CHAPTER 22

Application of Models to Conservation Planning for Terrestrial Birds in North America

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Bird conservation in the United States is a good example of the use of models in large-scale wildlife conservation planning because of its geographic extent, focus on multiple species, involvement of multiple partners, and use of simple to complex models. We provide some background on the recent development of bird conservation initiatives in the United States and the approaches used for regional conservation assessment and planning. We focus on approaches being used for landscape characterization and assessment, and bird population response modeling.

BIRD CONSERVATION INITIATIVES

Bird conservation planning in the United States is guided by four major partnership-driven initiatives organized around taxonomic groups of birds that differ fundamentally in aspects of their basic biology or role in sport recreation (e.g., waterfowl, landbirds, shorebirds, and waterbirds). Each initiative has assessed the conservation status of each species under its purview based on parameters such as population size, population trend, and vulnerability to external threats. The assessment results have been used to determine which species are most in need of conservation action. Continental or national population goals and recommended conservation actions have been assigned to the species of highest priority. Each of these broad-scale plans has been (or is in the process of being) stepped down to ecoregional scales. The four plans attempt to provide basic guidance on the conservation needs of each species in the respective groups they cover, although the degree to which each succeeds in this effort depends to a large extent on the amount and quality of information currently available. In chronological order of initiative formation, the current guiding documents produced by the partnerships at the national or international scale are the North American Waterfowl Management Plan (NAWMP; NAWMP Plan Committee 2004), the Partners in Flight (PIF) North American Landbird Conservation Plan (Rich et al. 2004), the U.S. Shorebird Conservation Plan (Brown et al. 2001), and Waterbird Conservation for the Americas (Kushlan et al. 2002).

The development of these four national/international bird conservation planning efforts catalyzed the formation of the North American Bird Conservation Initiative (NABCI) in 1999 to facilitate integration and cooperation among the various initiatives. The North American Bird Conservation Initiative also provided more formal links between Canada, the United States, and Mexico. Supplementing the efforts of these taxonomically based planning initiatives are individual species initiatives for which strong constituencies have developed (e.g., Northern Bobwhite Conservation Initiative, North American Grouse Management Strategy). Prior to the development of NABCI, no consistent geographic framework existed in which to integrate the emerging regional conservation plans. As a response to that need, NABCI delineated ecologically distinct regions with similar bird communities, habitats, and resource management issues. These regions range in size from 52,000 to 2.9 million km^2 and are known as Bird Conservation Regions, or BCRs (Fig. 22-1).

With the development and implementation of the NAWMP in the mid-1980s came a recognition that the conservation actions required to restore declining populations needed to be applied at landscape scales and targeted to specific geographies where the biological impacts would be most profound. Regional partnerships of federal and state natural resource management agencies and private conservation organizations formed what are now known as joint ventures (JVs), understanding that their conservation actions needed to be coordinated to produce cumulative, positive, and ecologically relevant impacts. These JVs began to develop biological models (Cowardin and Johnson 1979, Cowardin et al. 1995, Reynolds et al. 1996) to link waterfowl numbers to specific acreage targets. These models have been further refined with the use of geographic information systems (GIS) to create spatially explicit hypotheses predicting where habitat acres could most efficiently and economically achieve target objectives. This process has recently been dubbed "Conservation Design."

United under the NABCI mission "to deliver the full spectrum of bird conservation through regionally based, biologically driven, landscape oriented partnerships," the original waterfowl JVs have now accepted responsibility for implementing conservation objectives for "all birds" (i.e., waterfowl, waterbirds, shorebirds, and landbirds). In addition, new JVs have formed to guide

FIG. 22-1

Regions for bird conservation planning in North America (n = 67 Bird Conservation Regions).

conservation efforts in areas where none previously existed. Each of these regional conservation partnerships is encouraged to "step down" national and international population goals for all birds to the BCR scale and to develop spatially explicit habitat objectives needed to reach identified goals.

The Five Elements process of conservation design (Will et al. 2005), as proposed by PIF for implementation of all bird conservation at the ecoregional scale, entails (1) Landscape Characterization and Assessment; (2) Bird Population Response Modeling; (3) Conservation Opportunities Assessment; (4) Optimal Landscape Design; and (5) Monitoring and Evaluation. This chapter addresses newly developing geospatial techniques for assessing landscapes and patterns of landbird distribution and abundance in response to habitat characteristics. These capabilities will allow conservation planners to evaluate the capacity of landscapes and ecoregions to support priority species at desired levels. Although the focus of this chapter is on landbird applications, the same or similar approaches could be applied to other species of conservation concern. We defer discussion of multispecies response modeling, imperative to the Fourth Element of conservation design, to Noon et al. (this volume).

GIS-BASED HABITAT ASSESSMENT AND LANDSCAPE CHARACTERIZATION

A landscape-scale assessment of the current amount and condition of habitat types across an ecoregion, along with a characterization of the ability of those habitat types to support and sustain bird populations, is fundamental to the conservation design process. Habitat assessment and landscape characterization should not only describe the current amounts of different habitat types across an ecoregion but also summarize patch characteristics and landscape configurations that define the ability of a landscape to sustain healthy bird populations. Ultimately, landscape characterization should provide the capacity to assess the relative current and potential contributions of different land parcels to meet conservation objectives most efficiently.

If we are to conduct a habitat assessment, land-cover data that can be consistently applied across biologically appropriate scales (e.g., ecosystems, ecoregions) must be available. The National Land Cover Dataset (NLCD) 2001 (Homer et al. 2007) provides "seamless, consistent" land-cover data at a 30 m^2 cell resolution for the conterminous United States (http://www.epa.gov/mrlc/nlcd.html; though see Thogmartin et al 2004*a*). However, NLCD 2001 is limited in its ability to distinguish between fine classifications within general habitat types and also has issues with accuracy in some regions. The current version of NLCD classified Landsat Thematic Mapper imagery into 21 categories of terrestrial land cover, but in the conterminous United States these include only three classes of forested upland (deciduous, mixed, and evergreen), one class of shrubland, one class of herbaceous upland (grasslands/herbaceous), and two classes of wetland (woody wetland and emergent herbaceous wetlands).

More detailed land-cover data are available from other sources for almost all portions of the United States, but none of these other sources can currently be applied in a consistent fashion across the entire country. Land-cover products from the Gap Analysis Program (GAP; http://gapanalysis.nbii.gov) provide more detailed habitat classifications on a state-by-state basis. In addition, regional GAP analysis projects are now underway, which will provide consistent land cover across major regions of the United States (e.g., Southwest, Southeast, and Northwest Regional Gap Analysis projects).

Another source of habitat information that could be useful for some bird conservation design applications is the Landscape Fire and Resource Management Planning Tools Project (LANDFIRE) data set (Rollins et al. 2003), which provides regionally consistent data across much of the United States for existing vegetation composition and structure, wildland fuel loads, historical vegetation conditions, and historical fire regimes (see http://www.landfire.gov).

Aerial photography is an alternative that provides a source of high-resolution, detailed land-cover data (Paine and Kiser 2003). It provides improved classification of specific habitat types and seral stages along with better definition of patch boundaries compared to land-cover data derived from satellite imagery (e.g., NLCD). However, aerial photography also suffers from human subjectivity in interpreting the photo images, inconsistency between observers, issues with photo availability and quality (they vary with year and season), and higher costs in time and money. Automated land-cover classification as implemented with, for instance, Feature Analyst (Visual Learning Systems, Missoula, MT), offers the potential for some future relief in these matters.

All the sources mentioned here are available for conducting assessments of the amounts of different habitat types across large spatial extents. Which sources are most appropriate will depend on the location and extent of the area of interest, the desired level of detail for discriminating habitat types, availability, and resources in terms of time and money available for conducting a project.

A critical consideration for the proper use of these spatial data is their accuracy. Many spatial data are most accurate at a minimum mapping unit that is coarser than the resolution of the data. For instance, the NLCD 1992 (Vogelmann et al. 2001) possessed a spatial resolution of 30 m^2, but the minimum mapping unit has been suggested to be at least 1 ha, an order of magnitude coarser. At a regional scale relevant to conservation design, such coarseness is generally not prohibitive. A larger issue is the limited and often poorly classified thematic resolution of the spatial data. Most image classification methods, such as classification trees, poorly classify rare land covers (Stehman et al. 2003). Given that many species are of conservation concern because of declines in the abundance of their habitat, such habitat misclassification is particularly problematic given that it makes it difficult if not impossible to correctly assess a species' habitat. In addition, any given land cover class label may not be consistent across map products. Thogmartin et al. (2004*a*) found in the NLCD 1992, for instance, that pasture/hay was confused with herbaceous grassland in the upper midwestern United States. Thogmartin et al. (2004*a*) also reported that emergent herbaceous wetlands were more likely to be mapped in one mapping region as compared to others despite each mapping region occurring in the same ecoregion. Further, it is unknown if the seams that were observed in the NLCD 1992 have been rectified for the NLCD 2001. These sorts of mapping errors can percolate into mapped models of species-habitat associations, yielding misleading conservation decisions.

In addition to an assessment of how much of different habitat types exist within a region of interest, a characterization of landscape attributes can be important. Landscape characterization typically involves calculating metrics describing the size, shape, and configuration of habitat patches as well as the level of spatial heterogeneity within the region. Landscape characterization is important because these patterns are often linked to ecological processes (Gustafson 1998), such as increased amounts of habitat edge or other measures of fragmentation relating to increased predation rates (Andren and Anglestam 1988, Hartley and Hunter 1998). Metrics that should be considered for measurement as part of landscape characterization include those for size and shape of patches (total area, core area, perimeter, width), landscape composition (proportional cover of a given land-cover class, richness and evenness of land-cover classes), configuration of patches in the landscape (contagion, dispersion, isolation), and neighborhood characteristics (distance between similar patches, distance to important features such as water or roads) (Li et al. 2005).

Various computer applications exist to assist in calculating metrics for landscape characterization. Most GIS programs (e.g., ArcGIS 9.2 [Environmental Systems Research Institute, Redlands, CA], GRASS 6.2 [GRASS Development Team 2006], ERDAS Imagine 8.7 [Leica Geosystems GIS and Mapping, Atlanta, GA], IDRISI Andes [Clark Labs, Worcester, MA]) have functions for calculating many of these metrics, although usually on an individual basis. Several software applications specifically designed for calculating these metrics make this process easier and faster. These include FRAGSTATS (McGarigal et al. 2002) and IAN (DeZonia and Mladenoff 2004). In addition, extensions for GIS programs such as ArcView and GRASS exist to enhance capacity of these programs for calculating these metrics.

In addition to land-cover data depicting amount and configuration of different habitat types across ecoregions, other data relating to the physical and climatic aspects of the environment can also be very useful in conservation design applications for birds, especially in developing species-habitat models. The National Elevation Dataset (NED) provides seamless 10 and 30 m digital elevation data across the conterminous United States as well as Alaska and Hawaii (<http://ned.usgs.gov/>). These data can be particularly useful in describing elevational and moisture gradients that are important in defining bird distributions. Other digital data sources relating to physical characteristics include the National Hydrography Dataset (NHD; <http://nhd.usgs.gov/>), which depicts surface water features such as lakes, rivers, and streams; and databases on soil types, the General Soil Map (<http://www.ncgc.nrcs.usda.gov/products/datasets/statsgo>) for the United States (updated in 2006 and providing data at a 1:250,000 scale), and the Soil Survey Geographic Database (<http://www.ncgc.nrcs.usda.gov/products/datasets/ssurgo>), which contains detailed county-level soils data and is scheduled for completion in 2008. Digital climatological data for use in GIS applications are also available for such metrics as temperature, precipitation, humidity, and radiation. Two examples of accessible databases are the Spatial Climate Analysis Service (<http://www.ocs.orst.edu/prism/>) and the Daymet U.S. Database (<http://www.daymet.org/>).

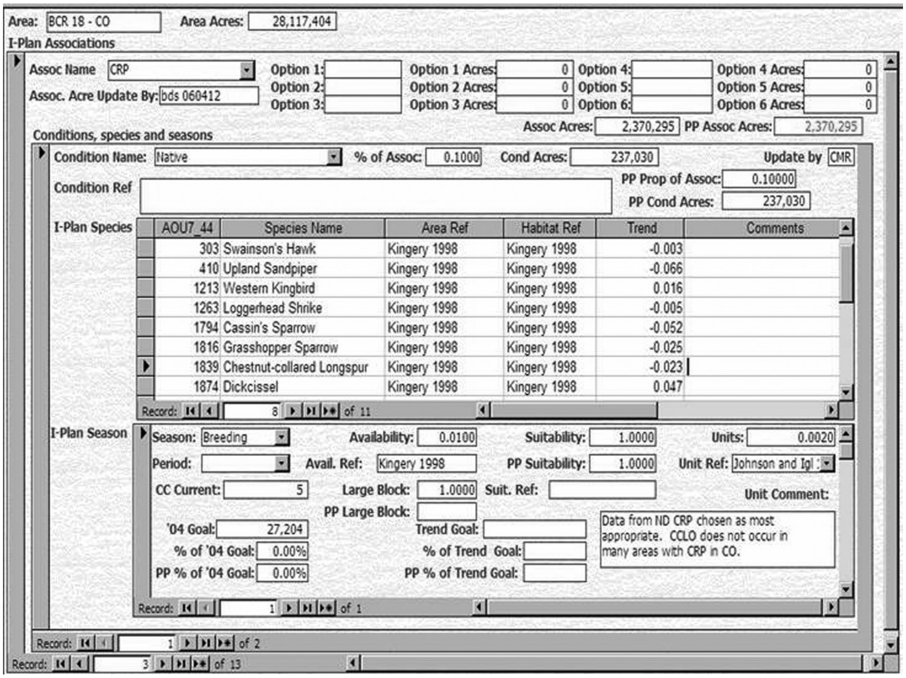
APPROACHES TO LINKING BIRD DISTRIBUTION AND ABUNDANCE WITH HABITAT ASSESSMENTS AT THE BCR SCALE

Database Models

Database models are decision support tools employing decision rules for characterizing species-habitat associations (Thogmartin et al. 2006*a*). The Playa Lakes Joint Venture (PLJV) employed a database decision support tool for modeling species-habitat associations in the Shortgrass and the Central Mixed-grass Prairie Bird Conservation Regions (BCRs 18 and 19, respectively). These two regions include portions of six states: Colorado, Kansas, Nebraska, New Mexico, Oklahoma, and Texas. The PLJV has regional responsibility for priority species associated with both wetland and terrestrial systems. The JV needed a tool that would enable planning for all 53 priority species within their landscape and allow users to view habitat implementation implications for all species simultaneously and quickly. In response to that need, JV staff and partners developed the Hierarchical All-Bird Strategy (HABS), a system for maintaining and manipulating bird information within a relational Access-based database linked to a GIS (Fig. 22-2; Dobbs 2006). The best available land-cover data were acquired from a variety of sources and integrated into a seamless layer encompassing the entire JV planning unit. Land-cover types were cross-walked and renamed to reflect commonalities (e.g., for New Mexico, "Chihuahuan Mesquite Upland Scrub" and "Western Great Plains Mesquite Woodland and Shrubland" were grouped together as "Mesquite"). Spatial data depicting the location of roads, wetlands, soils, hydrography, and other information pertinent to conservation planning were also brought into the GIS.

The primary geographical planning polygon (within the PLJV boundaries) in the HABS database hierarchy is the portion of a state within a BCR, termed an "area." One of the goals of the PLJV is the development of Area Implementation Plans based on the HABS database. Within each area, general habitat types are defined, and within each habitat type, various habitat conditions are quantified. For example, where the acreage of riparian forest is given as a habitat type, the amount of that acreage that is composed of late successional cottonwood forest with understory vegetation is reported. Because habitat conditions are not well classified by large-scale land-cover data sets, and they vary annually and seasonally, various sources of information and expert opinion were used to approximate percentages of condition within each habitat, assuming average climatic conditions. The amounts of habitat in all condition categories were ultimately expressed in number of acres.

Data on the densities of priority species were compiled from both published and unpublished literature and were assigned to each habitat condition; bird density data were standardized to acres. Where density data were not available


Area: BCR 18 - CO Area Acres: 28,117,404
I-Plan Associations
Assoc Name CRP Option 1: Option 1 Acres: 0 Option 4: Option 4 Acres: 0
Assoc. Acre Update By: bds 060412 Option 2: Option 2 Acres: 0 Option 5: Option 5 Acres: 0
Option 3: Option 3 Acres: 0 Option 6: Option 6 Acres: 0
Conditions, species and seasons Assoc Acres: 2,370,295 PP Assoc Acres: 2,370,295
Condition Name: Native % of Assoc: 0.1000 Cond Acres: 237,030 Update by CMR
Condition Ref PP Prop of Assoc: 0.10000
PP Cond Acres: 237,030
I-Plan Species

AOU7_44	Species Name	Area Ref	Habitat Ref	Trend	Comments
303	Swainson's Hawk	Kingery 1998	Kingery 1998	-0.003	
410	Upland Sandpiper	Kingery 1998	Kingery 1998	-0.066	
1213	Western Kingbird	Kingery 1998	Kingery 1998	0.016	
1263	Loggerhead Shrike	Kingery 1998	Kingery 1998	-0.005	
1794	Cassin's Sparrow	Kingery 1998	Kingery 1998	-0.052	
1816	Grasshopper Sparrow	Kingery 1998	Kingery 1998	-0.025	
1839	Chestnut-collared Longspur	Kingery 1998	Kingery 1998	-0.023	
1874	Dickcissel	Kingery 1998	Kingery 1998	0.047	

Record: 8 of 11
I-Plan Season Season: Breeding Availability: 0.0100 Suitability: 1.0000 Units: 0.0020
Period: Avail. Ref: Kingery 1998 PP Suitability: 1.0000 Unit Ref: Johnson and Igl :
CC Current: 5 Large Block: 1.0000 Suit. Ref: Unit Comment:
PP Large Block:
'04 Goal: 27,204 Trend Goal: Data from ND CRP chosen as most appropriate. CCLO does not occur in many areas with CRP in CO.
% of '04 Goal: 0.00% % of Trend Goal:
PP % of '04 Goal: 0.00% PP % of Trend Goal:
Record: 1 of 1
Record: 1 of 2
Record: 3 of 13

FIG. 22-2

A screen shot of the HABS Database details the components of the model for chestnut-collared longspur (*Calcarius ornatus*) in eastern Colorado in Conservation Reserve Program (CRP) grasslands (Dobbs 2006). "Assoc." = habitat name.

for an area, density values that were most similar in location and habitat condition were assigned, often adjusted using BBS relative abundance maps (Fig. 22-3; Sauer et al. 2007). Data comparability is an issue when dealing with data from multiple sources. In the case of the PLJV HABS database, the data from most of BCR 18 was from one source (Rocky Mountain Bird Observatory); this was not the case for BCR 19.

Additional correction factors were applied, if needed, to the species-habitat models to account for suitability or availability of habitat. Following are three examples of how particular data or needs were addressed:

1. Prairie-dog (*Cynomus* spp.) colonies host high densities of burrowing owls (*Athene cunicularia*), but Butts (1973) noted that in Oklahoma only 40% of all colonies across the landscape were utilized by owls. This correction factor was applied to the total acres of prairie-dog colonies in Oklahoma to modify estimates of number of owls.

2. Many grassland species in the region require a minimum patch size (Herkert 1994, Winter 1998, Johnson and Igl 2001). The standard management

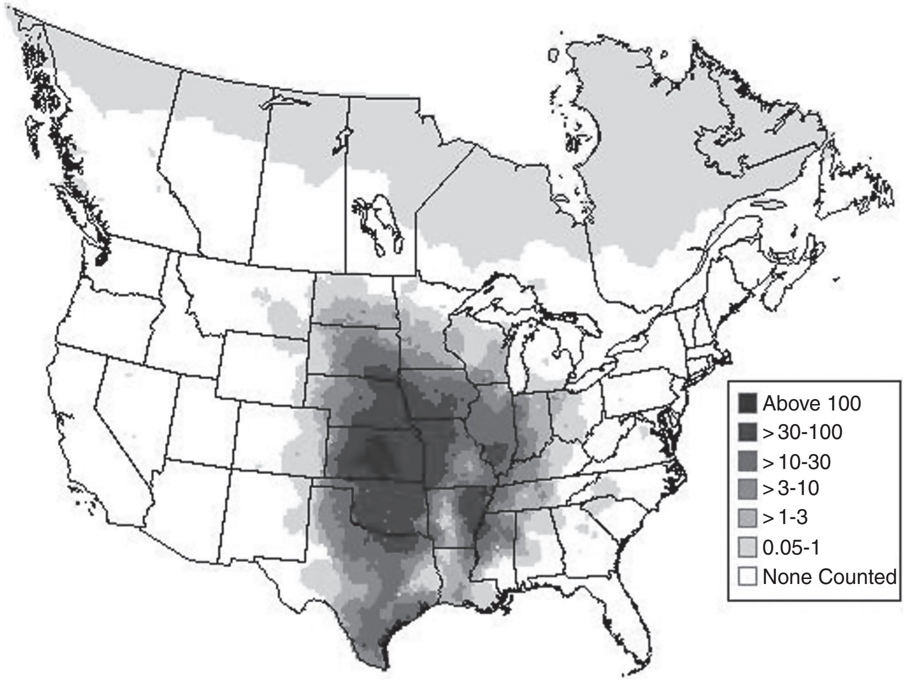


FIG. 22-3

North American Breeding Bird Survey relative abundance maps for dickcissel (*Spiza americana*) 1994–2003 (Sauer et al. 2007). Based on these data, the density for dickcissel from central Kansas was divided by 10 to determine an appropriate density for the eastern panhandle of Texas in the HABS database.

unit in the region is 160 acres. Because an initial analysis showed that less than 0.1% of all grassland areas were patches less than 40 acres, it was decided that accounting for minimum patch size requirements less than 40 acres was not necessary.

3. For species requiring more than 160 acres, more complex GIS models, similar to the Habitat Suitability Index (HSI) models described later in this chapter, were developed to identify blocks that are large enough to meet the needs of these species. For example, lesser prairie-chicken (*Tympanuchus pallidicinctus)* may require 5,000 acres or more of appropriate habitat (R. Rogers, Kansas Department of Wildlife and Parks, personal communication), and they are also affected by proximity to or amount of surrounding, potentially hostile habitat (Crawford and Bolen 1976). One of the lesser prairie-chicken model products that was included in HABS is a "large block factor" that describes the percentage of a particular habitat within a polygon that is actually suitable for this species (Fig. 22-4).

FIG. 22-4

Lesser prairie-chicken (*Tympanuchus pallidicinctus*) habitat in west-central Kansas. Occupied prairie-chicken areas are within gray lines (Kansas Department of Wildlife and Parks data) and PLJV-modeled habitat in crosshatch.

Bird densities are then multiplied by habitat condition acres and correction factors across all area habitats within HABS to arrive at a current estimated carrying capacity (a population estimate) for each area. HABS compares that figure to population goals and calculates the percentage of the goal already achieved. Habitat objectives, if needed to fully meet the goal, are determined by plugging varying acreage or percent of condition options into the HABS database to assess various means of reaching 100% of the population goal. Various habitat management options are typically available to meet a species' population goals, depending on the number of habitat types utilized or differing densities by condition. Once a habitat objective (needed number of acres of each habitat type) has been determined for one species, HABS can quickly project resulting declines or increases in other species' populations to be expected as a result of the targeted habitat changes for the first species. This provides planners with the ability to evaluate the differing effects of management on multiple species within the same area. Once the desired number of acres in each habitat condition in each area is determined, these recommendations are included in Area

Implementation Plans and made available to conservation practitioners. The HABS database and processes described here provide a valuable tool to managers for assessing and predicting impacts of habitat manipulations.

GIS-Based Habitat Suitability Models

Habitat Suitability Index models have been used to evaluate wildlife habitat and the effects of management activities and development since the early 1980s. Habitat Suitability Index models estimate habitat suitability on a scale of 0 (not suitable habitat) to 1 (highly suitable habitat) based on an assessment of resource attributes considered important to a species' abundance, survival, or reproduction (U.S. Fish and Wildlife Service 1980, 1981). Important habitat attributes (e.g., herbaceous ground cover, tree canopy cover, stem densities) are individually modeled based on a mathematical or graphical relationship, resulting in individual suitability indices (SIs) for each attribute. Overall habitat suitability, or the HSI, is calculated as some mathematical combination of the individual SIs. The HSI is typically calculated as the geometric mean of the individual SIs, although more complex formulas can be used, depending on how the SIs are thought to interact. Habitat Suitability Index models are developed from existing knowledge; this knowledge can be in the form of published studies, relationships derived from existing data or expert opinion, or hypothesized responses to habitat and other environmental correlates. Validation of HSI models is an important component of the modeling process because it tests how successfully the model has described the species-habitat relationship. Until models are validated, they represent hypotheses about these habitat relationships. However, even without final validation, HSI models may be useful for improved decision making and increased understanding of habitat relationships.

Traditionally HSI models were applied to an area or landscape habitat attributes were measured at a sample of locations within mapped land cover types or vegetation types and HSI values calculated. Habitat quality for the area was then summarized in terms of habitat units, which represent the product of the mean HSI score in each vegetation type and the area of land in that vegetation type, summed across the study area. Recent developments in HSI modeling have resulted in models that can be applied to large landscapes through the utilization of GIS. As with the database model previously described, these models typically rely on data layers derived from remote sensing and other existing spatial databases or large-scale inventories. Habitat Suitability Index values are calculated for each pixel in the landscape (Fig. 22-5A), and the distribution of HSI values for all the pixels in a landscape can be summarized in many different ways (Fig. 22-6; and see Dijak and Rittenhouse, this volume). Because of the focus on broad spatial extents and their use of GIS technology, these "next generation" HSI models can better address ecological and landscape effects on wildlife such as area sensitivity, edge effects, interspersion, landscape composition,

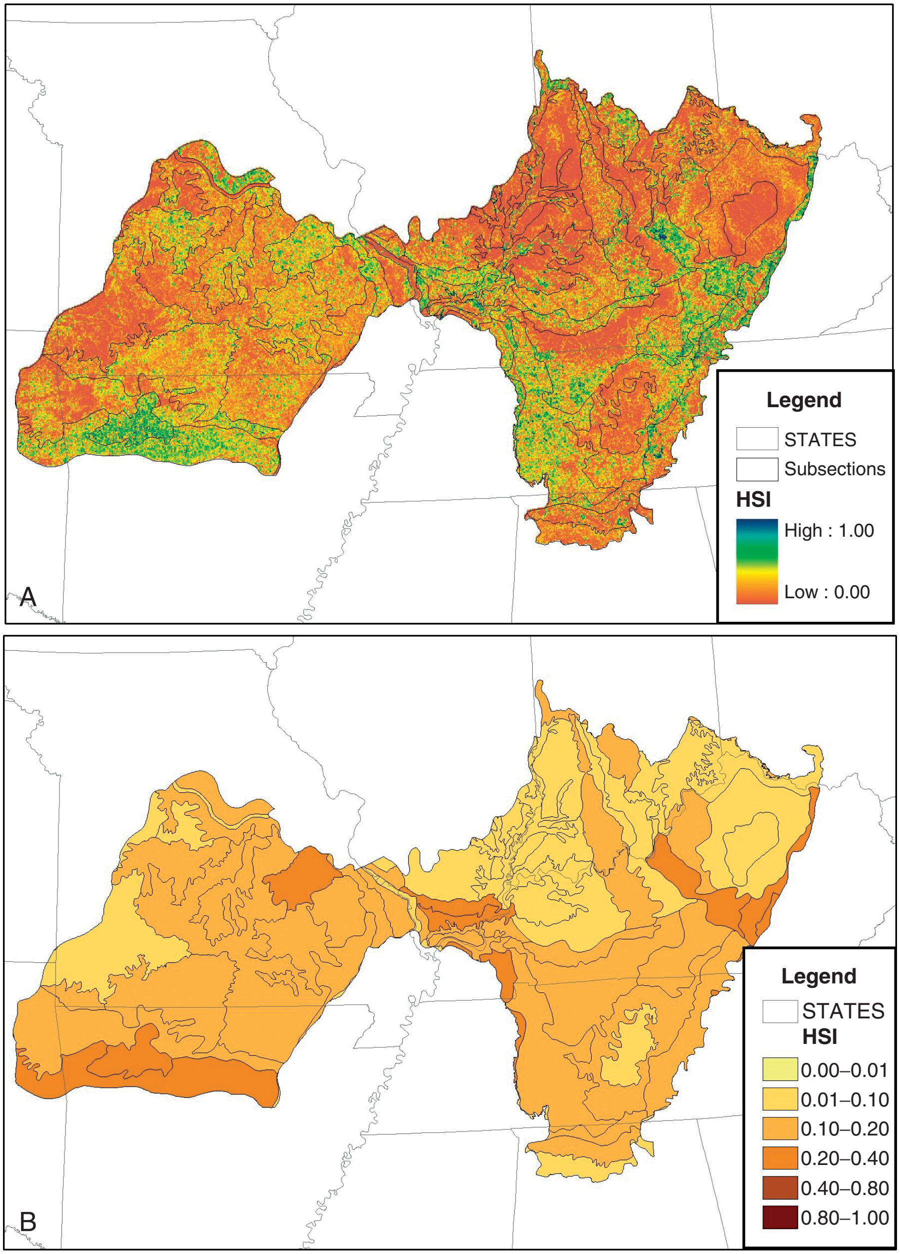


FIG. 22-5

Application of a habitat suitability model for Acadian flycatcher (*Empidonax virescens*) to the Central Hardwoods Bird Conservation Region in the Midwestern United States. Habitat suitability values are plotted at the 30 m pixel level (A) and mean habitat suitability values for ecological subsections (B). Because the models include data layers that were spatially interpolated from point data, the values are not spatially accurate at the pixel level but should be representative at the subsection level.

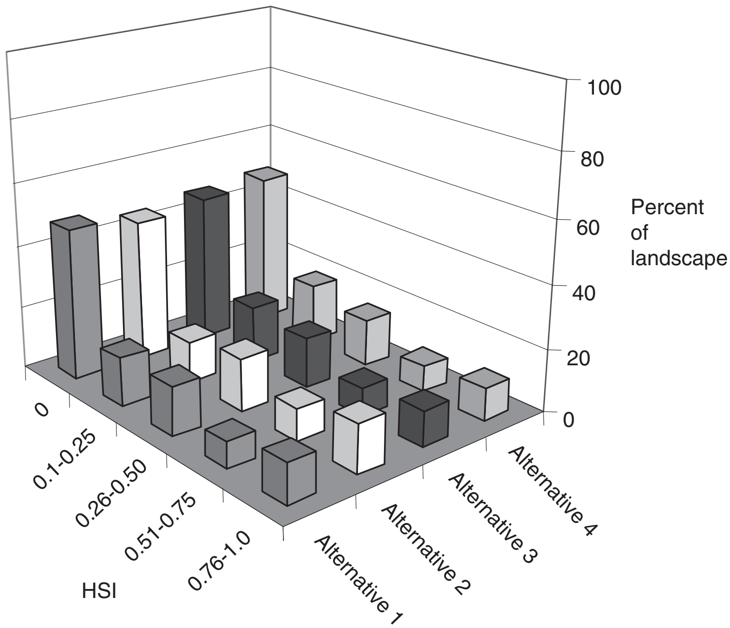


FIG. 22-6

Comparison of the distribution of HSI values for cerulean warblers in five classes of habitat suitability for four management alternatives on the Hoosier National Forest in Indiana, USA.

and juxtaposition of resources (Gustafson et al. 2001; Larson et al. 2003, 2004; Rittenhouse et al. 2007; Dijak and Rittenhouse, this volume).

Habitat Suitability Index models were recently developed for 40 bird species for application to bird conservation planning in the West Gulf Coastal Plain and the Central Hardwoods Bird Conservation Regions (Tirpak et al., in press). The goals of this approach are to summarize available habitat for high concern species in a region; to produce habitat-based estimates of bird numbers; and to link with other models in order to demonstrate how succession, disturbance, and management may affect the amount of habitat over time. A major challenge to applying models at this scale is the data needs. Any variables used in the SIs have to be mapped at a relevant pixel size across the entire region of interest. Landcover and landform features are generally available in GIS coverages spanning states, countries, or continents, but features such as vegetation structure may only be mapped as part of inventories on some managed lands such as state or national forests.

One approach to addressing this need in the United States is to spatially model vegetation structure based on plot data from the U.S. Forest Service Forest Inventory and Analysis (FIA) program (<http://fia.fs.fed.us>) and the GIS coverages mentioned previously. The FIA program measures vegetation features on plots distributed across forest land in the United States at a density of one plot per 6,000 acres. Tirpak et al. (2008) defined 36 potential strata in each ecological subsection within two BCRs by intersecting six possible NLCD forest classes with six landforms. For each forest patch defined by the intersection of NLCD class and landform class, they randomly selected an FIA plot from the pool in that stratum and applied its attributes to that patch. The result is a spatial map of any of the forest attributes measured by FIA. While at the subsection level, the overall composition and pattern are representative of forest conditions; at the pixel or patch level, they are not spatially accurate.

We plotted HSI values for 30 m pixels (Fig. 22-5A) and mean HSI values for the ecological subsection level (Fig. 22-5B) for the Acadian flycatcher (*Empidonax virescens*) in the Central Hardwood Bird Conservation Region. The model is composed of five SI functions that incorporate the following variables: landform, land cover, forest age class, distance to water, canopy cover, forest patch size, and percent forest. Coverages in GIS for forest age class and canopy cover were derived from FIA data as described previously. Because these methods produce maps of HSI values at a 30 m pixel size, there might be the temptation to interpret them at a finer scale (Fig. 22-5A). However, this would not be appropriate because suitability values derived from the spatially interpolated FIA data are not spatially accurate at the 30 m pixel scale but should be representative at larger scales such as ecological subsections (Fig. 22-5) (Tirpak et al. 2008).

These models can be used in bird conservation to identify subsections within BCRs with the highest habitat suitability to help focus conservation efforts. Because FIA data and national land cover data are periodically updated, the models can also be used to show changes in habitat suitability over time at the ecological subsection level, or to evaluate changes in suitability under simulated or hypothetical changes in landscapes. As part of model validation efforts, mean predicted HSI values were regressed on mean breeding bird survey counts at the ecological subsection scale. As expected, for most species, HSI values were positively related to the count data, demonstrating a link between predicted habitat suitability and population levels (T. Jones-Farrand, University of Missouri; J. Tirpak, U.S. Fish and Wildlife Service, personal communications). Furthermore, these regressions can be used to predict habitat-based estimates of population size for ecological subsections under similar assumptions used by Rosenberg and Blancher (2005) to estimate continental populations of birds from Breeding Bird Survey data. Future work by these investigators will determine if the addition of the spatially interpolated forest structure data from FIA substantially improved the models compared to those only based on existing spatial data such as land cover and land use, land form, and forest type. If spatially accurate input data are available, the resulting HSI maps will be spatially accurate at the level of resolution of the input data. This level of accuracy is more likely for project- or ownership-level planning than for regional-level planning.

Statistical Models

Various statistical techniques are useful for developing species-habitat relationship models (e.g., Pearce and Boyce 2006, Austin 2007); Scott et al. (2002) provided a good treatise on the subject. The majority of these habitat relationship models employ some form of regression model to characterize the relationship between species and their habitats. Such models can be developed for prediction or for elucidating ecological processes. Traditionally, the most commonly used statistical technique has been generalized linear modeling (Morrison et al. 1992, Trexler and Travis 1993, Jones et al. 2002). Continual improvements in the power and sophistication of personal computers and statistical software have given ecologists greater access to more sophisticated regression techniques and alternative modeling approaches. Some of these approaches are derived from classical statistical theory (e.g., hierarchical models), whereas others trace their origins to machine learning and data mining (e.g., classification and regression trees).

The most notable modern regression techniques are those based on generalized linear models (GLMs) that favor the logistic, Poisson, and negative binomial distributions over the normal (Gaussian) distribution (Hosmer and Lemeshow 1989, Agresti 1990, Menard 1995, Hastie and Pregibon 1997, Long 1997, Venables and Ripley 1997). All three of these regression approaches are parametric because they make the assumption that the data conform to a particular frequency distribution. Hierarchically based modeling techniques represent a more recent development (Bryk and Raudenbush 1992, Snijders and Bosker 1999, Thogmartin et al. 2004*b*). Hierarchical modeling is a generalization of linear modeling in which regression coefficients are themselves given a model whose parameters are also estimated from data. Hierarchical models, also called multilevel or random-coefficient models, are employed when correlated behavior occurs in the explanatory variables. Such correlated behavior often results from complex survey designs such as a clustered or multistage sample design. For instance, in any wildlife survey, observers may differ in how they count a species of interest (e.g., some observers may tend to overcount, whereas others may tend to undercount). This observer-related correlation is a nuisance, and failure to accommodate such nuisance behavior leads to undue bias in the parameter estimates for the remaining explanatory variables in the model.

As an alternative to using regression methods, it is possible to draw inferences about species-habitat relationships using approaches that are derived in other fields from pattern recognition and artificial intelligence (Ripley 1996). Of these techniques, the most commonly used approaches in ecology are classification and regression trees (CARTs; Breiman et al. 1984) and neural networks (Ripley 1996). Tree-based methods have the ability to detect structure in large, complex data sets in ways that might not be suspected *a priori*. Tree models are fit by a recursive binary splitting of the data set to create homogeneous groups (Clark and Pregibon 1992). The algorithms used in these analyses attempt to produce the most homogeneous groupings (nodes) of the response variable, thereby reducing the within-group measure of dispersion (i.e., variance or mean square deviance). Response variables can be either continuous (regression tree) or categorical (classification tree). Explanatory variables in either type of model can be continuous, categorical, or a combination of the two. Classification and regression trees have been widely used in developing habitat and landscape relationship models in ecology (Michaelsen et al. 1987, Moore et al. 1991, O'Connor et al. 1996, O'Connor and Jones 1997, Fertig and Reiners 2002). More recently developed techniques such as multivariate adaptive regression splines (MARS; Friedman 1991) have yet to see widespread use in addressing ecological problems. Unfortunately, these procedures require modestly sized data sets ($n \geq 150$; T. Jones, U.S. Fish and Wildlife Service, personal communication). We do not discuss these CART methods further in this chapter. Austin (2007) described these and other methods, which may be of interest to those developing species-habitat models.

With such a rich set of tools available to model species-habitat relationships, it can be difficult to determine which statistical method is best in any given situation. Survey data collected by biologists are often in the form of counts (e.g., birds counted along transects, seals counted at haul outs, bird and bat carcasses found at radio towers). When the sample size is sufficiently large and nonzero values are observed in most of the sampled units, the outcome may be considered continuous, and statistical methods that assume the data are normally distributed can be applied. As the sample size becomes smaller, however, at least three things can be expected. First, the number of counts observed in each survey decreases, and the distribution of counts becomes highly skewed (Fig. 22-7). Second, the proportion of survey units with zero values increases, thereby inflating the distribution of the outcome at zero. Third, differences in the number of counts that could have been observed in sample surveys, simply because of differences in the populations at risk of experiencing the event, become more pronounced, thus violating the underlying assumption of normally distributed data.

In these cases, it is usually more appropriate to employ Poisson-based regression models (Long 1997, Jones et al. 2002). The Poisson regression model assumes an underlying Poisson distribution, which is defined as

$$P(X) = (e^{-\mu}\mu^{\chi})/X!$$

where $P(X)$ is the probability of X occurrences and X is the count of events. As the mean (μ) of X increases, the Poisson distribution approximates a normal or Gaussian distribution (Long 1997), but the Poisson-based regression model is still often preferred because it is bounded by zero at its minima. Use of a linear regression model with count data results in the possibility of predicting a negative abundance estimate, a result that is not biologically sensible. There are two important assumptions of Poisson regression models. The first is that the data follow a Poisson distribution. In a Poisson, the variance is assumed to equal

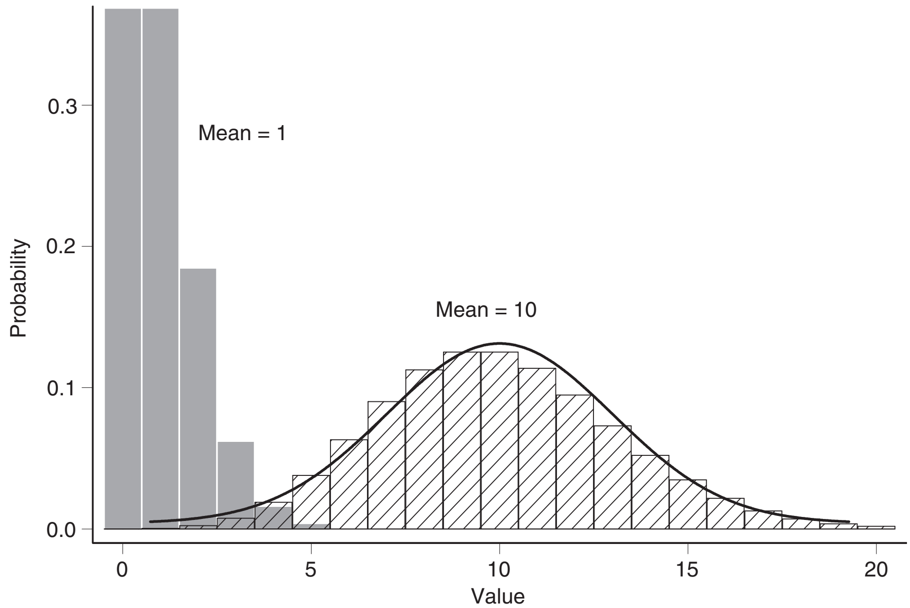


FIG. 22-7

Count data used in bird-habitat relationship modeling are often skewed, as in the case when the mean count for a survey (e.g., point count, Breeding Bird Survey route count) is 1. When the mean count of a survey reaches 10, the distribution is often roughly normally distributed (thick line).

the mean. The second assumption is that the data are independent. This latter assumption is typical of all generalized linear models but can be relaxed to accommodate various correlated data.

We present an example using Poisson regression for modeling bird abundance over large areas by modeling rare warbler abundance in the Appalachians of the United States with a hierarchical spatial count model (Thogmartin et al. 2004*b*, 2006*c*, 2007). These models were developed to aid in directing scarce conservation resources to those areas in which the resources would be most effective as opposed to broadly, but diffusely, applying the conservation resources over the region.

The relative abundance of worm-eating warbler (*Helmitheros vermivorus*) and Kentucky warbler (*Oporornis formosus*) in the Appalachians (Bird Conservation Region 28) was modeled as a function of explanatory variables. The response variable in these models was annual BBS counts collected between 1981 and 2001 (Fig. 22-8). Environmental explanatory variables included those associated with land-cover composition and configuration, topographical position, climate, brown-headed cowbird (*Molothrus ater*; a common nest parasite) abundance, deer forage, and annual acid rain deposition. This latter variable was

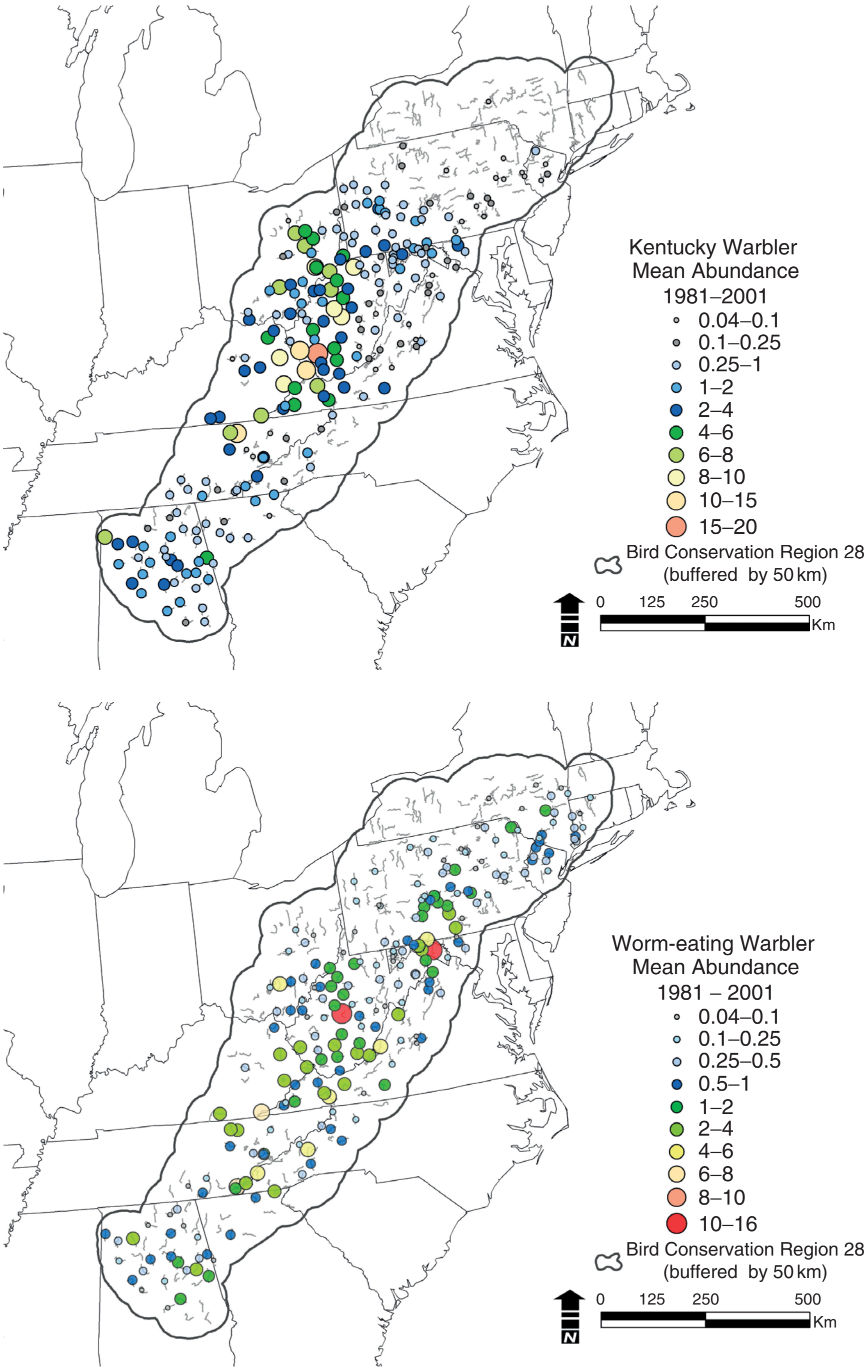


FIG. 22-8

(continued)

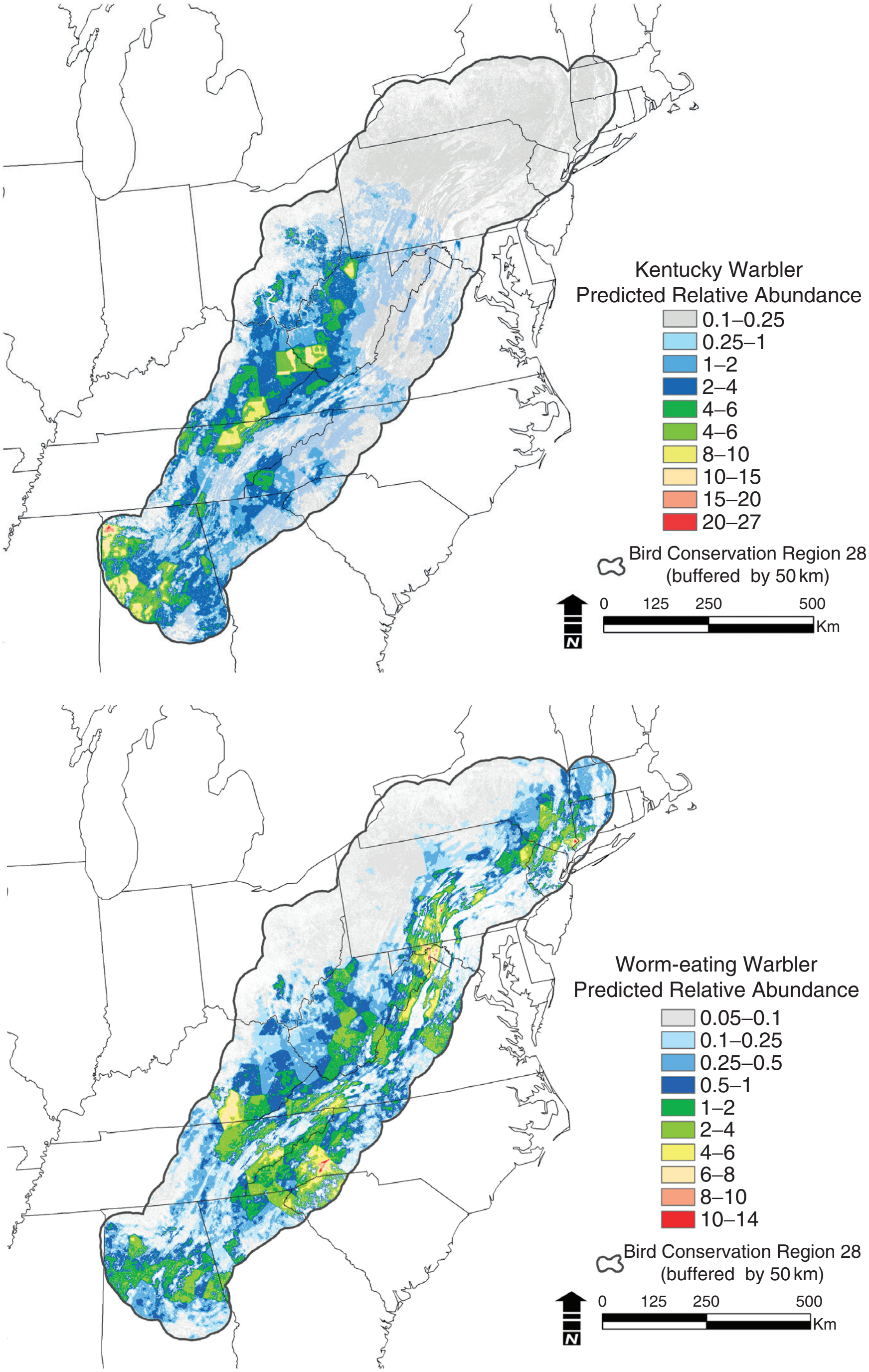


FIG. 22-8 cont'd

(continued)

FIG. 22-8 cont'd

(First Panel) Bubble plots indicating location and magnitude of mean Kentucky and worm-eating warbler relative abundance in the Appalachians, 1981–2001, as determined by the North American Breeding Bird Survey. (Second Panel) Predicted relative abundance circa 1995 for the Kentucky and worm-eating warbler in the Appalachians as determined by a hierarchical spatial count model.

considered in conjunction with soil pH to assess whether acid rain may be affecting regional warbler abundance through eggshell thinning and subsequent nest failure (Hames et al. 2002). The hierarchical aspect of these models included random effects associated with observer differences, year effects, and potential spatial autocorrelation in route counts (Thogmartin et al. 2004*b*, 2006*c*, 2007).

The model results for these two warblers were decidedly dissimilar (Table 22-1). Neither species appeared to be influenced by acid deposition, although there was a trend for higher abundance of both species in areas in which acid deposition was buffered by basic soils (W. E. Thogmartin, unpublished information). The commonality between the worm-eating and Kentucky warblers was in the effect of deciduous forest composition. As was expected, both species increased in abundance as deciduous forest increased in the landscape. The worm-eating warbler also increased in abundance as white-tailed deer (*Odocoileus virginianus*) forage increased and as precipitation decreased. The Kentucky warbler was more abundant in moister landscapes, and paradoxically in areas in which brown-headed cowbirds were most abundant.

Mapping these models was instructive in identifying spatial patterns in predicted abundance (Fig. 22-9) and therefore helping planners identify target areas for conservation actions. Both species were largely absent from the northern portion of the BCR. Kentucky and worm-eating warblers were more abundant west and east of the Appalachian divide, respectively. Peaks of predicted abundance for the Kentucky and worm-eating warblers occurred in southeastern Kentucky and western North Carolina, respectively.

One benefit of mapping predicted relative abundance is in locating gaps in our ability to manipulate or control conservation action (W. E. Thogmartin and J. J. Rohweder, U.S. Geological Survey, unpublished information) (Fig. 22-9). Fig. 22-9 illustrates that the location of the predicted peak of worm-eating warbler abundance is largely outside direct governmental stewardship (i.e., it occurs on land over which government or conservation agencies have little or no direct control). Much of the peak predicted abundance lies on private land to the north and east of the Green River Game Lands (North Carolina

Table 22-1 Parameter Estimates (with 2.5% and 97.5% Credibility Limits) from Spatial Hierarchical Count Models Describing Predicted Relative Abundance in the Appalachians, Circa 1981–2001, for the Kentucky and Worm-Eating Warblers. Estimates in Bold are those that Differ Credibly from Zero

	Kentucky Warbler			Worm-eating Warbler		
Variable	**LCL**	**Median**	**UCL**	**LCL**	**Median**	**UCL**
Slope of the temporal trend	−0.041	−**0.029**	−0.016	−0.012	0.004	0.021
Forest (%)	0.241	**0.483**	0.713	0.587	**0.990**	1.395
Deer Forage (%)	−0.112	0.012	0.138	0.162	**0.335**	0.499
Brown-headed Cowbird Relative Abundance	0.076	**0.272**	0.484	−0.193	0.107	0.403
Forest Edge Density (km/km^2)	−0.112	0.067	0.251	−0.150	0.069	0.293
Oak/Elm (%)	−0.058	0.117	0.284	−0.155	0.066	0.275
Mean Wetness Potential[a]	−0.500	−**0.287**	−0.078	−0.364	−0.076	0.212
Area-weighted Mean Patch Size of Forest	−0.148	−0.010	0.139	−0.563	−0.232	0.086
Wooded Wetland (%)	−0.187	0.086	0.347	−0.551	−0.272	0.016
Mean Precipitation	−0.487	−0.188	0.089	−0.801	−**0.441**	−0.089
Acid Deposition	−0.037	0.025	0.089	−0.055	0.032	0.120
Soil pH	−0.190	0.017	0.239	−0.279	−0.028	0.225
Acid Deposition × Soil pH	−0.048	0.010	0.067	−0.020	0.074	0.169
Intercept	−4.727	−0.642	2.210	−3.449	−0.809	0.506
Observer Effect	−4.070	−1.190	2.896	−2.405	−1.145	1.504

[a]*As determined by the topographic convergence index, ln([Catchment Area (m^2/m)]/tan(Slope(degrees)])).*

Wildlife Resources Commission) and Hickory Nut Gorge (The Nature Conservancy), respectively. Future efforts to conserve this species would benefit most by focusing conservation efforts in those areas where the species is predicted to be highly abundant.

A benefit of working with models of abundance, as opposed to those predicting occurrence (presence-absence), is that there is the potential to estimate population size. There is a need, in such an endeavor, to translate from a metric of relative abundance to true population size. The current impediments to direct estimation of population size from BBS data are too many to recount here (see Thogmartin et al. 2006*b*), but Rosenberg and Blancher (2005) have devised one approach that we employ here as a means of initiating discussions in this area. Using the methods employed by Rosenberg and

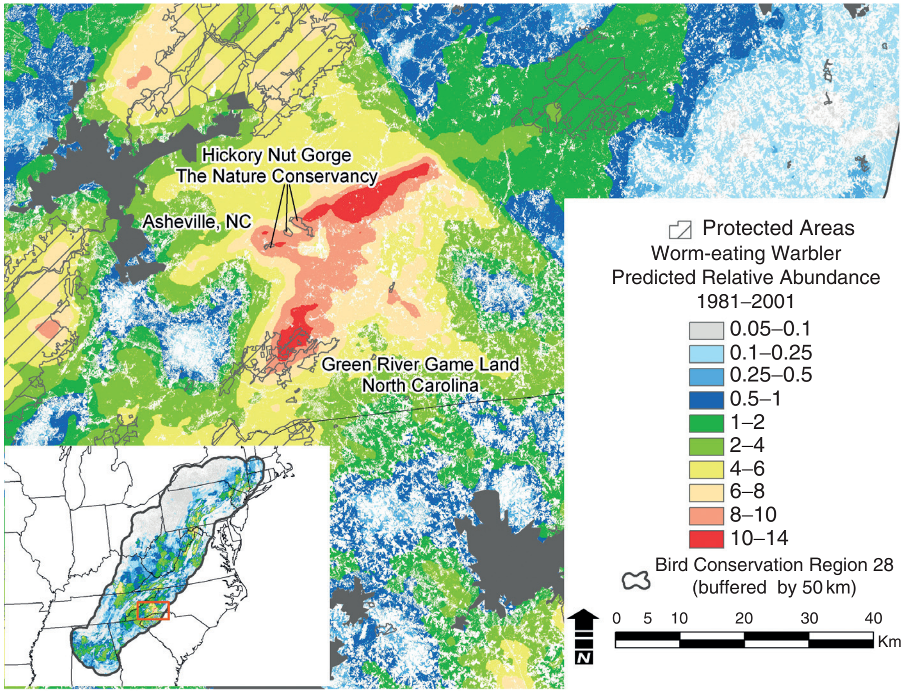


FIG. 22-9

Mapping the conservation estate relative to maps of predicted occurrence and abundance can aid in identifying gaps in stewardship. This example is conservation areas overlying worm-eating warbler relative abundance as determined from a spatial hierarchical count model.

Blancher (2005), we adjusted our previously described model estimates by factors accounting for the facts that (1) it is males of the species that are principally counted by the BBS; (2) these counts vary over the course of the survey day (i.e., typically highest nearest dawn); and (3) these species are generally heard at distances less than presumed by the standard survey methodology. Thus, the translation of relative abundance to population size occurs as 11,665 (relative estimate of the number of worm-eating warblers) $\times$ 2 (pair adjustment) $\times$ 1.29 (time-of-day adjustment) $\times$ 10.24 (detectability adjustment) = 308,180 worm-eating warblers in the Appalachian Mountains, circa 1995. Similarly, 21,181 $\times$ 2 $\times$ 1.11 $\times$ 4 = 188,087 Kentucky warblers circa 1995. These numbers are approximately 20% lower than those estimated for this region based on the global population estimates in the PIF North American Landbird Conservation Plan (Rich et al. 2004) (i.e., 389,000 and 243,600 birds, respectively), possibly because BBS sites are inequitably distributed in the Appalachians.

DISCUSSION

Not all the components of PIF's Five Elements of Conservation Design (Will et al. 2005) have been fully integrated into bird conservation planning at BCR scales in the United States. Most efforts to date have been directed toward (1) landscape characterization and assessment and (2) "population response" modeling focused on developing the ability to link data depicting the distribution and abundance of a bird species with habitat variables quantifiable across relatively large spatial scales. We describe here three conceptually different approaches that have been applied toward those ends. While we believe the products from those efforts are immediately useful and should help to establish a foundation for the next steps in the Five Elements process, each methodology has both similar and distinct sets of advantages and disadvantages. Planners and other end users should employ those methods most suited to their specific need and capacity. Some factors to consider are described next.

Complex Species-Habitat Relationships

Most species-habitat relationships are complex, involving many variables and interactions. Although the HABS database approach is perhaps the least able to incorporate such complex relationships, it is able to bring species-habitat relationship data from existing models into the database as a means of incorporating this information into the development of habitat objectives. The HSI and statistical models are better able to incorporate complex functions characterizing a species' relationship with its environment. These characterizations may occur over a range of spatial resolutions and extents.

Both the HABS database tools and the HSI models characterize the environmental requirements within which the species *may* occur (e.g., habitat suitability). Statistical models based on abundance surveys describe associations between the observed abundance of species and their habitats. However, if an important variable is missing from the design of any of these tools or models, any approach will likely misrepresent species-habitat relationships. As an example, many of the large-scale data sets used in model building may not contain habitat-specific or microhabitat variables that are known to be important components of species-habitat relationships (e.g., measures of bare ground, litter depth, vegetation density, species composition, etc.). Other important variables that often are not included are associated with nonbiological habitat factors or nonhabitat ecological factors such as competition, predation, or disease.

Data Constraints and Limitations

One of the biggest flaws in all these approaches is that the response data upon which they are based is often seriously constrained. Such constraints include temporal and spatial correlation and effects associated with the observation process (e.g., observer differences, species detectability). As an example, in the hierarchical spatial count models described previously, the most obvious limitation in the survey data is that they come from a roadside survey that does not account for imperfect detection (Thogmartin et al. 2006*b*,*c*). In addition, there are substantial gaps in the availability of landscape-scale bird data to be used in databases and models. As a result, conclusions must often be extrapolated from more localized data and relationships. Database and HSI models can be more conceptual and based on hypothesized relationships formulated from literature review, data, or expert opinion.

Assumptions

Because our knowledge of species-habitat relationships typically is limited and imperfect, it is important to identify the assumptions that are made in developing these tools or models. Habitat conditions are often difficult to quantify accurately, and deriving bird density estimates from different sources using different methodologies may not produce comparable and valid results. As a result, tools or models often must be based on limited data and conceptual knowledge of the factors that influence species' abundance, distribution, and vital rates. One of the concerns with the HABS database approach, for example, is that a large number of assumptions, many of them untested, enter into the basic models for many species. Uncertainty remains about whether species that are patchily distributed, or that occupy habitats not well represented within a GIS framework, are appropriately characterized by this approach. The key assumption associated with statistical models is that the final model that is chosen correctly characterizes the relationship between the response and the explanatory variables. Numerous model diagnostics and validation procedures are needed to assess the worthiness of a statistical model (Shifley et al., this volume), but too often this aspect of statistical model building is given short shrift. After a decision support tool or a model is developed, it is important that targeted research be conducted to test underlying assumptions in order to improve the accuracy of the estimates and models in the future.

Uncertainty

One of the weaknesses of HABS database tools and HSI models, as currently implemented, is that they do little to represent the uncertainty associated with the various assumptions in the models (see Millspaugh et al., this volume). This uncertainty arises from a number of sources including stochastic effects on species distributions, ambiguities in the presumed species-habitat relation, and inadequacies in data. However, Monte Carlo simulation can be used to calculate confidence intervals for HSI scores from uncertainty in input variables (Bender et al. 1996), and fuzzy math (Ferson et al. 1998) can be used to calculate reliability bounds on HSI scores from both statistical and structural uncertainty in the model (Burgman et al. 2001). Predictions from statistical models are usually accompanied by measures of uncertainty like standard errors or confidence intervals. These should be interpreted cautiously, however, because statistical models are usually built from data limited in their geographic scope, and statistical inference is appropriate only to the population sampled and sometimes only the sample. In these cases application of the model to a broader geographic area is a subjective inference, the observer assumes the data were representative of the broader area, and the original standard errors and confidence intervals are likely underestimates.

Model Fit

Because HABS database tools and HSI models are usually not evaluated using empirical data, it is unclear how well they capture the patterns in species occurrence and abundance, or in species-habitat relationships. Statistical models can be assessed by an array of goodness of fit procedures, measures of explained variability, measures of model parsimony relative to model fit, etc. Goodness of fit measures, however, evaluate how models fit the data they were built from. Usually, there is need to apply any of these types of models to a broader geographic scope than the original data. Therefore, validation with independent data is important for all these approaches. Some efforts are currently underway to validate HSI models developed for bird conservation planning in the Central Hardwoods and West-Gulf Coastal Plain BCRs (T. Jones-Farrand, University of Missouri; J. Tirpak, U.S. Fish and Wildlife Service; F. Thompson, U.S. Forest Service; D. Twedt, U.S. Geological Survey; personal communications).

Flexibility and Adaptability

The value of HABS database tools and HSI models, especially in an adaptive management context, is their flexibility and ability to be refined in the face of new data (e.g., new species, habitats, or habitat conditions). Unfortunately, this is rarely the case with most applications of statistical models, which upon their completion are often never revised. Statistical models are rarely updated in the face of new information, principally because of their "costly time to production" (although see below).

Spatial Scalability

Spatial scale is the integration of resolution and extent, and the ability of tools and models to be spatially scalable is important in conservation planning, which must incorporate decisions at multiple spatial scales. All the approaches mentioned here can scale to virtually any spatial extent. Where they differ is in the resolution to which they most appropriately apply. An asset of database decision support tools and the HSI models is that they are readily scalable. The HABS tool was designed to describe the area encompassed by the Playa Lakes Joint Venture and to operate at the spatial extent of a Bird Conservation Region × State intersection. It is possible to scale the applications down to the county level, but scaling below that level would not be appropriate. The relationships for the birds in the tool are fitted to conform to *a priori* notions for different areas at that scale. In HSI models, unless there is a specific recognition of the scales to which the relationships apply, the results of the models can be applied at any scale convenient to the user. The finest spatial resolution for the hierarchical spatial count model is ostensibly the finest resolution of the response (i.e., the BBS count). In the application described previously, the finest resolution is approximately 25 km^2 because the models are built from a route count, which is an aggregate of counts from the 50 survey stops on a BBS route. It is possible to map the model results at a finer resolution; Thogmartin et al. (2004*b*, 2006*c*, 2007) mapped at a finer resolution (1 ha), but there is some question as to the validity of interpolating to a finer resolution the results of a model derived from coarsely resolved data (McPherson et al. 2006). There are some efforts to statistically model species response using data from the individual stops on a BBS route (e.g., Hepinstall et al. 2002, Thogmartin 2002), which would then lower the "floor" of the spatial resolution to an area surveyed at a stop (i.e., 2–200 ha; Thogmartin et al. 2006*b*).

Future Projections

An important need in bird conservation is the ability to project real or hypothetical changes in landscapes and birds that may result from management decisions or environmental change. The HABS database method is capable of predicting these kinds of changes by plugging potential changes in habitat amounts and condition into the database to immediately project the effects on multiple bird species populations. If methods exist to update or project habitat and landscape conditions, both HSI and statistical models can be used to generate new predictions from these updated or predicted future conditions. For example, HSI models have been linked to outputs from LANDIS, a forest-landscape simulation model, to predict the consequences of forest management decisions, succession, and disturbance on wildlife habitat (Shifley et al. 2006). Similar approaches could be used to evaluate the simulated effects of urban and suburban development, fire, expansion of exotic plant species, and perhaps in the future, global climate change.

Time and Cost

The amount and kinds of resources required to produce the types of planning tools and models discussed here vary, and their component costs and time required are additional factors to consider when deciding which of the planning tools a user will develop. Comparing the products of each approach dollar for dollar or hour for hour is beyond the scope of this chapter; rather we will attempt to summarize the components and the relative amount of each component involved in each approach. First, each requires specialized software and computer hardware with above-average computing capacity; included in this component is the cost of maintaining these computer resources. Each approach also requires land-cover data; the end user must choose between low-cost and readily available data with lower resolution and higher quality data that might have to be purchased, reclassified in some way before it can be applied seamlessly across large landscapes, or newly created. Both the HABS database approach and HSI models require extensive literature searches. In addition, the database approach requires substantial time to populate the database (i.e., data entry). The kinds of technical expertise needed to work with sophisticated land-cover data sets, build complex biological models, and program computers will be a cost in each application, but likely is greater for statistical models than HSI models, and least for the database approach, the number of species being equal. In all cases, collaboration among this team of computer, mathematical/statistical, GIS, and biological experts is crucial to developing the tools or models that truly answer the questions being asked by conservation planners. Finally, all approaches become more time intensive as the number of species or habitat types to be addressed in the database or model increases.

Finally, each of these approaches has an inherent set of assumptions that should affect the user's confidence in, and use of, the products. They will undoubtedly misrepresent spatial patterns of bird population parameters at least somewhere on the landscape, even if just in response to changes in land cover and land use over time. The crucial importance of incorporating tool and model evaluation, assumption testing, and adaptive management concepts into conservation planning efforts is clear. However, the costs associated with these evaluations and refinements are not well understood.

SUMMARY

Partners in Flight (PIF), a public-private coalition for the conservation of land birds, has developed one of four international bird conservation plans recognized under the auspices of the North American Bird Conservation Initiative (NABCI). Partners in Flight prioritized species most in need of conservation attention and set range-wide population goals for 448 species of terrestrial birds. Partnerships are now tasked with developing spatially explicit estimates of the distribution and abundance of priority species across large ecoregions and identifying habitat acreages needed to support populations at prescribed levels. The PIF Five Elements process of conservation design identifies five steps needed to implement all bird conservation at the ecoregional scale. We reviewed the application of some newly developing geospatial techniques,

tools, and models that are being used for (1) landscape characterization and assessment and (2) bird population response modeling, the first two elements in the Five Elements process. Habitat assessment and landscape characterization describe the current amounts of different habitat types and summarize patch characteristics and landscape configurations that define the ability of a landscape to sustain healthy bird populations and are a valuable first step to describing the planning area before pursuing more complex species-specific models. Spatially linked database models, landscape-scale habitat suitability models, and statistical models are viable alternatives (in order of increasing complexity and data needs) to predicting habitat suitability or bird abundance across large planning areas to help assess conservation opportunities, design landscapes to meet population objectives, and monitor change in habitat suitability or bird numbers over time. Decisions by conservation planners about what approach to use in a particular circumstance should be based on their specific needs and capability and should consider (1) complexity of species-habitat relationships; (2) data constraints; (3) model assumptions, uncertainty, fit, flexibility, scalability, and ability to make future projections; and (4) cost and time required.

ACKNOWLEDGMENTS

The planning tools discussed in this chapter were first described collectively at a Partners in Flight workshop held in St. Louis, Missouri, in April 2006. The slides from these and numerous other presentations related to landbird conservation planning, brief biographies of authors, and other pertinent information can be viewed at <www.partnersinflight.org/events/conserv_design_wkshp_0406/default.htm>. We thank all those who participated in the workshop for their insightful questions and comments, which improved our ability to prepare this manuscript. We also thank M. Suárez and an anonymous reviewer for their review of an early draft.

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