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Ecological Modeling and Simulation Using Error and Uncertainty Analysis Methods (Project CS-1097)

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1 Executive Summary

The Strategic Environmental Research and Development Program (SERDP) of the Department of Defense (DoD) is sponsoring research on the application of error and uncertainty analysis to ecological models used in military land-use management. Increasingly, the ecological models used in DoD ecosystem and land-use management are spatially explicit, relying on spatially distributed and georeferenced data as model input. The spatial inputs to these models, commonly in the form of geographical information system (GIS) data layers, have varying degrees of uncertainty associated with them. This uncertainty needs to be propagated throughout the entire modeling and simulation process so that: (1) model results can be presented to the ecosystem/land manager as a probability distribution of possible outcomes, and (2) the contribution of uncertainty in spatial data to overall model uncertainty can be quantified as part of an error budget analysis.

Effective analysis of spatial uncertainty in ecological models is hampered, however, by a relative lack of general methods and the tools (software) implementing those methods. Analysis is also constrained by the common absence of metadata characterizing the error and uncertainty in spatial data (e.g., the map layers of a Geographical Information System [GIS]). To address these constraints, our project (SERDP Conservation Thrust Area Project CS-1097) has developed a general methodology for spatial sensitivity analysis of ecological models using categorical spatial data (e.g., maps of vegetation type) as model input, and we have developed the software to implement that methodology. The approach uses geostatistics and Monte Carlo simulation to propagate uncertainties in GIS data layers through the entire modeling process. Importantly, our approach provides for the analysis of model sensitivity to uncertainty in spatial data in the absence of an explicit characterization of the error and uncertainty in that data. Our results from a number of case studies indicate that ecological models may often be relatively insensitive to the spatial uncertainty characteristic of maps of the quality commonly used by military land and ecosystem managers. There are circumstances, however, in which uncertainty in spatial data can lead to significant uncertainty (variability) in model output that has important consequences for land and ecosystem management decisions. The value of our methods and tools resides in their ability to make those determinations based on a robust quantitative analysis that is easy to implement.

In 2001, we completed a literature review to determine the need for, and feasibility of, evaluating temporal uncertainties in spatial data (e.g., changes in spatial uncertainty over time). From this review and a consideration of the availability of data on temporal changes in spatial data (particularly for our Fort Hood, TX case study), we determined that further consideration of this issue was neither warranted nor feasible. We therefore made no attempt to implement an analysis of temporal changes in spatial uncertainty in Golden-cheeked Warbler at Fort Hood.

We completed our Fort Hood case study involving demographic modeling of Golden-cheeked Warbler (*Dendroica chrysoparia*) at Fort Hood, Texas. In brief, we concluded that the demographic model used for the case study was insensitive to the level of spatial uncertainty believed by Fort Hood endangered species personnel to be present in the existing map of Golden-cheeked Warbler at Fort Hood. Thus while other analyses have demonstrated that the model, and by extension the Golden-cheeked Warbler is sensitive in important ways to larger-scale changes in habitat abundance and distribution (e.g., a change from a persistent to a declining population), the model is insensitive to the degree of error that is likely to be present in the existing habitat map, and efforts to reduce that error are uncertainty would have no consequences for the model results. Efforts to improve the habitat map with respect to uncertainty in the edges of large patches or the distribution of small isolated patches would not be warranted. Effort would be better spent in reducing uncertainty in juvenile survivorship. This case study is an example of the applicability of our methods and illustrates the nature of their impact on conservation management decisions on military installations.

Through a joint activity with Dr. Tom Sisk's Effective Area Model project (CS-1100), we have demonstrated that our methodology and software is applicable to any computer simulation model that reads digitized maps of categorical data as model input. Dr. Sisk provided us with a habitat map for their study area in Arizona. We then used our techniques to generate alternative versions of that map representing different levels of uncertainty in patch edges (Figure 9) that were returned to Dr. Sisks's team. Those maps were then utilized by Dr. Sisk's team in a spatial sensitivity analysis of the EAM model. Thus, if we were provided with the normal input maps for the Fort Hood Avian Simulator (FHASM), we could generate alternative maps reflecting spatial uncertainty in those maps, and they could be used in a spatial sensitivity analysis of FHASM. Alternatively, our software could be ported to the FHASM team and they themselves could generate those maps.

In October 2001, we held a small workshop on spatial error and uncertainty analysis at Northern Arizona University, Flagstaff, AZ. Three SERDP Conservation projects were represented (CS-1096, CS-1097, and CS-1100). A report associated with that workshop will be provided to SERDP under separate cover. The participants in the workshop concluded that the following were priority needs for future research:

1. Definition and adoption of metadata standards enforcing the inclusion of information on true spatial error and uncertainty with spatial data (maps and GIS layers).

2. Creation and distribution of software tools for analysis of spatial error and uncertainty in spatial data and models that can be used by GIS operators, environmental modelers, and spatial analysts without expertise in error and uncertainty analysis.

3. Investigation into sources, characterization and propagation of error and uncertainty in spatial data derived from satellite and airborne remote-sensing platforms (e.g., land-use/land-cover maps).

The principle objective of our project is to identify and implement methods for the analysis of error and uncertainty of spatial data in spatially explicit ecological models. The development of these methods for spatial error and uncertainty analysis is done in coordination with Dr. George Gertner and SERDP Conservation Thrust Area Project CS-1096. Methods and tools (e.g., computer codes) developed and implemented by CS-1097 will be transferred to Project CS-1096 for incorporation within that project's error budget framework and toolbox. Methods and software from CS-1097 will also be compatible with the specifications and requirements of the DoD U.S. Army Corps of Engineers' (USACE) Land Management System (LMS).

2 Problem Statement and Background

Ecological models used in the ecosystem management of military installations increasingly rely on spatially distributed and georeferenced data (digital maps) as model input. Like any data, any measurements, these spatial data, commonly in the form of geographical information system (GIS) data layers, have uncertainty associated with them. This uncertainty needs to be propagated throughout the entire modeling and simulation process so that: (1) model results can be presented to the ecosystem/land manager as a probability distribution of possible outcomes reflecting uncertainty in the spatial data, and (2) the contribution of uncertainty in spatial data to overall model uncertainty can be quantified as part of an error budget analysis. The latter provides for cost effective allocation of resources to minimize, to the extent possible, uncertainty in model input, and consequently model output, with the aim of reducing the range of potential outcomes the manager must evaluate.

Effective analysis of spatial uncertainty in ecological models is hampered, however, by a relative lack of general methods and the tools (software) implementing those methods. Analysis is also constrained by the common absence of metadata characterizing the error and uncertainty in spatial data (e.g., the map layers of a GIS). To address these constraints, we are investigating general methods for the analysis of of spatial uncertainty in ecological models, and developing software to implement those methodologies.

Our approach to the problem is derived from parametric uncertainty analysis of deterministic ecological simulation models (e.g., Gardner et al., 1981), itself an extension to modeling of the more general error analysis of uncertainties in physical measurements (Bevington and Robinson, 1992; Taylor, 1997). In applying this perspective, mapped spatial variables (e.g, the distribution of wildlife habitat or vegetation type) are the focus of the analysis rather than the traditional model parameters (e.g., rate constants, initial conditions), and geo/spatial statistics, the statistics of spatially distributed and dependent quantities, replace the conventional multivariate statistics of parametric uncertainty analysis. This perspective assumes a measurement, in this case a digital map, that has associated uncertainty. The uncertainty has many sources, the particulars of which depend on how the map was generated. The uncertainty may or may not be documented and quantified; usually it is not. The purpose of the uncertainty analysis is to study and understand how the uncertainty in the measured map(s) propagates through a simulation model and is expressed as uncertainty (variability) in model output. This understanding and quantification of uncertainty in model output and the error propagation properties of the model provides: (1) improved understanding of the model itself, (2) model output in the form of a realistic range or distribution of model outcomes rather than a single result with its communication of an artificial sense of precision, and (3) information on which spatial data contributes most to significant uncertainty in model output and where improved measurements (better maps) could most reduce that uncertainty. All of this understanding provides for more informed management decisions when using spatially structured ecological models as part of the decision process.

This "error analysis" perspective differs from the more theoretical perspectives of landscape and spatial ecology when they use models to understand how spatial pattern (structure) influences ecological processes (function) (e.g., With and King, 2001). In both cases, variability in spatial inputs are propagated through models and the influence on model output analyzed. But there are important differences. Most significantly, the uncertainty in spatial data considered in the error/uncertainty analysis is generally far less than that of the theoretical structure-function analysis because the former is constrained by the "best" estimate of the original map (and the measured uncertainty in that map if available). The variability, the range, in spatial input considered by the structure-function analysis is usually large, as the analysis seeks to understand the full domain of the relationship between spatial structure and ecological function. As a consequence, the variability (uncertainty) in model output will generally be smaller in the spatial error analysis than in the structure-function analysis. And as a result, it can be simultaneously true, for example, that changes in the distribution of habitat can significantly influence the ecological processes described by a model while the error/uncertainty in the observed maps has an insignificant impact on model results. Both perspectives are important; both analyses have their place. They differ in their application and interpretation depending upon the questions being asked. Our project focuses on the spatial error analysis of ecological models as part of a larger error budget approach in coordination with Conservation Thrust Area Project CS1096 (Dr. George Gertner, PI). The broader perspective of spatial structure-function should not be overlooked, however, because land-use management decisions involving large-scale changes of spatial properties (e.g., destruction of habitat) are part of ecosystem management but outside the scope of the spatial error analysis focus of this project and better addressed from the perspective of spatial structure function analysis.

As noted above, the uncertainty in maps available as model inputs is most often not documented or quantified. It is as if a physical measurement has been provided with no indication of the confidence limits, relative error, sampling error, or precision of the measurement (a common enough occurrence). It is increasingly commonplace to report the classification error matrix (the confusion matrix) as a summary of the accuracy of thematic maps, especially maps generated by classification of remote sensing data (Congalton, 1991). These error matrices, however, lack information on the spatial distribution and dependence of mapping error. As such, they cannot be used to propagate spatially dependent uncertainty through simulation models. Other presentations of uncertainty in spatial data are exceedingly rare. Accordingly, we look to the work of Robert H. Gardner and others on non-spatial ecological simulation models for guidance in defining methods for dealing with the normal absence of quantified uncertainty in the spatial data used as model input. These methods often take the form of "sensitivity analysis" in which operationally well defined variability is imposed on the original data as a surrogate for the unavailable "true" uncertainty. For example, in parametric uncertainty analysis it may be assumed that all parameters are normally distributed, and error is attributed to the available input values by specifying a coefficient of variation for each parameter. This "relative error" is applied as a standard deviation on each parameter by assuming the available parameter data are mean values. These sensitivity analyses are often the only recourse in the absence of true documented, quantified uncertainty. Importantly, these sensitivity analyses are often the first stage of a more complete uncertainty analysis, providing information on those model inputs (in this case digital maps) to which the model is most sensitive and whether and where attention and resources should be applied to measure and quantify the true uncertainty in model inputs. We seek an analogous approach for spatial uncertainty analysis of ecological models.

Geographers, spatial analysts, and geostatisticians have been interested in the issue of uncertainty in spatial information for a long time (Burrough, 1986; Isaaks and Srivastava, 1989), virtually since the inception of digital GIS and to some extent by cartographers before that. A family of techniques known as stochastic simulation has emerged from these communities as a common approach to characterizing uncertainty in spatial data (Journel, 1996; Kyriakidis, 2001), although fuzzy set approaches are used as well (Altman, 1994; Zhu, 2001). Spatial uncertainty remains a priority issue within those communities (Burrough and McDonnell, 1998). Uncertainty in spatial data is, for example, one of the ten research priorities of the University Consortium for Geographic Information Science (UCGIS, 1996). Nevertheless, there are few readily available techniques and tools to address uncertainty in spatial data. As late as 1998, Burrough and McDonnell (1998, p. 263) noted "...no general, integrated practical tools for statistical error propagation in GIS [yet] exist." This despite the fact that "Many important components have been developed and are readily available to researchers and several research studies on error propagation are current" (Burrough and McDonnell, 1998, p. 263). This situation persists today.

Existing methods are largely found within the geostatistics and GIS research communities, and they have been particularly slow in penetrating into the ecological modeling community (Goodchild and Case, 2001). Among the environmental sciences, characterization of uncertainty in spatial data and the propagation of that uncertainty through numerical models is best developed in the areas of soil science and hydrology (e.g., Bierkens and Burrough, 1993a,b; Heuvelink, 1998). Only in the past decade, and to a more limited extent, have these techniques been developed for and applied to problems of community, population, and conservation ecology. Rossi et al. (1993) used stochastic conditional simulation to estimate, with uncertainty, the density of adult corn rootworms over northwestern Iowa, but there was no propagation of the density estimates through a simulation model. Phillips-Marks:96 (1996) combined kriging estimation variance and Monte Carlo simulation to analyze the propagation of interpolation errors, an important component of spatial uncertainty, through a model of spatial variability in potential evapotranspiration. Mowrer (1997) used sequential Gaussian simulation to create maps of three variables predicting old-growth forest conditions that reflected spatial uncertainty in those variables. These maps were combined in a simple GIS overlay operation. There was no propagation through a computer simulation model, although Mowrer (1997) noted that they could be used in that way. Similarly, Soares et al. (1997) used stochastic simulation and a neural net model to predict the spatial distribution of lichen biodiversity. McKelvey and Noon (2001) incorporated uncertainties in animal location and map classification into a model of spotted owl habitat use, but again there was no propagation of spatial error through a simulation model. As a demonstration, Shortridge (2001) propagated uncertainty in a digital elevation model (DEM) arising from topographic data with different spatial resolutions through a cartographic GIS model to predict bigcone spruce habitat. As noted by Heuvelink (1998, p. 107): "Although as yet the use of error propagation in GIS is far from a routine exercise, within the environmental sciences uncertainty analyses are by now quite common." However, only one of the 13 examples cited by Heuvelink (1998) involved organisms or species (the work of Rossi et al. (1993) cited above). The rest involved soils, hydrology, and DEMs. Common within the environmental sciences, broadly defined? Perhaps, but uncommon in the fields of ecology and ecological modeling as applied to conservation ecology. Clearly, there is a particular need for research and development of methods and tools for spatial error and uncertainty analysis of ecological models, especially models of the sort used in conservation ecology.

Error and uncertainty in spatial data arise from a variety of sources, including natural variability, inaccuracies in geographic coordinates, measurement error and misclassification in the field, errors that arise in the processing and interpretation of data (e.g., land-cover classification of remote sensing imagery), and interpolation error. These and other sources of spatial data error have been well defined by Burrough (1986), Goodchild and Gopal (1989), Hunsaker et al. (2001) and others. Operationally, from the perspective of developing and implementing general methods of spatial uncertainty analysis, it is useful to characterize spatial error and uncertainty as: (1) error in categorical data (e.g., soil or vegetation type) and (2) error in continuous quantitative data (e.g., vegetation height or population density). The most appropriate methods of spatial error analysis are fundamentally determined by these broad categories. General methods appropriate to these basic data types may then be refined if necessary to reflect differences in the source of that error or uncertainty.

We approach the problem of uncertainty in spatial data from the perspective of ecological modelers involved in applying ecological models to problems of conservation in ecosystem and land-use management. Thus our primary focus is on how to quantify error and uncertainty in spatial data presented as input for an ecological model, how to propagate that uncertainty through a simulation model, and how to relate the resulting variability in model output to uncertainty in model input.

Beyond simply identifying appropriate methods, it is important that these methods be implemented as usable and practical tools. Methods must be translated into software and incorporated into modeling and analysis systems. The software developed as part of research and development in a 6.1 Basic Research project such as the one described here need not be, and are unlikely to be, the "polished" product distributed as part of a decision support system. Nevertheless, the selected approaches and methods of analysis should be implemented as functional tools, tested on and applicable to real world situations, and consistent with the design specifications of the systems for which they are ultimately destined.

2.1 CS-1097 Project Objectives

1. Identify, evaluate, and implement methods for quantifying error and uncertainty in spatial data used in ecological models.

2. Incorporate error and uncertainty in spatial data into a general methodology for error and uncertainty analysis of ecological models.

3. Test and demonstrate this methodology and the associated software with case studies.

4. Transfer our methods and software to Dr. George Gertner and CS-1096 for incorporation into the CS-1096 error budget framework and toolbox.

5. Insure that our methods and software are compatible with, and available for incorporation into the DoD Land Management System (LMS) or other SERDP land management tools and software.

In this Annual Report we document our achievements and findings for the fourth and final year (2001) of Conservation Thrust Area Project CS1097. This project is focussed on error and uncertainty analysis of spatial data as used in ecological models. This focus "bores in" on one component of Dr. George Gertner's error budget (re CS-1096) and, consequently, supports and complements that broader approach. Our focus on spatial error and uncertainty and ecological models has been coordinated with Dr. Gertner and CS-1096.

3 Year 2001 Objectives

Our milestones for 2001 were:

1. Literature review to determine the feasibility and need for evaluating temporal uncertainty in spatial data. This is a go-no go item.
2. Pending the results of the go-no go decision on Milestone 1, implement analysis of temporal changes in spatial uncertainty for the golden-cheeked warbler (GCW) model at Fort Hood.
3. Document case study at Fort Hood.
4. Investigate transition of methods to the Fort Hood Avian Simulation Model (FHASM)
5. Final Report to SERDP

4 Achievements

4.1 General Methodology

From our survey of existing methods and approaches for quantifying error and uncertainty in spatial data, we have identified *stochastic simulation* as the most broadly applicable approach to incorporating spatial error and uncertainty into ecological models. Stochastic simulation uses geostatistics to generate a probability distribution for a spatial variable z, conditioned by available data including spatial autocorrelation in z and covariance with other spatial variables. Monte Carlo simulation is then used to sample this distribution and generate multiple alternative realizations (maps) of z that reflect the error and uncertainty in z. These maps are input to Monte Carlo simulation of the spatially structured ecological models utilizing that spatial data. Stochastic simulation is a widely recognized approach for addressing spatial uncertainty in geological and geographical applications (e.g., Geographical Information Systems). It is much less widely applied to ecological modeling, apparently because of lack of familiarity rather than any inappropriateness of the approach. We therefore adopted stochastic simulation as a primary method for incorporating uncertainty in spatial data into ecological models.

Our general methodology for the incorporation of uncertainty in spatial data into simulations with spatially explicit ecological models is illustrated in Figure 1. The approach uses geostatistics and Monte Carlo simulation to propagate uncertainties in GIS data layers through the entire modeling process. We have populated this framework with the appropriate methods and tools. In 1998 we focussed on methods and tools for stochastic simulation to generate multiple realizations of one or more data maps (left of Figure 1). In 1999 and 2000 we further refined these methods and tested their implementation with case studies at Fort Knox and Fort Hood. The case studies also served to exercise and test the entire methodology (center and right of Figure 1). In 2000 we also explored methods of spatial error and uncertainty analysis at a more theoretical level. We applied a more theoretical approach for generating alternative spatial inputs to a generalized version of the avian demographic model used in our cases studies (With and King, 2001), and we applied the techniques used in our case studies to an alternative ecological model (Jager et al., 2000, , and in preparation).

Our methodology lies on the far right of the spectrum of spatial structure illustrated in Figure 2. Our methods are more constrained to represent observed details of cartographic pattern than methods involving neutral landscape models (With and King, 1997). As a consequence, the generated variability is reduced, but better reflects observed error and uncertainty in spatial pattern.

Spatial data used in ecological models may be either categorical (e.g., vegetation type) or continuous (e.g., population density). Different techniques of stochastic simulation are appropriate to each. Accordingly we have separated our investigation of methods into (1) the treatment of categorical spatial data and (2) the treatment of continuous spatial data. To date, the project has focused on error and uncertainty analysis of categorical spatial data because categorical spatial data is more commonly used as input to spatially explicit ecological models, and because all our case studies have involved categorical spatial data.

We acquired and installed software libraries implementing methods for stochastic simu-

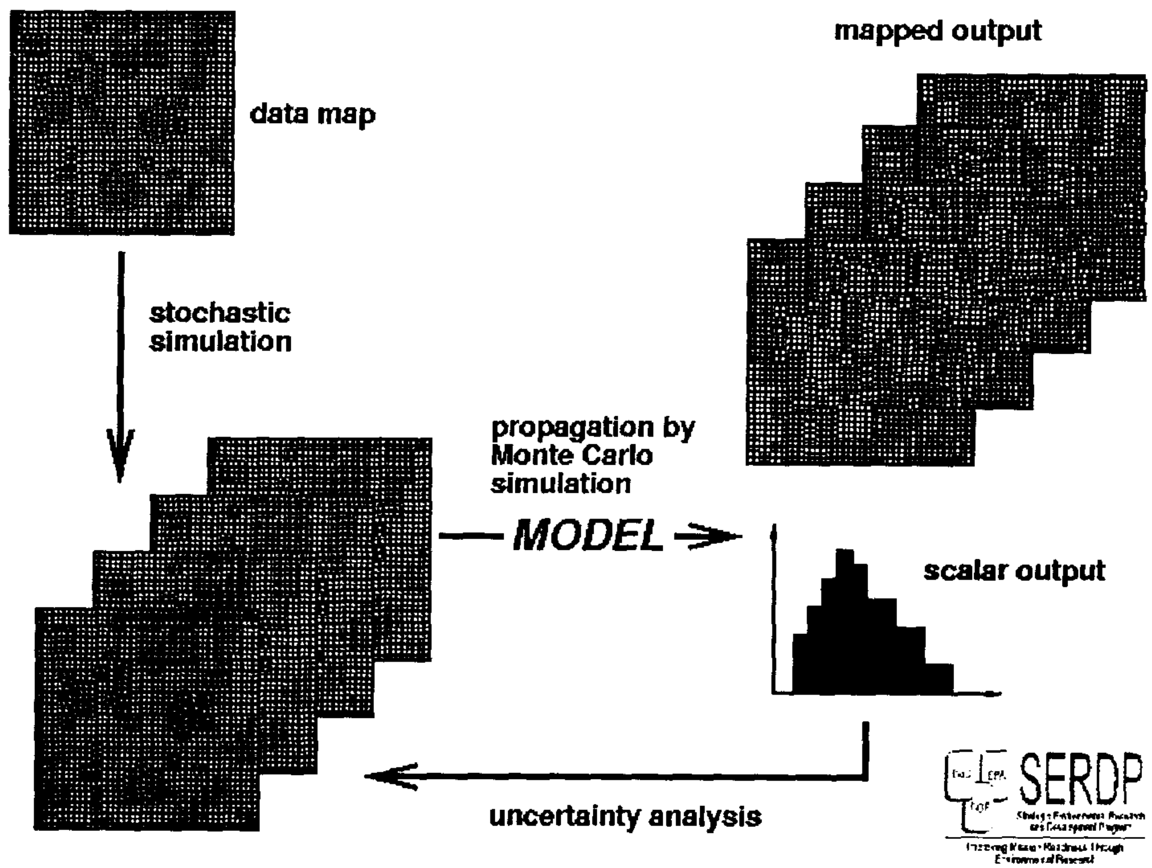


Figure 1: An analytical framework for spatial error and uncertainty analysis of ecological models

None (random)		SPATIAL STRUCTURE	Observed (cartographic)
p_i	landscape indices	CONSTRAINT	geostatistics
neutral landscape models		LANDSCAPE GENERATOR	stochastic simulation
random	fractal hierarchical contagion		

Figure 2: A spectrum of spatial structure and approaches to generating variability in spatial data (maps) used as input to ecological models.

lation of spatial data. These include the GSLIB (Deutsch, 1998) and gstat (Pebesma, 1998) library. Both libraries are freely available and provide cost effective and portable tools. These libraries have been enhanced and supplemented with additional software developed by project participants B. L. Jackson and H. I. Jager. We selected Arc/Info as the GIS component of our software implementation and as the user interface.

We identified sequential indicator simulation as the most appropriate general method of stochastic simulation for categorical data in ecological models. This is true of our case studies in particular, and for ecological models in general. We utilized this technique as implemented in gstat 2.0g (Pebesma, 1998) in our case studies at Fort Knox and Fort Hood. Details of this implementation can be found in our 1999 Annual Report and on our website.

4.2 Issues of Temporal Uncertainty in Spatial Data (Milestones 1 and 2)

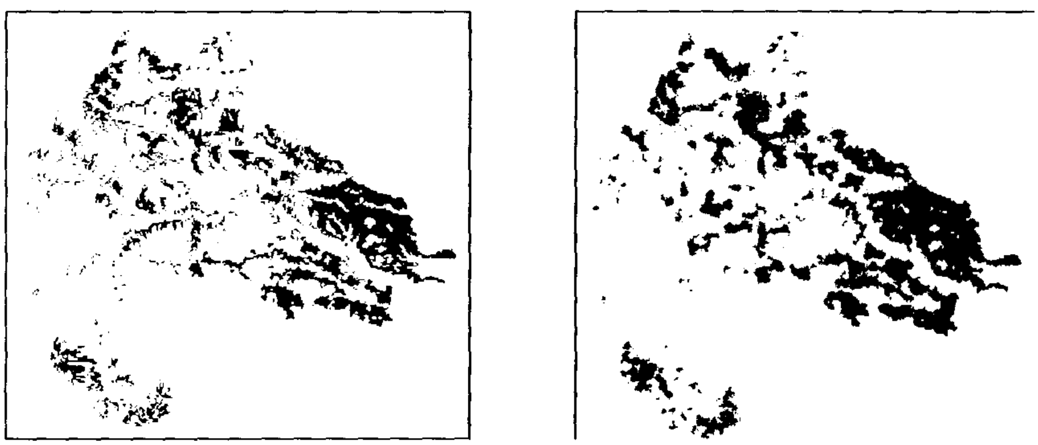
We completed a literature review to determine the need for, and feasibility of, evaluating temporal uncertainties in spatial data (e.g., changes in spatial uncertainty over time). From this review and a consideration of the availability of data on temporal changes in spatial data (particularly for our Fort Hood, TX case study), we determined that further consideration of this issue was neither warranted nor feasible. We therefore made no attempt to implement an analysis of temporal changes in spatial uncertainty in Golden-cheeked Warbler at Fort Hood.

4.3 Fort Hood Case Study (Milestone 3)

We completed our Fort Hood case study involving demographic modeling of Golden-cheeked Warbler (*Dendroica chrysoparia*) at Fort Hood, Texas. Early results of this case study were presented at the 2000 Annual Conference of the U.S. Regional Association of the International Association of Landscape Ecologists (April 2000, Fort Lauderdale, FL). Final results of the case study will be documented as a peer reviewed journal article in a manuscript targeted at a journal of conservation biology (Section 6).

In brief, we parameterized the avian demographic model described above for Golden-cheeked Warbler at Fort Hood, TX (Table 2), and we obtained a map of Golden-cheeked Warbler habitat at Fort Hood from Jon Horne of the Texas Nature Conservancy and Fort Hood Endangered Species program. Figure 3 compares this original map with a map of the uncertainty in patch edge generated by stochastic simulation. By varying the density of the sampling grid which generates input for the stochastic simulation, we can adjust the amount of uncertainty in patch edge (Figure 4). A larger, more dense, sample (e.g., 20% in Figure 4) results in less uncertainty in the location of patch edge. We found these maps useful in communicating with the endangered species management team at Fort Hood. For example, after looking at a range of uncertainty maps generated with samples ranging from 1%-50%, Jon Horne indicated that he felt the uncertainty generated by the 20% (or even 50%) samples best reflected his understanding of the uncertainty in the mapping of Golden-cheeked Warbler habitat at Fort Hood.

Golden-cheeked Warbler Habitat, Fort Hood, Texas



Original map

Composite map of ten stochastic simulations showing uncertainty in patch edge

Figure 3: Comparison of original habitat map for Golden-cheeked Warbler at Fort Hood, TX with map of uncertainty generated by stochastic simulation. The composite map (right) shows the probability that a generated map was classified as habitat. Blue indicates pixels where all maps were classified as habitat; reds indicate a declining probability that a pixel was classified as habitat.

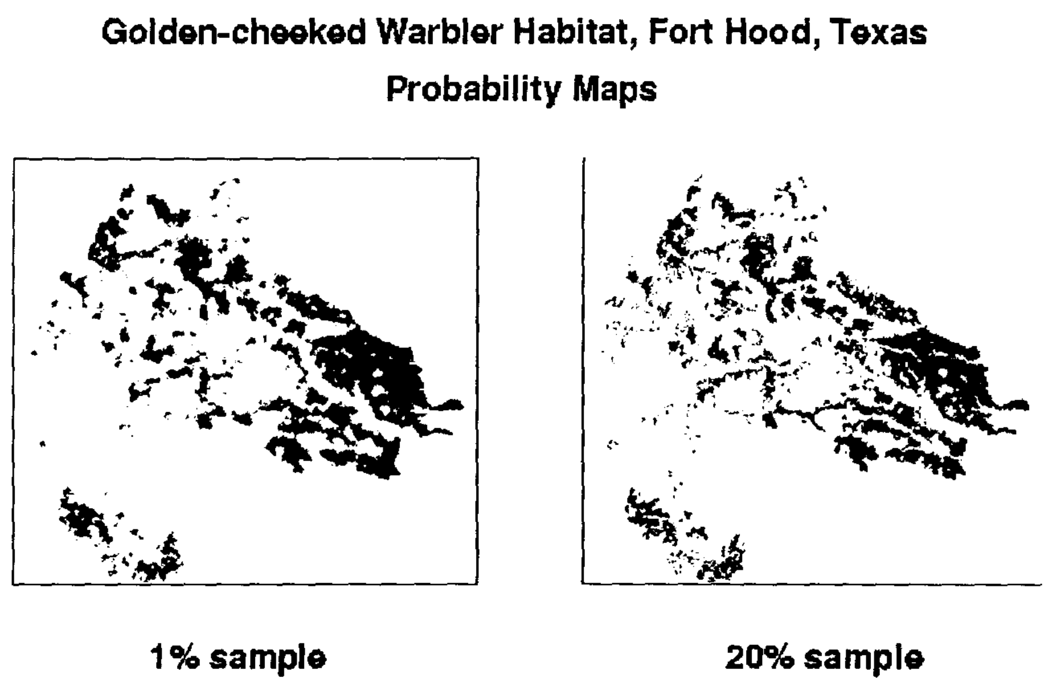


Figure 4: Maps of the probability that a pixel is classified as habitat in the alternative maps of Golden-cheeked Warbler habitat at Fort Hood generated by stochastic simulation.

Table 1: Life history parameters for Golden-cheeked Warbler used as model input at Fort Hood, Texas.

Parameter	Value
Territory size (A_T)	1.7 ha
Gap crossing ability	< 30 m
Clutch size (C)	3–4
Incidence function parameters:	
β_0	-1.386
β_1	0.0
β_2	0.0
Juvenile survivorship (s_0)	0.25
Adult survivorship (s)	0.66
Age of first reproduction (α)	1 yr
Longevity (L)	7 yr
Maximum nesting success ($S_{\max}$)	0.8
Edge:area index k where $S_i = 0.5S_{\max}$	0.75
Shape parameter θ	10.

The distribution of net lifetime maternity predicted by the avian demographic model for Golden-cheeked warbler at Fort Hood using each of the 10 habitat maps generated by stochasitic simulation using a 1% sample (Figure 4) is shown in Figure 5. The very small coefficient of variation indicates that the avian demographic model parameterized for Golden-cheeked Warbler at Fort Hood is insensitive to the uncertainty in patch edge generated by the 1% sample input to the stochastic simulation. The model will be even less sensitive to the level of uncertainty in the habitat map input generated by a 20% sample (Figure 4).

In this particular circumstance, the model is more sensitive to variability in non-spatial demographic parameters than to the spatial uncertainty in mapped habitat generated by the stochastic simulation. A 5% reduction in juvenile survivorship is sufficient to shift the simulated population from a state of slightly increasing population size to one of declining numbers (Figure 6). The variability in habitat maps did not result in variability in spatially-determined demography sufficient to alter the qualitative state of the simulated population (i.e., all values of net lifetime maternity were greater than one) (Figure 5).

We also completed additional analyses utilizing alternative techniques for the propogation of uncertainty in the habitat map for the Golden-cheeked warbler at Fort Hood. These alternatives arose in our March 2000 discussions with the Fort Hood staff on how the Golden-cheeked Warbler habitat map was generated. The results of these alternative analyses are consistent with the results presented here: our spatially-structured avian demographic model is insensitive to the level of uncertainty believed to be present in the Golden-cheeked Warbler habitat map for Fort Hood, Texas.

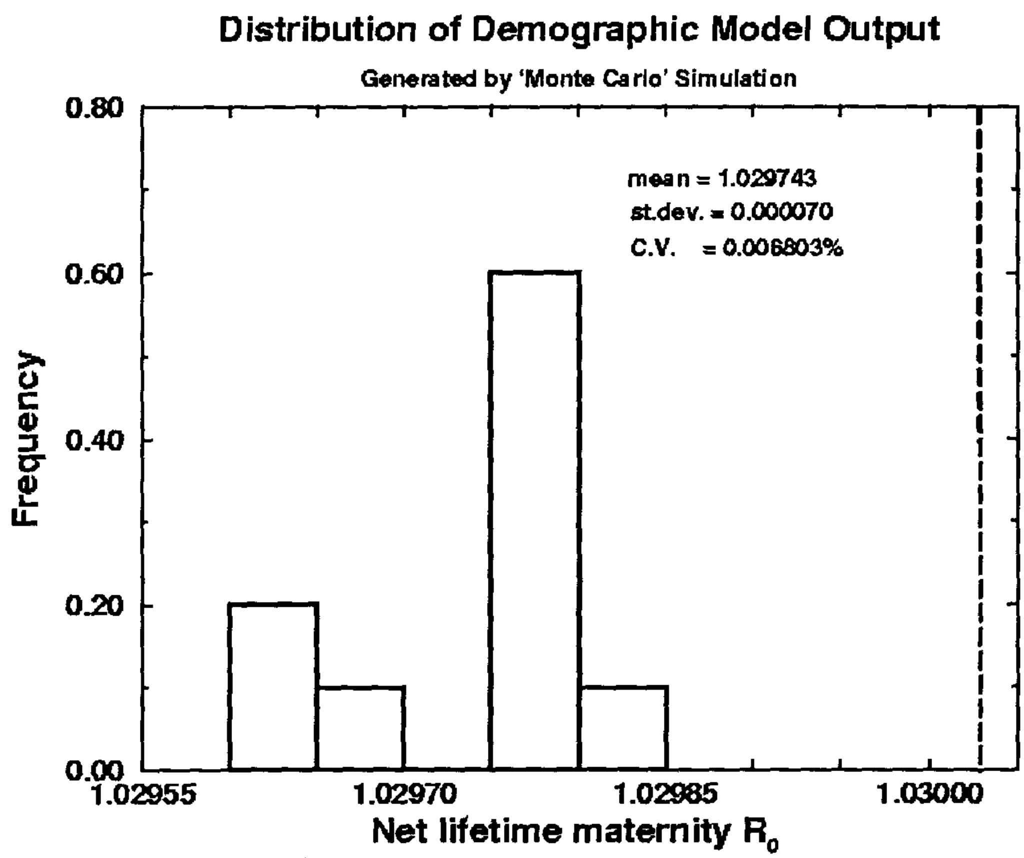


Figure 5: The distribution of net lifetime maternity predicted by the avian demography model for the 10 habitat maps generated with a 1% sample (Figure 4) input to the stochastic simulation for Golden-cheeked warbler at Fort Hood. The vertical red line indicates the value for the original habitat map.

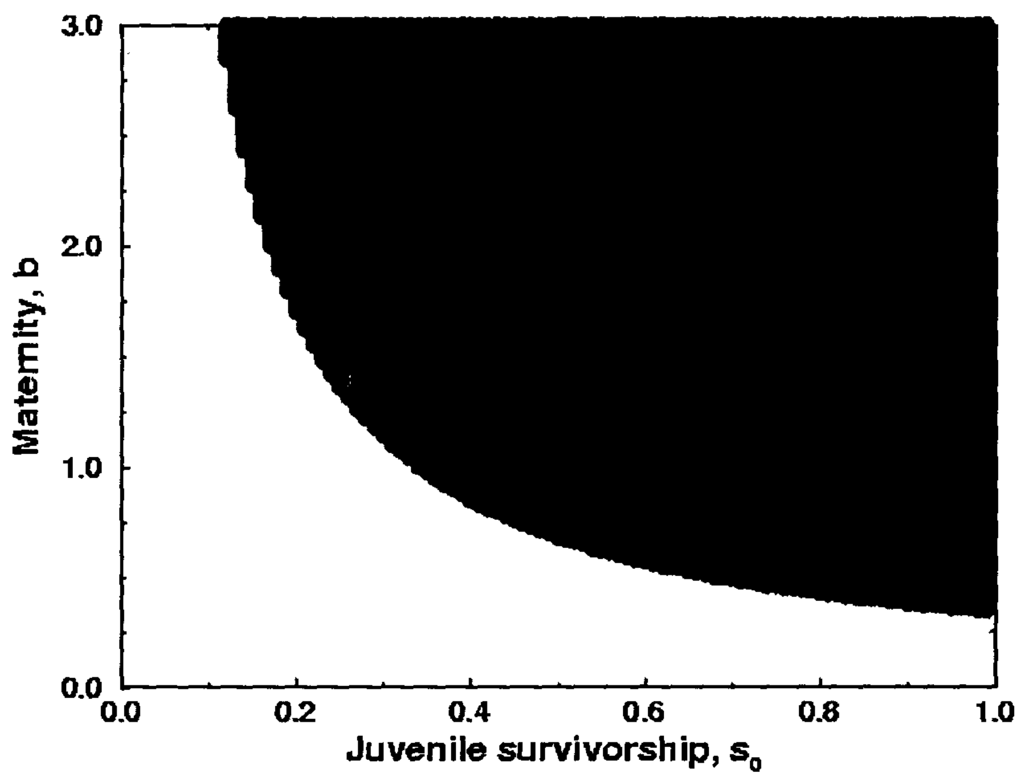


Figure 6: Net expected lifetime maternity R_0 as a function of age-specific maternity b and juvenile survivorship s_0. The shaded region indicates where $R_0 \geq 1.0$ and the population is at steady state or increasing. Outside this region the population $R_0 < 1.0$ and the population will decline. The filled circle indicates the combination of parameter values for the base run of the model for Golden-cheeked warbler at Fort Hood, Texas.

Which does not mean that the model is completely insensitive to spatial structure. Figure 7 shows one of ten randomizations of the Golden-cheeked Warbler habitat map from Fort Hood, where we kept the total amount of Golden-cheeked Warbler the same as in the original map, but randomized the spatial distribution of that habitat. The distribution of modeled net lifetime maternity R_0 for those ten randomized maps is shown in Figure 8. Note that the coefficient of variation (an index of sensitivity) is larger than for the alternative maps constrained by the geostatistical structure of the orginial map (Figure 5). But more importantly the entire distribution is shifted to much smaller values < 1.0, indicating that the model predicts the current persistence of the population is in large part a function of the spatial structure of the habitat, it's aggregation. Additional analysis of the model by With and King (2001) results in the same conclusion. Thus the model is simultaneously sensitive to the spatial distribution of habitat while essentially insensitive to potential error in the observed habitat map comparable to that shown in Figure 4.

Therefore, if a land/ecosystem manager were using this model to manage Golden-cheeked Warbler at Fort Hood, TX, they could conclude that while large-scale changes in the distribution of the bird's habitat could result in declining populations, the model is insensitive to the degree of error that is likely to be present in the existing habitat map, and efforts to reduce that error are uncertainty would have no consequences for the model results. Efforts to improve the habitat map with respect to uncertainty in the edges of large patches or the distribution of small isolated patches would not be warranted. Effort would be better spent in reducing uncertainty in juvenile survivorship.

In the analyses we have completed to date, our case-study model of spatially structured avian demographics has been insensitive to the level of spatial uncertainty we have investigated. It is not appropriate, however, to extrapolate from this small sample of model- and case-study specific results to a general conclusion about the importance of uncertainty in spatial data. Nor is it reasonable to deduce that analysis of spatial uncertainty will not provide managers any additional information to aid in the prediction of environmental effects on military operations.

First, the results of a specific analysis are dependent upon the amount of uncertainty present in the spatial data being analyzed. In the installation-specific case-study analyses we have completed so far, we have propagated only a fairly limited amount of spatial uncertainty. This limited uncertainty reflects the type and amount of uncertainty appropriate to the case studies. As noted in our 1999 Annual Report, our completed case studies lie on the far right of a spectrum of possible spatial structure and constraints on spatial uncertainty (Figure 2). Our case studies have been constrained to reproduce observed details of cartographic pattern and this constrains the amount and type of spatial uncertainty being analyzed. As a consequence, the generated variability is reduced, but better reflects error and uncertainty in spatial pattern observed in our case studies. In other analyses, not tied to a specific installation, where we relaxed the cartographic constraint (working to the center-left of the spectrum in Figure 2), we have shown that the avian demographic model used in our case studies is sensitive to uncertainty in the size, distribution, and geometry of habitat patches (With and King, 2001). Variability in spatial structure influenced the model's prediction of whether the landscape supports a growing population or a declining population. We have also shown with a slightly different model that although uncertainty in spatial data

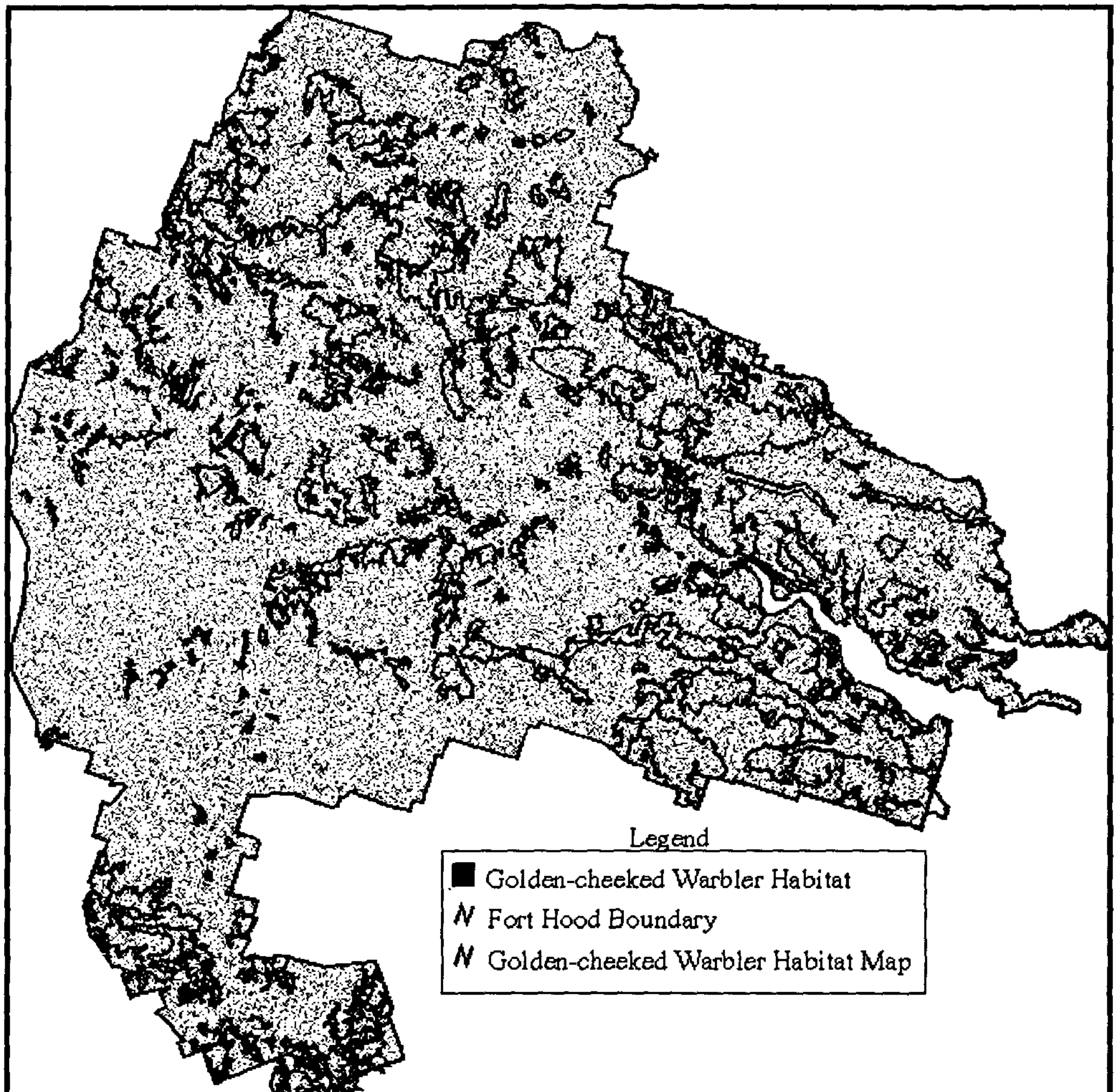


Figure 7: A randomized distribution of Golden-cheeked Warbler habitat at Fort Hood

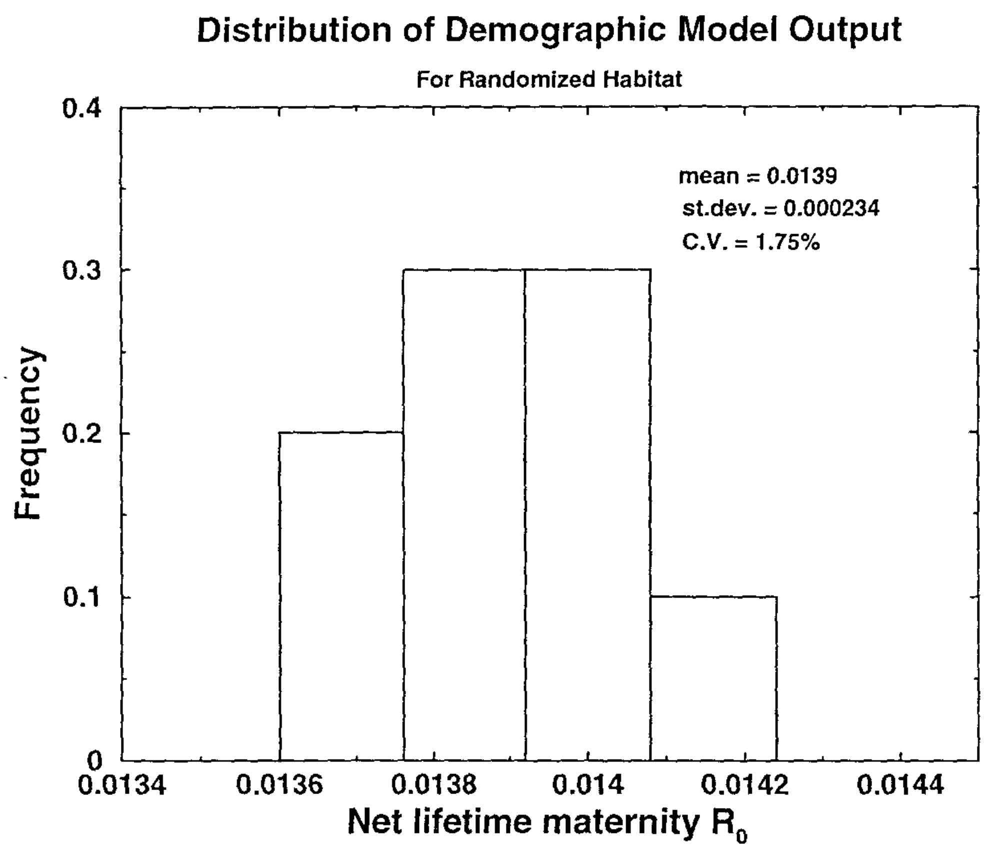


Figure 8: The distribution of net lifetime maternity predicted by the avian demography model for the 10 random habitat maps used as input to the stochastic simulation for Golden-cheeked warbler at Fort Hood. Compare with Figure 5 and note the shift in scale of the net lifetime maternity axis to much smaller values < 1.0.

resulted in relatively little variation in overall population growth rate, the spatial uncertainty was sufficient in some situations to yield qualitatively different predictions about population viability (i.e., prediction of population decline versus population increase) (Jager et al., 2000). In summary, the type and amount of uncertainty present in the maps of a specific application will influence the significance or importance of uncertainty in spatial data. Applications and installations with greater uncertainty in spatial data are likely to yield results showing that uncertainty in spatial data is significant.

Second, the results of an analysis are also dependent upon the specifics of the model under investigation. Even differences in the biological parameterization of the same model can lead to differences in sensitivity to spatial uncertainty. In our case study with Golden-Cheeked Warbler (GCW) at Fort Hood, Texas we parameterized the avian demographic model to reflect the fact that GCW is less sensitive to cowbird parasitism than some other neotropical migrants. This naturally reduced the model's sensitivity to uncertainty in patch edges where cowbird parasitism is most important. In a different parameterization of the model for a species only slightly more sensitive to edge-related cowbird parasitism, we found that the same spatial variability at Fort Hood to which the GCW version of the model was insensitive resulted in qualitative changes in the model's predictions for a species with greater susceptibility to cowbirds. The incorporation of spatial uncertainty shifted the model's predictions from a stable or slightly increasing population to a declining population headed towards extinction. Similarly, for a slightly modified version of the GCW model in which juvenile survivorship is a function of patch edge:area ratio (in the case-study model juvenile survivorship is independent of spatial pattern), we found that the level of spatial variability to which the case-study model was insensitive led again to qualitative changes in the model predictions. Incorporation of the uncertainty in patch edges resulted in a shift in prediction from a stable or increasing population to a declining population. In summary, the importance or significance of spatial uncertainty is dependent upon the model being examined. Different models applied to the same installation's spatial data, or even the same model parameterized for different species can show different sensitivities to the same amount of spatial uncertainty. Models must be evaluated on their own right.

Finally, it is important to note that results that demonstrate a model is insensitive to spatial uncertainty actually provide managers with useful information. If a model proves to be insensitive to observed uncertainty in spatial data, it means that the manager can be less concerned about the quality or uncertainty of spatial data available for the application of that model on that installation. But it is only by first having and applying methods of spatial error and uncertainty analysis that a determination of that importance can be made.

Our methods allow one to evaluate the significance and importance of uncertainty in spatial data on a case by case basis. Our current sample is quite small, but as this process continues a better understanding will develop of when spatial uncertainty is likely to be significant and when it is not. Patterns in the combinations of model structure and parameterization with type and level of uncertainty in spatial data that lead to significant or nonsignificant responses to spatial uncertainty are likely to emerge. However, because the significance of uncertainty in spatial data is dependent upon a variety of application-specific properties (some of which we have described here), we believe that primary value of our methodologies is that they can actually be use to determine if and when spatial uncertainty is significant in individual cases. The issue is not whether spatial uncertainty is significant in a necessarily limited number of case studies, but whether the methodologies make it possible to make that determination.

4.4 Transition of Methods to Fort Hood Avian Simulator Model (FHASM) (Milestone 4)

Our general methodolgy is applicable to any computer simulation model that reads digitized maps of categorical data as model input. We have demonstrated that generality in a joint activity with Dr. Tom Sisk's Effective Area Model project (CS-1100). Dr. Sisk provided us with a habitat map for their study area in Arizona. We then used our techniques to generate alternative versions of that map representing different levels of uncertainty in patch edges (Figure 9) that were returned to Dr. Sisks's team. Those maps were then utilized in a spatial sensitivity analysis of the EAM model. Results of that analysis were presented by Dr. Sisk at the 2001 Conservation Thrust Area IPR. Thus, if we were provided with the normal input maps for the Fort Hood Avian Simulator, we could generate alternative maps reflecting spatial uncertainty in those maps, and they could be used in a spatial sensitivity analysis of FHASM. Alternatively, our software could be ported to the FHASM team and they themselves could generate those maps.

4.5 Technical Papers and Presentations

With, K.A., and A.W. King. 2001. Analysis of landscape sources and sinks: the effect of spatial pattern on avian demography. *Biological Conservation* 100:75–88.

King, A. W., T.L. Ashwood, B.L.Jackson, and H.I. Jager. Spatial sensitivity analysis of ecological models. Poster presented at the Partners in Environmental Technology Technical Symposium and Workshop. Washington, D.C., November 27-29, 2001.

King, A.W., and K.A. With. 2002. Dispersal success on spatially structured landscapes: when do spatial pattern and dispersal behavior really matter. Ecological Modelling 147:23–39.

The following manuscripts documenting various aspects of our project's results are currently in preparation:

Jager, H. I., A. W. King, N. H. Shumaker, T. L. Ashwood, and B. L. Jackson. Spatial uncertainty analysis of ecological models. For submission to a general ecology journal.

King, A. W., T. L. Ashwood, B. L. Jackson, and H. I. Jager. Propagation of spatial error and uncertainty in landscape models. For submission to Landscape Ecology.

King, A. W. T. L. Ashwood, B. L. Jackson, and H. I. Jager. Spatial sensitivity analysis of an avian demographic model and the implications for management of species of conservation concern. For submission to Conservation Biology or Biological Conservation.

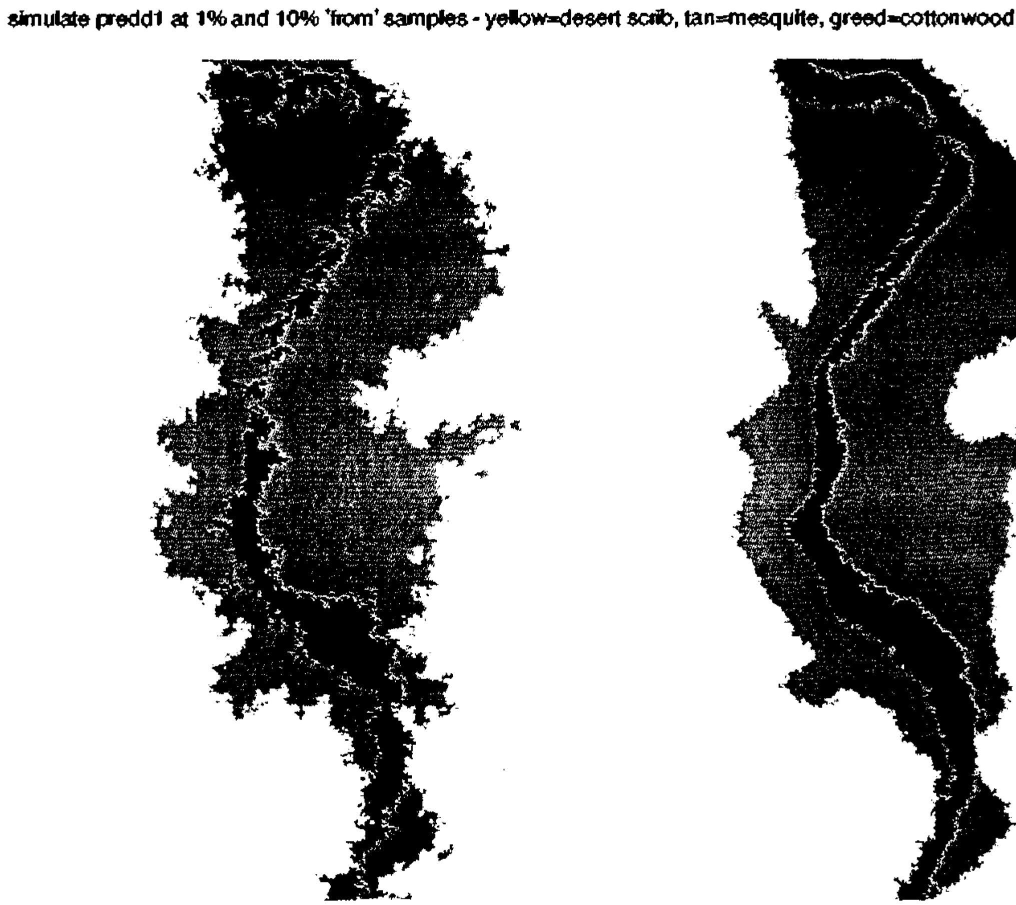


Figure 9: Alternative maps of a riparian habitat map from the CS-1100 project generated by stochastic simulation.

King, A. W., T. L. Ashwood, B. L. Jackson, and H. I. Jager. Methods of spatial error and uncertainty analysis for spatially explicit ecological models. For submission to Ecological Applications.

5 Future Needs

In October 2001, we held a small workshop on spatial error and uncertainty analysis at Northern Arizona University, Flagstaff, AZ. Three SERDP Conservation projects were represented (CS-1096, CS-1097, and CS-1100). A report associated with that workshop will be provided to SERDP under separate cover. The participants in the workshop concluded that the following were priority needs for future research:

1. Definition and adoption of metadata standards enforcing the inclusion of information on true spatial error and uncertainty with spatial data (maps and GIS layers).

2. Creation and distribution of software tools for analysis of spatial error and uncertainty in spatial data and models that can be used by GIS operators, environmental modelers, and spatial analysts without expertise in error and uncertainty analysis.

3. Investigation into sources, characterization and propagation of error and uncertainty in spatial data derived from satellite and airborne remote-sensing platforms (e.g., land-use/land-cover maps).

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