FINAL REPORT

ADAPTIVE DECISION SUPPORT FOR LANDSCAPE-LEVEL CONSERVATION OF BIRDS IN EARLY SUCCESSIONAL HABITATS ON PRIVATE LANDS IN GEORGIA

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INTRODUCTION

Background of BQI

Early succession and grassland landscapes provide important breeding or wintering habitat to many bird species. However, much of this habitat in the southeastern U.S. has been lost to urbanization, reforestation, and to changes in agricultural practices (USDA 1995, 2001). In the latter half of the 20th century, the introduction of “clean farming” methods increased farm yields, but degraded habitat for a number of bird species (Best et al. 1995, Rodenhouse et al. 1995). Concurrently, populations of a number of grassland birds declined throughout the region since the mid-1960s (Sauer et al. 2001); of these, several, including grasshopper sparrow (*Ammodramus savannarum*), eastern meadowlark (*Sturnella magna*), and prairie warbler (*Dendroica discolor*), have been identified as species of management concern (Hunter et al. 1992, U.S. Fish and Wildlife Service 1995).

Of particular interest throughout the southeast, and especially in Georgia, is the plight of the northern bobwhite (*Colinus virginianus*) population. The northern bobwhite is a bird recognized and valued by many Georgians, and sport hunting for the bird generates much interest and revenue. However, the Georgia population of the bobwhite has decreased by 4.0% annually over the period 1966-2000, and by 5.0% annually within the period 1980-2000 (Sauer et al. 2001).

To reverse the northern bobwhite population trend, in 1999 the Wildlife Resources Division (WRD) of the Georgia Department of Natural Resources launched a conservation incentive program for rural private landowners. The Bobwhite Quail Initiative (BQI) is targeted at 17 Georgia counties of the upper coastal plain physiographic province. The objective of the program is to improve habitat quality for the northern bobwhite and for associated early-succession-habitat songbirds. Implicit assumptions in this objective are that (1) northern bobwhites respond to habitat modifications, and (2) habitat modifications beneficial to northern bobwhite populations are also beneficial to sympatric species; that is, the northern bobwhite serves as a suitable “umbrella” species for a suite of early-succession-habitat birds.

Habitat restoration across the landscape is effected principally through landowner financial incentives. Landowners, through consultation with WRD biologists, propose specific habitat modifications and activities to be pursued on each parcel nominated for enrollment in the program. All proposals are scored by the WRD, and those that meet a minimum score established by the WRD are enrolled in the program. A secondary function of the BQI is to provide technical assistance to landowners regardless of their enrollment status, or desire to enroll, in the program.

In addition to site visits to evaluate cooperator compliance, monitoring programs for bobwhite and winter songbirds are an important component of the program. The University of Georgia Warnell

School of Forestry and Natural Resources (WSFNR) is cooperating with the WRD to conduct these surveys both at enrolled (treatment) and non-enrolled (control) sites.

In its first two years of existence, the BQI demonstrated increases in northern bobwhite calling activity and abundance of wintering songbirds on treated sites relative to control sites. Despite the apparent early success of the program, the BQI cooperators have discussed among themselves many further questions:

1) What are the specific conservation objectives of this program? Are they based solely on habitat outcomes, on bobwhite outcomes, or on community outcomes? Are program costs to be recognized in the objectives? What defines success/failure of the program?

2) Are increased call counts (or songbird detections) indicative of increased bird abundance?

3) Have habitat modifications altered underlying survival and reproductive parameters of the bobwhite, or have they merely attracted outside birds and/or increased detection of a non-increasing population of birds?

4) Are habitat modifications beneficial to other early-succession bird species?

5) What trade-offs exist among multiple species for the same habitat management action?

6) Are certain habitat incentives more cost-effective than others for achieving conservation goals?

7) Are effects of habitat manipulations dependent on the landscape context?

Landscape-scale management, uncertainty, and adaptive management

Fundamentally, the BQI program involves the management of a large, agricultural landscape, involving numerous ownerships and complex ecological relationships. There are a number of implications of these factors. First, management decisions potentially operate at numerous spatial scales, from (at the broadest scale) statewide incentive programs, to (at the local scale) the decision of landowners to participate, and if so, specifically how. Second, the ecological processes that drive bobwhite and other bird populations are controlled by many factors, themselves operating at multiple scales, and only partially responsive to management actions. This sets up a situation where the predicted relationship between management actions (BQI) and bird response is both complex, and subject to great uncertainty, a theme in common with other complex systems (e.g., Conroy et al. 2003).

Adaptive resource management (ARM) explicitly recognizes uncertainty in resource decision making; seeks an optimal resource decision given the available decision alternatives; and seeks to reduce uncertainty via prediction-based monitoring (Walters 1986, Johnson et al. 1997, Johnson and Williams 1999, Conroy et al. 2003). We approached the BQI problem in the framework of ARM, and developed a decision model based on hierarchical modeling of available data, as the first step in a prototypical, adaptive landscape approach to bobwhite/ early succession bird restoration.

OBJECTIVES

We conducted a collaborative study to bring a more adaptive focus to the BQI and deliver consequent conservation benefits to this region of Georgia. Although the program now has certain adaptive elements in place, it lacks mechanisms to explore the effect of alternative decision options, to exploit information feedback from the system to better guide future decision making, and to make optimal decisions under scientific uncertainty. Our work provides a decision support system that will provide important benefits to the state resource agency. Among these are:

1) Identification of a measurable community-based management objective that captures the agency's resource goals;

2) The ability to explore the cost-effectiveness of alternative decisions;

3) The ability to make superior management decisions in the face of uncertainty with respect to competing, plausible biological hypotheses;

4) Full exploitation of monitoring data to reduce uncertainty and to increase management performance over time; and

5) Greater resultant transparency and public accountability in the decision-making process.

METHODS

Decision modeling framework

We employed the principles of adaptive resource management and adaptive optimization (Walters and Hilborn 1978, Walters 1986, Williams 1996) that have been used successfully in the harvest management of waterfowl (Johnson et al. 1997, Johnson and Williams 1999) and in habitat management for forest birds (Moore et al. 2005). Our work proceeded in 4 stages (Nichols et al. 1995):

1) Quantifying the objective function,

2) Specifying decision alternatives,

3) Developing and optimizing alternative decision models, and

4) Adaptation of decision making using monitoring results.

Quantifying the objective and specifying decision alternatives

Our first step was to quantify an objective function that captures community goals for bird conservation. We started the process of quantifying the objective by convening a meeting with BQI project personnel to discuss program goals (Appendix C). In this meeting we identified outcomes that are requisite in evaluating whether the program succeeds or fails. We also determined the extent to which the program pursues community rather than single-species objectives; whether objective outcomes are measurable by the current (or by any) monitoring program, and decided whether and how program costs should be factored in to the objective function.

In this same meeting, we worked with the BQI project personnel to identify a set of decision alternatives that may be expressed in decision models. These addressed management options focused at the field and at the landscape levels.

Developing and optimizing alternative decision models

We worked with project collaborators – both at the June 2003 workshop, and in subsequent meetings and conference calls – to identify and construct a set of decision models. Theses models collectively express the current, principal biological uncertainties in managing habitat for the stated objectives. That is, each model, for a given management action, predicts unique (relative to other models) population outcomes according to a plausible biological hypothesis. These alternative hypotheses were derived from published or unpublished data, based on ecological theory, or based on our collective, expert opinion. We strived to obtain models that could predict quantities that serve as input to the objective function and that can be assessed against monitoring data.

Given the objective function, the decision set, the set of alternative models, and a measure of prior belief (relative certainty) in each model, an optimal decision may be sought for any state of the managed system (Williams 1996). The complexity of the system state, models, and decision set will dictate the optimization approach used. For sufficiently simple models, dynamic optimization (Dreyfus and Law 1977) may be used; otherwise, a simulation-based or heuristic approach is required (Williams 1989). We used primarily simulation-based exploration of alternative decisions, but also considered formal optimization approaches.

Adaptation of decision making using monitoring results.

The last stage of our work provides a mechanism that links monitoring results to model predictions, whereby model belief weights can be adjusted and future decision making can be adapted to the acquisition of new knowledge. Because of the discontinuance of monitoring programs midway through our study, this effort is largely hypothetical, but does provide a basis for setting monitoring priorities, assuming the eventual re-ramping of monitoring programs for BQI. In addition, our efforts provide a decision-making context for the design of monitoring efforts elsewhere within the bobwhite range.

Study area

The BQI program was initiated with three focus areas that included 17 counties in the Upper Coastal Plain of Georgia (Figure 1). The three focus areas were composed of East (Bulloch, Burke, Jenkins, and Screven Counties), Central (Bleckley, Dodge, Emanuel, Houston, Laurens, and Treutlen Counties), and Southwest Regions (Colquitt, Crisp, Dougherty, Lee, Mitchell, Sumter, and Terrell Counties). This research was conducted on sites in all counties except Colquitt, Crisp, Houston, and Mitchell Counties.

Major land uses in all three regions consisted of intensive row crop agriculture and timber/fiber production. Agricultural row crop production was dominated by cotton, peanuts, soybeans, corn, and winter wheat. Center-pivot irrigation was commonly used to irrigate crops in the Southwest and Central Regions, and was used less frequently to irrigate crops in the East Region. The agricultural fields in the study area tended to be large in size with little or inadequate transition zones capable of providing suitable bobwhite habitat. Historically, fencerows or hedgerows that were composed mainly of scattered trees and shrubs with an abundance of grassy and weedy understory separated two or more fields. Today, these important transition zones have either had changes in their vegetative structure that make them unsuitable bobwhite habitat or they have been eliminated to create one contiguous crop field out of two or more smaller fields. Forest production in the study area was dominated by plantations of loblolly pine (*Pinus taeda*) and slash pine (*P. elliotti*), although longleaf pine (*P. palustris*) plantings were increasing in all regions. In the first three to five years after pine plantations are established, good bobwhite habitat often exists. Afterwards, pine plantations become too dense to allow adequate understory vegetation growth, and bobwhite habitat is lost until thinning and prescribed fire or other soil disturbance can be applied to increase herbaceous understory (Rosene 1969). The majority of pine stands in the study area had basal area and understory vegetation characteristics that did not constitute suitable bobwhite habitat.

Field methods, data collection, and spatial data organization

Covey-call-count indices were used to evaluate bobwhite populations on sample BQI and non-BQI sites over a broad regional scale (13 of 17 potential counties). During covey-call-counts, observers listen for the “koi-lee” covey-calls (Stoddard 1931) given by bobwhite (almost always before sunrise) during autumn. Before conducting call-count surveys, observers were trained by listening to recorded covey-calls and by spending several mornings in the field listening to calling coveys pointed out by experienced observers.

Covey-call-count surveys were conducted from mid-October to mid-December on a sample of fields including those enrolled in the BQI program from 1999 to 2001. At least 500 meters separated each survey point to minimize duplicate observations between surveys conducted in the same area. Survey points were set up at least one day in advance of the survey to ensure that observers could efficiently locate points the morning of the survey. Observers were instructed to minimize disturbance when traveling to survey points on the morning of the survey. Surveys were not conducted during periods of sustained rainfall. Each survey utilized one of three potential covey call techniques: quadrat surveys, point counts, or two-observer surveys.

Quadrat Surveys

The quadrat technique utilizes a 0.25-km^2 (25 ha, 500 x 500 m) quadrat to survey calling coveys. Four observers are required, with one observer positioned along the midpoint of each quadrat line. Observers were instructed to arrive at survey points at least 45 minutes before sunrise, and surveys officially began 40 minutes before sunrise. Observers recorded compass bearings, estimated distances, and approximate locations for each calling covey detected on standardized data sheets and field maps. Once the first call was detected, calling coveys were recorded for a 10-minute interval in order to minimize duplicate observations (as coveys often begin to move and initiate their daily activities soon after calling) and to standardize survey methods. Once the survey period expired, observers met to compare results in order to determine individual covey locations. Each unique covey location was plotted on a final field map. For each covey that was detected by more than one observer, the intersection of compass bearings to the covey was used to plot the approximate location. If only one observer detected a particular covey, the estimated distance to the covey along the compass bearing was used to plot the approximate location. Surveys were ended at the official time of sunrise if no calls were detected by this time.

Point Count Surveys

Point counts (single-observer call-counts) were used to survey bobwhite populations on remaining sample sites in 1999 and 2000, and all sample sites in 2001. It was assumed that an observer could hear calling coveys at a distance of up to 500 meters (W. E. Palmer, Tall Timbers Research Station, personal communication). A single observer was positioned where as much of the area of interest as possible was covered by the assumed maximum hearing distance. Survey protocol for point counts was the same as for quadrat surveys, and approximate locations of detected coveys were determined by estimating distance to the covey along the compass bearing.

Two-observer Surveys

In 2000, a few two-observer call-count surveys were used. However, these made up a very small portion (about 13%) of the total number of call-count surveys conducted in 2000. Going into the 2000 field season, it was assumed that the 350-meter two-observer design would be a reasonably quantitative and less labor-intensive survey method compared to the quadrat method. Time constraints prohibited employment of many such surveys, and this technique was discontinued by 2001. Observers were spaced approximately 350 meters apart. Survey protocol for two-observer surveys was the same as for quadrat surveys.

Spatial Organization

For each survey, we determined a centroid which would represent the location of the survey in a geographic information system (GIS; Figure 2). A centroid was also determined for the fields which had contracts with BQI during the study period (Figure 3). We then created a nested grid of hierarchical landscape levels based on biological and management factors (Figure 4). The finest level consisted of a 1-km^2 grid considered to be the field level units (“Field”, L1). This level represents the individual BQI fields and the attendant factors. This field level was then nested within a grid of 9-km^2 polygons (“Complex”, L2). We believe that this field complex level encompasses the likely scale at which northern bobwhite community dynamics are occurring. These field complexes were then nested within a grid of 144-km^2 cells (“Aggregation”, L3). This scale represents a grouping of BQI management practices and their impacts. These management aggregates were finally nested within a grid of 2304-km^2 cells (“Region”, L4). These cells represented a management region and are roughly the size of a Georgia county.

Model development

In order to estimate the true abundance of coveys, we developed a model which consisted of two related components. The first component estimates the detection rates of calling coveys in the survey. With the estimated detection rates, we were then able to adjust counts in each field to reflect the estimated abundance. These estimates were then used as data in the landscape modeling in order to estimate habitat, management, and spatial relationships.

Detection Modeling

The methodology and results of the detection modeling are described more fully in Hamrick and Carroll (2005). Essentially, joint detections of calling coveys were determined by independent observers using programs CAPTURE and MARK to model individual heterogeneity in observer detection (capture) probabilities. The result was that the strongest data support was for a single homogenous detection probability. The average per observer detection probability under this homogenous model was 0.33 (95% CI 0.23-0.45). Based on these results, we proceeded with all subsequent modeling based on the homogeneous detection model.

Landscape Modeling

The landscape modeling has three inputs: the raw count data adjusted to reflect density, the absence (control) or presence (BQI contract) of management, and the habitat information derived from the 1998 Georgia GAP landcover map. These data sources affect the modeling in that density and management practices may vary by location and year, while habitat values vary only by location.

Habitat and Management Relationships

In order to model the effect of habitat and management at each hierarchical level, we used a hierarchical linear model (Wong and Mason 1985, Snijders and Bosker 1999, Howell et al. in press). The model may be described by first considering a single-level linear model:

$$Y_i = \alpha_0 + \alpha_1 X_{1i} + \ldots + \alpha_P X_{Pi} + r_i, \tag{1}$$

where Y_i is the number of coveys and $X_{1i} \ldots X_{Pi}$ are the habitat and management variables measured in field unit i, α_0 is the intercept, $\alpha_1 \ldots \alpha_P$ are the coefficients, and r_i is the error assumed to be normally distributed with a mean of zero and variance σ_1^2. Next we assumed that observations that occur within the same field complex are more similar to each other than to observations which occur outside of that complex. We modeled this by assuming that the intercept in eq. (1) varies between field complex units based on a set of habitat and management variables $W_{1j} \ldots W_{Sj}$ measured for each field complex. The influence of these variables was modeled by expressing the level-one intercept (α_0) as a linear function of these habitat and management measures:

$$\alpha_{0j} = \beta_0 + \beta_1 W_{1j} + \ldots \beta_S W_{Sj} + \mu_{2j}, \tag{2}$$

where $\beta_0 \ldots \beta_S$ are the level-2 coefficients, μ_{2j} is the random effect of complex j, and $W_{1j} \ldots W_{Sj}$ are the level-2 habitat measures for complex j. The random effect μ_{2j} represents the spatial random group effect associated with each level-2 unit that is not explained by the model, and we assumed it to be normally distributed with mean zero and variance σ_2^2. The complete two-level linear model can be expressed by substituting eq. (2) for α_{0j} in eq. (1):

$$Y_{ij} = \beta_0 + \beta_1 W_{1j} + \ldots \beta_S W_{Sj} + \mu_{2j} + \alpha_1 X_{1ij} + \ldots + \alpha_P X_{Pij} + r_i. \quad (3)$$

We performed similar substitutions for each additional hierarchical level, i.e.,

$$\beta_{0k} = \chi_0 + \chi_1 V_{1k} + \ldots \chi_R V_{Rk} + \mu_{3k}, \text{ and} \quad (4a)$$

$$\chi_{0l} = \delta_0 + \delta_1 U_{1l} + \ldots \delta_C U_{Cl} + \mu_{4l}, \quad (4b)$$

with corresponding random effect terms μ_{3k} and μ_{4l} distributed normally with zero mean and variances σ_3^2 and σ_4^2, respectively. The final form of model is

$$Y_{ijkl} = \delta_0 + \delta_1 U_{1l} + \ldots \delta_C U_{Cl} + \mu_{4l} + \chi_1 V_{1kl} + \ldots \chi_R V_{Rkl} + \mu_{3kl} + \beta_1 W_{1jkl} + \ldots$$

$$\beta_S W_{Sjkl} + \mu_{2j} + \alpha_1 X_{1ijkl} + \ldots + \alpha_P X_{Pijkl} + r_{ijkl}, \quad (5)$$

where Y_{ijkl} is the number of coveys in field *i* of complex *j* of aggregation *k* of region *l*. We assumed that the relationship between counts and habitat or management variables did not vary among spatial units with a hierarchy, leading to a model in which there were no interactions between variables at different spatial scales.

Temporal Action of Management

In order to relate our management variables, which varied over time, to predicted numbers of coveys, we developed two alternative model forms that used different degrees of lag between management and the subsequent population response. The first form of the model related covey numbers in a given year as a function of the management performed that year and the habitat values. Expressed as

$$N_{ijklt} = f(M_{ijklt}, Z_{ijkl}),$$

where in field *i* of complex *j* of aggregation *k* of region *l*, N_{ijklt} is the estimated number of coveys in year *t*, M_{ijklt} is a vector of the management practices in year *t*, and Z_{ijkl} is a vector of habitat attributes. The second form of the model related numbers of coveys in a given year as a function of management in the previous year and the habitat values. Expressed as

$$N_{ijkl,t+1} = f(M_{ijklt}, Z_{ijkl}),$$

where in field *i* of complex *j* of aggregation *k* of region *l*, $N_{ijkl,t+1}$ is the estimated number of coveys in year *t*+1, M_{ijklt} is a vector of the management practices in year *t*, and Z_{ijkl} is a vector of habitat attributes.

Global Model selection and Construction of Model Set

Within each hierarchical level we measured habitat attributes from the Georgia GAP landcover map and aggregated BQI management practices. The map designates portions of the landscape into 44 classes based on land cover type. From these classes, we selected specific variables for each hierarchical level (Table1). With increasing spatial grain, we combined certain classes to create a more general landcover type. We then measured the total area at the appropriate hierarchical level of each landcover type per cell. Management variables were based on BQI practices on contract fields during the study period (Table 1). We assigned each field to one of the Field-scale (1 km^2) cells and to that cell's corresponding parent cells. We then summed the extent (acreage or length) of each practice type over the fields in each cell of each hierarchical level. In order to test the impact of prolonged management, at the field complex level (L2) we created an average number of years under management weighted by the total area of the member fields. Based on combinations of these variables, we developed a set of 36 models that considered bird outcomes as a response to combinations of (a) contemporary (M_1), time-lagged (M_T), or no (M_0) management inputs; (b) presence (H_1) or absence (H_0) of habitat variables; and (c) random effects (RE) occurring at one or more landscape scales (L_1, L_2, L_3, L_4, L_{12}, L_{1234}). The specific management or habitat variables appearing in a model depended on the landscape scale(s) represented in the model. For example, the $L_3M_1H_1$ model contained only the 3 management and 3 habitat variables measured at the 144-km^2 scale (Table 1); the $L_{1234}M_1H_1$ model contained the entire set of management and habitat variables.

Statistical analysis

Each candidate model was fit using Markov Chain Monte Carlo (MCMC) methods as implemented in BUGS software, version 1.3 (Lunn 2003). For the habitat and management relationship variables, we assigned diffuse normal prior distributions to reflect a lack of prior knowledge about model parameters. Each model was run for 55,000 iterations with the first 4000 discarded as burn-in. We then ranked the candidates based on Akaike Information Criterion (AIC; Burnham and Anderson 2002). Out of a concern that the models were all either very small (those containing only random effects) or very large (those also containing habitat and/or management effects), we tried a strategy of conditioning model selection on a subset of habitat and management variables. We fit the global model $L_{1234}M_1H_1$ and noted which variables had sizeable distribution mass to one side or the other of zero (Figures 5-8). We then restricted the total set of available habitat and management variables down to a smaller set containing those variables not centered at or near 0 (Table 1, boldface type), and re-fit the 36 models as above.

Simulation exercise

To evaluate various sources of uncertainty, we developed a scenario based on a representative sample of 36 fields in 4 complexes. We chose complexes that offered contrasting values in levels of management and types of habitat. Our alternative decisions consisted of all possible combinations of 2 fields selected from among the 36. For each random draw of a pair of fields, we used the following process to simulate the response (predicted number of bobwhites) on each field in the pair:

1) First, one of 4 alternative models was assigned randomly, depending on a prior model probability (ranging from 0 to 1).

2) For a given model, parameter values were drawn from a normal distribution with the mean and standard deviation estimated from the corresponding statistics of the posterior distribution for the parameter from the indicated model.

3) Conditioned on the selected model, randomly drawn parameter values, and predictor variables for the selected field, a predicted mean value for number of bobwhites was generated.

4) A random integer outcome was then generated from a Poisson distribution with mean equal to the above predicted value.

The total for two random outcomes was returned as the objective value.

We encoded the above steps in a Python program, which randomly took 315,000 samples from among the unordered field combinations, sampling each of the $\binom{36}{2}$ combinations approximately 500 times. We investigated simulation outcomes under each of five model weighting scenarios: model-averaged (weighted average over the AIC weights for the four models), and probability 1.0 weight on each alternative model (i.e., certainty assumed for each model in turn).

RESULTS AND DISCUSSION

Posterior estimates for parameters associated with the unrestricted set of habitat and management variables varied by model, but were generally in line with our expectations when an effect was present (Figures 5-8). One exception was open pine at the Field level (Fig. 5). While we expected a positive association, the majority of the mass of the posterior distribution was negative. This was likely due to the nature of the landcover class, which may represent several types of open pine, some of which are not quality habitat for northern bobwhite. The urban and agriculture categories, present in the Aggregation and Region levels, varied similarly between the two levels (Fig 7-8). At the Aggregation level, urban was largely negative and agriculture was positive. At the Region level these relationships reversed themselves. In the global model, the posterior is mostly centered on zero for the Region level effects, while the Aggregation effects encompassed zero only in the tails of their posteriors. This may be evidence of an interaction between these two variables in the model or between the multiple hierarchical levels of the variables.

All BQI management variable associations were either positive or centered about zero. These effects were found at all of the spatial scales we investigated, suggesting local as well as region-wide positive effects from BQI on northern bobwhite abundance. Under our models, even fields not enrolled in BQI would experience positive effects so long as they were within the BQI regions.

The results of the model selection with the restricted and unrestricted variable sets are summarized in Table 2. Under either approach, the Complex-level, RE-only model ($L_2M_0H_0$) was the top-ranked model, and it took ≥50% of the share of model weight from the set (Table 2). This result suggests that larger scale demographic processes may be dominating habitat and management factors at this scale. But more weight was distributed to the remaining models (i.e., smaller values of ΔAIC) in the restricted-variable model set than in the unrestricted-variable model set. This was expected, as the pre-screening process excluded variables that were unlikely to have appeared in any parsimonious model.

Models were similarly ranked between the two approaches, except for model $L_{12}M_1H_0$ (Table 2). In the unrestricted-variable model set, this model received 1/150 of the weight for the top model and about 1/10 of the weight for the $L_2M_1H_0$ and $L_2M_0H_1$ models. However, in the restricted-variable model set, it received almost half the weight of the top model and approximately 2.5 times the weight of the $L_2M_1H_0$ and $L_2M_0H_1$ models. The exclusion of the clearcut class from some Field-level habitat variables for the restricted-variable model set may have been responsible for the positive difference in parsimony for this model. Alternatively, this result could have been due to the dropping of two management variable at this level.

Two models containing only landscape-scale random effects ($L_2M_0H_0$ and $L_{1234}M_0H_0$) received substantial weight (≥50% and ≥8%, respectively) and low rank (1 and ≤4, respectively) under either approach (Table 2). These models propose that quail response is insensitive to both management and habitat, suggesting that the flip of a (biased) coin predicts bird occurrence on a field about as well as any more sophisticated method. These models are of management interest only for the reason that, if true, they indicate that management practices are ineffective in increasing or decreasing quail abundance. Better (more realistic) null models of management are those that contain habitat effects, but no management effects. When all RE-only models are excluded from the set of unrestricted-variable models, 5 models receive AIC weight of ≥1%: $L_2M_0H_1$ (46%), $L_2M_1H_0$ (44%), $L_{12}M_1H_0$ (4%), $L_2M_1H_1$ (3%), and $L_2M_TH_0$ (2%). For the restricted-variable set, 6 models receive weight ≥1% when RE-only models are excluded: $L_{12}M_1H_0$ (50%), $L_2M_1H_0$ (23%), $L_2M_0H_1$ (18%), $L_2M_1H_1$ (6%), $L_{12}M_TH_0$ (2%), and $L_2M_TH_0$ (1%). Models that proposed a one-year lag effect of management were consistently ranked behind corresponding contemporary-effects models.

Our simulation exercise (Table 3) illustrates how it is possible to use these models to rank candidate fields for selection. However, the closeness of the mean objective values, and the high sensitivity of the ranking to the underlying model (for example the combination [19, 24] ranked third or fourth under two models, and not in the top 20 under the other two) both suggest that the manifest uncertainty in this system could strongly influence decision making. Therefore, reduction of this uncertainty, through improved monitoring and adaptive management, potentially has management value.

CONCLUSIONS AND RECOMMENDATIONS

We have successfully built, parameterized, and evaluated alternative models that express the relationship between field and complex habitat characteristics and management practices, and predicted number of bobwhite coveys. These models can be used to evaluate alternative management practices, and to rank candidate fields for inclusion in incentive programs based on their predicted contribution to covey production. These predictions, however, are subject to a great deal of uncertainty, which degrades the ability to make optimal choices for candidate fields. Some of this uncertainty is largely beyond the control of managers: for example, random fluctuations in covey numbers because of weather conditions. However, additional uncertainty was manifested in the parameter estimates of the different models from at least three sources: (1) inadequate spatial and temporal replication of covey count and habitat data used to build the alternative models, (2) incomplete covey detection and spatial and temporal heterogeneity in observer detection rates, (3) uncertainty in discriminating between possible biological processes as represented by the alternative models. The first of these must be remedied by the collection of additional spatial and temporal replicates over the scope of the study area, to allow for better estimation of parameters, and we recommend that these additional data be collected in designed studies. The second requires further work on the calibration and testing of covey call-count indices and we likewise recommend further studies directed at this problem.

The last source of uncertainty, that due to the lack of discrimination among alternative models, would be helped by addressing (1) and (2), because more precise predictions could then be made under each alternative model. However, there are limits to how much this source of uncertainty could be reduced by this approach, and it likely could not be eliminated; we would anticipate that even given very precise models, there would still remain a great deal of structural uncertainty. The remedy to this source of uncertainty is to move forward under adaptive management. Adaptive management requires, however, that a monitoring program be in place, so that predictions under the alternative models can be compared to monitored state of the bobwhite system. Monitoring is also needed, of course, to evaluate the actual (versus assumed) success of any management decisions (i.e., choices of fields to be included in the program). Restoration and continuance of a monitoring program for BQI should be a top priority.

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APPENDICES (supplemental CDs)

A. Program code, databases, and model results (Disk 1)

B. GIS data (Disks 1 and 2)

C. Presentations and summary of June 2003 workshop (Disk 1)

Table 1. Management and habitat variables at 4 landscape scales related to northern bobwhite abundance derived from the 1998 Georgia GAP landcover map and Georgia Bobwhite Quail Initiative practices (variables used in restricted-variable model set appear in **bold**).

Scale	Management Variables	Habitat Variables (GAP landcover class index)
1 – Field (1 km^2)	**Field Borders**[2] Hedgerows[3]	**Row Crop** (83) **Pasture** (80) **Utility** (20) Clearcut (31) **Open Pine**[1]
2 – Complex (9 km^2) (9 Fields)	**Years Enrolled** Field borders[2] Hedgerows[3] **Pivot + Fallow**[4]	**Hardwood**[5] **Wetland**[6] Evergreen[7] **Transportation** (18)
3 – Aggregation (144 km^2) (16 Complexes, 144 Fields)	**Number of Fields** Field borders[2] **Hedgerows**[3]	Evergreen[7] **Agriculture**[8] **Urban**[9]
4 – Region (2304 km^2) (16 Aggregations, 256 Complexes, 2304 Fields)	**Practice Acres**	**Urban**[8] Agriculture[9]

1. All open or sparse pine classes: Open Loblolly-Shortleaf (422), Sandhill (512), Longleaf Pine (620)
2. Dry and irrigated field borders
3. Dry and irrigated hedgerows
4. Pivot corner acres and fallow patch acres
5. All hardwood classes (excluding montane): Hardwood Forest (412), Xeric Hardwood (413), Liveoak (420), Mixed Pine Hardwood (434), Bottomland Hardwood (900)
6. All wetland classes: Cypress-Gum Swamp (890), Freshwater Marsh (930), Shrub Wetland (980), Evergreen forested Wetland (990)
7. All evergreen classes (excluding montane): Open Loblolly-Shortleaf (422), Loblolly-Shortleaf Pine (440), Loblolly-Slash Pine (441), Sandhill (512), Longleaf Pine (620)
8. All urban classes: Low Intensity Urban – Nonforested (22), High Intensity Urban (24), Parks Recreation (72), Golf Course (73), Forested Urban – Deciduous (201), Forested Urban – Evergreen (202), Forested Urban – Mixed (203)
9. All Agricultural classes: Pasture, Hay (80) and Row Crop (83)

Table 2. Top 10 predictive models of northern bobwhite abundance (landscape scale levels | management effects | habitat effects) and model weights for model sets including (A) all management and habitat variables in global model and (B) subset of variables in global model. Model weights also provided for the model set that excludes models containing only landscape scale random effects (RE-only models).

(A) All variables in global model					(B) Subset of variables in global model				
	Including RE-only		Excluding RE-only			Including RE-only		Excluding RE-only	
Model	ΔAIC	Weight	ΔAIC	Weight	Model	ΔAIC	Weight	ΔAIC	Weight
2 | 0 | 0	0	0.765363	–	–	2 | 0 | 0	0	0.496859	–	–
1234 | 0 | 0	3.7	0.120343	–	–	12 | 1 | 0	1.69	0.213429	0	0.502168
2 | 0 | 1	5.36	0.052476	0	0.459129	2 | 1 | 0	3.28	0.096381	1.59	0.226769
2 | 1 | 0	5.44	0.050418	0.08	0.441126	1234 | 0 | 0	3.7	0.078125	–	–
12 | 1 | 0	10.1	0.004905	4.74	0.04292	2 | 0 | 1	3.77	0.075438	2.08	0.177493
2 | 1 | 1	10.55	0.003917	5.19	0.034272	2 | 1 | 1	6.01	0.024614	4.32	0.057913
2 | T | 0	11.68	0.002226	6.32	0.019479	12 | T | 0	8.61	0.006708	6.92	0.015783
12 | T | 0	16.77	0.000175	11.41	0.001529	2 | T | 0	8.87	0.00589	7.18	0.013859
2 | T | 1	17.81	0.000104	12.45	0.000909	2 | T | 1	12.03	0.001213	10.34	0.002855
12 | 0 | 1	19.15	5.31E-05	13.79	0.000465	1234 | 1 | 0	12.61	0.000908	10.92	0.002136

Table 3. Results of simulations to rank combinations of fields[1], taking into account complex- and site-level predictors, model uncertainty, and stochastic uncertainty in responses.

	Model									
	1-Average		2-L2_N_N		3-L2_N_0		4-L2_0_N		5-L12_N_0	
rank	pair	Mean	pair	Mean	pair	mean	pair	mean	pair	mean
1	(06, 19)	18.60	(00, 08)	26.48	(08, 25)	21.77	(01, 07)	9.97	(01, 26)	19.08
2	(03, 05)	18.49	(01, 08)	26.45	(19, 21)	21.76	(00, 07)	9.92	(06, 07)	19.02
3	(01, 03)	18.29	(06, 08)	25.71	(01, 08)	21.65	(03, 05)	9.87	(19, 24)	18.99
4	(01, 21)	18.19	(05, 08)	25.58	(19, 24)	21.59	(09, 11)	9.82	(01, 24)	18.96
5	(00, 01)	18.05	(01, 06)	25.46	(02, 06)	21.58	(01, 09)	9.82	(04, 22)	18.91
6	(05, 06)	18.03	(02, 08)	25.41	(22, 23)	21.50	(01, 08)	9.82	(20, 25)	18.91
7	(02, 05)	18.01	(01, 03)	25.36	(01, 23)	21.41	(15, 16)	9.81	(03, 06)	18.87
8	(00, 06)	18.01	(01, 07)	25.35	(02, 18)	21.41	(01, 02)	9.80	(24, 25)	18.86
9	(03, 21)	18.00	(03, 06)	25.17	(00, 20)	21.39	(05, 15)	9.77	(06, 24)	18.86
10	(00, 03)	17.95	(06, 07)	25.13	(08, 19)	21.38	(04, 10)	9.76	(20, 24)	18.84
11	(07, 08)	17.94	(02, 03)	25.11	(00, 24)	21.31	(01, 16)	9.75	(24, 26)	18.82
12	(01, 06)	17.88	(03, 08)	25.04	(05, 23)	21.27	(11, 17)	9.72	(06, 08)	18.76
13	(01, 07)	17.88	(05, 06)	25.02	(04, 21)	21.26	(10, 17)	9.71	(08, 19)	18.75
14	(04, 24)	17.88	(01, 02)	25.01	(00, 19)	21.26	(02, 07)	9.71	(01, 23)	18.75
15	(04, 21)	17.83	(00, 01)	24.97	(04, 25)	21.24	(07, 11)	9.71	(06, 21)	18.67
16	(18, 24)	17.78	(03, 05)	24.97	(00, 08)	21.23	(06, 13)	9.70	(01, 06)	18.65
17	(05, 08)	17.78	(01, 04)	24.89	(02, 24)	21.20	(09, 14)	9.68	(04, 26)	18.64
18	(01, 23)	17.75	(04, 07)	24.86	(02, 26)	21.20	(06, 09)	9.68	(06, 26)	18.62
19	(02, 19)	17.74	(02, 04)	24.82	(21, 26)	21.19	(01, 14)	9.67	(07, 20)	18.60
20	(05, 24)	17.65	(00, 04)	24.80	(20, 24)	21.19	(14, 16)	9.66	(01, 21)	18.60

1. Cluster characteristics: better habitat/more management (fields 0-8), better habitat/less management (fields 9-17), poorer habitat/more management (fields 18-26), poorer habitat/less management (fields 27-35).

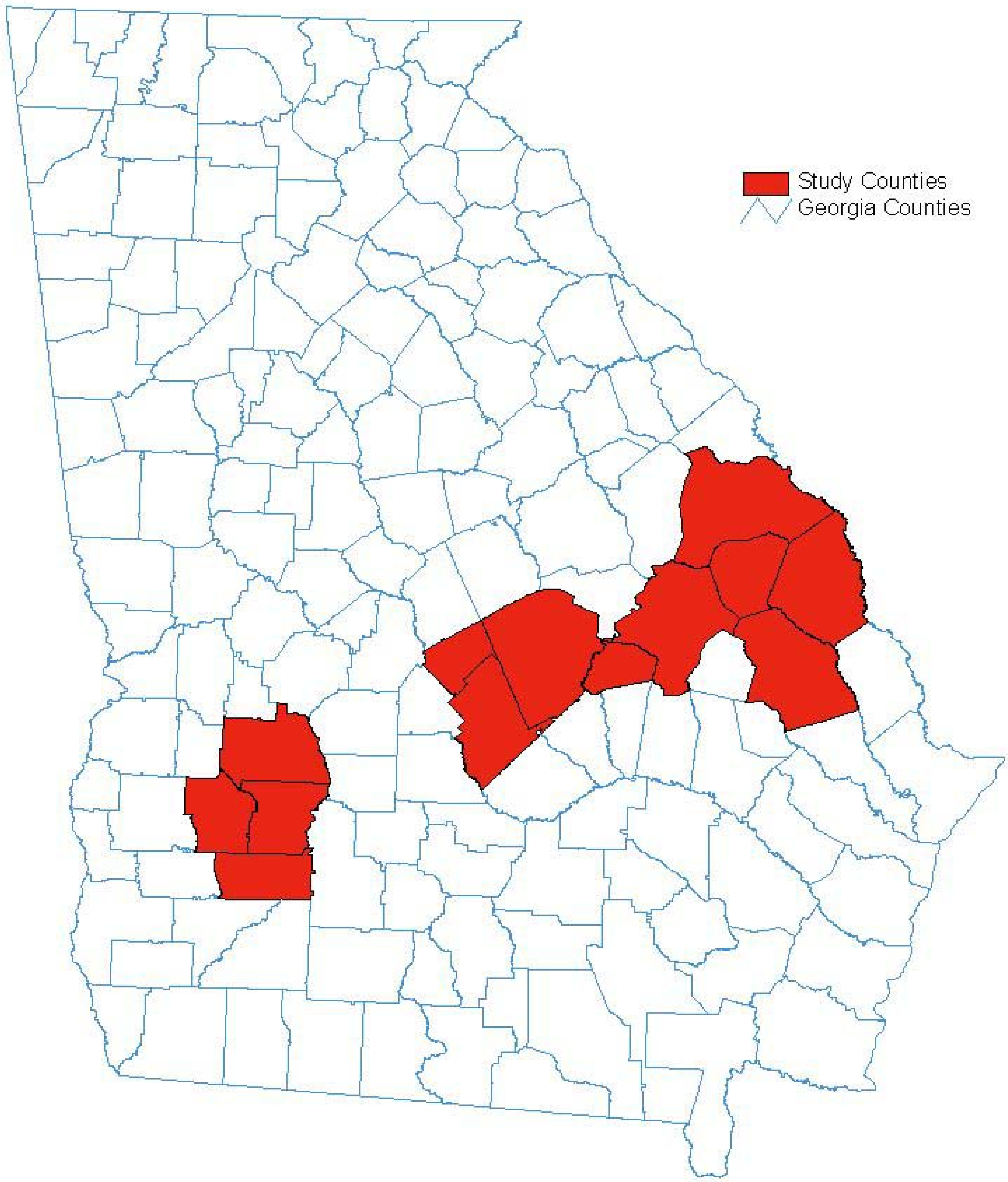

Figure 1. Georgia counties enrolled in the Bobwhite Quail Initiative (BQI) that were surveyed for numbers of autumn coveys, 1999-2001.

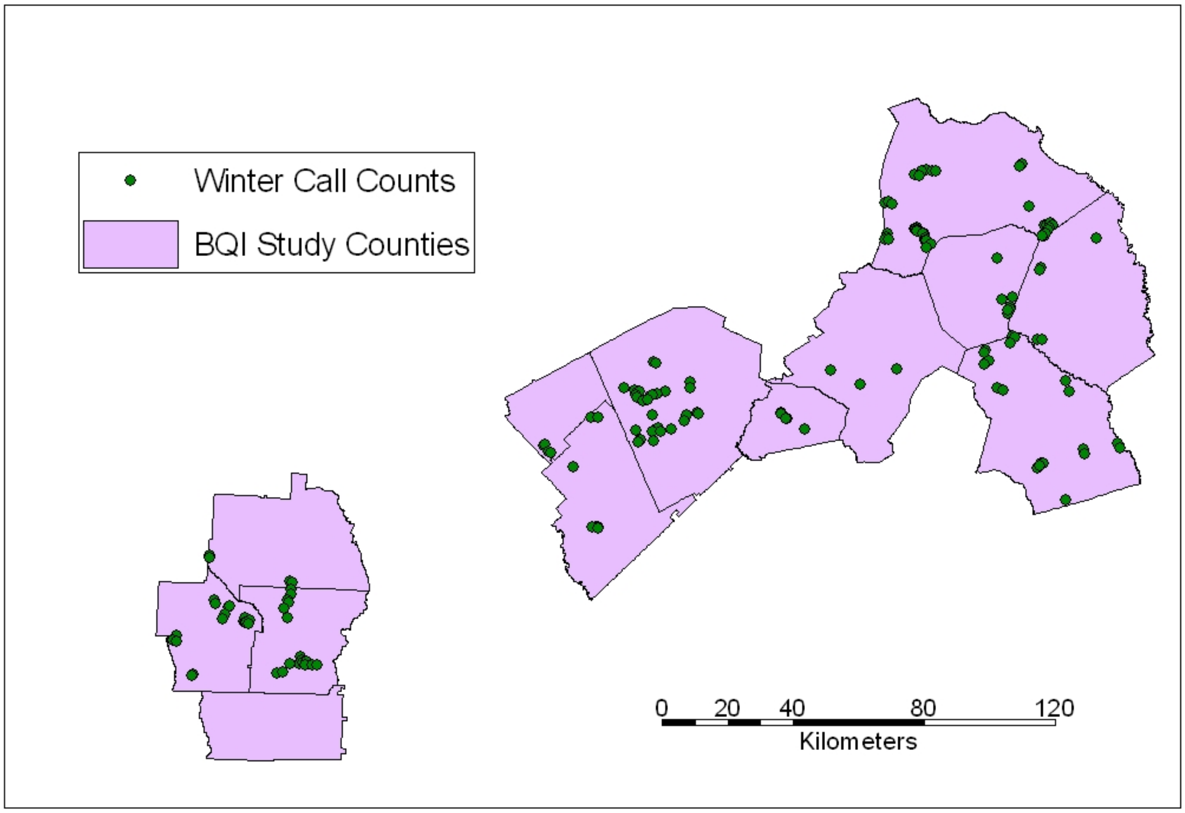

Figure 2. Locations of autumn call counts on BQI counties surveyed from 1999-2001.

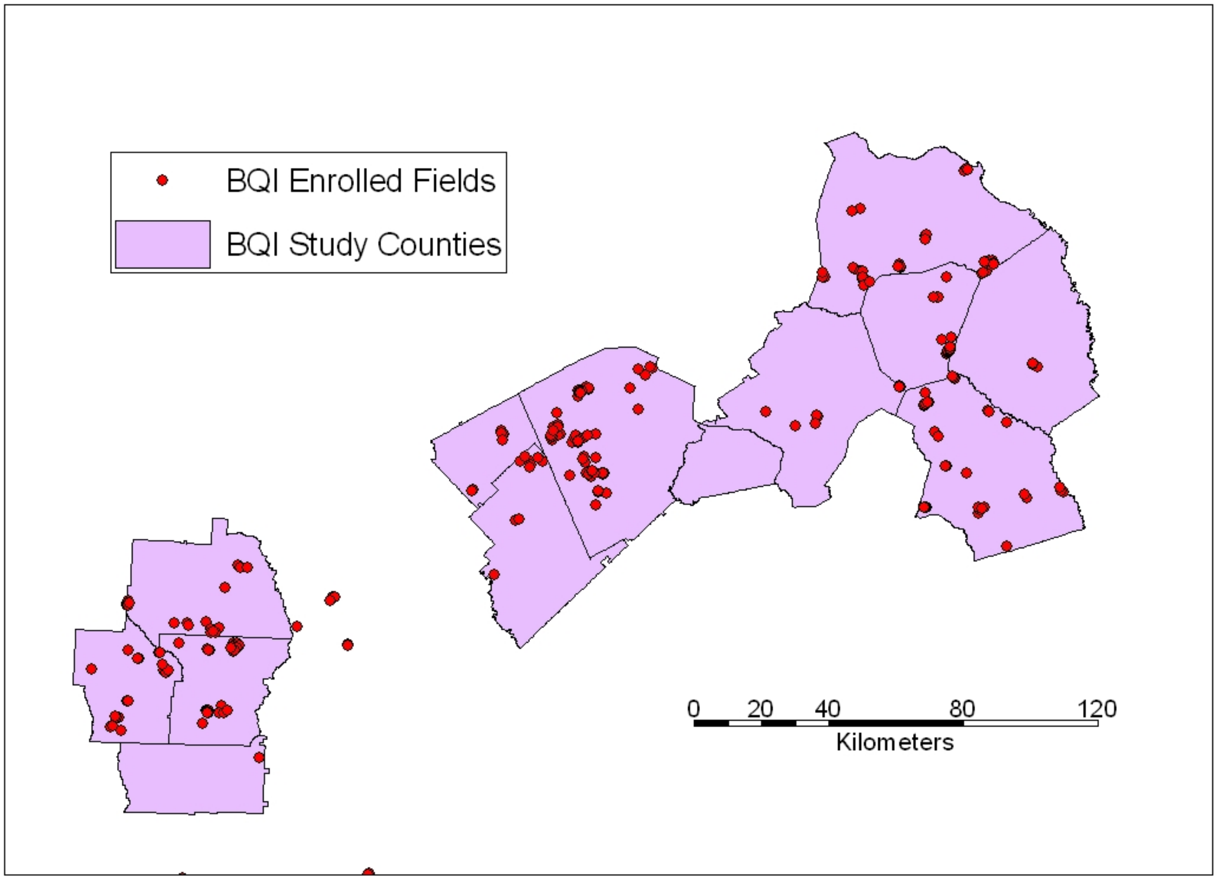

Figure 3. Centroids for fields enrolled in BQI from 1999-2001 in the study counties.

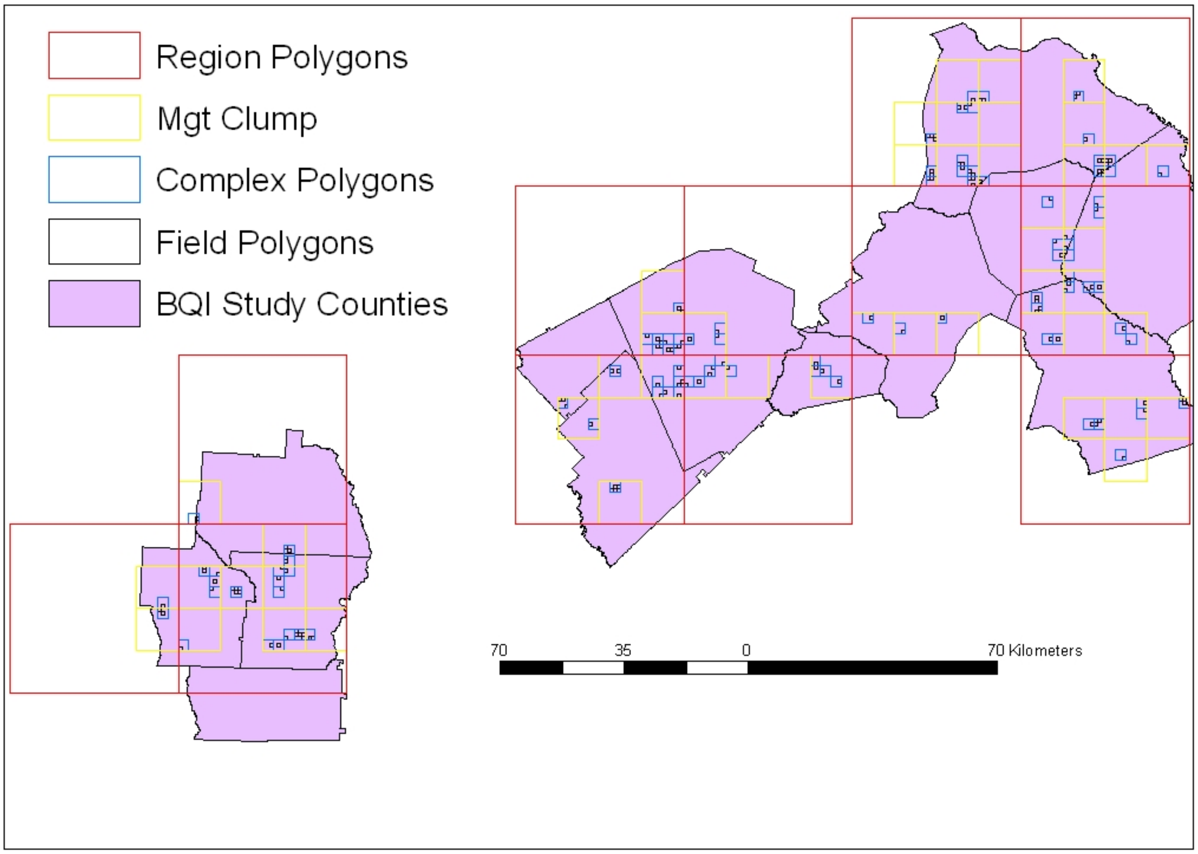

Figure 4. Hierarchy of spatially nested units used for modeling responses of northern bobwhite coveys to habitat and BQI management from 1999-2001.

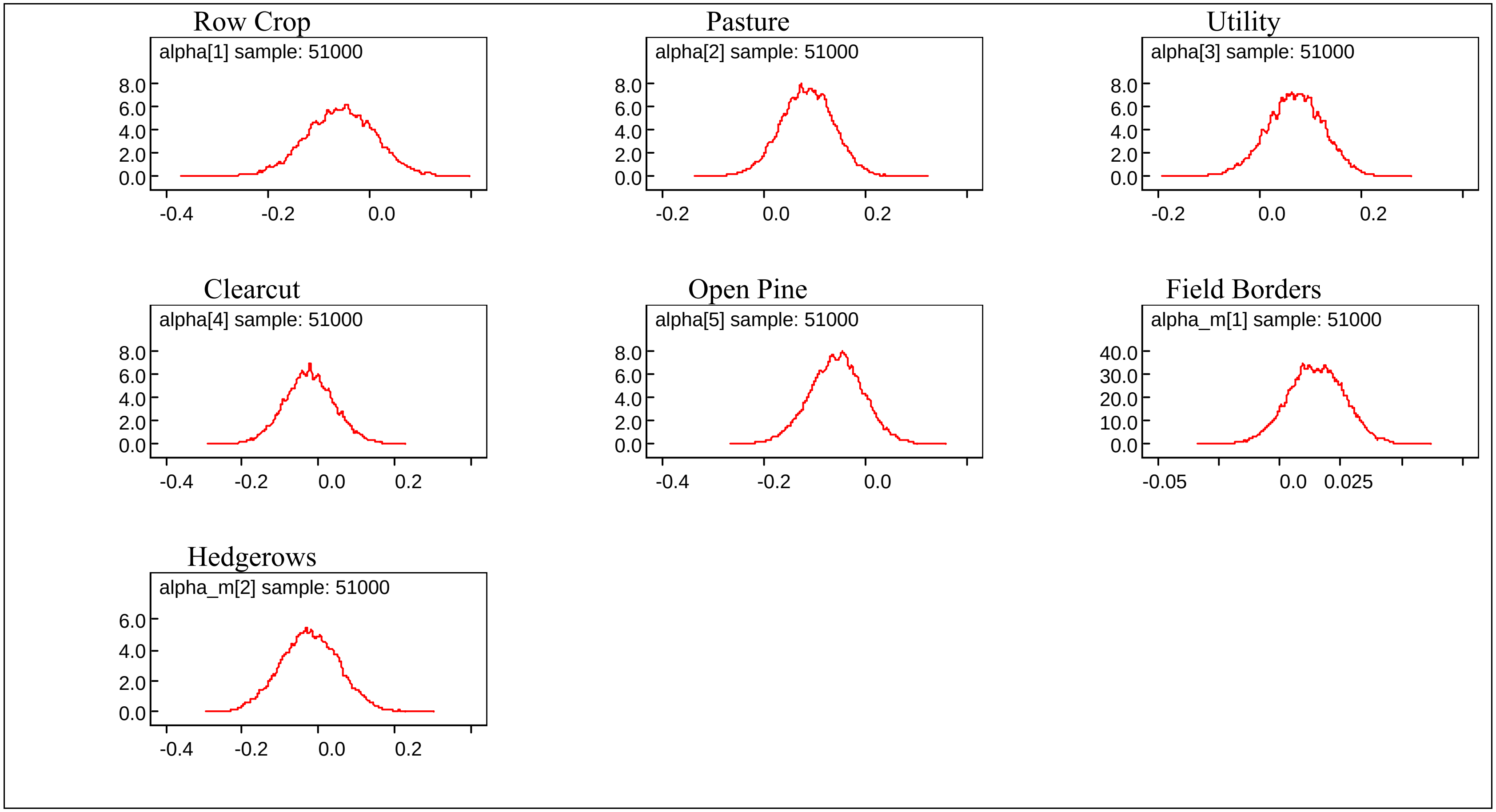

Figure 5. Posterior distributions of parameters associated with Field (1 km^2) level variables associated with habitat from the 1998 Georgia Gap landcover map and BQI management practices from 1999-2001 when fitting the global model $L_{1234}M_1H_1$ using Markov Chain Monte Carlo.

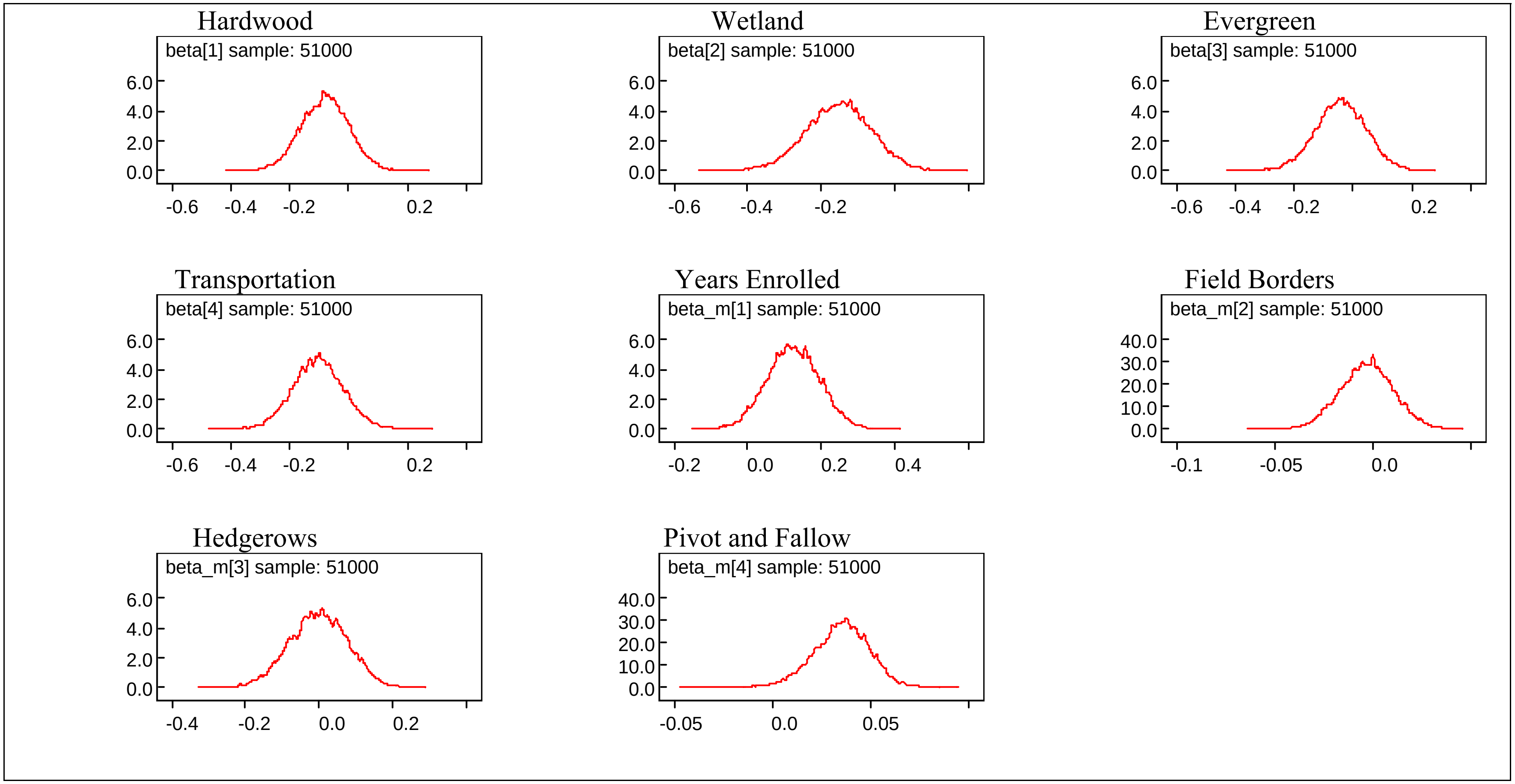

Figure 6. Posterior distributions of parameters associated with Complex (9 km^2) level variables associated with habitat from the 1998 Georgia Gap landcover map and BQI management practices from 1999-2001 when fitting the global model $L_{1234}M_1H_1$ using Markov Chain Monte Carlo.

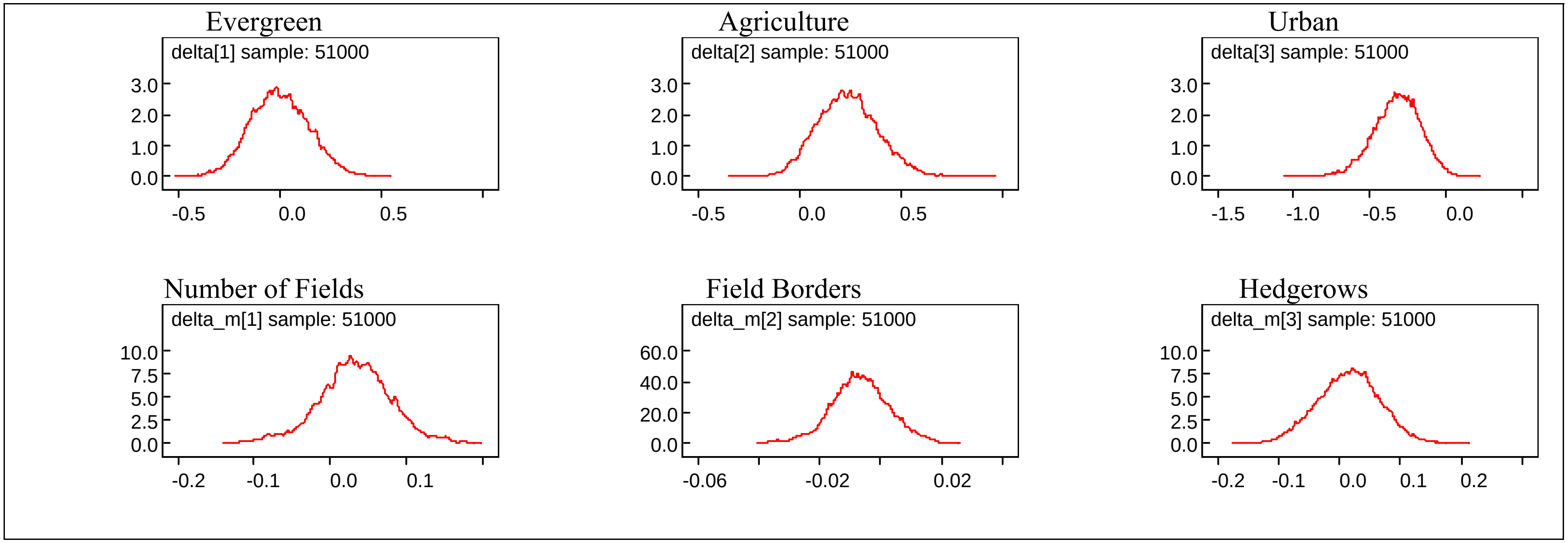

Figure 7. Posterior distributions of parameters associated with Aggregation (144 km^2) level variables associated with habitat from the 1998 Georgia Gap landcover map and BQI management practices from 1999-2001 when fitting the global model $L_{1234}M_1H_1$ using Markov Chain Monte Carlo.

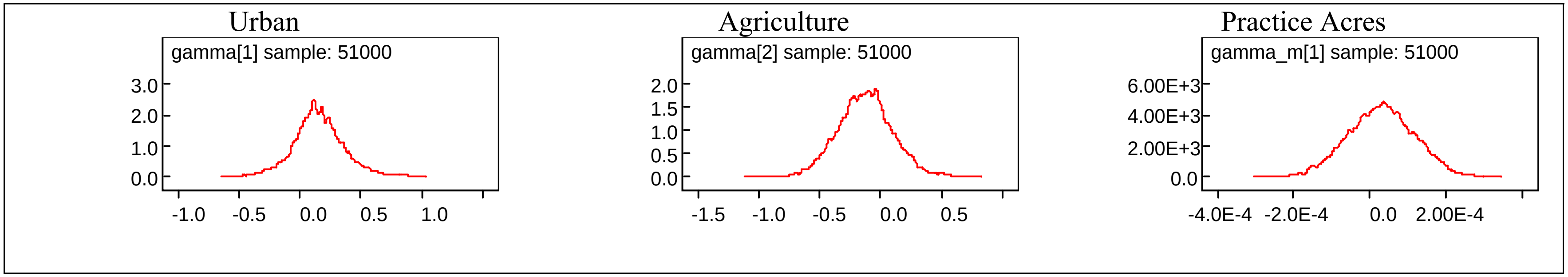

Figure 8. Posterior distributions of parameters associated with Region (2,304 km^2) level variables associated with habitat from the 1998 Georgia Gap landcover map and BQI management practices from 1999-2001 when fitting the global model $L_{1234}M_1H_1$ using Markov Chain Monte Carlo.