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# Discordant Data and Interpretation of Results from Wildlife Habitat Models

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## Abstract

Wildlife habitat management is an important part of natural resource management. As a result, there are a large number of models and tools for wildlife habitat assessment. A consequence of the many assessment tools is inconsistency when comparing results between tools, which may lead to potential confusion management decisions. Our objective was to compare results from two wildlife habitat models – one being relatively coarse (HUC5) scale and not spatially dynamic and the other being finer scale spatial data based on a 30 m spatial resolution –for habitat assessment of three species across the West Cascades of Oregon: Northern spotted owl, pileated woodpecker, and western bluebird. The coarse-scale model predicted more habitat for the two specialist species (owl and bluebird), whereas the fine-scale model predicted more habitat for the generalist (woodpecker). Spatial evaluation of fine-scale models suggested habitat pattern that was not revealed by coarse-scale models. Differences in model assumptions, variables used, and flexibility of variable treatment account for differences in model performance. These findings suggest that cautious interpretation of results is needed given the constraints of each model. Coarse-scale models may help prioritize management treatments across space, but further fine-scale and site-specific analyses enhance information needed for making habitat management decisions.

**Keywords:** habitat model; spatial statistics; state-and-transition model; West Cascades; wildlife conservation; wildlife habitat

## Introduction

Wildlife and habitat conservation of wildlife populations and habitat are among the premier objectives of natural resources management (Morzillo et al. 2014), for both ecological (e.g., Grimm 1995) and social (Decker et al. 2001) reasons. With declining budgets and personnel, yet expectations to meet an increasing number of guidelines and provisions for wildlife, managers need information for making decisions systematically and efficiently (Bryan and Crossman 2008). Consequently, numerous modeling approaches and tools exist for decision-making about wildlife and management of its habitat across many spatial and temporal scales (e.g., Westoby et al. 1989, McCann et al. 2006, Campomizzi et al. 2008, McRae et al. 2008, Phillips and Dudík 2008).

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A benefit of the myriad of models and tools available for evaluating wildlife habitat is that researchers and managers can choose a tool to best fit management and planning needs. Furthermore, advancements in the wildlife sciences and technology allow for the tools to be improved over time in their ability to measure habitat accuracy and precision (e.g., Aarts et al. 2008). However, a potential issue with the large number of models and tools is that they vary in assumptions used, data inputs, assessment methods, selected variables, applicable scale of analysis, observational unit, results and their interpretation, and uncertainty attributed to any of those elements (Tsoar et al. 2007; McRae et al. 2008). For example, an assumption of using vegetation-based state-and-transition models (STMs) to evaluate wildlife habitat is that the land cover characteristics modeled by STMs are pertinent the species of focus at the scale of analysis (Morzillo et al. 2012). This may not be an issue given a particular analysis, but could raise concern if data are used without clear understanding of data constraints and limitations.

Conversely, the drawback of multiple models and tools is that it is possible to achieve different results when multiple methods are applied to the same research or management question. For example, Long et al. (2009) compared resource utilization functions to resource selection functions to evaluate elk (*Cervus canadensis*) and mule deer (*Odocoileus hemionus*) habitat based on data derived from radiotelemetry. In that study, the number of variables identified as significant varied between models for each species; ranking of variables and directionality were not always consistent. Those differences have potential to substantially impact habitat management actions for features such as water availability (Long et al. 2009).

Similar inconsistencies and confusion can result when different data sources are used for habitat assessments. For example, Landsat imagery is commonly used as land cover data and basis for landscape-level evaluations of habitat. Classification of land cover data can vary in terms of definition of variables identified, translation of spectral information into variables, the extent and type of field data for validation, and whether validation is completed. Maxie et al. (2010) compared aerial photograph-based forest stand composition classification of black bear (*Ursus americanus*) and moose (*Alces alces*) habitat using Forest Resource Inventory versus satellite-derived land cover estimates. Only moderate levels of agreement existed between datasets because of differences between forest classification criteria, measurement methods, and time between image creation and field validation (Maxie et al. 2010). Yet, both datasets are frequently used by managers and practitioners, suggesting that variation in habitat assessments for species also exists across the wildlife management discipline.

Different habitat models are expected to produce different results; this is exactly the irony that we highlight. In our experience, inconsistent information from different models can lead to discordant interpretation and confusion in determining the “best” approach and logical explanation of results. Resource managers are generally well-versed in model interpretation for their discipline, but others who are less knowledgeable also have access to data and model output. Users can have difficulty or limited interest in understanding the rationale for and extent of data limitations, and the appropriateness of particular inferences made from the data and analysis. As a result, misinformation in communication and incomplete comprehension of results may have profound impacts on natural resources and policies governing them. Thus, there is a need for data users to share a common understanding of the underlying reasons for inconsistent predictions often produced by multiple assessment techniques, and how data limitations contribute to assessment scope.

Our objective is to provide a simple example to highlight inconsistencies that can exist between competing assessments of wildlife habitat that differ in assumptions, input variables, model type, and data structure – all of which confound interpretation of results – and provide reasons as to why such differences occur. To do this, we used two approaches to habitat analysis: a mid-to-coarse watershed-scale approach (HUC5) and a relatively fine (30 m) pixel-scale approach based on Landsat TM imagery. Our hypothesis is that comparative estimates of habitat for a specialist species will be less variable than for a generalist (Tsoar et al. 2007), and we provide reason as to why such differences occur. We used three species that are indicators for three different and broad forest habitat types: a specialist for late-successional and old-growth forest, a moderate specialist for open-canopy and early successional forest, and a generalist for a range of forest types. Then, we used basic spatial statistics to assist in explanation of factors that may attribute to differences between the analyses. It is important to note that habitat models only were used for comparative purposes for this exercise, and details about the development of the specific models are beyond the scope of this manuscript.

## Methods

### *Study Area*

Our study area included the Oregon West Cascades ecoregion (Level III; Omernik 2004) within Oregon. This includes an area of 21,680 square kilometers (5,357,244 acres) that extends from the Columbia River on the north, to west-central Oregon on the south, to the Cascades crest on the east, and to the mid-Willamette Valley on the west (Figure 1). Forest vegetation within the ecosystem is dominated by Douglas-fir and Douglas fir-mix, with oak at lower elevations and hemlock and other true firs at higher elevations. Seasons are defined by cold and wet winters, and dry warm summers. A total of 57 watersheds were defined at the HUC5 level across the ecoregion.

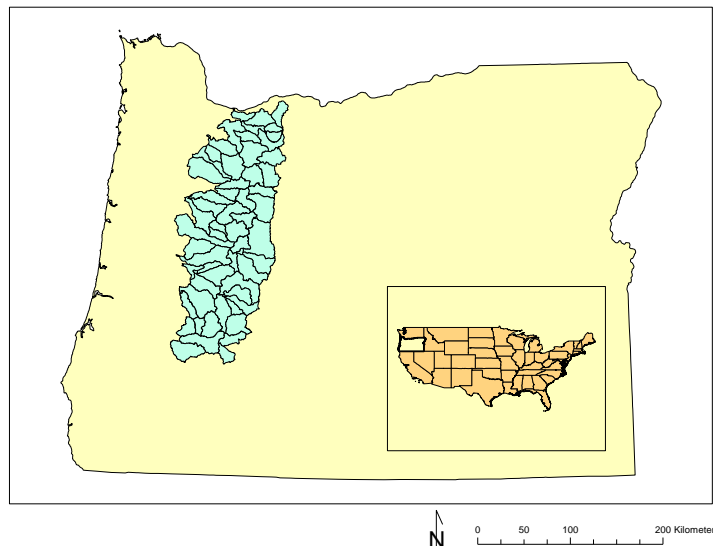


Figure 1. Oregon West Cascades (OWC) Ecoregion. Small polygons indicate HUC5 watershed boundaries.

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*Species of Focus*

We selected three focal species for this analysis: the Northern Spotted Owl (NSO; *Strix occidentalis*), Pileated Woodpecker (PIWO; *Dryocopus pileatus*), and Western Bluebird (WEBL; *Sialia mexicana*). These species were selected because they serve as management indicator species for particular forest types (USFS 2006), habitat characteristics can be linked to habitat models at both the coarse and fine scale, sufficient scientific information exists for construction of both coarse and fine-scale models, and regional habitat models are available.

The NSO is federally listed as threatened throughout its range as a result of habitat degradation and, more recently, the expanding range of the Barred Owl (*Strix varia*; USFWS 2008). The NSO is typically associated with mature and old-growth forests that are cool and moist (USFWS 2008) and is an indicator species for those forest types (USFS 2006). Habitat characteristics include relatively large trees, as well as closed and multiple-layered canopy; nesting may take place in cavities or on “platforms” of broken-topped trees (Forsman et al. 1984). Numerous studies have evaluated habitat characteristics for this species (e.g., Forsman et al. 1984, Buchanan et al. 1995; Pierce et al. 2005, USFWS 2008).

The PIWO is a mid-sized woodpecker that is an indicator species among cool forests (USFS 2006). It inhabits a range of medium to large tree sizes, and relatively closed and multi-layered canopy among a variety of forest types. Recent research on this species in the western US has focused on both dry (e.g., Bull et al. 2007, Nielsen-Pincus and Garton 2007) and wet (Aubry and Raley 2002, Hartwig et al. 2006) forest types.

The WEBL is a medium-sized songbird that is an indicator of open forests (USFS 2006). It is adapted to a variety of forest types, ranging from rangelands to cool, moist forests. In western Oregon, habitat analysis of this species suggests that it can respond well to a variety of forest management treatments (Hansen et al. 1995), and in regenerating forests (Marshall et al. 2003).

*Approaches to habitat assessments*

Coarse-scale habitat models were developed using a state-and-transition modeling framework. State-and-transition models (STMs) allow for simulation of landscape-level ecological processes (Westoby et al. 1989; Bestelmeyer et al. 2003). STMs can be used to simulate vegetation dynamics such as succession, disturbance, and applied to scenarios that seek to represent actual and potential management activities and changes in potential future vegetation characteristics. Such simulations allow managers to test “what if?” scenarios about how decisions about land use may affect natural resources. STMs were used to divide the landscape into state classes that characterized the structure and composition of vegetation.

Forest STMs were constructed for the Integrated Landscape Assessment Project (ILAP; Johnson and O’Neil 2001, Hemstrom et al. 2007; Halofsky et al. 2014). Because habitat information was needed to “dock” with STMs, habitat assessments were limited to STM vegetation constraints and assumptions (Halofsky et al. 2014). STM structure is similar to box and arrow diagrams, where boxes represent structural attributes and arrows represent drivers of change (Halofsky et al. 2014). In this case, the STMs operate at the HUC5 (5th-field watershed) scale; forest characteristics are summed for each watershed (i.e., but spatial distribution of forest characteristics within each watershed are unknown; Halofsky et al. in press). Input variables for STMs included four categories of forest

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characteristics: tree size (quadratic mean diameter), canopy cover (percentage closure), canopy layers (none, single, multiple), and cover type (dominant forest type) derived from Johnson and O'Neil (2001).

Methods from Morzillo et al. (2014) were followed to link STM output to habitat characteristics. Species-habitat relationships were derived from the scientific literature for each species, and matched to variable categories used in STM output (Halofsky et al. 2014). Each category of forest characteristics from STMs was classified binomially, such that a "1" indicated those characteristics that represented habitat for each species, and a "0" represented non-habitat characteristics (Morzillo et al. 2014; Appendix 1). Therefore, STM state classes do not measure wildlife habitat directly, but rather provide vegetation characteristics that may be associated with habitat. This approach has been demonstrated for many management questions (Wisdom et al. 2002, Barbour et al. 2005; Wonzell et al. 2007, Evers et al. 2011).

Fine- (pixel-) scale habitat models were developed based on spatially explicit models constructed for the Coastal Landscape Analysis and Modeling Study (CLAMS; McComb et al. 2002, Spies et al. 2007), with forest attribute information derived from gradient analysis and nearest-neighbor imputations based on Landsat TM imagery (GNN; Ohmann and Gregory 2002). From these models, a habitat capability index (HCI) was derived for each species (Appendix 2). Each HCI contained two habitat components: individual pixel and landscape. Input data included identification of key habitat variables for each species derived from empirical information in the scientific literature. Habitat relationships were translated into simple linear relationships for each variable, and then integrated to form multi-variable HCIs following methods used by McComb et al. (2002) and Spies et al. (2007; Appendix 2). The individual pixel scale corresponded to an assessment of a nesting suitability metric, whereas the landscape scale incorporated a moving window to calculate a foraging suitability metric.

Assumptions of this approach include those described by McComb et al. (2002), including identification of an optimal value for each habitat variable, and that habitat selection occurs across scales extending from a single point. Consistent with the CLAMS models, we truncated the continuous HCI variable to binomial "habitat" and "non-habitat" by defining species habitat as having a HCI score that surpassed a minimum threshold value (Appendix 2). Fine-scale models were constructed using Python programming within ArcGIS 10 software (ESRI, Redlands, CA). Supporting databases for this analysis were stored in raster format at 30 m resolution. HCI values for each species were output into 30 m resolution raster files. HCI summaries included the average and standard deviation of HCI values within each stratum. Because field data were not used to validate either model, inferences made are limited to general comparisons between the two models for this discussion only.

### *Statistical analysis*

We completed two calculations as a basis for illustrating implications of different model assumptions, input variables, model type, and data structure on interpretation of results. First, we examined differences in total habitat between the two models. For the coarse-scale approach, habitat area was aggregated to the HUC5 level (Wigington et al. 2012) to calculate total habitat area per watershed. For the fine-scale approach, we calculated habitat area for each watershed based on HCI scores that surpassed the minimum threshold for each of our focal species (McComb et al. 2002). T-tests and Pearson's correlation were used to compare total habitat and mean habitat area on a HUC5 level.

Second, we used spatial statistics to enhance general observed variation in patterns of habitat resulting from the different models. Moran's Index (Moran's I) was used to measure spatial autocorrelation and assesses correlation between location proximity and attribute similarity (Wong and Lee 2005). For this statistic, observed values of neighboring features (watersheds) were compared to expected values across an entire study extent. Neighboring features that have similar values whether high or low resulted in a positive index value. Negative values imply that neighboring features were different, and values of zero imply no significant spatial autocorrelation between neighboring attributes. Although Moran's I leads to the identification of spatial autocorrelation by measuring the attribute similarity of neighboring features, it does not have the ability to distinguish between similarities in high values ("hot-spots") or low values ("cold-spots").

The general G-statistic (Getis and Ord 1992) was applied as a complimentary analysis to Moran's I for further assessment of "clusters" of similar values across the entire study area (Wong and Lee 2005). While Moran's I measures the similarity of neighboring feature values, the general G-statistic indicates whether clusters are composed of high or low values. Therefore, the general G-statistic determined whether neighboring features tend to share either high or low concentrations of some value and makes those comparisons across the landscape extent (Mitchell 2005). The test statistic for the general G-statistic is a z-score. A positive z-score indicates that high attribute values are spatially clustered, whereas a negative z-score indicates spatial clustering of low attribute values. Thus, the G-statistic indicates whether clustering is occurring, and associated z-scores provide a measure of statistical weight of the clustering. We also used paired t-tests and Pearson's correlation statistics to more closely examine relationships and patterns of differences across the study area.

## Results

For the coarse-scale approach, NSO habitat totaled 12,017 square kilometers (55% of total) across the study area, and PIWO habitat totaled 11,124 square kilometers (51% of total). WEBL habitat area totaled 1,941 square kilometers (9% of total). For illustration purposes, habitat values were normalized by total area in the watershed to account for variation in watershed total area (Figure 2). The normalization process takes the area of species habitat estimated by the coarse-scale assessment and divides it by the fine scale habitat area. Watersheds with greater proportions of NSO habitat occurred along eastern and southern watersheds, corresponding to relatively middle and higher elevations. PIWO habitat trends were similar to those of NSO, but with lower values at the relatively highest elevations. Watersheds with relatively greater proportions of WEBL habitat were among watersheds in the western portion of the study area, corresponding to relatively lower elevations.

For the fine-scale approach, NSO habitat comprised of 7,148 square kilometers (33% of study area). PIWO habitat totaled 18,758 square kilometers (87% of study area). We calculated mean HCI scores for each watershed by averaging the HCI scores for all 30m cells that fell within each watershed. Mean ( $\pm$  SD) HCI score for the NSO across all in the watersheds was 0.27 ( $\pm$  0.11). Mean values illustrated a spatial gradient. Scores were generally lower in the northwestern portion of the study area, but greater in the eastern and southern portions (Figure 3). Mean ( $\pm$  SD) HCI score for the PIWO across all watersheds was 0.54 ( $\pm$  0.10). No single watershed had an overall average HCI score that was above the minimum threshold for preferred WEBL habitat. Spatial distribution of PIWO scores was more variable than the NSO, yet the trend of relatively lower HCI scores in the northwestern watershed areas was similar. The lowest PIWO HCI scores occurred in the centrally located watersheds in the northern half of

the study extent. Mean ( $\pm$  SD) HCI score for the WEBL across all watersheds was 0.05 ( $\pm$  0.04). The higher WEBL HCI scores occurred in the northwestern extent of the study area. The lowest average HCI scores existed in the northeastern and southern portions of the area.

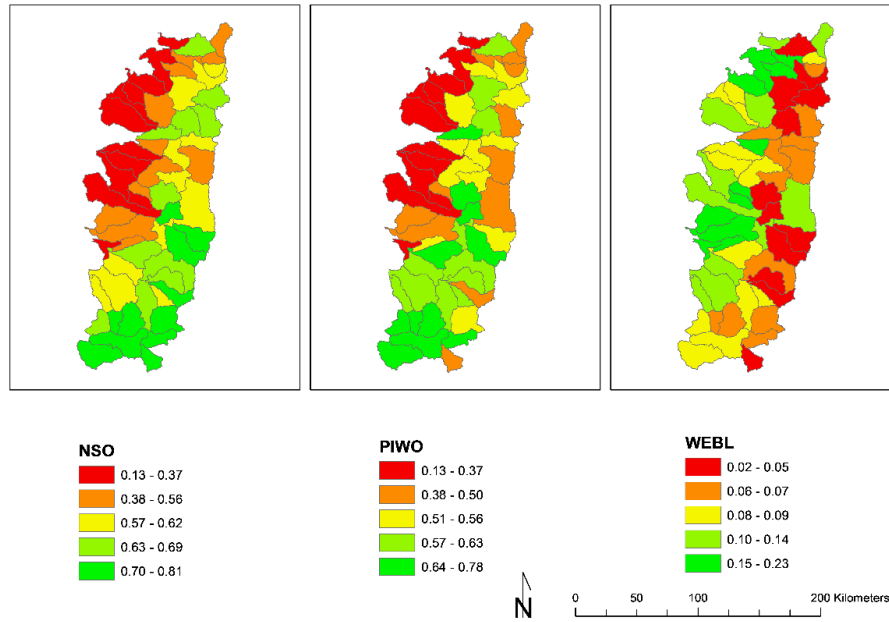


Figure 2. Coarse-scale habitat areas normalized by watershed area for the NSO, PIWO, and WEBL. Legends are structured by quantile distribution. Polygons indicate individual watersheds.

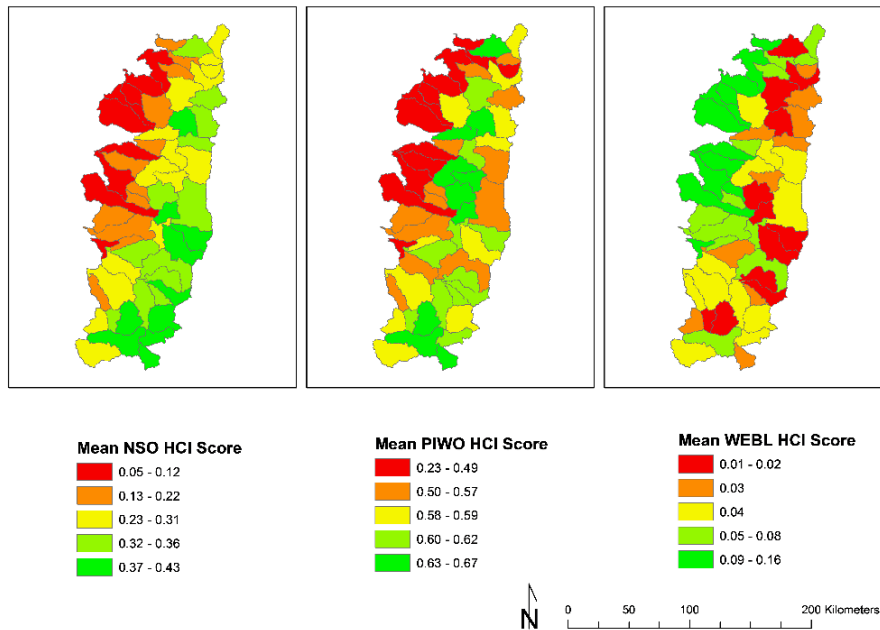


Figure 3. Mean HCI score for the NSO, PIWO, and WEBL using coarse-scale models. Legends are structured by quantile distribution. Polygons indicate individual watersheds.



We compared the habitat areas that resulted from the coarse- and fine-scale models (Figure 4 illustrates fine-scale HCI model output for one watershed using the WEBL as an example). Differences in habitat area between the two models existed for all three species. Fine-scale habitat area for the NSO and WEBL were less than that predicted by the coarse-scale model (NSO: 33% versus 55% of study area, respectively; WEBL: 3% versus 9%). PIWO habitat area produced by the fine-scale model was greater than the coarse-scale (87% versus 51%). Model results were statistically different according to t-test results for all three species ( $p < 0.05$ ). The resulting model areas were found to be highly correlated for the NSO and PIWO ( $R^2 = 82\%$  and  $92\%$ , respectively), but less so for the WEBL ( $R^2 = 67\%$ ).

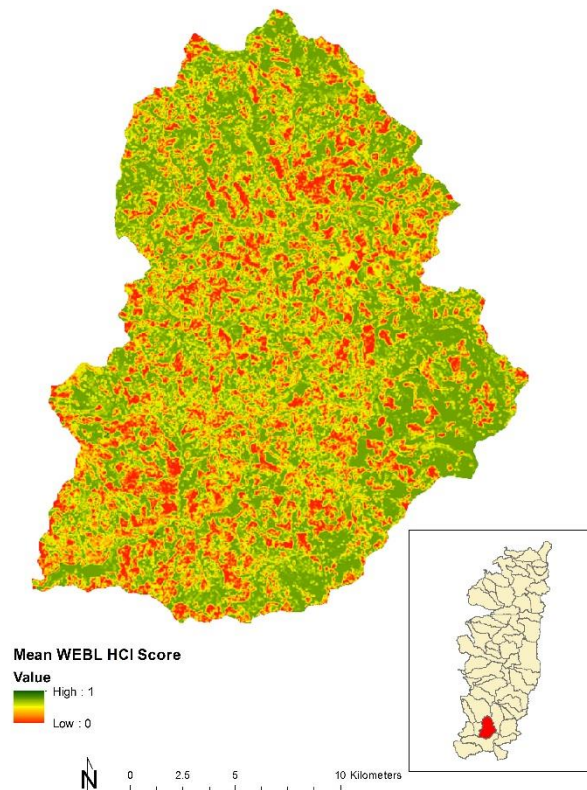


Figure 4. Illustration of fine-scale HCI output for one watershed using the WEBL as an example. Polygons indicate HCI score derived based on individual pixel and landscape scores.

Moran's I results were similar and positive for all three species (NSO = 0.77; PIWO = 0.74; WEBL = 0.75), and statistically significant ( $p < 0.05$ ). These values suggest that watersheds tend to be located next to other watersheds with similar HCI values.

We calculated the general G-statistic and resulting z-scores for all three species based on their resulting HCI scores above the threshold minimum (Figure 5). Although the G-statistics for the three species differed, G-statistics tended to be higher in the center of the study area, and all watersheds had low values in the northwestern areas. The

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NSO differed from the other two species in that it tended to be bimodal, with concentrations of high and low G-statistics with fewer moderate values. High G-statistic values indicate conglomerations of high HCI values.

The z-scores were similar in spatial distribution for two species; the NSO and PIWO. Negative z-scores, which infer spatial clustering of low attribute values, tended to occur in the northwest portion of the ecoregion. Positive z-scores, which suggest spatial clustering of high attribute values tended to occur in the south and east regions of the ecoregion for the NSO. The WEBL, however, had a strong concentration of positive z-scores in the northwest and western watershed areas, with relatively neutral z-scores throughout the rest of the watersheds.

### **Conclusion**

Managers have many options to choose from when seeking to evaluate wildlife habitat. Models are constructed based on individual study objectives, and vary based on assumptions, data, variables, scales of analysis, units of observation, applicable interpretation of results, and uncertainty. Yet inattention to such differences can result in inaccurate and confusing interpretations of and inferences from results. Our objective was to highlight differences in model structure and function that could result in misinterpretations and why those differences occur. We used two models to illustrate these differences: a “coarse”-scale model derived from STMs, and a “fine”-scale model derived from habitat suitability models at a 1-ha scale. Results of both models were amalgamated to the HUC5 scale.

Coarse-scale models revealed a greater amount of habitat for the NSO and WEBL, whereas the fine-scale estimate was greater for the PIWO. Several possible reasons exist for this discrepancy. One reason is that the fine-scale model affords greater flexibility with implementation of individual variables. For example, both NSO models contained a variable representing tree size, and the same categories of tree size were applied for each model. However, in the fine-scale model, two additional calculations were applied to the tree size variable. First, in the nesting suitability sub-index (Appendix 2), the fine-scale model gives greater weight to the largest tree size category, whereas all tree size categories are considered equally in the more-rigid coarse-scale model (Appendix 1). Thus, ability to weight variables by the fine-scale model provides opportunity for greater focus on large trees and inherently old growth for the NSO. Second, the fine-scale model incorporates a landscape-level metric that considers habitat suitability within a radius distance of each pixel, whereas the watershed-level amalgamation of the coarse-scale model does not allow for a neighborhood metric. Because the NSO is a habitat specialist for old forest, we expect that the fine-scale habitat model’s ability to emphasize larger trees within a certain distance from nesting habitat to result in greater accuracy than the coarse scale at the watershed level. However, ground-truthing and extensive model validation would be needed to test this assertion.

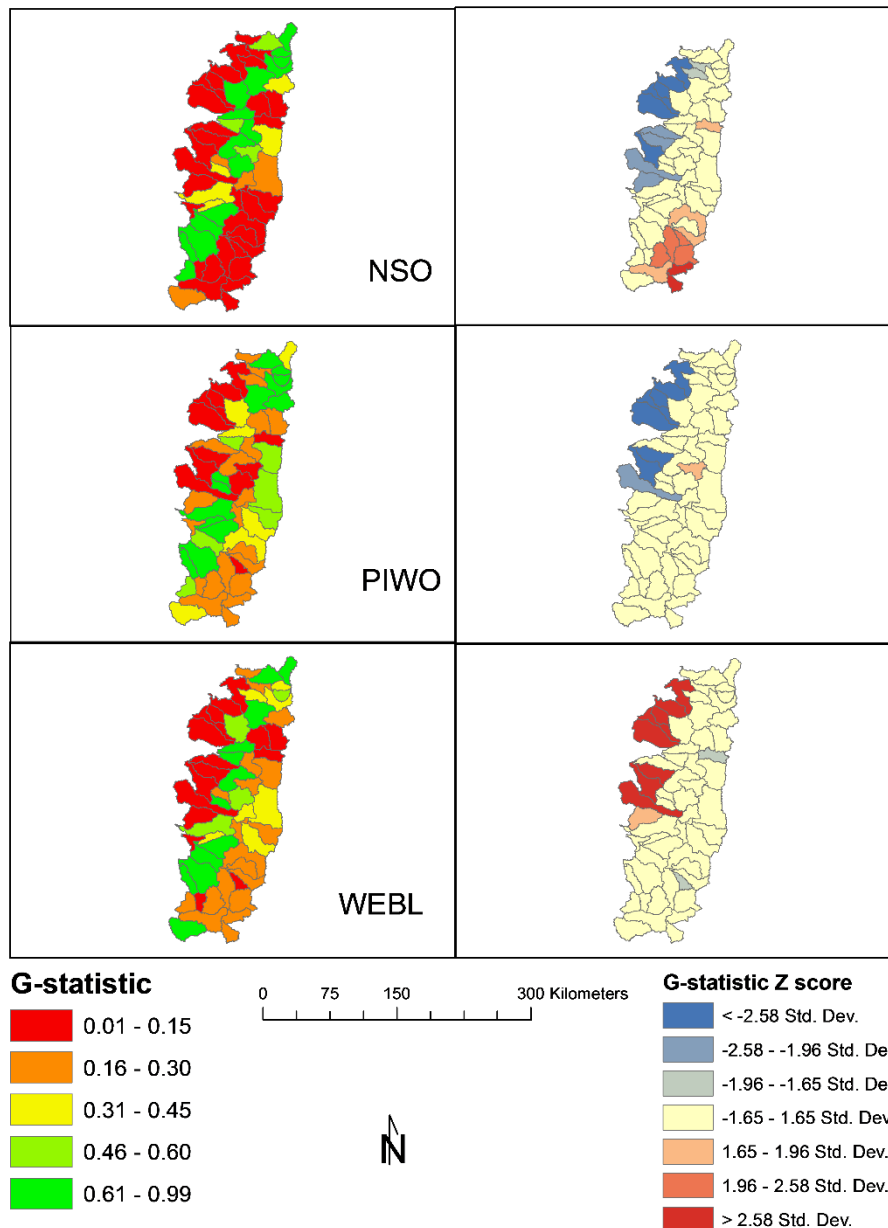


Figure 5. G-statistics results for the NSO, PIWO, and WEBL. Polygons indicate individual watersheds. G-statistics tended to be higher in the center of the study area.

Differences in variables used also affect variation between the two WEBL and PIWO models. Both WEBL models incorporate canopy cover with a minor (10%) difference in decisions rules defining “open forests.” Snags, a critical nesting component for both WEBL and PIWO, are considered in the fine-scale model, whereas the STM decision rules disallow the inclusion of snags. We suspect that the inclusion of snags in the WEBL fine-scale model results in a more-conservative yet accurate estimate of habitat compared to the broader variable categories derived from the STMs. In addition, the PIWO fine-scale inclusion of Douglas-fir density, the dominant tree

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species throughout western Oregon, also likely contributed to inclusion of more area than the STM focus on particular cover types based on ecosystem associations. Ultimately, our results suggest that individual variables incorporated in models may influence directional differences when comparing specialists (NSO and WEBL) and generalist (PIWO).

Each model type also considers different assumptions for landscape-level habitat characteristics. The study area consists of relatively large elevation changes, from <1,000 feet near the floor of the Willamette Valley, to more than 11,000 feet at the summit of Mt. Hood. Watersheds used for STM amalgamation of habitat have potential to encompass a broad elevation range and ecosystem types. This helps explain coarse-scale distributions that roughly align with ecological communities. Examples include concentrations of NSO habitat among eastern portions of the study area (Douglas fir and true-firs), PIWO among middle elevations (largest Douglas firs and snags), and WEBL among lower elevations (open forests and regenerating clearcuts). Thus, illustrated consistencies between models in general patterns of habitat at the broadest landscape level may support the premise that coarse-scale models are easy to understand and yet are limited in their ability to only provide a broad-brush general evaluation of habitat distribution (Hemstrom et al. 2007).

Emerging patterns from fine-scale models reveal some additional information beyond the coarse-scale models. The highest G-statistics existed among watersheds in the center of the study area, which correspond to mid-elevations, particularly steep gradients that provide limited accessibility, and public lands. The preponderance of high and low G-statistic values for NSO supports the specialist characteristic of this species and its linkage with mid-elevation old growth forest (Forsman et al. 1984). Low G-statistic values at low elevations may not only serve as guidance for lack of forest with old-growth characteristics, but also potential for low-elevation forests that are likely to be occupied by the range-expanding barred owl (USFWS 2008, Dugger et al. 2011). High G-statistic values for PIWO at mid-elevations may indicate areas with larger trees (and therefore potential for larger snags) and higher densities of large Douglas fir. However, some relatively high G-statistic values for PIWO also existed in high elevations, which may be attributed to high snag density among areas experiencing recent large-scale wildfires among public lands including wilderness areas along the Cascade Crest. Although mean HCI scores for WEBL tend to be concentrated among open forests at low elevations (high and positive G-statistic z-scores), distribution of regenerating clearcuts at mid-elevations have potential to provide open canopies often associated with WEBL. High G-statistic values at relatively higher elevations may be misleading however, as elevation likely limits WEBL from inhabiting those areas. Ultimately, fine-scale analysis can complement coarse-scale results by revealing concentrations of habitat within and between watersheds.

Variation in calculation of metrics occurs regularly in wildlife habitat analysis. For example and among the most-studied metrics, several methods exist for estimating individual home range. Among the simplest methods, the minimum convex polygon (MCP) is based on construction of an external boundary that using linkages between estimated locations. Since development of the MCP (Mohr 1947), several additional methods have been developed including parametric adaptive kernel (Worton 1989), local nearest neighbor convex hull (Getz and Wilmsers 2004), and Brownian bridge (e.g., Horne et al. 2007). Beyond spatial metrics, additional measurements also are used to assess factors that may influence temporal variation of home ranges and related behaviors (e.g., Massei et al. 1997, Kjør et al. 2008). Although non-parametric methods often are considered more-accurate, a more important point is

that each analysis method incorporates different assumptions and statistical methods that ultimately are affected by quality of observational data used to parameterize each model.

The impetus for this analysis was to provide guidance for explaining differences between wildlife habitat models, and why such differences might occur. Such differences are critical for understanding the limitations of the data for all habitat models. The coarse-scale model provides an aggregated estimate of area, and a first-glance overview of where habitat resources may be distributed on the landscape. The fine-scale models may provide greater insight to intra-watershed habitat distribution, and complement initial assessments at the coarse scale. Neither of these methods are suitable for site-level analysis, which would require more-detailed study of local characteristics and habitat revised approach to variable selection. It is critical that managers and planners using such models for decision-making understand the strengths and limitations of each model, and how those strengths and limitations impact the ability to make inferences for land management.

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**Appendix 1.** Coarse scale habitat models as derived from STM state classes. Cover types presented are the subset of those identified for the Oregon West Cascades that corresponded to at least one of the three focal species.

		<b>Northern spotted</b>	<b>Pileated</b>	<b>Western</b>
		<b>owl</b>	<b>woodpecker</b>	<b>bluebird</b>
<b>Cover type</b>	Douglas fir	X	X	X
	Douglas fir / Grand fir	X	X	
	Douglas fir mix	X	X	X
	Douglas fir / oak	X	X	X
	Douglas fir/ White fir	X	X	X
	Mountain hemlock	X		
	Oak			X
	Oak / Douglas fir		X	
	Red fir / White fir	X	X	
	Silver fir mix	X	X	X
	Western hemlock	X	X	
<b>Size class</b>	Grass Forb			X
	Open Shrub			X
	Seedling / sapling			X
	Pole			X
	Shrub			X
	Small tree			X
	Medium tree	X	X	X
	Large tree	X	X	X
	Giant tree	X	X	
<b>Canopy closure</b>	Open			X
	Medium	X	X	
	Closed	X	X	
	Post-disturbance			X
<b>Canopy layers</b>	Single			X
	Multiple	X	X	

**Appendix 2.** Fine scale habitat models as derived from CLAMS models. Adapted from McComb et al. (2002) and Spies et al. (2007).

### 1. Northern Spotted Owl

$$HCI_f = \sqrt[3]{NSI^2 LCI_f}$$

where

HCI = habitat capability index

$f$  = focal pixel

NSI = nesting suitability index

LSI = landscape suitability index

The NSI is calculated using a 3 \* 3 pixel “moving matrix” around a focal pixel. The spatial resolution of the forest attribute data that we applied was 30 m<sup>2</sup> (0.56 ha); therefore, this also becomes the resolution of the focal pixel. The NSI has an emphasis on the density of trees within the moving matrix that is split among four size classes (Johnson and O’Neil 2001).

$$NSI_f = \frac{\sum_{i=1}^9 (d1 + d2 + d3^2 + d4) / 4}{9}$$

where

NSI = Nesting Suitability Index

$f$  = focal pixel

d1 = tree density (10-25 cm)

d2 = tree density (25-50 cm)

d3 = tree density (>75 cm)

d4 = diameter diversity index

The LSI <sub>$f$</sub>  is also calculated within a focal pixel and combines three separate measurements that take into account different search radii around a focal pixel.

$$LSI_f = \sqrt[6]{S_1^3 * S_2^2 * S_3}$$

where

$f$  = focal pixel

S<sub>1</sub> = habitat index in 0.3 km radius of focal pixel

S<sub>2</sub> = habitat index in 0.8 km radius of focal pixel

S<sub>3</sub> = habitat index in 2.4 km radius of focal pixel

The minimum threshold HCI score = 0.37.

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## 2. Pileated Woodpecker

$HCI_f = \text{minimum}(HNI_f, FHI_f)$

where

HSI = Habitat Suitability Index

$f$  = focal pixel

NHI = nesting habitat sub-index

FHI = foraging habitat sub-index

Nesting habitat sub-index:  $NHI_f = (0.4 * MS_f) + (0.6 * LS_f)$

where

NHI = nesting habitat sub-index

MS = medium snag score

LS = large snag score

$f$  = focal pixel

*IF S5075T<sub>f</sub> ≥ 3.5 THEN MS<sub>f</sub> = 1.0, ELSE MS<sub>f</sub> = S5075T<sub>f</sub> \* 0.2857*

where

S5075T = number of snags (50 < dbh ≤ 75 cm)/ha

MS = medium snag score

$f$  = focal pixel

*IF S75T<sub>f</sub> ≥ 1.9 THEN LS<sub>f</sub> = 1.0, ELSE LS<sub>f</sub> = S75T<sub>f</sub> \* 0.5263*

where

S75T = number of snags (dbh >75 cm and height >5 m)/ha

LS = large snag score

$f$  = focal pixel

Forage Score at Pixel Level:  $F_i = NHI_i(0.333) + TS_i(0.333) + LS_i(0.333)$

where

$F_i$  = forage score for pixel  $i$

NHI = nesting habitat sub-index (included as a snag availability index)

TS = live tree score

LS = downed log score

$i$  = pixel

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$$\text{IF } T50_i \geq 180_i \text{ THEN } TS_i = 1.0 \text{ ELSE } TS_i = T50_i * 0.0056$$

where

T50 = Douglas-fir (dbh > 50 cm)/ha

TS = live tree score

$i$  = pixel

$$\text{IF } LS50_i \geq 23 \text{ THEN } LS_i = 1.0 \text{ ELSE } LS_i = LS_{50_i} * 0.0435$$

where

LS50 $_i$  = mean volume (m<sup>3</sup>/ha) of logs > 50 cm diameter (large end)

LS = downed log score

$i$  = pixel

Foraging Habitat Sub-Index: FHI

where

FHI = foraging habitat for a 1236 m radius analytical window centered on focal pixel  $i$

$F_i$  = forage score for pixel  $i$

$i$  = pixel

$n$  = number of pixels in analytical window

$$(\sum_{i=1}^n F_i) / n$$

The minimum threshold HCI score = 0.33.

### 3. Western Bluebird

$$HCI_f = \sum_{i=1}^9 TS_i$$

where

TS = territory-level score

$f$  = focal pixel

$i$  = pixel within window

Territory-level scoring

$$TS_i = [(LS_i(0.6) + SS_i(0.4))CI_i]^{1/2}$$

where

TS = territory-level score

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$LS$  = large snag availability index

$SS$  = small snag availability index

$CI$  = canopy index

$i$  = pixel within window

$$IF S50T_i \geq 5 THEN LS_i = 1.0, ELSE LS_i = S50T_i * 0.2$$

where

$S50T$  = number of snags (dbh > 50-cm and > 5-m tall) / ha

$LS$  = large snag availability index

$i$  = pixel within window

$$IF S2550T_i \geq 11 THEN SS_i = 1.0, ELSE SS_i = S2550T_i * 0.09$$

where

$S2550T$  = number of snags (25 < dbh ≤ 50-cm and > 5-m tall) / ha

$SS$  = large snag availability index

$i$  = pixel within window

$$IF CC_i \geq 20\% THEN CI_i = 0.0, ELSE CI_i = [(20-CC_i) / 20]$$

where

$CC$  = canopy closure (%)

$CI$  = canopy index

$i$  = pixel within window

The minimum threshold HCI score = 0.3