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Tools and Technology

A Method for Mapping Hunting Occurrence Using Publicly Available, Geographic Variables

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ABSTRACT The spatial distribution of land available for hunting has received scant attention in the literature, but it fundamentally affects the feasibility of wildlife management. Modeling the distribution of hunting lands can be logistically difficult because of data requirements and the dynamic nature of landscapes and landowner preferences. We describe one approach to address this challenge using spatially explicit logistic regression models that accurately predict whether each parcel of land in North Carolina, USA, was hunted using free and publicly available geographic predictors. We collected data to develop and validate models from surveys of nonindustrial ($n = 1{,}936$) and industrial ($n = 670$) private landowners conducted during 2016 in North Carolina. Property size and housing and road density predicted whether hunting occurred correctly on 96% of nonindustrial parcels. Property size, housing and road density, and distance to the nearest city correctly predicted whether hunting occurred for 94% of industrial parcels. These results suggest wildlife managers may be able to accurately map and quantify where hunting occurs using relatively few publicly available geographic predictors. Future refinement of the methodology and model parameters is likely needed in different regions, with independent data sets, before adopting widespread implementation of underlying methods. This mapping method will facilitate assessing the efficacy of hunting as a wildlife management tool for overabundant species. Similarly the mapping approach would improve wildlife population estimates based on hunter harvest data by providing a more rigorous estimate of land that is huntable per harvested animal reported.

KEY WORDS hunter access, hunting, industrial private land, logistic regression, nonindustrial private land, North Carolina, spatial modeling, urbanization, wildlife population modeling.

Declines in recreational hunting threaten wildlife conservation in North America by reducing the ability to manage overabundant species and reducing funding for all wildlife conservation activities. The proportion of the United States population that hunts has declined steadily for several decades, as have overall hunter numbers in some regions (Outdoor Foundation 2014, USFWS 2015). Reduced access to hunting land limits the ability to control overabundant wildlife populations (Riley et al. 2003, Storm et al. 2007, Stedman et al. 2008, Siemer et al. 2016). For instance, when hunting pressure is inadequate to control deer (e.g., *Odocoileus* spp., *Hemionus* spp.) overabundant populations can eliminate forest regeneration and simplify plant communities (Allombert et al. 2005, Frerker et al. 2014, Jenkins et al. 2014). Declines in hunter numbers also reduce the political and economic clout of one stakeholder group that has demonstrated conservation leadership for over a century in North America (Teisl and O'Brien 2003, Cooper et al. 2015).

This issue is most important in areas where most hunting occurs on private land (e.g., the eastern United States),

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though nearly a third (28%) of western U.S. hunters also rely on private land for hunting (U.S. Department of the Interior and U.S. Department of Commerce 2012). Population management alternatives to recreational hunting, including contraception–sterilization and targeted culling, have been formulated and explored, especially in urban contexts (Rudolph et al. 2000, DeNicola and Williams 2008, Rutberg and Naugle 2008), but are less feasible because of cost, limited public support, and unproven efficacy on free-ranging populations (Stewart 2011, Massei and Cowan 2014).

Understanding the dynamics of hunting across diverse landscapes requires understanding social and geographic processes outside the control of hunters. Urbanization, land parcelization, and shifting landowner preferences are creating an urgent need to better understand the dynamic distribution of private land available for hunting. Nonindustrial private properties (e.g., owned by families) have grown smaller over time, largely due to parcelization caused by intergenerational transfer and incentives (e.g., tax write-offs) for keeping land intact typically do not offset economic benefits of dividing and developing land (Sampson and DeCoster 2000). Similarly, parcel size has declined for industrial private lands largely due to the forest-products industry monetizing timberland in response to relatively high corporate taxes and market-related pressures (Lonnstedt 2007, Zhang et al. 2012). Since the 1980s, virtually all large industrial forest-products companies either converted themselves into real estate investment trusts (REITs) to receive special tax designations or sold their land holdings to institutional investors that allow forestry operations to continue (Zhang et al. 2012). Land parcelization of both private property types is further exacerbated by expansion of low-density housing development into traditionally rural areas, particularly in areas adjacent to protected lands (Peterson et al. 2013). Although geographic variables (e.g., parcel size, housing density) associated with urbanization have not been used to spatially model land available for hunting, Poudyal et al. (2008) did model the effects of urbanization (e.g., urban population, average forest parcel size) on hunting demand. In conducting a county-level comparison of the southeastern United States, their study suggested that a 1% proportion increase in urban population equated to a 12% decrease in hunting demand county-wide. At the same time, large-scale movement of people from metropolitan areas to peri-urban landscapes may play a role in the decline of lands available for hunting via changing preferences among landowners. Between 1994 and 1997, 80% of new housing construction occurred outside of urban areas, and during 2005–2009, 100,000 people in the United States moved from cities to peri-urban landscapes annually (Campa et al. 2011, Rupasingha et al. 2015). Urbanites relocating to more rural communities can bring values and perspectives that did not previously predominate in those areas, including less support for hunting (Stedman and Heberlein 2001).

Modeling both the amount and location of huntable land is important for 2 reasons: 1) efficacy of recreational hunting as a management tool depends on the amount and distribution of huntable land and, 2) frequent use of harvest data to produce population estimates or density indices for huntable wildlife species requires a rigorous spatial denominator of hunted land rarely known outside public hunting areas. We begin addressing the need to model huntable land with a case study in North Carolina, USA. North Carolina presents a suitable study area because it is majority privately owned, experiencing rapid urbanization, and had approximately 335,000 active hunters during the time frame of this study (Sharpe 2010, Ewing et al. 2011, Allen et al. 2012, Peterson et al. 2012, U.S. Department of the Interior and U.S. Department of Commerce 2012).

METHODS

We mapped the entire state of North Carolina, splitting land into 4 distinct property categories: public land, municipalities, private nonindustrial land outside municipalities (hereafter, nonindustrial), and private industrial land outside municipalities (hereafter, industrial). All spatial modeling was done in a vector environment to ensure maximum precision for property boundaries and limit potential interpolation biases associated with a raster environment. Law dictated whether land in the first 2 categories was hunted. We conducted a policy review to designate every publicly owned (i.e., local, state, federal) property in the state as hunted or not hunted. Similarly, we designated municipalities as not hunted because discharging a firearm within these boundaries was prohibited. Selective hunting (restricted to archery hunting for white-tailed deer [*Odocoileus virginianus*]) occurred within 58 of 553 North Carolina municipalities in 2016, but the amount of land hunted in these cases is presumably very low because property sizes are relatively small and hunters are required to obtain permission from landowners. We conducted surveys to determine whether hunting was allowed on nonindustrial and industrial properties (Fig. 1).

Sampling

We used a state-wide spatial database of North Carolina landowners from the Department of Agriculture and Consumer Services as the primary sampling frame (2014) so that landowner responses and geographic predictors could be spatially linked to corresponding sample properties. We divided the database into industrial and nonindustrial sample frames using a partial string search of 235 keywords indicative of industrial ownership (available online in Supporting Information). The partial string method allowed us to identify partial consistencies (e.g., LLC, Inc.) present in many industrial property owner names without having to include more specific terms. For example, a property owned by Beech Tree Inc. was correctly labeled as industrial even though the words beech or tree were not contained in the keyword list. We tested this approach by reviewing 10 random sets of 500 properties each, with a 92% classification accuracy. The 8% misclassification rate was attributed to 2 scenarios. First, a nonindustrial landowners' name or partial name (e.g., Betty Church) was included in the

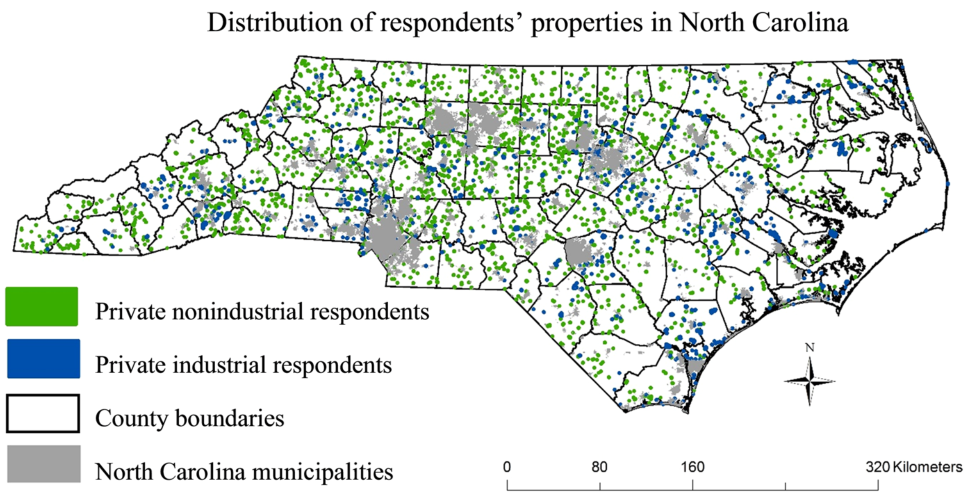

Figure 1. Location of respondents' private nonindustrial properties ($n = 1{,}936$), private industrial properties ($n = 670$), and municipalities, North Carolina, USA, 2016.

industrial keyword list (e.g., Church), which resulted in that property being labeled industrial when it was in fact nonindustrial. It was not feasible for us to correct these misclassification events individually because we were separating >3,000,000 properties. Second, an industrial keyword was not present in the 50,000-property sample we reviewed. We use industrial as an umbrella term to incorporate every privately owned property not owned by private citizens. Thus, industrial properties were diverse and ranged from restaurants and churches owning <1 ha to timberland corporations and land conservancies owning properties >10,000 ha.

We used different modes to sample nonindustrial (mail) and industrial landowners (phone) so that we could strategically target individual(s) with knowledge or authority over hunting-related decisions on the property. This distinction was needed because pretesting indicated the public relations or land-use specialists who made decisions about hunting access for industrial property owners would not be reached by mail addressed to the company. Phone methods allowed us to track down the decision-makers for these companies. For each property type, we stratified properties into 6 size categories: <0.40, 0.40–2.02, 2.03–4.05, 4.06–8.10, 8.11–80.93, >80.93 ha (<1.0, 1.01–5.0, 5.01–10.0, 10.01–20.0, 20.01–200, >200 acres, respectively). This stratified sampling approach ensured we would receive adequate response numbers across all sizes of properties, despite most properties being in the smallest size classes. We removed duplicate listings of landowner(s) who partially or fully owned multiple properties to prevent oversampling.

Private nonindustrial properties.—Survey implementation for nonindustrial properties occurred during June and July 2015. We mailed self-administered surveys to 8,400 randomly selected, nonindustrial landowners in North Carolina (1,600 to each of the 5 smallest property strata and 400 to the largest property strata). We mailed a prenotice letter to landowners describing the purpose of the research, followed by a questionnaire envelope 1 week later, a reminder postcard 2 weeks after that, and a second questionnaire envelope, if needed, 2 weeks later. The second questionnaire envelope was mailed only to landowners who had not completed and returned the first. Each questionnaire envelope contained a research overview document, a questionnaire, a consent form, and a prestamped envelope for return mailing (Dillman et al. 2014).

Of the 8,400 questionnaires mailed, 53 (0.6%) were undeliverable; 1,936 usable questionnaires were returned for an overall response rate of 23.2%. Within-strata response rates increased as property size strata increased (<0.40 ha = 17.8% response rate, 0.40–2.02 = 18.9%, 2.03–4.05 = 24.1%, 4.06–8.10 = 25.7%, 8.11–80.93 = 27.8%, >80.93 = 29.6%). This was expected because research indicates mail survey response rates are greatest in rural areas where properties tend to be larger (Fowler 2009, Dillman et al. 2014). To evaluate nonresponse bias, we randomly selected and telephoned 300 (50 from each property strata) nonrespondents to ask them whether their property was hunted (Chavez et al. 2005). Of those nonrespondents we were able to contact, we achieved a 65% compliance rate ($n = 54$). We attempted to contact each nonrespondent 4 times, twice during normal business hours (0900–1700, Monday–Friday), once after business hours on a weekday, and once on a weekend (Dillman et al. 2014) before removing them from the contact list. We used point estimates and 95% confidence intervals (CI) on the differences to compare the degree to which hunting was allowed on the property of respondents and nonrespondents.

Private industrial properties.—Survey implementation for industrial properties occurred between July and November 2016. We attempted to contact 2,400 randomly selected, industrial landowners in North Carolina via telephone (400 from each of the 6 property strata). We obtained telephone numbers from the North Carolina Secretary of State Corporations Division. We attempted to contact each industrial property 4 times during normal business hours (0900–1700, Monday–Friday: Dillman et al. 2014) before removing them from the sample. Of the 2,400 industrial properties in the sample, 230 (9.6%) could not be reached (e.g., incorrect telephone number listed, the entity had dissolved), and 670 industrial properties participated for an overall response rate of 30.9% (within-strata response rates: <0.40 ha = 31.4% response rate, 0.40–2.02 = 27.5%, 2.03–4.05 = 34.9%, 4.06–8.10 = 35.1%, 8.11–80.93 = 33.9%, >80.93 = 22.6%).

We employed the theory of continuum of resistance to evaluate for nonresponse bias of industrial landowners (Kypri et al. 2004). The theory of continuum of resistance operates under the assumption that the effort required to elicit a response is indicative of an individual's (or entities in our case) propensity to respond; thus, late respondents are comparable to nonrespondents. We partitioned respondents into 3 groups based on whether they had participated early (first attempt at contact, $n = 423$), participated in the intermediate (second or third attempt at contact, $n = 188$), or participated late (fourth and final attempt at contact, $n = 59$). We compared these groups using point estimates and 95% CIs on the differences. This research was approved by the North Carolina State University Institutional Review Board for the Protection of Human Subjects in Research (nonindustrial survey: IRB # 5680, Mar 2015; industrial survey: IRB # 7832, May 2016).

Model Development and Assessment

We created separate logistic regression models for property types (i.e., nonindustrial, industrial) so that we could account for and include differing geographic predictor variables for each property type. These models included assumptions of random sampling of hunted and not hunted properties. For both property type models, the dependent variable was whether a property was hunted (binary: 0 = hunted, 1 = not hunted). We selected 4 explanatory variables of interest: property size, housing density, road density, and distance to nearest city. When incorporating landscape-level geographic variables into a model, it is important to evaluate their effects at multiple spatial scales because the most important spatial scale often differs based on the independent variable of interest as well as the dependent variable being predicted (Piorecky and Prescott 2006, Altmoos and Henle 2010, Wang et al. 2012). No similar efforts to model private hunting lands were available; therefore, we evaluated a wide range of spatial scales from <20 ha to >17,000 ha (radii of 0.25, 0.50, 1.0, 2.0, 5.0, 7.0, 10.0, 12.0, 15.0 km) that would account for both human (e.g., hunter and public safety) and ecological (e.g., access to adequate habitat and resources) factors surrounding sample properties. The fact that best scales for spatial variables were all within the range considered, versus at one end, suggests the range was sufficiently wide.

We used 2010 TIGER shapefiles from the U.S. Census Bureau to generate housing density values at the 9 scales around sample properties. First, we calculated housing density at the census block level (smallest geographic unit used by U.S. Census Bureau). We then calculated housing density on and surrounding sample properties by multiplying density (i.e., housing units per ha) of the census block it fell within by the area inside the buffer created by each of the 9 spatial scales being tested. For properties that overlapped multiple census blocks, we subdivided the property by census block, calculated density for each portion, and then averaged the housing density for each portion into an aggregate measure for the parcel in question. We obtained a comprehensive road network layer from the North Carolina Department of Transportation to generate road density values at each spatial scale around sample properties. We clipped road data to properties at each spatial scale and summed all road lengths with each area to generate road density using the spatial join with sum feature in ArcGIS 10.3 (ESRI, Redlands, CA, USA). We obtained a municipality layer from the North Carolina Department of Transportation and generated the distance in kilometers from sample properties to the closest city. We used the U.S. Census Bureau's definition of a city, which is defined as an urban area with >50,000 residents. We used the edge of properties as the reference point when measuring Euclidean distance to the nearest city, instead of the centroid, to control for property size.

Prior to modeling, we assessed collinearity of independent variables using a correlation coefficient threshold of $|r| \geq 0.65$, and did not detect collinearity problems (Loyn et al. 2001). We used data transformations (i.e., log, cubic, quadratic) on the distance to nearest city variable to examine potential nonlinear relationships. We used a log transformation for nonindustrial properties and a cubic transformation for industrial properties to normalize skewness associated with many properties being relatively close to city boundaries and few properties being extremely rural.

For both property types, we conducted a 2-step process because landscape-level variables needed to be evaluated at multiple spatial scales: 1) selecting best-fit spatial scales for landscape-level variables, and 2) selecting optimal predictive models where all models being compared used the best-fit spatial scale for landscape-level variables. To select the spatial scale at which the landscape-level geographic variables had the greatest predictive effect, we fit full logistic regression models that included all combinations of scales for housing and road densities (9 spatial scales for housing density × 9 spatial scales for road density = 81 models) and chose the model with the combination of housing and road density that had the lowest Akaike Information Criterion (AIC) score (Foster and Stine 2004). This process was only used to select the scale for housing and road density that was best supported by data, and is a standard practice for developing spatially explicit predictive models (Piorecky and Prescott 2006, Altmoos and Henle 2010, Wang et al. 2012).

We then used the best-supported spatial scales in model selection to identify optimal models for predicting whether private properties were hunted. Starting with single, full models, we conducted best-subsets logistic regression on all possible combinations of variables, with the exception of interaction and transformation terms (unless explicitly stated above), and used AIC criteria to determine the optimal model (King 2003, Foster and Stine 2004). We considered models within ΔAIC <2 as candidate models. To facilitate interpretation of model coefficients, we included a standardized odds ratio (SOR) for each variable (Chinn 2000). Models were geographic in nature; therefore, it was necessary to test for spatial autocorrelation (SAC) on model residuals (Carl and Kuhn 2007). We conducted a Global Moran's I analysis on the residuals from the optimal model to evaluate for SAC, but it was not present in either model ($P = 0.39$ for nonindustrial properties, $P = 0.34$ for industrial properties). We used both threshold-dependent and threshold-independent methods to assess model accuracy and overall performance. Area under the curve (AUC) of the receiver operating characteristic is a threshold-independent method commonly used in classification models and provides a single, discriminant value for correctly predicting any one outcome (Fielding and Bell 1997). Area under the curve values range from 0.5 to 1.0, with 1.0 indicating flawless predictions and 0.5 indicating predictions no better than random (Hanley and McNeil 1982). Predictive models with an AUC metric >0.7 are considered useful (Swets 1988, Manel et al. 2001, Boyce et al., 2002). We used 10-fold cross-validation to generate AUC values for these models (Buckland and Elston 1993). We used confusion matrices as the threshold-dependent method for defining the overall prediction accuracy of the models (Ruttimann 1994). We determined overall accuracy by evaluating the misclassification rate of predicted to observed values. We compared confusion matrices at 0.01 increments (range = 0.20–0.80) to determine the probability threshold for each model that resulted in the greatest prediction accuracy. A probability cut-point of 0.58 for nonindustrial properties and a probability cut-point of 0.68 for industrial properties maximized prediction accuracy (Table 1). We calculated variance inflation factors to evaluate potential for multicollinearity in the optimal models for predicting whether industrial and nonindustrial private property was hunted (Table 2). We managed spatial databases, generated geographic variable values, and tested for SAC using ArcGIS 10.3 (ESRI). We conducted model selection and assessment using JMP Pro 13 (SAS Institute Inc., Cary, NC, USA).

RESULTS

The nonindustrial model correctly predicted whether a nonindustrial property was hunted 96% of the time, and the industrial model had a prediction accuracy of 94% (Table 1). For both property-type models, threshold-independent analysis revealed an average AUC value of 0.76, and median AUC was slightly greater (0.77) for the industrial than nonindustrial (0.75) property-type models, supporting model utility. Property size, housing density, and road density were variables in both models, and distance to nearest city was an additional variable in the model predicting whether hunting occurred on industrial properties (Table 2).

For nonindustrial landowners, the respondent sample had a point estimate of 0.42 for proportion of properties hunted and the nonrespondent sample had a point estimate of 0.41, yielding a mean difference in point estimates of 0.01 (95% CI of the difference = −0.07–0.09), thereby suggesting the sample was representative of the proportion of North Carolina private, nonindustrial landowners' properties that were hunted. For private industrial landowners, early respondents had a point estimate of 0.85, intermediate respondents had a point estimate of 0.72, and late respondents had a point estimate of 0.73. The mean difference in point estimates (early − intermediate = 0.13; early − late = 0.12; intermediate − late = 0.01) were all relatively small and had 95% CIs for the differences overlapping zero (95% CIs: early − intermediate = −0.04–0.30; early − late = −0.08–0.30; intermediate − late = −0.05–0.07), suggesting the sample was representative of the proportion of North Carolina private, industrial landowners' properties that were hunted.

Table 1. Threshold-dependent assessment for determining the best probability cut-point in maximizing classification accuracy for predictions of whether a property was hunted for nonindustrial and industrial properties, North Carolina, USA, 2016.

Model	Probability cut-point	Classification accuracy
Nonindustrial	0.50	80%
	0.58	96%
Industrial	0.50	84%
	0.68	94%

Nonindustrial Spatial Model

The best-fit spatial scales of landscape-level predictors for nonindustrial properties were housing density at 0.5 km and road density at 2 km. Housing density at 1 km and road density at 2 km was a candidate model (ΔAIC = 0.94) in the spatial scale analysis. Best subsets regression revealed 2 candidate models for predicting whether nonindustrial properties were hunted. The optimal model contained property size and housing and road density (Table 2). The addition of distance to nearest city constituted a candidate model (ΔAIC = 1.54). In the optimal model, property size was the strongest predictor (SOR = 3.30) and positively related to a property being hunted. Conversely, housing density (SOR = 0.79) and road density (SOR = 0.78) were negatively related to a property being hunted.

Industrial Spatial Model

The best-fit spatial scales of landscape-level predictors for industrial properties were housing density at 12 km and road density at 0.5 km. Candidate models in spatial scale analysis were housing density at 12 km and road density at 1 km (ΔAIC = 0.99), and housing density at 15 km and road density at 0.5 km (ΔAIC = 1.18). The optimal model for predicting whether an industrial property was hunted contained property size, housing and road density, and distance to nearest city (Table 2). In this model, property size was the strongest predictor (SOR = 3.92) and positively related to a property being hunted. Distance to nearest city (SOR = 0.68), and housing (SOR = 0.45) and road density (SOR = 0.45) were negatively related to a property being hunted in the optimal model.

The Hunting Landscape of North Carolina

This modeling effort predicted most of the landscape (75.4%) in North Carolina was huntable (Figs. 2,3). Public

Table 2. Optimal models for predicting whether industrial and nonindustrial private property was hunted in North Carolina, USA, 2016.

	Coefficient	Odds ratio	Standardized odds ratio	Variance inflation factor
Nonindustrial model[a]				
Intercept	−0.11			
Property size (ha)	0.077*	1.08	3.30	1.004
Housing density (0.5 km)	−0.006*	0.99	0.79	1.856
Road density (2 km)	−0.016*	0.98	0.78	1.860
Industrial model[b]				
Intercept	−0.31			
Property size (ha)	0.01*	1.01	3.92	1.852
Housing density (12 km)	−0.00003*	0.99	0.45	1.171
Road density (0.5 km)	−0.09*	0.91	0.45	1.997
Distance to nearest city[3]	−0.0000006*	0.99	0.68	1.061

*$P \leq 0.05$.
[a] $n = 1,936$, McFadden's $R^2 = 0.20$, percent correct = 96%.
[b] $n = 670$, McFadden's $R^2 = 0.14$, percent correct = 94%.

land constituted 11.2% of the landscape and 78.6% of that land type was reported as hunted (Fig. 2; Table 3). Private nonindustrial land constituted 58.3% of the landscape and the model predicted 85.2% of that land type was huntable. Private industrial land constituted 22.4% of the landscape and the model predicted 75.5% of that land type was huntable. The percent of huntable land predicted by property strata generally increased with property size (Table 3).The percent of huntable land predicted by county ranged from 21.2% to 96.8% (Fig. 4). Counties with the greatest percent of huntable land predicted were concentrated in the relatively rural coastal plain (Tyrrell = 94.1%, Jones = 94.7%, and Hyde = 96.8%). Counties with the lowest percent of huntable land predicted were concentrated in the more developed piedmont (Mecklenburg = 21.2%, Forsyth = 36.1%) and in a county (Swain = 25.6%) largely within the Great Smokey Mountain National Park where hunting is illegal. The greatest proportion of huntable land predicted in North Carolina occurred in the coastal plain region followed by the piedmont and mountain regions, respectively (Fig. 4).

DISCUSSION

Our modeling technique accurately predicted whether hunting was allowed on private lands using only publicly available geographic variables as model predictors. We adapted the modeling process from extensive research predicting species occurrence. This large body of research suggests that AUC values >0.7 and an overall classification accuracy >80% are satisfactory model metrics that allow for useful insights to be applied to best management practices (Altmoos and Henle 2010, Royle et al. 2014, Moran-Ordonez et al. 2017). This in turn suggests our method for modeling whether private lands are hunted with AUC values >0.7 and classification accuracies >90% provides management applications in North Carolina, and proof of concept for use elsewhere. Key principles for species distribution modeling (e.g., adequate sample size, spatial scale selection, spatial autocorrelation evaluation, model validation and assessment; Merow et al. 2014, van Proosdij et al. 2016, Moran-Ordonez et al. 2017) guided this effort to model whether hunting occurred on private property. Further, the inclusion of absence data in the sample (i.e., properties that were not hunted) may be easier in

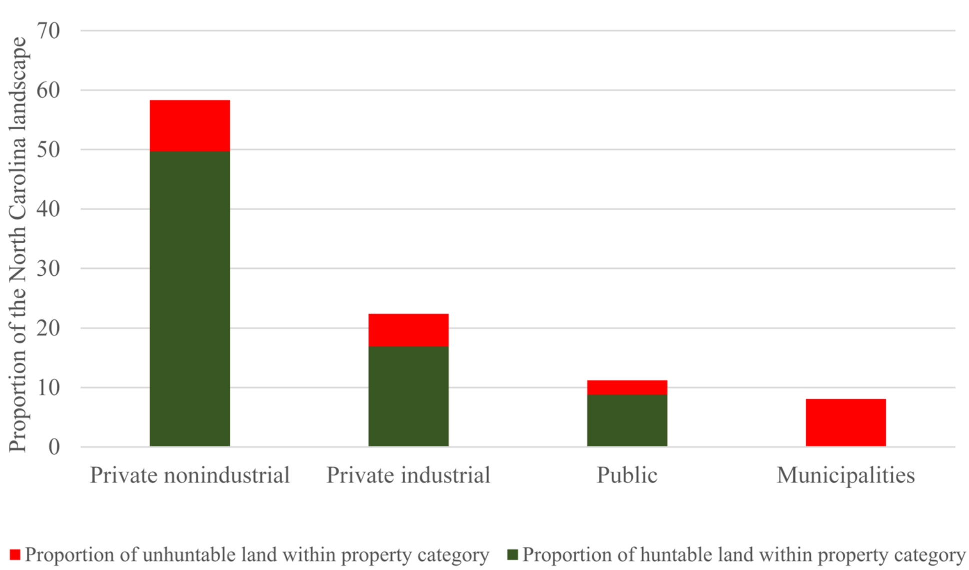

Figure 2. The proportion of land that was huntable and unhuntable within each property category in North Carolina, USA, 2016.

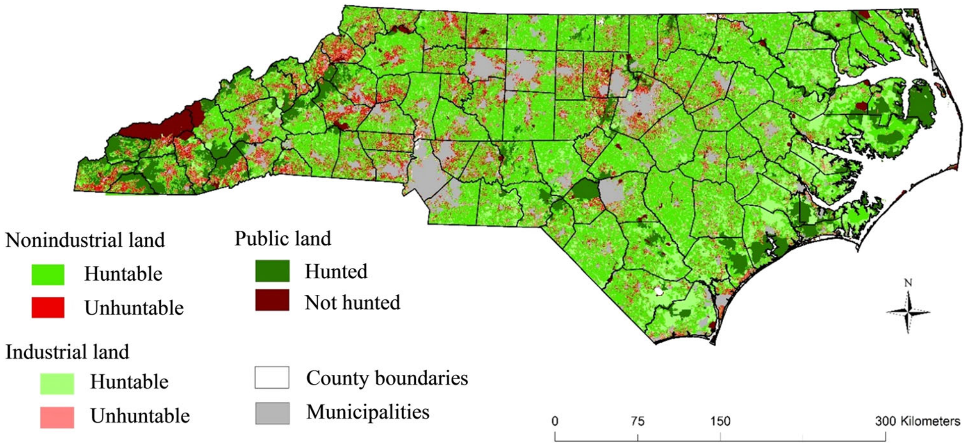

Figure 3. A depiction of the contemporary hunting landscape based on predictive models, North Carolina, USA, 2016.

Table 3. Percent of huntable properties and hectares by property size strata for each property type in North Carolina, USA, 2016.

	Property strata (ha)					
	<0.40	**0.40–2.02**	**2.03–4.05**	**4.06–8.10**	**8.11–80.93**	**>80.93**
Public land[a]						
% hunted properties	30	22	34	37	50	70
% hunted ha	17	22	35	38	55	83
Nonindustrial land[b]						
% hunted properties	13	29	55	78	97	100
% hunted ha	14	33	57	80	99	100
Industrial land[c]						
% hunted properties	25	34	40	46	60	92
% hunted ha	26	35	40	46	67	96

[a] Pubic land includes ~5,000 properties and 1,500,000 ha. Public land constitutes 11.2% of the total land area in North Carolina.
[b] Nonindustrial land includes ~1,800,000 properties and 8,000,000 ha. Nonindustrial land constitutes 58.3% of the total land area in North Carolina.
[c] Industrial land includes ~500,000 properties and 3,000,000 ha. Industrial land constitutes 22.4% of the total land area in North Carolina.

human-dimensions research applications because the absence of many human activities can be easier to confirm than the absence of elusive wildlife species.

Key differences between the optimal model for predicting whether hunting occurred on nonindustrial properties and the model predicting whether hunting occurred on industrial properties may relate to a tendency for industrial properties to be clustered together (Scott 1988, Kirkwood 2003). This clustering of industrial properties may explain why the housing density variable had a peak effect at a larger spatial scale in the industrial model because clusters of industrial buildings near a given property may deflate

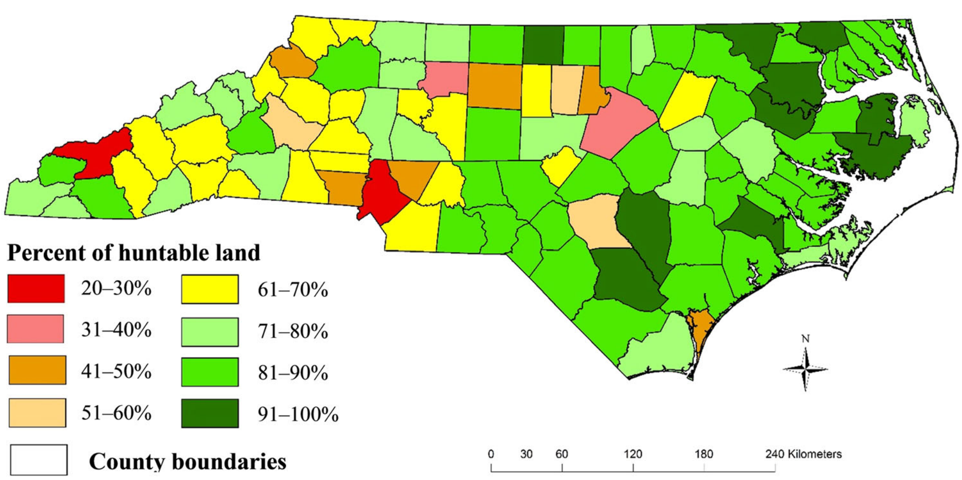

Figure 4. The estimated percent of land that was huntable by county based on predictive models, North Carolina, USA, 2016.

small-scale housing density numbers despite large building density. Similarly, spatial clustering of industrial properties may explain why distance to nearest city was in the optimal model for industrial properties, but not in the optimal model for nonindustrial properties (Scott 1988, Kirkwood 2003). Specifically, demand for hunting access would be greater nearer to large population centers, but the demand may only predict hunting among clusters of industrial properties where safety concerns may be lower than among residential properties.

Although hunting may continue in rapidly urbanizing areas like North Carolina, hunter densities likely will increase on fragmented landscapes that consisted of large numbers of small properties. Lovely et al. (2013) provided additional support for this claim, reporting deer hunter density and deer harvest density were greatest on relatively small properties (2.0–4.0 ha) in urbanizing areas of Virginia, USA. Future research is needed to unravel how these shifting dynamics are altering the efficacy of hunting as a management tool. It is conceivable that landscapes consisting of greater hunter densities on fewer hunted parcels could create a situation where intense hunting pressure on select hunted properties drive huntable wildlife to seek safety on the growing number of pseudo-refuges (i.e., properties that are not hunted). Logically, this situation has the potential to decrease harvest efficiency, and thus the utility of hunting as a management tool at the margins of urbanizing regions.

Wildlife management agencies relying on harvest data to create population estimates or density indices of game species could use these methods to provide a more rigorous denominator of land that is huntable (Downing 1980). Specifically, estimates of the area and distribution of land where harvest is allowed could be enlisted rather than following the more traditional practice of including all land where hunting is legal (or slight variations based on expert opinion).

Future research is needed to evaluate and improve models provided in this proof of concept project. Research exploring how landowner willingness to allow hunting differs based on species would provide valuable and actionable information for managers. These efforts would need to account for spatial gaps in the species distribution if they exist on the landscape. A land cover variable may facilitate species-specific models because land cover is strongly related to some types of hunting and differs by species pursued (e.g., bear, waterfowl). These adjustments may be less important for generalist species with wide ranges (e.g., 97.3% of hunted properties in our sample were hunted for white-tailed deer). Future research may improve assessments of where hunting occurs by asking hunters to list areas where they hunted as a means of validating reports from landowners. Finally, any effort to apply this modeling approach to other regions would need some ground-truthing with independent and region-specific data to evaluate if similar relationships exist between hunting occurrence and prediction variables. Once validated, these foundational models could be used to generate future measures of hunting occurrence by incorporating new geographic data as it becomes available.

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