Chapter 5. Using Habitat Models for Habitat Mapping and Monitoring

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5.1 Objective

This chapter provides guidance for applying existing habitat models to map and monitor wildlife habitat. Chapter 2 addresses the use of conceptual models to create a solid foundation for selecting habitat attributes to monitor and to translate these attributes into quantifiable and reportable monitoring measures. Most wildlife species, however, require a complex suite of multiple resources and environmental conditions. Therefore, monitoring single habitat attributes is often not sufficient to assess the true condition of habitat quality for a species. To quantify and map habitat as an integrated entity, more formal models of wildlife habitat are required. It is beyond the scope of this chapter to provide guidance to managers in building habitat models (e.g., Hegel et al. 2010, Manly et al. 2002, Morrison et al. 2008). Rather, this chapter is designed to help those who have decided to use existing habitat models or published habitat relationships for mapping and monitoring changes in habitat over time. We present five steps in the process of modeling and mapping habitat: (1) select an appropriate habitat model; (2) assemble relevant extant data; (3) apply the selected habitat model to estimate the amount, quality, and spatial distribution of habitat; (4) evaluate the model; and (5) monitor habitat through time.

5.2 Key Concepts

5.2.1 Habitat Models and Population Status

We do not advocate habitat monitoring as a surrogate for estimating the population status of a species. In general, most habitat models account for less than one-half the variation in species density or abundance (Morrison et al. 2008). For example, Cushman et al. (2008b) empirically evaluated a suite of habitat models for multiple species and found that even dozens of habitat attributes from multiple spatial scales were unable to explain most of the variance in species abundances. Even when a model indicates strong associations between the probability of species occurrence and habitat gradients, it will usually fail to explain most variability. Models can be effective in evaluating the suitability of habitat for the species, however, and for monitoring changes in this suitability over time. It is important to understand this distinction before proceeding with the content of this chapter.

5.2.2 The Relationship Between Habitat Modeling and Habitat Classification

A model is a simplified version of a real object or situation and can take many forms, including verbal descriptions, three-dimensional abstractions, schematic diagrams, and mathematical formulas. Wildlife habitat models represent the presumed or known relationships between a species and the various environmental components that are needed for survival and reproduction. Because habitat selection is based on the perception and behavioral responses of each species (Johnson 1980, Wiens 1976 in Girvetz and Greco 2007), it follows that habitat quality is specific to a species and highly scale dependent (chapter 2, section 2.2.6; Cushman et al. 2010b, Grand et al. 2004). No one set of environmental variables or spatial scales define habitat for all species. Given the individualistic nature of species-habitat relationships, independent habitat models should be produced for each emphasis species. In practice, habitat quality is often defined for species groups, but such practice should consider habitat selection characteristics of each species when forming species groups to ensure acceptable similarity in these factors (chapter 2, section 2.2.5).

Classification is the process of grouping objects into named types or classes based on shared characteristics or their relation to a set of criteria. Habitat classification involves grouping units of area (e.g., pixels, plots, **patches**, and landscapes) into classes based on if the area meets one or more criteria (e.g., minimum or mean values of the habitat attributes). The simplest form of classification is binary (habitat, nonhabitat), but classification can also result in several categories of habitat quality (high, medium, and low), or can be represented as a continuous function.

Habitat classification can be based on a single criterion or attribute (e.g., longleaf pine [*Pinus palustris*]-dominated overstory), but doing so may overestimate habitat because use of a single attribute does not consider other factors that need to be present for the single attribute to serve as habitat. Habitat quality is often a conditional function of the simultaneous conditions of several attributes, such that measuring one or a few attributes does not sufficiently assess their joint contribution toward habitat quality. When more than one attribute is used to classify habitat, a model is needed to describe the range of values for all selected attributes used to define habitat for a species. The output from the model becomes the criterion for classifying habitat.

5.2.3 Habitat Mapping

A habitat map is the spatial representation of a habitat model for an emphasis species or species group. It is not always necessary to create a map to classify or monitor habitat;

the outputs of a habitat model can sometimes be displayed in a table, and subsequent monitoring would focus on changes in the tabular values of the attributes. Habitat models often contain explicit spatial attributes, however, such as patch size or edge ratios, so a map becomes an important representation of the habitat model. In addition, for habitat monitoring to provide guidance for management actions at particular locations, the spatial pattern of habitat conditions must be evaluated. Habitat mapping is usually necessary to accomplish this evaluation.

When we spatially model habitat, our objective is to predict the quality of each location in the landscape as habitat for the emphasis species. This prediction may be either in the form of delineation of patches that are similar in their quality as habitat for the emphasis species or mapping habitat quality as a continuous variable that varies through space, rather than assuming that categories or discrete boundaries exist. Habitat patches are defined by discontinuities in the combined set of conditions identified in the model as affecting habitat use by the species. In many cases, it may be more appropriate to model habitat as a continuous variable, rather than as a mosaic of habitat and nonhabitat patches, given that often habitat quality continuously varies along environmental gradients rather than categorically differing between habitat classes across discrete boundaries (Cushman et al. 2010a, Evans and Cushman 2009, McGarigal and Cushman 2005, McGarigal et al. 2009).

Spatially explicit habitat models present unique challenges because of different data sources and associated map error. Glenn and Ripple (2004) reported significantly different habitat assessments for the same species in the same study area using digital aerial photos compared with satellite imagery. In particular, maps developed from satellite imagery had greater heterogeneity in vegetation than maps developed from aerial photos, resulting in different model outcomes for landscape composition and pattern. In a literature review, Glenn and Ripple (2004) noted that researchers and modelers do not consistently report the source of spatial data, the resolution, and the image processing techniques that are used in habitat models or assessments, so it is difficult to make biologically meaningful comparisons between studies.

When combining spatial data layers to define habitat patches, concerns about data accuracy and precision are compounded, because integrating individual data layers makes error estimation difficult (McGarigal and Cushman 2005; chapter 4, section 4.5.2). In addition, if using spatial layers in which polygons of component attributes have already been defined (i.e., vector data), map unit design, such as a **minimum map unit**, of these component data can limit the precision with which habitat patches can be identified. For example, if a forest management stand layer identifies only forest stands 10 acres (ac) or larger, it will not be possible to identify all habitat patches for a species that is regularly found in patches as small as 2 ac. Alternatively, patch delineation using raster data is limited by pixel resolution. Raster data allow for aggregating pixels into habitat patches based on rules that reflect our understanding of factors affecting a species' habitat selection (e.g., Girvetz and Greco 2007).

5.3 Process Steps for Habitat Mapping and Monitoring

5.3.1 Select an Appropriate Habitat Model

Depending on the intended use, practitioners have used many approaches for developing wildlife habitat models, such as statistically associating species occurrence records with multiple environmental variables, linking habitat to demographic models, and developing broad-scale landscape assessments. The models developed for these various objectives differ in their structure, or modeling framework. Before selecting an existing model for monitoring a species' habitat, learn about the modeling framework and its intended use. Beck and Suring (2009) identified 40 modeling frameworks used for creating wildlife habitat models beginning in the mid-1970s and extending to contemporary times. In addition, Elith and Leathwick (2009) and Hegel et al. (2010) provide thorough reviews of a broad range of modern statistical modeling approaches to predict habitat quality and species distributions. These publications will assist in determining the modeling framework of each model under consideration, and in deciding if it will meet the purpose of monitoring habitat.

A previously developed, locally defined habitat model for an emphasis species is uncommon, but if one exists, and it has a modeling framework conducive for mapping and monitoring habitat, it may be suitable for use. It is typically necessary to evaluate the usefulness of a model developed from another geographical area or time period. In general, it is not scientifically defensible to extrapolate findings beyond the scope of inference of a study, and the same principle applies to models. When a model developed for one area is applied to a different geographical area, the model's applicability is unknown until tested. The accuracy and error rates relevant to the original landscape do not necessarily apply to a new landscape, particularly when the new landscape differs in appreciable ecological ways, in terms of climate, topography, vegetation, prevalent disturbance regimes, and human influence.

To evaluate if a model from another geographic area can be applied locally in the context of habitat monitoring, first determine if it is based on empirical data or expert opinion, and if error rates and model accuracy were assessed using independent data. Second, determine if the model variables match the environmental conditions present in the area to which you will apply the model. Third, determine if sufficient data on the value and distribution of each model variable exist for the local study area. To apply a model to predict habitat quality, all of the independent variables that define the model should be measured using appropriate methods, at appropriate scales, and using sample sizes that ensure sufficient precision of statistical inference (chapter 3).

Finally, consider the distance between the local monitoring area and the location in which the model was developed and determine if the ecological dissimilarity between the two areas is too great to reliably use the model. Occasionally, it is necessary to use professional judgment and all available local information to modify the range of values for certain model attributes to reflect local conditions. For example, it might be necessary to reduce the range of canopy cover or tree diameter values to reflect conditions in a locale that are more xeric than where the original model was created. Such modifications will require validation by comparing model predictions with actual presence or abundance of the emphasis species in the area where managers will apply the model (section 5.3.4).

If several models are available from different geographic areas, a more rigorous approach is to conduct a meta-analysis, which is an analytical process that combines the habitat attribute values for all of the models and creates a generalized model. The task of conducting such a meta-analysis is not trivial, but will result in a scientifically defensible model (Gates 2002, Gurevitch and Hedges 1993, Hedges and Olkin 1985). Major challenges in meta-analysis include reconciling results of models that use different predictor variables, or are conducted at different spatial scales. Conducting formal meta-analysis of published models and habitat relationships will generally provide the most reliable inferences about the habitat factors of importance to the species of interest and the values of their parameters in a predictive model.

5.3.2 Compile Extant Data Required by the Selected Habitat Model

The data that need to be assembled will be governed by the nature of the habitat model. Often a habitat model will incorporate habitat attributes from a range of scales (e.g., Cushman and McGarigal 2002, Grand et al. 2004, Thompson and McGarigal 2002). For example, it may include plot-level attributes such as canopy cover and coarse woody debris, as well as patch-level attributes, such as vegetation cover type or patch size. It also may include landscape-level variables, such as the percentage of the local landscape in each cover type, the **contrast-weighted edge density**, **contagion**, or other measures of fragmentation (chapter 6 further addresses landscape pattern attributes and metrics). A well-conceived model will specify a list of the plot-, patch-, and landscape-level variables of interest and the spatial scale at which the landscape-level variables should be calculated (e.g., Grand et al. 2004, Thompson and McGarigal 2002).

If the habitat model includes only patch and landscape attributes, and if suitable land cover maps exist that depict the cover types included in the model with sufficient accuracy and at the correct spatial scale, then simply compile existing Geographic Information System (GIS) data (chapter 4, table 4.6 describes sources of existing vegetation maps) and apply the model directly.

Several recent examples of habitat suitability models are based entirely on attributes that can be measured from GIS data. For example, Larson et al. (2003) created GIS-based habitat suitability models for 12 species in southern Missouri, and Rittenhouse et al. (2007) created GIS-based habitat suitability models for 10 species in the Central Hardwoods region of the Midwestern United States. In both examples, the authors translated ecological requirements of the emphasis species into attributes that were easily obtained from a combination of inventory data from a local national forest, Forest Inventory and Analysis (FIA) data, land cover data, and state Gap Analysis Program data (http://gapanalysis.usgs.gov/gap-analysis/). The added advantage of a GIS-based habitat suitability model is that it allows for the incorporation of landscape-level attributes that are typically not part of a traditional, field-based model.

If the habitat model includes fine-grain attributes that need to be field-sampled, we recommend using a grid of vegetation plots over the entire study area to obtain these data. The FIA program is the most extensive source of existing plot-level data for habitat monitoring on forested lands (chapter 4, section 4.4.1), and these data have proven useful for deriving habitat attributes for a number of wildlife species. Several recent papers have shown the utility of the FIA system to provide large representative samples of quality environmental data for wildlife habitat modeling (Carroll et al. 2010, Dunk and Hawley 2009, Zielinski et al. 2010). Users need to evaluate if existing FIA data are sufficient at the scale of the habitat monitoring program, however, and at a scale appropriate for the emphasis species. In some instances, a higher spatial density of sampling points will be required to produce reliable habitat models over spatial extents the size of a national forest or smaller. Some Forest Service regions have intensified the FIA grid for analyses over smaller areas or at finer resolution. These intensified FIA grids are particularly valuable in obtaining higher resolution environmental data at the plot level for habitat modeling. Bear in mind, however, that FIA data eventually have their limitations even using grid intensification. The data may not be applicable for monitoring certain species whose habitat consists primarily of fine-grain attributes that are not measured at a sufficient scale using FIA protocols.

Whether using plot-, patch-, or landscape-level attributes, strive to use data sources and spatial scales for habitat monitoring comparable to those used in developing the model. If an important attribute for the emphasis species is not included in a model because of lack of data, or is derived from poor quality sources such that errors are high or from sources of very different spatial scales, then model results will be of unknown value, difficult to interpret, and harder to defend.

Specialized modeling approaches were developed to integrate habitat data derived from different spatial scales into composite analysis. For example, hierarchical variance partitioning (Cushman and McGarigal 2002) allows for quantifying the independent contributions of plot, patch, and landscape level variables to habitat quality. Similarly, hierarchical and multilevel models (e.g., Wilson et al. 2010) allow for robust multiscale analysis. As habitat quality is very often a product of multiple environmental variables at several scales, such hierarchical and multilevel modeling approaches are particularly valuable.

5.3.3 Apply the Selected Habitat Model

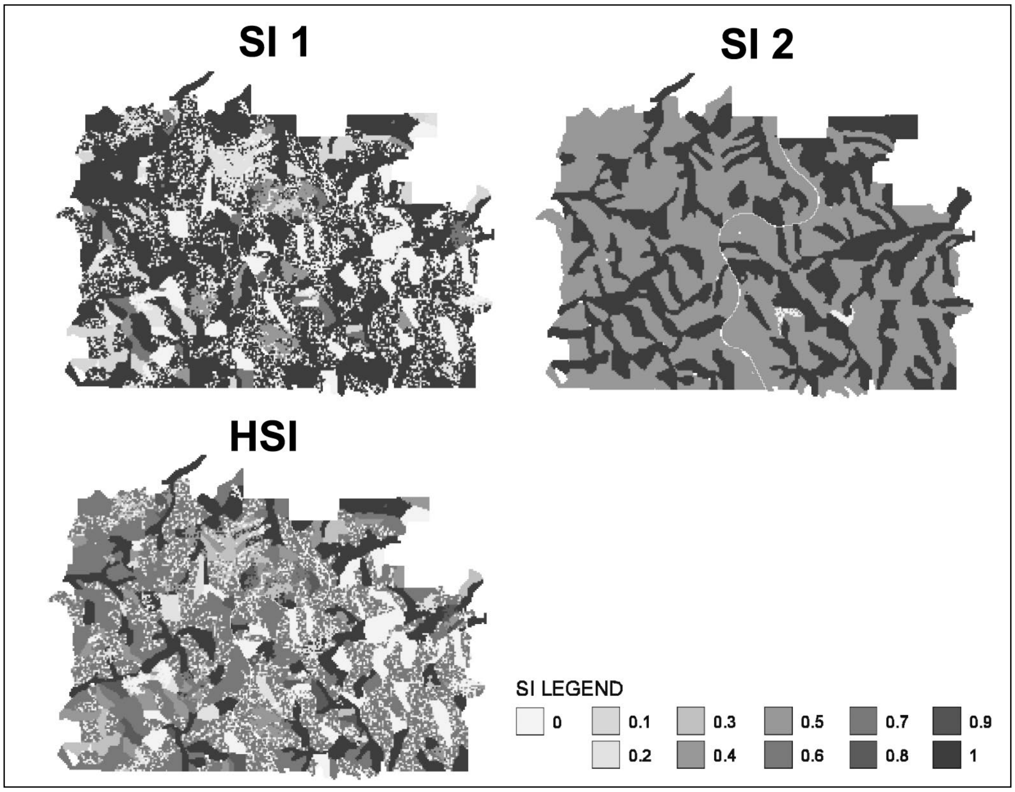
Although there are numerous ways for mapping habitat model outputs, two general approaches involve applying the model to either GIS coverages or plot data, followed by creating a habitat map through statistical modeling. The selected approach depends on the habitat model chosen and the extant data available for the monitoring program. When variables in the habitat model are available in extant or easily derived GIS coverages, the first approach applies. This approach involves simply applying the habitat model to the pixels (or polygons) in the GIS coverages to predict the occurrence of habitat (present/absent) or habitat quality (e.g., low, medium, or high, depending on the model output) at each pixel (or polygon). If some or all of the variables in the habitat model are not available as existing spatial layers throughout the area of interest but are available on a sample of ground plots, then the second approach applies. This approach involves applying the habitat model with data for each plot to calculate predicted habitat quality for the plot, then modeling these predictions as mathematical functions of extant GIS coverages across the monitoring area to produce a continuous habitat map. Hierarchical and multilevel statistical modeling approaches will likely be necessary to reliably combine plot and GIS data in this latter approach (Wilson et al. 2010).

In either case, applying the model will classify plots or pixels as habitat/not habitat in a binary classification, or as some measure of habitat quality in a continuous index or ordinal classification. To simplify the discussion, we describe an example using a binary habitat/not habitat classification. Depending on the nature of the model, several ways are available to implement this functional relationship. Typically, it will involve applying the mathematical function underpinning the model to the habitat attributes measured at each plot or pixel. Some common tools used to develop habitat models include linear regression, **logistic regression**, and classification and regression trees (Hegel et al. 2010). For more complex models, we advise using the same software tools to produce model predictions as were used in constructing the original habitat model. By applying the function to the observations (plots/pixels), the model will output predicted habitat for each plot.

Approach 1: Apply the Habitat Model to GIS Coverages and Map Through a Heuristic or Statistical Model

This first approach is an option in which all variables (or suitable surrogates) within the selected wildlife habitat model are available in complete spatial coverages and at the appropriate scale for the area defined in the habitat monitoring program. It is the simplest and least expensive method of mapping habitat, and relies on existing or easily derived map products that correspond closely with variables in the chosen wildlife habitat model. Examples of such map products include existing vegetation maps produced following the direction included in the Existing Vegetation Classification and Mapping Technical Guide (Warbington 2011). An easily derived habitat map might include data elements such as elevation and aspect from digital elevation models. These two types of map products can be combined using rule-based models in a GIS if known relationships exist between wildlife habitat and multiple landscape characteristics (figure 5.1).

Figure 5.1.—*Simple rule-based habitat models can be created and displayed in a Geographic Information System, such as this habitat suitability index (HSI) model for the southern red-backed salamander (*Plethodon serratus*) in the Mark Twain National Forest in southern Missouri. Suitability index (SI) 1 assigns greater suitability to pixels located in older stands, and SI 2 assigns greater suitability to pixels in more mesic land types as defined by slope and aspect. The HSI score is the geometric mean of the two SI values (adapted from Larson et al. 2003).*



Approach 2: Apply the Habitat Model to Plot Data and Map Through a Statistical Model

This approach is appropriate when some or all of the variables in a habitat model are not available as continuous coverages (i.e., wall-to-wall) but can be measured or derived only on a sample of locations throughout the monitoring area. In this case, use plot data (e.g., FIA data or data collected specifically for the monitoring program) to derive estimates of the plot-level attributes in the model and then predict habitat quality for each plot within the monitoring area by applying the model. Such cases will often use hierarchical or multilevel models (Wilson et al. 2010) because they combine habitat variables from different sources and different scales (such as FIA plots, digital elevation models, and other GIS coverages). Care must be taken to ensure that the sample of plot data is sufficient to reflect the distribution and condition of habitat across the analysis area. Generally speaking, for reliable application of habitat models, the analyst will require dozens to hundreds of plots to produce sufficiently precise estimates of habitat condition across the analysis area. The number of plots will depend on the size of the analysis area, the heterogeneity of habitat, and the complexity of the species-habitat relationship. Much larger samples of plots will be required for large, heterogeneous areas for species with complex habitat relationships.

After the habitat model has been applied to all plots (i.e., each plot has been labeled as habitat or nonhabitat) predictions can be made about the spatial distribution of habitat throughout the monitoring area. Therefore, the next step is to build a statistical mapping model to relate predictions of habitat presence or quality on the plots to coarser scale variables, such as topographically derived variables, remotely sensed imagery of vegetation, and derived products, which are available across the monitoring area. This mapping model can then be used to predict habitat quality across the area of interest.

Numerous statistical models can be used to accomplish the task. These models will vary in the level of effort required to generate them as well as their ability to successfully predict habitat quality. We describe two methods in the following section to illustrate a range of options for using plot data to build a habitat map for monitoring.

Simple Post-Stratification Model

This very simple mapping model involves stratifying the landscape based on existing GIS coverages related to variables in the habitat model. For example, strata might include high versus low elevation based on digital elevation models, or conifer versus hardwood versus nonforest based on an existing vegetation map. Similarly, strata might be defined by a combination of GIS coverages such as aspen (*Populus tremuloides*) stands at high elevation on southerly slopes, pinyon-juniper (*Pinus-Juniperus* spp.) stands adjacent to ponderosa pine (*P. ponderosa*) in certain geographic regions, or other combinations. The plots that fall in each of the strata can then be used to generate estimates of the proportion of habitat contained in each stratum, which is then mapped along with the standard error of these estimates. From a modeling perspective this approach is equivalent to modeling habitat/not habitat (observed or assigned to the plots) as a simple linear function of a suite of categorical predictor variables (strata). Ultimately, the prediction for any given pixel is simply the mean of the plot values (proportion of presences) for the stratum in which the pixel is found. For example, if 60 of 100 plots in the stratum were classed as habitat, every pixel in that stratum receives a score of 0.6. This process does not usually produce the most visually appealing maps, because a broad brush is applied to paint categories of proportion of expected habitat within each stratum, rather than providing a continuous prediction. These simple maps are directly tied to estimates produced by a forest inventory, however, which can be very helpful when looking for significant changes in habitat quantity or quality through time, or defending estimates in court.

Flexible Statistical Model

While the post-stratification approach described previously can capture much of the relationship between extant GIS data and observations of habitat quality on plots, more detailed information could be obtained by using more flexible statistical models to describe that relationship. When using flexible statistical models, the assignment of habitat/not habitat to inventory plots serves as the response variable, while plot characteristics, defined by ancillary spatial data sets (such as vegetation, topography, or other remote sensing products), are the explanatory variables. A variety of statistical modeling techniques can be used, including extensions to linear models (e.g., multiple linear regression: logistic regression, generalized linear models), generalized additive models, tree-based approaches such as classification and regression trees (Guisan and Thuiller 2005), Random Forests, Maxent (Phillips et al. 2006), or nearest neighbor imputation methods (chapter 4, section 4.5.2). Selected models can then be applied to all the ancillary data sets to produce a map of probability of habitat occurrence. The analyst then chooses a threshold in that probability surface based on application-specific criteria, above which a pixel is labeled as habitat.

Multiple logistic regression has emerged as the dominant statistical modeling tool in use today for developing single-species habitat relationships models (Hosmer and Lemeshow 2000). The logistic regression approach has a number of advantages. For example, logistic regression is relatively robust to departures from normality, produces easily interpretable models in which the relative effect and sign of each variable are readily apparent, and can be used in well-established multimodel and information theoretic approaches to identify the best alternative model within a large collection of candidate models (Burnham and Anderson 2002). Logistic regression is less effective, however, when species-environmental relationships are nonmonotonic (i.e., they do not consistently follow a mathematically functional relationship) or multimodal (i.e., the mathematical relationship has more than one peak). In particular, like all expressions of the generalized linear model, logistic regression is not appropriate when species express a multimodal response to multiple environmental gradients. In cases in which species-environment relationships are strongly nonlinear or multimodal, Random Forests has emerged as one of the more powerful prediction tools (Evans and Cushman 2009, Hegel et al. 2010). The major limitation of Random Forests is the difficulty in interpreting the species-environment relationship expressed in the model in terms of functional relationships using environmental variables. Maxent is an alternative modeling approach, which performs well when species-habitat relationships are complex and nonlinear (Phillips et al. 2006).

When compatible models must be built to predict habitat quality for multiple species, nearest neighbor imputation methods are a good choice (chapter 4, section 4.5.2; Ohmann and Gregory 2002). While maps in this latter case may not be as accurate for individual species, covariance between habitat quality for multiple species can be preserved.

For further understanding of these topics, we recommend the following papers.

- Cutler et al. (2007) provide an overview of Random Forests for classification problems.
- LeMay and Temesgen (2005) provide a brief summary of common imputation methods.
- Freeman and Moisen (2008) provide criteria for converting a probability surface into a presence/absence map.

5.3.4 Evaluate the Model and Provide Measures of Uncertainty

It is unwise to apply a habitat model developed elsewhere and assume that it will accurately reflect the habitat relationships and predict the habitat quality of a species of interest. Applying models developed in different regions may produce biased estimates of habitat quality and lead to poor management choices. Multiple court cases have indicated that for models to be defensible when challenged in court, they must be empirically validated. In actuality, a model can never be validated, in much the same way that a hypothesis can never be falsified. Johnson (2001) recommends that we evaluate models rather than validate them, because validation is an absolute term (something is either valid or not), whereas evaluation is a relative term.

The purpose of evaluation is to determine if the model is useful and if the model accuracy is sufficient for our needs. In addition, scientific defensibility requires demonstration that the model applies to the emphasis species in the analysis area. Therefore, evaluating the predictions of a habitat model by collecting independent data on the abundance or occurrence of the emphasis species in the monitoring area is important. Only by formally comparing predictions with observations of animals will it be possible to evaluate habitat model performance and produce rigorous estimates of error rates, which in turn are critical to legal and scientific defensibility of model predictions. In some instances, an existing model will be found to perform poorly when applied to a new geographical area. In such cases, we urge managers to seek partnerships with researchers to develop a new habitat model for the emphasis species based on local conditions and habitat relationships. Without evaluation, the performance of a model developed elsewhere to novel conditions will be unknown.

It is beyond the scope of this chapter to provide a complete description of the procedures for model evaluation. Generally speaking, however, such approaches involve collecting a large (in a statistical sense) and representative sample of abundance or occurrence data for the emphasis species in locations for which the model has produced predictions of habitat quality or quantity. When the model is applied to a collection of plots, then a new set of plots in the same area becomes the population of locations to be sampled for the emphasis species. If the model produces landscape maps, then each pixel is a potential sample location, and a sample is selected by stratifying across predicted habitat quality and collecting species occurrence data on as many widely distributed points as possible. The analysis then proceeds to compare predictions of habitat with observed occurrences in the validation sample. An error matrix is produced, describing omission and commission errors, accompanied by other statistical measures of model accuracy.

Although species occurrence data are essential for evaluating a habitat model, the opposite is not the case: the presence of habitat and/or habitat quality is not always a predictor of species' abundance (section 5.2.1,). Moreover, abundance is often a poor proxy for population performance (Van Horne 1983). The notion that habitat monitoring can serve as a proxy for population monitoring is based on two assumptions. First, that a threshold percentage of each type of habitat will ensure viability, and second, that the methodology used for monitoring habitat is sound. As referenced in section 5.2.1, Cushman et al. (2008b) empirically evaluated several of the key assumptions of the habitat proxy on proxy, including if habitat is a proxy for populations and if easily mapped and monitored habitat elements are proxies for habitat requirements for forest birds. Their results indicate that habitat relationships models, even those based on dozens of variables from multiple spatial scales, are unlikely to explain most of the variance in species abundances. Thus, the suggestion that habitat models can be used as surrogates for population monitoring to satisfy the viability requirement is dubitable. Secondly, they found that commonly used habitat elements derived from classified vegetation maps are equivocal proxies for habitat requirements, such that only a small fraction of species abundance patterns can be predicted based on the amount of mapped vegetation types in a landscape. Therefore, we caution managers that obtaining a desired condition of certain habitat attributes does not guarantee a desired population level for a species that depends on that habitat.

Population monitoring is essential for evaluating the assumed relationships between habitat and population status. Population and habitat monitoring should be considered together in forest planning (Cushman et al. 2008b, Cushman and McKelvey 2010, Noon et al. 2003, Schultz 2010). We strongly advocate for rigorous population monitoring for emphasis species to evaluate the link between coarse (vegetation monitoring) and fine (population status of focal species) elements.

5.3.5 Monitor Habitat Through Time

Select the monitoring intervals early in the monitoring design phase, i.e., how frequently to recalculate habitat quantity and quality. This decision is usually made on the basis of planning requirements. For example, a planning rule may require reevaluating ecological conditions within a plan area with respect to desired conditions statements every 5 years. Several considerations must take precedence, however. First, model predictions, strictly speaking, are valid only for the time that the data were collected. Given the financial and logistical limitations of the agency, plot data and GIS coverages are typically updated only occasionally and at long intervals. Therefore, ensure that all variables used in a model are of the same vintage and that, before recalculating habitat quality, all variables were updated using new measurements. If a model is rerun on data that include measurements from previous time periods, then the output will be less interpretable or defensible. Managers need to advocate for required resources to ensure a regular update of the environmental data for habitat models that are used for monitoring.

Another step in the monitoring design phase is to choose a metric to assess changes, spatially and statistically. If the model is applied to a collection of plots, then the product is predictions of habitat quality for those plots. Over multiple dates one obvious index to monitor change is the proportion of plots meeting criteria for habitat classes (such as habitat versus nonhabitat, or high, medium, or low quality habitat). As shown by the FIA program, when using large samples, proportion statistics can produce powerful estimates of the amount of habitat present in the monitoring area. When the model is applied to produce a map, then landscape pattern analysis is the appropriate approach to monitor change in habitat area and pattern (chapter 6). If habitat can be mapped accurately, landscape pattern analysis provides a large number of informative metrics to quantify habitat in the monitoring area, such as **connectivity**, fragmentation, and other spatial attributes of habitat pattern (chapter 6).

The goal of habitat monitoring is to track changes in the amount or quality of habitat in a plan area over time. Comparable and consistent models and environmental data as model inputs are essential. A conundrum exists, however, because adaptive management requires the continual improvement of management by incorporating improved knowledge of ecological relationships and the structure of the environment (Cushman and McKelvey 2010). Therefore, both models and data sources are expected to change over time, as additional research is conducted and incorporated into the localized meta-analysis, and as improved and updated inventory is conducted and new technologies for sensing, measuring, and mapping environmental variables are developed. Using habitat models as monitoring tools, therefore, will always be somewhat equivocal because of the impossibility of perfectly separating the effects of changing environmental conditions from changing models and data over time.

One simplistic way to avoid this dilemma is to fix a current model, data sources, scales, and methodologies and hold these items constant into the future to produce strictly comparable model predictions. Given the insufficiency of most current models, lack of extensive and accurate environmental data at multiple spatial scales, and lack of empirical data relating species to their environments, however, this approach of fixing model inputs cannot be accomplished for most species in most landscapes. Therefore, it is essential to adopt methods that flexibly incorporate improved knowledge.

The best approach for effective use of models in habitat monitoring is to keep detailed, formal documentation of the source of the model used, as well as details about the variables, the sources and vintage, spatial scale, and accuracy of data (chapter 9). This record is essential so that when the habitat model is reapplied in the future, often by new personnel, it will be possible to develop a model that will be as comparable as possible in its predictions to that used in the previous time period.

5.4 Conclusions

Most wildlife species require a complex suite of multiple resources and environmental conditions. To quantify and map habitat as an integrated entity more formal models of wildlife habitat are required. If a previously developed, locally defined habitat model for an emphasis species exists, and it has a modeling framework conducive for mapping and monitoring habitat, then feel fortunate and use it. More typically, it will be necessary to evaluate the usefulness of a model developed from another geographical area or time period. It is essential to evaluate if a model from another geographic area can be applied locally in the context of habitat monitoring. If several models are available from different geographic areas, conducting formal meta-analysis of published models and habitat relationships generally will provide the most reliable inferences about the habitat factors of importance to the species of interest and the values of their parameters in a predictive model.

After a model is selected the next step is to compile data required by the selected model for the extent of the analysis area. If an important variable for the emphasis species is not included in a model because of lack of data, or is derived from poor quality sources such that errors are high or from sources of very different spatial scales, then model results will be of unknown value, difficult to interpret, and harder to defend when used in a monitoring program. The next step is to apply the selected habitat model. Application of the model will classify plots or pixels as either habitat or not habitat in a binary classification, or as some measure of habitat quality in a continuous index or ordinal classification. After predictions are obtained it is essential to evaluate model performance and uncertainty. Scientific defensibility requires demonstration that the model applies to the emphasis species in the analysis area. Evaluating the degree to which the model predicts species occurrence in the analysis area is critical for legal and scientific defensibility. Evaluating the predictions of a habitat model by collecting independent data on the abundance or occurrence of the emphasis species in the monitoring area is important. The final step is to use the model to monitor habitat through time.

The presence of habitat and habitat quality are not always good predictors of species abundance (Cushman et al. 2008b), and abundance is often a poor proxy for population performance (Van Horne 1983). We caution managers that observing a desired condition of certain habitat elements does not guarantee a desired population level for a species that depends on that habitat. We also strongly advocate for rigorous monitoring of the populations of emphasis species to confirm the link between predicted habitat and actual population status.