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INTEGRATED BIRD MONITORING AND THE AVIAN KNOWLEDGE NETWORK: USING MULTIPLE DATA RESOURCES TO UNDERSTAND SPATIO-TEMPORAL VARIATION IN DEMOGRAPHIC PROCESSES AND ABUNDANCE

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INTRODUCTION

Demographic processes (birth, death, immigration, emigration) drive patterns in the distribution and abundance of birds. These demographic processes, in turn, are driven by many interacting environmental influences. Identifying relationships between environmental drivers, demographic processes, and bird distributions and abundances can lead to effective avian conservation and management (DeSante et al. 2005). Yet making these linkages across broad spatial extents and long time scales is a complex task involving collection and integration of many kinds of data from various sources. The Avian Knowledge Network (AKN: http://avianknowledge.net) represents a unique resource for identifying, accessing, and combining heterogeneous data sets, and for developing analytical techniques that can better inform bird conservation. Here we briefly outline the types of data housed within the AKN and advances and challenges for implementing exploratory analyses designed specifically to facilitate integrated bird monitoring.

DATA

Many types of avian monitoring data can be combined to lend insight into population change (Baillie 1990). The most commonly collected data types are presence-absence and count (observational) data. Indeed, broad-scale count data from the North American Breeding Bird Survey have been critical for assessing population status and trends of landbird populations and for setting conservation priorities (Rich et al. 2004, Sauer et al. 2008). Although useful for identifying spatial and temporal patterns in avian abundance and trends, such data do not typically provide information on demographic rates and so are limited in their ability to lend insight into causes of population change.

Broad-scale data on demographic rates of landbirds are primarily derived from networks of mist-netting and banding stations (Saracco et al., this volume). The richest source of these data for North America is the Monitoring Avian Productivity and Survivorship (MAPS) program (DeSante et al. 2004), for which data on roughly 800 000 individual birds has been collected at about 1000 banding stations between 1989 and 2007. MAPS uses constant-effort mist-netting data to index adult population size and productivity and capture-mark-recapture (CMR) data to estimate apparent adult survival, recruitment, and population growth rates for > 180 landbird species (DeSante and Kaschube 2007).

The AKN has created a data exchange schema for both observational data (>38 million bird observations are currently warehoused on the AKN) and, more recently, banding data (LePage, pers. comm.). MAPS data and other banding data sets are currently being mapped to this data schema and uploaded to the AKN. AKN has also accumulated spatially explicit data on at least 1500 environmental variables.

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ANALYTICAL ADVANCES AND CHALLENGES

One goal of the AKN has been to develop exploratory analyses that effectively screen huge sets of environmental variables to identify important predictors (and interactions) of bird distribution and abundance. Advances have derived largely from application of nonparametric machine-learning methods (computer algorithms that are designed to automatically identify patterns in a set of data) to observational bird data (Hochachka et al. 2007). Ideally, similar exploratory analyses would be applied to CMR data to identify important predictors of survival and recruitment rates.

Two principal challenges exist to the application of exploratory analyses to CMR data. First, application of machine-learning techniques would require incorporation of a parametric statistical CMR model within a machine-learning framework. Current machine-learning techniques apply to responses that are simple data points (e.g., a count or an indicator denoting presence). However, CMR data are not data points, rather they are vectors of ones and zeros (indicating encounter histories of individual birds) to which a parametric model must be applied to estimate the demographic rate of interest. We have begun to tackle this problem using a novel class of semiparametric statistical models that combines parametric and nonparametric modeling components within a Bayesian hierarchical modeling framework. This approach gives us access to the best features of both, including the ability to estimate uncertainty in predictions (from the statistical component), and the ability to efficiently detect important predictors (from the machine-learning component).

A second challenge to application of exploratory analyses to CMR data relates to the sparseness of these data compared to count or presence-absence data. CMR studies are conducted at a relatively few sites, in part, because of the intensive sampling effort (many repeated site visits) needed to precisely estimate demographic parameters. Furthermore, despite intensive local effort, precise site- and time- specific estimates of demographic rates for individual banding stations are difficult to obtain due to the 'data-hungry' nature of CMR models. The problem of data sparseness is often dealt with by pooling data across stations within a region (e.g., Saracco et al. 2008). Unfortunately, as data pooling increases, sample size (and spatial replication), and the number of covariates that can be screened and included in models, diminish.

One way to maximize spatial replication of CMR data is to incorporate a parametric spatial correlation structure into a hierarchical Cormack-Jolly-Seber (CJS) model (Saracco et al. in revision). This approach essentially borrows information from neighboring sites (or regions) to improve predictions at sampled sites and interpolate predictions between sites. Although these models will still typically require some degree of data aggregation, the scales at which predictions can be made are finer that those that could be attempted with standard analytical techniques. Additionally, because covariate data are often available for regions not sampled by mist-netting stations, inclusion of covariates in the spatial CJS model can improve interpolation of survival rates in those areas. Although the spatial model effectively improves sample sizes, it must still be recognized that samples will still be relatively small and will likely necessitate *a priori* identification of a small set of potentially important covariates based on exploratory analyses of count data (as described above).

Development and application of exploratory data analyses to CMR data represents just a first step to improving understanding of links between environmental conditions and bird populations. The next important step will be to integrate count, CMR, and environmental data within a single formal analytical framework. By integrating these various data types, we can improve the predictive accuracy of demographic rates and abundance through space and time. Advances in this realm include state space models that combine matrix population models with statistical models of count data (e.g., Thomas et al. 2005, Besbeas and Freeman 2006). These models, however, are in their infancy, and they do not include much complexity such as inclusion of spatial structure or large numbers of covariates. Advancing the state-of-the-art of these models will facilitate better use of the huge heterogeneous data sets contained within the AKN and provide critical insight into spatial and temporal variation in avian demographic rates and the distribution and abundance of birds.

LITERATURE CITED

Baillie, S.R. 1990. Integrated population monitoring of breeding birds in Britain and Ireland. Ibis 132:151–166.

Besbeas, P., and S. N. Freeman. 2006. Methods for joint inference from panel survey and demographic data. Ecology 87:1138–1145.

DeSante, D. F., and D. R. Kaschube. 2007. The Monitoring Avian Productivity and

Survivorship (MAPS) Program 2002 and 2003 Report. Bird Populations 8:46–115.

DeSante, D. F., M. P. Nott, and D. R. Kaschube. 2005. Monitoring, modeling, and management: why base avian management on vital rates and how should it be done?, pp. 795–804. *In* C. J. Ralph and T.D. Rich [eds.], Bird Conservation Implementation and Integration in the Americas. USDA Forest Service Gen. Tech. Rep. PSW-191.

DeSante, D. F., J. F. Saracco, D. R. O'Grady, K. M. Burton, and B. L. Walker. 2004. Some methodological considerations of the Monitoring Avian Productivity and Survivorship Program. Studies in Avian Biology 29:28–45.

Hochachka, W. M., R. Caruana, D. Fink, A. Munson, M. Riedewald, D. Sorokina, and S. Kelling, S. 2007. Data mining for discovery of pattern and process in ecological systems. Journal of Wildlife Management 71:2427–2437.

Rich, T. D., C. J. Beardmore, H. Berlanga, P. J. Blancher, M. S. W. Bradstreet, G. S. Butcher, D. W. Demarest, E. H. Dunn, W. C. Hunter, E. E. Inigo-Elias, J. A. Kennedy, A. M. Martell, A. O. Panjabi, D. N. Pashley, K. V. Rosenberg, C. M. Rustay, J. S. Wendt, and T. C. Will. 2004. Partners in Flight North American landbird conservation plan. Cornell Laboratory of Ornithology, Ithaca, NY.

Saracco, J. F., D. F. DeSante, M. P. Nott, and D. R. Kaschube. 2009. Using the MAPS and MOSI programs to monitor landbirds and inform conservation, pp. 651–658. *In* T. D. Rich, C. Arizmendi, D. W. Demarest, and C. Thompson [eds.], Tundra to Tropics: Connecting Birds, Habitats and People. Proceedings of the 4th International Partners in Flight Conference, 13–16 February 2008. McAllen, TX. Partners in Flight.

Saracco, J. F., J. A. Royle, D. F. DeSante, and B. Gardner. In revision. Modeling spatial variation in avian survival and residency probabilities. Ecology.

Saracco, J. F., D. F. DeSante, and D. R. Kaschube. 2008. Assessing landbird monitoring programs and demographic causes of population trends. Journal of Wildlife Management. 72:1665–1673.

Sauer, J. R., J. E. Hines, and J. Fallon. 2008. The North American Breeding Bird Survey, Results and Analysis 1966–2007. Version 5.15.2008. USGS Patuxent Wildlife Research Center, Laurel, MD.

Thomas, L., S. T. Buckland, K. B. Newman, and J. Harwood. 2005. A unified framework for modelling wildlife population dynamics. Australian and New Zealand Journal of Statistics 47:19–34.