Effects of Scale on Predictive Power of Two Bald Eagle Habitat Models

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Abstract: We examined the role scale plays in determining the predictive power of bald eagle (*Haliaeetus leucocephalus*) habitat models. We used a bald eagle roost habitat database that included 35 roost sites and 123 random sites located and characterized on the Chesapeake Bay from 1985–1988. A micro-habitat model, based on 6 micro-scale variables correctly classified 80% of the roost sites. A macro-habitat model, based on 10 macro-scale variables, correctly classified only 63% of the roost sites. A mixed model, incorporating the significant micro- and macro-scale variables, correctly classified 89% of the roost sites. Our results suggest there is a tradeoff between model performance (predictive power), model development costs, and model application.

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Wildlife species select habitat through a hierarchy of decisions that start at a geographic scale and continue to finer scales until an individual decides to perch on a particular branch on a tree or rest in a given thicket (Johnson 1980). One goal of wildlife-habitat models is to document the relationships that exist at these various scales. A second goal is to develop the model in such a way that makes it useful for management (Salwasser 1986), either by predicting where suitable habitat exists or by predicting how management actions will affect habitat suitability. Wildlife-habitat models can be developed by researchers at any scale to meet the first goal. Model utility (the second goal), however, favors model development at the same

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scale as management operation. Although it is possible to develop models that incorporate several different scales simultaneously, economics may limit the number of scales that can be developed.

In general, models based on micro-scale habitat variables that require field mensuration tend to be more expensive to develop and apply than models based on macro-scale habitat variables measured in a remotely-sensed fashion (e.g., from aerial photos or satellite imagery). Macro-scale models also are becoming more economical to develop and apply as national and regional databases become more widely available. Therefore, model builders tend to opt for development of the more economical macro-scale wildlife-habitat models.

The selection of a scale for model development must in part be determined by the biology of the wildlife species under study. Habitat selection by some species, such as small mammals, is determined primarily by micro-scale habitat features (Dueser and Shugart 1979, Healy and Brooks 1988), such that macro-scale habitat models are unlikely to result in high predictive power.

Selection of scale is influenced also by the planned management application. Management may be conducted at a fairly broad, geographic scale. Model development at this scale is desirable so that model results can be directly incorporated into the management scheme.

The goal of this study was to compare the predictive power of a bald eagle roost habitat model based on micro-scale variables with a roost habitat model based on macro-scale variables. We also discuss the tradeoffs in final model selection for management application.

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Methods

The study area was the northern Chesapeake Bay, extending from the Bay Bridge at Annapolis, Maryland, northward to the Conowingo Dam on the Susquehanna River, a distance of 3,426 km. The area included 2,472 km of bay, river, and creek shoreline and much of the Baltimore metropolitan area. Forested habitat ranged from bottomland hardwood forests on the western shore to mixed pine (*Pinus* spp.)-hardwood forests on the eastern shore. The Baltimore area on the western shore was highly developed, whereas the eastern shore consisted of agricultural land with an interspersion of small woodlots.

We located 35 roost sites from 1985–1988 by tracking radio-tagged bald eagles from the late afternoon until they roosted in the evening (Buehler et al. 1991*a*). We also randomly selected 123 trees and sites from throughout the study area for comparison with the roost-site habitat.

A roost site was defined as the area enclosed by a minimum convex polygon connecting all perimeter trees in which we observed eagles roosting. Roost sites varied from a single-tree site used on only 1 occasion to communal sites involving many roost trees used traditionally year after year (Buehler et al. 1991*a*).

We defined micro-scale variables as habitat measurements that had to be made in the field, whereas macro-scale variables were habitat measurements made on aerial photos, standard U.S. Geological Survey (USGS) topographic maps, or derived from the USGS Land Use and Land Cover (LULC) database (Anderson et al. 1976).

We measured 6 micro-scale variables for each roost site. We measured roost tree diameter at breast height (dbh), and we measured roost tree height and surrounding canopy height. We estimated roost tree accessibility to an eagle as the total arc (0°–360°) that was unobstructed by other tree canopies for a distance of 10 m out from the trunk and 3 m below the tree's crown. We noted the presence of snags in 11.3 m-radius circular plots centered on each roost tree. We defined snag presence at each roost site as the percent of roost tree plots that contained at least 1 snag. We counted the number of trees >10-cm dbh on each circular plot and calculated tree density as the number of trees per plot divided by the plot area (0.04 ha). Because we considered each roost site the basic sampling unit, we averaged values for tree dbh, tree height, canopy height, access, and tree density across all roost trees at a roost site to generate a mean value for each variable and each roost site. These mean values were used to develop the logistic-regression models. Similar measurements were made on each randomly-selected tree.

We measured 10 macro-scale variables for each roost site located. We digitized all shoreline boundaries using USGS 7.5-min topographic maps and we digitized all building using 1985 1:12,000 color aerial photos. We used ARC/INFO (Environ. Systems Res. Inst., Inc., Redlands, Calif.) to measure the distance on the digitized maps from each roost site to the nearest water of any kind, the Chesapeake Bay, rivers, creeks, ponds, buildings, and roads. To calculate building density at each site, we used ARC/INFO to count all buildings within 500 m of each site and divided by the area (78.5 ha). We used ARC/INFO to overlay the site location onto the USGS LULC database (Anderson et al. 1976) to identify land cover at each site, and to measure the distance from the site to the nearset USGS LULC habitat edge.

We defined a randomly-selected site as an 11.3 m-radius circular plot, centered on each randomly-selected tree. We made similar measurements on these sites as were made on the roost sites.

We used the LOGIST procedure (SAS Inst., Inc. 1986) to develop logistic regression models, with the micro- and macro-scale habitat variables serving as the independent variables and the roost-site classification (roost or random) serving as the dependent variable in the models.

To determine the classification accuracy of each model, we used a modified-jackknife procedure (Meyer et al. 1986). We wanted to compare the classification accuracy for roost sites with the classification accuracy for random sites. Because the number of roost sites sampled (N = 35) was much less than that for random sites (N = 123), we used all roost sites in determining model classification accuracy for roosts, whereas we randomly selected with replacement 35 random sites to test the model classification accuracy for random sites. In both cases, we used the jackknife approach of withholding 1 observation, developing the model, and using the withheld observation to test the model. We used the number of actual roost sites that were correctly classified as roost sites by each model as a measure of the predictive power of the model. We selected the significant variables in each model ($P \leqslant 0.05$) to develop a combined model to determine the upper limit on the predictive capability of our modeling effort.

Results

The micro-scale variables were significant predictors of the roost-site classification ($P < 0.001$) (Table 1). Three variables (tree height, the presence of snags, and tree access) were significantly related to the roost classification in the logistic regression ($P \leq 0.05$), whereas tree dbh, canopy height, and tree density were not ($P >$ 0.05). Based on this model, 28 of 35 roost sites (80%) and 32 of 35 random sites (91%), respectively, were correctly classified.

The macro-scale variables also were significant predictors of the roost-site classification ($P < 0.001$) (Table 2). Five variables (land cover type, distance to the Chesapeake Bay, distance to ponds, distance to water of any type, and building density) were significantly related to the roost classification in the logistic regression model ($P < 0.05$). Based on this model, 22 of 35 roost sites (63%) and 32 of 35 random sites (91%), respectively, were correctly classified.

Table 1. Logistic regression model based on micro-scale explanatory variables of bald eagle roost habitat, Chesapeake Bay, Maryland, 1985–1988.

Explanatory variable	Parameter estimate	Parameter SE	X^2	P
Tree height	0.344	0.109	10.03	0.001
Snags present	0.089	0.030	8.64	0.003
Tree access	0.015	0.005	7.70	0.006
Tree dbh	0.041	0.022	3.55	0.059
Canopy height	0.122	0.078	2.44	0.119
Trees/ha	0.001	0.001	0.73	0.392

Classification Table

		Predicted		
		Roost	Random	Total
Observed	Roost	28	7	35
	Random	3	32	35
	Total	31	39	70

Table 2. Logistic regression model based on macro-scale explanatory variables of bald eagle roost habitat, Chesapeake Bay, Maryland, 1985–1988.

Explanatory variable	Parameter estimate	Parameter SE	X^2	P
Land cover type	2.848	0.847	11.30	0.001
Distance to Bay	−0.171	0.076	5.04	0.025
Distance to pond	−1.122	0.513	4.79	0.029
Distance to water	−2.655	1.246	4.54	0.033
Building density	−0.188	0.093	4.08	0.043
Distance to creek	0.174	0.109	2.56	0.110
Distance to building	−0.582	0.629	0.86	0.355
Distance to river	0.051	0.073	0.49	0.485
Distance to edge	−3.119	5.028	0.38	0.535
Distance to road	0.247	0.801	0.10	0.757

Classification Table

		Predicted		
		Roost	Random	Total
Observed	Roost	22	13	35
	Random	3	32	35
	Total	25	45	70

Table 3. Logistic regression model based on micro-scale and macro-scale explanatory variables of bald eagle roost habitat, Chesapeake Bay, Maryland, 1985–1988.

Explanatory variable	Parameter estimate	Parameter SE	X^2	P
Tree height	0.421	0.107	15.61	0.001
Tree access	0.013	0.005	5.64	0.018
Land cover type	2.828	1.334	4.50	0.034
Distance to water	−3.749	1.902	3.89	0.049
Distance to pond	−1.326	0.698	3.61	0.058
Snags present	0.044	0.034	1.66	0.198
Building density	−0.088	0.727	1.47	0.225
Distance to Bay	−0.055	0.114	0.23	0.632

Classification Table

		Predicted		
		Roost	Random	Total
Observed	Roost	31	4	35
	Random	1	34	35
	Total	32	38	70

The 8 significant micro- and macro-variables combined also were significant predictors of the roost-site classification ($P < 0.001$) (Table 3). Although all variables included in this model were significant in the original models, only 4 variables (tree height, tree access, land cover type, and distance to water), were significantly related to the roost classification in the combined logistic regression model ($P \leq 0.05$). Based on this combined model, 31 of 35 roost sites (89%) and 34 of 35 random sites (97%), respectively, were correctly classified.

Discussion

Our results suggest that bald eagle roost habitat models may lose predictive power as the scale becomes larger and that a combination of micro- and macro-scale variables ultimately lead to the most parsimonious model (fewest parameters) with the greatest predictive power.

Bald eagles may be more discriminating in roost habitat selection at a micro scale. Bald eagle roosts on the Chesapeake Bay and elsewhere provide protected environments where eagles can avoid buffeting by prevailing winds (Stalmaster and Gessaman 1984, Keister et al. 1985, Buehler et al. 1991*b*). These habitat characteristics may be recognizable only to an eagle at a micro scale. If true, there should be greater difference between described eagle habitat at this scale and what is available at random, such that micro-habitat models would be able to discriminate between roost and random sites more easily.

Livingston et al. (1990), however, developed macro-scale bald eagle nesting habitat models in Maine with correct classification rates ranging from 75% to 100%. Although inclusion of micro-scale variables may have improved classification accuracy in some of Livingston et al.'s models, overall accuracy of their macro-scale models appears to be very good. The inclusion of 39 variables in the original modeling effort by Livingston et al. (1990), suggests selection of an appropriate array of variables may be as important as scale in determining model performance and development and application efficiency. Macro-scale variable measurement may be more economical on a per variable basis. The point where time spent measuring a large number of macro-scale variables on aerial photos or maps is more efficient than time spent in the field measuring a more limited set of micro-scale variables is yet to be determined. Care needs to be taken in the variable selection phase of model development to ensure that variables strongly related to actual habitat selection are included.

Our results suggest that a combined micro-macro approach to habitat modeling that may be consistent with the species' actual hierarchical habitat selection process, may lead to the best wildlife-habitat models. We envision eagles making gross habitat selection decisions consistent with the scale at which the USGS LULC database was developed (1:250,000), before focusing in on individual tree characteristics to select an actual roost site. Using the USGS LULC database to identify gross land cover and measuring 2 simple tree characteristics (height and access) appears to mimic this habitat selection process and lead to accurate classification of roost sites.

Finally, about 3% of random sites were classified as roost sites in the combined model. These sites could represent either true roost sites that we did not locate or potential roost habitat. In either case, it would be important to consider including these sites when developing roost habitat management plans because they are structurally similar to actual roosts.

Management Implications

Managers are faced with a series of decisions involving tradeoffs when identifying the scale and variables to be used in developing wildlife-habitat models for a specific management area. Managers want optimal model accuracy but need economically efficient models that are applicable across the management area (Salwasser 1986). *A priori* selection of important variables is difficult, such that extraneous variables may have to be measured to identify the minimum set of variables needed for desired model accuracy. In some cases, such as in the bald eagle roost habitat model example, these desires are in conflict. A combination of a limited number of micro- and macro-scale variables can be 1 solution.

In addition, inclusion of micro-scale variables in the model development phase may identify variables that could be estimated by macro-scale variables in the model application phase. For bald eagle habitat, it is possible to estimate tree height and tree access from aerial photos (Howard 1970). If these parameters are estitmated accurately, a macro-scale model could be developed that has excellent predictive power and broad applicability.

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