Predicting Bird Habitat Quality From a Geospatial Analysis of FIA Data

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Abstract.—The ability to assess the influence of site-scale forest structure on avian habitat suitability at an ecoregional scale remains a major methodological constraint to effective biological planning for forest land birds in North America. We evaluated the feasibility of using forest inventory and analysis (FIA) data to define vegetation structure within forest patches, which were delineated from independent geospatial data sets of ecological subsection, forest type, and landform class. We used Swainson's warbler (*Limnothlypis swainsonii*, Audubon) as a model to demonstrate how to integrate FIA data with geospatial data sets to estimate and monitor habitat suitability for a priority bird species in the West Gulf Coastal Plain/Ouachita Mountains Bird Conservation Region.

Introduction

The goal of the North American Landbird Conservation Plan is to create landscapes capable of sustaining bird populations at prescribed levels (Rich *et al.* 2004). To achieve this goal, the plan identified a three-step process:

1. Develop rangewide population objectives for each bird species.
2. Allocate these objectives to specific regions (e.g., Bird Conservation Regions (BCRs).
3. Translate these population objectives to habitat objectives within each region.

The first two steps of this process have been completed for most of the land birds breeding in the United States and Canada (Panjabi *et al.* 2005) and it is at the third step where conservation planning efforts stand today for most species.

Translating population targets to habitat objectives requires the development of models that explicitly state the relationship between bird numbers and habitat conditions. Given the number of land bird species covered by the North American Landbird Conservation Plan (448 species), the diversity of habitats they occupy, and the range in quantity and quality of available information for these species, it is not surprising that many modeling approaches are being explored to establish these relationships. Statistical models (e.g., hierarchical models, neural networks, regression procedures) provide an objective assessment of patterns in data, but are generally most suitable when large representative data sets are available to parameterize them. Statistical models are data hungry because they require relatively complex functions to compensate for the biases inherent in counting wild bird populations (Morrison 1998). When sufficient data do not exist (e.g., rare, nocturnal, or hard-to-sample species), a Habitat Suitability Index (HSI) framework provides one of the few practical alternatives for modeling species-habitat relationships. HSI models use *a priori* information to identify variables that affect the quality of a habitat for a given species, and this information is also used to create functions that relate habitat suitability to these key habitat requirements (Schamberger *et al.* 1982). HSI models have the desirable properties of scalability (landscape-scale parameters such as percent forest in the landscape can be easily incorporated into these models), intuitiveness,

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and portability across sites, which make them useful in many circumstances (Larson *et al.* 2003).

Whether using a statistical or an HSI approach, current ecoregional-scale land bird planning relies mainly on landscape-scale spatial data (e.g., Dettmers *et al*. 2002). This is more a matter of necessity than preference, because spatially explicit site-level information (e.g., basal area) does not exist at the scale of an entire BCR (tens of millions of hectares), whereas landscape-scale data are much more readily available (e.g., landscape metrics derived from satellite image-based land cover classification); therefore, planning is limited to species that respond most strongly to landscape-scale factors (e.g., forest patch size preferences of the wood thrush [*Hylocichla mustelina*, Gmelin]; Driscoll *et al*. 2005). Because most species select habitat at multiple scales, our limited ability to assess habitat conditions at finer scales inhibits analyses of the suitability of an ecoregion for multiscale sensitive species.

Forest inventory and analysis (FIA) offers a potential data source to address these limitations. FIA data are collected to estimate the volume, growth, and condition of forest resources within large geographic extents (e.g., counties, states, ecological units, watersheds, or BCRs). FIA data could also provide information on habitat-specific forest structure attributes across large areas, which can be used to assess the suitability of an area for various bird species. Our objectives were to assess the utility of FIA data (1) to characterize avifaunal habitat structure in a spatially explicit manner at an ecoregional scale, and (2) to use this information to assess the sustainability of priority bird species in these landscapes.

Methodology

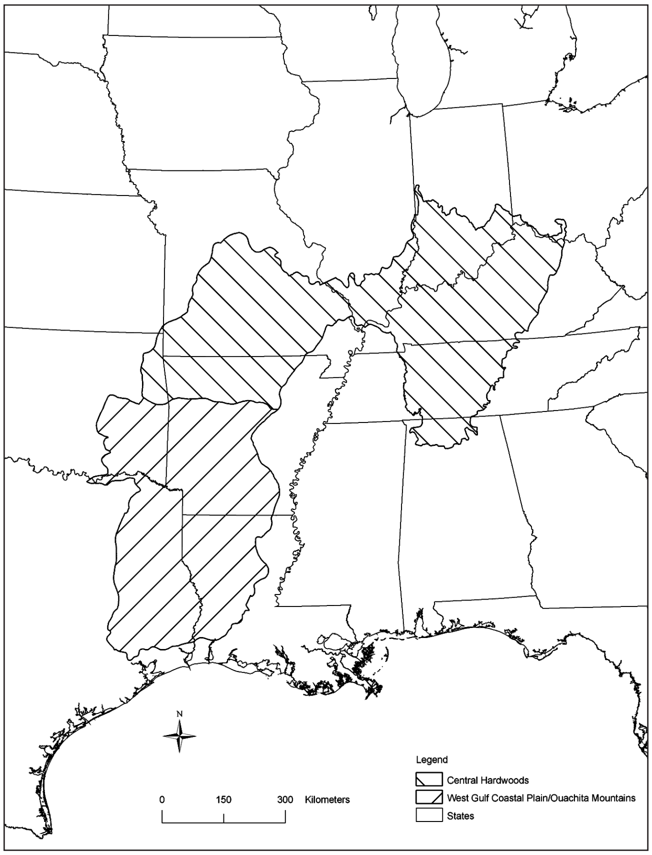
Avian Models

We developed HSI models for 40 priority bird species in the Central Hardwoods and the West Gulf Coastal Plain/Ouachita Mountains BCRs (fig. 1). We identified priority birds as species that utilize forested habitats with a total Partners in Flight regional combined score ≥ 20 (see Rich *et al*. 2004) or species designated as a Bird of Conservation Concern by the U.S. Fish and Wildlife Service in either BCR. To develop HSI models, we first performed a thorough literature review to identify site- and landscape-scale habitat factors that affected the occupancy, density, and/or productivity of each species. Empirical data derived from these sources formed the basis for individual suitability functions. We combined these suitability functions in biologically meaningful ways to produce overall habitat suitability estimates for density and productivity. Once initial models were developed, we solicited reviews from two to five experts for each species and revised models based on reviewer comments.

Geographic Information System Data

We constrained potential model variables to those available via nationally consistent geodata sets to maintain a uniform classification system across state boundaries within BCRs and to ensure our methodology was easily transferable to other forested biomes. We selected four nationally available geodata sets to define site and landscape conditions: ecological subsec-

Figure 1.—*Location of Central Hardwoods and West Gulf Coastal Plain/Ouachita Mountains Bird Conservation Regions, 2006.*



tions, the National Land Cover Dataset (NLCD), the National Elevation Dataset (NED), and the National Hydrography Dataset (NHD).

Our map of ecological subsections was based on the National Ecological Unit Hierarchy (Keys *et al.* 1995), which depicts relatively homogenous regions of topography, geology, climate, and potential natural communities. We therefore assumed subsection boundaries would capture a large amount of the variation in the broad-scale abiotic features that affect the composition and structure of the avian community within a BCR.

We used the NLCD 1992 to define the spatial location of forests and categorize forestlands into broad classes. NLCD 1992 delineates 21 land cover classes at 30-m resolution; 7 of these classes represent wooded land cover types that we used to define specific avian cover types: transitional, deciduous, evergreen, mixed, shrubland, orchard/vineyard, and woody wetlands (Vogelmann *et al*. 2001). Additionally, we included low-density residential as a forested land cover to capture the suburban shade tree habitats that are used by some priority species (e.g., orchard oriole [*Icterus spurious*, Linnaeus]).

Landforms (e.g., ridges, valleys) are local topographic features that can have a profound effect on both the flora and fauna of a forest community. Because no nationally consistent data set exists for this feature, we created our own classification from the nationally available NED, which maps elevation in meters at 30-m resolution (Gesch *et al*. 2002). We generated a landform geodata set from five NED-derived variables: relief, slope, aspect, local topographic position index (TPI), and landscape TPI. We separated areas of high and low relief by examining the standard deviation (SD) of elevation values within a 500-m radius moving window. We considered areas with an SD < 2 to be low relief and areas with an SD ≥ 2 to be high relief. We used a 5-percent threshold to separate high slope and low slope locations. We defined high-exposure (drier) slopes as those with aspects between 157.5 and 292.5 degrees (i.e., south by southeast to west by northwest) and all other aspects as low-exposure (moister) slopes. We placed areas lacking an aspect into a third category (flat). Derivation of TPI was based on a protocol developed by Jenness Enterprises (Jenness 2006), where the elevation at a pixel is compared to the mean elevation within a user-defined neighborhood. We calculated two separate TPI functions to highlight both local (500-m radius) and landscape (1500-m radius) effects and categorized the resulting spatial products into three classes: > 1 SD above the mean, > 1 SD below the mean, and within 1 SD of the mean. We defined 6 landform classes (floodplains, valleys, mesic slopes, terraces, xeric slopes, and ridges) based on the 108 unique combinations of values from the previously mentioned 5 variables.

Lastly, we used medium-resolution NHD (USGS 1999) to define the location of streams and other small water bodies that were not adequately captured by the NLCD but were important habitat cues for many priority species (e.g., Louisiana waterthrush [*Seiurus motacilla*, Vieillot]).

FIA Data

The geodata sets described previously allowed us to characterize landscape composition and structure, but we relied on FIA data to provide information about site-level forest structure. Staff from FIA's Spatial Data Services (SDS) center in St. Paul, MN, queried plot data to obtain unique plot numbers and location coordinates for 20,522 plots located within the two BCRs. These plots were sampled between 1986 and 1995, the years associated with the periodic inventories closest in date to the NLCD 1992 data set. Although true plot location coordinates were not made available to us, we were able to download publicly available PLOT, COND, and TREE tables for each state intersecting the BCRs (http://www.ncrs.fs.fed.us/4801/tools-data/data/). The three FIA tables for each state were imported into an Access (Microsoft, Redmond, WA) relational database, then combined and queried to generate tables containing plot-level summaries of the variables needed for our habitat models.

FIA does not measure all the key forest attributes for avian habitat selection on all phase 2 plots; therefore, we fit a regression equation to predict small (< 2.54 cm diameter at breast height [d.b.h] woody stem density (a derived phase 3 plot variable) from basal area and tree density (phase 2 plot variables). Similarly, we estimated overstory canopy cover from tree diameter and pole and sawtimber tree density based on an equation developed by Law *et al*. (1994). All other forest structure attributes were summarized directly from FIA data. We created a summary table containing all forest structure variables and joined this table to the forest patch attribute table via the FIA plot identification number common to both tables.

The sampling intensity of periodic and annual FIA plots is not adequate for spatial interpolation (e.g., kriging) on forest structural attributes because the distance between plots is much greater than the distance over which these attributes are spatially correlated (Coulston *et al*. 2004). The spatial limitations of FIA's sampling design, coupled with privacy protections that restrict public access to exact plot locations, necessitated the development of an ecologically meaningful protocol for populating each forest patch in our landscape with FIA plot attributes. To accomplish this, we devised a stratification procedure that first defined our BCRs as patches of unique combinations of variables (i.e., strata), then identified the FIA plots within each of these unique combinations, and, finally, assigned each patch an FIA plot that had the same strata characteristics.

We stratified each BCR by ecological subsection, NLCD forest class, and landform type because we believed that these variables accounted for the greatest amount of variation in forest structure at the landscape scale. To avoid creating singular strata (i.e., unique combinations of variables associated with only one FIA plot) that would prohibit data accessibility, we used a reduced number of strata. Thus, we aggregated NLCD into six classes: deciduous, mixed, evergreen, woody wetland, transitional-shrubland, and nonforest. This stratification produced a map that contained 36 unique strata combinations (6 NLCD classes × 6 landform classes) in each ecological subsection.

SDS personnel spatially joined actual FIA plot locations to these strata and returned an attribute table containing plot identification numbers (but not coordinates) and the values for each of the three strata. Plot identification numbers allowed us to link each plot and its known strata values to our summary table of FIA and derived forest structure attributes. Due to potential security issues associated with some linkages, strata values for a small proportion of plots were not provided to us. Nonetheless, our stratification scheme allowed us to associate approximately 97 percent of FIA plots on private land and 60 percent of FIA plots on public land with our geospatial strata.

An inherent artifact of this approach is the wide range of FIA data plots associated with each strata; common strata combinations contained > 200 plots whereas rare combinations contained ≤ 1. To prevent all patches in a single strata combination from being represented by a relatively small number of plots, we established a six-plot minimum threshold for definition of all strata combinations and developed decision rules to guide aggregation of strata to achieve a minimum of 6 FIA plots. First, we identified all strata combinations within an ecological subsection that contained < 6 FIA plots and determined the proportion of the subsection represented by that unique landform-NLCD combination. If a stratum covered < 5 percent of the subsection, we considered it a rare strata and combined it with a similar NLCD class within the same landform (e.g., plots from floodplain woody wetlands would be aggregated with plots from floodplain deciduous). If a stratum covered > 5 percent of the subsection, we combined strata among similar landforms within the same NLCD classes (e.g., plots from floodplain woody wetlands would be aggregated with plots from valley woody wetlands). Through iterative applications of these rules, we combined strata across similar NLCD and landform classes to achieve the six-plot threshold. In some small and predominately nonforested subsections, we combined strata from different subsections to reach the six-plot threshold. In these cases, we combined subsections within the same ecological section before combining between different ecological sections. Once all strata were assigned at least six FIA plots, we assigned an FIA plot to every forested patch in our study area. We used a modified random number generator to assign an FIA plot identification number to each patch from the corresponding pool of plots associated with each unique combination of strata.

Spatial Assignment of FIA and Derived Forest Structure Variables

To spatially map FIA variables, we created individual geodata sets of each forest structural variable by reclassification on the variable of interest. This produced geodata sets wherein every pixel in a forest patch received the attribute value (e.g., basal area) measured on the plot assigned to that patch. Because all attributes of a plot are assigned together, the covariance structure of the FIA data was maintained and improbable combinations of attributes (e.g., high sawtimber tree density and low basal area) were avoided. We caution that the final product of this procedure is a spatially explicit depiction of forest structure attributes; however, it is not spatially exact (i.e., each pixel has a value, but it is not necessarily the value that would be observed at that location). Despite this, because the final model outputs will be summarized by subsection and FIA data are representative of forest conditions within subsections, spatial exactness of these attributes within a subsection is not required.

Results/Discussion

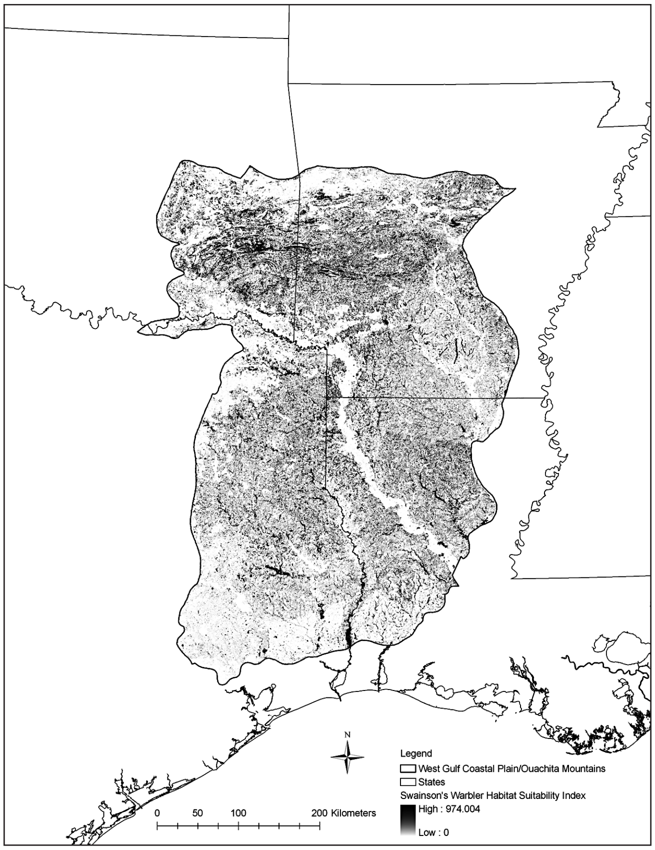
To illustrate our methodology, we present an example of a habitat suitability assessment for Swainson's warbler in the West Gulf Coastal Plain/Ouachita Mountains BCR. Swainson's warbler is a neotropical migrant that breeds in a variety of habitat types including canebrakes and palmetto thickets in mature bottomland hardwood stands in the Southeast, rhododendron thickets in the southern Appalachian Mountains, and 7- to 10-year-old pine plantations in eastern Texas (Brown and Dickson 1994). What these habitats have in common is a high density of small stems in the understory. Graves (2002) observed Swainson's warblers in habitats with a mean of 34,773 small stems per hectare and routinely found this warbler on sites with > 70,000 small stems per hectare. Regardless of location, Swainson's warblers are typically found in predominantly forested landscapes, and Eddleman *et al.* (1980) suggested contiguous forest tracts > 350 ha may be needed for the species to occur consistently.

Based on this information, we constructed an HSI model that contained six parameters related to bird density: landform, land cover, age class, forest patch size, percent forest in the local (1 km) landscape, and small stem density. The first suitability index (SI1) combined six landform (derived from NED), seven land cover (derived from NLCD), and five age (grass-forb, shrub-seedling, sapling, pole, and sawtimber; derived from FIA) classes into a single matrix that defined unique combinations of these variables. We directly assigned SI values to these combinations based on habitat suitability data from Hamel (1992). We also included forest patch size (SI2; derived from NLCD) in our model because of the presumed preference of Swainson's warblers for interior forest sites. We assumed forest patch sizes > 350 ha were adequate for Swainson's warblers and based a logistic function on data from Eddleman *et al.* (1980) describing this relationship. Nonetheless, forest patch size requirements are likely influenced by the percentage of forest in the local (1-km radius) landscape (SI3; derived from NLCD). Warblers in predominantly forested landscapes may use smaller forest patch sizes that may not be occupied in predominantly nonforested landscapes (Rosenberg *et al.* 2003). We considered landscapes with < 20 percent forest to be poor habitat and landscapes with > 80 percent forest to be excellent habitat (Donovan *et al*. 1997) regardless of forest patch size. We used the maximum of SI2 and SI3 where patch size and landscape composition influences were competing. Lastly, we included small stem density (SI4; derived from FIA) as a variable due to the affinity of this species for thick and dense understories in all occupied habitats. Site-level factors (landform, land cover, age class matrix, and small stem density) were weighed evenly in the overall calculation of habitat suitability by calculating the geometric mean of the individual SI values from the site-level factors. Furthermore, we weighed site- and landscape-scale factors evenly in the final suitability index score by calculating a geometric mean of site-level factors multiplied by the occupancy value from the maximum of the landscape factors (equation 1).

$$\mathrm{HSI} = (((\mathrm{SI1} * \mathrm{SI4})^{0.500}) * \mathrm{Max}\ (\mathrm{SI2\ or\ SI3}))^{0.500}$$

By applying these SI functions to the appropriate data layers, we derived estimates of habitat suitability for Swainson's warblers throughout the West Gulf Coastal Plain/Ouachita Mountains (fig. 2). By subsequently relating the SI values to known abundances from point counts and other surveys, we estimated abundance of Swainson's warblers within individual subsections and, in aggregate, the entire BCR. This process has permitted a transparent mechanism to assess the comparability of "bottom-up" population estimates to the "top-down" target population numbers in the North American Landbird Conservation Plan. Additionally, we have used this same approach to assess the suitability of the West Gulf Coastal Plain/Ouachita Mountains BCR for productivity. By coupling density and productivity SIs, we are able to more accurately estimate the sustainability of Swainson's warbler populations in these habitats.

Figure 2.—*Distribution of habitat suitability index values for Swainson's warblers, West Gulf Coastal Plain/Ouachita Mountains Bird Conservation Regions, circa 1992.*



These results have important implications for ecoregional land bird planning, particularly in predominantly forested landscapes. In agricultural landscapes where forest cover is limited, such as the Mississippi Alluvial Valley, forest patch size and structure have an overriding influence on the suitability of a particular site for forest birds (Twedt and Loesch 1999). Conversely, in forested landscapes such as the Central Hardwoods or the Gulf Coastal Plains, forest blocks are relatively large, and the main determinant of habitat suitability for many species is the structure of the forest within the patch (Conner and Dickson 1997).

The HSI approach described here was applied by combining FIA periodic inventory data with independently available geospatial data sets, all of which are benefiting from recent enhancements. Horizontal accuracy of FIA plot location coordinates continues to improve with advances in field protocols and Global Positioning System technology. The NED data set, used for modeling landform, is being edited and enhanced, with spatial resolutions of 10 m in some locales. Ecoregion and NHD delineations continue to be refined and integrated at multiple scales. The imminent completion of an updated NLCD (2001) not only will provide temporal benefits, but also will deliver per-pixel estimates of percentage of forest canopy and percentage of impervious surface. New geospatial data sets are on the horizon too, including a nationwide 30-m data set of forest stand height derived from digital elevation model and Shuttle Radar Topography Mission data. While these revisions and new data sets are expected to provide further support for wildlife habitat assessments, they still do not provide the detailed forest structure attributes required for many HSI models. In the absence of wall-to-wall mapping of forest structure via remote sensing (e.g., Light Detection and Ranging and high spatial resolution optical sensors), integration of FIA with geospatial strata offers a viable solution to assessing forest structure attributes over large areas. With the advent of annual FIA surveys, the HSI approach offers a cost-effective habitat monitoring tool for a variety of forest species over broad areas.

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