}} + \text{area}_{\text{forest}}$	8689.5	2.8

**TABLE 2** Covariate coefficients  $\alpha$  for detection probability  $p$  and coefficients  $\beta$  for site abundance  $\lambda$  from the top N-mixture model for moose count data in Montana, 2012–2016.

$p$	$\alpha$	SE	$z$	$p$
(intercept)	-2.155	0.277	-7.8	<0.001
Week2	-0.126	0.029	-4.3	<0.001
Week3	-0.035	0.028	-1.3	0.213
Week4	-0.417	0.033	-12.5	<0.001
Week5	-0.415	0.033	-12.4	<0.001
Responses	0.191	0.017	11.2	<0.001
Forest	-0.600	0.071	-8.4	<0.001
Effort	0.313	0.052	6.0	<0.001
$\lambda$	$\beta$	SE	$z$	$p$
(intercept)	3.975	0.250	15.9	<0.001
area <sub>habitat</sub>	0.408	0.073	6.2	<0.001

stabilised at or above  $K=300$ , which we used for final estimates. There was no evidence of problematic overdispersion as estimated by marginal,  $\hat{c}_m=0.90$  and site-sum  $\hat{c}_s=0.86$  measures of overdispersion. Furthermore, qq plots of both site-sum and observation residuals showed good fit of the negative binomial mixture estimates (Figures S1 and S2).

Predicted weekly detection probability estimates averaged 0.10 per site-year-week (range 0.01–0.29; Figure 3) and yielded cumulative detection probabilities of 0.06–0.77 across the 5-week period of each study year. Predictions of abundance averaged 136 ( $\overline{SD}_{site}=14.7$ ) and ranged 17–416 moose per site-year. Corresponding density estimates averaged 0.099 (range 0.002–0.439) moose/km<sup>2</sup> across entire sites and averaged 0.200 (range 0.017–0.799) moose/km<sup>2</sup> when limiting area to only that of shrub or forest cover within each site (Figure 3). Statewide abundance totals across the five-year study period averaged 10,755 moose ( $\overline{SD}_{year}=151.8$ ) and ranged from a minimum of 9925 (in 2016) to 11,620 (in 2014; Figure 4).

## 4 | DISCUSSION

Querying a sample of deer-elk hunters for observations of a non-target species yielded thousands of georeferenced moose detections per year, and analysis in a temporally structured framework yielded estimates of both detection probability and abundance. Statistical estimates of abundance at this scale are unprecedented for moose in Montana (DeCesare et al., 2016) and are encouraging for long-term monitoring over space and time. We leveraged infrastructure, staff and phone calls already committed to annual hunter harvest phone surveys when collecting these data. On average, this added 1153h ( $SD=125$ ) of person-hours specific to collection of these data, annually but would likely require more in jurisdictions where such surveys are not already in place.

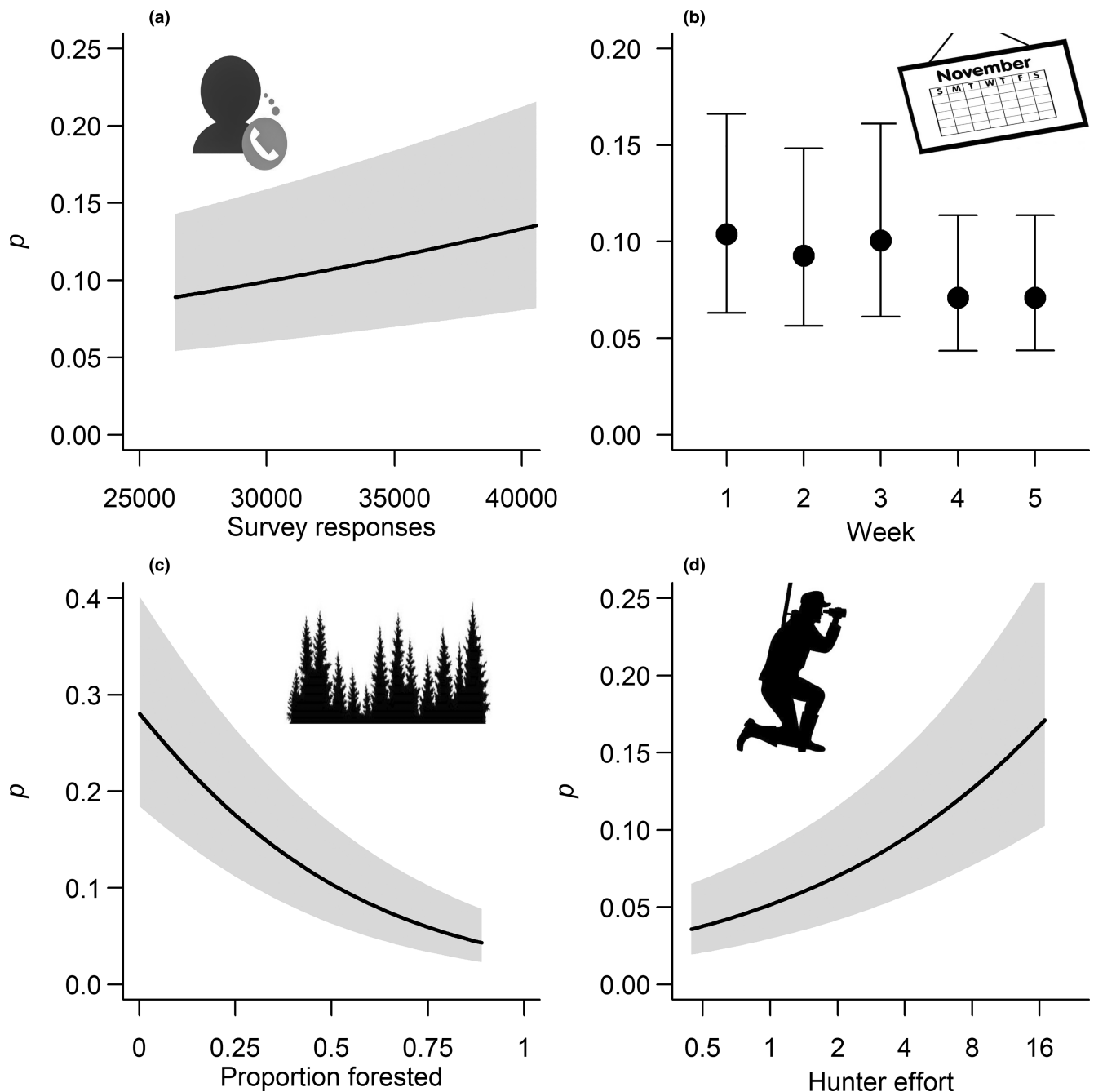
Survey effort varied across years, sites and week according to the number of respondents per year, spatiotemporal variation in

hunter effort per site-year, and week of the hunting season. In accordance with previous studies, variation in these metrics of effort corresponded to variation in detection probability (Figure 2; Dillon et al., 2020; Rich et al., 2013). Detection probability also decreased with increases in proportionate forest cover per site, akin to effects of forest cover on aerial sightability of ungulates (Griffin et al., 2013) and other applications of n-mixture models to observation data in forested environments (O'Kelly et al., 2018). The combined effect of these covariates yielded a wide range of predicted detection probabilities among sites (0.06–0.77 per year) with important effects on the translation of observation counts to predicted abundance estimates (Figure 3). While raw counts of moose observations were dense in some areas, such as portions of southwestern portion of Montana, model predicted density estimates were also high in some areas with lower raw counts, such as the more forested portions of northwestern Montana (Figure 3).

Recent evaluations of n-mixture models have raised awareness of the potential for biased results when failing to meet various model assumptions (Barker et al., 2018; Dennis et al., 2015; Kéry, 2018; Knape et al., 2018; Link et al., 2018). Results of n-mixture models are particularly sensitive to double counting of the same individuals, overdispersion in abundance or detection, or identifiability problems (Kéry, 2018; Knape et al., 2018; Link et al., 2018). In our case, we consolidated observations that overlapped in space and time to reduce the potential for double counting, and multiple goodness-of-fit evaluations supported that our models were identifiable and overdispersion low. However, we surely failed to meet the assumption that heterogeneity in detection probability was fully specified by our limited set of covariates (Link et al., 2018), and potential for biased abundance predictions remains.

While we are unable to validate these results across their full extent due to limited independent moose population data, some comparisons to other data can be made. A single moose density estimate generated from applying camera-trap sampling to a subset of moose HD106 in the Fisher River drainage in northwest Montana yielded comparable and overlapping density estimates ( $d_{2012-2016}=0.167-0.187$  moose/km<sup>2</sup> from this study vs.  $d_{camera}=0.15$  [95% CI: 0.11–0.21] moose/km<sup>2</sup>; N. J. DeCesare, unpublished data). Vetting of our results with local biologists' expert opinion and aerial minimum count data (not population estimates) suggested general agreement in some HDs but cases of likely under- and over-estimation in other areas. Thus, model predictions may be interpreted as indicative of relative abundance more so than absolute abundance in some local situations, where detection probability estimates do not fully meet assumptions (Barker et al., 2018).

We recommend interpretation of these estimates in tandem with raw input data for moose management in Montana. Ultimately, monitoring of trends in both model-based abundance estimates as well as raw observation input data should be indicative of relative spatial and temporal trends in both moose populations and the likelihood of hunters encountering moose. This combination of information should be a robust platform for management where allocation of moose hunter opportunity is a primary goal. Furthermore, using our

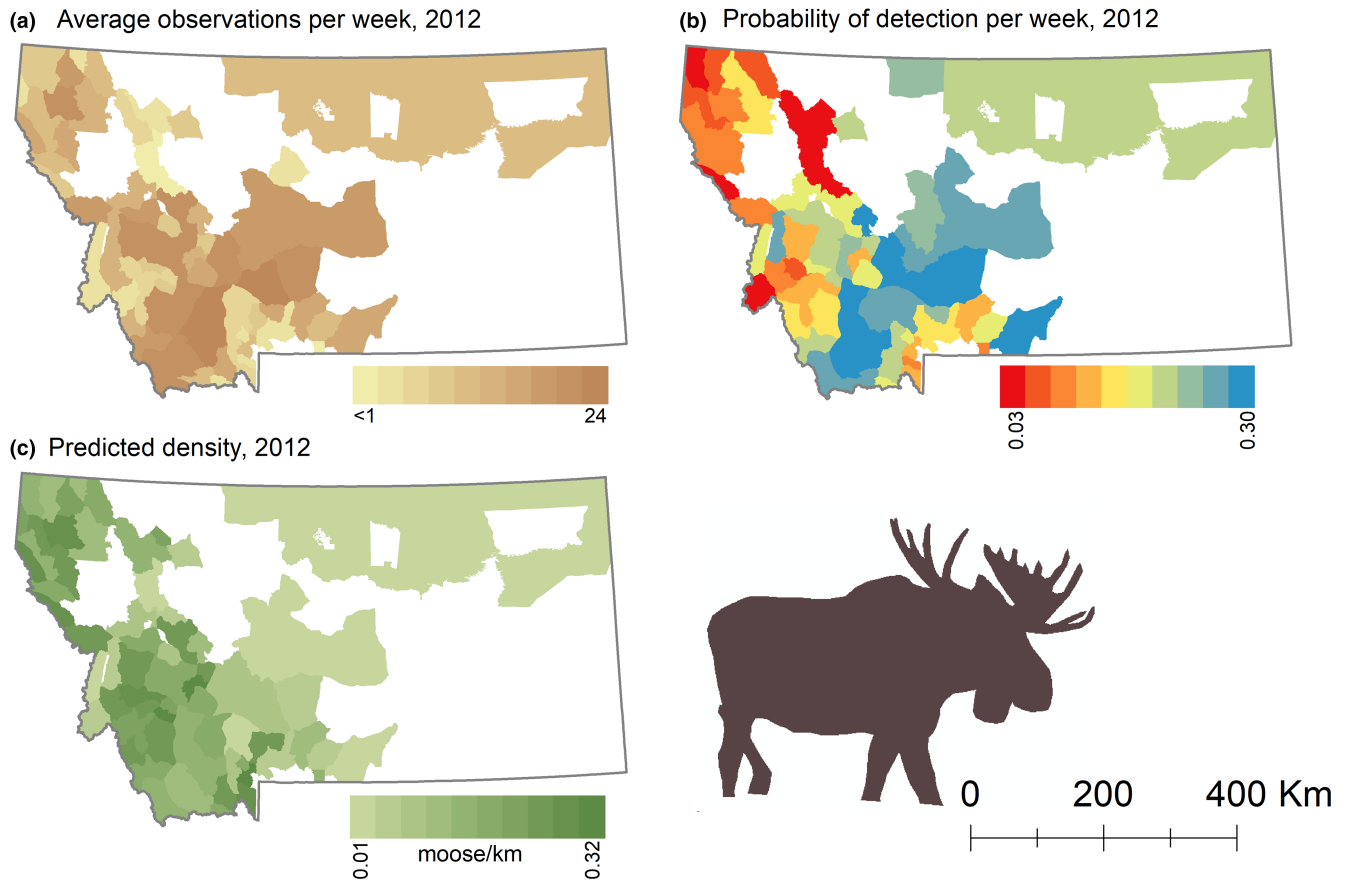


**FIGURE 2** Predicted effects of (a) the number of survey respondents, (b) week of hunting season, (c) proportion of forested land cover within each site and (d) hunter effort (hunter-days per  $\text{km}^2$ ), on the probability of moose detection, Montana, 2012–2016.

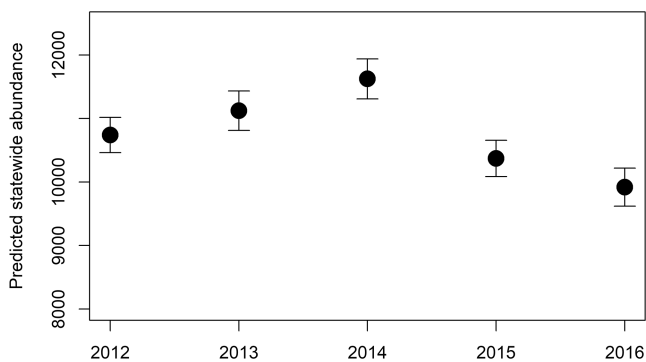
population estimates as one input to an integrated population model that also incorporates a biological model of moose population dynamics, empirical vital rate data (e.g. Newby & DeCesare, 2020) and other survey data (DeCesare et al., 2016) for moose in this region would likely improve the rigour of local predictions as well as their utility for management (McCaffrey & Lukacs, 2016).

Founding a species monitoring program on citizen science methodologies relies on truthfulness and accuracy of hunter recall (Beaman et al., 2005; Jones et al., 2020) as well as retention of public engagement in both hunting and providing observation data

(Dambly et al., 2021). In our case, we assumed that location data were sufficiently accurate and consistent across observers for us to screen data for double counting using spatiotemporal information. However, inaccuracy in spatial location data may insert extra heterogeneity into such data and could bias our estimates of detection probability low and inflate population estimates. Regarding retention of observers, the observations are a passive extension of hunting season management, and do not require prior recruitment, scheduling, or time commitment outside of the publics' efforts to participate in hunting. However, response rates of public citizens



**FIGURE 3** Statewide maps of (a) the weekly average of observations summed per moose hunting district (HD), (b) n-mixture model predictions of weekly probability of detection by HD and (c) n-mixture model predicted density of moose by HD for an example study year, 2012, Montana.



**FIGURE 4** Predicted statewide moose abundance estimates and 95% confidence limits summarised from 10,000 Monte Carlo simulations of site-year abundance estimates according to model-estimated mean and standard deviation per site-year, Montana, 2012–2016.

providing such information to Montana Fish, Wildlife and Parks (MFWP) over the phone may be sensitive to survey fatigue and declines in participation over time (de Koning et al., 2021; Porter et al., 2004). Recent advances in hunter survey through mobile apps (e.g. Boyce & Corrigan, 2017) may offer improvements to both of these challenges if they reduce the time between observation and

reporting, add tools for mapping locations and simplify participation (LaBonte & Kilpatrick, 2019).

#### AUTHOR CONTRIBUTIONS

Nicholas J. DeCesare, Justin A. Gude and Kevin M. Podruzny conceived the ideas and designed methodology; Kevin M. Podruzny collected the data; Nicholas J. DeCesare analysed the data and led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

#### ACKNOWLEDGEMENTS

We thank K. Wash, A. Feddes and other MFWP harvest survey staff for their time and effort collecting these data. We also thank V. Boccadori, E. Bradley, A. Feddes, B. Lonner, J. Newby and C. Peterson for helpful feedback on this work. Funding for this project was provided by the general sale of hunting and fishing licences in Montana, the annual auction of moose hunting licences (Montana Codes Annotated 87-2-724) and Federal Aid in Wildlife Restoration grant W-157-R7.

#### CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to declare with regards to this work.



## DATA AVAILABILITY STATEMENT

Detailed location data for moose and observations of moose by hunters are available from Montana Fish, Wildlife and Parks (<https://fwp.mt.gov/>) under certain conditions specified in Montana Codes Annotated 87-6-222. Model input data, aggregated to the level of hunting district, are available at the Dryad Digital Repository: <https://doi.org/10.5061/dryad.jdfn2z3gg> (DeCesare, 2023).

## STATEMENT ON INCLUSION

Our study brings together authors living and working within the state and country where the study was carried out.

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

**Figure S1.** QQ plots of site-sum randomised-quantile residuals against standard normal residuals for fit of the top model to count data for moose in Montana, 2012–2016. Under a good fit residuals should be close to the identity line (see Knape et al. 2018 for more information).

**Figure S2.** QQ plots of observation randomised-quantile residuals against standard normal residuals for fit of the top model to count data for moose in Montana, 2012–2016. Under a good fit residuals should be close to the identity line (see Knape et al. 2018 for more information).

**How to cite this article:** DeCesare, N. J., Podruzny, K. M., & Gude, J. A. (2023). Leveraging hunters as citizen scientists for monitoring non-target species. *Ecological Solutions and Evidence*, 4, e12260. <https://doi.org/10.1002/2688-8319.12260>