ECOLOGICAL, ECONOMIC, AND SOCIAL DYNAMICS ASSOCIATED WITH EXURBAN DEVELOPMENT IN SOUTHERN APPALACHIA

by

PAIGE FITHIAN BARLOW

(Under the Direction of Michael J. Conroy and Jeffrey Hepinstall-Cymerman)

ABSTRACT

Exurban development, the construction of low-density residential homes in a rural landscape, is the fastest growing type of land use in the United States and is prominent in the southern Appalachian region. Associated parcelization and forest fragmentation is of concern for ecological, economic, and social reasons. To investigate exurban development in Macon County, North Carolina, we modeled the relationship between avian occupancy and multi-scale attributes at National Forest, land trust, and unprotected sites via a Bayesian approach that accounts for false positive and false negative detections. Before modeling avian occupancy and exurban development, we evaluated our model parameterization through simulations. We then followed a structured decision making (SDM) process with owners of large, forested property (30 ha property with 22 ha of forest) to investigate alternative forest management options. Although SDM has typically been applied to decision problems involving public resources, we illustrate the ability of SDM to incorporate value-based and technical information, balance multiple objectives, and address uncertainty in the case of private resource management. Our occupancy model parameterization generated accurate and precise posterior distributions. Landscape- and local-scale covariates influenced avian occupancy more than site-scale covariates, and landscape composition and elevation had a greater effect on posterior occupancy probabilities than configuration. The Black-throated Blue Warbler and Wood Thrush had the lowest posterior occupancy probabilities of the six focal species. National Forest sites had high occupancy, but land trust sites exhibited patterns similar to unprotected sites. The most promising forest management action was crown thinning timber harvest under the Present-Use Value program. The least promising forest management actions were selling 1 ha and personal use of the forest, with or without a conservation easement. Landowners reported that they enjoyed participating in the SDM project, and after reviewing the results of the decision network, 69% said they would reconsider what they are currently doing to manage their forest. Our findings can provide guidance to U.S. Forest Service decision-makers, county planners, land trusts, and landowners as they decide how to respond to exurban development, and our occupancy model and SDM can be useful methods for future studies.

INDEX WORDS: exurban development; forest fragmentation; parcelization; occupancy model; false positive detection; Neotropical migrant; forest-dwelling bird; southern Appalachia; structured decision making; conservation easement; Present-Use Value program; land trust; National Forest

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by

PAIGE FITHIAN BARLOW

BS, University of Richmond, 2006

MS, Virginia Polytechnic Institute and State University, 2009

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PAIGE FITHIAN BARLOW

Major Professors:	Michael J. Conroy Jeffrey Hepinstall-Cymerman
Committee:	John F. Chamblee Robert J. Cooper John C. Maerz

Electronic Version Approved:

Maureen Grasso
Dean of the Graduate School
The University of Georgia
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DEDICATION

This dissertation is dedicated

to my parents, Patricia Fithian and Rodney Barlow,

in thanks for their constant support.

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

The problem: parcelization and forest fragmentation

Parcelization and the fragmentation of forestland have implications for the three components of sustainability: ecological, economic, and social dynamics (Salwasser et al. 1993, Rickenback and Gobster 2003). In many areas, parcelization and forest fragmentation is occurring as a result of exurban development (Brown et al. 2005, Hansen et al. 2005). Exurban development is characterized by the construction of low-density residential homes in a rural landscape, often near natural amenities (Brown et al. 2005, Wade and Theobald 2010). Exurban development is the fastest growing type of land use in the United States, and growth in exurban development is expected to continue (Theobald 2001, Brown et al. 2005, Hansen et al. 2005, Theobald 2005).

Urban and exurban development are considered principal causes of worldwide habitat loss (Brown et al. 2005, Hansen et al. 2005). The construction of roads, yards, and buildings associated with exurban development often lead to smaller and more isolated patches of native habitat, less interior habitat, more edge, more anthropogenic disturbances, and the loss of native vegetation structure and diversity (Andrén 1994, Theobald et al. 1997, Best 2002, Fahrig 2003, Chace and Walsh 2006, Bonier et al. 2007, Husté and Boulinier 2011).

Habitat loss and degradation can have profound impacts on wildlife diversity and population persistence. Birds are commonly selected as a focal taxon for investigating the effects of land use (McDonnell and Hahs 2008) because their ecology is well known and birds appear to respond to their surroundings at multiple spatial scales (Orians and Wittenberger 1991, Pearson 1993, Hostetler and Holling 2000). To manage the effects of exurban development on wildlife, such as songbirds, it is important to understand how birds respond to land use patterns. Specifically, elucidating the relationship between avian occupancy and landscape composition and configuration and determining the spatial scale at which species respond can help stakeholders to make decisions about development and wildlife conservation (Hostetler 1999, Villard et al. 1999, Lerman and Warren 2011, Pennington and Blair 2011).

Parcelization can lead to changes in local economies and additional development and conversion of forested land into more intense human land uses, particularly residential subdivisions (Harper et al. 1990, Mehmood and Zhang 2001, Best 2002, Gobster and Rickenbach 2004). Also, parcelization is associated with changes in social dynamics (Rickenback and Gobster 2003). As a result of parcelization, the number of forestland owners increases, the average parcel size decreases, and new landowners bring more diverse objectives and values to the community (Egan and Luloff 2000, Smith and Krannich 2000, Kendra and Hull 2005, Ko and He 2011, Mehmood and Zhang 2001). Residents may experience a loss of community identity and sense of place as the community changes (Cumming and Norwood 2012).

Approaches to study and address forest loss and degradation

Occupancy models

The relationship between avian occupancy and factors associated with exurban development can be investigated through the use of occupancy models. Occupancy models have been used widely by ecologists because they provide information about species' use of sites but only require data on detection/non-detection of species from repeat samples of sites (MacKenzie et al. 2002, 2003; Royle and Nichols 2003). When explanatory variables are included in functions with occupancy probability as an independent variable, the relationship between anthropogenic or environmental attributes and occupancy can be quantified. Incorporating explanatory variables also allows inference about the heterogeneity among sites and surveys. Unbiased inference about state variables and covariate coefficients is facilitated by accounting for imperfect detections.

In general, there are two types of imperfect detections: false negative detections, defined as not detecting a species when it is present, and false positive detections, defined as detecting a species when it is not present. Quantitative methods to account for false negative detections, in particular, have been widely adopted in occupancy models (Bayley and Peterson 2001; MacKenzie et al. 2002, 2003; Royle and Nichols 2003; Tyre et al. 2003) and other ecological models (Williams et al. 2001). However, many methods that estimate a false negative detection probability assume that false positive detections did not occur. Studies have shown that observers of all experience levels make false positive errors and if analyses assume there are no false positive detections but data contain false positive errors, inference about occupancy probabilities and covariate coefficients will be biased (Genet and Sargent 2003; Royle and Link 2006; Lotz and Allen 2007; Simons et al. 2007; Alldredge et al. 2008; Simons et al. 2009; McClintock et al. 2010a, 2010b). Because false positive detections are unlikely to be eliminated through study design, it is important to develop and employ methods that account for both classes of imperfect detection.

Structured decision making

Ecological, economic, and social concerns can be integrated in decision-making about exurban development through the use of structured decision making (SDM). SDM enables decision makers to balance multiple objectives given constraints and uncertainty and facilitates rigorous, transparent decision-making (Funtowicz and Ravetz 1993, Conroy et al. 2008, Martin et al. 2009). Key features of SDM are the recognition of the distinction between value-based information and technical information and the explicit integration of both types of information in the decision-making process (Keeney and McDaniels 1999, Gregory and Keeney 2002, Wilson and McDaniels 2007, Conroy et al. 2008). Compared to decisions that do not explicitly define objectives, weight conflicting objectives, and incorporate uncertainty, decisions made through an SDM process are expected to produce desirable outcomes more often (Conroy and Peterson 2013).

The main components of SDM are a definition of the decision problem, objectives based on the stakeholders' values, attributes to make objectives measurable, decision options that could help the stakeholders achieve their objective(s), one or more models to describe the expected outcomes of decision options, and a method to evaluate the degree to which each decision option is expected to fulfill the stakeholders' objectives (Hammond et al. 1999, Dorazio and Johnson 2003, McCarthy and Possingham 2007, Wilson and McDaniels 2007, Conroy et al. 2008, Irwin et al. 2011, Conroy and Peterson 2013). These components can be developed through an iterative process where stakeholders provide input and the facilitator and technical consultants synthesize information while attempting to remain value-neutral (Phillips 1984, Wilson and McDaniels 2007, Miller et al. 2010, Raymond et al. 2010, Irwin et al. 2011, Conroy and Peterson 2013). Typically, SDM has been a valuable process for working with diverse stakeholders to analyze decision problems related to a common resource, such as water or wildlife populations (e.g., Kuikka et al. 1999, Bromley et al. 2005). However, SDM could also benefit an individual who wants a rigorous way to make a decision about a privately-held resource, such as a large, forested property.

Study site

We developed and applied occupancy models to study the relationship between exurban development and avian occupancy and we conducted SDM workshops with the owners of large, forested properties (30 ha property with 22 ha of forest) in Macon County, North Carolina, USA. Macon County is in the southern Appalachian region, a biologically rich area that contains twelve Audubon Global Important Bird Areas (SAMAB 1996, National Audubon Society 2010). At the same time, the aesthetic and recreational opportunities, low cost of living, low taxes, and lack of zoning regulations in the southern Appalachian region have contributed to exurban development (Marcouiller et al. 2002, Gragson and Bolstad 2006). Generally, exurban development has occurred as retirees, urban commuters, and people in the market for vacation homes have purchased properties that were formed by subdividing former agroforestry lands (Wear and Greis 2002, Cho et al. 2003, Hansen et al. 2005, Gragson and Bolstad 2006). New residents in Macon County have built houses on forested slopes at high elevations and on previously farmed properties that have reverted to forest (Gragson and Bolstad 2006).

There is also a history of conflict over private property rights and land use regulations in Macon County. Many landowners think the county’s rapid growth is detrimental, but there has not been agreement about an appropriate response (Cho et al. 2005, Gragson and Bolstad 2006, Cho et al. 2009, Cumming and Norwood 2012). There have been various attempts to pass land use regulations in Macon County throughout the past 30 years, but they have largely failed (Cumming and Norwood 2012). Stalled land use decision making has been attributed to the lack of effective opportunities for citizens to express their perspectives, consider potential options, and learn from each other in a respectful and productive setting (Susskind et al. 1999, Lando 2003, Senecah 2004, Stewart et al. 2004, Cumming and Norwood 2012). Consequently, existing land conservation is largely done voluntarily by citizens though conservation easements with local land trusts.

Dissertation objectives and structure

The remainder of this dissertation consists of three research chapters and a concluding chapter. In Chapter 2, we developed an occupancy model that makes inferences about occupancy probabilities and the effects of covariates while accounting for false positive and false negative detections. We present our model in the context of existing occupancy models that have addressed false positive detection and note the contributions of our model, including a Bayesian framework and incorporation of heterogeneity across sites and surveys. By using covariates to model heterogeneity in occupancy and detection, we show how inference can be made about the relationship between environmental or anthropogenic factors and occupancy or detection. Through simulations, we evaluated our model and compared its performance to that of a model that assumed there were no false positive detections. We discuss model performance in a variety of simulated data scenarios, consider the reasons for apparent patterns in model performance, and provide guidance to scientists who would like to select a model parameterization to make inference about occupancy, false positive detection, and false negative detection probabilities in addition to the effects of environmental or anthropogenic factors on these parameters.

In Chapter 3, we applied the occupancy model we developed in Chapter 2 to study the relationship between exurban development and avian occupancy in Macon County, North Carolina. Our focus was on six species of forest-dwelling, Neotropical migrant birds (Black-and-White Warbler, Blue-headed Vireo, Black-throated Blue Warbler, Canada Warbler, Veery, and Wood Thrush), and covariates at three spatial scales: site (within 100m of the point count location), local (within 200m of the point count location), and landscape (within 1000m of the point count location). We developed candidate models based on hypothesized effects of exurban development on occupancy and detection probabilities, performed Bayesian model selection and model averaging with a Bayesian Information Criterion weights approximation, and evaluated models' predictive ability. Species-specific posterior distributions of occupancy probabilities and covariate coefficients from top models and from multi-model inference identified influential attributes of exurban development at multiple spatial scales and provided information about their relationship with forest-dwelling, Neotropical migrant birds. Also, by comparing posterior occupancy probabilities and covariate values at sites in the Nantahala National Forest, land trust sites, and unprotected sites, we gained understanding about the current distribution of the focal species, contributions of the National Forest and land trusts to avian conservation, and ways to help direct future land management decision-making. We also demonstrated application of our new occupancy model parameterization, which generates inference about heterogeneity in occupancy and detection probabilities while accounting for both types of imperfect detection.

In Chapter 4, we discuss accompanying a group of Macon County landowners through a series of SDM workshops. Since land use planning has been unsuccessful at the county-level, we focused on individuals' decision making about private forest management. Outreach to owners of large forests is important for forest conservation and has implications for the economic and social dynamics of the community. We illustrate how SDM can be useful to private landowners as they make decisions about land management. Our decision context was forest management on large properties (30 ha property with 22 ha of forest) in Macon County because we expected these parcels to offer high-quality wildlife habitat and to potentially face parcelization pressure. We gathered a group of landowners with diverse backgrounds and land use values to represent a complete range of land use objectives and decision options. We evaluated the expected performance of the decision options through a Bayesian decision network, and we highlighted decision options that were most and least often expected to fulfill landowners' objectives.

In Chapter 5, we summarize the dissertation, synthesize the results of our research, consider how our findings could be used by conservation organizations and county planners to address exurban development, parcelization, and forest fragmentation, and we note the potential for broader applications of the methods developed in this dissertation.

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CHAPTER 2

INFERENCE ABOUT OCCUPANCY WHEN FALSE POSITIVE AND FALSE NEGATIVE ERRORS OCCUR AND THERE IS HETEROGENEITY ACROSS SITES AND SURVEYS: EVALUATING BAYESIAN APPROACHES THROUGH SIMULATIONS [1]

[1] Barlow, P.F., M.J. Conroy, and J. Hepinstall-Cymerman. To be submitted to *Ecology*.

Abstract

Many ecological models estimate the probability of false negative detections in order to generate accurate estimates of the parameter of primary interest (e.g., abundance, occupancy probability, survival probability). However, false positive detections are also known to occur in ecological data, and if this type of imperfect detection is not accounted for in models, estimates will be biased. We build on previous attempts to account for false positive and false negative detections in occupancy models, while addressing some of the criticisms of an existing model, and present a Bayesian formulation of an occupancy model that accounts for both types of imperfect detection. To make inference about false positive and false negative detection probabilities, our models use a subset of data with confirmed observations, either confirmed presences (CP model) or both confirmed presences and confirmed absences (CACP model). Through simulations, we evaluate the CACP and CP models with vague and informative priors in a variety of data scenarios. We also investigate the accuracy and precision of posterior probabilities from the CACP and CP models when heterogeneity in occupancy and detection probabilities was simulated through covariates that were site-specific or site- and survey-specific. When simulated data contained false positive errors, the CACP and CP models always generated posterior distributions that were more accurate and more precise than the model that assumed there were no false positive errors. In the simulations with covariates and confirmed presences and confirmed absences, the CACP model with vague priors for false positive detection probabilities performed better than the other approaches considered. When confirmed absences were not available, model performance was more scenario-specific. We discuss model performance in the variety of simulated data scenarios, consider the reasons for apparent patterns in model performance, and provide guidance to scientists who would like to select a model

parameterization to make inference about occupancy, false positive detection, and false negative detection probabilities in addition to the effects of environmental or anthropogenic factors on these parameters.

Introduction

Many methods of ecological data collection are subject to imperfect detection. In general, there are two types of imperfect detections: false negative detections, defined as not detecting a species when it is present, and false positive detections, defined as detecting a species when it is not present. Quantitative methods to account for false negative detections, in particular, have been widely adopted in occupancy models (Bayley and Peterson 2001; MacKenzie et al. 2002, 2003; Royle and Nichols 2003; Tyre et al. 2003) and other ecological models (e.g., mark-recapture, distance estimation, and band recovery models; Williams et al. 2001).

Occupancy models have been used widely by ecologists because they provide information about species' use of sites but only require data on detection/non-detection of species from repeat samples of sites (MacKenzie et al. 2002, 2003; Royle and Nichols 2003). Hence, occupancy modeling can provide valuable inference about species' distribution and habitat use with comparatively low-intensity data collection. When explanatory variables are included in functions with occupancy probability or detection probability as independent variables, the relationship between anthropogenic or environmental attributes and occupancy or detection can be quantified. Incorporating explanatory variables also allows inference about the heterogeneity among sites and surveys. Unbiased inference about state variables and covariate coefficients is facilitated by accounting for imperfect detections.

Although accounting for false negative errors in models has a long-standing history, the need to account for false positive detections has received increased attention recently. Previously, many methods that estimated a false negative detection probability assumed that false positive detections did not occur. However, from experiments with wildlife vocalization playback, it has been shown that observers of all experience levels make false positive errors and that instructing observers to only record detections about which they are certain does not eliminate false positive errors (Genet and Sargent 2003; Lotz and Allen 2007; Simons et al. 2007; Alldredge et al. 2008; Simons et al. 2009; McClintock et al. 2010a, 2010b; Miller et al. 2012). Further, computer simulations have demonstrated that if data contain false positive errors but analyses assume there are no false positive detections, estimates of occupancy probability and covariate coefficients will be biased (Royle and Link 2006, McClintock et al. 2010b). Because false positive detections are unlikely to be eliminated through study design and because analyses that fail to account for them generate biased results, it is important to develop and employ methods that account for both classes of imperfect detection.

So far, two parameterizations of occupancy models accounting for both classes of imperfect detection have been developed in Royle and Link (2006) and Miller et al. (2011). Royle and Link (2006) generalize the MacKenzie et al. (2002) occupancy model as a finite mixture model with state-specific probabilities of false positive and false negative detections. However, there is symmetry in the likelihood of this model (hereafter, the Royle-Link model) so that there is not a unique set of solutions for parameter values. For example, the following two sets of parameter values have identical likelihoods under the Royle-Link model: 1) 75% of sites occupied, 30% true positive detection rate, and 10% false positive detection rate and 2) 25% of sites occupied, 10% true positive detection rate, and 30% false positive detection rate (Royle and

Link 2006). To address this problem, Royle and Link (2006) restrict the parameter space so that the true positive detection probability (1 – false negative detection probability) is greater than the false positive detection probability.

However, this assumption has received criticism. For example, the Royle-Link model cannot identify a "phantom" species, a species that is not present in the study area but is detected (McClintock et al. 2010b). Since all detections for the "phantom" species are false positive errors, Royle and Link (2006)'s assumption that the true positive detection probability is greater than the false positive detection probability is violated, and results would suggest that the "phantom" species is actually present. Additionally, in the Royle-Link model, false positive errors and true positive detections cannot be distinguished if there is heterogeneity in detection probabilities (Fitzpatrick et al. 2009, McClintock et al. 2010b).

It is not possible to distinguish false negative and false positive detections with standard occupancy data (McClintock et al. 2010b), so Miller et al. (2011) proposed occupancy models (hereafter, the Miller models) that estimate false negative and false positive detection probabilities using additional information about the detection process. In the multiple detection state model, one detection method is used, but detections are classified as either detections in which false positive errors are possible (unconfirmed detections) or detections in which false positive errors are not possible (confirmed detections). Miller et al. (2011) also developed a model that uses data from multiple detection methods, each of which produces a different rate of confirmed detections. As Miller et al. (2011) noted, the multiple detection state model in which all detections are unconfirmed is equivalent to the Royle-Link model. Through simulations, Miller et al. (2011) demonstrated that both of their models generated estimates of occupancy probability that were more accurate and precise than the Royle-Link model and the MacKenzie et al. (2002) model that assumed no false positive errors.

The Miller models appear to successfully address the problem of symmetry in the Royle-Link model likelihood and avoid assumptions about the magnitude of the true positive detection probability relative to the false positive detection probability. However, how heterogeneity among sites and surveys affects estimates of occupancy when there are false positive errors remains unresolved. The Miller models have not been thoroughly evaluated when occupancy and detection probabilities vary with covariates. In some of their simulations, Miller et al. (2011) simulated heterogeneity in true positive detections by generating data with site-specific detection probabilities drawn from a beta distribution with a fixed mean and variance of 0.01. However, none of the Miller models estimated heterogeneity in the true positive detection probability. Rather than trying to model heterogeneity, Miller et al. (2011) investigated whether estimation of the false positive detection probability would be affected if data had heterogeneity in the true positive detection probability.

Finally, the Royle-Link and Miller models were developed in a frequentist approach with model selection. Occupancy models such as the Royle-Link and Miller models are complex and have latent variables, and these types of models have specifically been highlighted as well suited to a hierarchical Bayesian modeling approach in which explicit state and detection model components are developed. Hierarchical Bayesian formulations of population models are advantageous for many reasons and have recently received much attention (McCarthy 2007, Royle and Dorazio 2008, Link and Barker 2010, Kery and Schaub 2012). First, Bayesian analysis allows intuitive probability statements about parameters conditional on data. This can be contrasted with frequentist inference that instead involves long-run frequencies and variability from many hypothetical replicates of sample data conditional on fixed parameters. Bayesian methods are also well-suited to small samples because they do not depend on asymptotic properties as do frequentist methods. Also Bayesian models propagate measures of uncertainty through model components. Finally, Bayesian methods are appropriate for adaptive management when results from one monitoring season update prior knowledge for generating posterior distributions in the next monitoring season (McCarthy 2007, Royle and Dorazio 2008, Link and Barker 2010).

Therefore, the goals of our work were to develop an occupancy model that, first, accounts for false negative and false positive detections in a Bayesian framework and, second, models heterogeneity in occupancy and detection through covariates. By incorporating covariates to model heterogeneity in occupancy and detection, inference can be made about the relationship between environmental or anthropogenic factors and occupancy or detection, and posterior occupancy and detection probabilities should be more accurate compared to posterior probabilities from models that do not account for the heterogeneity present in data.

Model descriptions

We developed a hierarchical Bayesian model based on the Miller et al. (2011) multiple detection state (MDS) model that includes heterogeneity in the occupancy, false negative detection, and false positive detection probabilities. We focus on the MDS model, rather than the multiple detection method model in Miller et al. (2011), as the MDS model could require less intensive data collection, and thus be more appealing to researchers. We used simulations to evaluate the performance of various modeling approaches in different scenarios of simulated data.

In the MDS model, non-detections were always unconfirmed while detections could be unconfirmed or confirmed. That is, when a species was not detected, it was never known if the species was absent or if the species was present but not detected (a false negative error). However, when a species was detected, sometimes researchers could confirm that the species was indeed present, but in other instances, presence could not be confirmed and the detection could actually be a false positive error. This could be the case in many fish and wildlife applications where the sampling method detects a species indirectly (i.e., by vocalizations, hair, feces) and/or the study organism is cryptic, mobile, or resembles other species. In other applications, such as completely surveying sites for distinctive plants (Falster et al. 2001) or in epidemiology studies where specialized tests can effectively determine the presence or absence of a disease with certainty (Feigelson et al. 1994, Shea et al. 1994), it may be possible to have both confirmed absences (data without false negatives) and confirmed presences (data without false positives). More intensive sampling methods that can establish confirmed absences and/or confirmed presences could be applied to a small subset of samples while the remaining samples receive a less intensive sampling method.

We constructed a Bayesian occupancy model for circumstances in which there are both confirmed and unconfirmed absences and confirmed and unconfirmed presences (hereafter, the confirmed absences and presences model or CACP model) and a Bayesian occupancy model for applications where there are only unconfirmed absences but confirmed and unconfirmed presences (hereafter, the confirmed presences model or CP model). While the CP model may be applicable to ecological research more frequently than the CACP model, we evaluate both the CACP and CP models in this study for several reasons. First, we expect that the CACP model could be relevant in some applications, such as vegetation studies. Second, performance of the occupancy model can be more fully evaluated when data with both confirmed absences and confirmed presences are modeled. Posterior distributions should be more accurate and precise with confirmed absences and confirmed presences compared to only confirmed presences, given a data set of a particular size, because more information about the detection process is available.

As in standard single-season occupancy models, both of our models assume that the occupancy state does not change within a season and that detections at each site and at subsequent visits to a site are independent. Our models also assume that detection confirmation is independent across sites and surveys; whether an observation was confirmed or unconfirmed during a survey is independent of the confirmation state during a previous survey. In occupancy models, each of the i=1, 2, …, R sites is occupied (z_i=1) or not (z_i=0). Whether a site is occupied can be considered the realization of a Bernoulli trial with probability of occupancy, ψ ($z_i \sim$ Bern(ψ)). The occupancy probability can be constant across sites or vary depending on site-specific covariates.

At an occupied site, a true positive detection may occur on sampling occasion t=1, 2, …, T with probability *p11*, or a false negative detection may occur with probability (1-*p11*). At an unoccupied site, a false positive detection may occur with probability *p10*, or a true negative detection may occur with probability (1-*p10*). The true positive detection probability (*p11* = Prob(y_{it}=1 | z_i=1)) or false positive detection probability (*p10* = Prob(y_{it}=1 | z_i=0)) may be constant across sites and sampling occasions or may vary depending on covariates. Covariates can be included though a logit-linear model, for example logit(ψ_i)=$\alpha_0 + \alpha_1 * x_i$ or logit($p11_{\mathrm{it}}$)=α_0 + $\alpha_1 * x_{it}$.

Whether an observation of detection or non-detection is confirmed can also be considered the realization of a Bernoulli trial with probability of confirmation, *b*. The observation confirmation probability can be constant for observations of presence or absence and across sites and sampling occasions or may vary depending on covariates.

In summary, the data are whether the species was detected (y_{it} = 1) or not (y_{it} = 0), whether observations were confirmed (c_{it} = 1) or not (c_{it} = 0), and the values of any covariates in the model. The unknown latent state is whether the site is occupied (z_i = 1) or not (z_i = 0), and unknown parameters are the occupancy probability (ψ), true positive detection probability (*p11*), false positive detection probability (*p10*), observation confirmation probability (*b*), and intercepts and coefficients for any logit-linear models incorporating covariates.

Confirmed absences and presences (CACP) model

If we assume that observation confirmations are made without error (we will discuss this assumption and examples of confirmed absences more below), three types of detections may occur:

1) a confirmed presence, occurring with probability $\text{Prob}(y_{it}=1 \mid z_i=1, c_{it}=1) = \psi * b * 1$),
2) an unconfirmed true positive, occurring with probability $\text{Prob}(y_{it}=1 \mid z_i=1, c_{it}=0) = \psi * (1-b) * p11$, or
3) an unconfirmed false positive, occurring with probability $\text{Prob}(y_{it}=1 \mid z_i=0, c_{it}=0) = (1-\psi) * (1-b) * p10$.

Similarly, a non-detection may be

1) a confirmed absence, occurring with probability $\text{Prob}(y_{it}=0 \mid z_i=0, c_{it}=1) = (1-\psi) * b * 1$,
2) an unconfirmed false negative, occurring with probability $\text{Prob}(y_{it}=0 \mid z_i=1, c_{it}=0) = \psi * (1-b) * (1-p11)$, or

3) an unconfirmed true negative, occurring with probability (Prob(y_{it}=0 | z_i=0, c_{it}=0) = (1-ψ) * (1-b) * (1-$p10$)).

We simulated data such that the observation confirmation probability was the same for confirmed absences and confirmed presences. This is not required but served as the starting point for model development. Therefore, b was used to simulate data with confirmed observations, but b was not needed in the predictive model. Observations can be considered outcomes of Bernoulli trials with the probabilities in Fig. 2.1. Later we will discuss the performance of the model in simulated scenarios where data had observation confirmation errors.

Confirmed presences (CP) model

In the CACP model, the observation confirmation probability was independent of the occupancy state. Regardless of whether the site was occupied or not, the observation confirmation probability was b. However, in the CP model, the probability of having a confirmed presence (Prob(c_{it}=1 | z_i=1)) is b, but the probability of having a confirmed absence (Prob(c_{it}=1 | z_i=0)) is 0. Therefore, whether a detection is confirmed was modeled as the realization of a Bernoulli trial with confirmation probability, z_i*b, and a prior distribution was assigned for b. This step was not required to generate posterior distributions in the CACP model. In the CP model, observations can be considered outcomes of Bernoulli trials with the probabilities in Fig. 2.1, but because the probability of having a confirmed absence is 0, the bottom-left cell is undefined.

Simulation study: methods

Evaluating model performance

To evaluate the performance of the CACP and CP models, we simulated data for three visits to 250 sites, fit models to the data, investigated biases and precision in parameters' posterior distributions, and determined whether parameter values used to simulate data were included in 95% Bayesian credible intervals (BCIs). Below, we will discuss the details of different scenarios under which we simulated data to evaluate various features of our models (also summarized in Table 2.1). Data were simulated in R version 2.15.3 (R Core Team 2013), and models were run in OpenBUGS version 3.2.2 (Lunn et al. 2009) using the R2OpenBUGS package (see Sturtz et al. 2005 as R2OpenBUGS was originally written as R2WinBUGS). We ran three Markov Chain Monte Carlo (MCMC) chains with 100,000 iterations, a burn in of 50,000, and thinning of one (Brooks and Gelman 1998, Link and Eaton 2011). Convergence was assessed with the Gelman-Rubin potential scale reduction factor (R-hat), and chains were considered converged if R-hat ≤ 1.04 (Brooks and Gelman 1998, Gelman and Shirley 2011).

For each scenario, 100 data sets were simulated using the same parameter values, and a model was used to generate parameters' posterior distributions for each data set. For each data set, we fit an occupancy model and calculated the absolute error as the difference between the mean of the parameter's posterior distribution and the parameter value used to simulate data. Therefore, a negative absolute error indicates underestimation, and a positive absolute error indicates overestimation. We evaluated posterior probabilities through a measure of the absolute error rather than the relative error because we were not comparing numbers of very different magnitudes and, in some simulations, the true value was zero, making a measure of the relative error undefined. For each data set, we also calculated the width of BCIs and determined whether the values used to simulate data were contained in the BCIs. If a model had not converged after 100,000 iterations, we did not include posterior probabilities from that model run in summary results for the simulated scenario. For each scenario, we calculated the number of model runs with convergence, percent of converged model runs in which the BCI contained the value used to simulate data, mean absolute error of parameters' posterior probabilities, and mean BCI width. We also made boxplots of absolute errors from model runs that converged.

Basic scenarios: combinations of parameter values and priors

First, we evaluated the basic parameterization of the CACP and CP models without covariates. We simulated data from twelve scenarios with varying probabilities of occupancy, true positive detection, and false negative detection (Table 2.2). For all simulations, the observation confirmation probability used to generate data was 0.03. We selected 0.03 to represent a low rate of observation confirmation that may be feasible to reach while conducting fieldwork. This is also a smaller observation confirmation probability than was evaluated by Miller et al. (2011); the smallest observation confirmation probability they used to generate data was 0.1. Since it may be difficult to confirm observations when collecting data, it is desirable for the models to generate accurate and precise posterior probabilities with a low rate of observation confirmation.

We also investigated model performance with vague (U(0,0.5)) and informative (Beta(1,9)) priors for the false negative detection probability. We constrained the false positive probability to be less than 0.5, which suggests that if a site is unoccupied, an observer is more likely to make a true negative detection than a false positive detection. This constraint seems consistent with the probability of false positive detections seen in controlled experiments

(Farmer et al. 2012, Miller et al. 2012) and could aid model convergence without introducing unrealistic assumptions.

Using an informative prior for the false positive probability may help improve the precision of posterior distributions and avoid parameter identifiability problems that may arise when modeling both a false positive detection probability and a false negative detection probability. A right-skewed prior distribution with a small mean seems realistic based on results from a variety of controlled experiments that tested observer identification of species. In an internet survey designed to replicate avian point counts, the sample mean for the false positive detection rate was 0.10 and the sample variance was 0.0088 (Farmer et al. 2012), suggesting a Beta(1,9) prior distribution (see Appendix A for more details). Results from a field experiment where observers recorded detections for broadcast frog calls indicated that false positive probabilities for observers ranged from <0.01 to about 0.065 with more observers having smaller false positive probabilities (Miller et al. 2012). It is important to keep in mind that for this study, we investigated the general utility of using an informative prior for the false positive detection probability, compared to a vague prior. However, for application to a particular dataset, consideration must be given to justify a particular prior distribution.

We evaluated the CACP model with two priors for the false positive detection probability (two modeling approaches) using simulated data with twelve parameter value combinations (twelve data scenarios), resulting in twenty-four combinations of data scenarios and modeling approaches. We evaluated the CP model with two priors for the false positive detection probability and two priors for the observation confirmation probability (four modeling approaches) using simulated data with twelve parameter value combinations (twelve data scenarios) resulting in forty-eight combinations of data scenarios and modeling approaches.

We considered CP model performance with vague (U(0,1) or Beta(0.5,0.5)) or informative priors (U(0.01,0.05) or Beta(10,300)) for the observation confirmation probability. A vague prior for the observation confirmation probability may be appropriate, for example, if 5% of the sites in a dendrology study are completely surveyed for mature members of a tree species. Researchers could *a priori* expect that the probability of observation confirmation would be 0.05 and could construct a corresponding prior. A vague prior for the observation confirmation probability may be suitable when data are collected through avian point counts or anuran call surveys, both of which may have confirmed presences, for example, when an animal is seen instead of only heard. In the CACP and CP models, priors for the occupancy probability and true positive detection probability were always vague: U(0,1) when the prior for the false positive detection probability was U(0,0.5) or Beta(0.5,0.5) when the prior for the false positive detection probability was Beta(1,9).

Errors in confirmed observations

Since our models and the Miller models depend on a subset of data with confirmed observations, we simulated data with errors in confirmed observations to evaluate the robustness of our models. For the CACP model, we simulated data that had a 0.1 probability of observation confirmation error. That is, if an observer made a confirmed observation at a site that was occupied, the probability that the observation was a confirmed presence was 0.9, but the probability that the observation was a confirmed absence was 0.1. Similarly, if an observer made a confirmed observation at a site that was not occupied, the probability that the observation was a confirmed absence was 0.9, but the probability that the observation was a confirmed presence was 0.1. Overall, there was a 0.006 probability of a confirmed observation error (2*0.03*0.1), since there was a 0.03 probability of an observation confirmation, a 0.1 probability of error among confirmed observations, and errors could be made in confirmed presences or confirmed absences. For the CP model, we simulated data so that there was a 0.005 probability of a confirmed presence when the site was actually unoccupied.

Data were simulated under twelve parameter value combinations (Table 2.2). The prior distributions for the false positive detection probability that resulted in the most accurate and precise posterior distributions when data did not have observation confirmation errors were used. A vague prior for the observation confirmation probability was used for the CP model. Therefore, we evaluated the CACP and CP models in twelve combinations of data scenarios and modeling approaches.

Phantom species

In addition to parameter value combinations nine through twelve (Table 2.2) in which the false positive detection probability was greater than the true positive detection probability, we also simulated data for a "phantom" species, a species that had a zero probability of occupancy and true positive detection but a positive probability of false positive detection (0.05 in our simulations). We evaluated the CACP and CP models under these four parameter value combinations and in the "phantom" species scenario because the Royle-Link model is known to identify estimates through the assumption that the true positive detection probability is greater than the false positive detection probability and the simulation study in Miller et al. (2011) did not include scenarios in which the true positive detection probability was less than the false positive detection probability.

We fit CACP and CP models to data with and without observation confirmation errors, and we used the prior for the false positive detection probability that resulted in the most accurate and precise posterior distributions in the parameter value combinations when data did not have observation confirmation errors. For the CP model, an uninformed prior distribution for the observation confirmation probability was used.

Models with covariates

After establishing the performance of the basic parameterization of the CACP and CP models without covariates, we evaluated the CACP and CP models with covariates describing heterogeneity in occupancy, true positive detection, and false positive detection probabilities. We simulated data with one explanatory variable affecting the occupancy probability and one explanatory variable affecting the true positive detection probability to represent a hypothetical study of landscape effects on avian occupancy. Specifically, we simulated site-specific values for percent forest cover in the landscape (Fig. A.1), which affected occupancy probabilities, and site- and survey- specific values for temperature (Fig. A.2), which affected true positive detection probabilities.

We simulated data using three sets of intercept and coefficient values that quantified the effects of the covariates on occupancy or true positive detection probability (Table A.1). The main difference between the three combinations of covariate parameter values was the effect of percent forest cover on occupancy probability (Fig. A.3). In the first scenario, occupancy probability was highest at an intermediate level of percent forest cover. There was a quadratic function relating the percent forest cover to the occupancy probability, so there was an intercept and two coefficients for which to generate posterior distributions. In the second scenario, occupancy probability was highest at a high level of percent forest cover. However, there was a quadratic function relating the percent forest cover to the occupancy probability, so again, there was an intercept and two coefficients for which to generate posterior distributions. In the third scenario, there was a linear function relating the percent forest cover to the occupancy probability, so there was an intercept and one coefficient for which to generate posterior distributions. In all three scenarios (hereafter, strong quadratic, weak quadratic, and linear), there was a linear function relating the temperature to the true positive detection probability, but the intercept and coefficient terms varied slightly between scenarios.

We also simulated false positive detection probabilities that decreased over three time periods ($p_{10,t1}$ = 0.1, $p_{10,t2}$ = 0.07, $p_{10,t3}$ = 0.04). This was meant to represent the case where data are collected over time, say three months, and as an observer gains experience, their false positive detection probability decreases.

When covariate data were included in an occupancy model, the data were standardized to have a mean of zero and variance of one, as this is a common approach to aid convergence (e.g., Zipkin et al. 2009, Royle et al. 2005). As was the case when evaluating the models without covariates, we investigated model performance with vague (U(0,0.5)) or informative (Beta(1,9)) priors for the false positive detection probability. Since we modeled the effects of covariates on the occupancy or true positive detection probability through a logit-linear equation, all covariate coefficients were modeled with a N(0,0.368) prior, which is a vague Jeffrey's prior for a parameter on the logit scale (Lunn et al. 2012). Intercept terms had vague priors (U(0,1) or Beta (0.5,0.5)) and were logit-transformed before inclusion in the logit-linear equation.

We evaluated the CACP model in the strong quadratic, weak quadratic, and linear scenarios with vague or informative priors for false positive detection probabilities using data with or without observation confirmation errors. When data did not have observation confirmation errors, we evaluated the CP model in the strong quadratic, weak quadratic, and linear scenarios with vague or informative priors for false positive detection probabilities and with vague or informative priors for the observation confirmation probability. When evaluating the CP model using data with observation confirmation errors, we had a similar procedure except we only used vague priors for the observation confirmation probability.

Model assuming no false positive detections

In addition to evaluating the performance of the CACP and CP models under the many simulated data scenarios that we described above, we also fit a model assuming that false positive detections could not occur to the simulated data sets. We fit the no false positives model to data from the twelve parameter value combinations (Table 2.2), phantom species scenario, and three covariate scenarios. By comparing posterior distributions from the CACP and CP models to posterior distributions from no false positives model, we can assess the degree of improvement in accuracy and precision that results from accounting for both types of imperfect detection.

Simulation study: results

Models without covariates

When data contained false positive detections, the CACP and CP models, which accounted for false positive errors, generated more accurate posterior probabilities than the model that assumed there were no false positives (Fig. 2.2). Posterior occupancy probabilities from the no false positives model were biased high and imprecise. The CACP models generated unbiased posterior occupancy probabilities and had similar precision when different priors were used for the false positive detection probability, but when data had observation confirmation errors, posterior probabilities from the CACP model were less precise. The CP models with the informative prior for the observation confirmation probability or the vague prior for the observation confirmation probability and the informative prior for the false positive detection probability generated posterior occupancy probabilities that were essentially unbiased. The CP model with vague priors for the observation confirmation probability and the false positive detection probability resulted in posterior occupancy probabilities that were biased low, while the CP model with observation confirmation errors produced posterior occupancy probabilities that were biased high.

Also, when data contained false positive detections for phantom species, the models that accounted for false positive errors generated more accurate posterior probabilities than the no false positives model (Fig. 2.3). Not surprisingly, the most accurate and precise posterior occupancy probabilities resulted when there were confirmed absences and no observation confirmation errors, and posterior probabilities were biased slightly higher when there were no confirmed observations (confirmed presences were impossible because the phantom species was absent from all sites). Posterior distributions from models accounting for false positive errors were most biased and least precise when there were observation confirmation errors. However, posterior false positive detection probabilities from the CACP and CP models were accurate and precise (Table B.9).

In addition to patterns in model performance that are evident across the variety of simulated data scenarios (Figs. 2.1 and 2.2), some patterns can be determined by examining specific scenarios (Tables B.1-10). In particular, when the simulated occupancy probability was small, posterior occupancy probabilities tended to be biased high. Conversely, when the simulated occupancy probability was large, posterior occupancy probabilities tended to be biased low. Also, when the simulated true positive detection probability was small, occupancy probability posterior distributions had wider BCIs.

Models with covariates: posterior occupancy probabilities

In the strong quadratic, weak quadratic, and linear scenarios, posterior occupancy probabilities from the no false positives model were biased high and imprecise (Figs. 2.3, 2.5, 2.7). All of the models that accounted for false positive errors were more accurate and precise than the no false positives model.

In the strong quadratic scenario, all of the models accounting for false positive errors generated essentially unbiased posterior occupancy probabilities (Fig. 2.4). The only possible exception occurred with the CACP model with informative priors for the false positive detection probabilities when there were observation confirmation errors, which produced posterior occupancy probabilities that were slightly biased high. Posterior occupancy probability distributions from the CACP models were less precise when there were observation confirmation errors, compared to posterior occupancy probability distributions from data without observation confirmation errors. All CP models performed similarly and resulted in posterior occupancy probability distributions that were accurate and precise.

In the weak quadratic scenario, unbiased posterior occupancy probabilities were generated from the CACP models when there were no observation confirmation errors and from the CP models with informative priors for the false positive detection probabilities (Fig. 2.6). Posterior occupancy probabilities were biased slightly low when the CACP models were applied to data containing observation confirmation errors and when the CP models with vague priors for the false positive detection probabilities were used. When data did not have observation confirmation error, the CACP and CP models with vague priors for the false positive detection probabilities produced more outliers in which posterior occupancy probabilities were biased low compared to models using informative priors for the false positive detection probabilities.

In the linear scenario, unbiased posterior occupancy probabilities were obtained with the CACP models when data did not have observation confirmation errors, but posterior probabilities were biased low when there were observation confirmation errors (Fig. 2.8). All of the CP models generated accurate posterior occupancy probabilities. Posterior distributions from all models accounting for false positive errors were precise, but posterior distributions from the CACP models with observation confirmation errors were least precise. Also, posterior occupancy probability distributions from the CP model with vague priors for the false positive detection probabilities and the observation confirmation probability were more precise than posterior occupancy probability distributions obtained when informative priors for the false positive detection probabilities were used. The CP model with informative priors for the false positive detection probabilities and the observation confirmation probability generated the most outliers.

So far we have considered errors in posterior occupancy probabilities across all values of the covariate, but the performance of the CACP and CP models can also be evaluated by studying errors at specific covariate values. In the strong quadratic scenario, the no false positives model especially overestimated posterior occupancy probabilities at low and high values of the covariate (Fig. 2.10). In the weak quadratic and linear scenarios, posterior occupancy probabilities were overestimated by the no false positives model at low values of the covariate (Figs. 2.12 and 2.14). Also in the linear scenario, posterior occupancy probabilities were underestimated by the no false positives model at high values of the covariate (Fig. 2.14). Errors in posterior occupancy probabilities from the CACP and CP models appeared greatest near the inflection point(s) of the curves representing occupancy probabilities as a function of the covariate (Figs. 2.11, 2.13, and 2.15).

The occupancy probability BCIs generated from the no false positives model also had low frequencies of containing the simulated occupancy probabilities in the strong quadratic, weak quadratic, and linear scenarios (Tables C.1-3). More details on model convergence and posterior true positive detection, false positive detection, and observation confirmation probabilities can be found in Tables C.1-3.

Models with covariates: inference about relationships with covariates

In many studies, the occupancy probability may be considered the main variable of interest, but posterior distributions describing the relationship between environmental or anthropogenic factors and occupancy probabilities may provide important ecological insights as well. In the strong quadratic scenario, posterior distributions for covariate coefficients generated from the no false positives model were imprecise (Fig. 2.5). Covariate coefficient posterior probabilities from all models accounting for false positive errors were unbiased, except posterior probabilities from the CP model with vague priors were biased low when there were observation confirmation errors. Posterior probabilities from the CP models with informative priors for the false positive detection probabilities were biased slightly low. The CACP models produced posterior distributions that were less precise when there were observation confirmation errors.

In the weak quadratic scenario, the no false positives model resulted in covariate coefficient posterior probabilities that were biased high and imprecise (Fig. 2.7). Most of the models accounting for false positive errors also generated covariate coefficient posterior probabilities that were biased high, although they were more accurate and precise than posterior probabilities from the no false positives model.

In the linear scenario, covariate coefficient posterior probabilities from the no false positives model were biased low (Fig. 2.9). Coefficient posterior probabilities that were biased low also resulted from the following models: the CACP model with informative priors for the false positive detection probabilities, CACP models with observation confirmation errors, CP model with informative priors for the false positive detection probabilities and vague prior for the observation confirmation probability, CP model with vague priors for the false positive detection probabilities and observation confirmation probability when data had observation confirmation errors, and CP model with vague priors for the false positive detection probabilities and informative prior for the observation confirmation probability. The most accurate covariate coefficient posterior probabilities were generated by the CP model with vague priors for the false positive detection probabilities and observation confirmation probability and CP model with informative priors for the false positive detection probabilities and observation confirmation probability.

Discussion

Through simulations, we have demonstrated the ability of the CACP and CP models to generate posterior occupancy probabilities while accounting for two types of imperfect detection: false negative errors and false positive errors. The CACP and CP models add to the existing suite of occupancy modeling approaches by modeling both types of imperfect detection as well as heterogeneity in occupancy and detection, while making minimal assumptions about parameter values. We have extended the work of Miller et al. (2011) by formulating a Bayesian model that uses a subset of data with confirmed observations to model false positive and false negative detection probabilities, and we have explored the use of vague and informative priors.

Our models and the Miller models are predicated on having data with confirmed observations, and we evaluated the robustness of our models to errors in the confirmation of observations through simulations. We showed that even when there were observation confirmation errors, the CACP and CP models generated more accurate and precise posterior distributions than the no false positives model. In many cases, a small rate of observation confirmation errors did not appreciably affect the performance of the CACP or CP models. Further, we demonstrated that the CACP and CP models generated accurate posterior probabilities with very small rates of confirmed observations (3% compared to 10% in Miller et al. (2011)). We also illustrated that the CACP and CP models could generate accurate and precise posterior distributions when the true positive detection probability was less than the false positive detection probability. Also suspected phantom species may be identified if the mean of the posterior distribution for occupancy and the upper bound of the BCI are small and if the BCI for the true positive detection probability is very wide. Moreover, our occupancy models generated accurate inferences about the relationship between covariates and site-specific occupancy probabilities and between covariates and site- and survey-specific true positive detection probabilities. Our study is the first to use simulations to evaluate the performance of occupancy models that generate inference about false positive detection probabilities, in addition to true positive detection probabilities, when occupancy and detection probabilities exhibit heterogeneity modeled through covariates.

We consider the models with covariates to be of more relevance and interest to researchers because it is highly unlikely that, in nature, occupancy and detection would be constant across sites and surveys and because modeling parameters related to covariates provides inference about the effects of environmental and anthropogenic factors on the organism of interest. If a scientist expects that the data they collect will resemble our simulated data, in that data cover variables' parameter spaces, our simulation results may provide recommendations for model parameterizations to consider. Alternatively if a scientist's data only cover a restricted section of the parameter space, they may wish to evaluate the model parameterizations by running their own simulations (Appendix D) or to study patterns in parameters' posterior distributions when parameters take particular values (Appendix B).

Our simulations indicated that when it is possible to obtain data with confirmed absences in addition to confirmed presences, the CACP model with vague priors for the false positive detection probabilities may be most suitable. Not only is this approach more convenient because it does not require justification of an informative prior, but it generated more accurate and precise posterior distributions in our simulations with covariates. Regardless of the priors for false positive detection probabilities, the CACP models performed similarly in the strong quadratic scenario, unless there were observation confirmation errors (Fig. 2.4). In that case, posterior occupancy probabilities from the CACP model with informative priors for false positive detection probabilities were more accurate. There also may be some indication that the CACP model with vague priors for false positive detection probabilities generated more accurate posterior distributions for covariate coefficients in the weak quadratic and linear scenarios when there were not observation confirmation errors (Figs. 2.6 and 2.8).

Model performance was not as consistent when data only had confirmed presences and covariate effects were modeled. In the strong quadratic scenario with observation confirmation errors, the CP model with informative priors for false positive detection probabilities produced more accurate posterior distributions for covariate coefficients (Fig. 2.5). When data did not have observation confirmation errors in the strong quadratic scenario, the CP models performed similarly. In the weak quadratic scenario, the CP model with informative priors for false positive detection probabilities generated the most accurate posterior occupancy probabilities, with and without observation confirmation errors (Fig. 2.6). Using the vague prior for the observation confirmation probability did not improve inference in the weak quadratic scenario. In the linear scenario without observation confirmation errors, the CP model with vague priors for false positive detection probabilities and the observation confirmation probability generated the most accurate posterior distributions for coefficients (Fig. 2.9). However, if there were observation confirmation errors, the CP model with informative priors for false positive detection probabilities produced more accurate posterior distributions for coefficients.

In addition to judging model suitability from our simulations based on accuracy and precision patterns, considering why different model parameterizations performed in particular ways in various data scenarios may help scientists choose occupancy model parameterizations for their research. For example, perhaps vague priors were appropriate unless data did not contain sufficient information to generate accurate posterior distributions for all the parameters in a model. Using vague priors avoided the potential bias introduced when the prior influences the posterior distribution in a way not supported by the data. Vague priors generated accurate posterior distributions in the CACP model (which contains extra information in the form of confirmed absences) in all data scenarios, CP model in the strong quadratic scenario without observation confirmation errors, and CP model in the linear quadratic scenario without observation confirmation errors. Including observation confirmation errors introduced complexities in the data, and simulating data from a weak quadratic function produced data that may not have contained enough information for accurate inference about the effect of the covariate. Hence, CP models with informative priors for false positive detection probabilities generated more accurate posterior distributions in the strong quadratic scenario with observation confirmation errors, the weak quadratic scenario, and the linear scenario with observation confirmation errors.

We can also consider possible reasons behind the patterns observed in simulations of the CACP and CP models without covariates. Results from simulations without covariates indicated that posterior occupancy probabilities were biased high when the actual occupancy probability was small. With a small occupancy probability, few sites are expected to be occupied, and many sites are expected to be unoccupied. Therefore, there are more opportunities for false positive detections than true positive detections. In other words, without considering what the false positive detection probability and the true positive detection probability are, there are many sites where false positive detections can be made and few sites where true positive detections can be made. Consequently, some false positive detections in the data may be attributed mistakenly to true positive detections in the modeling procedure, resulting in overestimation of the occupancy probability. Likewise, when the actual occupancy probability was large, posterior occupancy probabilities were biased low perhaps because some true positive detections in the data were attributed mistakenly to false positive detections in the modeling procedure. Also, when the actual true positive detection probability was small, there were few true positive detections in the data. Since the data did not contain much information about detections at occupied sites, the occupancy probability posterior distribution was imprecise and had a wide BCI.

To apply our models, a researcher would need to collect detection histories from multiple visits to sites, noting detections and non-detections as well as whether they were confirmed or unconfirmed. Sites can be selected and survey visits can be planned as in typical sampling designs for occupancy modeling. However, the method used to obtain detections and classify them as confirmed or unconfirmed should depend on the focal organism and habitat. For example, in an avian survey, point counts can be conducted and confirmed detections could be established if there is both visual and auditory detection or if multiple independent observers detect a species. A method for determining whether a detection is confirmed is suitable if the probably of having an error in the confirmed observations is small enough so that model results would be robust to any errors, such as in the simulated case we demonstrated.

When selecting a model parameterization, scientists should consider the available data that could contribute to the development of informative priors, how priors might influence posterior distributions, how much information is contained in the data upon which inference is being made, and how many parameters are being modeled. The CACP and CP models provide flexible frameworks that can be adapted to specific research applications. Our models can be applied to research situations where there are both confirmed absences and confirmed presences or where there are only confirmed presences, and models can be adapted for cases where confirmed absences and confirmed presences have the same probability or different probabilities.

A useful area of future work could be the potential for modeling heterogeneity in false positive detection probabilities with covariates. In this study, we modeled false positive detection probabilities that varied across three time periods, but within a time period, the false positive detection probability was constant among sites and surveys. This may be a reasonable approach as false positive detection probabilities are expected to be small with low variance among observers and surveys (Farmer et al. 2012, Miller et al. 2012). If a suitable modeling approach is developed, it could provide further ecological insights into the processes generating false positive and false negative errors and could improve the accuracy of posterior distributions, but modeling site- and survey-specific false positive detection probabilities in addition to true positive detection probabilities could make problems with parameter identifiability or model convergence more likely.

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Table 2.1: Scenarios in which data were simulated to evaluate a) the confirmed absences and presences (CACP) model and b) the confirmed presences (CP) model where *p10* is the false positive detection probability and *b* is the observation confirmation probability. The prior for *p10* that resulted in the most accurate and precise posterior distribution in the basic scenarios was used in the scenarios with observation confirmation errors and in the phantom species scenarios. In the CP model with covariates, an informative prior for *b* was only used when there were no observation confirmation errors.

a

Conditions	Basic scenarios	Observation confirmation errors	Phantom species	Covariates	No false positives
12 parameter value combinations	x	x			x
Informative prior for *p10*	x	Best prior from basic scenarios	Best prior from basic scenarios	x	
Vague prior for *p10*	x	Best prior from basic scenarios	Best prior from basic scenarios	x	
Errors in observation confirmations		x	x	x	
Phantom species			x		x
Three sets of intercept and coefficient values				x	x

b

Conditions	Basic scenarios	Observation confirmation errors	Phantom species	Covariates	No false positives
12 parameter value combinations	x	x			x
Informative prior for *p10*	x	Best prior from basic scenarios	Best prior from basic scenarios	x	
Vague prior for *p10*	x	Best prior from basic scenarios	Best prior from basic scenarios	x	
Informative prior for *b*	x			No observation confirmation errors	
Vague prior for *b*	x	x	x	x	
Errors in observation confirmations		x	x	Vague prior for *b*	
Phantom species			x		x
Three sets of intercept and coefficient values				x	x

Table 2.2: Scenarios with varying probabilities of occupancy (ψ), true positive detection (*p11*), and false positive detection (*p10*) in which data were simulated for evaluating occupancy model parameterizations.

Scenario	ψ	*p11*	*p10*
1	0.7	0.6	0.05
2	0.7	0.6	0.15
3	0.7	0.2	0.05
4	0.7	0.2	0.15
5	0.3	0.6	0.05
6	0.3	0.6	0.15
7	0.3	0.2	0.05
8	0.3	0.2	0.15
9	0.7	0.02	0.05
10	0.7	0.1	0.15
11	0.3	0.02	0.05
12	0.3	0.1	0.15

a

	$z_i = 0$	$z_i = 1$
$c_i = 0$	*p10*	*p11*
$c_i = 1$	0	1

b

	$z_i = 0$	$z_i = 1$
$c_i = 0$	*p10*	*p11*
$c_i = 1$	undefined	1

Figure 2.1: Probabilities of detections (true or false) in a) the confirmed absences and presences (CACP) model and b) the confirmed presences (CP) model given occupancy (z) and observation confirmation (c) states at site i and false positive (*p10*) and true positive (*p11*) detection probabilities.

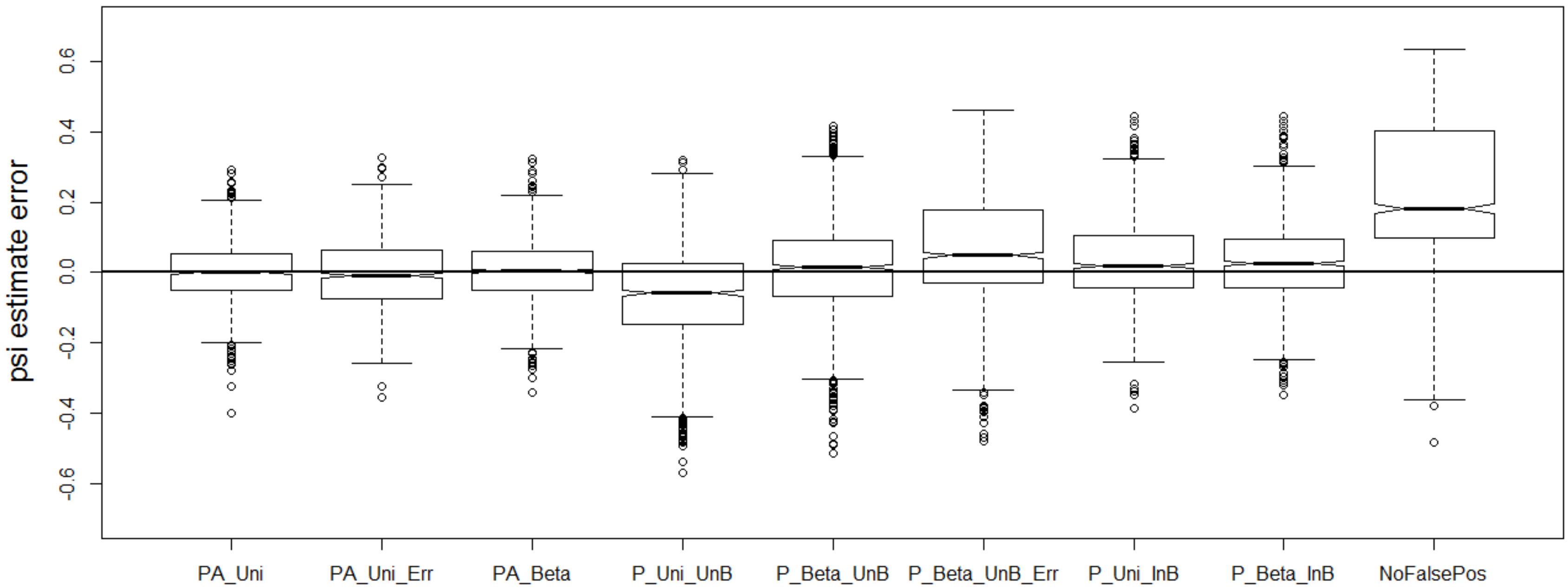


Figure 2.2: Absolute error of posterior occupancy probabilities from nine occupancy model parameterizations applied to simulated data sets from twelve parameter value combinations. Absolute error was calculated as the difference between the mean of the parameter's posterior distribution and the parameter value used to simulate data. Results are presented from all converged model runs: PA = data with confirmed presences and confirmed absences, P = data with confirmed presences, Err = data with observation confirmation errors, Uni = U(0,0.5) prior for the false positive detection probability, Beta = informative Beta(1,9) prior for the false positive detection probability, UnB = vague prior for the observation confirmation probability, and InB = informative prior for the observation confirmation probability. NoFalsePos indicates the model that assumed there were no false positive detections, but data used to fit the model contained false positive errors. Notches are placed around the medians, and if the notches of two plots do not overlap, there is strong evidence that those medians differ. The box of each plot includes the first through third quartile. Whiskers extend to the most extreme data point that is no more than 1.5 times the interquartile range from the box. Small circles represent outliers.

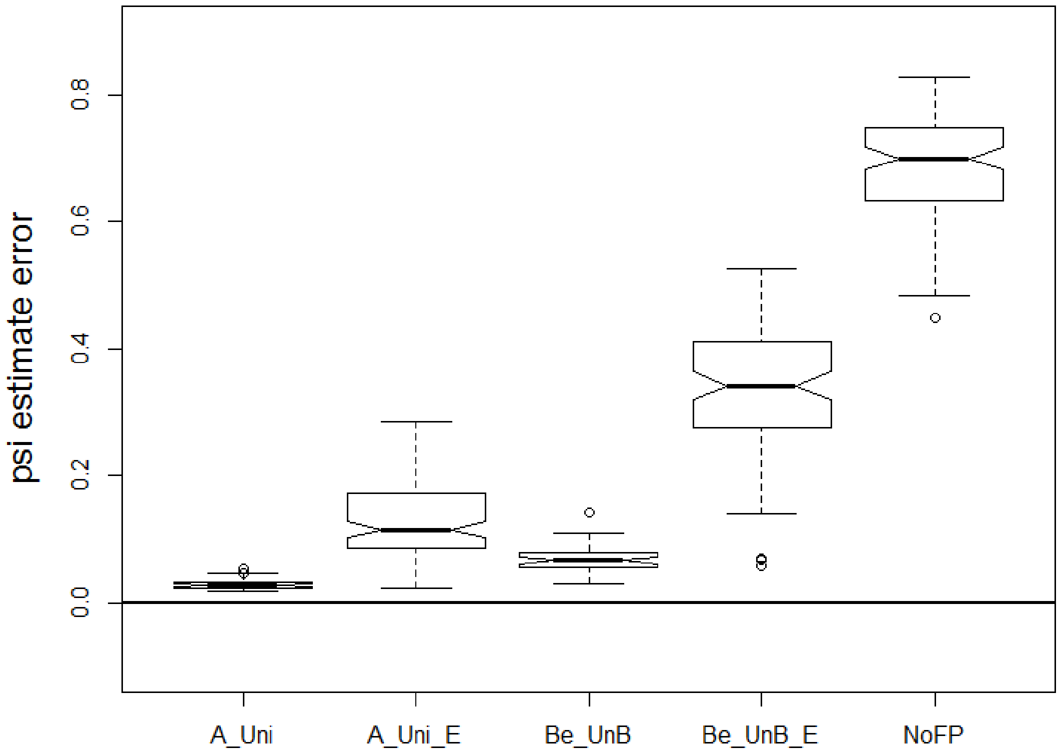


Figure 2.3: Absolute error of posterior occupancy probabilities from five occupancy model parameterizations applied to simulated data sets for phantom species. Results are presented from all converged model runs: A = data with confirmed absences, E = data with observation confirmation errors, Uni = U(0,0.5) prior for the false positive detection probability, Be = informative Beta(1,9) prior for the false positive detection probability, and UnB = vague prior for the observation confirmation probability. NoFP indicates the model that assumed there were no false positive detections. Box plot layout details can be found in the Figure 2.2 legend.

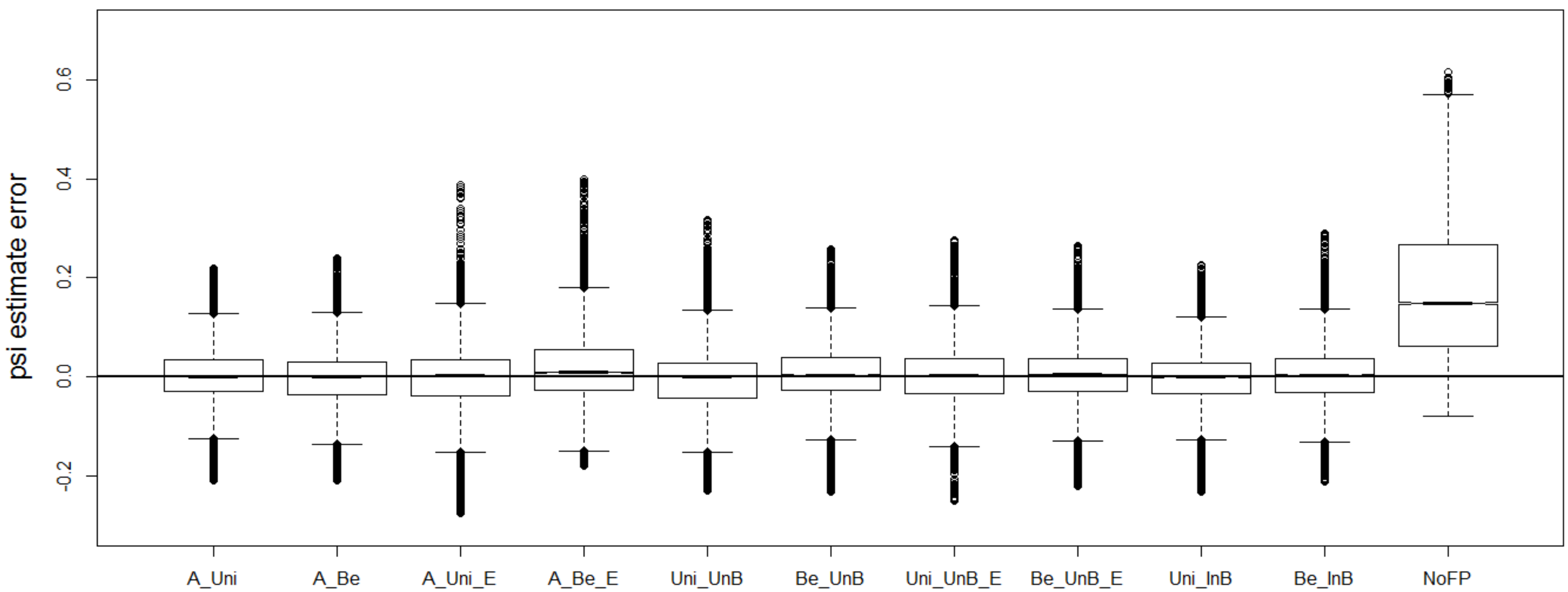


Figure 2.4: Absolute error of posterior occupancy probabilities from eleven occupancy model parameterizations applied to simulated data sets from the scenario where occupancy probabilities were affected by a covariate through a strong quadratic function. Results from all converged model runs are presented: A = data with confirmed presences and confirmed absences, otherwise data have confirmed presences only; E = data with observation confirmation errors, otherwise data do not have observation confirmation errors; Uni = U(0,0.5) prior for the false positive detection probability; Be = informative Beta(1,9) prior for the false positive detection probability; UnB = vague prior for the observation confirmation probability; and InB = informative prior for the observation confirmation probability. NoFP indicates the model that assumed there were no false positive detections. Box plot layout details can be found in the Figure 2.2 legend.

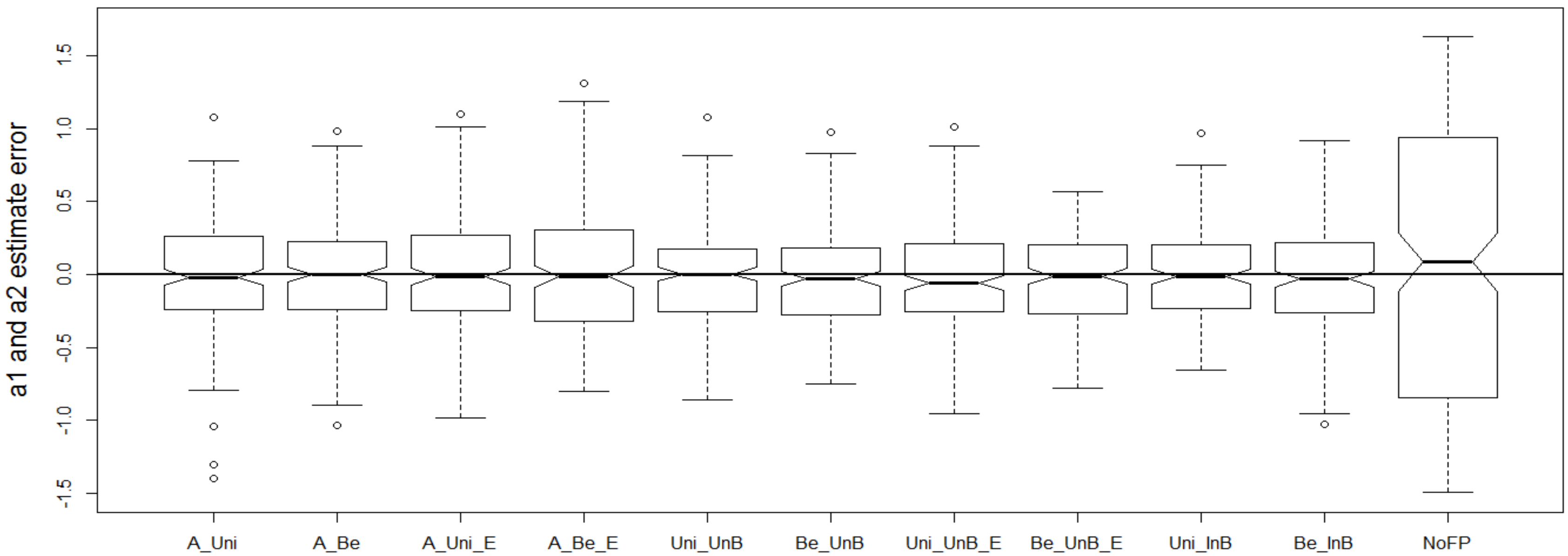


Figure 2.5: Absolute error of the mean of covariate coefficient posterior distributions from eleven occupancy model parameterizations applied to simulated data sets from the scenario where occupancy probabilities were affected by a covariate through a strong quadratic function. Errors in the coefficient for the linear term (*a1*) and in the coefficient for the quadratic term (*a2*) are presented from all converged model runs. Box plot layout details can be found in the legends in Figs. 2.2 and 2.4.

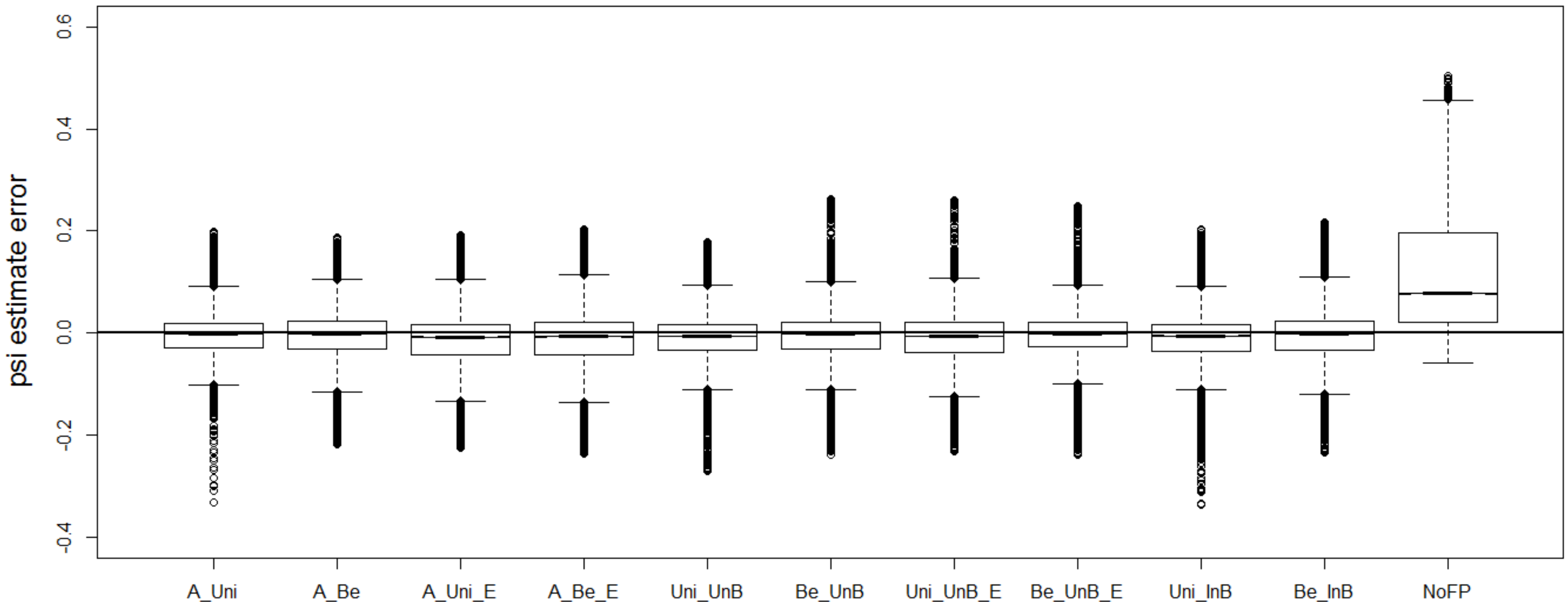


Figure 2.6: Absolute error of posterior occupancy probabilities from eleven occupancy model parameterizations applied to simulated data sets from the scenario where occupancy probabilities were affected by a covariate through a weak quadratic function. Box plot layout details can be found in the legends in Figs. 2.2 and 2.4.

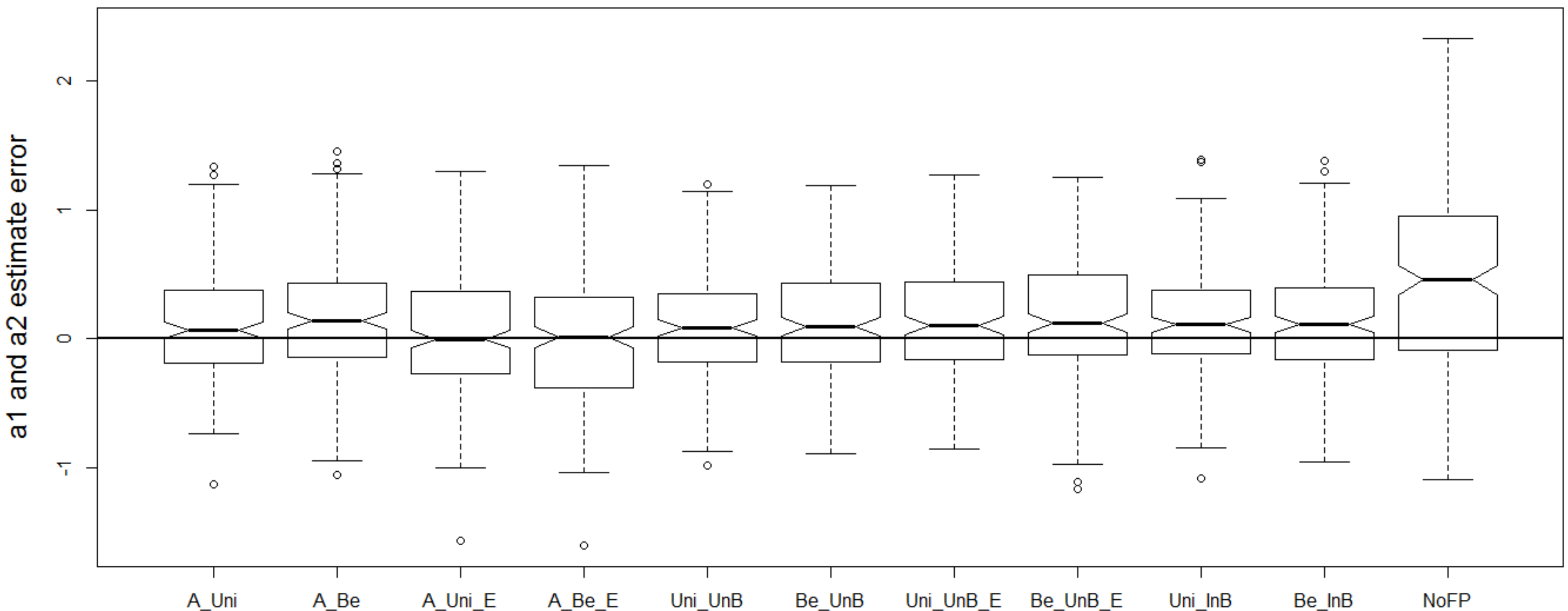


Figure 2.7: Absolute error of the mean of covariate coefficient posterior distributions from eleven occupancy model parameterizations applied to simulated data sets from the scenario where occupancy probabilities were affected by a covariate through a weak quadratic function. Errors in the coefficient for the linear term (*a1*) and in the coefficient for the quadratic term (*a2*) are presented from all converged model runs. Box plot layout details can be found in the legends in Figs. 2.2 and 2.4.

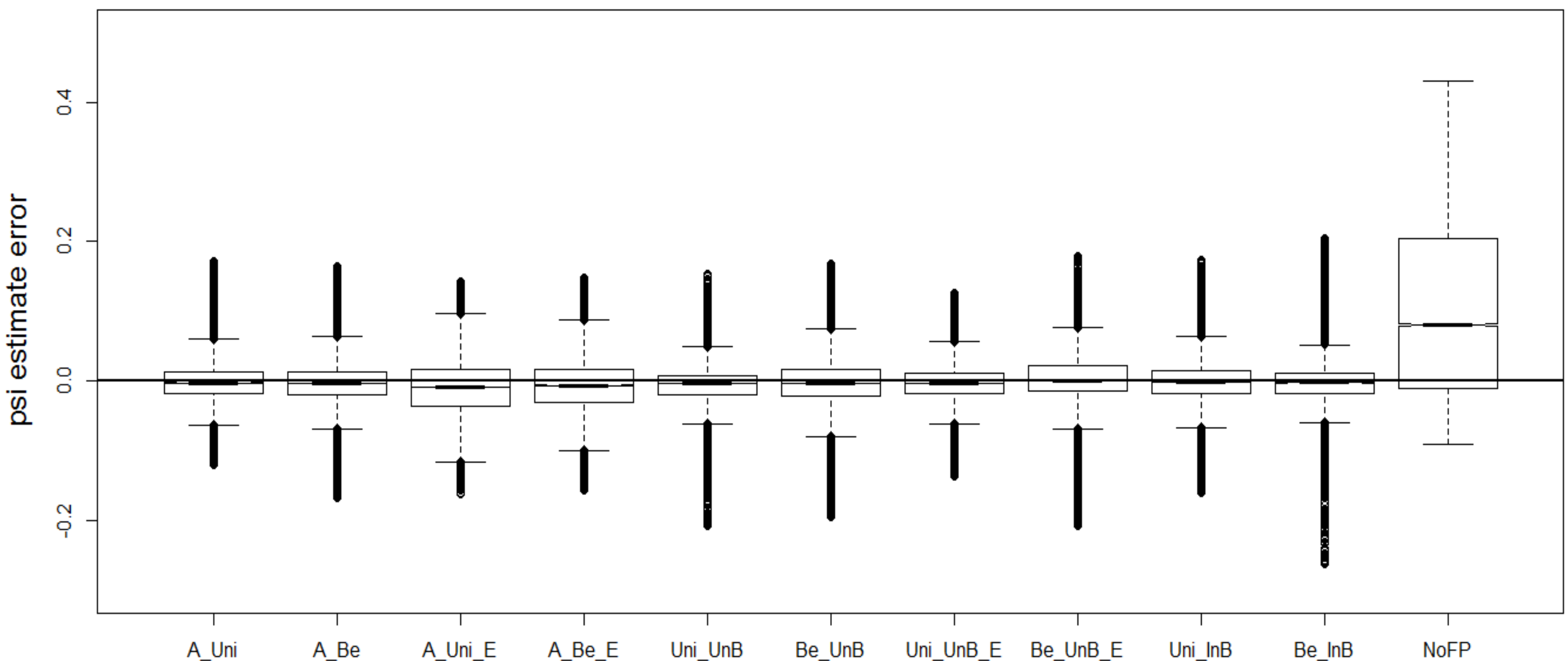


Figure 2.8: Absolute error of posterior occupancy probabilities from eleven occupancy model parameterizations applied to simulated data sets from the scenario where occupancy probabilities were affected by a covariate through a linear function. Box plot layout details can be found in the legends in Figs. 2.2 and 2.4.

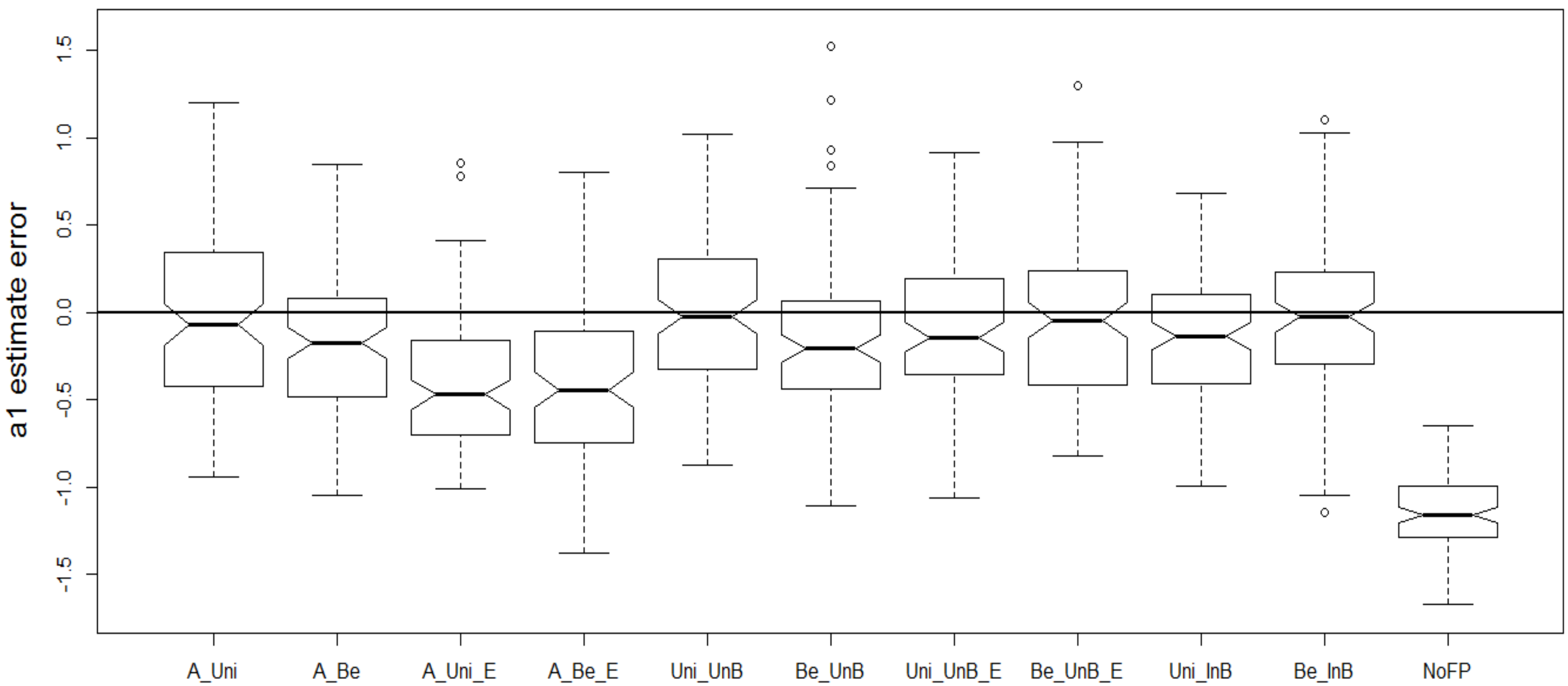
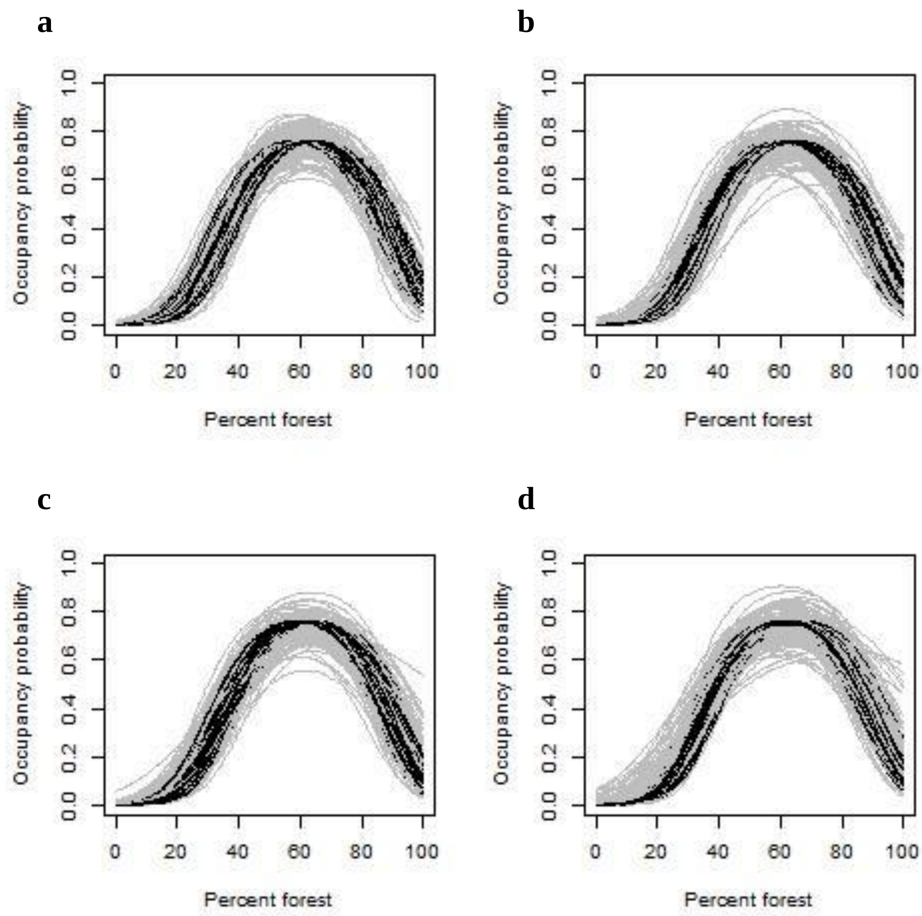
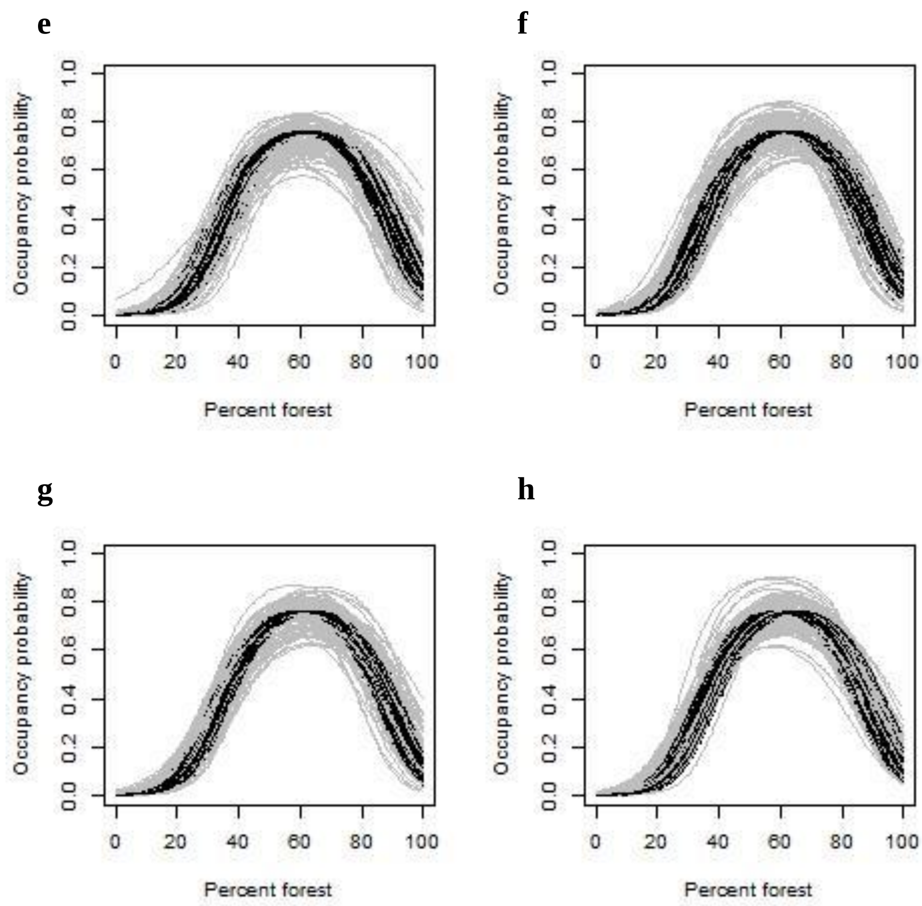


Figure 2.9: Absolute error of the mean of covariate coefficient posterior distributions from eleven occupancy model parameterizations applied to simulated data sets from the scenario where occupancy probabilities were affected by a covariate through a linear function. Errors in the coefficient for the linear term (*a1*) are presented from all converged model runs. Box plot layout details can be found in the legends in Figs. 2.2 and 2.4.


a
b
c
d
Occupancy probability
0.0
0.2
0.4
0.6
0.8
1.0
0
20
40
60
80
100
Percent forest


e
f
Occupancy probability
0.0 0.2 0.4 0.6 0.8 1.0
0 20 40 60 80 100
Percent forest
g
h

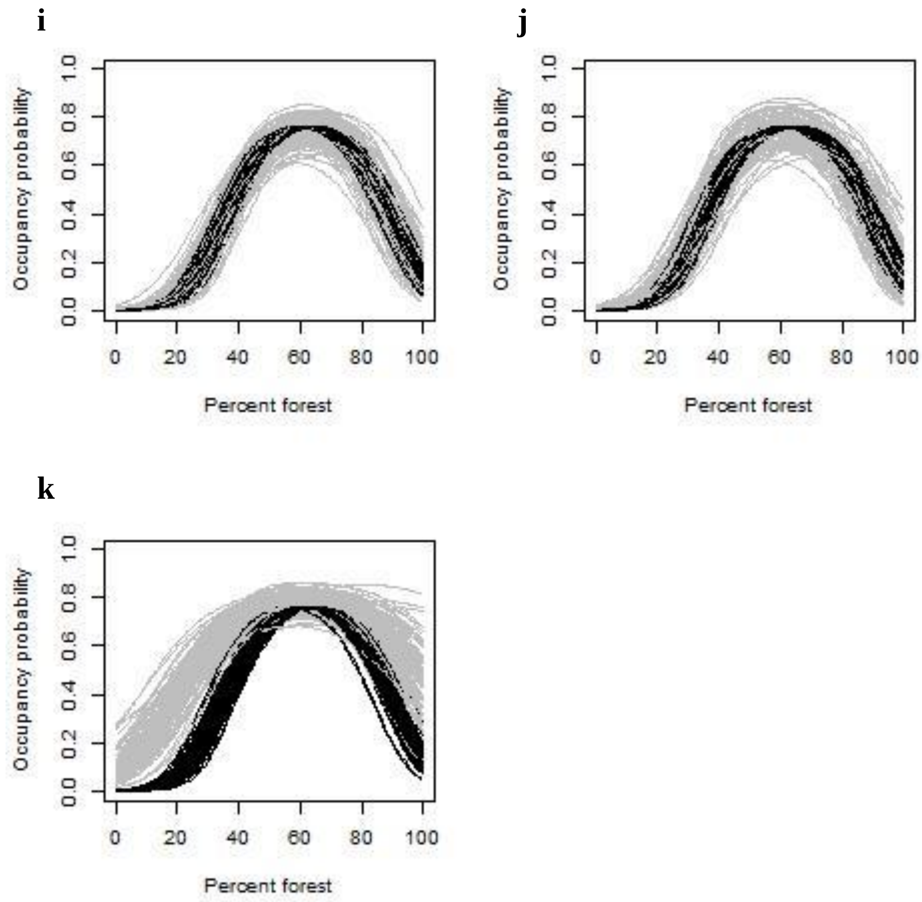
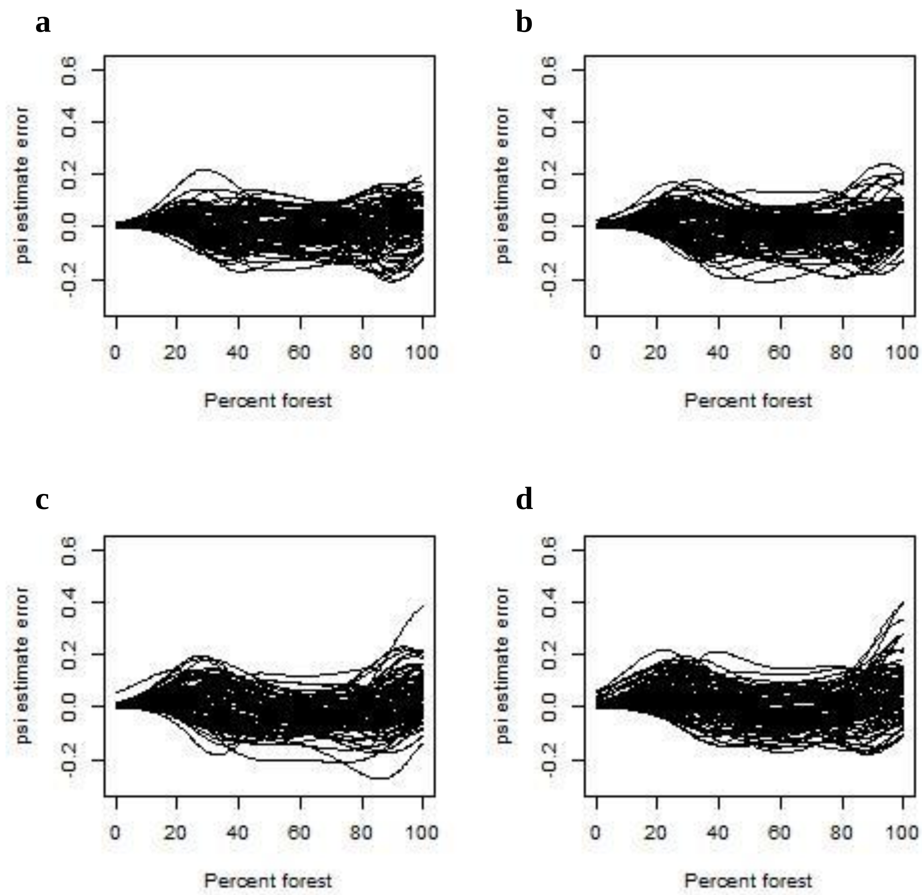
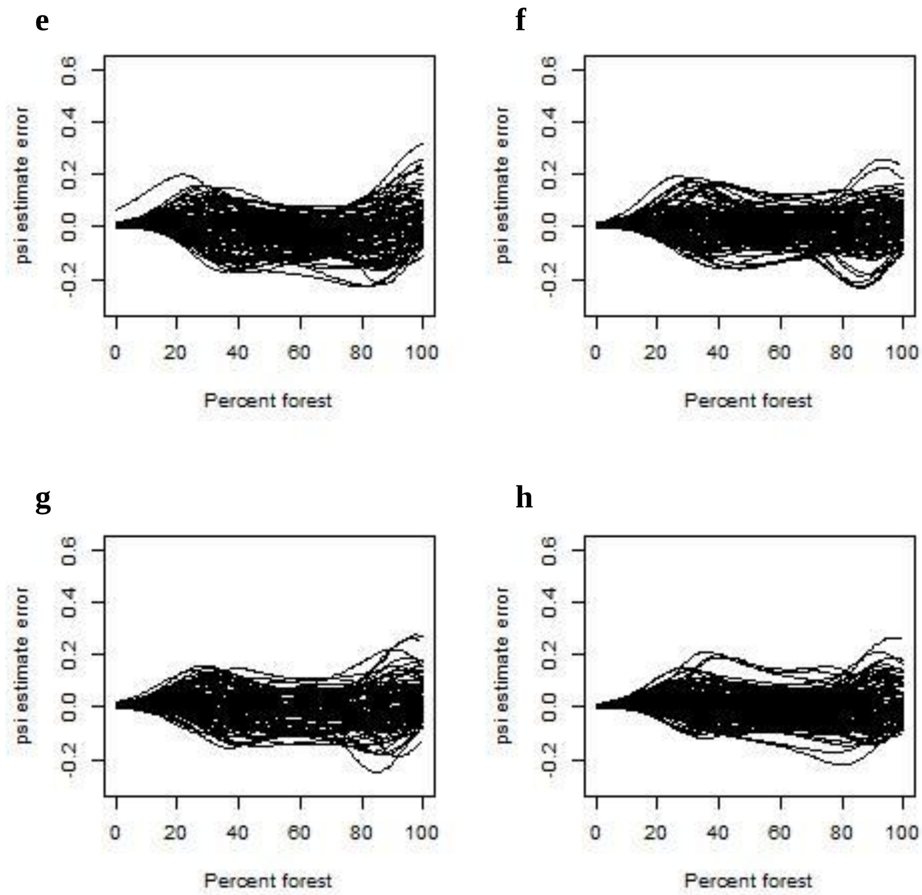


Figure 2.10: Simulated (black lines) and inferred (grey lines) effects of percent forest cover on occupancy probabilities from the strong quadratic scenario. Posterior probabilities are presented from all converged models out of those fit to 100 simulated data sets: a) = CACP model with the vague prior for the false positive detection probability (*p10*), b) = CACP model with the informative prior for *p10*, c) CACP model with the vague prior for *p10* and observation confirmation errors, d) CACP model with the informative prior for *p10* and observation confirmation errors, e) CP model with the vague prior for *p10* and the vague prior for the observation confirmation probability (*b*), f) CP model with the informative prior for *p10* and the vague prior for *b*, g) CP model with the vague prior for *p10*, the vague prior for *b*, and observation confirmation errors, h) CP model with the informative prior for *p10*, the vague prior for *b*, and observation confirmation errors, i) CP model with the vague prior for *p10* and the informative prior for *b*, j) CP model with the informative prior for *p10* and the informative prior for *b*, and k) model assuming no false positive errors.


a
b
c
d
psi estimate error
Percent forest
-0.2
0.0
0.2
0.4
0.6
0
20
40
60
80
100


e
f
g
h
psi estimate error
Percent forest
0.6
0.4
0.2
0.0
-0.2
0
20
40
60
80
100

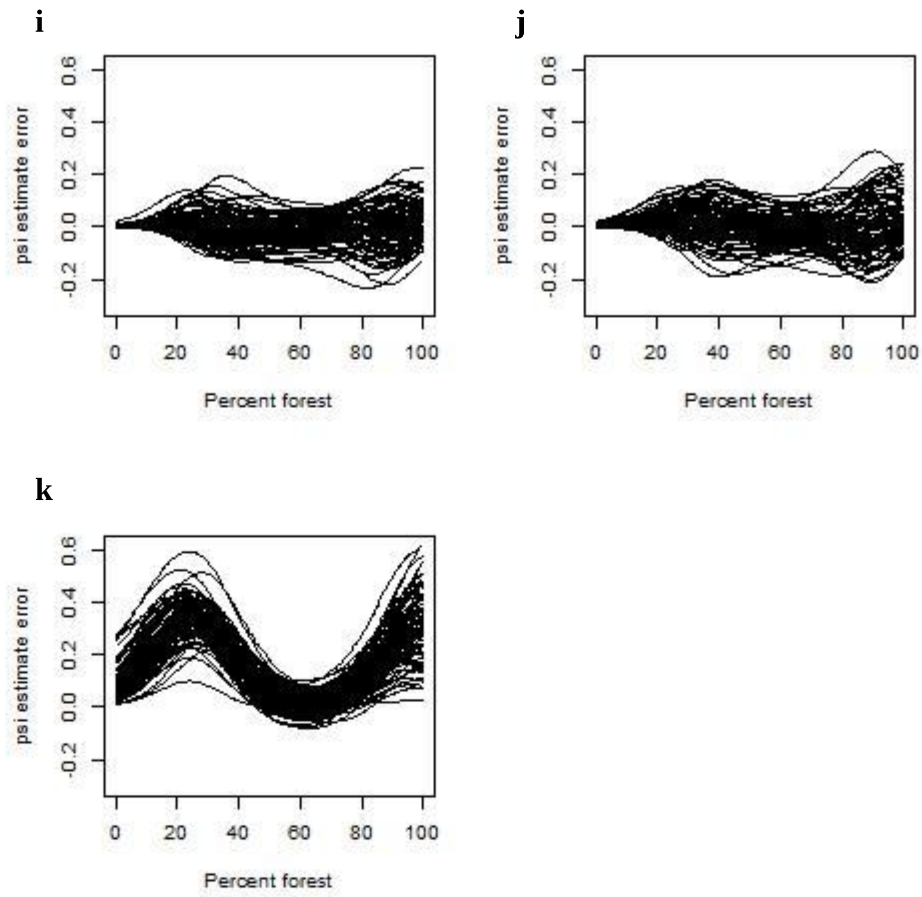
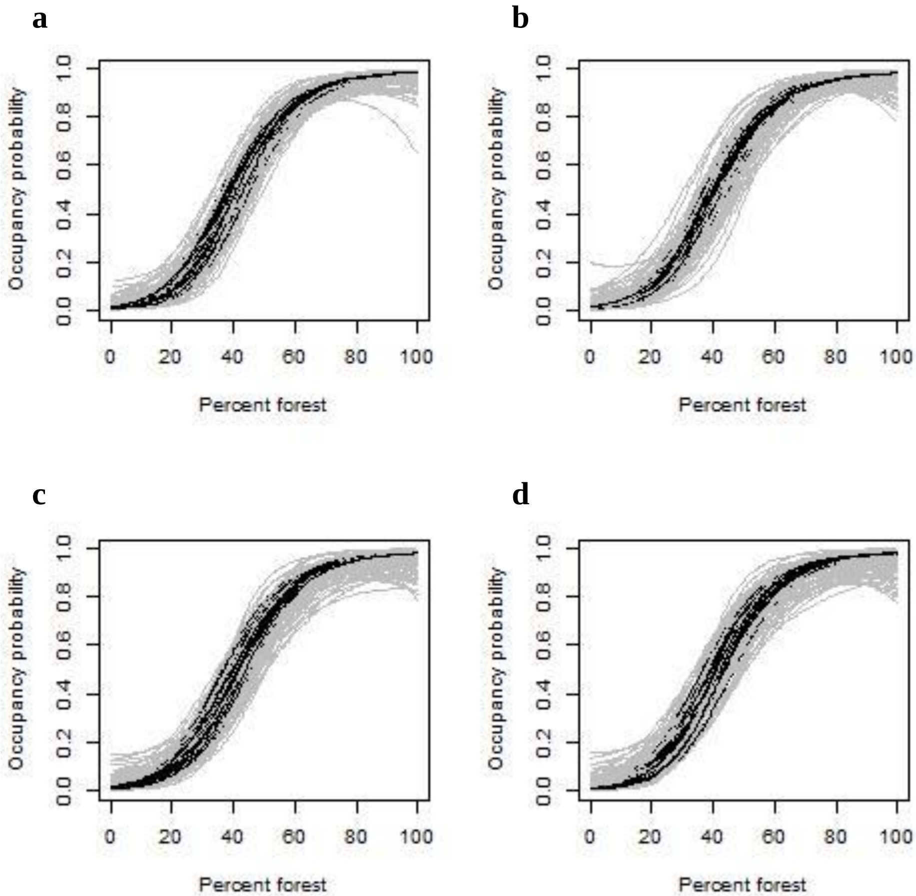
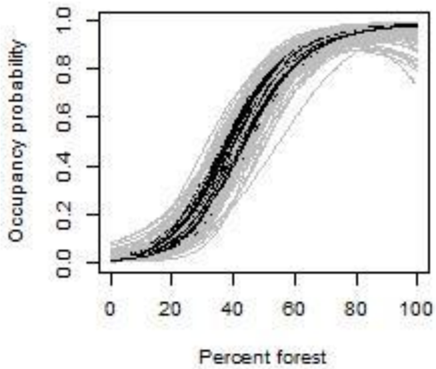


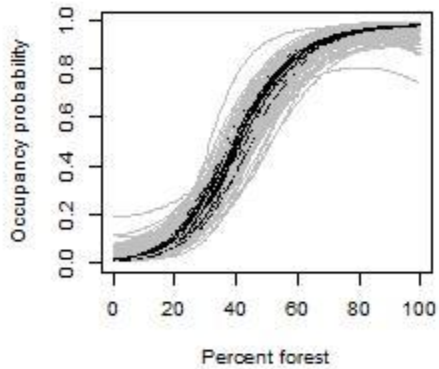
Figure 2.11: Absolute errors of posterior occupancy probabilities as a function of covariate values from the strong quadratic scenario. Results are presented from all converged models out of those fit to 100 simulated data sets: a) = CACP model with the vague prior for the false positive detection probability (*p10*), b) = CACP model with the informative prior for *p10*, c) CACP model with the vague prior for *p10* and observation confirmation errors, d) CACP model with the informative prior for *p10* and observation confirmation errors, e) CP model with the vague prior for *p10* and the vague prior for the observation confirmation probability (*b*), f) CP model with the informative prior for *p10* and the vague prior for *b*, g) CP model with the vague prior for *p10*, the vague prior for *b*, and observation confirmation errors, h) CP model with the informative prior for *p10*, the vague prior for *b*, and observation confirmation errors, i) CP model with the vague prior for *p10* and the informative prior for *b*, j) CP model with the informative prior for *p10* and the informative prior for *b*, and k) model assuming no false positive errors.


a
b
c
d
Occupancy probability
0.0
0.2
0.4
0.6
0.8
1.0
0
20
40
60
80
100
Percent forest

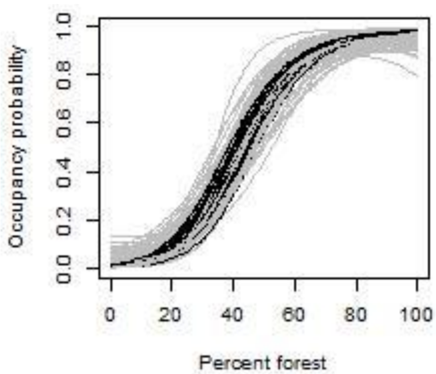
e


Occupancy probability
0.0
0.2
0.4
0.6
0.8
1.0
0
20
40
60
80
100
Percent forest

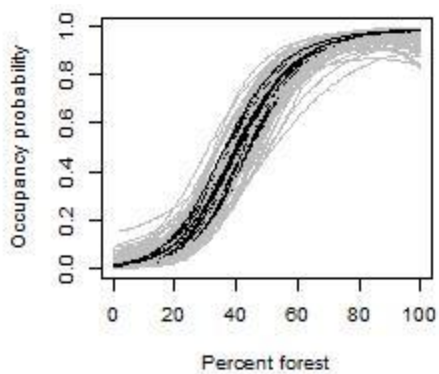
f


Occupancy probability
0.0
0.2
0.4
0.6
0.8
1.0
0
20
40
60
80
100
Percent forest

g


Occupancy probability
0.0
0.2
0.4
0.6
0.8
1.0
0
20
40
60
80
100
Percent forest

h


Occupancy probability
0.0
0.2
0.4
0.6
0.8
1.0
0
20
40
60
80
100
Percent forest

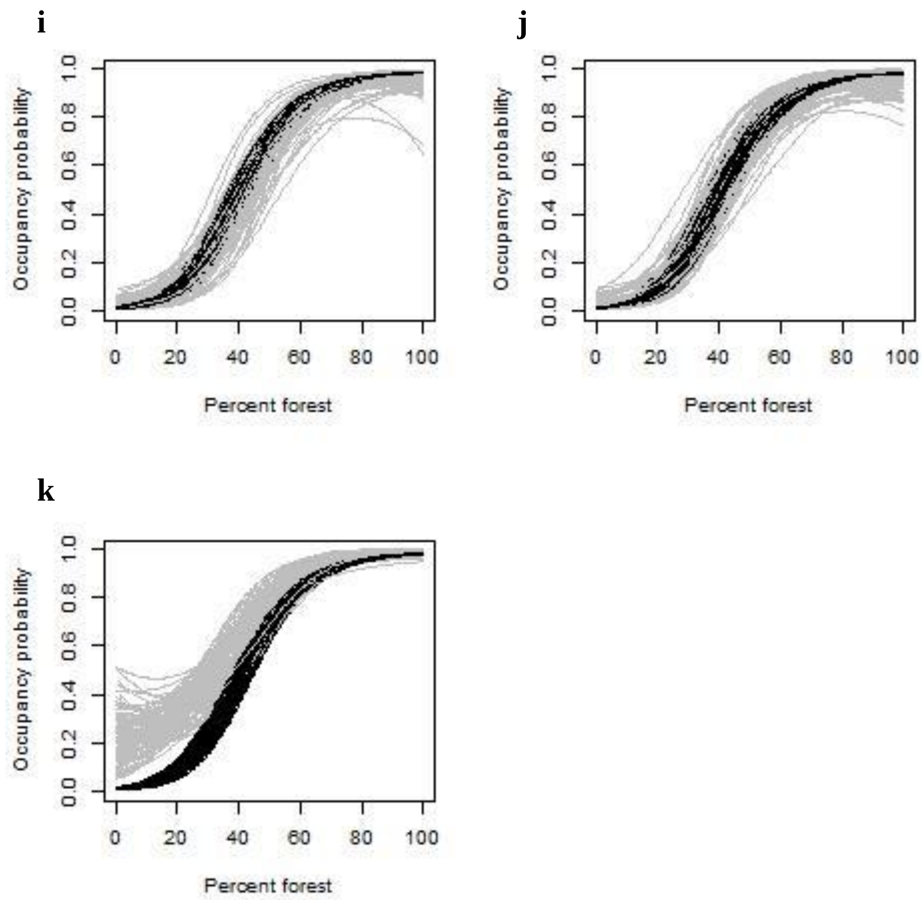
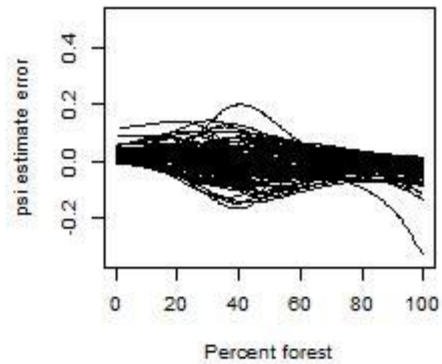
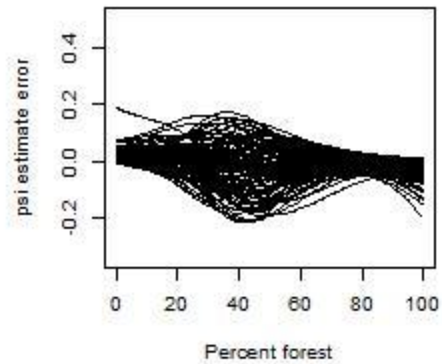


Figure 2.12: Simulated (black lines) and inferred (grey lines) effects of percent forest cover on occupancy probabilities from the weak quadratic scenario. Plot details can be found in the Figure 2.10 legend.

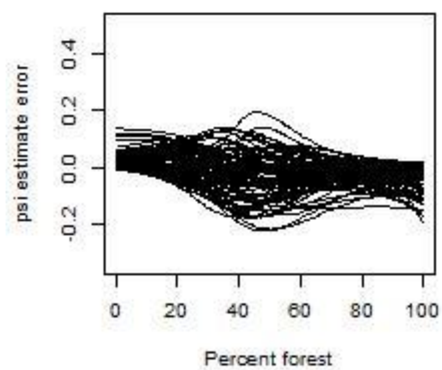
a


psi estimate error
0.4
0.2
0.0
-0.2
0
20
40
60
80
100
Percent forest

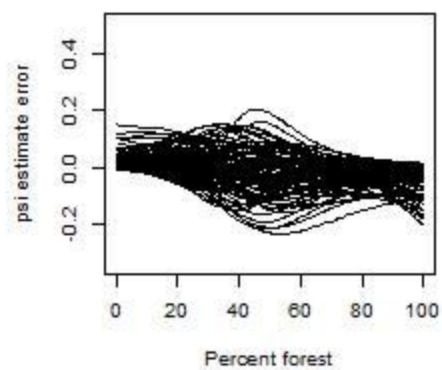
b

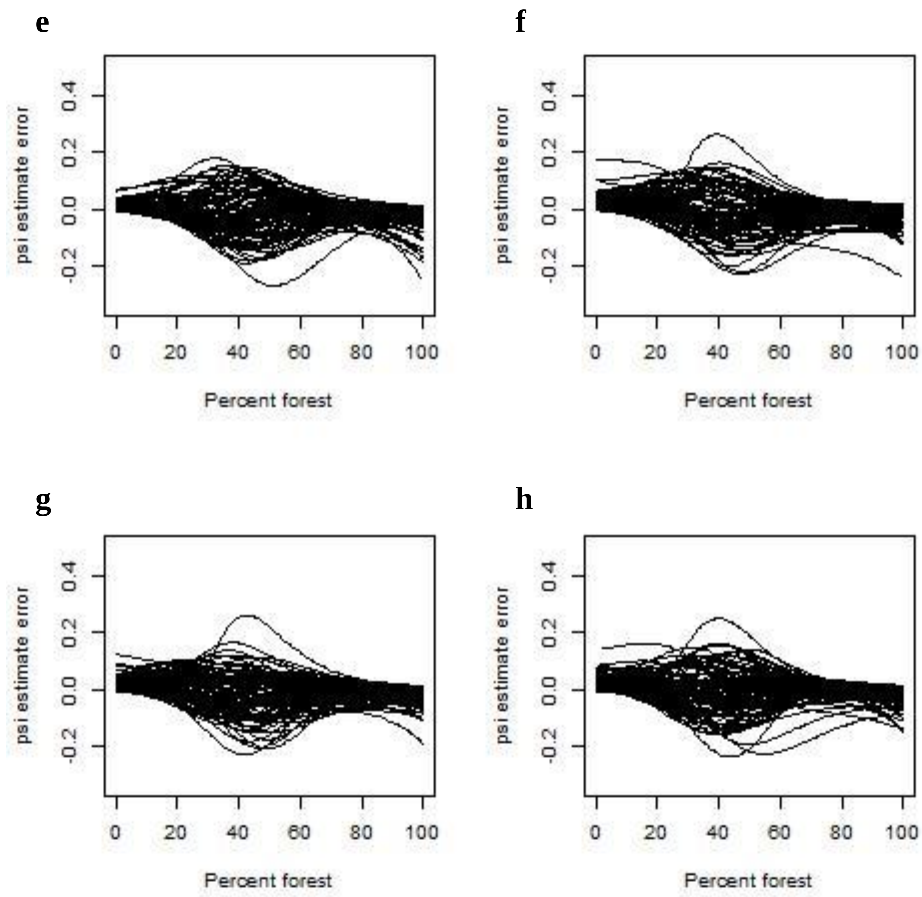

psi estimate error
0.4
0.2
0.0
-0.2
0
20
40
60
80
100
Percent forest

c

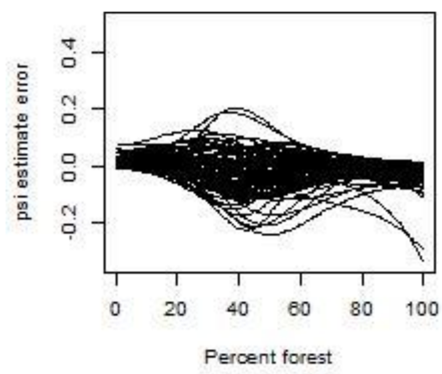

psi estimate error
0.4
0.2
0.0
-0.2
0
20
40
60
80
100
Percent forest

d

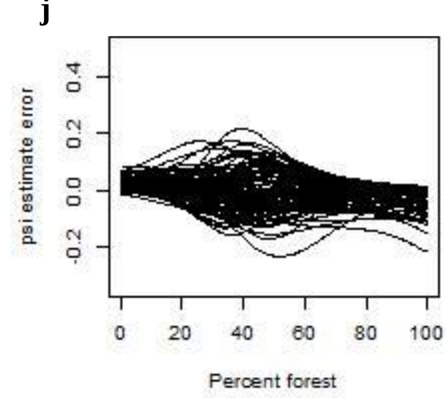

psi estimate error
0.4
0.2
0.0
-0.2
0
20
40
60
80
100
Percent forest


e
f
g
h
psi estimate error
Percent forest
0.4
0.2
0.0
-0.2
0
20
40
60
80
100

i



j



k

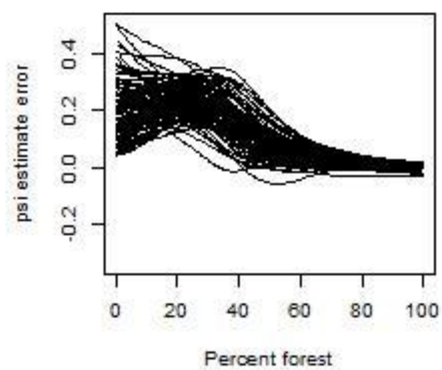
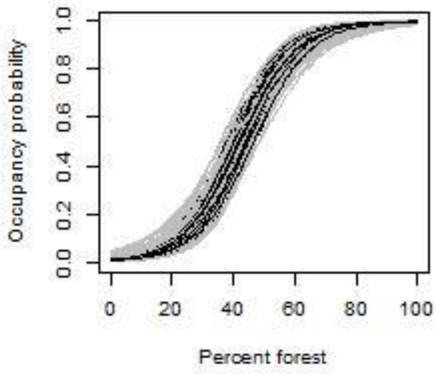
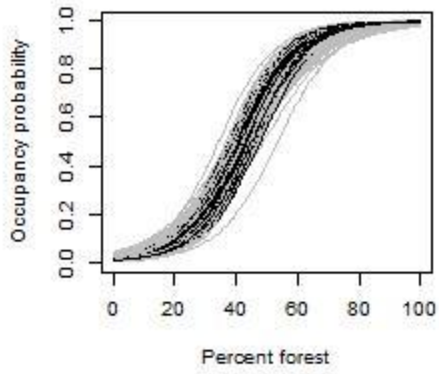


Figure 2.13: Absolute errors of posterior occupancy probabilities as a function of covariate values from the weak quadratic scenario. Plot details can be found in the Figure 2.11 legend.

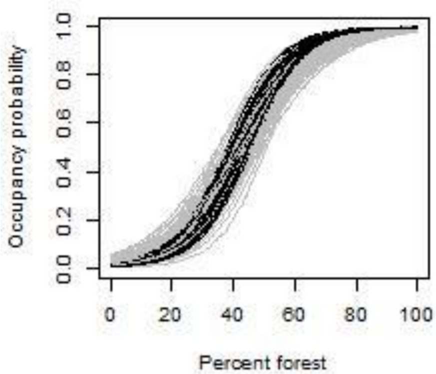
a


Occupancy probability
0.0
0.2
0.4
0.6
0.8
1.0
0
20
40
60
80
100
Percent forest

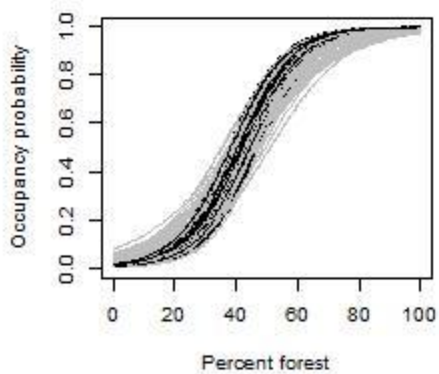
b

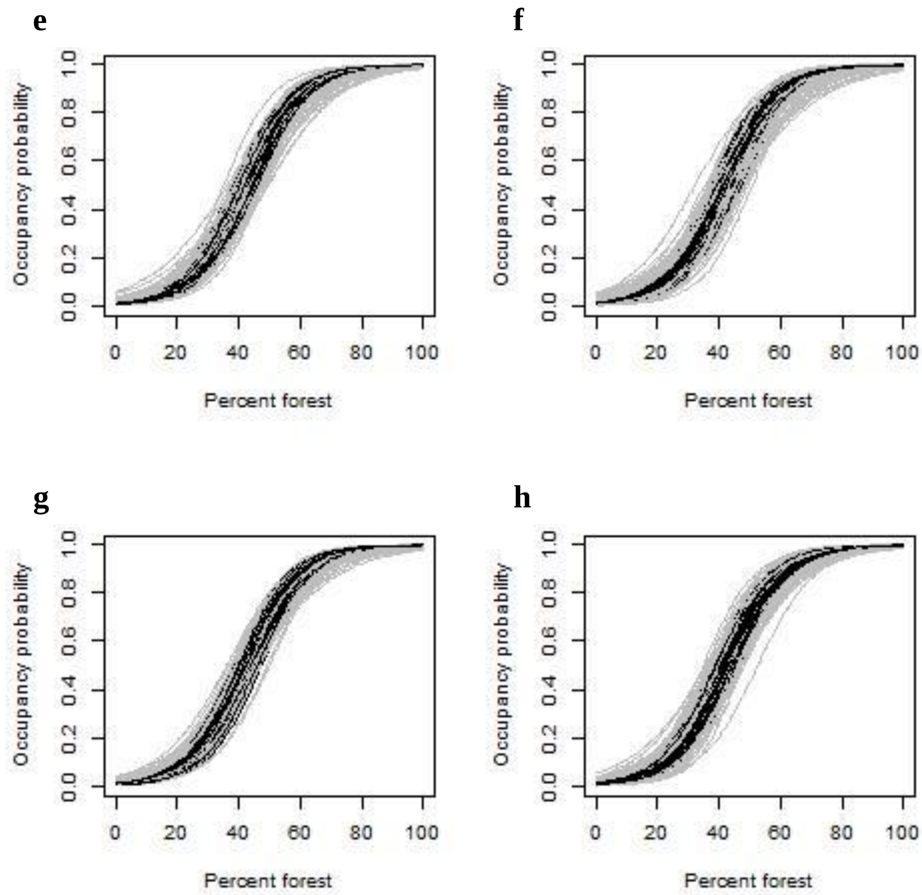

Occupancy probability
0.0
0.2
0.4
0.6
0.8
1.0
0
20
40
60
80
100
Percent forest

c


Occupancy probability
0.0
0.2
0.4
0.6
0.8
1.0
0
20
40
60
80
100
Percent forest

d


Occupancy probability
0.0
0.2
0.4
0.6
0.8
1.0
0
20
40
60
80
100
Percent forest


e
f
g
h
Occupancy probability
Percent forest
0.0
0.2
0.4
0.6
0.8
1.0
0
20
40
60
80
100

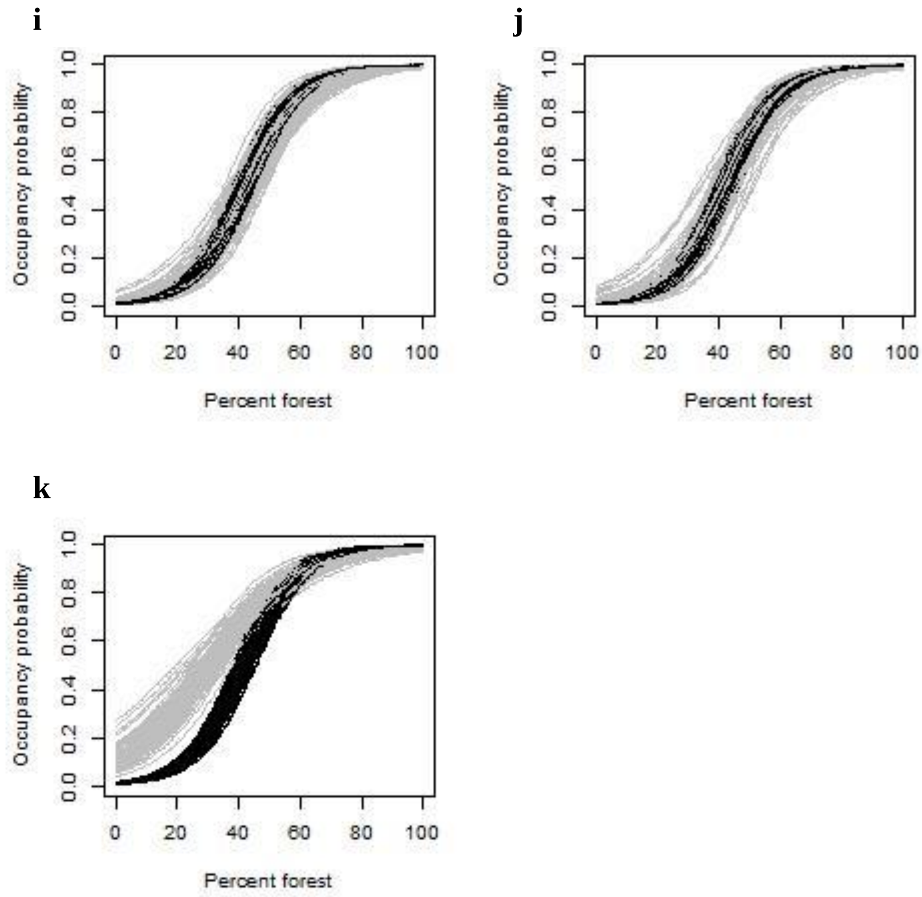
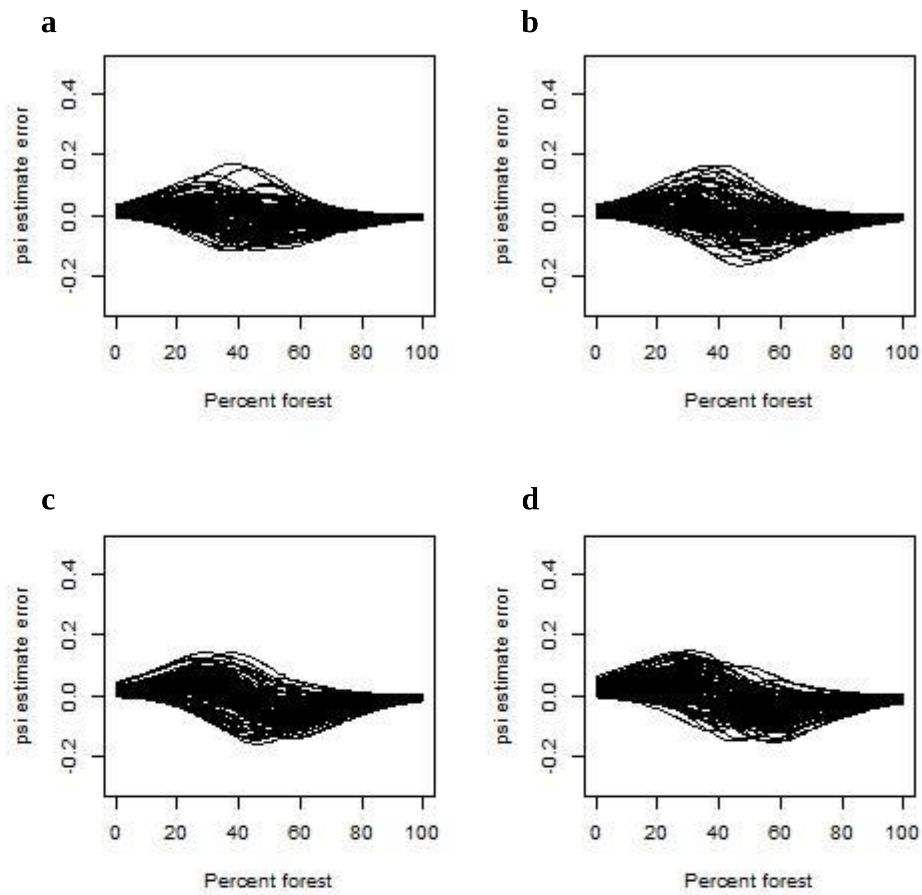
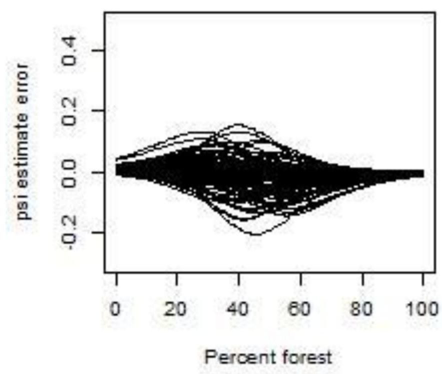


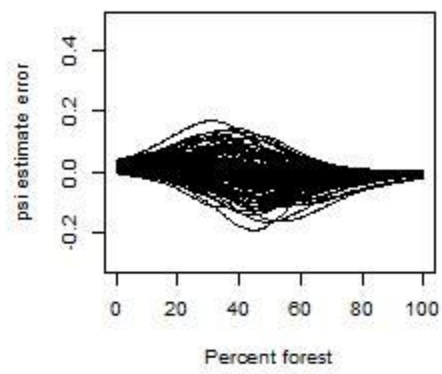
Figure 2.14: Simulated (black lines) and inferred (grey lines) effects of percent forest cover on occupancy probabilities from the linear scenario. Plot details can be found in the Figure 2.10 legend.


a
b
c
d
psi estimate error
-0.2
0.0
0.2
0.4
0
20
40
60
80
100
Percent forest

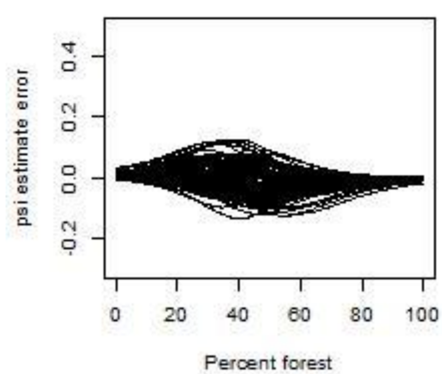
e


psi estimate error
-0.2
0.0
0.2
0.4
0
20
40
60
80
100
Percent forest

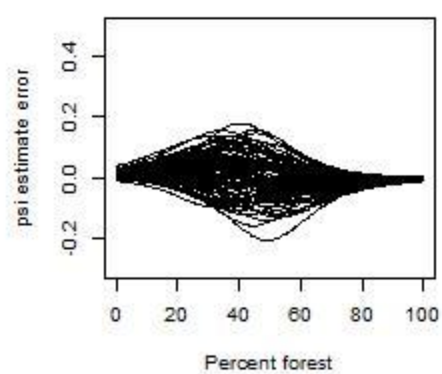
f


psi estimate error
-0.2
0.0
0.2
0.4
0
20
40
60
80
100
Percent forest

g


psi estimate error
-0.2
0.0
0.2
0.4
0
20
40
60
80
100
Percent forest

h


psi estimate error
-0.2
0.0
0.2
0.4
0
20
40
60
80
100
Percent forest

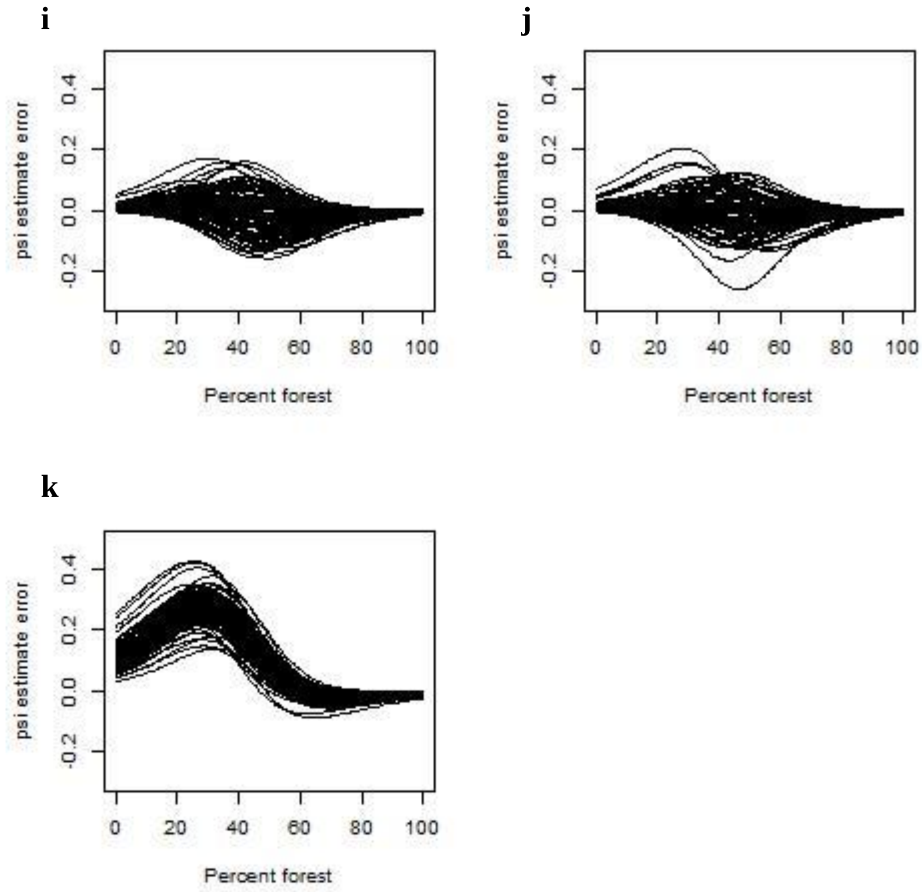


Figure 2.15: Absolute errors of posterior occupancy probabilities as a function of covariate values from the linear scenario. Plot details can be found in the Figure 2.11 legend

CHAPTER 3

MULTI-SCALE EFFECTS OF EXURBAN DEVELOPMENT ON BIRDS AT PROTECTED AND UNPROTECTED SITES: AN APPLICATION OF AN OCCUPANCY MODEL ACCOUNTING FOR FALSE POSITIVE AND FALSE NEGATIVE DETECTIONS [2]

[2] Barlow, P.F., M.J. Conroy, and J. Hepinstall-Cymerman. To be submitted to *Ecological Applications*.

Abstract

Exurban development, the construction of low-density residential homes in a rural landscape, is the fastest growing type of land use in the United States and is prominent in the southern Appalachian region. A potential consequence of exurban development is the loss and fragmentation of native habitat. We used a Bayesian model that accounts for false positive and false negative detections to make inferences about how the occupancy of six forest-dwelling, Neotropical migrant birds is related to multi-scale attributes of exurban development. We performed Bayesian model selection and model averaging with a Bayesian Information Criterion weights approximation, and we evaluated models' predictive ability. Results indicated that landscape- and local-scale covariates influenced posterior occupancy probabilities more than site-scale covariates and that landscape composition and elevation had a greater effect on occupancy probabilities than configuration. The Black-throated Blue Warbler and Wood Thrush had the lowest posterior occupancy probabilities of the focal species. National Forest sites had high occupancy, but land trust sites exhibited patterns similar to unprotected sites. Our findings can provide guidance to land use planners and land trusts as they decide how to respond to exurban development. Also, our study demonstrates the application of an improved occupancy model that can generate more accurate inference by accounting for both types of imperfect detection while describing heterogeneity.

Introduction

Exurban development is the fastest growing type of land use in the United States (Theobald 2001, Brown et al. 2005, Hansen et al. 2005). Exurban development is characterized by the construction of low-density residential homes in a rural landscape that previously had been dominated by native vegetation and agriculture, and it often occurs near natural amenities such as protected areas, outdoor recreation, pleasant weather, and attractive scenery (Brown et al. 2005, Wade and Theobald 2010). Currently, exurban land use covers about 25% of the lower 48 states, and eastern decision forests in the southeastern and mid-Atlantic U.S. are some of the areas where exurban development has been most extensive (Brown et al. 2005, Hansen et al. 2005). Growth in exurban development is expected to continue (Theobald 2005).

Urban and exurban development are considered principal causes of worldwide habitat loss (Brown et al. 2005, Hansen et al. 2005). The construction of roads, yards, and buildings leads to the loss and fragmentation of native habitat, affecting native plants and animals (Boulinier et al. 2001, Pidgeon et al. 2007, Merenlender et al. 2009, Suarez-Rubio et al. 2013). As a result of exurban development, patches of native habitat are smaller and more isolated, there is more edge, new habitat types are introduced, and anthropogenic disturbances (e.g., noise, pollution, and pedestrians) are more common (Andrén 1994, Fahrig 2003, Husté and Boulinier 2011). Frequently, native vegetation is lost, the structure is changed, or the quality declines because of exurban development (Theobald et al. 1997, Chace and Walsh 2006, Bonier et al. 2007).

Birds are commonly selected as a focal taxon for investigating the effects of land use (McDonnell and Hahs 2008) because their ecology is well known and birds appear to respond to their surroundings at multiple spatial scales (Orians and Wittenberger 1991, Pearson 1993, Hostetler and Holling 2000). However, the response of birds to exurban development varies among species (Blair 1996, Villard et al. 1999, Crooks et al. 2004, Hansen et al. 2005). Generally, birds that are Neotropical migrants, forest-dwelling, area-sensitive, ground-nesters, or habitat specialists appear most sensitive to exurban development (Askins 1995, Allen and O'Connor 2000, Marzluff 2001, Chace and Walsh 2006, McKinney 2006).

When assessing the effects of land use on wildlife, land use patterns typically are measured through a variety of metrics that, to varying degrees, quantify landscape composition and configuration. However, it often can be difficult to disentangle the role of landscape composition versus configuration. Overall, previous studies have found that birds respond more strongly to composition, often requiring a minimum amount of habitat to occupy an area (McGarigal and McComb 1995, Fahrig 2003). This appears especially true when the landscape has at least 20% habitat (Andrén 1994, Fahrig 1997). How habitat elements are arranged (i.e., landscape configuration) is influential for some species, particularly those with low vagility, high site fidelity, and high mortality in unsuitable habitat (Fahrig 1998, Villard et al. 1999, Lichstein et al. 2002). For example, distance between patches and amount of edge may be important features of landscape configuration (Faaborg et al. 1995, Robinson et al. 1995, Boulinier et al. 2001).

The scale at which land use patterns are measured is also important (Villard et al. 1999). Different factors may drive the distribution of a species at different scales, and the influence of a factor on the distribution of a species may vary across multiple scales. For example, broad-scale features, such as biogeographical history and climatic gradients, may determine where species occur at a large scale, but fine-scale attributes, such as habitat condition and species interactions, may explain where species occur at the local scale (Bergin et al. 2000, Boulinier et al. 2001, Betts et al. 2007, Whittingham et al. 2007, Lindstrom et al. 2013).

Also, when land use data are collected at multiple spatial scales, data are hierarchically structured, and this results in dependence among spatial scales (Moore and Swihart 2005). Data from large spatial scales contain information from smaller scales (Bergin et al. 2000). Consequently, analyses may tend to show that variables at large spatial scales are more influencial than variables at small spatial scales simply due to the hierarchical structure of the data. In fact, many previous studies have found that large scale variables had a greater effect than small scale variables (Saab 1999, Bergin et al. 2000, Mitchell et al. 2001). However, studies have also found that some variables were only important at small scales and, for some species, variables from small scales most influenced occurrence (Saab 1999, Bergin et al. 2000).

Overall, it seems that there is no single scale that is optimal for the study of all avian species and the scale at which patterns affect birds varies depending on the bird's life history (Mitchell et al. 2001, Lee et al. 2002). Identifying which land use features are influential and the spatial scale at which birds respond to them will help inform avian conservation and land use planning (Hostetler 1999, Lerman and Warren 2011, Pennington and Blair 2011).

Development in southern Appalachia

In this project, we focus on exurban development in the southern Appalachian region. The aesthetic and recreational opportunities, low cost of living, low taxes, and lack of zoning regulations in the southern Appalachian region have contributed to exurban development (Marcouiller et al. 2002, Gragson and Bolstad 2006). Generally, exurban development has occurred as retirees, urban commuters, and people in the market for vacation homes have purchased properties that were formed by subdividing former agroforestry lands (Wear and Greis 2002, Cho et al. 2003, Hansen et al. 2005, Gragson and Bolstad 2006).

Our study region is Macon County, North Carolina, the site of one of the National Science Foundation's Long Term Ecological Research (LTER) sites, Coweeta. New residents in

Macon County have built houses on forested slopes at high elevations and on previously farmed properties that have reverted to forest (Gragson and Bolstad 2006). Up to 43% of the properties in Macon County are owned by people whose primary residence is elsewhere, and people from every state in the U.S. own property in Macon County (Norwood 2009). Florida residents alone own 24% of properties in Macon County (Norwood 2009).

Focal species

The southern Appalachian region is a biologically rich area (SAMAB 1996). In addition to hosting species that are abundant throughout the South, the cooler and wetter climate in the southern Appalachian region also supports species that are more common in the North, including species in refugia from the last glaciation (Gragson and Bolstad 2006). Specifically, there is a rich avian community in the southern Appalachian region such that the area contains twelve Audubon Global Important Bird Areas (National Audubon Society 2010).

We chose six focal species among forest-dwelling, insectivorous, Neotropical migrant birds: Black-and-white Warbler (*Mniotilta varia*, BAWW), Blue-headed Vireo (*Vireo solitaries*, BHVI), Black-throated Blue Warbler (*Setophaga caerulescens*, BTBW), Canada Warbler (*Cardellina Canadensis*, CAWA), Veery (*Catharus fuscescens*, VEER), and Wood Thrush (*Hylocichla mustelina*, WOTH). We focused on these species because the populations of many Neotropical migrants have been declining in recent decades (Askins 1995). In addition, our study region has a relatively high percent forest cover, but amenity-driven residential development has contributed to forest fragmentation, especially at higher elevations on previously undeveloped slopes (Gragson and Bolstad 2006). Also, our study region comprises the southern terminus of some of our focal species' breeding ranges. If breeding habitat is degraded in this area due to development or climate change, birds may be forced to occupy habitat at higher elevations or more northern latitudes. Therefore, understanding the relationship between elevation, land use patterns, and avian occurrence is important to managing exurban development.

Quantifying the relationship between exurban development and avian occupancy

Our first goal was to understand the relationship between the occupancy of forest-dwelling, Neotropical migrant birds and anthropogenic and environmental factors in an area known to be experiencing exurban development by 1) generating posterior occupancy and detection probabilities for the focal species and 2) generating posterior distributions for species-specific covariates related to land use and land cover (LULC) attributes at multiple spatial scales. Our second goal was to compare LULC attributes and posterior occupancy probabilities at sites in the Nantahala National Forest, sites managed by local land trusts, and public or private sites without conservation measures. Posterior occupancy probabilities will provide information about the current distribution of the six focal species in Macon County, and posterior distributions for covariate coefficients will indicate the relationship between multi-scale LULC attributes and occupancy, which can help direct future land management decisions.

To achieve these goals, we extended the Bayesian model from Miller et al. (2011) to describe heterogeneity in occupancy probabilities while accounting for false positive and false negative detection errors (Ch. 1). Accounting for false negative errors (i.e., ordinary lack of detection of animals that are present) has a long-standing history, but these methods typically assumed that false positive detections did not occur (e.g., MacKenzie et al. 2002). However, experiments with wildlife vocalization playback indicate that observers of all experience levels make false positive errors (i.e., species misidentification) (Genet and Sargent 2003; Lotz and Allen 2007; Simons et al. 2007; Alldredge et al. 2008; McClintock et al. 2010a, 2010b), and computer simulations have demonstrated that if data contain false positive errors but analyses assume there are no false positive detections, estimates of occupancy probability and covariate effects will be biased (Royle and Link 2006, McClintock et al. 2010b). Because false positive detections are unlikely to be eliminated through study design and because analyses that fail to account for them generate substantially biased results, it is important to employ methods that account for both types of imperfect detection.

Methods

Selecting point count sites

We conducted point counts at sites in the Nantahala National Forest, on fee simple or conservation easement properties managed by local land trusts, and on unprotected public and private properties across Macon County. These observations allowed us to quantify and compare covariates and occupancy probabilities at sites under a range of conservation approaches.

Unprotected sites

We sampled randomly-selected sites throughout Macon County that represented the range of LULC classes and elevations because inference is ordinarily less reliable outside the sampled range of independent variables and because the shapes of functions can be estimated more accurately if a range of independent variable values is sampled. First, we created a layer in ArcGIS with 10,000 random points that were at least 200m apart. We identified the points that were within 200m of roads so that we could feasibly access the points; however, below we will discuss how we selected the specific point count locations to reduce the effects of roads. Next, we used the selected random points to sample Macon County's parcel layer and a 2006 land cover and land use map, and we used attributes from these layers to create strata for stratified random sampling.

The strata were based on elevation (< 800m or > 1000m), the year structures on the property were built (no structures, before 1980, or after 1999), whether the property was part of a subdivision (yes or no), percent forest within 1000m (< 50% or > 80%), percent agriculture within 1000m (< 10% or > 25%), and percent developed within 1000m (< 10% or > 25%). All combination of elevation, year of structures, and subdivision state were combined with the following LULC classes to create strata: high percent forest with low percent agriculture and developed, high percent agriculture with low percent forest and developed, high percent developed with low percent forest and agriculture, and high percent agriculture and developed with low percent forest. For sampling during the second breeding season, we also added a mid-elevation class (800-1000m).

Once points were randomly selected from each stratum, we drove to each location, assessed on-the-ground conditions, and asked permission to conduct point counts if the point was on private property. Since the majority of our sites were on private property and we needed verbal consent before we could collect data, we sometimes had to visit properties multiple times in order to meet landowners, describe the project, and ask permission. Because of the time involved with this process and because we needed to start sampling early in the breeding season in order to collect enough data, we occasionally chose sites opportunistically. If we could not contact a landowner or if a landowner declined to participate, we might ask at nearby properties if we saw signs of landowner presence, find a nearby public site, or select another random site in the stratum where we would ask permission. Sometimes points were strategically selected so that we could maximize the number of points visited per day. If a remote point was selected through the stratified random sampling protocol, we occasionally replaced it with another point from the random points GIS layer in a more accessible location. Once we had the majority of the sites established, we plotted the percent forest, percent agriculture, and percent developed within 1000m of our sites in each of the elevation classes and compared these plots to similar plots from the 10,000 random points. We targeted the final sites for our study by identifying gaps in our sample sites.

We selected the specific site at which to conduct the point count so that we were far as possible from roads while being within hearing distance of the greatest number of habitat types as possible. We positioned the point count site to detect birds in many habitat types because we were interested in the effects of exurban development on many types of birds. We collected data for all passerines and Picidae species although we only present results for forest-dwelling, Neotropical migrants here. If the property was large enough to fit two sites 200m apart, we situated one site in the forest and one site in an area near a house, lawn, or agricultural area.

National Forest sites

We sampled National Forest sites because nearly 50% of the land in Macon County is part of the Nantahala National Forest (Norwood 2009). Also, these sites represented the end of the range of some covariate values and served as reference points to the developed sites. We selected sites in the Coweeta Basin, a 2,327ha portion of the Nantahala National Forest that is home to the USFS Coweeta Hydrologic Laboratory and Coweeta LTER, that could be sampled in one morning. The sites were split between the high and low elevation classes. We identified the sites through the random points GIS layer, located them on the ground, and assessed accessibility. We selected the actual location at which to conduct the point counts by walking at least 200m into the forest in the direction of the random points in the GIS layer. We also sampled sites adjacent to the Bartram Trail at two locations near Franklin and two locations near Highlands. The general locations were selected for accessibility, and the specific sites at which point counts were conducted were selected by walking at least 200m along the trail from the parking area and then ensuring the point was surrounded by forest.

Land trust sites

We sampled properties managed by local land trusts because while Macon County has a history of conflict and stalemate with regards to county-level land use planning, conservation easements have been used by landowners and land trusts to conserve land and manage development (Best 2002, Cho et al. 2005a). The properties we sampled were fee simple properties or had conservation easements. A conservation easement is a legal agreement in which a property owner restricts some of their ownership rights, for example, the right to subdivide or mine the land. The landowner retains ownership and can sell or bequeath the property, but the terms of the conservation easement continue with the property title for all future owners. Qualifying landowners may receive federal income and capital gains tax deductions, state income tax credits, lower property taxes, and/or lower estate taxes. With a fee simple property, the land trust gains ownership of the land through purchase or donation and manages all the ownership rights of the property.

We sampled all of the fee simple properties owned by local land trusts by situating the point count location at the center of each site. The land trusts also facilitated our contact with the owners of properties with conservation easements. At the properties with conservation easements where we obtained permission, we located the point count sites at the center of the properties. If a property was large enough to fit two sites 200m apart and had multiple LULC classes, we situated one site in the forest and one site in an area near a house, lawn, or agricultural area.

Point count protocol

We conducted point counts between twilight (approximately 30 minutes before sunrise, when artificial illumination is not needed to see) and 10:00am during the breeding season from early May to early July in 2010 and 2011 (Ralph et al. 2005). Each point count lasted eight minutes, and two independent observers collected data during each point count. Each observer recorded the species they heard or saw and indicated whether the species was within 25m and/or between 25m and 100m. Sites were visited three times: during the early, middle, and late stages of the breeding season. The particular sites sampled on a given day and the order in which they were visited was determined strategically to reach the maximum number of sites during a morning and to vary the time of day at which site were visited. One observer collected data in both breeding seasons, and there were two observers who each collected data in one breeding season (University of Georgia IACUC approval, A2013 02-006-Y2-A0).

Occupancy model

We used a Bayesian occupancy model that included occupancy state, true positive detection, and false positive detection components (see Appendix E for example code). Our model distinguished the true positive and false positive processes through a subset of data with confirmed presences. Even with few confirmed presences (e.g., 3% of detections) the model has been shown to generate accurate and precise posterior distributions (Miller et al. 2011, Ch. 1). We considered detections to be confirmed when, during a point count, both independent observers detected a species within 25m.

We incorporated site-specific covariates in the occupancy state component, survey-specific covariates in the true positive detection component, and a year effect in the false positive detection component. As in standard single-season occupancy models, our model assumed that the occupancy state did not change within a season. Each of the $i = 1, 2, \ldots, Q$ sites was occupied ($z_i = 1$) or not ($z_i = 0$). Whether a site was occupied can be considered the realization of a Bernoulli trial with probability of occupancy, ψ_i ($z_i \sim \text{Bern}(\psi_i)$). At an occupied site, a true positive detection could occur on sampling occasion $t = 1, 2, \ldots, T$ with probability $p11_{it}$, or a false negative detection could occur with probability ($1 - p11_{it}$). At an unoccupied site, a false positive detection could occur with probability $p10_s$, or a true negative detection could occur with probability ($1 - p10_s$) for breeding season $s = 1, 2, \ldots, U$. Covariates were included though a logit-linear function, for example $\text{logit}(\psi_i) = \alpha_0 + \alpha_1 * x_i$ or $\text{logit}(p11_{\text{it}}) = \alpha_0 + \alpha_1 * x_{it}$.

We modeled a constant observation confirmation probability across sites and sampling occasions. The probability of having a confirmed presence ($\text{Prob}(c_{it} = 1 \mid z_i = 1)$) was b, but the probability of having a confirmed absence ($\text{Prob}(c_{it} = 1 \mid z_i = 0)$) was 0. Therefore, whether a detection was confirmed was modeled as the realization of a Bernoulli trial with confirmation probability, $z_i * b$. So if a detection was confirmed, the site was known to be occupied ($\text{Prob}(y_{it} = 1 \mid c_{it} = 1, z_i = 1) = 1$) and could not be unoccupied ($\text{Prob}(y_{it} = 1 \mid c_{it} = 1, z_i = 1) =$ undefined). If a detection was unconfirmed, it could be a true positive at an occupied site ($\text{Prob}(y_{it} = 1 \mid c_{it} = 0, z_i = 1) = p11_{it}$) or a false positive at an unoccupied site ($\text{Prob}(y_{it} = 1 \mid c_{it} = 0, z_i = 0) = p10_s$).

In summary, the data were:

1) whether the species was detected (y_{it} = 1) or not (y_{it} = 0),

2) whether observations were confirmed (c_{it} = 1) or not (c_{it} = 0), and

3) values of covariates in the model.

The unknown values were:

1) whether the site was occupied (z_i = 1) or not (z_i = 0),

2) the occupancy probability (ψ_i),

3) true positive detection probability ($p11_{it}$),

4) false positive detection probability ($p10_s$),

5) observation confirmation probability (b), and

6) intercepts and coefficients in logit-linear functions incorporating covariates.

Complex models with latent variables, such as our occupancy model, have specifically been highlighted as well suited to a hierarchical Bayesian modeling approach in which explicit state and detection model components are developed (McCarthy 2007, Royle and Dorazio 2008, Link and Barker 2010, Kéry and Schaub 2012). As part of the Bayesian formulation, we had to select prior distributions for model parameters. Based on simulations in Chapter 1, we found that uniform priors were most suitable for models with confirmed presences, linear covariate effects, and no observation confirmation errors. Because we had no reason to expect observation confirmation errors *a priori* and did not have directly applicable studies upon which to base informative priors, we used U(0,1) priors for *b*, year-specific true positive detection probabilities, and parameters that were logit transformed before being incorporated as intercepts in the functions relating covariates to occupancy and true positive detection probabilities. We used U(0,0.5) priors for the year-specific false positive detection probabilities, which suggests that if a site is unoccupied, an observer is more likely to make a true negative detection than a false positive detection. This constraint is consistent with the probability of false positive detections seen in controlled experiments (Farmer et al. 2012, Miller et al. 2012) and could aid model convergence without introducing unrealistic assumptions. We used a N(0,0.368) prior for all covariate coefficients since this is a vague Jeffrey's prior for a parameter on the logit scale (Lunn et al. 2012). For example, in the function, *lpsi*[i] = *lpsi0* + *a1***x1*[i], *a1* had a N(0,0.368) prior, *lpsi0* = log(*psi0*/(1-*psi0*)), and *psi0* had a U(0,1) prior (Royle and Dorazio 2008).

We ran models in OpenBUGS version 3.2.2 (Lunn et al. 2009) using the R2OpenBUGS package and R version 2.15.3 (R Core Team 2013, see Sturtz et al. 2005). We ran three Markov Chain Monte Carlo (MCMC) chains with at least 100,000 iterations, a burn in of at least 50,000, and thinning of 5. Initial values were selected from a N(0,1) distribution for covariate coefficients, from a U(0,1) distribution for $p11_s$ and intercepts before logit transformation, and from a U(0,0.25) distribution for b and $p10_s$. Convergence was assessed with the Gelman-Rubin potential scale reduction factor (R-hat), and chains were considered converged if R-hat ≤ 1.04 for ψ_i, b, $p11_s$, $p10_s$, and parameters in logit-linear functions (Brooks and Gelman 1998, Gelman and Shirley 2011). If a model had not converged after 100,000 iterations, we re-ran with 200,000 iterations and a burn in of 150,000. If a model took an inordinate amount of time to run (e.g., > 48h) or if R-hat > 1.04 after re-running with more iterations, we judged that convergence had failed. After convergence, we obtained the mean of parameters' posterior distributions and 95% Bayesian credible intervals (BCI).

Candidate models

Candidate models included site (10x10m plot within 100m of point count location), local (12.5 ha area within 200m of point count locations), and/or landscape (314 ha area within 1000m of point count locations) scale covariates. We measured spatial patterns at these three scales because patterns at a small scale can highlight mechanisms and those at a large scale give context (Wiens 1989, Allen and Hoekstra 1992, Saab 1999). Avian studies have typically assessed landscapes within a 314 ha area (Pearson 1993, Soderstrom and Part 2000, Graham and Blake 2001), and previous studies found that landscape patterns in a 5-50 ha area around point count sites had the strongest effect on passerine distributions while scales under 0.79 ha were not informative (Morelli et al. 2013, Schindler et al. 2013). Also, studies have shown that some long-distance migrants are most active within a 4 ha area (Zach and Falls 1979, Anders et al. 1998, Morton et al. 1998, Evans et al. 2008) and are typically recaptured within a 12.5 ha area (Villard 1991).

For each of the six focal species, we ran four sets of candidate models. The first set of models had constant occupancy probabilities and four candidate models describing the true positive detection probabilities (Table 3.1). The second set of models had the top model(s) describing the true positive detection probabilities from model set one and 13 candidate models with site-scale covariates affecting the occupancy probabilities (Table 3.2). The third set of models had the top models(s) describing the true positive detection probabilities from model set one and 31 candidate models with local- and/or landscape-scale covariates affecting the occupancy probabilities (Table 3.3). The fourth set of models had the top models from model sets two and three plus models with interactions among the site-scale covariates and the local- and/or landscape-scale covariates. Because the site-scale covariates were indicator variables, we modeled two kinds of interactions: different intercepts or different intercepts and slopes at the two values of the indicator variable.

Modeling false positive detection probabilities

All candidate models had year-specific false positive detection probabilities because the observer composition varied between the two breeding season. Also, the observer who collected data in both seasons may have learned during the first season and thus had a different detection probability in the second season. Since we expected that the false positive detection probability would be less variable across sites and surveys than the true positive detection probability, we built models that accommodated more heterogeneity in true positive detection probabilities. This kept the number of parameters manageable and aided parameter identifiability and inference.

Candidate models of true positive detection probabilities

In all candidate models, the year affected the true positive detection probabilities (Table 3.1). Julian date, sky condition, and time of day were additional variables that occurred in some candidate models. The sky variable indicated sunny/cloudy or foggy/rainy conditions, and the time of day was measured as the number of minutes after 5:59am. Continuous covariates were standardized to have a mean of zero and variance of one, as this is a common approach to aid convergence (e.g., Royle et al. 2005). The same observer recorded the year, date, time, and sky condition for point counts during both breeding seasons.

Candidate models of occupancy probabilities

Models with site-scale covariates

For the second set of candidate models, we designed 13 models with site-scale (within 100m of point count sites) indicator variables affecting occupancy probabilities (Table 3.2). The indicator variables described whether or not a site had more than 50% deciduous canopy cover, more than 50% evergreen canopy cover, high structural complexity, high invasive species cover, presence of coarse woody debris, presence of insect infestation, or presence of at least one snag. High structural complexity was defined as high broadleaf deciduous complexity, high broadleaf evergreen complexity, or both high broadleaf deciduous complexity and high broadleaf evergreen complexity. A site had high broadleaf deciduous complexity if there was at least 5% cover in each of the understory, shrub, and ground layers, and a site had high broadleaf evergreen complexity if there was at least 1% cover in each of the understory, shrub, and ground layers. A site was considered to have high invasive species cover if there was at least 5% cover of one invasive species.

We expected that occupancy probabilities would be most affected by deciduous canopy cover, evergreen canopy cover, and structural complexity since these are the variables that contribute most to the general structure of the forest. We expected higher occupancy probabilities with high canopy cover or high complexity since the forest would likely provide more shelter, nesting, and feeding resources. We expected occupancy probability to be slightly higher if coarse woody debris, snags, or insect infestation were present (Lohr et al. 2002, Twedt and Somershoe 2009, Amo et al. 2013). However, we expected occupancy probability to be slightly lower if there was high invasive species cover (Mills et al. 1989).

An observer who specialized in southern Appalachian vegetation and did not participate in the point counts collected data for the site-scale covariates. He visited the sites at the end of the breeding season after we had finished conducting point counts. However, limited resources prevented the collection of site-scale covariates at all of the point count sites. Therefore, we strategically selected the sites for site-scale covariate sampling that represented the range of LULC classes and elevations at the point count sites and were easily accessible to the observer since he was not familiar with the sites from the point counts. If there was site-scale LULC heterogeneity, the observer described the vegetation structure and composition at multiple plots (10x10m), but since we focus on forest-dwelling birds in this study, we used the covariates from the most forested plot at a site.

Since some sites had missing values for site-scale covariates, we imputed these values via their respective prior distributions and the specified model structure. For example, we imputed the missing deciduous canopy cover values by modeling whether there was more than 50% deciduous canopy cover as the realization of a Bernoulli trial with probability D and a U(0,1) prior for D. Then we could obtain the posterior distribution of D and each of the missing deciduous canopy cover variable values.

Models with local- and/or landscape-scale covariates

For the third set of candidate models, we designed 31 models with continuous variables at local- and/or landscape-scales affecting occupancy probabilities (Table 3.3). The landscape-scale (within 1000m of point count sites) variables were derived from a 2006 land cover and land use map that was developed for Coweeta LTER and used the same classification scheme as National Land Cover Dataset (NLCD) maps. We used the 8 cell neighbor rule in FRAGSTATS version 4 (McGarigal et al. 2012) to compute percent forest, percent developed, mean forest patch area, mean shape index for forest patches, and forest clumpiness index. Developed was defined as open space, including single family residential homes, lawns, and golf courses (21); low intensity (22); medium intensity, including developments and neighborhoods (23); or high intensity, including roads (24). The shape index measures the complexity of a patch's shape, which is related to the amount of edge (McGarigal et al. 2012). If a patch is a square, its shape index is 1, and as a patch becomes more irregular, the shape index increases. The clumpiness index measures the aggregation of a patch type in a landscape and thus assesses fragmentation (McGarigal et al. 2012). The index ranges from -1 (maximum patch disaggregation) to 1 (maximum patch aggregation), with 0 corresponding to random patch distribution.

We measured the following local-scale (within 200m of point count sites) variables: mean elevation, percent forest, percent developed, percent house with forest, and percent house with lawn. We computed the local-scale percent cover covariates by digitizing a 200m buffer around each point count site using aerial photographs of Macon County and NLCD 2001 classes, and we calculated the mean elevation within 200m of point count sites in FRAGSTATS.

We expected that occupancy probabilities would be most affected by percent forest, and next, by percent developed because previous studies have indicated that landscape composition is a primary driver of avian distribution (Andrén 1994, Fahrig 1997, McGarigal and McComb 1995). We expected that these factors would influence occupancy probabilities at the local- (200m radius) and landscape-scale (1000m radius), with percent forest having a larger effect at the local scale and percent developed having a larger effect at the landscape scale, since variability was greater at those scales. Third, we expected forest patch attributes to affect occupancy probabilities because the forest area, amount of interior forest, and amount of edge can be related to the level of disturbance, level of predation, and habitat structure, and some studies have found that landscape configuration can influence avian distributions (Fahrig 1998, Villard et al. 1999). Specifically, we expected that occupancy probabilities would be higher at higher values of percent forest, mean forest patch area, forest clumpiness index, and elevation and that occupancy probabilities would be lower at higher values of percent development, percent house with lawn, and mean shape index for forest patches.

We excluded covariates with Pearson's $r > 0.3$ from consideration in candidate models (Table F.1). We built models focused on percent forest (Models 1, 2, 13, and 14) or percent developed (Models 5, 9, 15, and 16) because we expected these covariates to most affect occupancy probabilities. Percent forest was correlated with many measures of forest patches (exceptions are Models 3 and 4), so we included percent developed with forest patch covariates in models (Models 6-8, 10-12, and 17-24). Finally, we designed models with interactions of covariates at the same scale (Models 25-31). Percent forest, percent developed, or percent house with forest was included in each of the models with interactions because we thought these covariates would have large effects on occupancy probabilities.

Model selection

We conducted model selection using the Bayesian Information Criterion (BIC) as an approximation to Bayes factors (Schwarz 1978, Kass and Raftery 1995, Link and Barker 2006, Link and Barker 2010, St-Louis et al. 2012). We used uniform prior model weights because they favor parsimony and thus may contribute to higher predictive ability (Link and Barker 2006, Thomson et al. 2007, St-Louis et al. 2012). Also, posterior model weights appear robust to the choice of priors for parameters when uniform prior model weights are used with logistic regression (Link and Barker 2006). The uniform priors were calculated as: $\pi_i = \frac{1}{R}$ where *R* is the number of candidate models. BIC and posterior model weights were calculated as in St-Louis et al. (2012).

For each species, models from the first candidate set were included in the second and third sets of candidate models if they had a posterior model weight of at least 0.05. Models from the second and third candidate set were included in the fourth set of candidate models if they had a posterior model weight of at least 0.01. The top model(s) from the fourth candidate set were defined as the fewest models that together had at least 0.5 of the posterior model weight. For each focal species, we plotted the means of occupancy probability posterior distributions and 95% BCIs from top model(s) as a function of the covariate(s) in the top model(s) to determine the effects of the covariate(s).

Model averaging

Model averaging helps account for uncertainties in the model selection process by using posterior probabilities from multiple models to make inferences, and multi-model inference tends to have better predictive ability than single top model approaches (Raftery et al. 1997, Burnham and Anderson 2002, Johnson and Omland 2004, Link and Barker 2006, Thomson et al. 2007).

A primary objective of this project was to quantify the relationship between occupancy and attributes related to exurban development; however, posterior distributions may have a 95% BCI that includes zero, indicating that whether the covariate influenced occupancy positively or negatively could not be determined. When the goal is to determine the effect of a covariate on occupancy, the calculation of the model-averaged posterior mean for a parameter may be misleading if a mean from a posterior distribution in which the 95% BCI spans zero is included, although including a wide BCI when calculating the model-averaged posterior variance for a parameter is important to capture the posterior distribution's precision, or lack thereof. In tabular form, we present model-averaged posterior means and variances for intercept and coefficient parameters that were calculated with posterior distributions that had 95% BCIs that spanned zero. Model-averaged means of intercept and coefficient parameters that only used posterior distributions with 95% BCIs that did not span zero were used in a function to predict occupancy probabilities. The occupancy probability predictions were plotted against covariate values to represent the model-averaged effects of covariates on occupancy probabilities.

Assessing models' predictive ability

Model selection and multi-model inference are valuable tools for discriminating among candidate models, but it is also important to investigate the ability of models to generate accurate predictions, particularly if the predictions will be used by decision makers (Zipkin et al. 2012). The area under the receiver operating characteristic (ROC) curve (AUC) measures a model's ability to correctly determine which sites are occupied (Hosmer and Lemeshow 2000). To create the ROC curve, the ratio of true positives (i.e., the species occupied the site and the model predicted it) to false positives (i.e., the species did not occupy the site but the model predicted the site was occupied) is plotted using various cutoff values (i.e., thresholds in occupancy probabilities that separate occupied and unoccupied sites). The AUC can range from 0 to 1, where 0.5 suggests the model performs no better than random and larger values indicate more discriminatory ability.

We generated ROC curves and calculated AUC values for each species' top model(s) using the R package ROCR (Sing et al. 2005). We obtained means of the posterior distributions for ψ_i, which represented predicted states, and z_i, which represented true states, from a top model. Currently, ROCR can only accommodate one variable with an undefined cutoff value, so we reclassified the z_i to 1 if $z_i \geq 0.5$ and 0 otherwise.

Given that AUCs were calculated using means from the posterior distributions for the true states along with the predicted states, we also examined means of the posterior distributions for ψ_i at sites known to be occupied from confirmed detections. We calculated the proportion of these sites with posterior occupancy probabilities < 0.5.

Results

Occupancy probabilities

We conducted point counts and collected local- and landscape-scale covariate data at 272 sites (Fig. 3.1) and site-scale covariate data at 138 sites during two breeding seasons. We computed posterior occupancy probabilities at each site for each of the six focal species. Occupancy ranged from extremely low to very high for the BAWW (0.01-0.90; Fig. 3.2), BHVI (0.01-1.00; Fig. 3.3), CAWA (0.00-0.92; Fig. 3.4), and VEER (0.00-0.95; Fig. 3.5). However, posterior occupancy probabilities were low to moderate for the BTBW (0.00-0.57; Fig. 3.6) and WOTH (0.07-0.44; Fig. 3.7). These results were based on 157 detections and 23 confirmed presences for the BAWW, 407 detections and 50 confirmed presences for the BHVI, 134 detections and 20 confirmed presences for the BTBW, 41 detections and 11 confirmed presences for the CAWA, 125 detections and 16 confirmed presences for the VEER, and 185 detections and 11 confirmed presences for the WOTH out of 816 possible occasions for detection.

Relationship between covariates and posterior occupancy probabilities

Top models

The covariate that appeared most frequently in top models was percent forest within 200m (BAWW, BTBW, WOTH) followed by percent forest within 1000m (CAWA, VEER), percent developed within 200m (BHVI, VEER), and elevation (CAWA, VEER). Percent developed within 1000m (CAWA) and the forest clumpiness index (BHVI) each appeared in one top model. However, zero was included in the 95% BCI for the coefficients of percent developed within 1000m for CAWA and percent forest within 1000m and percent developed within 200m for VEER.

The relationships between covariates and posterior occupancy probabilities were determined from the means of parameters' posterior distributions and 95% BCIs for each focal species (Figs. 3.2-13). As percent forest within 1000m or 200m and elevation increased, posterior occupancy probabilities tended to increase (Figs. 3.2, 3.6, 3.7, 3.10, 3.11a, and 3.13). As percent developed within 1000m or 200m and forest clumpiness index increased, occupancy probabilities tended to decrease (Figs. 3.3, 3.4b, 3.5a, 3.8, 3.9, 3.11b, and 3.12).

Model averaging

In addition to examining posterior distributions from top models, the relationship between covariates and occupancy can also be inferred through model-averaging. Posterior occupancy probabilities increased for all six species as elevation increased (Fig. 3.14), decreased in four species as percent developed within 1000m increased (Fig. 3.15), and decreased in three species as percent developed within 200m increased (Fig. 3.16). However, the VEER showed a pattern of increasing posterior occupancy probabilities with increased percent developed within

1000m (Fig. 3.15). Also, as percent house with lawn increased, posterior occupancy probabilities decreased for the BAWW (Fig. 3.17). The BAWW, BTBW, CAWA, and WOTH showed similar increases in posterior occupancy probabilities with increased percent forest within 1000m (Fig. 3.18) and within 200m (Fig. 3.19). Likewise, as percent house with forest increased, posterior occupancy probabilities increased for the VEER (Fig. 3.20). As forests became more aggregated on the landscape, posterior occupancy probabilities decreased for the BAWW, BHVI, and VEER (Fig. 3.21). Posterior occupancy probabilities also decreased for the BAWW, BHVI, and WOTH as the mean shape of forest patches became more regular (i.e., less complex, more square-shaped; Fig. 3.22). Additionally, landscapes with larger mean forest patch areas had larger WOTH posterior occupancy probabilities (Fig. 3.23). Although the results discussed above have focused on parameters with 95% BCIs that did not include zero, some of the results presented in Tables 3.4-9 include parameters with 95% BCIs that spanned zero.

Covariate patterns at National Forest, land trust, and unprotected sites

National Forest, land trust, and unprotected sites exhibited different patterns in covariate values. These sites tended to cluster in two elevation classes, with National Forest sites at higher elevations (775m and 1350m) than the land trust or unprotected sites (650m and 1150m; Figs. 3.10a, 3.11a, and 3.13a). National Forest sites had high percent forest; all had at least 60% and most had over 90% forest within 200m. The land trust sites did not have low percent forest; all were at least 20%. There was a large range in percent forest at the unprotected sites (0-100%), but more sites had low percent forest than high percent forest (Figs. 3.2, 3.6, 3.7, 3.10b, and 3.13b). The patterns seen for percent forest at National Forest, land trust, and unprotected sites were generally reversed for percent developed (Figs. 3.8, 3.11b, and 3.12). Avian occupancy at

National Forest, land trust, and unprotected sites responded similarly to covariates. For comparable covariate values, there was no evident pattern in posterior occupancy probabilities distinguishing National Forest, land trust, and unprotected sites.

Detection probabilities

Model-averaged false positive detection probabilities ranged from 0.01 for the BAWW in year one (Table 3.4), CAWA in both years (Table 3.7), and VEER in year one (Table 3.8) to 0.25 for the BHVI in year one (Table 3.5). For all species and years, model-averaged false positive detection probabilities were less than model-averaged true positive detection probabilities (Tables 3.4-9). For all six species, the top models had year-specific true positive detection probabilities (Tables 3.10-15). Model-averaged true positive detection probabilities ranged from 0.30 for the BAWW in year one (Table 3.4) to 0.82 for the BTBW in year two (Table 3.6). For all species, model-averaged true positive detection probabilities were greater in year two than in year one (Tables 3.4-9).

The true positive detection probability function with quadratic effects of Julian date was in models for the BHVI and VEER that had posterior weight of at least 0.01 (Tables 3.11 and 3.14). The WOTH had models with posterior weight of at least 0.01 that included quadratic effects of Julian date and linear effects of time of day and sky condition on the true positive detection probability (Table 3.15). However, zero was often included in the 95% BCI for parameters in these true positive detection probability functions (Table 3.5, 3.8, and 3.9).

Predictive ability of models

Predictive ability of a top model, as measured by the AUC, was greatest for the BAWW (0.93) and least for the WOTH (0.66; Table 3.16). Considering the proportion of sites known to be occupied from confirmed detections at which posterior occupancy probabilities were < 0.5, the predictive ability of a top model was greatest for the BHVI (0.21) and least for the WOTH (1.00; Table 3.16). The proportion was also < 0.5 for the BAWW and VEER but > 0.5 for the BTBW and CAWA (Table 3.16). When a species had two top models, the model with the larger posterior model weight also had greater predictive ability.

Discussion

Occupancy probabilities

Posterior occupancy probabilities were highly variable across sites for all six species. Unsurprisingly, some sites had extremely low posterior occupancy probabilities, for example, sites with low percent forest and high percent developed. However, it is noteworthy that for the BTBW and WOTH, the most suitable sites only had 0.57 and 0.44 posterior occupancy probabilities, respectively. This pattern could be related to the fact that of the six focal species, populations of the BTBW, CAWA, and WOTH are thought to be declining in the southern Appalachian region, while studies have suggested that the other focal species have stable or increasing populations (Sauer et al. 2003, Sauer et al. 2008). Although the CAWA had high occupancy probabilities at some sites, those sites were exclusively in the National Forest at high elevation.

In addition, the BTBW, CAWA, and WOTH were the only species for which over half of the sites known to be occupied from confirmed detections had occupancy probabilities from the top model(s) that were < 0.5. This suggests that the models for the BTBW, CAWA, and WOTH may not have strong predictive ability. The BTBW, CAWA, and WOTH's pattern of occupancy may not be well described by the candidate models used in this study, or low occupancy may have contributed to a small number of true presence detections, which affected inference about occupancy. However, the AUC for each species' top model(s) was high. The median AUC from all species' top model(s) was 0.9 out of 1.0, and all models had AUC > 0.5, indicating predictive ability better than random assignment of occupancy states. The BAWW and VEER had top models with the most discriminatory ability.

Relationship of covariates and posterior occupancy probabilities

Posterior occupancy probabilities for the focal species generally increased as percent forest increased or as percent developed decreased, as expected. However, some species' posterior occupancy probabilities were related to covariates in ways we did not anticipate. CAWA occupancy was most affected by elevation had less response to percent forest or percent developed. Only the BAWW showed decreasing occupancy with increasing percent house with lawn. Perhaps a response to this covariate was not seen with other species because the BAWW was more closely associated with areas characterized by houses with lawns. The BAWW is known to have a broad habitat tolerance, inhabit heterogeneous landscapes with second-growth and open woodlands, and be associated with edges (Lichstein et al. 2002).

It is likely that BHVI and VEER occupancy was more closely associated with patterns in percent developed than percent forest because the measures of percent forest did not fully describe these species' habitats. BHVI occupancy responded to percent developed within 200m but not to percent forest. This could be because the BHVI was the only focal species closely associated with coniferous forest (Morton and James 2014). As coniferous forests were less abundant in Macon County compared to deciduous or mixed forest, perhaps the measure of percent forest did not adequately describe the BHVI's habitat. Also, occupancy of VEER was not related to percent forest but increased with increasing percent house with forest and increasing percent developed within 1000m. These patterns might reflect the VEER's preference for early successional or disturbed forest (Bevier et al. 2005).

Occupancy for the BAWW, BHVI, and VEER decreased when forest patches were more aggregated, according to the clumpiness index. This could fit with our knowledge of the BHVI's life history as they are thought to inhabit openings and edges (Morton and James 2014). How model results reflect the biological role of forest aggregation for the BAWW and VEER is less obvious. First, we can consider that the clumpiness index was in the top model for the BHVI but was not in the top model for the BAWW or VEER. Also, the clumpiness index was negatively correlated with percent forest and the mean forest patch area (Table F.1, Fig. F.1). Thus, as percent forest and mean forest patch area increased, the clumpiness index decreased. This suggests that there were lower measures of aggregation at sites with high percent forest and mean forest patch area because small patches of other LULC classes occurred among large forest patches. The role of the clumpiness index may be conceptualized in a more biologically meaningful way if the negative relationship with percent forest and mean forest patch area is considered.

Similarly, the forest shape index was positively correlated with percent forest and mean forest patch area (Table F.1, Fig. F.1). This indicates that as percent forest and mean forest patch area increased, forest patches became more irregular in shape. Results suggest that BAWW, BHVI, and WOTH occupancy increased with increasing irregularity of forest patches. The

BHVI is known to occupy openings and edges, and the WOTH may occur at forest edges as well (Evans et al. 2011, Morton and James 2014). However, these results also could be related to the correlation of the shape index with percent forest and mean forest patch area.

In addition, WOTH occupancy increased with increasing mean forest patch area. This result is not surprising as the WOTH is considered an area-sensitive species, as are many of the other focal species (Evans et al. 2011). Again, when interpreting this result we recall that mean forest patch area was positively correlated with percent forest and the top model for the WOTH had the lowest predictive ability out of the top models for all focal species (Table F.1, Fig. F.1).

After examining species-specific responses to LULC attributes, we also considered the effects of scale on occupancy. The focal species showed a similar response to percent forest within 200m and within 1000m. However, more species were affected by percent developed within 1000m than within 200m. This was likely because there was greater variability within 1000m, and many sites had 0% developed land within 200m. On the other hand, percent forest and percent developed within 200m were in top models more often than these metrics within 1000m.

Notably, none of the models with posterior weights of at least 0.01 included site-scale covariates. While these results could suggest that local- and landscape-scale attributes have a greater effect on avian occupancy, they do not mean that site-scale factors are inconsequential. Landowners' efforts to maintain a high percent forest and low percent development on their properties could contribute to higher probabilities of avian occupancy. Also, collecting site-scale covariate data at only 51% of sites and using a modeling-based approach to impute missing values could have affected inference about the relationship of occupancy to these covariates.

The results also highlight the importance of regional land use to the occupancy of forest-dwelling, Neotropical migrant birds. To date, there has been little land use planning or regulation in Macon County. While many Macon County landowners think the rapid growth occurring in the county is detrimental, there has not been agreement about an appropriate response (Cho et al. 2005b, Gragson and Bolstad 2006, Cho et al. 2009, Cumming and Norwood 2012). There have been various attempts to pass land use regulations in Macon County throughout the past 30 years, but they have largely failed (Cumming and Norwood 2012). Our results suggest the importance of large-scale LULC patterns, which can only be managed through large-scale decision-making. If the occurrence of forest-dwelling, Neotropical migrant birds is a goal of stakeholders in Macon County, they might best pursue this goal by resuming efforts to address county-level land use planning but through a more productive decision-making process than used in the past, such as structured decision making (Conroy and Peterson 2013, Ch. 3). Also, land trusts can focus on the landscape scale when making conservation decisions.

Comparison of National Forest, land trust, and unprotected sites

National Forests may provide important refugia for forest-dwelling, Neotropical migrant birds as surrounding areas experience exurban development or as a changing climate leads to a shift in the distributions of plants and animals to higher elevations than currently seen. However, conservation easements or fee simple properties owned by land trusts may not provide substantially different habitats that those found on unprotected properties. This is evidenced by the fact that sites in the National Forest tended to have high values for covariates that were positively related to avian occupancy (elevation and percent forest within 1000m and within 200m) and low values for covariates that were negatively related to avian occupancy (percent developed within 1000m and within 200m). Meanwhile, sites on land trust properties had covariate values that were distributed in a pattern similar to covariate values from unprotected properties. However, the land trust sites did not have low values for covariates that were positively related to avian occupancy (percent forest within 1000m or within 200m) or high values for covariates that were negatively related to avian occupancy (percent developed within 1000m or within 200m).

To increase their conservation impact for forest-dwelling, Neotropical migrant birds, land trusts may want to target conservation on properties that adjoin National Forest land, are at high elevation, have a high percent forest on the property and in the vicinity, and/or have a low percent development on the property and in the vicinity. Also, U.S. Forest Service decision-makers should consider the importance of high elevation National Forest areas to sensitive species that may loose habitat through development or climate change.

Approach to modeling and multi-model inference

The analyses presented in this paper were conducted with a new occupancy model parameterization that accounts for false positive and false negative detections while quantifying the relationship between occupancy probabilities and covariates. How to best address false positive detections is a recent area of research, and we hope to further this work by our demonstration of a successful application of our model, presentation of precise posterior distributions, and explanation of the biologically-meaningful interpretation of parameters' posterior probabilities. Our models are an improvement over existing occupancy models because they describe heterogeneity in occupancy probabilities and false negative detection probabilities more accurately by accounting for false positive detections. For example, model-averaged false positive detection probabilities for the BHVI were 0.25 in the first breeding season and 0.14 in the second breeding season. These were the largest false positive detection probabilities among the focal species, possibly because the BHVI's song closely resembles the Red-eyed Vireo's song. If we had conducted our analysis with a model assuming that false positive detections did not occur, occupancy and covariate coefficient posterior distributions would likely have been biased, thus impairing inference about the relationship between exurban development and avian occupancy.

While our models do not explicitly model spatial autocorrelation, we attempted to reduce the amount of autocorrelation in our data by spacing point counts at least 200m apart since we recorded detections within 100m. This procedure for achieving point count independence is consistent with previous studies (e.g., Mitchell et al. 2001, DeWan et al. 2009). If spatial structure remains beyond that which is modeled through covariates, occupancy probabilities and precision may be overestimated and inference about the role of predictor variables may be biased (Legendre 1993, Moore and Swihart 2005, Poley et al. 2014). While the goal of this study was to first tackle the problem of false positive errors, future work that also investigates spatial autocorrelation could be fruitful. Since Bayesian hierarchical models have also been used to explicitly model spatial autocorrelation, addressing spatial autocorrelation could be a natural extension of our models (Hoeting et al. 2002, Magoun et al. 2007, Chelgren et al. 2011, Johnson et al. 2013, Poley et al. 2014).

Summary

We used a new occupancy model accounting for false positive and false negative detections to quantify the effects of multi-scale LULC covariates on the occupancy probabilities of six forest-dwelling, insectivorous, Neotropical migrant birds. We used a BIC weights approximation to a full Bayesian model averaging analysis to conduct model selection and model averaging. Additionally, we assessed the predictive ability of each species' top model(s) by calculating the AUC and proportion of sites known to be occupied from confirmed detections that had occupancy probabilities < 0.5.

These recent methodological advances allowed us to study avian occupancy at National Forest, land trust, and unprotected sites and to understand the relationship between exurban development in southern Appalachia and avian occupancy. Occupancy tended to be greatest at sites at high elevations, with high percent forest, or with low percent development. Results indicated that landscape composition was more influential than configuration. Avian occupancy appeared to be affected by landscape- and local-scale attributes, but there was little evidence of site-scale effects. National Forest sites generally had high occupancy, but land trust sites and unprotected sites had similar occupancy. Conservation efforts may be most needed for the BTBW and WOTH.

These finding could provide National Forest management ideas, signal a conservation strategy for local land trusts, and encourage discussion about county-level decision making. Also, management may be facilitated if remote-sensing data at the landscape- and local-scale, rather than intensive site-scale data, can be used to investigate the relationship between exurban development and wildlife (Mitchell et al. 2001). Landscape models are also expected to be more generaliable than local- or site-specific models (Mitchell et al. 2001).

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Table 3.1: Candidate models with covariates affecting the true positive detection probability (*p11*). The covariates included in each model are represented with x's.

	Model			
Covariate	1	2	3	4
Year	x	x	x	x
Julian date		x	x	x
(Julian date)^2		x	x	x
Sky condition			x	x
Time of day				x

Table 3.2: Candidate models with site-scale covariates affecting the occupancy probability (ψ). The covariates included in each model are represented with x's.

	Model												
Covariate	1	2	3	4	5	6	7	8	9	10	11	12	13
Deciduous canopy >= 50%	x			x	x	x	x	x	x	x	x	x	x
Evergreen canopy >= 50%		x		x	x	x	x	x	x	x	x	x	x
High complexity			x	x					x				
Deciduous canopy >= 50% and High complexity interaction									x				
Evergreen canopy >= 50% and High complexity interaction									x				
Coarse woody debris					x					x			
Deciduous canopy >= 50% and Coarse woody debris interaction										x			
Evergreen canopy >= 50% and Coarse woody debris interaction										x			
Snag						x					x		
Deciduous canopy >= 50% and Snag interaction											x		
Deciduous canopy >= 50% and Snag interaction											x		
Insect infestation							x					x	
Deciduous canopy >= 50% and Insect infestation interaction												x	
Evergreen canopy >= 50% and Insect infestation interaction												x	
Invasive species								x					x
Deciduous canopy >= 50% and Invasive species interaction													x
Evergreen canopy >= 50% and Invasive species interaction													x

Table 3.3: Candidate models with landscape- and local-scale covariates affecting the occupancy probability (ψ). Landscape-scale covariates were measured in a circle of radius 1000m from the point count site while local-scale covariates were measured in a circle of radius 200m from the point count site. The covariates included in each model are represented with x's.

	Model															
Covariate	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Elevation (200m)	x	x			x	x	x	x							x	
Percent forest (1000m)	x	x														
Percent developed (1000m)					x	x	x	x	x	x	x	x				
Percent forest (200m)			x	x									x	x		
Percent house with forest (200m)		x		x										x		
Percent developed (200m)															x	x
Percent house with lawn (200m)									x	x	x	x				x
Mean forest patch area (1000m)																
Mean shape index forest patches (1000m)			x	x		x	x			x	x					
Forest clumpiness index (1000m)						x		x		x		x				

Covariate	Model 17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
Elevation (200m)									x			x			
Percent forest (1000m)															
Percent developed (1000m)										x	x				
Percent forest (200m)													x		
Percent house with forest (200m)												x	x		x
Percent developed (200m)	x	x	x	x	x	x	x	x	x					x	x
Percent house with lawn (200m)		x				x	x	x						x	
Mean forest patch area (1000m)	x	x													
Mean shape index forest patches (1000m)			x	x		x	x			x					
Forest clumpiness index (1000m)			x		x	x		x			x				
Elevation and Percent developed (200m) interaction									x						
Percent developed and Mean shape index forest patches (1000m) interaction										x					
Percent developed and Forest clumpiness index (1000m) interaction											x				
Elevation and Percent house with forest (200m) interaction												x			
Percent forest and Percent house with forest (200m) interaction													x		
Percent developed and Percent house with lawn (200m) interaction														x	
Percent developed and Percent house with forest (200m) interaction															x

Table 3.4: Posterior probabilities for the Black-and-white Warbler from models with covariates affecting the occupancy probability (ψ) and the true positive detection probability (*p11*) that had at least 0.01 posterior weight. For each model, the mean of parameters' posterior distributions are presented, and 95% Bayesian credible intervals are shown in parentheses. NA indicates a parameter was not included in the model. Model averaged probabilities are also presented for each parameter, as applicable, in terms of the posterior mean and, in parentheses, the posterior variance. The intercept for the occupancy probablity function not on the logit scale is represented by *psi_0*. *Elev*, *PForest1000m*, *PForest200m*, *PDevel1000m*, *PDevel200m*, *PHouseForest*, *PHouseLawn*, *ShapeForest*, and *ClumpyForest* are on the logit scale and are coefficients for covariates. The true positive detection probabilities (*p11_yr1* and *p11_yr2*) and the false positive detection probabilities (*p10_yr1* and *p10_yr2*) from the first and second breeding season are shown. The probability of an observation being confirmed is *b*.

ψ (landscape, local)	1	3	9	13	14	16	20
p11	1	1	1	1	1	1	1
psi_0	0.29 (0.16, 0.47)	0.31 (0.16, 0.50)	0.27 (0.15, 0.42)	0.33 (0.18, 0.52)	0.34 (0.19, 0.53)	0.29 (0.16, 0.47)	0.30 (0.18, 0.44)
Elev	0.72 (0.16, 1.39)	NA	NA	NA	NA	NA	NA
PForest1000m	1.88 (1.16, 2.81)	NA	NA	NA	NA	NA	NA
PForest200m	NA	2.30 (1.45, 3.43)	NA	2.26 (1.45, 3.36)	2.28 (1.45, 3.41)	NA	NA
PDevel1000m	NA	NA	-0.86 (-1.47, -0.35)	NA	NA	NA	NA
PDevel200m	NA	NA	NA	NA	NA	-1.24 (-2.21, -0.51)	-0.94 (-1.91, -0.21)
PHouseForest	NA	NA	NA	NA	-0.29 (-1.08, 0.38)	NA	NA
PHouseLawn	NA	NA	-1.35 (-2.25, -0.59)	NA	NA	-1.48 (-2.43, -0.72)	NA
ShapeForest	NA	0.54 (-0.10, 1.27)	NA	NA	NA	NA	0.71 (0.19, 1.38)
ClumpyForest	NA	NA	NA	NA	NA	NA	NA
p11_yr1	0.32 (0.21, 0.45)	0.29 (0.19, 0.42)	0.36 (0.22, 0.53)	0.28 (0.18, 0.42)	0.28 (0.18, 0.41)	0.33 (0.19, 0.51)	0.37 (0.23, 0.51)
p11_yr2	0.4	0.40	0.41	0.40	0.40	0.40	0.39

	(0.31, 0.50)	(0.31, 0.49)	(0.32, 0.52)	(0.32, 0.49)	(0.32, 0.49)	(0.31, 0.51)	(0.28, 0.51)
p10_yr1	0.01 (0.00, 0.03)	0.01 (0.00, 0.03)	0.03 (0.01, 0.06)	0.01 (0.00, 0.03)	0.01 (0.00, 0.03)	0.02 (0.00, 0.06)	0.01 (0.00, 0.04)
p10_yr2	0.10 (0.05, 0.15)	0.09 (0.04, 0.13)	0.10 (0.05, 0.15)	0.08 (0.04, 0.13)	0.08 (0.04, 0.13)	0.09 (0.04, 0.14)	0.12 (0.07, 0.18)
b	0.08 (0.05, 0.12)	0.07 (0.04, 0.11)	0.09 (0.05, 0.14)	0.07 (0.04, 0.11)	0.07 (0.04, 0.11)	0.08 (0.05, 0.13)	0.09 (0.05, 0.14)

ψ (landscape, local)	21	
p11	1	AVG
psi_0	0.32 (0.19, 0.47)	0.32 (7.6E-3)
Elev	NA	NA
PForest1000m	NA	NA
PForest200m	NA	2.26 (2.4E-1)
PDevel1000m	NA	NA
PDevel200m	-0.94 (-1.85, -0.27)	-1.02 (2.0E-1)
PHouseForest	NA	NA
PHouseLawn	NA	-1.37 (1.8E-1)
ShapeForest	NA	0.65 (1.1E-1)
ClumpyForest	-1.34 (-2.51, -0.49)	NA
p11_yr1	0.34 (0.22, 0.48)	0.30 (4.7E-3)
p11_yr2	0.41 (0.31, 0.52)	0.40 (2.2E-3)
p10_yr1	0.01 (0.00, 0.04)	0.01 (1.2E-4)
p10_yr2	0.12 (0.07, 0.17)	0.09 (6.4E-4)
b	0.09 (0.05, 0.14)	0.07 (3.4E-4)

Table 3.5: Posterior probabilities for the Blue-headed Vireo from models with covariates affecting the occupancy probability (ψ) and the true positive detection probability (*p11*) that had at least 0.01 posterior weight. Year-specific true positive detection probabilities (*p11_yr1* and *p11_yr2*) and false positive detection probabilities (*p10_yr1* and *p10_yr2*) are shown along with the intercept for the true positive detection probablity equation not on the logit scale (*p11_0*) and coefficients for covariates on the logit scale (*Year2Detect* an indicator variable where 0 = first breeding season and 1 = second breeding season, *JulianDate*, and *JulianDate*^{2}). Additional details can be found in the Table 3.4 legend.

ψ (landscape, local)	15	19	20	20	21	21	
p11	2	1	1	2	1	2	AVG
psi_0	0.51 (0.38, 0.65)	0.54 (0.42, 0.68)	0.56 (0.43, 0.69)	0.54 (0.42, 0.67)	0.53 (0.41, 0.65)	0.51 (0.40, 0.63)	0.52 (3.9E-3)
Elev	0.92 (0.52, 1.40)	NA	NA	NA	NA	NA	NA
PDevel200m	-1.46 (-2.25, -0.81)	-1.04 (-1.72, -0.50)	-1.19 (-1.87, -0.63)	-1.15 (-1.82, -0.60)	-1.08 (-1.72, -0.56)	-1.05 (-1.68, -0.54)	-1.07 (9.0E-2)
ShapeForest	NA	0.61 (0.18, 1.13)	0.58 (0.18, 1.07)	0.57 (0.18, 1.03)	NA	NA	0.58 (5.1E-2)
ClumpyForest	NA	-0.73 (-1.35, -0.21)	NA	NA	-0.81 (-1.46, -0.24)	-0.79 (-1.43, -0.24)	-0.80 (9.5E-2)
p11_yr1	NA	0.64 (0.53, 0.74)	0.62 (0.52, 0.73)	NA	0.64 (0.53, 0.74)	NA	0.64 (2.9E-3)
p11_yr2	NA	0.78 (0.70, 0.85)	0.76 (0.68, 0.83)	NA	0.78 (0.71, 0.85)	NA	0.78 (1.4E-3)
p11_0	0.59 (0.48, 0.72)	NA	NA	0.58 (0.47, 0.71)	NA	0.60 (0.48, 0.72)	0.60 (3.7E-3)
Year2Detect	0.56 (-0.03, 1.15)	NA	NA	0.62 (0.05, 1.19)	NA	0.71 (0.11, 1.32)	0.71 (9.5E-2)
JulianDate	0.11 (-0.21, 0.45)	NA	NA	0.06 (-0.24, 0.38)	NA	0.11 (-0.23, 0.47)	0.11 (3.1E-2)
JulianDate^2	0.35 (0.00, 0.76)	NA	NA	0.30 (-0.02, 0.67)	NA	0.30 (-0.05, 0.71)	0.30 (3.7E-2)
p10_yr1	0.13 (0.07, 0.21)	0.14 (0.07, 0.22)	0.13 (0.06, 0.21)	0.13 (0.06, 0.21)	0.14 (0.07, 0.22)	0.14 (0.07, 0.22)	0.24 (1.9E-3)
p10_yr2	0.25 (0.16, 0.33)	0.23 (0.15, 0.32)	0.21 (0.13, 0.30)	0.22 (0.14, 0.30)	0.24 (0.16, 0.33)	0.25 (0.17, 0.33)	0.14 (1.5E-3)
b	0.12 (0.08, 0.15)	0.11 (0.08, 0.15)	0.11 (0.08, 0.14)	0.11 (0.08, 0.15)	0.12 (0.08, 0.15)	0.12 (0.07, 0.16)	0.12 (3.3E-4)

Table 3.6: Posterior probabilities for the Black-throated Blue Warbler from models with covariates affecting the occupancy probability (ψ) and the true positive detection probability (*p11*) that had at least 0.01 posterior weight. Additional details can be found in the Table 3.4 legend.

ψ (landscape, local)	1	3	5	13	14	
p11	1	1	1	1	1	AVG
psi_0	0.04 (0.01, 0.08)	0.09 (0.04, 0.15)	0.05 (0.02, 0.10)	0.09 (0.04, 0.15)	0.08 (0.03, 0.14)	0.09 (8.4E-4)
Elev	1.99 (1.27, 2.85)	NA	2.15 (1.48, 2.96)	NA	NA	2.07 (1.6E-1)
PForest1000m	1.53 (0.89, 2.27)	NA	NA	NA	NA	NA
PForest200m	NA	1.85 (1.23, 2.57)	NA	1.88 (1.28, 2.58)	2.07 (1.39, 2.87)	1.90 (1.2E-1)
PDevel1000m	NA	NA	-0.79 (-1.32, -0.33)	NA	NA	NA
PHouseForest	NA	NA	NA	NA	0.32 (-0.19, 0.77)	NA
ShapeForest	NA	0.29 (-0.05, 0.63)	NA	NA	NA	NA
p11_yr1	0.68 (0.51, 0.84)	0.61 (0.45, 0.80)	0.72 (0.55, 0.87)	0.61 (0.45, 0.79)	0.60 (0.45, 0.78)	0.61 (7.6E-3)
p11_yr2	0.83 (0.70, 0.93)	0.81 (0.66, 0.93)	0.85 (0.73, 0.93)	0.82 (0.67, 0.94)	0.82 (0.68, 0.93)	0.82 (4.7E-3)
p10_yr1	0.05 (0.02, 0.09)	0.04 (0.00, 0.07)	0.06 (0.03, 0.09)	0.03 (0.00, 0.07)	0.03 (0.00, 0.07)	0.03 (3.3E-4)
p10_yr2	0.03 (0.02, 0.05)	0.03 (0.01, 0.06)	0.03 (0.02, 0.06)	0.03 (0.01, 0.06)	0.03 (0.01, 0.06)	0.03 (1.3E-4)
b	0.15 (0.10, 0.23)	0.14 (0.08, 0.21)	0.16 (0.10, 0.24)	0.14 (0.08, 0.21)	0.14 (0.08, 0.21)	0.14 (1.1E-3)

Table 3.7: Posterior probabilities for the Canada Warbler from models with covariates affecting the occupancy probability (ψ) and the true positive detection probability (*p11*) that had at least 0.01 posterior weight. *ElevPDevl200m* and *ElevPHouseForest* are on the logit scale and are coefficients for covariates. Additional details can be found in the Table 3.4 legend.

ψ (landscape, local)	1	2	5	7	8	13	25
p11	1	1	1	1	1	1	1
psi_0	0.02 (0.00, 0.05)	0.02 (0.00, 0.05)	0.02 (0.01, 0.06)	0.02 (0.00, 0.06)	0.02 (0.01, 0.06)	0.04 (0.01, 0.08)	0.02 (0.00, 0.05)
Elev	2.35 (1.40, 3.55)	2.52 (1.51, 3.82)	2.53 (1.60, 3.72)	2.57 (1.59, 3.81)	2.47 (1.47, 3.75)	NA	2.54 (1.59, 3.75)
PForest1000m	1.12 (0.38, 1.99)	0.92 (0.15, 1.81)	NA	NA	NA	NA	NA
PForest200m	NA	NA	NA	NA	NA	1.97 (1.12, 3.02)	NA
PDevel1000m	NA	NA	-0.63 (-1.32, -0.06)	-0.65 (-1.35, -0.06)	-0.43 (-1.13, 0.18)	NA	NA
PDevel200m	NA	NA	NA	NA	NA	NA	-0.58 (-3.26, 1.98)
ElevPDevel200m	NA	NA	NA	NA	NA	NA	-1.00 (-3.07, 1.02)
PHouseForest	NA	-0.67 (-1.57, 0.06)	NA	NA	NA	NA	NA
ElevPHouseForest	NA	NA	NA	NA	NA	NA	NA
ShapeForest	NA	NA	NA	-0.05 (-0.60, 0.47)	NA	NA	NA
ClumpyForest	NA	NA	NA	NA	-0.60 (-1.36, 0.04)	NA	NA
p11_yr1	0.35 (0.17, 0.59)	0.35 (0.17, 0.59)	0.36 (0.16, 0.59)	0.35 (0.16, 0.60)	0.35 (0.17, 0.58)	0.39 (0.18, 0.64)	0.35 (0.16, 0.59)
p11_yr2	0.39 (0.24, 0.55)	0.39 (0.24, 0.55)	0.39 (0.24, 0.56)	0.39 (0.24, 0.56)	0.38 (0.24, 0.55)	0.41 (0.24, 0.61)	0.41 (0.25, 0.58)
p10_yr1	0.01 (0.00, 0.02)	0.01 (0.00, 0.02)	0.01 (0.00, 0.02)	0.01 (0.00, 0.02)	0.01 (0.00, 0.02)	0.01 (0.00, 0.02)	0.01 (0.00, 0.02)
p10_yr2	0.00 (0.00, 0.02)	0.00 (0.00, 0.02)	0.00 (0.00, 0.02)	0.01 (0.00, 0.02)	0.00 (0.00, 0.02)	0.01 (0.00, 0.02)	0.01 (0.00, 0.02)
b	0.13 (0.07, 0.22)	0.13 (0.07, 0.22)	0.14 (0.07, 0.22)	0.13 (0.07, 0.23)	0.13 (0.07, 0.22)	0.15 (0.07, 0.26)	0.14 (0.07, 0.23)

ψ (landscape, local)	28	
p11	1	AVG
psi_0	0.02 (0.01, 0.06)	0.02 (1.9E-4)
Elev	2.52 (1.57, 3.73)	2.44 (3.1E-1)
PForest1000m	NA	1.11 (1.7E-1)
PForest200m	NA	NA
PDevel1000m	NA	-0.62 (1.1E-1)
PDevel200m	NA	NA
ElevPDevel200m	NA	NA
PHouseForest	-0.45 (-2.81, 1.87)	-0.51 (1.1)
ElevPHouseForest	-0.49 (-2.64, 1.67)	NA
ShapeForest	NA	NA
ClumpyForest	NA	NA
p11_yr1	0.36 (0.17, 0.59)	0.36 (1.3E-2)
p11_yr2	0.39 (0.24, 0.56)	0.39 (6.8E-3)
p10_yr1	0.00 (0.00, 0.02)	0.01 (2.4E-5)
p10_yr2	0.00 (0.00, 0.02)	0.00 (2.1E-5)
b	0.13 (0.07, 0.22)	0.13 (1.7E-3)

Table 3.8: Posterior probabilities for the Veery from models with covariates affecting the occupancy probability (ψ) and the true positive detection probability (*p11*) that had at least 0.01 posterior weight. *ElevPDevel200m* and *ElevPHouseForest* are on the logit scale and are coefficients for covariates. Year-specific true positive detection probabilities (*p11_yr1* and *p11_yr2*) and false positive detection probabilities (*p10_yr1* and *p10_yr2*) are shown along with the intercept for the true positive detection probablity equation not on the logit scale (*p11_0*) and coefficients for covariates on the logit scale (*Year2Detect* an indicator variable where 0 = first breeding season and 1 = second breeding season, *JulianDate,* and *JulianDate*^{2}). Additional details can be found in the Table 3.4 legend.

ψ (landscape, local)	1	1	2	5	8	14	15
p11	1	2	1	1	1	1	1
psi_0	0.08 (0.03, 0.15)	0.07 (0.03, 0.14)	0.08 (0.03, 0.15)	0.08 (0.03, 0.15)	0.07 (0.02, 0.14)	0.13 (0.07, 0.21)	0.08 (0.03, 0.15)
Elev	2.52 (1.79, 3.45)	2.53 (1.79, 3.45)	2.53 (1.77, 3.50)	2.43 (1.71, 3.34)	2.49 (1.70, 3.55)	NA	2.52 (1.78, 3.46)
PForest1000m	-0.18 (-0.72, 0.36)	-0.21 (-0.77, 0.33)	-0.04 (-0.62, 0.52)	NA	NA	NA	NA
PForest200m	NA	NA	NA	NA	NA	1.34 (0.80, 1.96)	NA
PDevel1000m	NA	NA	NA	0.59 (0.14, 1.11)	0.70 (0.25, 1.21)	NA	NA
PDevel200m	NA	NA	NA	NA	NA	NA	-0.22 (-0.96, 0.39)
ElevPDevel200m	NA	NA	NA	NA	NA	NA	NA
PHouseForest	NA	NA	0.46 (-0.03, 1.07)	NA	NA	0.81 (0.41, 1.25)	NA
ElevPHouseForest	NA	NA	NA	NA	NA	NA	NA
ClumpyForest	NA	NA	NA	NA	-0.9 (-1.71, -0.19)	NA	NA
p11_yr1	0.44 (0.31, 0.59)	NA	0.42 (0.29, 0.57)	0.42 (0.29, 0.57)	0.44 (0.31, 0.59)	0.50 (0.34, 0.67)	0.45 (0.31, 0.59)
p11_yr2	0.63 (0.50, 0.75)	NA	0.62 (0.50, 0.75)	0.62 (0.50, 0.74)	0.61 (0.49, 0.74)	0.68 (0.54, 0.82)	0.63 (0.50, 0.76)
p11_0	NA	0.42 (0.27, 0.60)	NA	NA	NA	NA	NA

Year2Detect	NA	1.00 (0.22, 1.83)	NA	NA	NA	NA	NA
JulianDate	NA	0.49 (0.10, 0.94)	NA	NA	NA	NA	NA
JulianDate^2	NA	0.03 (-0.32, 0.39)	NA	NA	NA	NA	NA
p10_yr1	0.01 (0.00, 0.03)	0.01 (0.00, 0.04)	0.01 (0.00, 0.03)	0.01 (0.00, 0.03)	0.01 (0.00, 0.03)	0.02 (0.00, 0.05)	0.01 (0.00, 0.03)
p10_yr2	0.03 (0.01, 0.06)	0.03 (0.01, 0.06)	0.03 (0.01, 0.06)	0.03 (0.01, 0.06)	0.03 (0.01, 0.06)	0.04 (0.02, 0.07)	0.03 (0.01, 0.06)
b	0.09 (0.05, 0.14)	0.09 (0.05, 0.14)	0.09 (0.05, 0.13)	0.09 (0.05, 0.13)	0.09 (0.05, 0.13)	0.10 (0.06, 0.16)	0.09 (0.05, 0.14)

ψ (landscape, local)	15	25	28	
p11	2	1	1	AVG
psi_0	0.07 (0.02, 0.14)	0.07 (0.03, 0.14)	0.08 (0.03, 0.15)	0.08 (9.9E-4)
Elev	2.53 (1.79, 3.48)	2.56 (1.79, 3.52)	2.47 (1.69, 3.46)	2.52 (1.8E-1)
PForest1000m	NA	NA	NA	-0.18 (7.7E-2)
PForest200m	NA	NA	NA	NA
PDevel1000m	NA	NA	NA	0.61 (6.3E-2)
PDevel200m	-0.28 (-1.00, 0.33)	-0.19 (-2.50, 1.77)	NA	-0.23 (1.6E-1)
ElevPDevel200m	NA	-0.05 (-1.62, 1.66)	NA	NA
PHouseForest	NA	NA	0.09 (-1.97, 1.99)	0.42 (4.9E-1)
ElevPHouseForest	NA	NA	0.40 (-1.54, 2.49)	NA

ClumpyForest	NA	NA	NA	NA
p11_yr1	NA	0.44 (0.31, 0.59)	0.42 (0.29, 0.57)	0.44 (5.4E-3)
p11_yr2	NA	0.63 (0.50, 0.77)	0.62 (0.50, 0.75)	0.63 (4.3E-3)
p11_0	0.43 (0.27, 0.61)	NA	NA	0.43 (7.4E-3)
Year2Detect	1.01 (0.22, 1.83)	NA	NA	1.01 (1.7E-1)
JulianDate	0.49 (0.11, 0.91)	NA	NA	0.49 (4.3E-2)
JulianDate^2	0.00 (-0.35, 0.36)	NA	NA	0.01 (3.3E-2)
p10_yr1	0.01 (0.00, 0.04)	0.01 (0.00, 0.03)	0.01 (0.00, 0.03)	0.01 (7.7E-5)
p10_yr2	0.03 (0.01, 0.06)	0.03 (0.01, 0.06)	0.03 (0.01, 0.06)	0.03 (1.3E-4)
b	0.09 (0.05, 0.14)	0.09 (0.05, 0.14)	0.09 (0.05, 0.13)	0.09 (5.0E-4)

Table 3.9: Posterior probabilities for the Wood Thrush from models with covariates affecting the occupancy probability (ψ) and the true positive detection probability (*p11*) that had at least 0.01 posterior weight. *PatchAreaForest* is on the logit scale and is a covariate coefficient. Year-specific true positive detection probabilities (*p11_yr1* and *p11_yr2*) and false positive detection probabilities (*p10_yr1* and *p10_yr2*) are shown along with the intercept for the true positive detection probablity equation not on the logit scale (*p11_0*) and coefficients for covariates on the logit scale (*Year2Detect* an indicator variable where 0 = first breeding season and 1 = second breeding season, *JulianDate*, *JulianDate*^{2}, *Time* in minutes since 5:59am, and *Sky* an indicator variable where 0 = sunny or cloudy and 1 = rain or fog). Additional details can be found in the Table 3.4 legend.

ψ (landscape, local)	1	3	5	13	13	14	15
p11	1	1	1	1	4	1	1
psi_0	0.26 (0.14, 0.43)	0.21 (0.10, 0.34)	0.29 (0.15, 0.46)	0.23 (0.11, 0.39)	0.35 (0.18, 0.56)	0.22 (0.11, 0.38)	0.27 (0.13, 0.47)
Elev	0.48 (0.05, 0.98)	NA	0.81 (0.33, 1.44)	NA	NA	NA	0.58 (0.17, 1.04)
PForest1000m	0.65 (0.19, 1.19)	NA	NA	NA	NA	NA	NA
PForest200m	NA	0.58 (0.09, 1.15)	NA	0.73 (0.28, 1.27)	0.74 (0.31, 1.23)	0.74 (0.28, 1.30)	NA
PDevel1000m	NA	NA	-0.73 (-1.39, -0.22)	NA	NA	NA	NA
PDevel200m	NA	NA	NA	NA	NA	NA	-0.62 (-1.54, -0.03)
PHouseForest	NA	NA	NA	NA	NA	-0.10 (-0.70, 0.37)	NA
PatchAreaForest	NA	NA	NA	NA	NA	NA	NA
ShapeForest	NA	0.72 (0.26, 1.25)	NA	NA	NA	NA	NA
ClumpyForest	NA	NA	NA	NA	NA	NA	NA
p11_yr1	0.47 (0.32, 0.65)	0.51 (0.35, 0.68)	0.46 (0.31, 0.63)	0.50 (0.32, 0.68)	NA	0.50 (0.32, 0.68)	0.47 (0.30, 0.65)
p11_yr2	0.56 (0.42, 0.71)	0.60 (0.47, 0.73)	0.54 (0.40, 0.69)	0.61 (0.46, 0.76)	NA	0.61 (0.46, 0.76)	0.57 (0.42, 0.73)
p11_0	NA	NA	NA	NA	0.40 (0.21, 0.62)	NA	NA

Year2Detect	NA	NA	NA	NA	0.34 (-0.41, 1.30)	NA	NA
JulianDate	NA	NA	NA	NA	-0.03 (-0.38, 0.31)	NA	NA
JulianDate^2	NA	NA	NA	NA	0.14 (-0.25, 0.50)	NA	NA
Time	NA	NA	NA	NA	-0.70 (-1.06, -0.38)	NA	NA
Sky	NA	NA	NA	NA	-0.34 (-1.34, 1.02)	NA	NA
p10_yr1	0.08 (0.03, 0.14)	0.10 (0.05, 0.16)	0.08 (0.03, 0.13)	0.10 (0.04, 0.16)	0.08 (0.02, 0.17)	0.10 (0.04, 0.16)	0.08 (0.02, 0.14)
p10_yr2	0.11 (0.06, 0.17)	0.12 (0.08, 0.17)	0.11 (0.05, 0.16)	0.12 (0.07, 0.18)	0.09 (0.04, 0.15)	0.13 (0.07, 0.18)	0.11 (0.05, 0.17)
b	0.05 (0.02, 0.10)	0.06 (0.03, 0.11)	0.05 (0.02, 0.09)	0.06 (0.03, 0.11)	0.04 (0.02, 0.08)	0.06 (0.03, 0.12)	0.05 (0.02, 0.10)

ψ (landscape, local)	17	17	20	20	21	
p11	1	4	1	4	1	AVG
psi_0	0.27 (0.14, 0.46)	0.40 (0.20, 0.62)	0.23 (0.12, 0.38)	0.33 (0.17, 0.53)	0.28 (0.14, 0.48)	0.25 (6.7E-3)
Elev	NA	NA	NA	NA	NA	0.57 (6.6E-2)
PForest1000m	NA	NA	NA	NA	NA	NA
PForest200m	NA	NA	NA	NA	NA	0.73 (6.4E-2)
PDevel1000m	NA	NA	NA	NA	NA	NA
PDevel200m	-0.36 (-1.15, 0.16)	-0.42 (-1.08, 0.04)	-0.39 (-1.26, 0.19)	-0.47 (-1.20, 0.04)	-0.54 (-1.36, -0.02)	-0.48 (1.3E-1)
PHouseForest	NA	NA	NA	NA	NA	NA
PatchAreaForest	0.63 (0.24, 1.09)	0.70 (0.23, 1.43)	NA	NA	NA	0.63 (5.4E-2)

ShapeForest	NA	NA	0.81 (0.34, 1.35)	0.68 (0.24, 1.19)	NA	0.77 (6.7E-2)
ClumpyForest	NA	NA	NA	NA	-0.03 (-0.59, 0.41)	NA
p11_yr1	0.46 (0.31, 0.63)	NA	0.51 (0.35, 0.68)	NA	0.47 (0.30, 0.66)	0.49 (8.7E-3)
p11_yr2	0.58 (0.43, 0.73)	NA	0.59 (0.45, 0.72)	NA	0.57 (0.41, 0.74)	0.59 (6.5E-3)
p11_0	NA	0.38 (0.25, 0.56)	NA	0.42 (0.27, 0.62)	NA	0.40 (9.0E-3)
Year2Detect	NA	0.32 (-0.31, 1.01)	NA	0.22 (-0.49, 0.95)	NA	0.30 (1.7E-1)
JulianDate	NA	0.00 (-0.30, 0.32)	NA	-0.03 (-0.38, 0.30)	NA	-0.02 (2.9E-2)
JulianDate^2	NA	0.13 (-0.19, 0.46)	NA	0.17 (-0.18, 0.56)	NA	0.15 (3.4E-2)
Time	NA	-0.65 (-0.96, -0.36)	NA	-0.66 (-1.00, -0.34)	NA	-0.68 (2.8E-2)
Sky	NA	-0.31 (-1.24, 1.00)	NA	-0.32 (-1.41, 1.40)	NA	-0.33 (3.8E-1)
p10_yr1	0.08 (0.02, 0.15)	0.06 (0.00, 0.13)	0.09 (0.04, 0.15)	0.07 (0.01, 0.14)	0.08 (0.01, 0.15)	0.09 (1.1E-3)
p10_yr2	0.11 (0.06, 0.17)	0.08 (0.03, 0.14)	0.12 (0.07, 0.17)	0.09 (0.04, 0.15)	0.11 (0.05, 0.17)	0.12 (8.1E-4)
b	0.05 (0.02, 0.10)	0.04 (0.02, 0.07)	0.06 (0.03, 0.11)	0.04 (0.02, 0.08)	0.05 (0.02, 0.11)	0.06 (4.9E-4)

Table 3.10: Candidate models for the Black-and-white Warbler with landscape-, local-, and site-scale covariates affecting the occupancy probability (ψ) and covariates affecting the true positive detection probability (*p11*) ranked by posterior model weight. The models with landscape- and local-scale covariates and the models with site-scale covariates affecting the occupancy probability (ψ) that had at least 0.01 posterior weight were included in the candidate set of models along with models that included landscape-, local-, and site-scale covariates. The site-scale covariate was an indicator variable, so for the models with landscape-, local-, and site-scale covariates, the indicator variable either led to a different intercept or both a different intercept and different slope(s). The models were evaluated with the Bayesian Information Criterion (BIC) and uniform prior weights.

ψ (landscape, local)	ψ (site)	*p11*	Effect of site	BIC	Prior	Posterior
13	NA	1	NA	781.15	0.04	0.76
9	NA	1	NA	785.57	0.04	0.08
1	NA	1	NA	785.99	0.04	0.07
21	NA	1	NA	788.21	0.04	0.02
14	NA	1	NA	788.29	0.04	0.02
20	NA	1	NA	788.35	0.04	0.02
16	NA	1	NA	788.84	0.04	0.02
3	NA	1	NA	789.46	0.04	0.01
NA	2	1	NA	861.45	0.04	0.00
13	2	1	Intercept	866.41	0.04	0.00
9	2	1	Intercept	870.09	0.04	0.00
1	2	1	Intercept	870.45	0.04	0.00
13	2	1	Intercept, Slope	872.50	0.04	0.00
21	2	1	Intercept	873.09	0.04	0.00
20	2	1	Intercept	873.16	0.04	0.00
16	2	1	Intercept	873.51	0.04	0.00
14	2	1	Intercept	873.55	0.04	0.00
3	2	1	Intercept	874.66	0.04	0.00
1	2	1	Intercept, Slope	881.82	0.04	0.00
9	2	1	Intercept, Slope	882.29	0.04	0.00
21	2	1	Intercept, Slope	883.66	0.04	0.00
20	2	1	Intercept, Slope	884.99	0.04	0.00
16	2	1	Intercept, Slope	885.40	0.04	0.00
14	2	1	Intercept, Slope	885.47	0.04	0.00
3	2	1	Intercept, Slope	886.34	0.04	0.00

Table 3.11: Candidate models for the Blue-headed Vireo with landscape-, local-, and site-scale covariates affecting the occupancy probability (ψ) and covariates affecting the true positive detection probability (*p11*) ranked by posterior model weight. Additional details can be found in the Table 3.10 legend.

ψ (landscape, local)	ψ (site)	*p11*	Effect of site	BIC	Prior	Posterior
21	NA	1	NA	1172.33	0.05	0.48
21	NA	2	NA	1172.36	0.05	0.47
20	NA	2	NA	1179.18	0.05	0.02
15	NA	2	NA	1179.47	0.05	0.01
20	NA	1	NA	1180.25	0.05	0.01
19	NA	1	NA	1181.03	0.05	0.01
NA	2	2	NA	1244.96	0.05	0.00
NA	2	1	NA	1247.96	0.05	0.00
21	2	1	Intercept	1255.81	0.05	0.00
21	2	2	Intercept	1256.08	0.05	0.00
20	2	2	Intercept	1263.02	0.05	0.00
20	2	1	Intercept	1264.13	0.05	0.00
15	2	2	Intercept	1264.30	0.05	0.00
19	2	1	Intercept	1264.38	0.05	0.00
21	2	1	Intercept, Slope	1267.17	0.05	0.00
21	2	2	Intercept, Slope	1267.24	0.05	0.00
20	2	2	Intercept, Slope	1274.84	0.05	0.00
20	2	1	Intercept, Slope	1275.84	0.05	0.00
15	2	2	Intercept, Slope	1277.03	0.05	0.00
19	2	1	Intercept, Slope	1281.61	0.05	0.00

Table 3.12: Candidate models for the Black-throated Blue Warbler with landscape-, local-, and site-scale covariates affecting the occupancy probability (ψ) and covariates affecting the true positive detection probability (*p11*) ranked by posterior model weight. Additional details can be found in the Table 3.10 legend.

ψ (landscape, local)	ψ (site)	*p11*	Effect of site	BIC	Prior	Posterior
13	NA	1	NA	489.96	0.06	0.87
14	NA	1	NA	494.96	0.06	0.07
3	NA	1	NA	496.53	0.06	0.03
5	NA	1	NA	498.33	0.06	0.01
1	NA	1	NA	498.46	0.06	0.01
NA	2	1	NA	571.25	0.06	0.00
13	2	1	Intercept	574.30	0.06	0.00
14	2	1	Intercept	579.06	0.06	0.00
13	2	1	Intercept, Slope	579.79	0.06	0.00
3	2	1	Intercept	580.62	0.06	0.00
5	2	1	Intercept	582.19	0.06	0.00
1	2	1	Intercept	582.44	0.06	0.00
14	2	1	Intercept, Slope	590.60	0.06	0.00
3	2	1	Intercept, Slope	592.07	0.06	0.00
5	2	1	Intercept, Slope	593.59	0.06	0.00
1	2	1	Intercept, Slope	593.63	0.06	0.00

Table 3.13: Candidate models for the Canada Warbler with landscape-, local-, and site-scale covariates affecting the occupancy probability (ψ) and covariates affecting the true positive detection probability (*p11*) ranked by posterior model weight. Additional details can be found in the Table 3.10 legend.

ψ (landscape, local)	ψ (site)	*p11*	Effect of site	BIC	Prior	Posterior
1	NA	1	NA	239.39	0.04	0.45
5	NA	1	NA	239.90	0.04	0.35
28	NA	1	NA	243.42	0.04	0.06
13	NA	1	NA	243.76	0.04	0.05
8	NA	1	NA	245.03	0.04	0.03
2	NA	1	NA	245.05	0.04	0.03
25	NA	1	NA	245.94	0.04	0.02
7	NA	1	NA	246.91	0.04	0.01
1	2	1	Intercept	324.16	0.04	0.00
5	2	1	Intercept	325.06	0.04	0.00
13	2	1	Intercept	328.39	0.04	0.00
28	2	1	Intercept	328.39	0.04	0.00
2	2	1	Intercept	329.89	0.04	0.00
8	2	1	Intercept	330.01	0.04	0.00
25	2	1	Intercept	331.05	0.04	0.00
7	2	1	Intercept	331.81	0.04	0.00
NA	2	1	NA	332.44	0.04	0.00
13	2	1	Intercept, Slope	334.21	0.04	0.00
1	2	1	Intercept, Slope	334.88	0.04	0.00
5	2	1	Intercept, Slope	335.05	0.04	0.00
28	2	1	Intercept, Slope	345.21	0.04	0.00
8	2	1	Intercept, Slope	345.57	0.04	0.00
7	2	1	Intercept, Slope	347.79	0.04	0.00
2	NA	1	Intercept, Slope	DNC	0.04	NA
25	NA	1	Intercept, Slope	DNC	0.04	NA

Table 3.14: Candidate models for the Veery with landscape-, local-, and site-scale covariates affecting the occupancy probability (ψ) and covariates affecting the true positive detection probability (*p11*) ranked by posterior model weight. Additional details can be found in the Table 3.10 legend.

ψ (landscape, local)	ψ (site)	*p11*	Effect of site	BIC	Prior	Posterior
15	NA	1	NA	512.56	0.03	0.49
1	NA	1	NA	513.41	0.03	0.32
15	NA	2	NA	516.60	0.03	0.07
1	NA	2	NA	517.83	0.03	0.04
5	NA	1	NA	518.05	0.03	0.03
25	NA	1	NA	518.83	0.03	0.02
8	NA	1	NA	520.68	0.03	0.01
2	NA	1	NA	520.97	0.03	0.01
28	NA	1	NA	521.05	0.03	0.01
14	NA	1	NA	521.67	0.03	0.01
15	2	1	Intercept	597.07	0.03	0.00
1	2	1	Intercept	597.51	0.03	0.00
15	2	2	Intercept	601.13	0.03	0.00
1	2	2	Intercept	602.05	0.03	0.00
5	2	1	Intercept	602.49	0.03	0.00
25	2	1	Intercept	603.17	0.03	0.00
NA	2	1	NA	604.47	0.03	0.00
14	2	1	Intercept	604.65	0.03	0.00
28	2	1	Intercept	605.00	0.03	0.00
2	2	1	Intercept	605.01	0.03	0.00
8	2	1	Intercept	605.25	0.03	0.00
NA	2	2	NA	609.39	0.03	0.00
15	2	1	Intercept, Slope	609.47	0.03	0.00
1	2	1	Intercept, Slope	609.83	0.03	0.00
15	2	2	Intercept, Slope	613.58	0.03	0.00
1	2	2	Intercept, Slope	614.31	0.03	0.00
5	2	1	Intercept, Slope	615.32	0.03	0.00
14	2	1	Intercept, Slope	616.31	0.03	0.00
8	2	1	Intercept, Slope	616.82	0.03	0.00
25	2	1	Intercept, Slope	621.46	0.03	0.00
28	2	1	Intercept, Slope	623.81	0.03	0.00
2	2	1	Intercept, Slope	623.82	0.03	0.00

Table 3.15: Candidate models for the Wood Thrush with landscape-, local-, and site-scale covariates affecting the occupancy probability (ψ) and covariates affecting the true positive detection probability (*p11*) ranked by posterior model weight. Additional details can be found in the Table 3.10 legend.

ψ (landscape, local)	ψ (site)	*p11*	Effect of site	BIC	Prior	Posterior
13	NA	1	NA	810.73	0.03	0.57
21	NA	1	NA	813.97	0.03	0.11
17	NA	1	NA	814.56	0.03	0.08
15	NA	1	NA	815.24	0.03	0.06
1	NA	1	NA	815.78	0.03	0.05
20	NA	1	NA	816.03	0.03	0.04
3	NA	1	NA	817.67	0.03	0.02
13	NA	4	NA	818.00	0.03	0.02
5	NA	1	NA	818.19	0.03	0.01
14	NA	1	NA	818.36	0.03	0.01
20	NA	4	NA	818.57	0.03	0.01
17	NA	4	NA	819.02	0.03	0.01
NA	2	1	NA	882.48	0.03	0.00
NA	2	4	NA	886.49	0.03	0.00
13	2	1	Intercept	893.04	0.03	0.00
21	2	1	Intercept	895.70	0.03	0.00
17	2	1	Intercept	897.09	0.03	0.00
20	2	1	Intercept	897.72	0.03	0.00
15	2	1	Intercept	897.94	0.03	0.00
13	2	1	Intercept, Slope	898.95	0.03	0.00
1	2	1	Intercept	899.24	0.03	0.00
3	2	1	Intercept	899.27	0.03	0.00
20	2	4	Intercept	899.75	0.03	0.00
13	2	4	Intercept	900.28	0.03	0.00
5	2	1	Intercept	901.99	0.03	0.00
17	2	4	Intercept	902.20	0.03	0.00
13	2	4	Intercept, Slope	906.84	0.03	0.00
21	2	1	Intercept, Slope	906.92	0.03	0.00
17	2	1	Intercept, Slope	907.17	0.03	0.00
20	2	1	Intercept, Slope	908.38	0.03	0.00
1	2	1	Intercept, Slope	909.23	0.03	0.00
3	2	1	Intercept, Slope	910.52	0.03	0.00
15	2	1	Intercept, Slope	910.88	0.03	0.00
20	2	4	Intercept, Slope	910.89	0.03	0.00
14	2	1	Intercept, Slope	911.98	0.03	0.00
17	2	4	Intercept, Slope	912.10	0.03	0.00

5	2	1	Intercept, Slope	912.54	0.03	0.00
14	2	1	Intercept	956.91	0.03	0.00

Table 3.16: Predictive ability of top models for the Black-and-white Warbler (BAWW), Blue-headed Vireo (BHVI), Black-throated Blue Warbler (BTBW), Canada Warbler (CAWA), Veery (VEER), and Wood Thrush (WOTH). The occupancy and true positive detection models in each species' top model(s) are indicated along with the posterior model weight(s). The predictive ability of each model is shown in terms of the area under the receiver operating characteristic curve (AUC) and the proportion of sites known to be occupied from confirmed detections at which the mean of the occupancy probability posterior distribution was less than 0.5.

Species	ψ (landscape, local)	*p11*	Posterior	AUC	$\psi < 0.5$ when $z = 1$
BAWW	13	1	0.76	0.93	0.32
BHVI	21	1	0.48	0.76	0.21
	21	2	0.47	0.74	0.26
BTBW	13	1	0.87	0.85	0.53
CAWA	1	1	0.45	0.92	0.56
	5	1	0.35	0.91	0.56
VEER	1	1	0.32	0.90	0.31
	15	1	0.49	0.90	0.46
WOTH	13	1	0.57	0.66	1.00

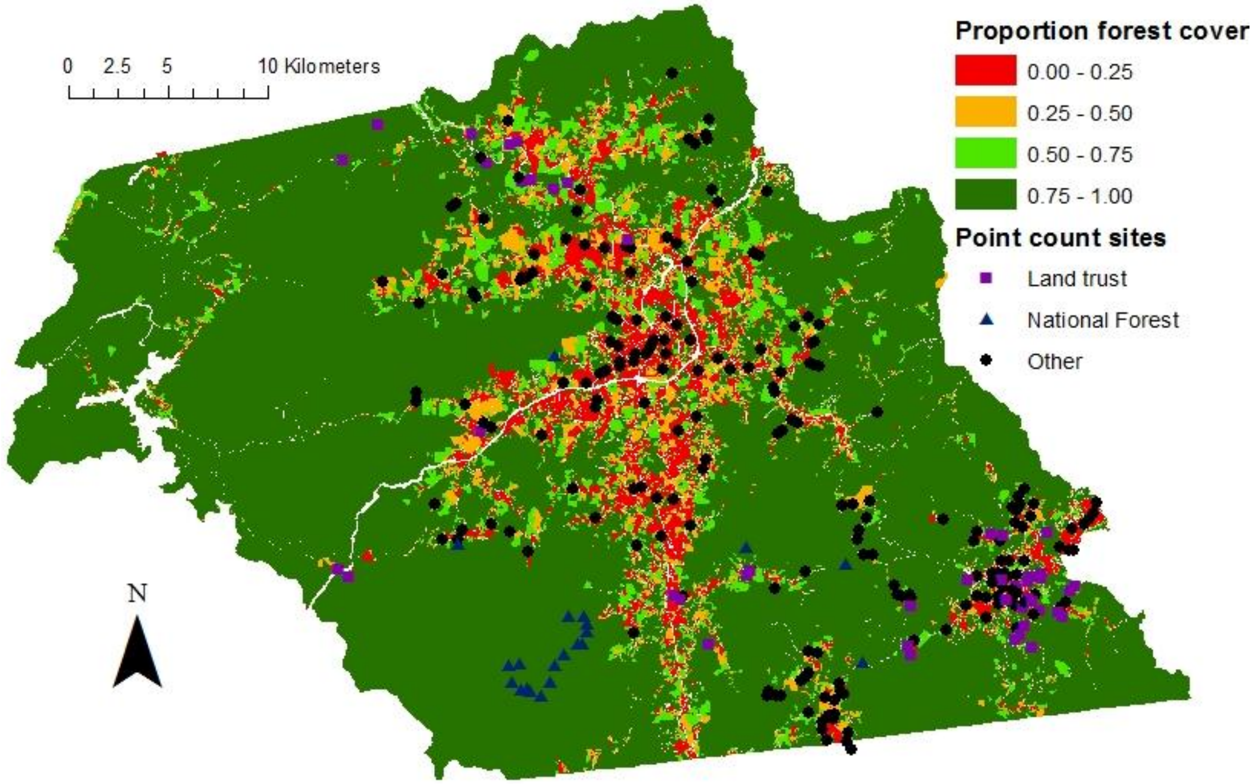


Figure 3.1: Point count sites in the Nantahala National Forest (blue triangles), on fee simple properties or properties with conservation easement that are managed by land trusts (purple squares), or on unprotected sites that were randomly selected to represent the range of land use and land cover classes and elevations (black circles) in Macon County, NC (displayed map extent). The percent forest cover on properties is shown. Narrow, white curves occur where large roads were present.

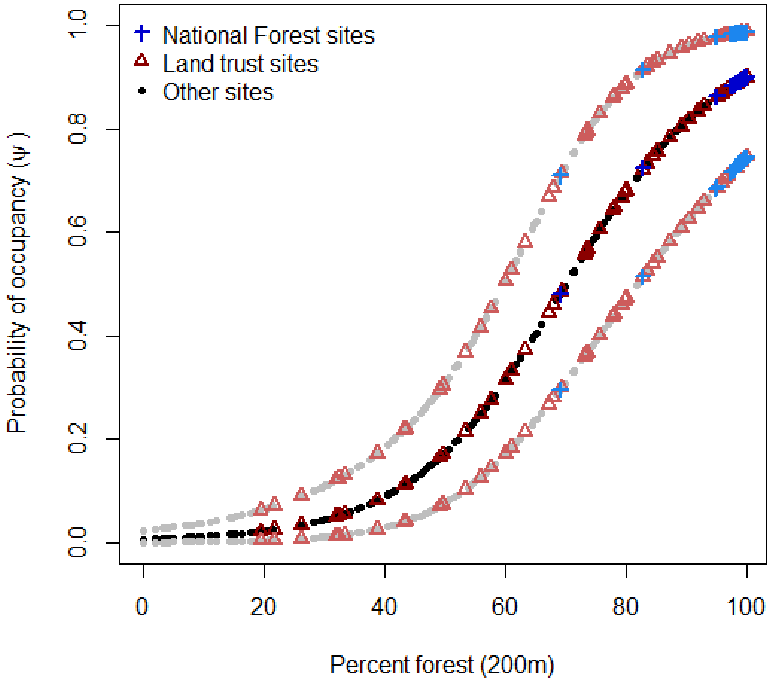


Figure 3.2: Posterior occupancy probabilities for the Black-and-white Warbler from the top-ranked model (ψ-13, *p11*-1, model posterior weight = 0.76) ordered by the percent forest within 200m of point count sites in the National Forest (blue crosses), on land trust properties (red triangles), or on unprotected properties (black circles). For each point count site, the mean of the posterior distribution is presented in dark shades and the 95% Bayesian credible interval is in pale shades.

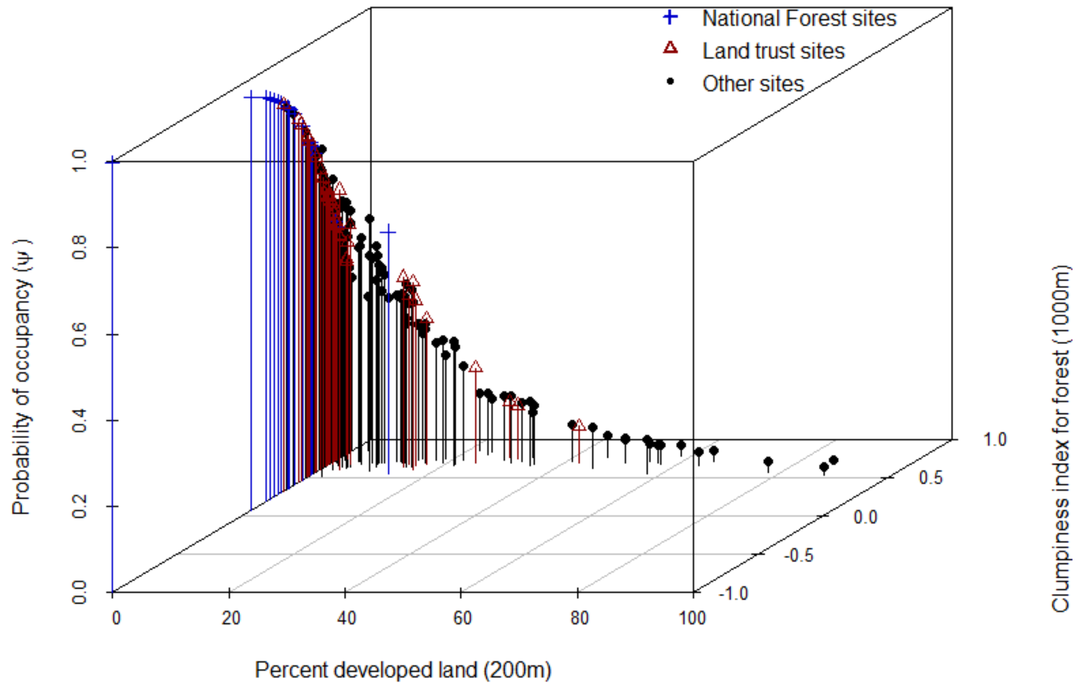


Figure 3.3: Posterior occupancy probabilities for the Blue-headed Vireo ordered by the percent developed land within 200m of point count sites and the forest clumpiness index within 1000m of point count sites in the National Forest (blue crosses), on land trust properties (red triangles), or on unprotected properties (black circles). These were the covariates in the occupancy function of the top-ranked models (ψ-21), but the two top-ranked models had different covariates in the true positive detection function (*p11*-1, model posterior weight = 0.48 and *p11*-2, model posterior weight = 0.47). For each point count site, the mean of the posterior distribution from the ψ-21, *p11*-1 model is shown. Estimates from the ψ-21, *p11*-2 model exhibited a very similar pattern.

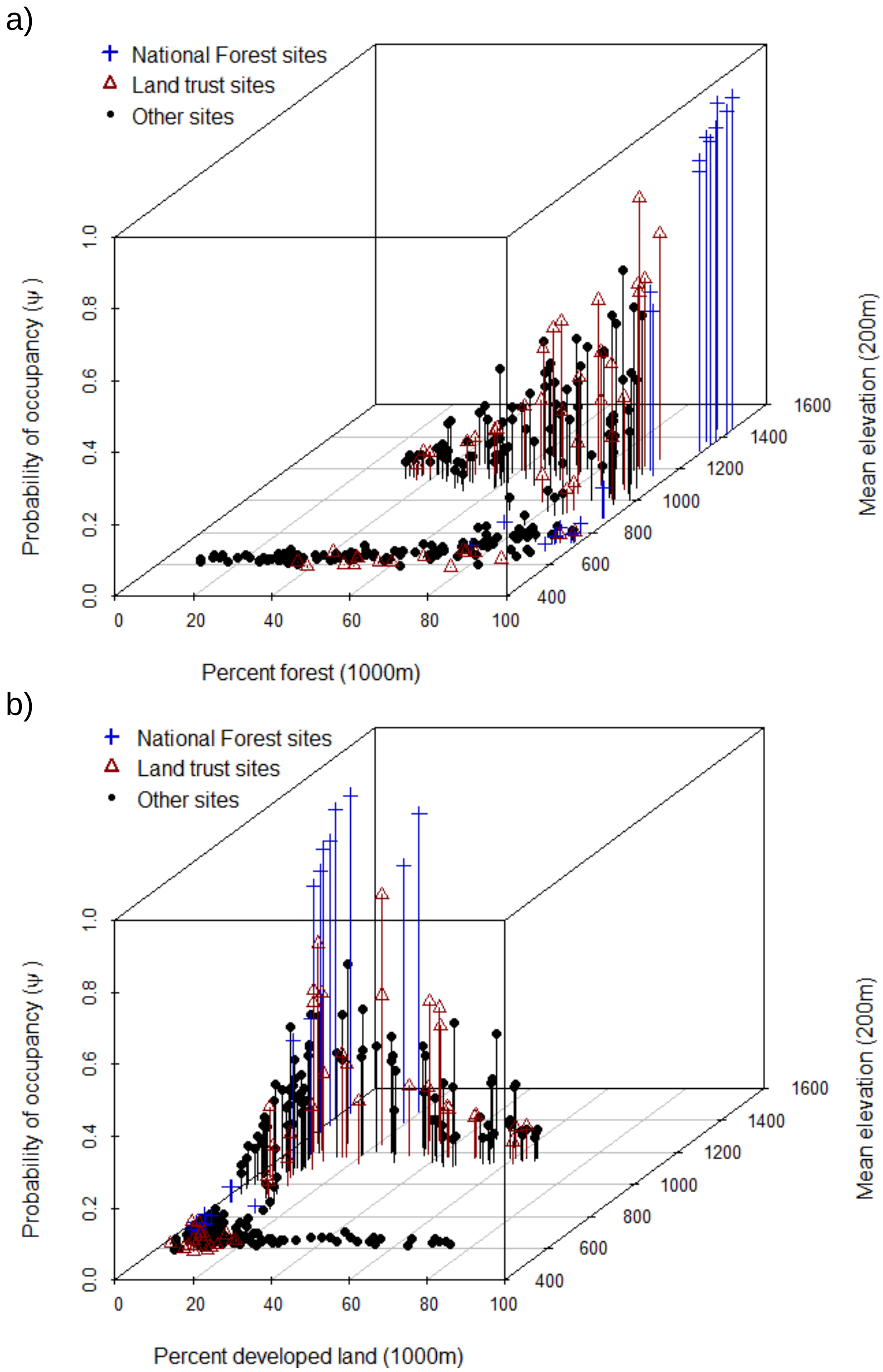
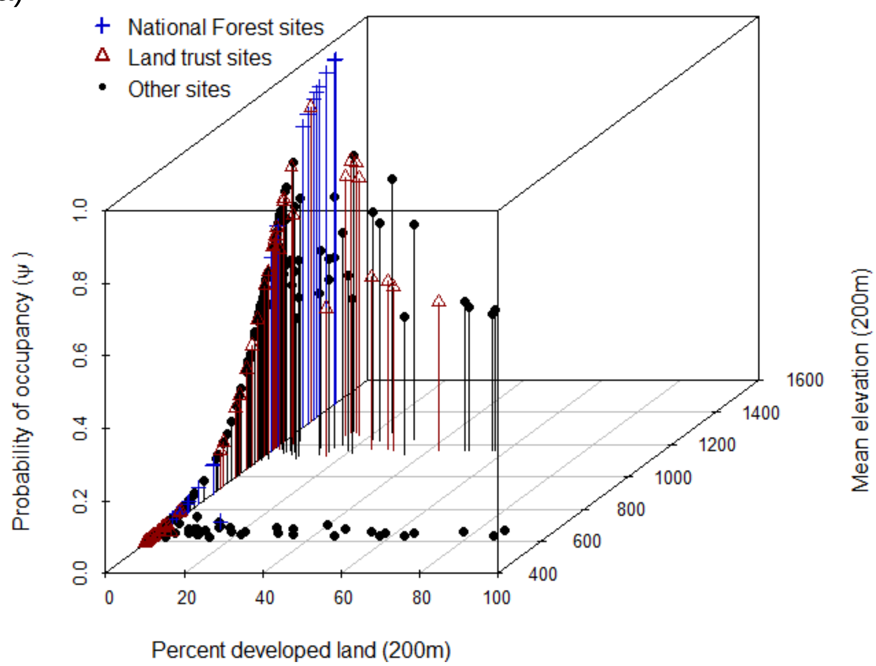


Figure 3.4: Posterior occupancy probabilities for the Canada Warbler ordered by a) the percent forest within 1000m of point count sites and the mean elevation within 200m of point count sites or b) the percent developed land within 1000m of point count sites and the mean elevation within 200m of point count sites in the National Forest (blue crosses), on land trust properties (red triangles), or on unprotected properties (black circles). These were the covariates in the two top-ranked models (a: ψ-1, *p11*-1, model posterior weight = 0.45, b: ψ-5, *p11*-1, model posterior weight = 0.35). For each point count site, the mean of the posterior distribution is shown.

a)



b)

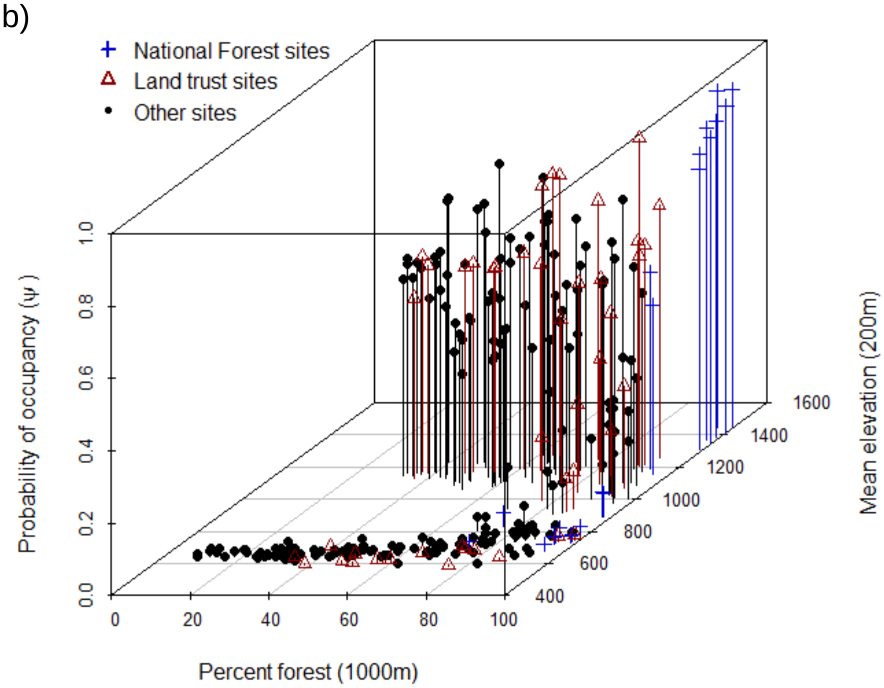


Figure 3.5: Posterior occupancy probabilities for the Veery ordered by a) the percent forest within 1000m of point count sites and the mean elevation within 200m of point count sites or b) the percent developed land within 200m of point count sites and the mean elevation within 200m of point count sites in the National Forest (blue crosses), on land trust properties (red triangles), or on unprotected properties (black circles). These were the covariates in the two top-ranked models (a: ψ-15, *p11*-1, model posterior weight = 0.49, b: ψ-1, *p11*-1, model posterior weight = 0.32). For each point count site, the mean of the posterior distribution is shown.

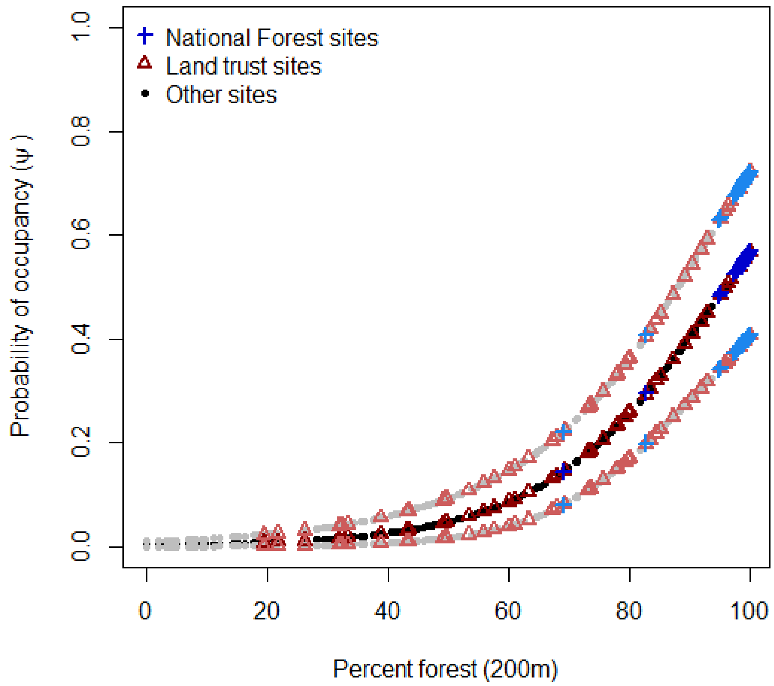


Figure 3.6: Posterior occupancy probabilities for the Black-throated Blue Warbler from the top-ranked model (*ψ*-13, *p11*-1, model posterior weight = 0.87) ordered by the percent forest within 200m of point count sites in the National Forest (blue crosses), on land trust properties (red triangles), or on unprotected properties (black circles). For each point count site, the mean of the posterior distribution is presented in dark shades and the 95% Bayesian credible interval is in pale shades.

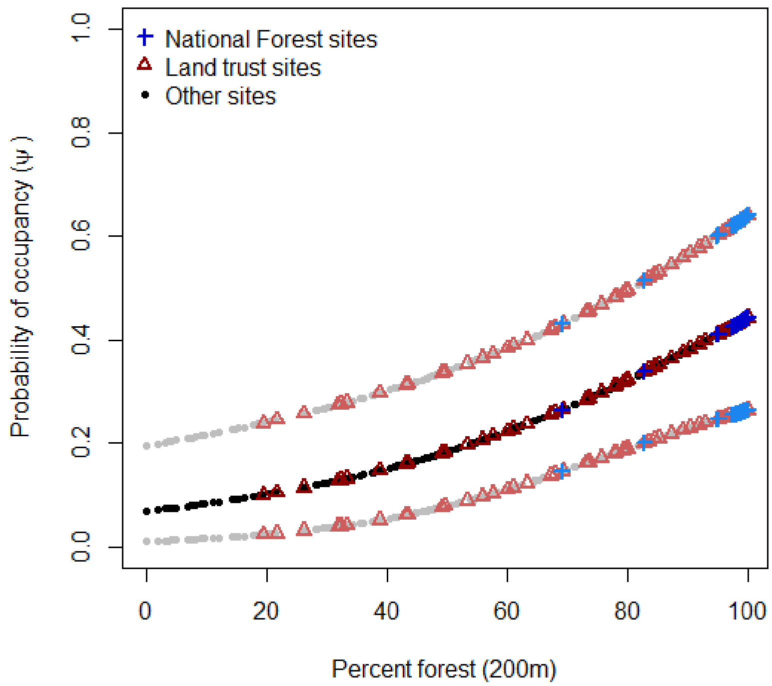


Figure 3.7: Posterior occupancy probabilities for the Wood Thrush from the top-ranked model (ψ-13, *p11*-1, model posterior weight = 0.57) ordered by the percent forest within 200m of point count sites in the National Forest (blue crosses), on land trust properties (red triangles), or on unprotected properties (black circles). For each point count site, the mean of the posterior distribution is presented in dark shades and the 95% Bayesian credible interval is in pale shades.

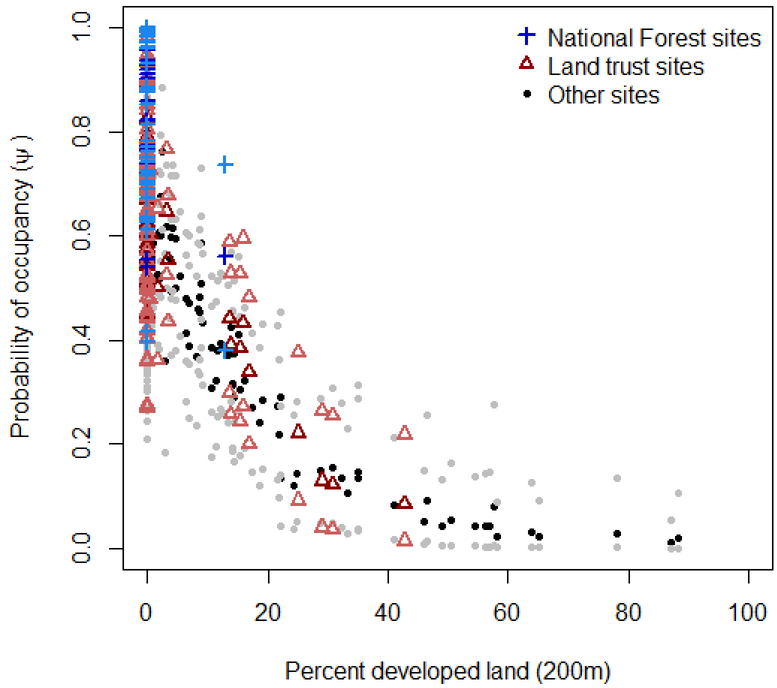


Figure 3.8: Posterior occupancy probabilities for the Blue-headed Vireo ordered by the percent developed land within 200m of point count sites in the National Forest (blue crosses), on land trust properties (red triangles), or on unprotected properties (black circles). This was one of two covariates in the occupancy function of the top-ranked models (ψ-21), but the two top-ranked models had different covariates in the true positive detection function (*p11*-1, model posterior weight = 0.48 and *p11*-2, model posterior weight = 0.47). For each point count site, the mean of the posterior distribution from the ψ-21, *p11*-1 model is presented in dark shades and the 95% Bayesian credible interval is in pale shades. Posterior occupancy probabilities from the ψ-21, *p11*-2 model exhibited a very similar pattern.

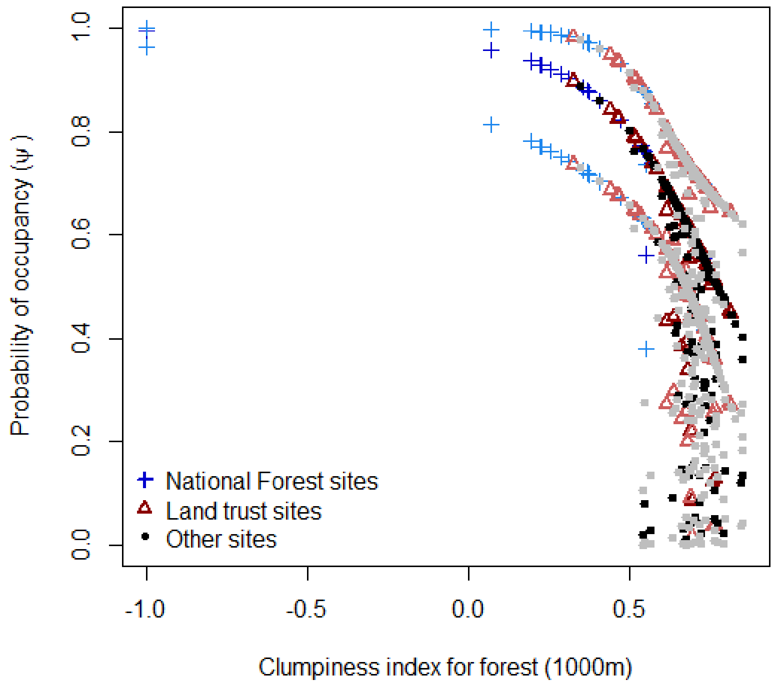
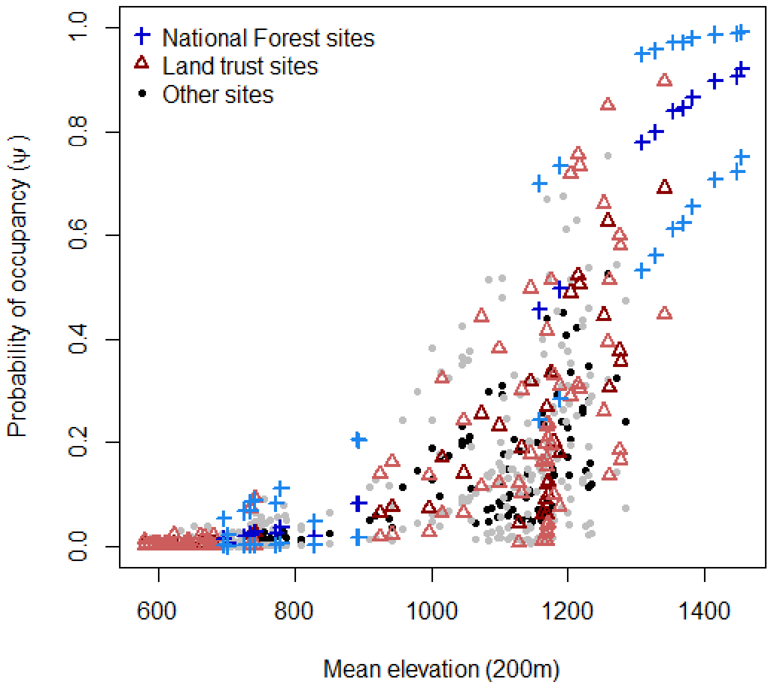


Figure 3.9: Posterior occupancy probabilities for the Blue-headed Vireo ordered by the forest clumpiness index within 1000m of point count site in the National Forest (blue crosses), on land trust properties (red triangles), or on unprotected properties (black circles). This was one of two covariates in the occupancy function of the top-ranked models (ψ-2 1), but the two top-ranked models had different covariates in the true positive detection function (*p11*-1, model posterior weight = 0.48 and *p11*-2, model posterior weight = 0.47). For each point count site, the mean of the posterior distribution from the ψ-21, *p11*-1 model is presented in dark shades and the 95% Bayesian credible interval is in pale shades. Posterior occupancy probabilities from the ψ-21, *p11*-2 model exhibited a very similar pattern.

a)



b)

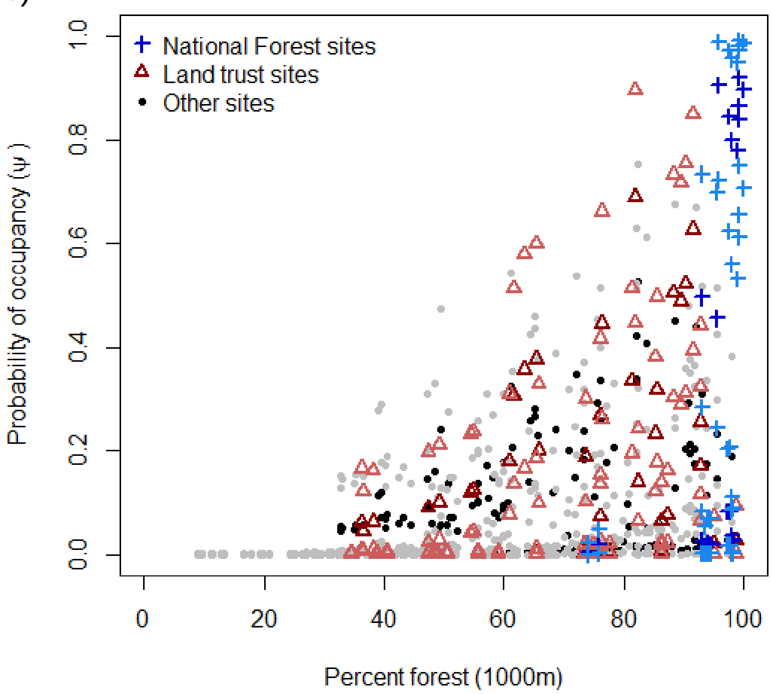


Figure 3.10: Posterior occupancy probabilities for the Canada Warbler ordered by the a) mean elevation within 200m of point count sites or b) percent forest within 1000m of point count sites in the National Forest (blue crosses), on land trust properties (red triangles), or on unprotected properties (black circles). These were the covariates in the occupancy function of the top-ranked model (ψ-1, *p11*-1, model posterior weight = 0.45). For each point count site, the mean of the posterior distribution is presented in dark shades and the 95% Bayesian credible interval is in pale shades.

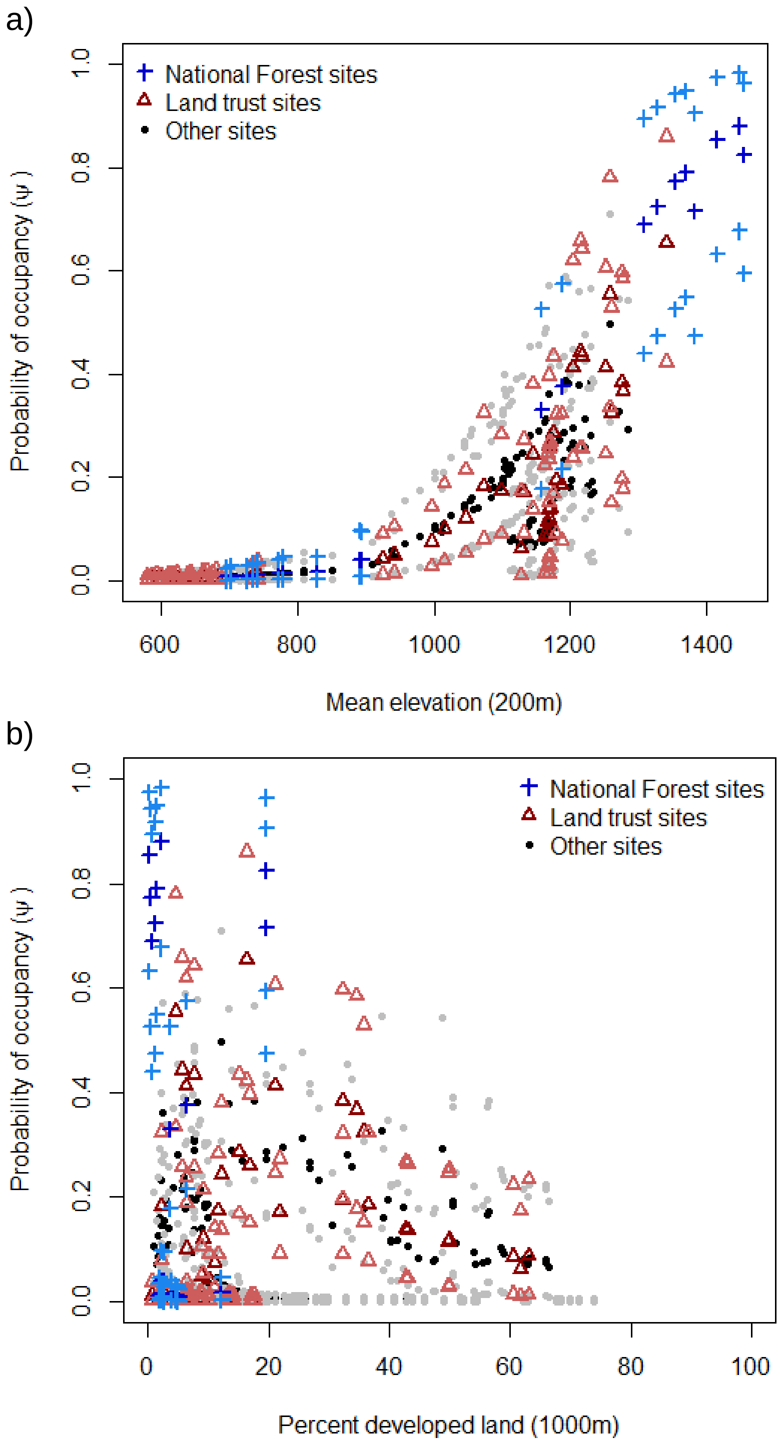


Figure 3.11: Posterior occupancy probabilities for the Canada Warbler ordered by the a) mean elevation within 200m of point count sites or b) percent developed land within 1000m of point count sites in the National Forest (blue crosses), on land trust properties (red triangles), or on unprotected properties (black circles). These were the covariates in the occupancy function of the second-ranked model (ψ-5, *p11*-1, model posterior weight = 0.35). For each point count site, the mean of the posterior distribution is presented in dark shades and the 95% Bayesian credible interval is in pale shades.

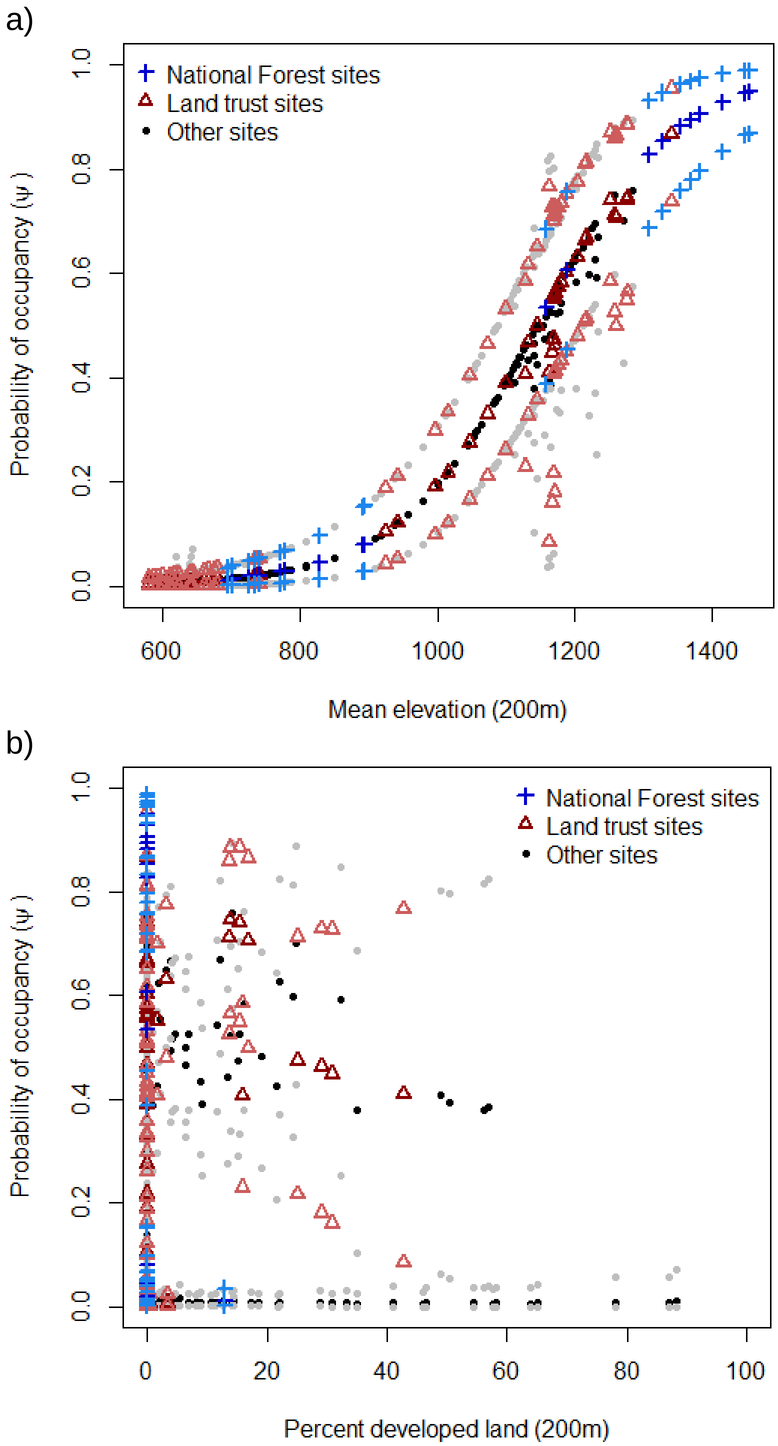
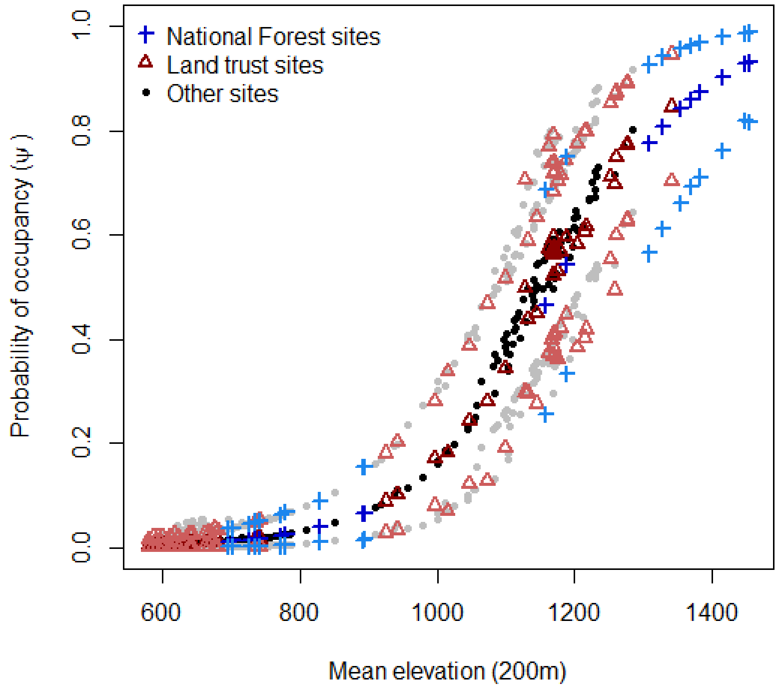


Figure 3.12: Posterior occupancy probabilities for the Veery ordered by the a) mean elevation within 200m of point count sites or b) percent developed land within 200m of point count sites in the National Forest (blue crosses), on land trust properties (red triangles), or on unprotected properties (black circles). These were the covariates in the occupancy function of the top-ranked model (ψ-15, *p11*-1, model posterior weight = 0.49). For each point count site, the mean of the posterior distribution is presented in dark shades and the 95% Bayesian credible interval is in pale shades.

a)



b)

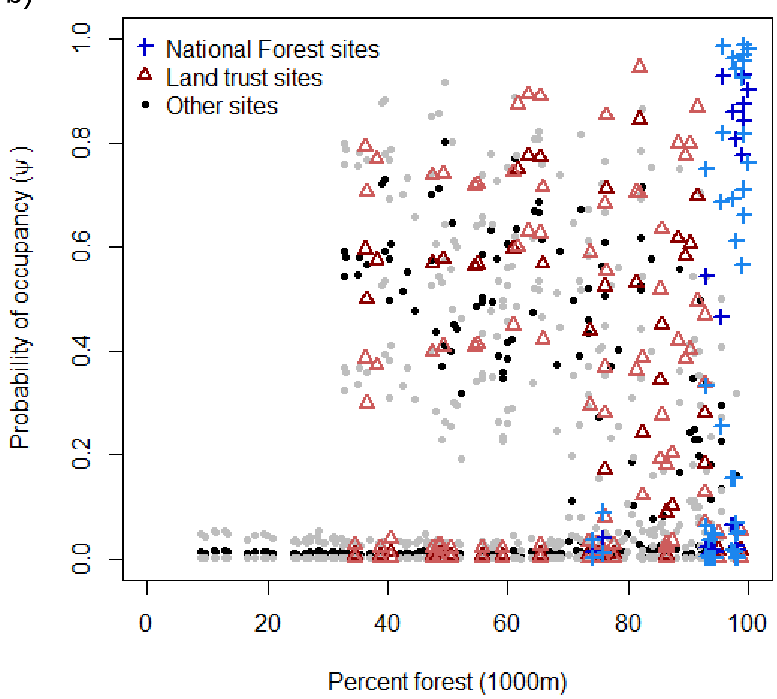


Figure 3.13: Posterior occupancy probabilities for the Veery ordered by the a) mean elevation within 200m of point count sites or b) percent forest within 1000m of point count sites in the National Forest (blue crosses), on land trust properties (red triangles), or on unprotected properties (black circles). These were the covariates in the occupancy function of the top-ranked model (ψ-1, *p11*-1, model posterior weight = 0.32). For each point count site, the mean of the posterior distribution is presented in dark shades and the 95% Bayesian credible interval is in pale shades.

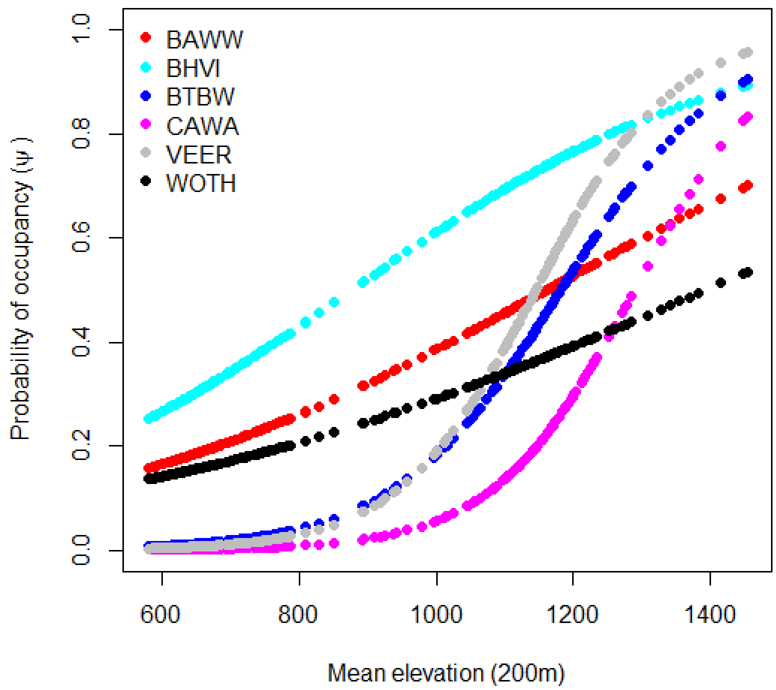


Figure 3.14: Relationship between the mean elevation within 200m of point count sites and occupancy for the Black-and-white Warbler (BAWW), Blue-headed Vireo (BHVI), Black-throated Blue Warbler (BTBW), Canada Warbler (CAWA), Veery (VEER), and Wood Thrush (WOTH). Occupancy probabilities were calculated from an equation including an intercept and coefficient derived from model-averaging of posterior probabilities that did not include zero in the 95% Bayesian credible interval.

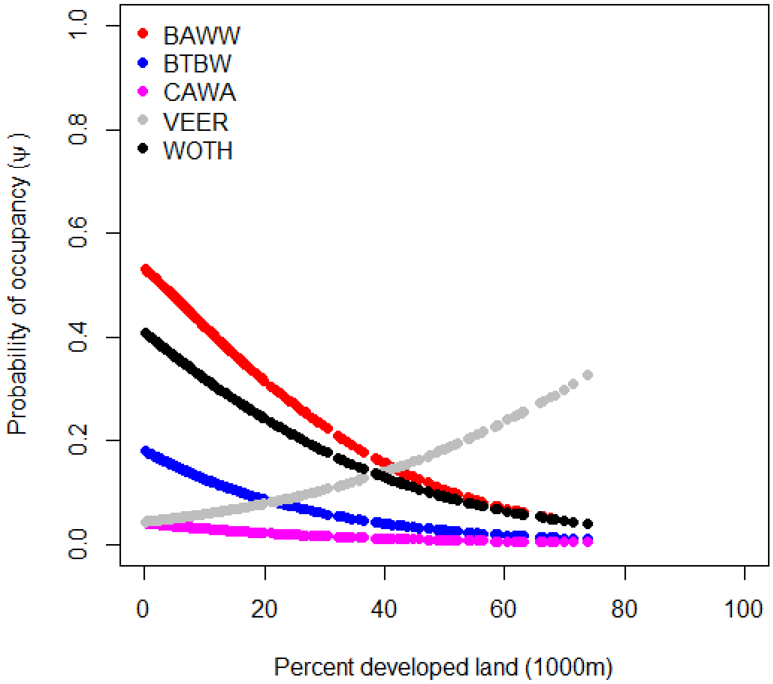


Figure 3.15: Relationship between the percent developed land within 1000m of point count sites and occupancy for the Black-and-white Warbler (BAWW), Black-throated Blue Warbler (BTBW), Canada Warbler (CAWA), Veery (VEER), and Wood Thrush (WOTH). Occupancy probabilities were calculated from an equation including an intercept and coefficient derived from model-averaging of posterior probabilities that did not include zero in the 95% Bayesian credible interval. The models for the Blue-headed Vireo (BHVI) that had posterior weights of at least 0.01 did not include this covariate.

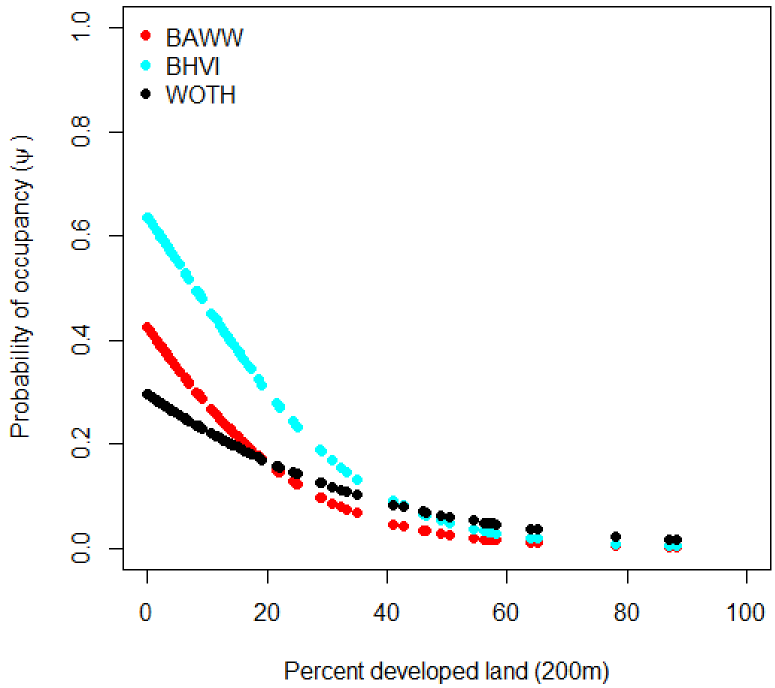


Figure 3.16: Relationship between the percent developed land within 200m of point count sites and occupancy for the Black-and-white Warbler (BAWW), Blue-headed Vireo (BHVI), and Wood Thrush (WOTH). Occupancy probabilities were calculated from an equation including an intercept and coefficient derived from model-averaging of posterior probabilities that did not include zero in the 95% Bayesian credible interval (BCI). The models for the Black-throated Blue Warbler (BTBW) that had posterior weights of at least 0.01 did not include this covariate, and the 95% BCI for the Canada Warbler (CAWA) and Veery (VEER) included zero.

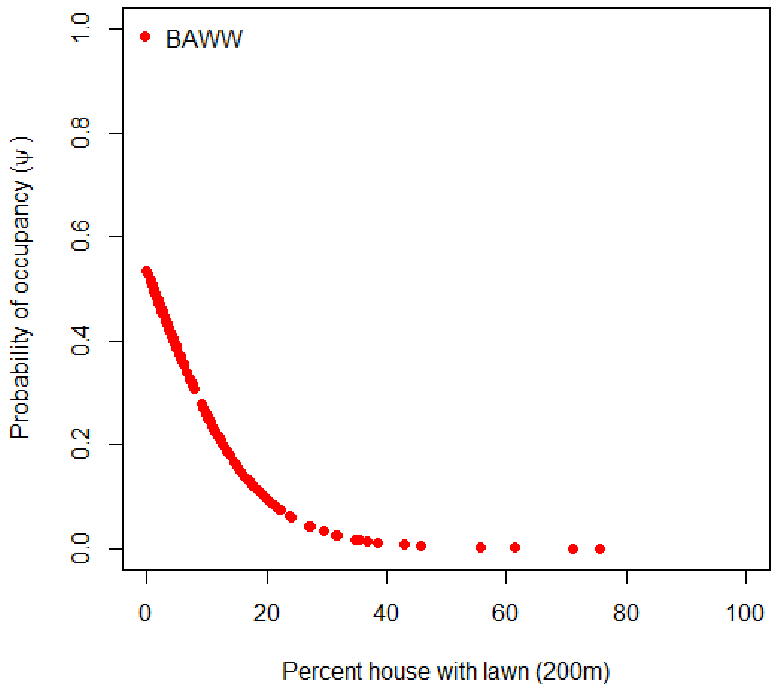


Figure 3.17: Relationship between the percent house with lawn within 200m of point count sites and occupancy for the Black-and-white Warbler (BAWW). Occupancy probabilities were calculated from an equation including an intercept and coefficient derived from model-averaging of posterior probabilities that did not include zero in the 95% Bayesian credible interval. The models for the Blue-headed Vireo (BHVI), Black-throated Blue Warbler (BTBW), Canada Warbler (CAWA), Veery (VEER), or Wood Thrush (WOTH) that had posterior weights of at least 0.01 did not include this covariate.

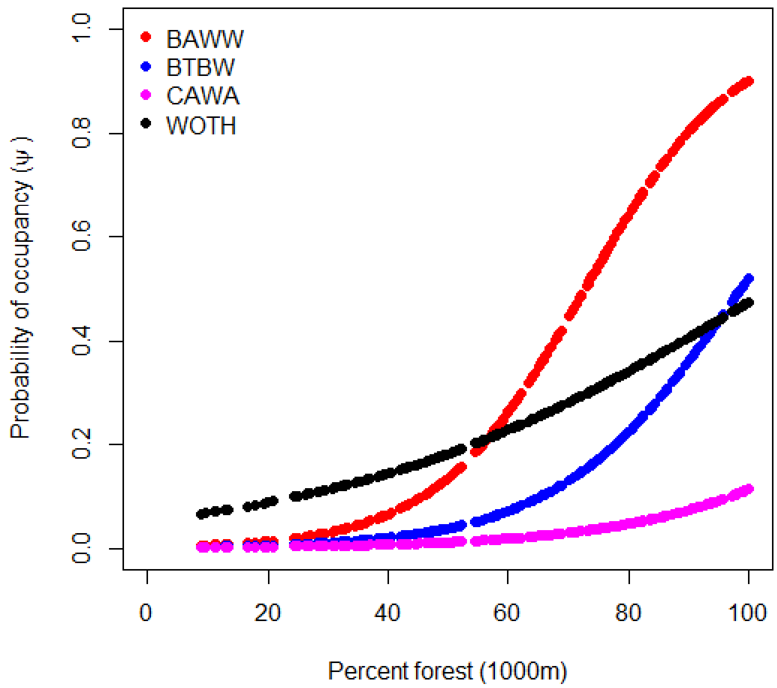


Figure 3.18: Relationship between the percent forest within 1000m of point count sites and occupancy for the Black-and-white Warbler (BAWW), Black-throated Blue Warbler (BTBW), Canada Warbler (CAWA), and Wood Thrush (WOTH). Occupancy probabilities were calculated from an equation including an intercept and coefficient derived from model-averaging of posterior probabilities that did not include zero in the 95% Bayesian credible interval (BCI). The models for the Blue-headed Vireo (BHVI) that had posterior weights of at least 0.01 did not include this covariate, and the 95% BCI for the Veery (VEER) included zero.

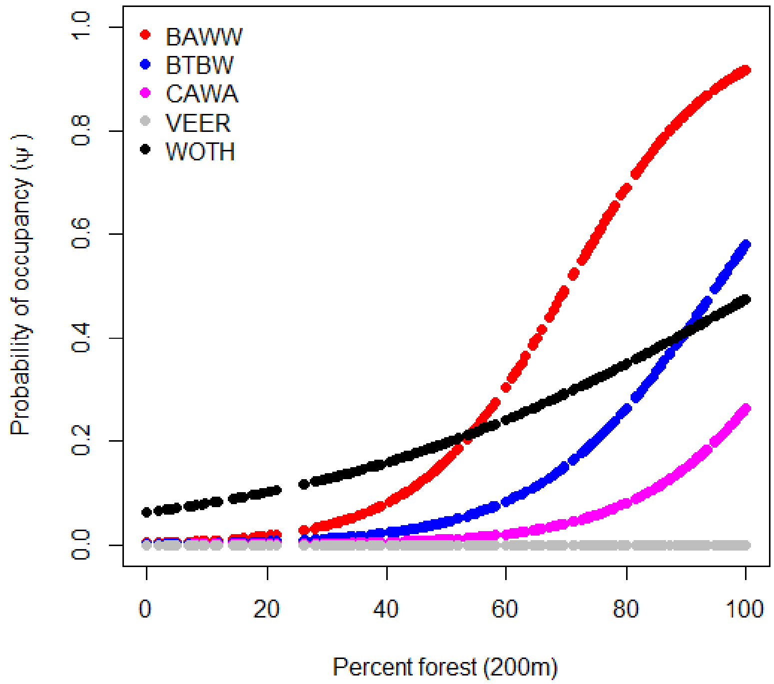


Figure 3.19: Relationship between percent forest within 200m of point count sites and occupancy for the Black-and-white Warbler (BAWW), Black-throated Blue Warbler (BTBW), Canada Warbler (CAWA), Veery (VEER), and Wood Thrush (WOTH). Occupancy probabilities were calculated from an equation including an intercept and coefficient derived from model-averaging of posterior probabilities that did not include zero in the 95% Bayesian credible interval. The models for the Blue-headed Vireo (BHVI) that had posterior weights of at least 0.01 did not include this covariate.

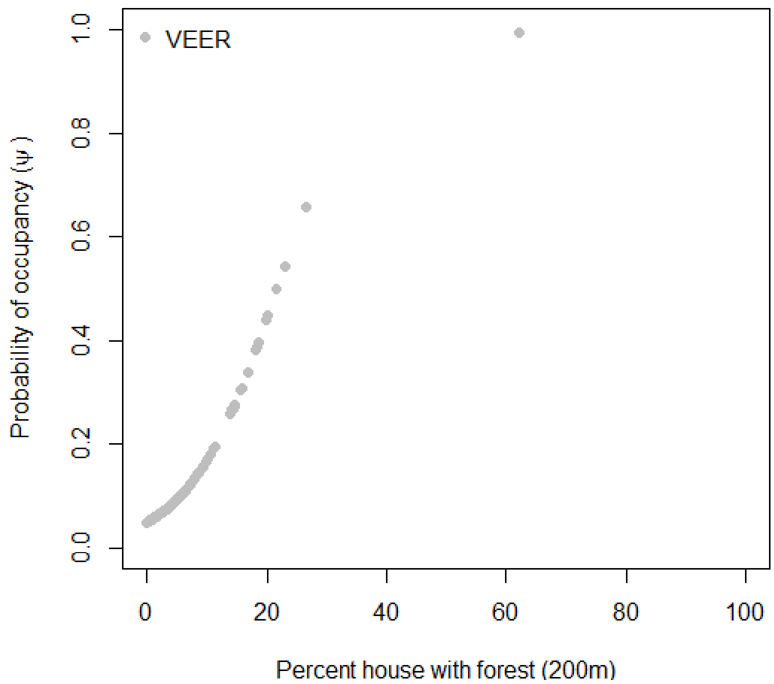


Figure 3.20: Relationship between the percent house with forest within 200m of point count sites and occupancy for the Veery (VEER). Occupancy probabilities were calculated from an equation including an intercept and coefficient derived from model-averaging of posterior probabilities that did not include zero in the 95% Bayesian credible interval. The models for the Blue-headed Vireo (BHVI) that had posterior weights of at least 0.01 did not include this covariate, and the 95% CI for the Black-and-white Warbler (BAWW), Black-throated Blue Warbler (BTBW), Canada Warbler (CAWA), and Wood Thrush (WOTH) included zero.

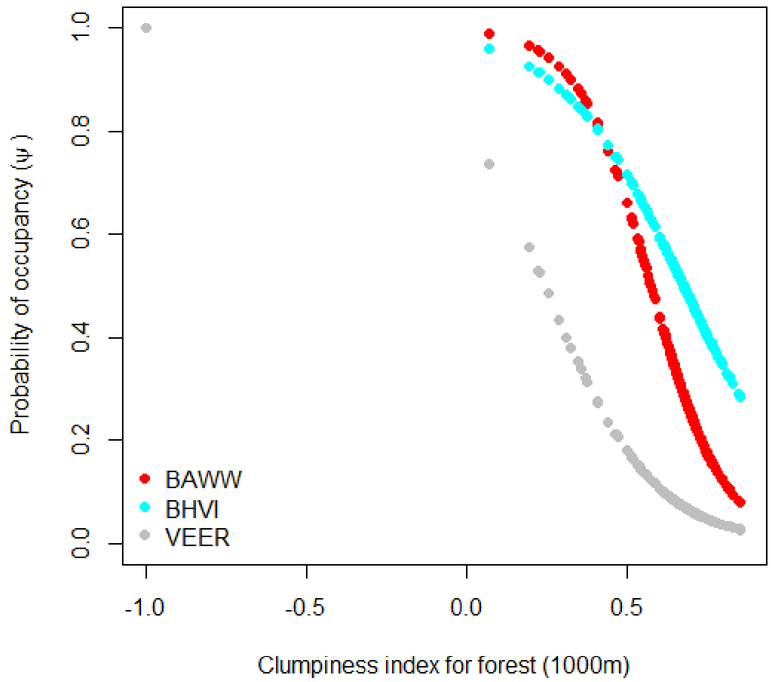


Figure 3.21: Relationship between the forest clumpiness index within 1000m of point count sites and occupancy for the Black-and-white Warbler (BAWW), Blue-headed Vireo (BHVI), and Veery (VEER). Occupancy probabilities were calculated from an equation including an intercept and coefficient derived from model-averaging of posterior probabilities that did not include zero in the 95% Bayesian credible interval (BCI). The models for the Black-throated Blue Warbler (BTBW) that had posterior weights of at least 0.01 did not include this covariate, and the 95% BCI for the Canada Warbler (CAWA) and Wood Thrush (WOTH) included zero.

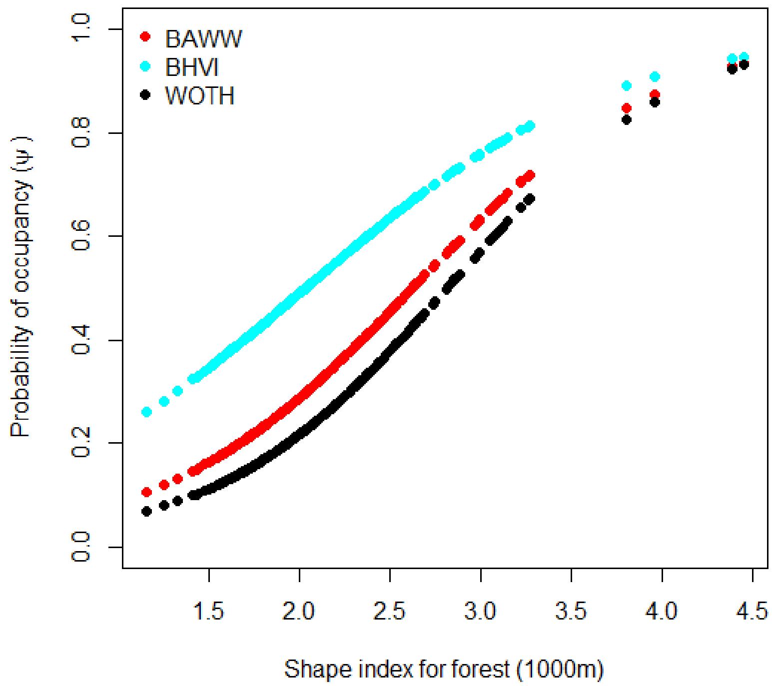


Figure 3.22: Relationship between the mean shape index for forest patches within 1000m of point count sites and occupancy for the Black-and-white Warbler (BAWW), Blue-headed Vireo (BHVI), and Wood Thrush (WOTH). Occupancy probabilities were calculated from an equation including an intercept and coefficient derived from model-averaging of posterior probabilities that did not include zero in the 95% Bayesian credible interval. The models for the Veery (VEER) that had posterior weights of at least 0.01 did not include this covariate, and the 95% CI for the Black-throated Blue Warbler (BTBW) and Canada Warbler (CAWA) included zero.

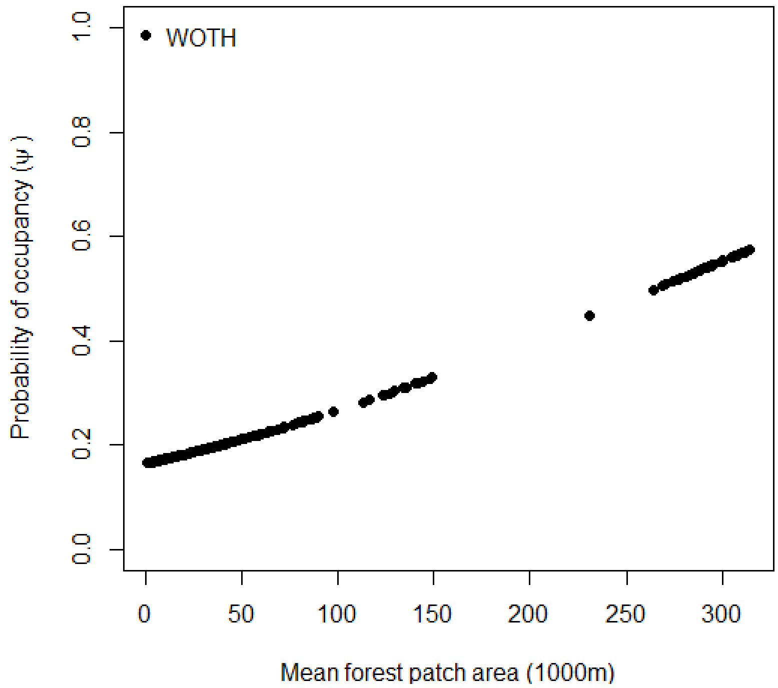


Figure 3.23: Relationship between the mean forest patch area within 1000m of point count sites and occupancy for the Wood Thrush (WOTH). Occupancy probabilities were calculated from an equation including an intercept and coefficient derived from model-averaging of posterior probabilities that did not include zero in the 95% Bayesian credible interval. The models for the Black-and-white Warbler (BAWW), Blue-headed Vireo (BHVI), Black-throated Blue Warbler (BTBW), Canada Warbler (CAWA), or Veery (VEER) that had posterior weights of at least 0.01 did not include this covariate.

CHAPTER 4

USING STRUCTURED DECISION MAKING WITH LANDOWNERS TO ADDRESS PRIVATE FOREST MANAGEMENT AND PARCELIZATION: BALANCING MULTIPLE OBJECTIVES AND INCORPORATING UNCERTAINTY [3]

[3] Barlow, P. F., M. J. Conroy, J. Chamblee, and J. Hepinstall-Cymerman. To be submitted to *Ecology and Society*.

Abstract

Parcelization and forest fragmentation are of concern for ecological, economic, and social reasons. Many factors influence why parcelization occurs, but attempts to keep large, private forests intact may be supported by a process that incorporates landowners' objectives while evaluating management decision options. We propose structured decision making (SDM) as an approach to address land use decision problems and to help the owners of large, forested parcels maintain their property. Advantages of SDM include incorporating value-based and technical information, balancing multiple objectives, and addressing uncertainty. While SDM has typically been applied to decision problems involving public resources, we illustrate the usefulness of SDM to private resource management. We followed an SDM process with landowners in Macon County, North Carolina, an area that has little land use regulation and a history of discordant, ineffective attempts to address land use and development. Through a series of workshops, landowners defined their objectives for their property, identified potential decision options for forest management, built a Bayesian decision network to predict the outcomes of decision options and quantify the degree to which possible outcomes would fulfill their objectives, and determined the most and least promising management actions. The most promising forest management action for an average large, forested property (30 ha property with 22 ha of forest) in Macon County, given landowners' values, was crown thinning timber harvest under the Present-Use Value program, in which enrolled property is taxed at the present-use value (growing timber for commercial harvest) rather than at the full market value. The least promising forest management actions were selling 1 ha and personal use of the forest, with or without a conservation easement. Landowners reported that they enjoyed participating in the SDM project, and after reviewing the results of the decision network, 69% said they would

reconsider what they are currently doing to manage their forest. The decision option that landowners most frequently thought would best meet their objectives before seeing results from the decision network (personal use of the forest with or without an easement, selected 62% of the time) did not match findings from the decision network regarding the best decision option. This highlights the usefulness of SDM and the importance of outreach to owners of large forests.

Introduction

The problem: parcelization and forest fragmentation

In the 1920s, forest cover in the United States stabilized after many decades of declines, but forest fragmentation has been ongoing since the early 1900s (Sampson and DeCoster 2000, Best 2002). Also, the rate and extent of parcelization has increased in recent decades and has become a modern focus of research and conservation (DeCoster 1998, Best 2002). Parcelization and fragmentation of forestland are of concern because they have implications for the three components of sustainability: ecological, economic, and social dynamics (Salwasser et al. 1993, Rickenback and Gobster 2003).

Parcelization is defined as the division of a larger tract with a single owner into multiple, smaller parcels with multiple owners (Best 2002, Ko and He 2011). As a result of parcelization, the number of landowners increases, and the average parcel size decreases (Kendra and Hull 2005, Ko and He 2011). For example, between 1978 and 1994, the number of owners of small, forested parcels (4-20 ha) more than doubled (Birch 1996, Gobster and Rickenbach 2004). About 61% of the owners of forested parcels in the contiguous U.S. own less than 4 ha of forestland (Butler 2008).

In the process of parcelization, forests are frequently fragmented by increased construction of roads and buildings (Best 2002). Fragmentation is defined as the division of contiguous forest into discrete patches. These smaller patches often exhibit greater isolation and less interior habitat, and fragmented forests often provide fewer ecosystem services compared to equivalent intact forests (Groom et al. 1999, Best 2002). For example, forest fragmentation is detrimental to wildlife (Boulinier et al. 2001, Best 2002, Brooks 2003), wildlife habitat (Theobold et al. 1997), and water quality (Wear et al. 1998, LaPierre and Germain 2005).

Parcelization can also lead to changes in local economies (Harper et al. 1990). Smaller parcels may not be economically viable for timber production due to the economies of scale (Greene et al. 1997, Mehmood and Zhang 2001), so regional wood supplies may decrease (Wear et al. 1999), landowners may not be able to depend on this traditional source of income, and further parcelization may result (Ko and He 2011). Parcelization can also lead to further development and the conversion of previously forested land into more intense human land uses, particularly residential subdivisions (Mehmood and Zhang 2001, Best 2002, Gobster and Rickenbach 2004).

Finally, parcelization is associated with changes in social dynamics (Rickenback and Gobster 2003). As the number of landowners increases, landowner density also increases, and new landowners bring more diverse objectives and values to the community (Egan and Luloff 2000, Smith and Krannich 2000, Mehmood and Zhang 2001). New forestland owners often have different objectives than traditional forestland owners who manage timber primarily for economic return (Kendra and Hull 2005, Rickenbach and Steele 2006). As the community changes, residents may experience a loss of community identity and sense of place (Cumming and Norwood 2012).

Because many modern forestland owners have diverse objectives that differ from the traditionally dominate objectives, properties are smaller, forests are more fragmented, and landowners may face increasing pressure to parcelize, forest management professionals may benefit from new approaches to assist landowners as they decide how to manage their forest (Kendra and Hull 2005). Also, traditional forestland owners who are facing changing social and economic pressures could benefit from forest managers' use of new tools to guide decisions that enhance the sustainability of forestland. We propose structured decision making as a process that can meet these unique challenges.

Approach: structured decision making with forestland owners

Structured decision making (SDM) is an approach that will suit the need of forestland owners to balance multiple land use objectives given economic constraints and uncertainty. Typically, SDM has been a valuable process for working with diverse stakeholders to analyze decision problems related to a common resource, such as water or wildlife populations (e.g., Kuikka et al. 1999, Bromley et al. 2005). However, SDM could also benefit an individual who wants to make a decision about a privately-held resource but wants a rigorous way to balance multiple personal objectives and incorporate uncertainty in the analysis. Also, by developing an SDM approach to help individual forestland owners, a forest management planner could develop a process that can be tailored to multiple clients. If forestland owners explicitly define their objectives and constraints, this information could help forest management planners and conservation groups better understand forestland owners' perspectives and needs, and thus more effectively conserve forestland.

SDM is based on decision analysis, the use of quantitative methods to evaluate decision options (Keeney 1992, Keeney and Raiffa 1993, Clemen 1996, Peterson and Evans 2003, Wilson and McDaniels 2007, Gregory et al. 2012, Conroy and Peterson 2013). A key approach of decision analysis and SDM is to recognize the distinction between value-based information and technical information while explicitly integrating both types of information in the decision-making process (Keeney and McDaniels 1999, Gregory and Keeney 2002, Wilson and McDaniels 2007, Conroy et al. 2008). SDM facilitates rigorous, transparent decision-making even when there is much technical uncertainty or multiple, competing values (Funtowicz and Ravetz 1993, Conroy et al. 2008, Martin et al. 2009). Decisions made through an SDM process are expected to produce desirable outcomes more often than decisions that do not explicitly define objectives, weight conflicting objectives, and incorporate uncertainty (Conroy and Peterson 2013).

The main components of SDM are a definition of the decision problem, objectives based on the stakeholders' values, attributes to make objectives measurable, decision options that could help the stakeholders achieve their objective(s), one or more models to describe the expected outcomes of decision options, and a method to evaluate the degree to which each decision option is expected to fulfill the stakeholders' objectives (Hammond et al. 1999, Dorazio and Johnson 2003, McCarthy and Possingham 2007, Wilson and McDaniels 2007, Conroy et al. 2008, Irwin et al. 2011). These components, which we will discuss in more detail below, are developed through an iterative process where stakeholders provide input and the facilitator and technical consultants synthesize information while attempting to remain value-neutral (Phillips 1984, Wilson and McDaniels 2007, Miller et al. 2010, Raymond et al. 2010, Irwin et al. 2011). We designed a SDM project focused on the management of large, forested properties in Macon County, North Carolina, USA, that involved a series of workshops with forestland owners.

Study site: Macon County, North Carolina, USA

For this study, we focused on forestland owners in Macon County, North Carolina, USA, because Macon County has experienced high rates of residential development, there is a history of conflict over private property rights and land use regulations, existing conservation is largely done voluntarily by citizens, the region is one of the most biodiverse in North America, and it is the headquarters of the Coweeta Long Term Ecological Research (LTER) program (Barnes 1991, Gragson and Bolstad 2006). Coweeta is one of 25 National Science Foundation-supported LTER sites. The Coweeta LTER study region includes 60 counties in the Blue Ridge province of the southern Appalachian Mountains, and Coweeta's research focus is the reciprocal influence of people and ecological systems across space and time (Gragson and Bolstad 2006).

The aesthetic and recreational opportunities, low cost of living, low taxes, and lack of zoning regulations in the southern Appalachian region have contributed to amenity migration (Marcouiller et al. 2002, Gragson and Bolstad 2006). Generally, amenity migration has occurred as retirees, second-home owners, and urban commuters have purchased properties that were formed by subdividing former agroforestry lands that had been owned by a relatively older, less educated, and more impoverished population (Wear and Greis 2002, Cho et al. 2003, Gragson and Bolstad 2006).

As the density of development has increased and landowners with diverse backgrounds and values have moved to the area, questions about land use regulation have been proposed. Many Macon County landowners think the rapid growth is detrimental, but there has not been agreement about an appropriate response (Cho et al. 2005, Gragson and Bolstad 2006, Cho et al. 2009, Cumming and Norwood 2012). There have been various attempts to pass land use regulations in Macon County throughout the past 30 years, but they have largely failed (Cumming and Norwood 2012). The failure may be due, in part, to a tradition of individual and family independence, perceived threats to property rights, misinformation spread by policy opponents, ineffective communication by organizers, and problems with the planning process itself (Falk and Lyson 1988, Cho et al. 2003, Cho et al. 2005, Cumming and Norwood 2012). Macon County is not unique in experiencing confrontational, and eventually stalled, land use decision making, and this experience has been attributed to the lack of effective opportunities for citizens to express their perspectives, consider potential options, and learn from each other in a respectful and productive setting (Susskind et al. 1999, Lando 2003, Senecah 2004, Stewart et al. 2004, Cumming and Norwood 2012).

Research statement

The purpose of this study is to illustrate how SDM can be implemented with landowners to assist them with land use decision making. We describe the procedure involved with conducting an SDM project with landowners and discuss advantages and challenges of using SDM in this context. In Macon County, we applied SDM to the question of forest management on large parcels (30 ha property with 22 ha of forest), and we present the forest management approaches that were identified as producing the best expected outcomes on average. Finally, we consider landowners' perception of the SDM project and the potential for land trusts and forest management planners to benefit from SDM in general and the results of this study in particular.

Methods

Recruiting landowners

To identifying landowners for the SDM workshops, we first interviewed 50 owners of large, forested properties in Macon County (University of Georgia IRB Human Subjects approval, study 2012108313). Interviewees were identified through a combination of snowball and random stratified sampling (Bernard 2002). In snowball sampling, initial participants are asked to recommend other people who might be interested in participating, so the sample grows through personal contacts. Since land use can be a controversial topic in Macon County, snowball sampling provided a way for us to be introduced to an interviewee by a mutual friend. This gave us credibility and helped the interviewee feel more comfortable and confident about talking with us. We produced a list of potential interviewees based on recommendations from prominent individuals in the community with whom P.F.B. had become acquainted during three previous years of research in Macon County and from colleagues at Coweeta, the Land Trust for the Little Tennessee (LTLT), the Highlands-Cashiers Land Trust, and the Highlands Plateau Audubon Society.

To increase sample size and the diversity of interviewees, we also used random stratified sampling. We used Macon County's parcel records to create ten strata for random sampling. The ten strata were formed through all combinations of the following criteria: landowner residency in Macon County (full time or not full time), conservation easement on the property (yes or no), buildings on the property (yes or no), length of ownership of the property (ownership began before 1994 or began after 1994). Next, we used the parcel records and a 2006 land cover and land use map that was developed for Coweeta LTER and used the same classification scheme as National Land Cover Dataset (NLCD) maps to identify parcels in each of the strata that were at least 20 ha in total area and contained at least 4 ha of forest. Also, a husband and wife who are local birding experts but did not meet the property area criteria were included because we anticipated that avian conservation would be a focus of the SDM process, this couple would be able to provide expertise, and they are known and respected in the community.

When we called a landowner, we explained the project and asked the landowner if they would participate in the interview (Appendix G). If the landowner agreed to the interview, we proceeded with the interview script (Appendix G) and took notes on the landowner's responses. If the landowner declined to participate in the interview, we selected a replacement landowner to call. After 50 landowners were interviewed, we identified the landowners that expressed interest in participating in the SDM workshops.

Typically when SDM is used to address a public natural resource management question, stakeholders representing different interests participate. Therefore, we wanted to include landowners with diverse socio-demographic backgrounds and property characteristics, as they are expected to be related to different land use values. Further, many scientists at Coweeta hypothesized that multi-generational landowners and new residents differ in land use values and practices, so we included both types of landowners. We contacted the landowners who said during the interview that they were interested in the workshops, asked about availability, and scheduled two series of workshops. Landowners were assigned to a workshop series based on their availability and the arrangement that would maximize landowner diversity within a series (Table 4.1). The two series were independent such that landowner composition remained constant within a series.

Workshops with landowners

The SDM workshops were held in the conference room at the U.S. Forest Service's Coweeta Hydrologic Lab in Otto, North Carolina. Ten landowners were in each series, each series consisted of four workshops, and all workshops were moderated by P.F.B. Three workshops were held in the summer of 2012, one workshop was held in the summer of 2013, and the workshops lasted about three hours each. When landowners were being recruited for the SDM project, we emphasized that participation in all four workshops would be important because each workshop built upon previous workshop. We selected landowners for the project whose schedules allowed participation in all four workshops, but we scheduled the specific dates and times of workshops according to landowners' availability. In addition, we provided nominal financial compensation to encourage attendance at all four workshops.

Objectives

The goal of the first workshop was for the landowners to identify their land use objectives. First, however, we had the landowners introduce themselves, and P.F.B. gave a presentation on SDM that included the components of SDM, why SDM is a useful approach to decision-making, and an example of SDM (Clemen 1996). After the presentation, we presented a general statement of the decision context: what can you do to your forest to maximize the achievement of your land use objectives? Throughout the project, we asked the landowners for their personal perspectives, but the analysis was not intended to apply to a specific property. Rather, we combined all of the landowners' perspectives and modeled average expectations for a large, forested property in Macon County to evaluate decision options for a typical property. Specifically, we considered a 30 ha property at 750 m elevation with 22 ha of forest, approximately the mean characteristics of the properties owned by the SDM participants as determined from parcel records and aerial photos of Macon County.

Next, we guided the landowners through an exercise (Appendix H) to identify their land use objectives (Keeney 1992). Landowners were presented with questions and given time to think about their responses silently. Then, the group reassembled to discuss landowners' thoughts (Martin et al. 2009). We reminded the landowners to focus on their objectives but, at this point, to not be concerned about apparent feasibility. During the discussion, we typed landowners' comments and projected them on a screen visible to all the landowners. This provided the landowners with an opportunity to articulate their values and interests, hear each other's objectives, and confirm that we understood them and made accurate transcriptions (Miller et al. 2010).

Between the first and second workshops, we constructed an objectives network based on the landowners' comments and emailed the draft objectives network to the landowners (McDaniels 2000). Landowners were encouraged to contact us prior to the second workshop if they had comments or revisions regarding the objectives network. An objectives network is a diagram in which fundamental and means objectives are distinguished. Fundamental objectives represent the primary values that are inherently important to the decision-maker, while means objectives serve as the path to achieving the fundamental objectives. The questions "why is the objective important?" and "how do we get there?" help to separate fundamental and means objectives (Keeney 1992, Clemen 1996, Conroy et al. 2008). We included all of the objectives mentioned by landowners in the objectives network, but explained that, later in the SDM process, each landowner could assign weights to the objectives reflecting their personal values.

Attributes, decision options, and nascent influence diagram

The goals for the second workshop were to review the objectives network, identify attributes to make the fundamental objectives measurable, brainstorm decision options, and begin to construct an influence diagram. Landowners were asked for any revisions to the objectives network, and once the fundamental objectives were finalized, we identified the fundamental objectives that lacked natural quantitative scales. Since decision options are assessed relative to fundamental objectives, there must be a way to measure the degree to which fundamental objectives are achieved (Wilson and McDaniels 2007). Attributes provide the scales to measure the degree to which an outcome from a decision option satisfies fundamental objectives (Failing et al. 2007, Gregory and Long 2009). When there was not a natural scale for a fundamental objective (e.g., dollars, hours, hectares, number of individuals), the landowners created a constructed scale with explicitly defined levels through consensus-based discussion (Keeney and Gregory 2005, Miller et al. 2010). Attributes were identified for each fundamental objective, both those with natural scales and those with constructed scales.

By first identifying fundamental objectives, creative ideas for decision options might be revealed (McDaniels 2000). When faced with a problem that requires a decision, people often turn to the suite of obvious, default decision options (Gregory and Long 2009). However, by going through the process of defining the decision context and identifying fundamental objectives, decision-makers may have valuable insights into potential decision options. For example, means objectives suggest the path that leads from decision options to fundamental objectives (Keeney 1992, Wilson and McDaniels 2007). The Macon County landowners identified decision options through consensus-based discussion (Miller et al. 2010). The landowners were encouraged to be creative and to think of many ways to achieve their fundamental objectives that could be implemented by a single landowner.

The last topic for the second workshop was the influence diagram. The objectives network provided the beginning framework for constructing an influence diagram (Marcot et al. 2001, 2006). An influence diagram consists of the nodes that represent variables connecting the decision options to the fundamental objectives and the arrows that represent the causal links between variables. Each node represents a variable that can take one of a discrete number of states (Marcot et al. 2001).

At the second workshop, we led the landowners through discussions about what nodes should be included and how arrows should connect nodes so that the influence diagram realistically described how forest management decisions affect fundamental objectives. The influence diagram, and later the Bayesian decision network, was built in Netica 4.09 (Norsys Software Corp.).

Final influence diagram, objective weights, and attribute scores

The goals of the third workshop were to finalize the influence diagram and to identify the landowners' objective weights and attribute scores. Ideally, the influence diagram should include the most important components while being as simple as possible (Phillips 1984, Peterson and Evans 2003). However, if there was disagreement about the components or structure that should be included in the influence diagram or if discussions highlighted an area where there was a lack of information, this structural uncertainty could be accounted for by designing multiple models. Each model could be considered a hypothesis of system behavior, and the suite of models could be incorporated when analyzing the decision options (Burgman 2005, Conroy et al. 2008, Martin et al. 2009).

The influence diagram provides the structure for the Bayesian decision network, a model that predicts the expected outcomes of each decision option and assesses how well the expected outcomes satisfy the fundamental objectives (Conroy et al. 2008, Miller et al. 2010, Irwin et al. 2011). To analyze the decision options in a Bayesian decision network, objective weights and attribute scores were also required.

An objective weight reflects the importance of the objective to the landowner, where a larger weight indicates greater importance. An attribute score reflects how satisfied a landowner would be if that level in the attribute scale occurred. Landowners completed worksheets to identify their objective weights and assign attribute scores (Appendix H). Each landowner was given a worksheet to complete on their own that used the swing weighting method to elicit objective weights (Clemen 1996). The worksheet presented sets of different scenarios, with each scenario highlighting one of the objectives. The scenarios were combined within a set so that similar objectives were grouped. In one scenario in a set, the lowest level in the attribute scale occurred for each objective. In the remaining scenarios, the lowest level in the attribute scale occurred for all but one objective, and for that objective, the highest level in the attribute scale occurred. Hence, the worst case scenario provided a reference against which to compare scenarios where each of the objectives swung to the best possible outcome. Landowners were asked to rank the scenarios within a set from the one with which they would be most satisfied to the one with which they would be least satisfied. In addition, landowners were asked to assign grades to the scenarios that corresponded to the ranking they chose. The grades indicated how satisfied the landowner would be if the scenario occurred. Since many people are familiar with a grade scale from 0 to 100, we asked landowners to use this scale, where 100 was complete satisfaction. Objective weights were determined by computing the proportion of points given to a scenario out of the total number of points assigned to all scenarios in the set, and the weights assigned to all objectives in a set summed to one.

Similarly, each landowner was given an attribute score worksheet to complete on their own. For each objective, the levels in the attribute scale were listed, and landowners assigned grades to each of the levels. The landowners used a scale from 0 to 100 to grade the attribute scale levels in a way that reflected their satisfaction if the attribute scale level occurred.

Conditional probabilities

There was a year separating the third and fourth workshops. During that time, we identified conditional probabilities to include in the Bayesian decision network, calculated expected utility values for each decision option, and compared the expected utility values for decision options to determine a decision recommendation. Probabilities are used to quantify the chance of an outcome occurring given an existing state or action. Specifically, conditional probabilities in the Bayesian decision network describe the likelihood of each level in a node being realized given states of influencing nodes (Oliver and Smith 1990, Marcot et al. 2001).

We searched the scientific literature for studies relevant to the southern Appalachian Mountains that reported, or provided data so that we could calculate, probabilities of outcomes given environmental conditions or relevant treatments. However, we found that scientific papers rarely presented results in this form. Often, researchers discussed the statistical significance or the effect size of treatments, and it was not clear how to use these results to infer probabilities of outcomes (Ellison 1996). Plus, using results from the literature may not be suitable due to differences in study sites or methodological short-comings such as failing to account for detection probability when estimating the effects of a treatment on a wildlife population. Therefore, we used the available scientific literature to support hypotheses about system dynamics, as reflected in the influence diagram, but to obtain probabilities we relied on expert opinion (Haas 1991, 2001; Clemen 1996; Peterson and Evans 2003).

Using expert opinion to generate values in a quantitative analysis may seem of questionable validity to scientists trained in controlled experiments founded on the notion of falsifiability (Gregory and Failing 2002). However, the expert opinions were elicited and used in a rigorous, transparent, and logical way (Martin et al. 2009). Also, it is important to recall the goal of SDM: to use currently available knowledge in a value-focused process to objectively evaluate decision options and identify the decision option with the greatest probability of achieving decision-makers' objectives. Often, a decision must be made regardless of the current state of knowledge, and SDM is a process to support decision-making so that underlying assumptions are made explicit, key uncertainties are identified, decision components are transparent, and, consequently, a desired outcome is more likely to be achieved (Marcot et al. 2001). Also, SDM is complimented by adaptive management in that models can be updated and decisions can be re-evaluated as more data become available (Nyberg et al. 2006, McFadden et al. 2011, Tyre and Michaels 2011). Further, the use of expert opinion is consistent with the call to integrate local knowledge in decision-making (Jasanoff 1990, Irwin and Wynne 1996, Fischer 2000, Failing et al. 2007). When more sources than journal publications are used, knowledge held by people outside of academia, such as land managers, become accessible (Johnson 1999, Raymond et al. 2010). Such an approach can increase knowledge while also cultivating inclusivity and buy-in by stakeholders (Raymond et al. 2010).

We sent conditional probability elicitation worksheets to 33 experts. These experts consisted of faculty at the University of Georgia (UGA), faculty who are affiliated with Coweeta LTER, graduate students at UGA who had conducted research at Coweeta, U.S. Forest Service employees at the Coweeta Hydrologic Laboratory, a Macon County government employee, staff from the LTLT (based in Macon County), and staff from Forest Stewards (a non-profit corporation based in a county neighboring Macon County that "promotes and implements forest stewardship"). Experts were asked to complete the conditional probability tables with probabilities that reflected average expected outcomes for an average large, forested parcel in Macon County assuming that best management practices were always used.

Responses from experts were compiled, checked to verify that instructions had been followed and the probabilities were realistic, and entered in the Bayesian decision network. Occasionally, some reformatting was required to integrate the experts' conditional probabilities with the landowners' work on the decision network and attribute scales (Appendix I). For each node in the Bayesian decision network for which we received probabilities from more than one expert, we made a new node for expert identity that affected the nature node. Through the expert identity node, we weighted each expert's probabilities equally, reflecting equal belief in each expert's contribution. Also, the landowners provided conditional probabilities related to the heritage outcomes, topics for which they were the best qualified experts, though consensus-based discussion. Through the use of probabilities, we incorporated environmental stochasticity and partial controllability in the estimates of outcomes following decision options (Williams et al. 1996, Conroy et al. 2008, Irwin et al. 2011).

Utility values

Utility functions combine the probability of outcomes and the landowners' satisfaction with outcomes such that the expected utility value indicates the relative suitability of the decision option. Expected utility values were calculated for each decision by a weighted average of the objective weights, attribute scores, and probabilities of outcomes (Peterson and Evans 2003). While each landowner completed an objective weights worksheet and an attribute scores worksheet, the worksheet results were kept anonymous because the Bayesian decision network was intended to describe an average large, forested parcel in Macon County rather than a specific individual's property and because we wanted to avoid appearing prescriptive when discussing recommended decision options given the cultural environment. Therefore, all combinations of objective weights and attribute scores were combined with the probabilities to calculate expected utility values. For each combination, decision options were evaluated by comparing the expected utility values, and the ranking of decision option was recorded. The frequency with which each decision option had the greatest or lowest expected utility suggested the relative potential each decision option had to meet landowners' objectives. Namely, the decision option with the largest expected utility value was the decision that was most likely to achieve the objectives (Conroy et al. 2008).

The expected utility value was calculated as:

$$\sum_{p=1}^{F} W_p \left(\sum_{s=1}^{G} U_s \left(\sum_{v=1}^{H} S_v \times \Pr(X_v | A) \right) \right)$$

where W indicates a first-order fundamental objective weight, U indicates a second-order fundamental objective weight, and S represents an attribute score. For each of the G second-order fundamental objectives (s = 1, 2, …, G) within a first-order fundamental objective (p = 1, 2, …, F), we weighted the attribute score for a possible outcome (v = 1, 2, …, H) by the probability of that outcome (X_v) given states of influencing nodes (A). Note that G may depend on p and H may depend on p and s.

Landowners' assessment

At the fourth workshop, held in the summer of 2013, we presented the completed Bayesian decision network and discussed the decision options that the network indicated were most or least likely to produce outcomes that would fulfill landowners' objectives. We also gave copies of the conditional probability tables to the landowners and asked for their feedback if they knew other experts who would like to contribute probabilities or if they thought any of the probabilities should be modified. Finally, we asked landowners to complete questionnaires (Appendix J) about their experience and impression of the SDM project.

One questionnaire was distributed before we presented results from the Bayesian decision network. This questionnaire asked landowners how they currently manage their forest, which decision options they expected the SDM process would indicate were most likely to achieve the defined objectives, and their openness to reconsidering how they currently manage their forest. The second questionnaire was distributed after we discussed the results of the Bayesian decision network, and it asked about landowners' willingness to reconsider how they currently manage their forest, interest in learning more about other management options, desire to apply SDM to decision-making about their property, and their level of understanding and enjoyment of the workshops.

We were interested in the landowners' assessment since the SDM project addressed land use, a controversial topic in Macon County, but employed a novel approach intended to facilitate understanding of landowners' perspectives, stimulate conversation among diverse landowners, cultivate the relationship between landowners and organizations that typically hold power in decision-making, conduct a place-based analysis that involved landowners through the entire project, and provide objective information relevant to landowners (Clarke and Slocombe 2004, Ogden and Innes 2009, Irwin et al. 2011, Cumming and Norwood 2012).

Results: application of SDM to private forest management

Objectives and attributes

Although there were two independent series of SDM workshops with ten landowners from diverse backgrounds and landownership histories in each, a small set of objectives were identified by all landowners. Landowners in both series had the fundamental objectives of maximizing forest health, safety, heritage preservation, and net income, but the landowners in Series 2 also had the fundamental objective of maximizing aesthetic enjoyment.

For some of these fundamental objectives, landowners also defined second-order fundamental objectives (Fig. 4.1). These second-order fundamental objectives described components of a first-order fundamental objective while remaining fundamental objectives themselves, rather than being means objectives. For example, for the first-order fundamental objective of maximizing forest health, the second-order fundamental objectives were maximizing native species diversity, minimizing exotic species abundance, and maximizing water quality.

Through consensus-based discussion, the landowners defined attribute scales to make each fundamental objective measurable (Fig. 4.1). The landowners defined a rural landscape as a large property with a blend of unfragmented forest and fields, little development, natural sounds, and no visual clutter, specifically no commercial visual clutter. The abundance of exotic species was compared to the range of exotic species abundance in the region, and levels of water quality were assessed relative to standard measures of contaminant concentrations, sedimentation, macro-invertebrate indicators, and fish indicators. Three components of native species diversity were considered: birds, herpetofauna, and trees. Birds were of interest because the southern Appalachian region has high avian species richness, many landowners are recreational birdwatchers, and P.F.B. conducted a study on avian occupancy in Macon County (Monkkonen 1994, Kark et al. 2007). Herpetofauna were included because the southern Appalachian region is a global biodiversity hotspot for salamanders, plus there are snake and turtle populations in the region that are of conservation concern (Murdock 1994, Petranka 1998). Tree species diversity was considered because different forest management practices are expected to affect the abundance of shade-tolerant and shade-intolerant tree species, and there are concerns about declines in the abundance of shade-intolerant trees throughout eastern temperate forests. Declines in shade-intolerant trees are problematic not only because of tree diversity but shade-intolerant trees, such as oaks and poplar, also tend to be more economically valuable (Schuler 2004, Clatterbuck et al. 2011) and are important resources for many wildlife species (Wentworth et al. 1992, Wolff 1996). The three components of native diversity were combined in one summary metric as described below.

Since some landowners noted that particular objectives were not important to them, representing values through the objective weights was an important way to incorporate personal perspectives. However, we found many errors in the completed worksheets designed to elicit objective weights from landowners. For example, the ranking order sometimes did not match the grade distribution. Since we did not know whether the error was in the ranking or the grading, we eliminated these responses and collated all of the correct grades for each set of scenarios across all landowners. If a landowner completed all components of the worksheet correctly, their grades were used to calculate a combination of objective weights (Table 4.2). The correct grades from landowners who did not correctly complete the entire worksheet were used to calculate a combination consisting of mean objective weights. In Series 1, the mean objective weights were used to calculate utilities because no landowner completed the entire worksheet correctly, but in Series 2, the objective weights from three landowners and the mean objective weights from the remaining landowners were used to calculate utilities (Table 4.2).

There were also errors in the worksheets that landowners used to assign grades to the attribute levels. Consequently, for Series 1, the attribute scores from three landowners and the mean attribute scores from the remaining landowners were used to calculate utilities (Table 4.3). For Series 2, utilities were calculated with attribute scores from five landowners and the mean attribute scores from the remaining landowners. Therefore, for Series 1, there were four combinations of objective weights and attribute scores, and for Series 2, there were 24 combinations of objective weights and attribute scores. Utilities were calculated under each combination, and the expected utilities of the decision options were compared.

Decision options

The landowners identified eleven decision options to include in the Bayesian decision network: no modification of the forest, personal use of the forest (e.g., collecting firewood, building and using recreational trails), crown thinning harvest through the Present-Use Value (PUV) program, group selection harvest through the PUV program, shelterwood harvest with residual trees through the PUV program, conservation easement with no modification of the forest, conservation easement with personal use of the forest, conservation easement with crown thinning harvest through the PUV program, conservation easement with group selection harvest through the PUV program, conservation easement with shelterwood harvest with residual trees through the PUV program, and sell 1 ha (approximately 5% of the forest) with personal use of the remaining forest. When landowners mentioned the decision options involving selling property, they noted that they did not consider this a desirable action but that it might be necessary. Details about the operation of conservation easements and the PUV program can be found in Appendices I and K.

Bayesian decision network

The decision options were linked to the fundamental objectives through a Bayesian decision network (Fig. 4.2). On average, two experts provided conditional probabilities for each node other than those for heritage or aesthetic objectives, for which landowners provided probabilities. The expert nodes in the decision network indicate how many experts contributed probabilities to a specific node. Eight experts provided conditional probabilities although we had contacted 33 experts. The conditional probabilities that were used to predict the effects of decision options are presented in Appendix L. When the landowners were shown the conditional probabilities during the fourth workshop, none requested revisions.

Recommended decision option

In both series, the decision options with the largest or smallest utility values varied depending on the combination of objective weights and attribute scores (Table 4.4). The best and worst decision options were defined as decision options within one point of the highest or lowest utility value, respectively. Overall, the decision option that was most consistently best was crown thinning in the PUV program, and the decision options that were most consistently worst were selling 1 ha and personal use of the forest with or without a conservation easement.

In Series 1, crown thinning or shelterwood harvest in the PUV program had the greatest frequency of being the best decision option, and personal use of the forest with or without a conservation easement had the greatest frequency of being the worst decision option. In Series 2, crown thinning in the PUV program had the greatest frequency of being the best decision option, and personal use of the forest with or without a conservation easement and selling 1 ha while using the remainder of the forest for personal activities had the greatest frequency of being the worst decision option. Under some combinations of objective weights and attribute scores, no modification of the forest with or without a conservation easement, shelterwood harvest in the PUV program with a conservation easement, and selling 1 ha were the best decision options. In certain combinations of objective weights and attribute scores, the worst decision options were shelterwood harvest in the PUV program with or without a conservation easement and group selection harvest in the PUV program with a conservation easement.

Landowners' assessments

Out of thirteen landowners who completed the questionnaires at the fourth workshop, five said at the beginning of the workshop that they currently use crown thinning under the PUV program, two use shelterwood harvesting under the PUV program, four do not modify the forest and do not have a conservation easement, and one does not modify the forest and has a conservation easement. These were options that the decision network suggested could be the best given various combinations of objective weights and attribute scores. Four landowners said they use the forest for personal activities without a conservation easement, the option that the decision network suggested was most consistently worst.

Only three landowners thought that crown thinning under the PUV program would best meet objectives, while two landowners selected no modification of the forest. Six landowners thought that personal use of the forest without a conservation easement would best fulfill objectives, and personal use with a conservation easement was selected by two landowners.

When asked, in general, if the results of the analysis would affect how they manage their forest, three landowners said yes, three said no, and seven said maybe. However, when asked specifically, no landowners said that they would not consider adopting a new forest management practice. Seven landowners said that they would use a new forest management practice, and six landowners responded maybe. Only one landowner said that they would discontinue what they are currently doing to their forest based on the results of the analysis. Five landowners indicated that they would not discontinue current practices, and seven landowners answered maybe.

In the questionnaire following the discussion of the decision network results, the number of landowners who indicated that they would generally reconsider what they are currently doing to manage their forest increased from three to nine. Two landowners said they would not reconsider, and two landowners responded maybe. However, only two landowners said they will investigate forest management options other than those they currently use. Seven landowners said they might, and four landowners responded that they would not. Two landowners would like to have the decision network tailored to their property, five landowners indicated they might be interested, and six landowners were not interested. Four landowners were willing to pay for a personalized decision network, but nine landowners were not.

Nine landowners indicated that they understood most of the material presented during the project, and four landowners understood about half of the material. Eleven landowners had a good experience participating in the project, while two landowners had an okay experience. Some aspects of the project that landowners found beneficial included: “meeting others with similar interests in forest conservation”, “group discussions of individual management practices and what things participants value”, “objectively evaluating our property and values”, “watching the decision network grow”, and “encouragement to do something beneficial”.

Discussion

Objectives related to parcelization and land conservation

Parcelization of forestland has consequences for the ecology, social dynamics, and economies of communities. In order to manage parcelization, it is important to understand how owners of large, forested properties make decisions, specifically to understand their objectives, knowledge, and perspectives about land management. If reducing parcelization is desired by stakeholders, ways to keep large properties intact that compliment stakeholders’ objectives should be identified (Best 2002).

Previous studies have found that parcelization may be fueled by landowners’ willingness to sell or peoples’ interest in purchasing parcelized forestland. Landowners may be interested in parcelization due to the expense of taxes, because they can make a profit when urbanization of rural areas leads to property value increases, or when they inherit the property but lack the means or interest to manage it (DeCoster 1998, Mehmood and Zhang 2001, Best 2002). People may be interested in buying forestland that has been parcelized because living in the woods is perceived as an attractive lifestyle (DeCoster 1998, Mehmood and Zhang 2001, Rickenback and Gobster

2003, Kendra and Hull 2005). Retirees comprise a growing demographic of new forestland owners in the southern U.S. (Birch 1997, Kendra and Hull 2005). Also, when forestland is parcelized, there are more properties available for purchase, properties have a lower price, and they may require less maintenance than large properties with intact forest.

The roles of net income, value for heritage preservation, and aesthetics were prominent in the literature and were discussed by Macon County landowners, many of whom are retirees. Through the SDM project, we identified a set of objectives in common among the participants. The objectives were diverse, spanning financial, ecological, cultural, aesthetic, and safety concerns, but there was not high variability among landowners. Also, as opposed to the working hypothesis of many scientists at Coweeta, multi-generational landowners and new residents did not appear to have different values and objectives. This unexpected pattern was also found by other researchers conducting social-ecological research concurrently in Macon County (Sakura Evans, personal communication).

Our findings are consistent with the notion behind SDM that stakeholders often do not have drastically different objectives, rather they may assign objective weights and attribute scores differently (Keeney et al. 1990, Gregory and Keeney 1994). Conflict can arise in the decision-making process when this distinction is not realized and people feel like they have to defend their objectives. Instead, building models that incorporate multiple objective weights and attribute score combinations can abate conflicts and increase stakeholder inclusion.

SDM potency and challenges

As SDM can be used to effectively integrate different stakeholders' values and reduce unproductive conflict that can mire decision-making processes, it has potential application to broad land use questions in Macon County. We have demonstrated how SDM can be used when there is one person with authority over a decision who wants to explicitly consider multiple objectives and uncertainty in system dynamics and future outcomes. In fact, there was substantial interest in this service becoming available as 54% of the landowners at the fourth workshop indicated that they might be interested in having a decision network made for their property and 31% of the landowners already said they would be willing to pay for this decision-support process.

Conservation and land use planning organizations can also benefit from using SDM to guide decisions about their internal operations or to support clients' decision-making. For example, when the LTLT provided input on this project, they expressed interest in using the results to help them better understand landowners' perspectives, communicate with landowners, and focus on conservation methods that might be more appealing to landowners and more effective at achieving the LTLT's and landowners' objectives. Further, SDM might be a way to make inroads in county-level decision-making about land use. The landowners who participated in our workshops found the project enjoyable, learned technical information, and reflected on value-based information. Also, there is evidence that some landowners may have formed new ideas about forest management that could affect how they manage their forests. If pressing county-level land use questions can be addressed in a process that avoids political tension, allows landowners to feel represented and respected, and effectively integrates value-based and technical information, future decision-making may be more successful than past attempts.

However, there are challenged involved with eliciting information for SDM. First, there may be linguistic uncertainty and miscommunication so that the researcher believes that the participants understand the material and what is being asked of them, the participants believe they are providing what the researcher is seeking, but the two actually do not match. This misunderstanding may not be apparent to the researcher or participants. In our project, 69% of the landowners at the fourth workshop said they understood most of the material and 31% said they understood about half of the material. Nevertheless, there were many errors in the objective weights and attribute scores worksheets. Perhaps the worksheet itself was confusing or maybe there was some more pervasive misunderstanding. Ideally, researchers would be assessing each participant's understanding and contributed information immediately and throughout the project, but this may not be feasible given the number of researchers, number of participants, and time constraints.

Additionally, there may be linguistic uncertainty and miscommunication between SDM researchers and scientific experts who are consulted. However, a more substantial challenge may be to communicate the purpose of SDM and the usefulness of expert opinion to scientists. Scientists often have not been trained to recognize the distinction between and proper roles of value-based judgments and technical judgments in the context of management and conservation (Failing et al. 2007). Also, scientists may consider anything besides randomly collected empirical data to be worthless. Consequently, scientific experts may resist the use of opinion in a decision network. We expect this, combined with experts' busy schedules and no direct benefit from participation, were the reasons we had a low response rate from experts (24%). In fact, two experts took the time to respond, not with conditional probabilities, but with questions or objections to the pursuit. Nevertheless, use of expert opinion is an established practice, especially in SDM applications where a decision must be made given the current best technical information, however incomplete it may be. Multiple models and uncertainty can be included in the decision network, and models can be refined through adaptive management.

Although we were not able to obtain conditional probabilities directly from the scientific literature, patterns indicated in the literature were consistent with the conditional probabilities we gathered from experts. For example, fire risk is very low in the southern Appalachian region (Lafon et al. 2005, Fowler and Konopik 2007). The erosion risk tends to increase when more trees are removed, but erosion risk is low if forest cover is high (Montgomery et al. 2000, Hood et al. 2002, Dhakal and Sidle 2003, Miller and Burnett 2007). Similarly, water quality is high if the forest cover is high, but as more trees are removed, water quality tends to decrease (Aust and Blinn 2004, Stednick et al. 2004). Also, the abundance of exotic species appears to increase as the intensity of the forest use increases (Belote et al. 2008, Burnham and Lee 2010). The effects of disturbance on the conservation value of the forest for birds (Norris et al. 2009, Twedt and Somershoe 2009) and herpetofauna (Semlitsch et al. 2009, Strojny and Hunter 2010, Tilghman et al. 2012, Hocking et al. 2013) may be variable, but generally, the conservation value is expected to decrease as disturbance increases. While the effects of disturbance on the abundance of shade-intolerant trees may be variable also, abundance typically increases with disturbance that opens increasing amounts of canopy cover (LeDoux 1999, Webster and Lorimer 2005, Richards and Hart 2011, Lhotka 2013).

Application of results from SDM with Macon County landowners

It is useful to think about the degree to which we captured landowners' objective weights and attribute scores and the robustness of results from the decision network. First, it is clear that there is not a single best management practice for large, private forests. Landowners' objectives and values regarding outcomes influenced which decision option was most suitable. If a landowner wanted to make a decision for their forest, the decision network should be tailored to their property, objectives, and values. Further, if there is more interest in directly understanding landowners' values and perspectives than in selecting a decision option, the objective weights and attribute scores in Tables 4.2 and 4.3 likely do not provide a representative sample. A larger sample size and more time to work with landowners to confirm their understanding and check the completeness of their responses would be required for a thorough study of landowners' value and perspectives as such, but this was not the goal of our study.

The effects of the conditional probabilities on the utility values can be investigated by considering the range of utility values and by varying the weights assigned to experts' opinions. Depending on the objective weights and attribute scores, the utility values of the various decision options could be very close. For example in Series 1 with objective weight and attribute score combination four, the utility values of the highest and lowest ranked decision options only differed by 4.96. When considering both series and all objective weight and attribute score combinations, the median difference between the highest ranked decision option and another option was 4.44, the first quartile difference was 2.24, and the third quartile difference was 7.17. When decision options have similar utility values, a top decision option is less apparent, and it suggests that utility values may not be highly robust to the choice of objective weights, attribute scores, and probabilities.

We explored the effect of the weights on experts' opinions in the decision network from Series 1 and objective weight and attribute score combination one, but as there are 34,992 combinations in which weights might be uniform across the experts in a node or 100% on one expert in a node, we did not do an exhaustive analysis with all expert weight combinations, all objective weight and attribute score combinations, and decision networks from both series. Based on our exploratory analysis, changing the weights on experts' opinions resulted in slightly different rankings of decision options. Specifically, the top few decision options could have the greatest utility value depending on which conditional probabilities were used. This would have implications for a project goal of identifying the single decision option with the greatest utility value. However, decision networks do not need to be treated as authoritative. They are meant to be decision support tools, so decision-makers could identify the few decision options that most consistently have high utility values and engage in additional decision-making strategies to arrive at a final decision.

For this project, we did not conduct a sensitivity analysis or calculate the value of information because the conditional probabilities in all of the nodes in our decision network were based on expert opinion and would benefit from reduced uncertainty and increased knowledge. Also, there were few intermediate nodes connecting decision options to objectives, and typical sensitivity analyses are less informative with this kind of model structure.

Based on our analysis, crown thinning in the PUV program appeared to be the most promising decision option, and selling 1 ha and personal use of the forest with or without a conservation easement seemed to be the decision options that were least likely to meet landowners' objectives. This makes sense as crown thinning causes a relatively low level of disturbance, landowners receive income from timber harvesting, and property taxes are reduced. Personal use of the forest causes a relatively low level of disturbance but there is no financial benefit. Also, establishing a conservation easement is more expensive than conducting a timber harvest. Selling property is detrimental to ecological and heritage objectives although there may be financial benefits.

Surprisingly, the decision analysis results were largely opposite of landowners' expectations. Most landowners (62%) thought personal use with or without a conservation easement would be the best decision option, while only 23% of the landowners thought crown thinning in the PUV program would best meet objectives. Nevertheless, about equal numbers of landowners conducted crown thinning (38%) and personal use without an easement (31%). This finding, plus the landowners' increased openness to reconsider their land use practices after discussing results from the decision analysis, highlights the usefulness of SDM in this context and the need for professionals to engage landowners in a two-way flow of information to support decision-making.

Conclusion

Parcelization of large, private forestlands is of research and conservation concern because it has implications for ecosystem health, local economics, and social dynamics. Landowners often have multiple objectives motivating their land use and affecting decision-making about the future of their property. While the relative importance of objectives may vary among landowners, many landowners have common objectives. Our SDM project with 20 owners of large, forested parcels in Macon County, found that crown thinning in the PUV program was the most promising forest management decision option, and selling 1 ha of forest or personal use of the forest, with or without a conservation easement, were the least promising options. SDM is a useful method to address parcelization and land use planning in Macon County and similar contexts.

SDM is a valuable process to help landowners explicitly define their objectives, creatively think about decision options, predict the effects of decision options relative to objectives, and quantify the degree to which decision options are expected to fulfill objectives. By participating in SDM, landowners may benefit by reflecting on their values, learning about decision options, and identifying decision options that are most likely to meet their objectives. Since SDM is participatory; transparently incorporates value-based and technical information; and accounts for environmental stochasticity, system uncertainty, and plurality of values; it is an effective process for rigorously evaluating options for decision problems that are incendiary or that have incomplete data.

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Table 4.1: Backgrounds of the landowners who participated in the structured decision making workshops held in 2012 and 2013 that addressed forest management on an average large, forested property (30 ha property with 22 ha of forest) in Macon County, NC. There were two workshop series that each included ten landowners (some properties were represented by more than one person). Data were obtained through interviews with landowners (Native to Macon County, Easement), land trust records (Easement), and county parcel records (remaining columns). We specify when landowners did not grow up in Macon County but had family members who lived in the county. When landowners owned multiple adjancent parcels, we determined the mean elevation, the sum of the area and value, and whether there was an easement on any part of the property. When landowners owned multiple disjunct parcels, we only considered parcels that were at least 8 ha in area (two landowners owned two parcels ≥ 8 ha). One landowner had two forest patches in one parcel. Although one property was < 8 ha, it was included because the landowners were well-regarded experts in the community. In an attempt to keep participant identity confidential, values were rounded to the nearest 10m for elevation, 5 ha for area, and $10,000 for value.

Series	Native to Macon County	Elevation (m)	Total area (ha)	Contiguous forest area (ha)	Land value	Building value	Easement
1	Yes	670	20	15	1,000,000	340,000	No
1	Yes	760, 980	35, 20	35, 20	850,000; 70,000	40,000; 0	No
1	Yes	720	30	25	1,00,000	340,000	No
1	Family	680	30	15	750,000	250,000	No
1	No	650	15	15	430,000	100,000	Yes
1	No	710	20	20	600,000	180,000	No
1	No	610	25	10, 5	360,000	80,000	Yes
1	No	890	20	20	350,000	0	No
2	Yes	700	65	65	1,560,000	0	No
2	Yes	650	50	10	1,270,000	120,000	No
2	Yes	650	5	5	190,000	270,000	No
2	Family	790	30	30	600,000	910,000	No
2	No	690	25	20	600,000	280,000	Yes
2	No	700, 750	20, 10	15, 10	680,000; 280,000	210,000; 0	No
2	No	1160	50	50	328,000	1,560,000	No

Table 4.2: Objective weights provided by landowners during structured decision making workshops held in 2012 and 2013 that addressed forest management on an average large, forested property (30 ha property with 22 ha of forest) in Macon County, NC. In two workshop series (a = Series 1, b = Series 2) that each included ten landowners, the landowners identified first-order objectives and second-order objectives, which described components of a first-order objective, and assigned weights to the objectives that reflected their relative importance to the landowner. The number of objective weight combinations in a series depended on the number of landowners who correctly completed weight elicitation worksheets. A combination was made for each landowner who correctly completed the entire worksheet. Otherwise, correct responses were averaged across landowners to create a mean combination. All combinations of objective weights and attribute scores within a series were used to calculate utility values that were used to evaluate decision options.

a)

First-order objectives	Mean combination
Maximize forest health	0.33
Maximize safety	0.25
Maximize heritage preservation	0.26
Maximize net income	0.16

First-order objectives	Second-order objectives	Mean combination
Maximize forest health	Minimize exotic species abundance	0.30
	Maximize water quality	0.40
	Maximize native species diversity	0.30
Maximize safety	Maximize human safety	0.49
	Minimize property damage	0.51
Maximize heritage preservation	Minimize future development	0.23
	Maximize percent of property in the family	0.27
	Maximize percent of income from the property	0.21
	Maximize rural landscape	0.29

b)

First-order objectives	Combination Mean	2	3	4
Maximize forest health	0.27	0.00	0.20	0.29
Maximize safety	0.33	0.00	0.20	0.14
Maximize heritage preservation	0.13	0.67	0.20	0.14
Maximize net income	0.07	0.00	0.20	0.14
Maximize aesthetics	0.20	0.33	0.20	0.29

First-order objectives	Second-order objectives	Combination Mean	2	3	4
Maximize forest health	Minimize exotic species abundance	0.23	0.25	0.00	0.11
	Maximize water quality	0.31	0.50	0.50	0.44
	Maximize native species diversity	0.46	0.25	0.50	0.44
Maximize safety	Maximize human safety	0.72	1.00	1.00	0.67
	Minimize property damage	0.28	0.00	0.00	0.33
Maximize heritage preservation	Minimize future development	0.28	0.20	0.20	0.14
	Maximize percent of property in the family	0.35	0.20	0.33	0.14
	Maximize percent of income from the property	0.15	0.20	0.13	0.14
	Maximize rural landscape	0.23	0.40	0.33	0.57

Table 4.3: Attribute scores provided by landowners during structured decision making workshops held in 2012 and 2013 that addressed forest management on an average large, forested property (30 ha property with 22 ha of forest) in Macon County, NC. In two workshop series (a = Series 1, b = Series 2) that each included ten landowners, the landowners identified attribute scales for each of their objectives. Landowners also scored each attribute level to reflect their satisfaction were the attribute level to occur. The number of combinations of attribute scores in a series depended on the number of landowners who correctly completed elicitation worksheets. A combination was made for each landowner who correctly completed the entire worksheet. Otherwise, correct responses were averaged across landowners to create a mean combination. All combinations of objective weights and attribute scores within a series were used to calculate utility values that were used to evaluate decision options.

a)

		Combination			
Objective	Attribute level	Mean	2	3	4
Exotic species abundance	Low	100	100	90	100
	Medium	57.5	50	37.5	70
	High	13.33	0	0	40
Water quality	High	100	100	100	100
	Medium	52	72.5	37.5	70
	Low	15	0	0	50
Native species diversity	Very high	100	90	100	100
	Moderately high	69	80	75	80
	Moderately low	40	70	25	60
	Very low	20	40	10	20
Human safety	High	100	100	100	100
	Moderate	67.5	90	0	70
	Low	28.75	75	0	50
Property damage	None	100	100	100	100
	Low	50	75	60	50
	High	19	50	25	20
Future development	None	100	100	100	100
	Up to two divisions	55	75	50	70

	More than two divisions	23.6	50	25	50
Percent of property in the family	100-67% of property	95	100	80	100
	66-34% of property	53.75	75	40	80
	33-0% of property	38.75	25	0	20
Percent of income from the property	100-67% of income	97.5	100	75	100
	66-34% of income	78.75	90	50	80
	33-0% of income	55	80	25	60
Rural landscape	Maintain	100	100	75	100
	Lose a little	65	75	50	80
	Lose a lot	24	25	25	50
Net income	Positive	100	100	100	100
	Even	63	90	50	70
	Negative	18	80	25	60

b)

Objective	Attribute level	Mean	Combination 2	3	4	5	6
Exotic species abundance	Low	60	100	80	100	100	100
	High	20	0	20	0	0	0
Water quality	High	93	100	80	100	100	100
	Low	7	0	10	0	0	0
Native species diversity	High	97	50	90	100	100	100
	Low	3	0	20	0	0	0
Human safety	High	100	20	100	100	100	90
	Moderate	14	10	50	10	5	10
	Low	7	0	0	0	0	0
Property damage	None	97	100	90	100	100	95
	Low	12	80	40	80	20	5
	High	0	75	10	10	0	0
Future development	None	97	90	50	100	100	100
	At least one division	30	2	20	10	10	0
Proportion of property in the family	100-51% of property	97	30	80	90	80	50
	50-0% of property	28	30	50	10	20	50
Proportion of income from the property	100-51% of income	50	10	50	70	60	70
	50-0% of income	50	10	50	50	10	30
Rural landscape	Maintain	92	100	60	100	100	100
	Lose	0	0	0	0	0	0
Net income	Positive	100	10	50	100	60	80
	Even	85	0	30	100	50	20
	Negative	25	0	10	50	40	0
Aesthetics	Good	83	100	90	100	100	100
	Bad	3	0	20	0	0	0

Table 4.4: Utility values calculated in Bayesian decision networks that were based on landowners' comments during structured decision making workshops held in 2012 and 2013. There were two workshop series (a = Series 1, b = Series 2) that each included ten landowners and addressed forest management on an average large, forested property (30 ha property with 22 ha of forest) in Macon County, NC. Utility values combine the probability of outcomes and the landowners' satisfaction with outcomes such that the utility value indicates the relative suitability of the decision option. Utility values were calculated using all combinations of objective weights and attribute scores, resulting in four weights and scores combinations for Series 1 and 24 weights and scores combinations for Series 2 (see Tables 4.2 and 4.3). The number of times a decision option was within one point of the highest utility value and the number of times a decision option was within one point of the lowest utility value are presented as the frequency of being the best or worst decision. Personal use of the forest could involve harvesting firewood or using recreational trails. The three commercial harvesting methods (thinning, group selection, and shelterwood) would occur through the Present-Use Value program. The no modification, personal use, and commercial harvesting decision options could also be combined with having a conservation easement.

a)

Decision options	Weights and scores 1	Weights and scores 2	Weights and scores 3	Weights and scores 4	Best decision frequency	Worst decision frequency
No modification	65.39	81.99	56.88	76.16	0	0
Personal use	63.50	80.55	54.67	74.72	0	3
Thinning	72.62	84.09	62.61	79.68	4	0
Group selection	71.61	82.44	60.94	78.66	0	0
Shelterwood	72.84	82.38	62.25	79.39	3	0
Easement with no modification	65.39	81.99	56.88	76.16	0	0
Easement with personal use	63.76	80.74	54.85	74.87	0	3
Easement with thinning	70.14	82.97	60.39	78.31	0	0
Easement with group selection	69.88	81.63	59.67	77.89	0	0
Easement with shelterwood	71.62	81.79	61.44	78.90	1	0
Sell 1 ha, remainder personal use	68.21	77.70	58.21	76.32	0	1

b)

Decision options	Weights and scores 1	Weights and scores 2	Weights and scores 3	Weights and scores 4	Weights and scores 5
No modification	41.05	37.30	52.42	49.14	48.27
Personal use	38.45	34.71	48.76	46.20	46.29
Thinning	50.61	38.34	51.52	48.25	53.00
Group selection	48.98	34.69	45.67	43.47	51.34
Shelterwood	49.61	33.82	43.82	41.97	51.45
Easement with no modification	41.05	37.30	52.42	49.14	48.27
Easement with personal use	38.45	34.71	48.76	46.20	46.29
Easement with thinning	47.34	37.18	50.44	47.42	51.15
Easement with group selection	46.13	33.84	44.85	42.80	49.76
Easement with shelterwood	47.40	33.19	43.19	41.46	50.22
Sell 1 ha, remainder personal use	48.92	33.00	42.08	39.67	51.00

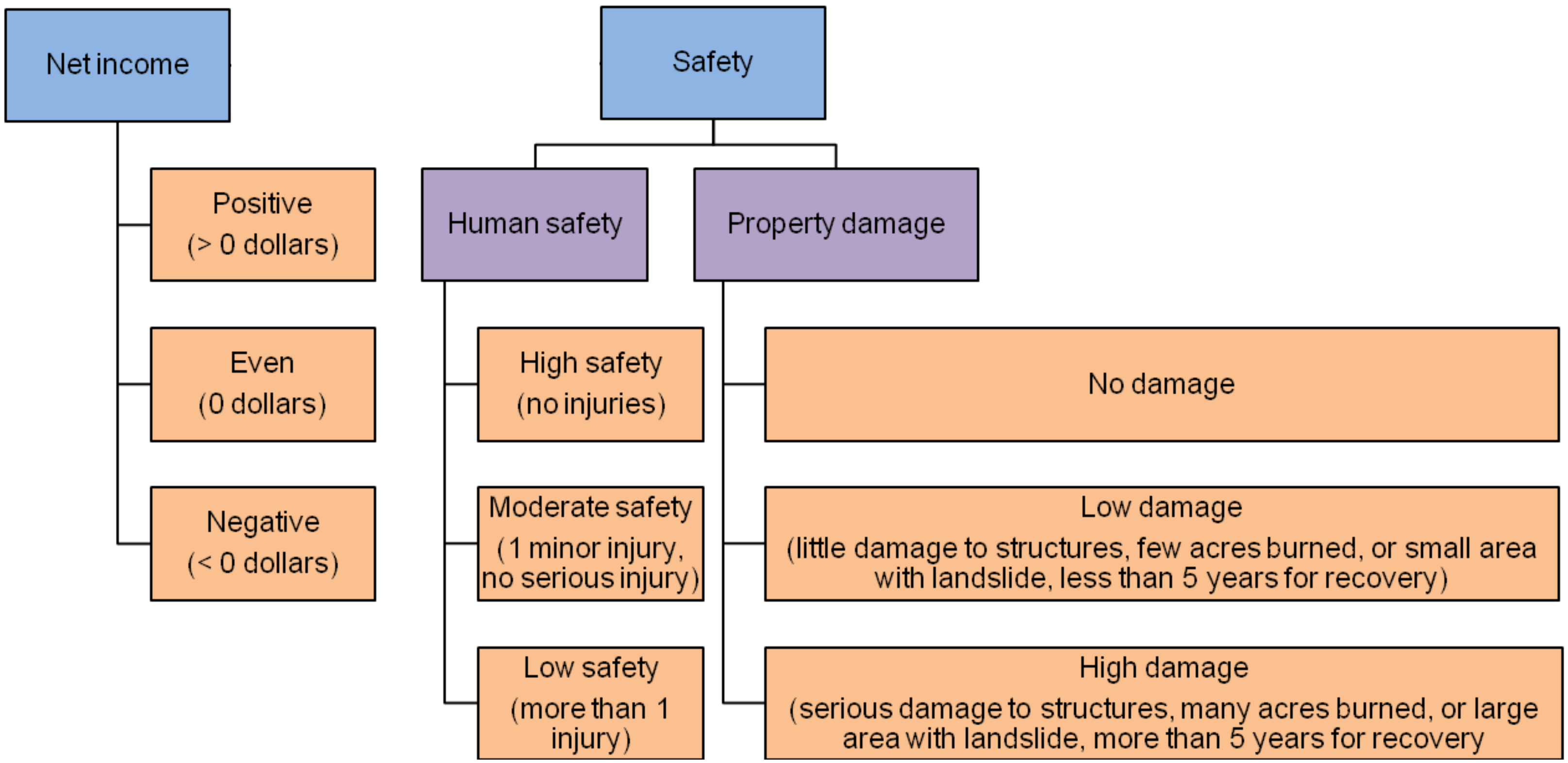
Decision options	Weights and scores 6	Weights and scores 7	Weights and scores 8	Weights and scores 9	Weights and scores 10
No modification	54.60	59.66	64.34	50.18	63.23
Personal use	52.08	56.41	61.40	47.16	59.59
Thinning	57.62	60.36	63.43	61.69	70.12
Group selection	54.89	56.05	59.31	60.07	66.79
Shelterwood	54.76	54.85	58.05	61.21	66.23
Easement with no modification	54.60	59.66	64.34	50.18	63.23
Easement with personal use	52.08	56.41	61.40	47.16	59.59
Easement with thinning	56.02	59.08	62.62	57.80	67.11
Easement with group selection	53.76	55.12	58.71	56.75	64.02
Easement with shelterwood	53.94	54.17	57.60	58.65	64.04
Sell 1 ha, remainder personal use	53.32	53.14	54.94	60.64	63.72

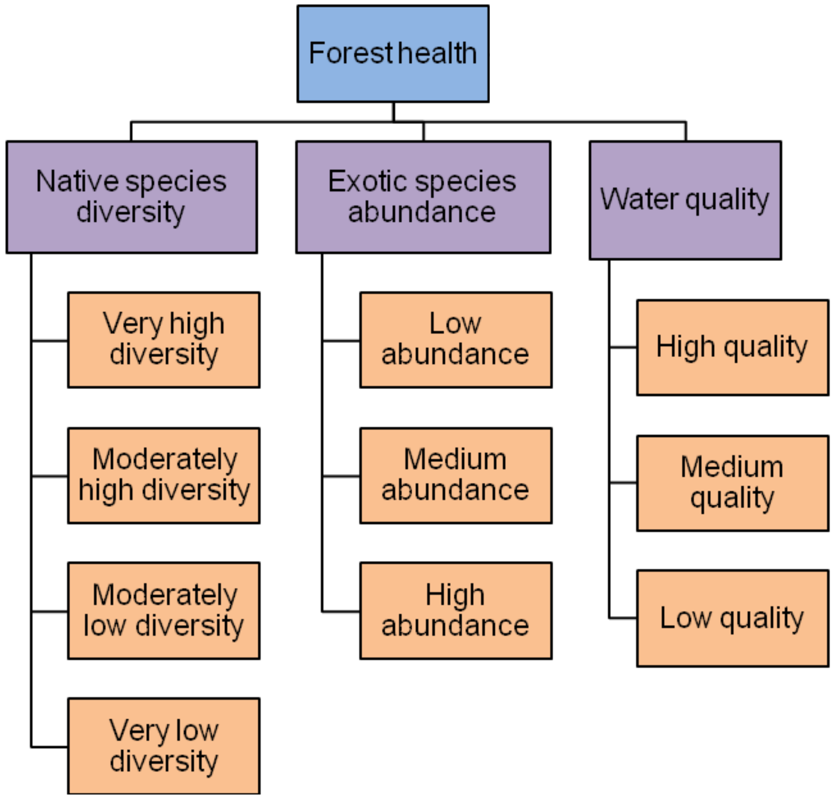
Decision options	Weights and scores 11	Weights and scores 12	Weights and scores 13	Weights and scores 14	Weights and scores 15
No modification	70.49	69.60	44.82	59.88	67.22
Personal use	65.85	65.42	41.91	56.28	62.57
Thinning	73.03	70.00	55.88	61.86	66.36
Group selection	67.19	64.48	54.26	57.60	59.85
Shelterwood	65.15	62.69	55.28	56.57	57.51
Easement with no modification	70.49	69.60	44.82	59.88	67.22
Easement with personal use	65.85	65.42	41.91	56.28	62.57
Easement with thinning	70.78	68.43	52.13	60.13	64.98
Easement with group selection	65.11	63.06	51.05	56.24	58.74
Easement with shelterwood	63.50	61.57	52.80	55.56	56.66
Sell 1 ha, remainder personal use	62.33	58.47	54.68	54.49	54.91

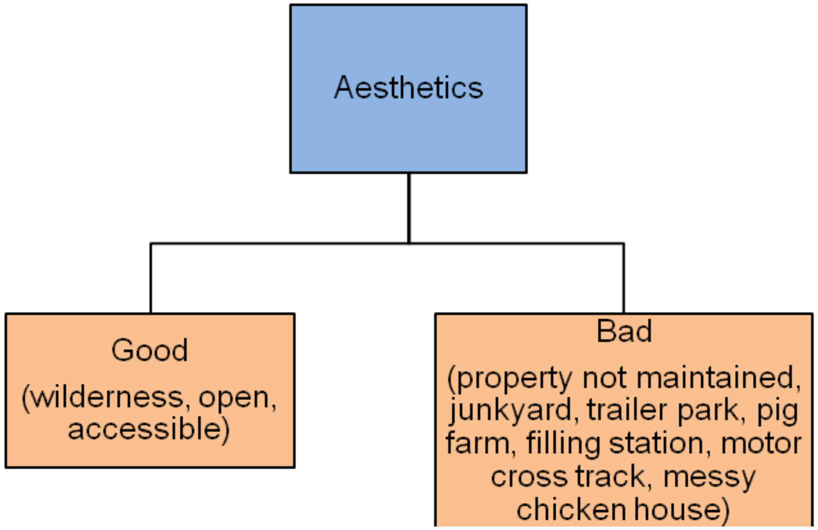
Decision options	Weights and scores 16	Weights and scores 17	Weights and scores 18	Weights and scores 19	Weights and scores 20
No modification	65.87	46.30	51.32	61.16	61.61
Personal use	61.66	43.70	47.92	56.58	57.55
Thinning	64.37	56.65	57.64	63.56	61.58
Group selection	58.46	55.17	54.35	57.69	56.07
Shelterwood	56.49	55.95	55.38	56.86	54.78
Easement with no modification	65.87	46.30	51.32	61.16	61.61
Easement with personal use	61.66	43.70	47.92	56.58	57.55
Easement with thinning	63.26	53.18	55.01	61.46	60.20
Easement with group selection	57.55	52.15	52.95	56.49	55.18
Easement with shelterwood	55.80	53.60	54.52	56.08	54.17
Sell 1 ha, remainder personal use	52.21	55.26	54.65	55.18	51.11

Decision options	Weights and scores 21	Weights and scores 22	Weights and scores 23	Weights and scores 24
No modification	49.32	56.64	60.69	62.05
Personal use	46.87	53.48	56.73	58.44
Thinning	59.01	65.89	65.21	63.40
Group selection	57.80	63.45	60.90	59.20
Shelterwood	58.81	63.86	59.80	57.96
Easement with no modification	49.32	56.64	60.69	62.05
Easement with personal use	46.87	53.48	56.73	58.44
Easement with thinning	55.77	62.34	62.73	61.81
Easement with group selection	55.03	60.59	58.76	57.84
Easement with shelterwood	56.68	61.65	58.15	56.91
Sell 1 ha, remainder personal use	58.37	61.90	57.72	54.61

Decision options	Best decision frequency	Worst decision frequency
No modification	8	0
Personal use	0	11
Thinning	23	0
Group selection	0	0
Shelterwood	5	1
Easement with no modification	7	0
Easement with personal use	0	11
Easement with thinning	0	0
Easement with group selection	0	1
Easement with shelterwood	0	1
Sell 1 ha, remainder personal use	1	13


Net income
Positive
(> 0 dollars)
Even
(0 dollars)
Negative
(< 0 dollars)
Safety
Human safety
High safety
(no injuries)
Moderate safety
(1 minor injury,
no serious injury)
Low safety
(more than 1
injury)
Property damage
No damage
Low damage
(little damage to structures, few acres burned, or small area
with landslide, less than 5 years for recovery)
High damage
(serious damage to structures, many acres burned, or large
area with landslide, more than 5 years for recovery


Forest health
Native species diversity
Exotic species abundance
Water quality
Very high diversity
Moderately high diversity
Moderately low diversity
Very low diversity
Low abundance
Medium abundance
High abundance
High quality
Medium quality
Low quality


Aesthetics
Good
(wilderness, open, accessible)
Bad
(property not maintained, junkyard, trailer park, pig farm, filling station, motor cross track, messy chicken house)

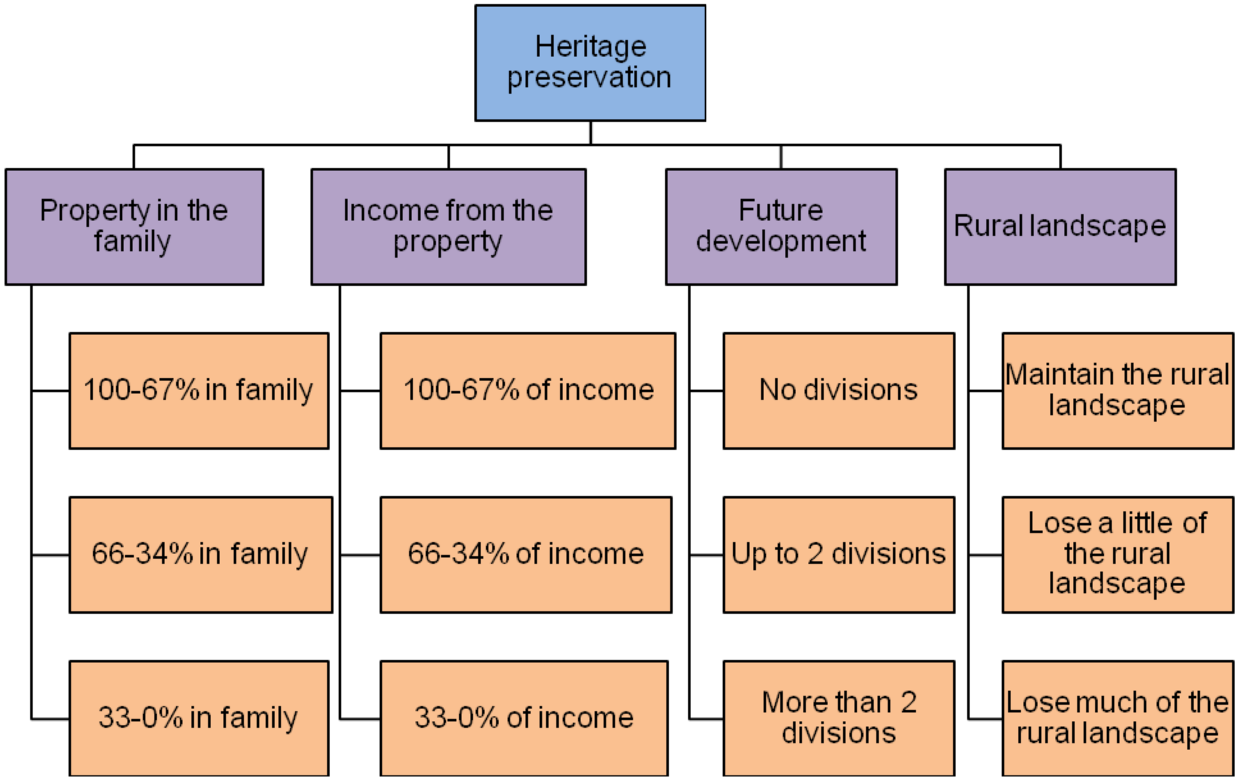
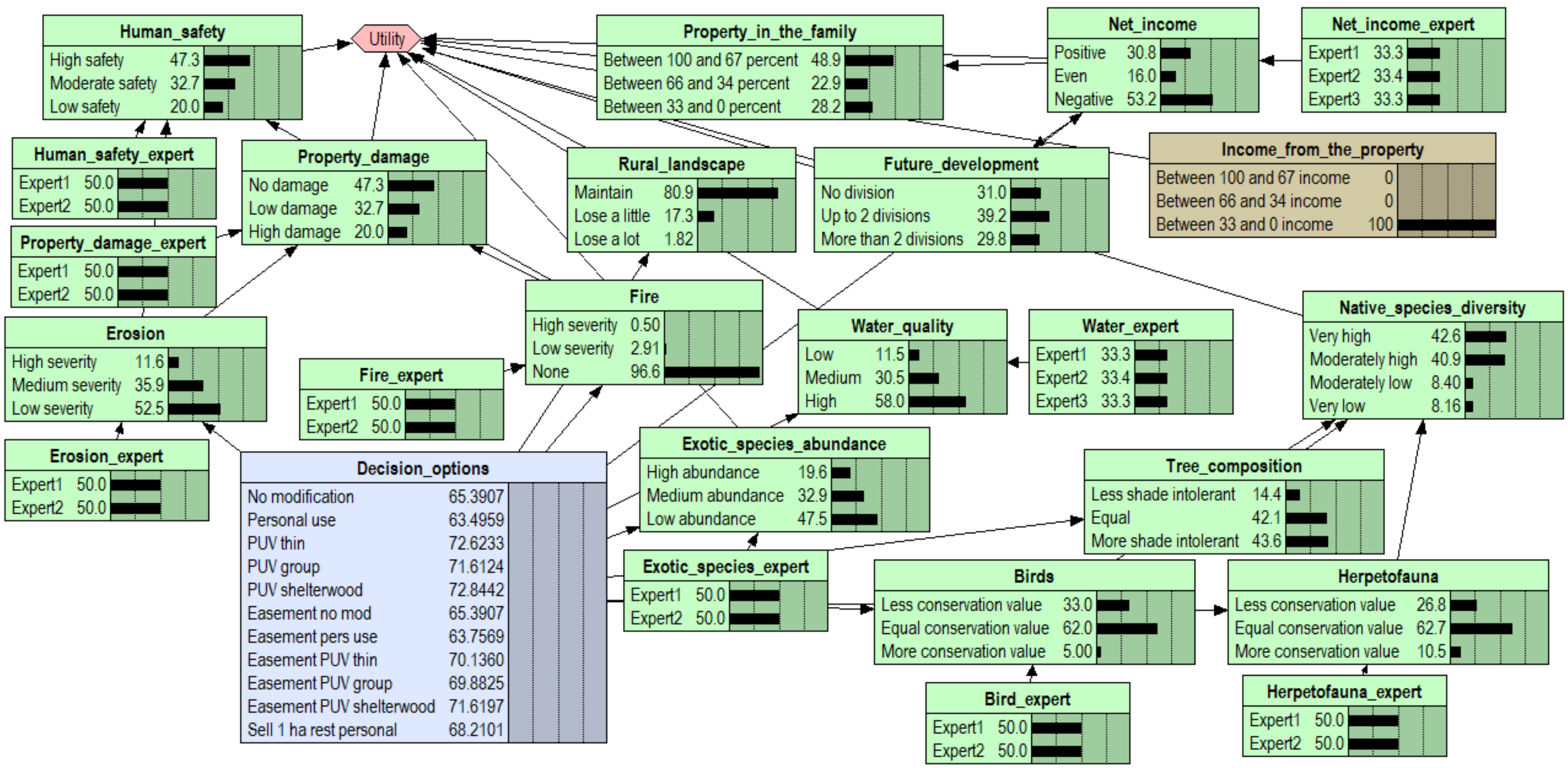


Figure 4.1: Objectives network based on landowners' comments during structured decision making workshops held in 2012 and 2013 that addressed forest management on an average large, forested property (30 ha property with 22 ha of forest) in Macon County, NC. There were two workshop series that each included ten landowners. The first-order fundamental objectives (blue), second-order fundamental objectives (purple), and attribute scales (orange) were similar in both workshop series. The meaning of levels in constructed attribute scales is provided. For some objectives, the number of levels in the attribute scale varied between workshop series, but the maximum number of levels are presented here. Also, the aesthetics objective was included in Series 2 only. See Figure 4.2 for additional details.

a)



Utility
Human_safety
High safety 47.3
Moderate safety 32.7
Low safety 20.0
Property_in_the_family
Between 100 and 67 percent 48.9
Between 66 and 34 percent 22.9
Between 33 and 0 percent 28.2
Net_income
Positive 30.8
Even 16.0
Negative 53.2
Net_income_expert
Expert1 33.3
Expert2 33.4
Expert3 33.3
Human_safety_expert
Expert1 50.0
Expert2 50.0
Property_damage
No damage 47.3
Low damage 32.7
High damage 20.0
Rural_landscape
Maintain 80.9
Lose a little 17.3
Lose a lot 1.82
Future_development
No division 31.0
Up to 2 divisions 39.2
More than 2 divisions 29.8
Income_from_the_property
Between 100 and 67 income 0
Between 66 and 34 income 0
Between 33 and 0 income 100
Property_damage_expert
Expert1 50.0
Expert2 50.0
Fire
High severity 0.50
Low severity 2.91
None 96.6
Erosion
High severity 11.6
Medium severity 35.9
Low severity 52.5
Fire_expert
Expert1 50.0
Expert2 50.0
Water_quality
Low 11.5
Medium 30.5
High 58.0
Water_expert
Expert1 33.3
Expert2 33.4
Expert3 33.3
Native_species_diversity
Very high 42.6
Moderately high 40.9
Moderately low 8.40
Very low 8.16
Erosion_expert
Expert1 50.0
Expert2 50.0
Decision_options
No modification 65.3907
Personal use 63.4959
PUV thin 72.6233
PUV group 71.6124
PUV shelterwood 72.8442
Easement no mod 65.3907
Easement pers use 63.7569
Easement PUV thin 70.1360
Easement PUV group 69.8825
Easement PUV shelterwood 71.6197
Sell 1 ha rest personal 68.2101
Exotic_species_abundance
High abundance 19.6
Medium abundance 32.9
Low abundance 47.5
Tree_composition
Less shade intolerant 14.4
Equal 42.1
More shade intolerant 43.6
Exotic_species_expert
Expert1 50.0
Expert2 50.0
Birds
Less conservation value 33.0
Equal conservation value 62.0
More conservation value 5.00
Herpetofauna
Less conservation value 26.8
Equal conservation value 62.7
More conservation value 10.5
Bird_expert
Expert1 50.0
Expert2 50.0
Herpetofauna_expert
Expert1 50.0
Expert2 50.0

b)

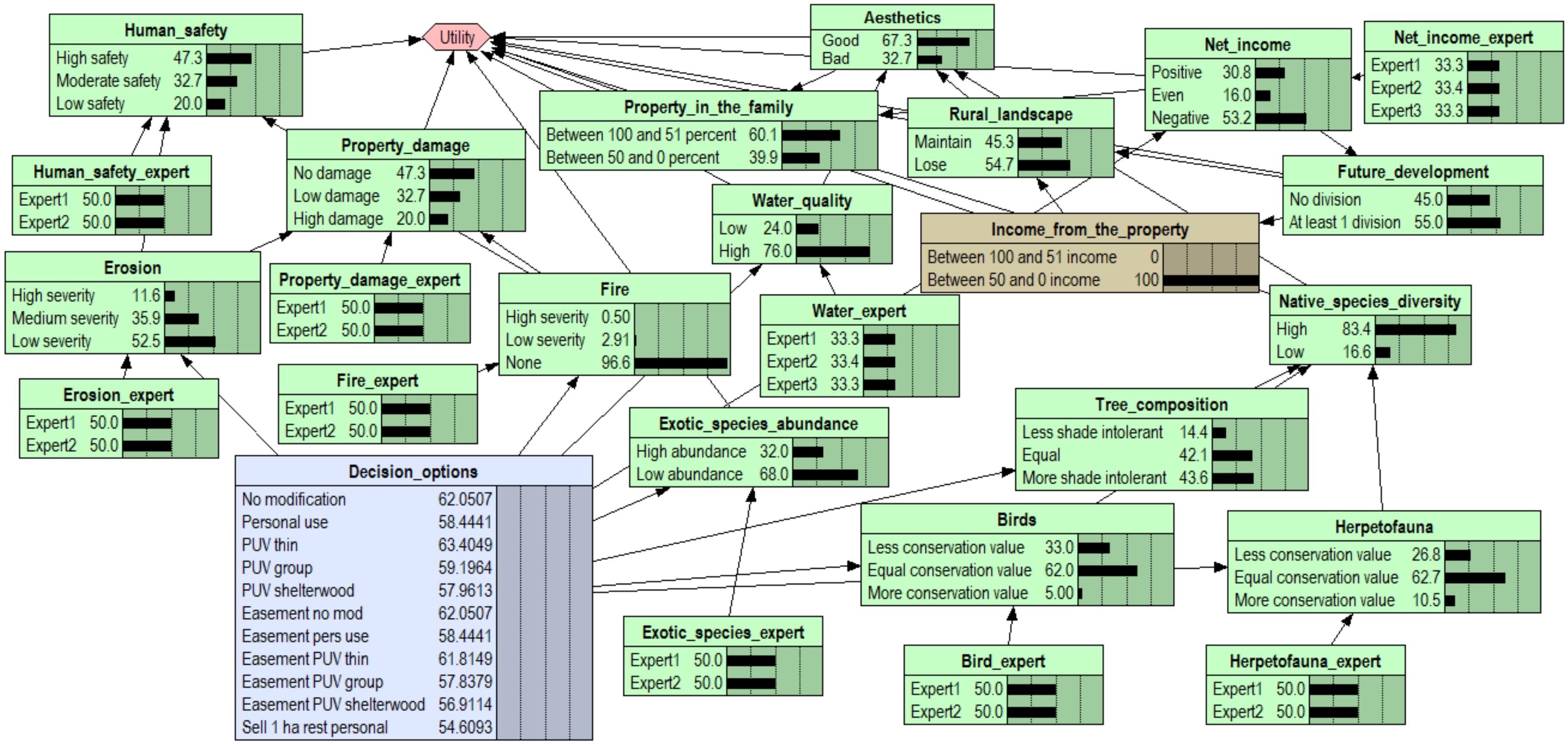


Figure 4.2: Bayesian decision networks based on landowners' comments during structured decision making workshops held in 2012 and 2013 that addressed forest management on an average large, forested property (30 ha property with 22 ha of forest) in Macon County, NC. There were two workshop series (a = Series 1, b = Series 2) that each included ten landowners. The decision network calculates utility values (shown in the blue box) through the pink hexagonal utility node for each decision option in the blue rectangular decision node. The decision option(s) with the greatest expected utility is most likely to achieve the landowners' objectives. Stochastic (green rectangular nodes) and deterministic (brown rectangular nodes) nature nodes link the decision options to the utility node. Arrows indicate dependencies such that the probabilities of each level in a node occurring are conditional on the states in antecedent nodes. The numbers next to the bars in a nature node depict the percent probability of that level occurring. Utility values from the mean objective weight and attribute score combinations are shown for both series (see Tables 4.2 and 4.3). The decision network was built in Netica 4.09 (Norsys Software Corp.)

CHAPTER 5

CONCLUSION

The focus of this dissertation has been the development and application of rigorous quantitative methods to address forest fragmentation and loss associated with exurban development. We considered the relationship between exurban development and ecological, economic, and social dynamics in Macon County, North Carolina. With false positive occupancy models, we investigated the influence of anthropogenic and environmental factors at multiple spatial scales on forest-dwelling, Neotropical migrant birds. Through a series of structured decision making (SDM) workshops with owners of large, forested properties (30 ha property with 22 ha of forest), we identified multiple ecological, economic, and social objectives held by landowners. We integrated value-based information from landowners with probabilities of outcomes from a suite of forest management decision options to identify the decision options that were most and least likely to meet landowners' objectives.

Chapter 2 is the first study to use simulations to evaluate occupancy models that generate inference about occupancy and true positive detection probabilities that exhibit heterogeneity while modeling false positive detection probabilities. Our models can be applied to research situations where there are both confirmed absences and confirmed presences (CACP model) or where there are only confirmed presences (CP model). The CACP and CP models generated more accurate and precise posterior distributions than the no false positives model even when the true positive detection probability was less than the false positive detection probability, there was a low rate of confirmed observations (3% compared to 10% in Miller et al. 2011), and there were observation confirmation errors. It may also be possible to identify phantom species (species that did not occupy any of the sampled sites but were erroneously detected) with our occupancy models. Additionally, our occupancy models generated accurate inferences about the relationship between covariates and site-specific occupancy probabilities and between covariates and site- and survey-specific true positive detection probabilities.

In Chapter 3, we applied the CP model that was evaluated in Chapter 2 to make inferences about the relationship between exurban development and occupancy of six species of forest-dwelling, Neotropical migrant birds at National Forest, land trust, and unprotected sites in Macon County. Results indicated that landscape composition influenced occupancy more than landscape configuration. Specifically, occupancy tended to be greatest at sites at high elevations, with high percent forest, or with low percent development. Also, occupancy appeared to be affected by landscape- and local-scale attributes more than site-scale characteristics. National Forest sites generally had high occupancy, but land trust sites and unprotected sites had similar occupancy. Conservation efforts may be most needed for the Black-throated Blue Warbler (BTBW) and Wood Thrush (WOTH), as these species had low to moderate posterior occupancy probabilities across sample sites.

In Chapter 4, our SDM project found that crown thinning through the Present-use Value (PUV) program was the most promising forest management decision option, and selling 1 ha of forest or personal use of the forest, with or without a conservation easement, were the least promising options. However, at the beginning of the project, most landowners (62%) thought personal use with or without a conservation easement would be the best decision option, while only 23% of the landowners thought crown thinning in the PUV program would best meet objectives. Landowners reported that participating in the SDM project was a good experience

(79%), and after reviewing the results of the decision network, 69% said they would reconsider what they are currently doing to manage their forest. The objectives held by each landowner were diverse, but contrary to expectation, there was not high variability among landowners.

Our findings could suggest conservation strategies for local organizations and encourage discussion about county-level decision making in response to exurban development and forest fragmentation. Since land trust sites had similar levels of avian occupancy compared to unprotected sites, land trusts may want to evaluate whether their conservation goals are being met through their current operations. SDM could be a useful process through which land trusts identify their objectives and compare their current operations to other options. For example, land trusts may want to consider habitat composition at the local- and landscape-scale instead of focusing on individual properties. Also, conservation easements were not one of the most promising forest management decision options in our SDM project, but they would better meet landowners' objectives if the financial costs could be reduced. Conservation of large, forested properties may be supported through increased education about the PUV program, choices of forest management planners, and information about likely outcomes from different harvesting methods. Bird conservation groups may want to consider ways to promote BTBW and WOTH conservation and may look to local Forest Service personnel for suggestions since avian occupancy was typically high at National Forest sites. Since WOTH are well-known and charismatic vocalists, bird conservation groups may have success generating interest in the larger community about their conservation. Renewed efforts to address county-level land use decision making could be beneficial, given the influence of land use at the landscape-scale on avian occupancy, and more successful than in the past if SDM is employed. The landowners who participated in our SDM project found the process enjoyable and helpful, so if SDM can be executed at the county-level while emphasizing that different objective weights and system models can be used, productive county-level decision making could be possible. Future research into the relationship between exurban development and wildlife should account for false positive detections, and our CACP and CP models are a useful new method to do this.

Literature cited

Miller, D.A., J.D. Nichols, B.T. McClintock, E.H. Campbell Grant, L.L. Bailey, and L.A. Weir. 2011. Improving occupancy estimation when two types of observational error occur: non-detection and species misidentification. Ecology 92:1422-1428.

APPENDIX A

DETAILS ABOUT METHODS FOR CHAPTER 2

Calculating an informative prior for the false positive detection probability

An internet survey designed to replicate avian point counts was completed by 52 observers from three self-reported skill levels: “Moderate” (n = 17), “Advanced” (n = 26), and “Expert” (n = 9) (Farmer et al. 2012). Farmer et al. (2012) played songs from six pairs of similar sounding bird species. One member of each species pair was randomly assigned to half of the scenarios, and the second half of the scenarios featured the other member. So for each species, false positives were possible in half of the scenarios. Farmer et al. (2012) reported the total number of false positives for a given species among all observer-scenarios and the number of completed observer-scenarios. So we calculated the false positive probability as total number of false positives for a given species among all observer-scenarios / (the number of completed observer-scenarios/2).

Table A.1: Parameter values used to simulate data in the three scenarios (strong quadratic, weak quadratic, and linear) where occupancy and detection probabilities were affected by covariates. Occupancy probabilities were simulated through a logit-linear model with intercept (psi_0 before undergoing a logit transformation), coefficient for the linear term (*a1*), and coefficient for the quadratic term (*a2*). True positive detection probabilities were simulated through a logit-linear model with intercept ($p11_0$ before undergoing a logit transformation) and coefficient for the linear term (*c1*). False positive detection probabilities were simulated for three time periods ($p10_{s1}$, $p10_{s2}$, $p10_{s3}$), and the observation confirmation probability was *b*.

	Strong quadratic	Weak quadratic	Linear
psi_0	0.7	0.7	0.7
a1	1.5	2.6	3.2
a2	-1.8	-0.4	NA
$p11_0$	0.5	0.5	0.5
c1	-2	-1.2	-2.5
$p10_{s1}$	0.1	0.1	0.1
$p10_{s2}$	0.07	0.07	0.07
$p10_{s3}$	0.04	0.04	0.04
b	0.03	0.03	0.03

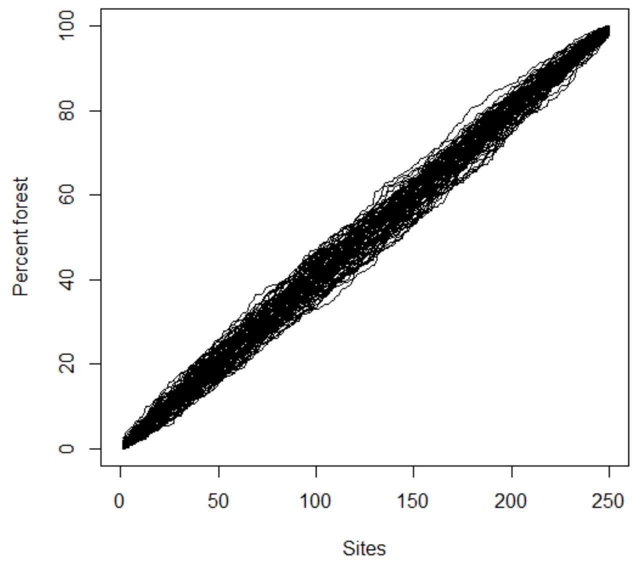


Figure A.1: Site-specific values for percent forest cover in the landscape from 100 simulated data sets. Sites are ordered by increasing levels of percent forest cover for display purposes.

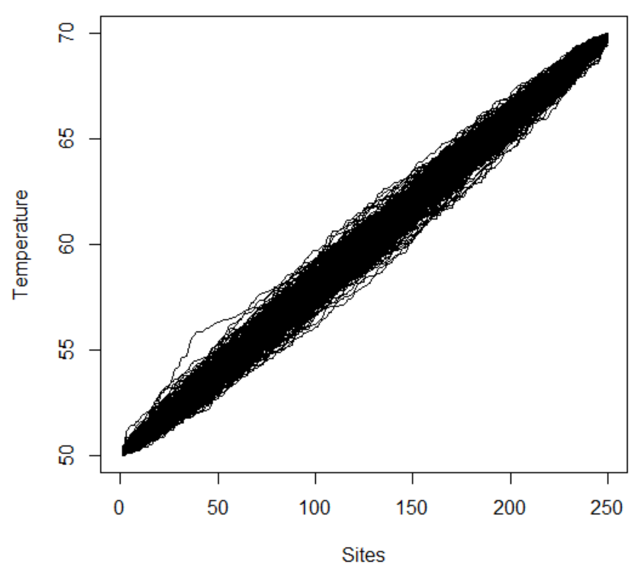


Figure A.2: Site- and survey-specific values for temperature from 100 simulated data sets. Sites are ordered by increasing levels of temperature for display purposes.

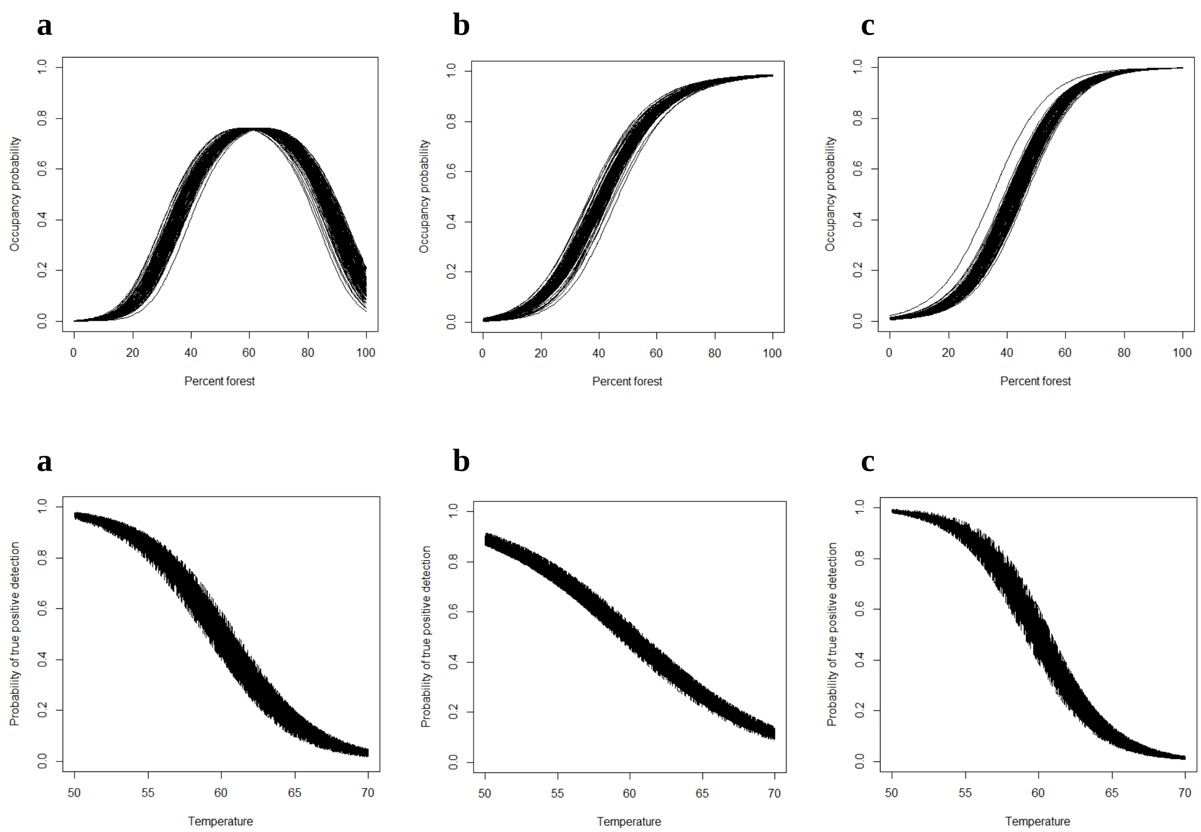


Figure A.3: Simulated effect of percent forest cover on occupancy probabilities and effect of temperature on true positive detection probabilities under three scenarios: a: strong quadratic, b: weak quadratic, c: linear.

Literature cited

Farmer, R.G., M.L. Leonard, and A.G. Horn. 2012. Observer effects and avian-call-count survey quality: rare-species biases and overconfidence. The Auk 129:76-86.

APPENDIX B

RESULTS FROM OCCUPANCY MODELS WITHOUT COVARIATES FOR CHAPTER 2

Table B.1: Summary of patterns in parameter posterior distributions when data were simulated so that the occupancy probability (ψ) was small (0.3) or large (0.7) and the true positive detection probability (*p11*) was greater than the false positive detection probability (*p10*). Posterior distributions were generated with seven models: CACP = confirmed absences and confirmed presences model, CP = confirmed presences model, Uninf *p10* = U(0,0.5) prior for *p10*, Inf *p10* = informative prior for *p10* (Beta(1,9)), Uninf *b* = vague prior for the observation confirmation probability (U(0,1) or Beta(0.5,0.5)), Obs conf errors = observation confirmation errors, No false positives model = model that assumed there were no false positive errors. BCI indicates the 95% Bayesian credible interval, and coverage refers to the case where the BCI contained the value used to simulate data.

	CACP, Uninf *p10*	CACP, Inf *p10*	CP, Uninf *p10*, Uninf *b*	CP, Inf *p10*, Uninf *b*	CACP, Uninf *p10*, Obs conf errors	CP, Inf *p10*, Obs conf errors	No false positives model
Small ψ --> ψ biased high				x	x	x	
Small ψ --> Low ψ BCI coverage							x
Small ψ --> Large *p11* BCI width	x	x				x	
Small ψ --> *p11* biased low					x	x	x
Small ψ --> Low rate of model convergence			x			x	
Large ψ --> ψ biased low	x		x	x	x	x	
Large ψ --> *p10* biased high	x				x		
Large ψ --> Large *p10* BCI width	x	x					
Large ψ --> High rate of model convergence			x				

Table B.2: Summary of patterns in parameter posterior distributions when data were simulated so that the occupancy probability (ψ) was small (0.3) or large (0.7) and the true positive detection probability (*p11*) was less than the false positive detection probability (*p10*). Additional details can be found in the Table B.1 legend.

	CACP, Uninf *p10*	CACP, Inf *p10*	CP, Uninf *p10*, Uninf *b*	CP, Inf *p10*, Uninf *b*	CACP, Uninf *p10*, Obs conf errors	CP, Inf *p10*, Obs conf errors	No false positives model
Small ψ --> ψ biased high	x	x	x	x	x	x	x
Small ψ --> Large ψ BCI width						x	
Small ψ --> Low ψ BCI coverage							x
Small ψ --> *p11* biased high	x	x					
Small ψ --> Low *p11* BCI coverage							x
Small ψ --> *b* biased high				x			
Small ψ --> Large *b* BCI width				x		x	
Large ψ --> ψ biased low			x	x	x	x	

Table B.3: Summary of patterns in parameter posterior distributions when data were simulated so that the true positive detection probability (*p11*) was small (0.2) or large (0.6) and the true positive detection probability was greater than the false positive detection probability (*p10*). Additional details can be found in the Table B.1 legend.

	CACP, Uninf *p10*	CACP, Inf *p10*	CP, Uninf *p10*, Uninf *b*	CP, Inf *p10*, Uninf *b*	CACP, Uninf *p10*, Obs conf errors	CP, Inf *p10*, Obs conf errors	No false positives model
Small *p11* --> Large ψ BCI width	x	x	x	x	x	x	x
Small *p11* --> *b* biased high			x			x	
Small *p11* --> Large *b* BCI width			x	x		x	
Large *p11* --> *p11* biased low							x
Large *p11* --> Low *p11* BCI coverage							x

Table B.4: Summary of patterns in parameter posterior distributions when data were simulated so that the false positive detection probability (*p10*) was small (0.05) or large (0.15) and the true positive detection probability (*p11*) was greater than the false positive detection probability. Additional details can be found in the Table B.1 legend.

	CACP, Uninf *p10*	CACP, Inf *p10*	CP, Uninf *p10*, Uninf *b*	CP, Inf *p10*, Uninf *b*	CACP, Uninf *p10*, Obs conf errors	CP, Inf *p10*, Obs conf errors	No false positives model
Small *p10* --> *p11* biased low					x		
Small *p10* --> *p10* biased high						x	
Small *p10* & Large ψ --> Low *p10* BCI coverage					x		
Large *p10* --> *p11* biased high					x		
Large *p10* --> *p10* biased low						x	
Large *p10* --> Low ψ BCI coverage							x

Table B.5: Performance of the confirmed absences and confirmed presences (CACP) model in simulated scenarios with twelve parameter value combinations and vague or informative priors for the false positive detection probability (*p10*). Parameter value combinations are summarized in Table 2.2. For each simulated scenario, 100 data sets were simulated, and a model was fit to each data set. The number of models out of 100 that converged is presented. Posterior distributions for the occupancy probability (ψ), true positive detection probability (*p11*), and false positive detection probability (*p10*) are summarized. The percent of converged model runs in which the 95% Bayesian credible interval (BCI) contained the value used to simulate data is presented, along with the absolute error in the mean of the posterior distribution relative to the value used to simulate data and BCI width. Both the error and the BCI width were calculated by averaging across model runs.

			Parameter estimates								
				ψ			*p11*			*p10*	
Parameter combination	Prior *p10*	Converge	Error	BCI cover	BCI width	Error	BCI cover	BCI width	Error	BCI cover	BCI width
1	U(0,0.5)	100	-0.03	95	0.21	0.01	94	0.13	0.02	92	0.14
2	U(0,0.5)	100	-0.02	96	0.27	0.00	95	0.14	0.01	95	0.20
3	U(0,0.5)	100	-0.02	93	0.35	-0.01	93	0.13	0.06	90	0.23
4	U(0,0.5)	100	-0.01	96	0.35	0.00	100	0.13	0.03	99	0.26
5	U(0,0.5)	92	0.00	95	0.19	0.00	97	0.22	0.00	96	0.07
6	U(0,0.5)	98	0.01	97	0.27	0.00	97	0.25	0.00	95	0.11
7	U(0,0.5)	100	0.01	95	0.34	-0.01	95	0.23	0.01	93	0.09
8	U(0,0.5)	100	0.01	94	0.36	-0.01	99	0.26	0.01	99	0.12
9	U(0,0.5)	100	0.01	90	0.34	0.00	100	0.05	0.01	99	0.14
10	U(0,0.5)	100	-0.01	96	0.36	0.00	96	0.10	0.00	98	0.23
11	U(0,0.5)	100	0.03	95	0.37	0.03	97	0.13	0.00	99	0.07
12	U(0,0.5)	100	0.03	93	0.35	0.03	96	0.22	0.00	96	0.12
1	Beta(1,9)	96	-0.01	99	0.21	0.00	97	0.13	0.01	98	0.13
2	Beta(1,9)	100	0.02	93	0.26	0.00	96	0.13	-0.02	97	0.19
3	Beta(1,9)	100	0.00	92	0.34	-0.01	96	0.12	0.02	99	0.18
4	Beta(1,9)	100	-0.01	92	0.35	0.00	97	0.13	-0.01	94	0.21
5	Beta(1,9)	91	0.01	93	0.20	-0.01	97	0.22	0.00	96	0.07
6	Beta(1,9)	100	0.02	95	0.28	-0.01	96	0.25	0.00	93	0.11
7	Beta(1,9)	100	0.00	94	0.34	0.00	94	0.24	0.01	90	0.08

8	Beta(1,9)	100	-0.01	93	0.35	0.00	97	0.27	0.00	97	0.11
9	Beta(1,9)	100	0.00	96	0.36	0.00	98	0.05	0.00	98	0.12
10	Beta(1,9)	100	0.00	94	0.36	0.01	93	0.10	-0.03	97	0.20
11	Beta(1,9)	98	0.03	91	0.37	0.02	98	0.12	0.00	97	0.07
12	Beta(1,9)	100	0.01	95	0.35	0.03	95	0.24	-0.01	97	0.12

Table B.6: Performance of the confirmed presences (CP) model in simulated scenarios with twelve parameter value combinations and vague or informative priors for the false positive detection probability (*p10*) and observation confirmation probability (*b*). Additional details can be found in the Table B.5 legend.

				Parameter estimates											
				ψ			*p11*			*p10*			*b*		
Parameter combination	Prior *p10*	Prior *b*	Converge	Error	BCI cover	BCI width	Error	BCI cover	BCI width	Error	BCI cover	BCI width	Error	BCI cover	BCI width
1	U(0,0.5)	U(0,1)	99	-0.05	95	0.27	0.03	92	0.15	0.04	97	0.17	0.01	97	0.04
2	U(0,0.5)	U(0,1)	99	-0.10	94	0.47	0.03	97	0.21	0.05	96	0.29	0.01	96	0.06
3	U(0,0.5)	U(0,1)	99	-0.23	90	0.76	0.00	94	0.23	0.09	83	0.29	0.04	90	0.16
4	U(0,0.5)	U(0,1)	99	-0.18	99	0.81	0.00	99	0.21	0.04	98	0.32	0.03	95	0.16
5	U(0,0.5)	U(0,1)	75	-0.01	99	0.22	0.02	95	0.25	0.00	96	0.08	0.01	96	0.06
6	U(0,0.5)	U(0,1)	89	0.00	93	0.38	0.02	99	0.32	0.00	93	0.15	0.01	96	0.08
7	U(0,0.5)	U(0,1)	89	0.00	97	0.76	-0.01	97	0.35	0.04	92	0.23	0.05	97	0.27
8	U(0,0.5)	U(0,1)	94	0.01	99	0.85	0.02	99	0.36	0.01	100	0.24	0.05	98	0.28
9	U(0,0.5)	U(0,1)	99	-0.13	99	0.82	0.01	99	0.09	0.02	99	0.29	0.03	99	0.15
10	U(0,0.5)	U(0,1)	100	-0.17	100	0.82	0.02	98	0.17	-0.01	100	0.31	0.03	99	0.15
11	U(0,0.5)	U(0,1)	99	0.05	100	0.89	0.05	95	0.20	0.01	100	0.20	0.04	100	0.28
12	U(0,0.5)	U(0,1)	99	0.06	100	0.88	0.04	97	0.27	0.00	99	0.25	0.04	100	0.25
1	Beta(1,9)	Beta(0.5,0.5)	80	-0.02	99	0.26	0.01	96	0.15	0.02	99	0.16	0.00	98	0.03
2	Beta(1,9)	Beta(0.5,0.5)	99	0.03	100	0.39	-0.01	100	0.17	-0.03	99	0.26	0.00	98	0.04
3	Beta(1,9)	Beta(0.5,0.5)	99	-0.11	98	0.80	-0.01	95	0.20	0.05	98	0.23	0.02	98	0.13
4	Beta(1,9)	Beta(0.5,0.5)	98	-0.04	100	0.82	0.00	99	0.18	-0.02	100	0.27	0.02	100	0.13
5	Beta(1,9)	Beta(0.5,0.5)	82	0.01	95	0.23	0.01	98	0.25	0.00	95	0.08	0.00	96	0.05
6	Beta(1,9)	Beta(0.5,0.5)	96	0.05	92	0.47	-0.02	96	0.34	-0.02	96	0.17	0.00	98	0.07
7	Beta(1,9)	Beta(0.5,0.5)	97	0.03	99	0.81	0.00	96	0.35	0.02	98	0.15	0.04	98	0.25
8	Beta(1,9)	Beta(0.5,0.5)	90	0.16	100	0.92	-0.01	99	0.28	-0.01	99	0.23	0.03	99	0.24
9	Beta(1,9)	Beta(0.5,0.5)	99	-0.08	100	0.83	0.01	99	0.07	0.01	99	0.19	0.02	100	0.14
10	Beta(1,9)	Beta(0.5,0.5)	99	-0.10	100	0.84	0.02	100	0.16	-0.04	99	0.24	0.02	99	0.14
11	Beta(1,9)	Beta(0.5,0.5)	97	0.10	99	0.92	0.03	98	0.16	0.01	100	0.15	0.04	99	0.27
12	Beta(1,9)	Beta(0.5,0.5)	97	0.14	99	0.93	0.03	99	0.26	-0.03	100	0.22	0.03	99	0.24
1	U(0,0.5)	U(0.01,0.05)	97	-0.05	99	0.27	0.02	95	0.15	0.04	96	0.17	0.00	94	0.03
2	U(0,0.5)	U(0.01,0.05)	100	-0.05	99	0.41	0.01	98	0.18	0.03	98	0.28	0.00	97	0.03
3	U(0,0.5)	U(0.01,0.05)	98	-0.04	98	0.62	-0.02	95	0.17	0.10	100	0.37	0.00	100	0.03
4	U(0,0.5)	U(0.01,0.05)	100	-0.03	100	0.64	-0.01	100	0.17	0.04	100	0.37	0.00	100	0.03
5	U(0,0.5)	U(0.01,0.05)	82	0.02	94	0.22	-0.01	100	0.24	0.00	99	0.08	0.00	100	0.03

6	U(0,0.5)	U(0.01,0.05)	91	0.04	98	0.39	-0.02	97	0.30	-0.01	97	0.15	0.00	100	0.03
7	U(0,0.5)	U(0.01,0.05)	96	0.09	99	0.71	-0.04	94	0.26	0.03	99	0.21	0.00	100	0.04
8	U(0,0.5)	U(0.01,0.05)	100	0.14	100	0.77	-0.02	100	0.25	0.02	100	0.26	0.00	100	0.04
9	U(0,0.5)	U(0.01,0.05)	100	0.02	100	0.63	0.01	100	0.06	0.03	100	0.33	0.00	100	0.03
10	U(0,0.5)	U(0.01,0.05)	100	-0.02	100	0.63	0.01	99	0.14	0.00	100	0.36	0.00	100	0.03
11	U(0,0.5)	U(0.01,0.05)	100	0.17	99	0.78	0.03	98	0.14	0.01	100	0.21	0.00	100	0.04
12	U(0,0.5)	U(0.01,0.05)	100	0.15	98	0.76	0.03	98	0.23	0.01	100	0.26	0.00	100	0.04
1	Beta(1,9)	Beta(10,300)	84	-0.02	99	0.24	0.01	100	0.14	0.01	96	0.15	0.00	99	0.02
2	Beta(1,9)	Beta(10,300)	96	0.01	100	0.37	-0.01	99	0.17	-0.02	100	0.25	0.00	100	0.03
3	Beta(1,9)	Beta(10,300)	99	-0.01	99	0.62	-0.02	93	0.17	0.05	100	0.26	0.00	100	0.03
4	Beta(1,9)	Beta(10,300)	100	0.04	100	0.61	0.00	100	0.15	-0.03	99	0.29	0.00	100	0.03
5	Beta(1,9)	Beta(10,300)	90	0.01	99	0.22	0.00	98	0.24	0.00	99	0.08	0.00	100	0.03
6	Beta(1,9)	Beta(10,300)	96	0.04	98	0.40	-0.01	97	0.31	-0.01	95	0.15	0.00	100	0.03
7	Beta(1,9)	Beta(10,300)	98	0.05	97	0.60	-0.02	99	0.27	0.01	98	0.12	0.00	100	0.04
8	Beta(1,9)	Beta(10,300)	99	0.08	97	0.69	0.00	100	0.28	-0.01	99	0.18	0.00	100	0.04
9	Beta(1,9)	Beta(10,300)	98	0.01	100	0.64	0.00	100	0.05	0.01	99	0.19	0.00	100	0.03
10	Beta(1,9)	Beta(10,300)	100	-0.01	100	0.64	0.02	95	0.14	-0.04	99	0.25	0.00	100	0.03
11	Beta(1,9)	Beta(10,300)	97	0.07	99	0.69	0.02	99	0.13	0.00	100	0.10	0.00	100	0.04
12	Beta(1,9)	Beta(10,300)	94	0.07	97	0.72	0.04	96	0.24	-0.02	98	0.16	0.00	100	0.04

Table B.7: Performance of the confirmed absences and confirmed presences (CACP) model when data had observation confirmation errors. Additional details can be found in the Table B.5 legend.

			Parameter estimates								
				ψ			*p11*			*p10*	
Parameter combination	Prior *p10*	Converge	Error	BCI cover	BCI width	Error	BCI cover	BCI width	Error	BCI cover	BCI width
1	U(0,0.5)	100	-0.07	80	0.23	0.02	95	0.14	0.06	60	0.15
2	U(0,0.5)	100	-0.07	88	0.30	0.02	88	0.15	0.06	78	0.20
3	U(0,0.5)	100	-0.07	93	0.36	-0.01	94	0.15	0.07	81	0.22
4	U(0,0.5)	100	-0.06	90	0.37	0.00	98	0.15	0.02	100	0.24
5	U(0,0.5)	87	0.02	91	0.20	-0.02	92	0.21	0.00	94	0.07
6	U(0,0.5)	95	0.04	94	0.28	-0.03	93	0.24	-0.01	93	0.11
7	U(0,0.5)	100	0.05	94	0.36	-0.03	89	0.21	0.02	88	0.10
8	U(0,0.5)	100	0.04	93	0.36	-0.01	99	0.24	0.01	97	0.13
9	U(0,0.5)	100	-0.04	94	0.37	0.01	98	0.05	0.00	97	0.11
10	U(0,0.5)	100	-0.04	98	0.36	0.01	99	0.11	-0.02	98	0.20
11	U(0,0.5)	100	0.07	89	0.37	0.03	92	0.12	0.00	96	0.07
12	U(0,0.5)	100	0.06	94	0.37	0.03	99	0.21	-0.01	99	0.13

Table B.8: Performance of the confirmed presences (CP) model when data had observation confirmation errors. Additional details can be found in the Table B.5 legend.

				Parameter estimates											
					ψ			*p11*			*p10*			*b*	
Parameter combination	Prior *p10*	Prior *b*	Converge	Error	BCI cover	BCI width	Error	BCI cover	BCI width	Error	BCI cover	BCI width	Error	BCI cover	BCI width
1	Beta(1,9)	Beta(0.5,0.5)	92	-0.02	100	0.26	0.01	97	0.15	0.02	100	0.16	0.00	95	0.03
2	Beta(1,9)	Beta(0.5,0.5)	98	0.05	99	0.37	-0.02	96	0.16	-0.04	100	0.25	0.00	96	0.04
3	Beta(1,9)	Beta(0.5,0.5)	99	-0.06	99	0.76	-0.01	97	0.19	0.05	100	0.25	0.02	96	0.11
4	Beta(1,9)	Beta(0.5,0.5)	100	-0.02	100	0.78	0.00	98	0.17	-0.02	99	0.27	0.02	99	0.12
5	Beta(1,9)	Beta(0.5,0.5)	82	0.04	91	0.23	-0.03	90	0.23	-0.01	100	0.08	0.01	96	0.05
6	Beta(1,9)	Beta(0.5,0.5)	88	0.15	80	0.45	-0.08	80	0.28	-0.04	90	0.17	0.00	97	0.06
7	Beta(1,9)	Beta(0.5,0.5)	96	0.12	100	0.85	-0.05	85	0.25	0.03	99	0.18	0.03	99	0.20
8	Beta(1,9)	Beta(0.5,0.5)	97	0.25	99	0.89	-0.01	99	0.24	-0.02	99	0.24	0.02	99	0.18
9	Beta(1,9)	Beta(0.5,0.5)	97	-0.06	100	0.81	0.01	100	0.06	0.01	100	0.19	0.02	97	0.13
10	Beta(1,9)	Beta(0.5,0.5)	100	-0.06	100	0.81	0.02	98	0.15	-0.04	98	0.24	0.02	98	0.13
11	Beta(1,9)	Beta(0.5,0.5)	97	0.21	99	0.90	0.02	95	0.12	0.01	99	0.18	0.02	100	0.18
12	Beta(1,9)	Beta(0.5,0.5)	97	0.21	100	0.91	0.04	93	0.23	-0.03	98	0.23	0.02	100	0.19

Table B.9: Performance of models when there was a phantom species. Errors refers to observation confirmation errors. Additional details can be found in the Table B.5 legend.

				Parameter estimates											
				ψ			*p11*			*p10*			*b*		
Confirmed data	Prior *p10*	Prior *b*	Converge	Error	BCI cover	BCI width	Error	BCI cover	BCI width	Error	BCI cover	BCI width	Error	BCI cover	BCI width
presences & absences	U(0,0.5)	NA	100	0.03	0	0.12	0.31	0	0.88	0.00	96	0.04	NA	NA	NA
presences & absences, with errors	U(0,0.5)	NA	100	0.13	0	0.25	0.14	0	0.37	0.00	97	0.05	NA	NA	NA
presences	Beta(1,9)	Beta(0.5,0.5)	55	0.07	0	0.76	0.40	0	0.99	0.00	100	0.06	0.29	100	0.99
presences, with errors	Beta(1,9)	Beta(0.5,0.5)	90	0.33	0	0.96	0.08	0	0.28	0.01	100	0.15	0.04	100	0.37
none: model assumes no false positives	NA	NA	100	0.69	0	0.63	0.08	0	0.11	NA	NA	NA	NA	NA	NA

Table B.10: Performance of the model assuming that false positive errors do not occur in simulations where data contained false positive errors. Additional details can be found in the Table B.5 legend.

		Parameter estimates					
			ψ			*p11*	
Parameter combination	Converge	Error	BCI cover	BCI width	Error	BCI cover	BCI width
1	100	0.05	63	0.13	-0.03	83	0.10
2	100	0.14	0	0.13	-0.05	38	0.10
3	100	0.10	84	0.35	0.00	96	0.11
4	100	0.19	30	0.26	0.01	99	0.09
5	100	0.14	3	0.15	-0.11	10	0.14
6	100	0.40	0	0.19	-0.19	0	0.12
7	100	0.38	3	0.50	-0.05	76	0.13
8	100	0.57	0	0.30	-0.01	98	0.10
9	100	-0.14	99	0.76	0.05	19	0.14
10	100	0.10	95	0.41	0.05	32	0.10
11	100	0.31	64	0.70	0.06	0	0.13
12	100	0.54	0	0.35	0.07	3	0.10

APPENDIX C

RESULTS FROM OCCUPANCY MODELS WITH COVARIATES FOR CHAPTER 2

Table C.1: Performance of eleven occupancy model parameterizations in the scenario where occupancy probabilities were affected by a covariate through a strong quadratic function. Whether simulated data had confirmed observations (conf obs) of presence (pres) or absence (abs) or observation confirmation errors is indicated. Models had vague (v) or informative (inf) priors for the false positive detection probability (*p10*) and observation confirmation probability (*b*), and all but one model accounted for false positive errors, which were present in all simulated data sets. The number of model runs out of 100 (one model run applied to each of 100 simulated data sets) that converged is presented. The absolute error of posterior occupancy probabilities (ψ) was calculated for each simulated site and each converged model run, and the mean error across sites and runs is presented. Similarly, the width of the 95% Bayesian credible interval (BCI) for each occupancy probability posterior distribution was calculated, and the mean BCI width is presented. Also, the percent of converged model runs in which the BCI contained the value used to simulate data is presented (cover). The mean error, mean BCI width, and coverage are also presented for the intercept (psi_0) before undergoing a logit transformation, the coefficient (*a1*) for the linear term, and the coefficient for the quadratic term (*a2*) in the equation quantifying the effect of a covariate on the occupancy probability; the intercept ($p11_0$) before undergoing a logit transformation and the coefficient (*c1*) for the linear term in the equation quantifying the effect of a covariate on the true positive detection probability; the false positive detection probability at three time periods ($p10_{s1}$, $p10_{s2}$, $p10_{s3}$); and the observation confirmation probability (*b*).

Model accounts for FP	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Conf obs	Pres, Abs	Pres, Abs	Pres, Abs	Pres, Abs	Pres	Pres	Pres	Pres	Pres	Pres	NA
Prior: *p10*	V	Inf	V	Inf	V	Inf	V	Inf	V	Inf	NA
Conf obs errors	No	No	Yes	Yes	No	No	Yes	Yes	No	No	NA
Prior: *b*	NA	NA	NA	NA	V	V	V	V	Inf	Inf	NA
Converge	100	100	98	100	97	99	97	99	94	100	100

***ψ* error**	0.00	0.00	0.00	0.01	-0.01	0.01	0.00	0.01	0.00	0.00	0.17
***ψ* cover**	95	95	92	88	95	94	96	97	98	95	36
***ψ* BCI width**	0.22	0.21	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.23
psi_0 error	-0.01	-0.01	-0.02	-0.01	-0.02	0.01	0.00	0.00	-0.01	0.00	0.06
psi_0 cover	95	96	95	94	97	92	96	97	98	95	77
psi_0 BCI width	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.25	0.24	0.20
***a1* error**	0.03	0.00	-0.11	-0.16	-0.04	0.03	-0.03	-0.06	0.05	-0.07	-0.82
***a1* cover**	96	92	92	86	93	95	96	99	98	97	9
***a1* BCI width**	1.37	1.36	1.29	1.23	1.37	1.40	1.36	1.37	1.43	1.35	0.76
***a2* error**	-0.03	-0.01	0.11	0.18	0.03	-0.10	-0.01	0.00	-0.05	0.01	0.93
***a2* cover**	92	94	94	86	96	98	97	99	99	95	3
***a2* BCI width**	1.41	1.40	1.33	1.30	1.40	1.45	1.40	1.44	1.45	1.42	0.85
$p11_0$ error	0.00	0.01	0.00	-0.01	0.01	0.00	0.00	0.00	0.00	0.00	-0.09
$p11_0$ cover	96	95	94	95	96	97	96	96	96	95	31
$p11_0$ BCI width	0.19	0.20	0.19	0.19	0.20	0.20	0.20	0.20	0.20	0.20	0.13
***c1* error**	-0.03	-0.09	-0.01	0.06	-0.10	-0.04	-0.07	-0.01	-0.02	-0.02	0.74
***c1* cover**	93	96	97	90	89	95	92	94	97	100	2
***c1* BCI width**	1.10	1.13	1.09	1.04	1.18	1.12	1.14	1.11	1.12	1.13	0.55
$p10_{s1}$ error	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	NA
$p10_{s1}$ cover	97	96	88	97	93	95	96	98	95	99	NA
$p10_{s1}$ BCI width	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	NA
$p10_{s2}$ error	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.01	0.00	0.00	NA
$p10_{s2}$ cover	93	93	95	94	96	96	94	95	98	99	NA

***p10$_{s2}$* BCI width**	0.10	0.09	0.10	0.09	0.10	0.10	0.10	0.10	0.10	0.09	NA
***p10$_{s3}$* error**	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.01	0.00	NA
***p10$_{s3}$* cover**	92	97	94	98	92	96	98	99	95	96	NA
***p10$_{s3}$* BCI width**	0.08	0.08	0.08	0.08	0.08	0.07	0.08	0.08	0.08	0.08	NA
***b* error**	NA	NA	NA	NA	0.00	0.00	0.00	0.00	0.00	0.00	NA
***b* cover**	NA	NA	NA	NA	91	97	96	94	97	99	NA
***b* BCI width**	NA	NA	NA	NA	0.04	0.04	0.04	0.04	0.03	0.03	NA

Table C.2: Performance of eleven occupancy model parameterizations in the scenario where occupancy probabilities were affected by a covariate through a weak quadratic function. Additional details can be found in the Table C.1 legend.

Model accounts for FP	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Conf obs	Pres, Abs	Pres, Abs	Pres, Abs	Pres, Abs	Pres	Pres	Pres	Pres	Pres	Pres	NA
Prior: *p10*	V	Inf	V	Inf	V	Inf	V	Inf	V	Inf	NA
Conf obs errors	No	No	Yes	Yes	No	No	Yes	Yes	No	No	NA
Prior: *b*	NA	NA	NA	NA	V	V	V	V	Inf	Inf	NA
Converge	98	100	97	95	94	94	89	96	90	95	99
ψ cover	99	97	92	90	98	97	98	96	97	97	49
***psi* BCI width**	0.19	0.19	0.19	0.19	0.19	0.20	0.20	0.19	0.19	0.19	0.17
ψ error	0.00	-0.01	-0.01	-0.01	-0.01	0.00	-0.01	0.00	-0.01	0.00	0.11
psi_0 error	-0.01	-0.02	-0.04	-0.02	-0.01	-0.02	-0.02	-0.01	-0.03	-0.01	0.08
psi_0 cover	100	92	91	91	97	96	93	93	93	96	74
psi_0 BCI width	0.28	0.28	0.28	0.28	0.29	0.29	0.30	0.30	0.30	0.29	0.22
***a1* error**	0.15	0.20	0.03	0.00	0.19	0.10	0.17	0.23	0.17	0.19	-0.06
***a1* cover**	97	97	96	93	100	98	99	98	98	96	98
***a1* BCI width**	2.05	2.11	1.91	1.88	2.17	2.11	2.15	2.24	2.16	2.19	2.40
***a2* error**	0.06	0.12	0.07	0.00	-0.02	0.12	0.07	0.09	0.09	0.07	0.94
***a2* cover**	98	95	92	92	100	98	98	98	99	98	36
***a2* BCI width**	2.06	2.15	1.90	1.89	2.17	2.09	2.15	2.26	2.16	2.17	1.71
$p11_0$ error	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.00	-0.04
$p11_0$ cover	93	96	99	96	90	93	97	94	96	99	65
$p11_0$ BCI width	0.13	0.13	0.13	0.13	0.14	0.14	0.14	0.14	0.14	0.14	0.11

***c1* error**	-0.04	-0.03	-0.04	-0.03	-0.05	-0.06	-0.06	-0.03	-0.06	-0.03	0.18
***c1* cover**	91	93	95	97	93	94	94	93	94	99	61
***c1* BCI width**	0.58	0.59	0.59	0.59	0.60	0.61	0.60	0.59	0.61	0.59	0.44
$p10_{s1}$ error	0.01	0.00	0.01	0.01	0.01	0.00	0.01	0.00	0.01	0.00	NA
$p10_{s1}$ cover	98	98	88	94	93	95	92	97	97	97	NA
$p10_{s1}$ BCI width	0.14	0.12	0.13	0.13	0.13	0.13	0.14	0.12	0.14	0.13	NA
$p10_{s2}$ error	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.01	0.01	NA
$p10_{s2}$ cover	96	94	96	95	97	93	97	95	91	97	NA
$p10_{s2}$ BCI width	0.12	0.11	0.12	0.11	0.12	0.11	0.12	0.11	0.12	0.11	NA
$p10_{s3}$ error	0.02	0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.02	0.01	NA
$p10_{s3}$ cover	94	97	91	94	93	98	94	97	98	98	NA
$p10_{s3}$ BCI width	0.10	0.09	0.10	0.09	0.10	0.09	0.10	0.09	0.10	0.09	NA
***b* error**	NA	NA	NA	NA	0.00	0.00	0.00	0.00	0.00	0.00	NA
***b* cover**	NA	NA	NA	NA	95	95	92	97	97	99	NA
***b* BCI width**	NA	NA	NA	NA	0.03	0.03	0.04	0.03	0.03	0.03	NA

Table C.3: Performance of eleven occupancy model parameterizations in the scenario where occupancy probabilities were affected by a covariate through a linear function. The coefficient for the linear term in the equation quantifying the effect of a covariate on the occupancy probability is *a1*. Additional details can be found in the Table C.1 legend.

Model accounts for FP	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Conf obs	Pres, Abs	Pres, Abs	Pres, Abs	Pres, Abs	Pres	Pres	Pres	Pres	Pres	Pres	NA
Prior: *p10*	V	Inf	V	Inf	V	Inf	V	Inf	V	Inf	NA
Conf obs errors	No	No	Yes	Yes	No	No	Yes	Yes	No	No	NA
Prior: *b*	NA	NA	NA	NA	V	V	V	V	Inf	Inf	NA
Converge	100	100	100	100	100	100	100	99	100	100	100
ψ cover	98	94	87	85	96	94	98	96	95	96	41
ψ BCI width	0.13	0.13	0.14	0.14	0.13	0.14	0.13	0.14	0.14	0.13	0.14
ψ error	0.00	0.00	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.10
psi_0 error	-0.01	-0.02	-0.05	-0.04	-0.03	-0.02	-0.02	0.00	-0.02	-0.01	0.09
psi_0 cover	98	92	91	93	92	96	99	93	95	96	42
psi_0 BCI width	0.24	0.24	0.23	0.23	0.25	0.25	0.25	0.25	0.24	0.25	0.17
***a1* error**	-0.03	-0.18	-0.40	-0.40	-0.03	-0.15	-0.09	-0.05	-0.13	-0.04	-1.15
***a1* cover**	98	96	80	78	97	93	98	97	98	96	6
***a1* BCI width**	1.99	1.86	1.68	1.70	2.04	1.96	1.99	2.03	1.95	2.02	1.19
$p11_0$ error	0.00	0.01	0.00	0.00	0.01	-0.01	0.00	0.00	0.00	0.00	-0.05
$p11_0$ cover	97	94	96	95	95	93	95	96	94	95	65
$p11_0$ BCI width	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.15	0.16	0.16	0.12
***c1* error**	-0.04	-0.02	0.00	0.00	0.00	-0.03	-0.02	0.03	0.00	0.00	0.72
***c1* cover**	95	99	96	93	95	97	96	96	97	98	3
***c1* BCI width**	1.00	1.00	1.00	1.00	1.00	1.02	1.00	0.97	1.00	0.99	0.61

***p10**$_{s1}$* **error**	0.01	-0.01	0.01	0.00	0.01	0.00	0.00	-0.01	0.01	0.00	NA
***p10**$_{s1}$* **cover**	97	97	95	96	94	96	96	94	93	94	NA
***p10**$_{s1}$* **BCI width**	0.13	0.12	0.13	0.12	0.13	0.12	0.12	0.12	0.13	0.12	NA
***p10**$_{s2}$* **error**	0.01	0.00	0.01	0.00	0.02	0.00	0.01	0.00	0.01	0.00	NA
***p10**$_{s2}$* **cover**	96	98	97	96	91	95	89	94	91	92	NA
***p10**$_{s2}$* **BCI width**	0.11	0.10	0.11	0.11	0.11	0.10	0.11	0.10	0.11	0.10	NA
***p10**$_{s3}$* **error**	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	NA
***p10**$_{s3}$* **cover**	96	99	96	99	96	99	97	96	97	98	NA
***p10**$_{s3}$* **BCI width**	0.09	0.08	0.10	0.09	0.09	0.09	0.09	0.09	0.09	0.08	NA
***b* error**	NA	NA	NA	NA	0.00	0.00	0.00	0.00	0.00	0.00	NA
***b* cover**	NA	NA	NA	NA	96	92	96	95	99	100	NA
***b* BCI width**	NA	NA	NA	NA	0.03	0.03	0.03	0.03	0.03	0.02	NA

APPENDIX D

EXAMPLE CODE FOR CHAPTER 2

Confirmed absences and presences model without covariates

```
true_psi<-0.3
true_p11<-0.02
true_p10<-0.05
true_b<-0.03

sim.data<-function(psi=true_psi,p11=true_p11,p10=true_p10,b=true_b,nsites=250,k=3)
{
  c<-array(0,dim=c(nsites,k))
  mu<-array(0,dim=c(nsites,k))
  y<-array(0,dim=c(nsites,k))
  z<-rbinom(nsites,1,psi)
  for (i in 1:nsites){
    for(j in 1:k){
      c[i,j]<-rbinom(1,1,b)
      mu[i,j]<-(1-z[i])*(1-c[i,j])*p10+c[i,j]*z[i]+z[i]*(1-c[i,j])*p11
      y[i,j]<-rbinom(1,1,mu[i,j])
    }
  }
  return(list(z=z,c=c,mu=mu,y=y,k=k,nsites=nsites))
}

reps=100
for(r in 1:reps){
  x<-sim.data()
  data<-list(y=x$y,nsites=x$nsites,k=x$k,c=x$c)
  library(R2OpenBUGS)
  sink("model.txt")
  cat("
  model {
    p10~dunif(0,0.5)
    p11~dunif(0,1)
    psi~dunif(0,1)
    for(i in 1:nsites){
      z[i]~dbern(psi)
      for(j in 1:k){
        mu[i,j]<-(1-z[i])*(1-c[i,j])*p10+c[i,j]*z[i]+z[i]*(1-c[i,j])*p11
```

```
      y[i,j]~dbern(mu[i,j])
    }
  }
}
",fill=TRUE)
sink()

inits<-function()list(psi=runif(1,0,1),p11=runif(1,0,1),p10=runif(1,0,0.17))
inits1<- inits()
inits2<- inits()
inits3<- inits()
inits<- list(inits1, inits2, inits3)
params<-c("psi","p10","p11")
settings<-c(100000,1,50000,3)
out=bugs(data=data,inits,parameters=params,model.file="model.txt",n.iter=settings[1],n.thin=settings[2],n.burnin=settings[3],n.chains=settings[4],codaPkg=FALSE,debug=FALSE,OpenBUGS.pgm="C:/OpenBUGS322/OpenBUGS.exe",working.directory=getwd())
```

Confirmed presences model without covariates

```
true_psi<-0.3
true_p11<-0.1
true_p10<-0.15
true_b<-0.03

sim.data<-function(psi=true_psi,p11=true_p11,p10=true_p10,b=true_b,nsites=250,k=3)
{
  c<-array(0,dim=c(nsites,k))
  mu<-array(0,dim=c(nsites,k))
  y<-array(0,dim=c(nsites,k))
  z<-rbinom(nsites,1,psi)
  for (i in 1:nsites){
    for(j in 1:k){
      if(z[i]==1){
        c[i,j]<-rbinom(1,1,b)
      }else{
        c[i,j]<-0
      }
      mu[i,j]<-(1-z[i])*(1-c[i,j])*p10 + (1-z[i])*c[i,j]*0 + c[i,j]*z[i]*1 + z[i]*(1-c[i,j])*p11
      y[i,j]<-rbinom(1,1,mu[i,j])
    }
  }
  return(list(z=z,c=c,mu=mu,y=y,k=k,nsites=nsites))
}

reps=100
for(r in 1:reps){
  x<-sim.data()
  data<-list(y=x$y,nsites=x$nsites,k=x$k,c=x$c)
  library(R2OpenBUGS)
  sink("model.txt")
  cat("
  model {
    p10~dunif(0,0.5)
    p11~dunif(0,1)
    psi~dunif(0,1)
    b~dunif(0,1)
    for(i in 1:nsites){
      z[i]~dbern(psi)
      for(j in 1:k){
        conf[i,j]<-z[i]*b
        c[i,j]~dbern(conf[i,j])
        mu[i,j]<-(1-z[i])*(1-c[i,j])*p10 + (1-z[i])*c[i,j]*0 + c[i,j]*z[i]*1 + z[i]*(1-
c[i,j])*p11
```

```
      y[i,j]~dbern(mu[i,j])
     }
   }
  }
  ",fill=TRUE)
  sink()

  inits<-
function()list(psi=runif(1,0,1),p11=runif(1,0,1),p10=runif(1,0,0.17),b=runif(1,0,0.25))
  inits1<- inits()
  inits2<- inits()
  inits3<- inits()
  inits<- list(inits1, inits2, inits3)
  params<-c("psi","p10","p11","b")
  settings<-c(150000,1,75000,3)
out=bugs(data=data,inits,parameters=params,model.file="model.txt",n.iter=settings[1],n.t
hin=settings[2],n.burnin=settings[3],n.chains=settings[4],codaPkg=FALSE,debug=FALS
E,  OpenBUGS.pgm="C:/OpenBUGS322/OpenBUGS.exe",working.directory=getwd())
```

No false positives model without covariates

```
true_psi<-0.7
true_p11<-0.6
true_p10<-0.15

sim.data<-function(psi=true_psi,p11=true_p11,p10=true_p10,nsites=250,k=3)
{
  y<-array(0,dim=c(nsites,k))
  z<-rbinom(nsites,1,psi)
  for (i in 1:nsites){
    for(j in 1:k){
      if(z[i]==1){
      y[i,j]<-rbinom(1,1,p11)
      }else{
      y[i,j]<-rbinom(1,1,p10)
      }
    }
  }
  return(list(z=z,y=y,k=k,nsites=nsites))
}

reps=100
for(r in 1:reps){
  x<-sim.data()
  data<-list(y=x$y,nsites=x$nsites,k=x$k)
  library(R2OpenBUGS)
  sink("model.txt")
  cat("
  model {
    p11~dunif(0,1)
    psi~dunif(0,1)
    for(i in 1:nsites){
      z[i]~dbern(psi)
      for(j in 1:k){
        mu[i,j]<-z[i]*p11
        y[i,j]~dbern(mu[i,j])
      }
    }
  }
  ",fill=TRUE)
  sink()

  inits<-function()list(psi=runif(1,0,1),p11=runif(1,0,1))
  inits1<- inits()
  inits2<- inits()
```

```
  inits3<- inits()
  inits<- list(inits1, inits2, inits3)
  params<-c("psi","p11")
  settings<-c(100000,1,50000,3)
out=bugs(data=data,inits,parameters=params,model.file="model.txt",n.iter=settings[1],n.t
hin=settings[2],n.burnin=settings[3],n.chains=settings[4],codaPkg=FALSE,debug=FALS
E,  OpenBUGS.pgm="C:/OpenBUGS/OpenBUGS322.exe",working.directory=getwd())
```

Confirmed absences and presences model with covariates

```
true_psi_0<-0.7
true_a1<-2.6
true_a2<- -0.4
true_p11_0<-0.5
true_c1<- -1.2
true_p10_s1<-0.1
true_p10_s2<-0.07
true_p10_s3<-0.04
true_b<-0.03
true_nsites<-250
true_k<-3
true_lpsi_0<-log(true_psi_0/(1-true_psi_0))
true_lp11_0<-log(true_p11_0/(1-true_p11_0))

true_survey1<-array(data=0, dim=c(250,3))
true_survey2<-array(data=0, dim=c(250,3))
true_survey3<-array(data=0, dim=c(250,3))
true_survey1[,1]<-1
true_survey2[,2]<-1
true_survey3[,3]<-1

sim.data<-function(lpsi_0=true_lpsi_0, a1=true_a1, a2=true_a2,
lp11_0=true_lp11_0, c1=true_c1,
p10_s1=true_p10_s1, p10_s2=true_p10_s2, p10_s3=true_p10_s3,
b=true_b, nsites=true_nsites, k=true_k,
survey1=true_survey1, survey2=true_survey2, survey3=true_survey3)
{
  forest0to100<-runif(true_nsites,0,100)
  forestIn<-scale(forest0to100)
  forest<-as.vector(forestIn[,1])
  temp50to70<-array(data=runif(true_nsites*true_k,50,70),dim=c(true_nsites,true_k))
  tempIn<-scale(temp50to70)
  temp<-array(data=NA,dim=c(true_nsites,true_k))
  temp[,1]<-as.vector(tempIn[,1])
  temp[,2]<-as.vector(tempIn[,2])
  temp[,3]<-as.vector(tempIn[,3])
  lpsi<-array(0,dim=c(nsites))
  psi<-array(0,dim=c(nsites))
  z<-array(0,dim=c(nsites))
  lp11<-array(0,dim=c(nsites,k))
  p11<-array(0,dim=c(nsites,k))
  p10<-array(0,dim=c(nsites,k))
  c<-array(0,dim=c(nsites,k))
  mu<-array(0,dim=c(nsites,k))
```

```
  y<-array(0,dim=c(nsites,k))

  for (i in 1:nsites){
    lpsi[i]<-lpsi_0+a1*forest[i]+a2*forest[i]*forest[i]
    psi[i]<-1/(1+exp(-lpsi[i]))
    z[i]<-rbinom(1,1,psi[i])
    for(j in 1:k){
      c[i,j]<-rbinom(1,1,b)
      lp11[i,j]<-lp11_0+c1*temp[i,j]
      p11[i,j]<-1/(1+exp(-lp11[i,j]))
      p10[i,j]<-p10_s1*survey1[i,j] + p10_s2*survey2[i,j] + p10_s3*survey3[i,j]
      mu[i,j]<-(1-z[i])*(1-c[i,j])*p10[i,j] + c[i,j]*z[i] + z[i]*(1-c[i,j])*p11[i,j]
      y[i,j]<-rbinom(1,1,mu[i,j])
    }
  }
  return(list(psi=psi,z=z,c=c,p11=p11,p10=p10,y=y,
  temp50to70=temp50to70,temp=temp,forest0to100=forest0to100,forest=forest,
  survey1=survey1,survey2=survey2,survey3=survey3,
  k=k,nsites=nsites))
}

reps=100
for(r in 1:reps){
  x<-sim.data()
  data<-list(y=x$y,nsites=x$nsites,k=x$k,c=x$c,forest=x$forest,temp=x$temp,
  survey1=x$survey1,survey2=x$survey2,survey3=x$survey3)
  library(R2OpenBUGS)
  sink("model.txt")
  cat("
  model {
    p11_0~dunif(0,1)
    psi_0~dunif(0,1)
    p10_s1~dunif(0,0.5)
    p10_s2~dunif(0,0.5)
    p10_s3~dunif(0,0.5)
    a1~dnorm(0,0.368)
    a2~dnorm(0,0.368)
    c1~dnorm(0,0.368)

    lpsi_0<-log(psi_0/(1-psi_0))
    lp11_0<-log(p11_0/(1-p11_0))

    for(i in 1:nsites){
      logitpsi[i]<-lpsi_0+a1*forest[i]+a2*forest[i]*forest[i]
      logitpsitrun[i]<-min(999,max(-999,logitpsi[i]))
      psi[i]<-1/(1+exp(-logitpsitrun[i]))
```

```
    z[i]~dbern(psi[i])
    for(j in 1:k){
      logitp11[i,j]<-lp11_0+c1*temp[i,j]
      logitp11trun[i,j]<-min(999,max(-999,logitp11[i,j]))
      p11[i,j]<-1/(1+exp(-logitp11trun[i,j]))
      p10[i,j]<-p10_s1*survey1[i,j] + p10_s2*survey2[i,j] + p10_s3*survey3[i,j]
      mu[i,j]<-(1-z[i])*(1-c[i,j])*p10[i,j]+c[i,j]*z[i]+z[i]*(1-c[i,j])*p11[i,j]
      y[i,j]~dbern(mu[i,j])
    }#survey
  }#site
 }#model
 ",fill=TRUE)
 sink()

 inits<-function()list(psi_0=runif(1,0,1),p11_0=runif(1,0,1),
 p10_s1=runif(1,0,0.17),p10_s2=runif(1,0,0.17),p10_s3=runif(1,0,0.17),
 a1=rnorm(1),a2=rnorm(1),c1=rnorm(1))
 inits1<- inits()
 inits2<- inits()
 inits3<- inits()
 inits<- list(inits1, inits2, inits3)
 params<-c("psi","psi_0","p10_s1","p10_s2","p10_s3","p11_0","a1","a2","c1")
 settings<-c(100000,1,50000,3)
out=bugs(data=data,inits,parameters=params,model.file="false.txt",n.iter=settings[1],n.th
in=settings[2],n.burnin=settings[3],n.chains=settings[4],codaPkg=FALSE,debug=FALSE
,  OpenBUGS.pgm="C:/OpenBUGS322/OpenBUGS.exe",working.directory=getwd())
```

Confirmed presences model with covariates

```
true_psi_0<-0.7
true_a1<-1.5
true_a2<- -1.8
true_p11_0<-0.5
true_c1<- -2
true_p10_s1<-0.1
true_p10_s2<-0.07
true_p10_s3<-0.04
true_b<-0.03
true_nsites<-250
true_k<-3
true_lpsi_0<-log(true_psi_0/(1-true_psi_0))
true_lp11_0<-log(true_p11_0/(1-true_p11_0))

true_survey1<-array(data=0, dim=c(250,3))
true_survey2<-array(data=0, dim=c(250,3))
true_survey3<-array(data=0, dim=c(250,3))
true_survey1[,1]<-1
true_survey2[,2]<-1
true_survey3[,3]<-1

sim.data<-function(lpsi_0=true_lpsi_0, a1=true_a1, a2=true_a2,
lp11_0=true_lp11_0, c1=true_c1,
p10_s1=true_p10_s1, p10_s2=true_p10_s2, p10_s3=true_p10_s3,
b=true_b, nsites=true_nsites, k=true_k,
survey1=true_survey1, survey2=true_survey2, survey3=true_survey3)
{
  forest0to100<-runif(true_nsites,0,100)
  forestIn<-scale(forest0to100)
  forest<-as.vector(forestIn[,1])
  temp50to70<-array(data=runif(true_nsites*true_k,50,70),dim=c(true_nsites,true_k))
  tempIn<-scale(temp50to70)
  temp<-array(data=NA,dim=c(true_nsites,true_k))
  temp[,1]<-as.vector(tempIn[,1])
  temp[,2]<-as.vector(tempIn[,2])
  temp[,3]<-as.vector(tempIn[,3])
  lpsi<-array(0,dim=c(nsites))
  psi<-array(0,dim=c(nsites))
  z<-array(0,dim=c(nsites))
  lp11<-array(0,dim=c(nsites,k))
  p11<-array(0,dim=c(nsites,k))
  p10<-array(0,dim=c(nsites,k))
  c<-array(0,dim=c(nsites,k))
  mu<-array(0,dim=c(nsites,k))
```

```
  y<-array(0,dim=c(nsites,k))

  for (i in 1:nsites){
    lpsi[i]<-lpsi_0+a1*forest[i]+a2*forest[i]*forest[i]
    psi[i]<-1/(1+exp(-lpsi[i]))
    z[i]<-rbinom(1,1,psi[i])
    for(j in 1:k){
      if(z[i]==1){
        c[i,j]<-rbinom(1,1,b)
      }else{
        c[i,j]<-0
      }
      lp11[i,j]<-lp11_0+c1*temp[i,j]
      p11[i,j]<-1/(1+exp(-lp11[i,j]))
      p10[i,j]<-p10_s1*survey1[i,j] + p10_s2*survey2[i,j] + p10_s3*survey3[i,j]
      mu[i,j]<-(1-z[i])*(1-c[i,j])*p10[i,j] + (1-z[i])*c[i,j]*0 + c[i,j]*z[i]*1 + z[i]*(1-
c[i,j])*p11[i,j]
      y[i,j]<-rbinom(1,1,mu[i,j])
    }
  }
  return(list(psi=psi,z=z,c=c,p11=p11,p10=p10,y=y,
  temp50to70=temp50to70,temp=temp,forest0to100=forest0to100,forest=forest,
  survey1=survey1,survey2=survey2,survey3=survey3,
  k=k,nsites=nsites))
}


reps=100
for(r in 1:reps){
  x<-sim.data()
  data<-list(y=x$y,nsites=x$nsites,k=x$k,c=x$c,forest=x$forest,temp=x$temp,
  survey1=x$survey1,survey2=x$survey2,survey3=x$survey3)
  library(R2OpenBUGS)
  sink("model.txt")
  cat("
  model {
    p11_0~dunif(0,1)
    psi_0~dunif(0,1)
    p10_s1~dunif(0,0.5)
    p10_s2~dunif(0,0.5)
    p10_s3~dunif(0,0.5)
    a1~dnorm(0,0.368)
    a2~dnorm(0,0.368)
    c1~dnorm(0,0.368)
    b~dunif(0,1)
```

```
    lpsi_0<-log(psi_0/(1-psi_0))
    lp11_0<-log(p11_0/(1-p11_0))

    for(i in 1:nsites){
      logitpsi[i]<-lpsi_0+a1*forest[i]+a2*forest[i]*forest[i]
      logitpsitrun[i]<-min(999,max(-999,logitpsi[i]))
      psi[i]<-1/(1+exp(-logitpsitrun[i]))
      z[i]~dbern(psi[i])
      for(j in 1:k){
        conf[i,j]<-z[i]*b
        c[i,j]~dbern(conf[i,j])
        logitp11[i,j]<-lp11_0+c1*temp[i,j]
        logitp11trun[i,j]<-min(999,max(-999,logitp11[i,j]))
        p11[i,j]<-1/(1+exp(-logitp11trun[i,j]))
        p10[i,j]<-p10_s1*survey1[i,j] + p10_s2*survey2[i,j] + p10_s3*survey3[i,j]
        mu[i,j]<-(1-z[i])*(1-c[i,j])*p10[i,j] + (1-z[i])*c[i,j]*0 + c[i,j]*z[i]*1 + z[i]*(1-
c[i,j])*p11[i,j]
        y[i,j]~dbern(mu[i,j])
      }#survey
    }#site
  }#model
  ",fill=TRUE)
  sink()

  inits<-function()list(psi_0=runif(1,0,1),p11_0=runif(1,0,1),b=runif(1,0,0.25),
  p10_s1=runif(1,0,0.17),p10_s2=runif(1,0,0.17),p10_s3=runif(1,0,0.17),
  a1=rnorm(1),a2=rnorm(1),c1=rnorm(1))
  inits1<- inits()
  inits2<- inits()
  inits3<- inits()
  inits<- list(inits1, inits2, inits3)
  params<-c("psi","psi_0","p10_s1","p10_s2","p10_s3","p11_0","a1","a2","c1","b")
  settings<-c(100000,1,50000,3)
out=bugs(data=data,inits,parameters=params,model.file="model.txt",n.iter=settings[1],n.t
hin=settings[2],n.burnin=settings[3],n.chains=settings[4],codaPkg=FALSE,debug=FALS
E,  OpenBUGS.pgm="C:/OpenBUGS322/OpenBUGS.exe",working.directory=getwd())
```

No false positives model with covariates

```
true_psi_0<-0.7
true_a1<-2.6
true_a2<- -0.4
true_p11_0<-0.5
true_c1<- -1.2
true_p10_s1<-0.1
true_p10_s2<-0.07
true_p10_s3<-0.04
true_nsites<-250
true_k<-3
true_lpsi_0<-log(true_psi_0/(1-true_psi_0))
true_lp11_0<-log(true_p11_0/(1-true_p11_0))

true_survey1<-array(data=0, dim=c(250,3))
true_survey2<-array(data=0, dim=c(250,3))
true_survey3<-array(data=0, dim=c(250,3))
true_survey1[,1]<-1
true_survey2[,2]<-1
true_survey3[,3]<-1

sim.data<-function(lpsi_0=true_lpsi_0, a1=true_a1, a2=true_a2,
lp11_0=true_lp11_0, c1=true_c1,
p10_s1=true_p10_s1, p10_s2=true_p10_s2, p10_s3=true_p10_s3,
nsites=true_nsites, k=true_k,
survey1=true_survey1, survey2=true_survey2, survey3=true_survey3)
{
  forest0to100<-runif(true_nsites,0,100)
  forestIn<-scale(forest0to100)
  forest<-as.vector(forestIn[,1])
  temp50to70<-array(data=runif(true_nsites*true_k,50,70),dim=c(true_nsites,true_k))
  tempIn<-scale(temp50to70)
  temp<-array(data=NA,dim=c(true_nsites,true_k))
  temp[,1]<-as.vector(tempIn[,1])
  temp[,2]<-as.vector(tempIn[,2])
  temp[,3]<-as.vector(tempIn[,3])
  lpsi<-array(0,dim=c(nsites))
  psi<-array(0,dim=c(nsites))
  z<-array(0,dim=c(nsites))
  lp11<-array(0,dim=c(nsites,k))
  p11<-array(0,dim=c(nsites,k))
  p10<-array(0,dim=c(nsites,k))
  c<-array(0,dim=c(nsites,k))
  mu<-array(0,dim=c(nsites,k))
  y<-array(0,dim=c(nsites,k))
```

```
  for (i in 1:nsites){
    lpsi[i]<-lpsi_0+a1*forest[i]+a2*forest[i]*forest[i]
    psi[i]<-1/(1+exp(-lpsi[i]))
    z[i]<-rbinom(1,1,psi[i])
    for(j in 1:k){
      if(z[i]==1){
        lp11[i,j]<-lp11_0+c1*temp[i,j]
        p11[i,j]<-1/(1+exp(-lp11[i,j]))
        y[i,j]<-rbinom(1,1,p11[i,j])
      }else{
        p10[i,j]<-p10_s1*survey1[i,j] + p10_s2*survey2[i,j] + p10_s3*survey3[i,j]
        y[i,j]<-rbinom(1,1,p10[i,j])
      }
    }
  }
  return(list(psi=psi,z=z,c=c,p11=p11,p10=p10,y=y,
  temp50to70=temp50to70,temp=temp,forest0to100=forest0to100,forest=forest,
  survey1=survey1,survey2=survey2,survey3=survey3,
  k=k,nsites=nsites))
}

reps=100
for(r in 1:reps){
  x<-sim.data()
  data<-list(y=x$y,nsites=x$nsites,k=x$k,forest=x$forest,temp=x$temp)
  library(R2OpenBUGS)
  sink("model.txt")
  cat("
  model {
    p11_0~dunif(0,1)
    psi_0~dunif(0,1)
    a1~dnorm(0,0.368)
    a2~dnorm(0,0.368)
    c1~dnorm(0,0.368)

    lpsi_0<-log(psi_0/(1-psi_0))
    lp11_0<-log(p11_0/(1-p11_0))

    for(i in 1:nsites){
      logitpsi[i]<-lpsi_0+a1*forest[i]+a2*forest[i]*forest[i]
      logitpsitrun[i]<-min(999,max(-999,logitpsi[i]))
      psi[i]<-1/(1+exp(-logitpsitrun[i]))
      z[i]~dbern(psi[i])
      for(j in 1:k){
        logitp11[i,j]<-lp11_0+c1*temp[i,j]
        logitp11trun[i,j]<-min(999,max(-999,logitp11[i,j]))
```

```
      p11[i,j]<-1/(1+exp(-logitp11trun[i,j]))
      mu[i,j]<-z[i]*p11[i,j]
      y[i,j]~dbern(mu[i,j])
    }#survey
  }#site
 }#model
 ",fill=TRUE)
 sink()

 inits<-function()list(psi_0=runif(1,0,1),p11_0=runif(1,0,1),
 a1=rnorm(1),a2=rnorm(1),c1=rnorm(1))
 inits1<- inits()
 inits2<- inits()
 inits3<- inits()
 inits<- list(inits1, inits2, inits3)
 params<-c("psi","psi_0","p11_0","a1","a2","c1")
 settings<-c(100000,1,50000,3)
out=bugs(data=data,inits,parameters=params,model.file="model.txt",n.iter=settings[1],n.t
hin=settings[2],n.burnin=settings[3],n.chains=settings[4],codaPkg=FALSE,debug=FALS
E,  OpenBUGS.pgm="C:/OpenBUGS322/OpenBUGS.exe",working.directory=getwd())
```

APPENDIX E

EXAMPLE CODE FOR CHAPTER 3

Model 1 from the first set of candidate models: constant occupancy probability and year-specific true positive detection probabilities

```
DataIn<-read.csv("BHVI.csv", header=TRUE)
#DETECTION VARIABLES
#format Julian date
JulianScale<-array(data=0,dim=816)
JulianScale[1:272]<-DataIn[,14]
JulianScale[273:544]<-DataIn[,15]
JulianScale[545:816]<-DataIn[,16]
JulianScaleIn<-scale(JulianScale)
JulianDate<-array(data=0,dim=c(272,3))
JulianDate[,1]<-as.vector(JulianScaleIn[1:272])
JulianDate[,2]<-as.vector(JulianScaleIn[273:544])
JulianDate[,3]<-as.vector(JulianScaleIn[545:816])
#minutes after 5:59am
TimeScale<-array(data=0,dim=816)
TimeScale[1:272]<-DataIn[,11]
TimeScale[273:544]<-DataIn[,12]
TimeScale[545:816]<-DataIn[,13]
TimeScaleIn<-scale(TimeScale)
Time<-array(data=0,dim=c(272,3))
Time[,1]<-as.vector(TimeScaleIn[1:272])
Time[,2]<-as.vector(TimeScaleIn[273:544])
Time[,3]<-as.vector(TimeScaleIn[545:816])
#sky condition
Sky<-array(data=0,dim=c(272,3))
Sky[,1]<-as.vector(DataIn[,17])
Sky[,2]<-as.vector(DataIn[,18])
Sky[,3]<-as.vector(DataIn[,19])
#format year for p11 detection: 2010=0, 2011=1
YearDetect<-array(data=0,dim=c(272,3))
YearDetect[,1]<-as.vector(DataIn[,10])
YearDetect[,2]<-as.vector(DataIn[,10])
YearDetect[,3]<-as.vector(DataIn[,10])
#format year for p10 detection
```

```
Year1Detect<-array(data=0,dim=c(272,3))
Ones<-rep(1,111)
Zeros<-rep(0,161)
Year1Detect[,1]<-c(Ones,Zeros)
Year1Detect[,2]<-c(Ones,Zeros)
Year1Detect[,3]<-c(Ones,Zeros)
Year2Detect<-array(data=0,dim=c(272,3))
Year2Detect[,1]<-YearDetect[,1]
Year2Detect[,2]<-YearDetect[,1]
Year2Detect[,3]<-YearDetect[,1]

#BIRD DATA
#format y
y<-array(data=NA,dim=c(272,3))
yIn<-as.vector(DataIn[,8:10])
ymatrix1<-as.matrix(DataIn[,4],nrow=272,ncol=1)
ymatrix2<-as.matrix(DataIn[,5],nrow=272,ncol=1)
ymatrix3<-as.matrix(DataIn[,6],nrow=272,ncol=1)
ynumeric1<-as.numeric(ymatrix1)
ynumeric2<-as.numeric(ymatrix2)
ynumeric3<-as.numeric(ymatrix3)
y[,1]<-ynumeric1
y[,2]<-ynumeric2
y[,3]<-ynumeric3
#format method
method<-array(data=NA,dim=c(272,3))
methodIn<-as.vector(DataIn[,11:13])
methodmatrix1<-as.matrix(DataIn[,7],nrow=272,ncol=1)
methodmatrix2<-as.matrix(DataIn[,8],nrow=272,ncol=1)
methodmatrix3<-as.matrix(DataIn[,9],nrow=272,ncol=1)
methodnumeric1<-as.numeric(methodmatrix1)
methodnumeric2<-as.numeric(methodmatrix2)
methodnumeric3<-as.numeric(methodmatrix3)
method[,1]<-methodnumeric1
method[,2]<-methodnumeric2
method[,3]<-methodnumeric3

#read in data relevant to model
data<-list(y=y, method=method, nsites=272, k=3, Year1Detect=Year1Detect,
Year2Detect=Year2Detect)

library(R2OpenBUGS)
#code for bugs
sink("Model1_p11.txt")
cat("
model{
```

```
  psi~dunif(0,1)

  p11_yr1~dunif(0,1)
  p11_yr2~dunif(0,1)

  p10_yr1~dunif(0,0.5)
  p10_yr2~dunif(0,0.5)
  b~dunif(0,1)

  #likelihood specification
  for(i in 1:nsites){
    z[i]~dbern(psi)

    for(j in 1:k){
      cert[i,j]<-z[i]*b
      method[i,j]~dbern(cert[i,j])

      p11[i,j]<-p11_yr1*Year1Detect[i,j] + p11_yr2*Year2Detect[i,j]

      p10[i,j]<-p10_yr1*Year1Detect[i,j] + p10_yr2*Year2Detect[i,j]

      mu[i,j]<-(1-z[i])*(1-method[i,j])*p10[i,j] + (1-z[i])*method[i,j]*0 +
method[i,j]*z[i]*1 + z[i]*(1-method[i,j])*p11[i,j]
      y[i,j]~dbern(mu[i,j])
    }#survey
  }#site
}#model
",fill=TRUE)
sink()

inits<-function()list(psi=runif(1,0,1), p11_yr1=runif(1,0,1), p11_yr2=runif(1,0,1),
p10_yr1=runif(1,0,0.25), p10_yr2=runif(1,0,0.25), b=runif(1,0,0.25))

inits1<- inits()
inits2<- inits()
inits3<- inits()

inits<- list(inits1, inits2, inits3)
#parameters to be monitored
params<-c("psi","z","p11_yr1","p11_yr2","p10_yr1","p10_yr2","b")
#MCMC settings (iterations, thinning, burnin, chains)
settings<-c(100000,5,50000,3)

out=bugs(data=data,inits,parameters=params,model.file="Model1_p11.txt",n.iter=setting
s[1],n.thin=settings[2],
n.burnin=settings[3],n.chains=settings[4],codaPkg=FALSE,debug=FALSE,
```

```
OpenBUGS.pgm="C:/OpenBUGS322/OpenBUGS.exe",working.directory=getwd())

Results<-out$summary
write.table(Results,file="Results-BHVI-Model1_p11.csv",sep=",")
```

Model 1 affecting ψ and Model 1 affecting *p11* from the second set of candidate models: year-specific true positive detection probabilities and site-scale deciduous canopy cover affecting the occupancy probabilities

```
DataIn<-read.csv("BHVI.csv", header=TRUE)
#DETECTION VARIABLES
#format Julian date
JulianScale<-array(data=0,dim=816)
JulianScale[1:272]<-DataIn[,14]
JulianScale[273:544]<-DataIn[,15]
JulianScale[545:816]<-DataIn[,16]
JulianScaleIn<-scale(JulianScale)
JulianDate<-array(data=0,dim=c(272,3))
JulianDate[,1]<-as.vector(JulianScaleIn[1:272])
JulianDate[,2]<-as.vector(JulianScaleIn[273:544])
JulianDate[,3]<-as.vector(JulianScaleIn[545:816])
#minutes after 5:59am
TimeScale<-array(data=0,dim=816)
TimeScale[1:272]<-DataIn[,11]
TimeScale[273:544]<-DataIn[,12]
TimeScale[545:816]<-DataIn[,13]
TimeScaleIn<-scale(TimeScale)
Time<-array(data=0,dim=c(272,3))
Time[,1]<-as.vector(TimeScaleIn[1:272])
Time[,2]<-as.vector(TimeScaleIn[273:544])
Time[,3]<-as.vector(TimeScaleIn[545:816])
#sky condition
Sky<-array(data=0,dim=c(272,3))
Sky[,1]<-as.vector(DataIn[,17])
Sky[,2]<-as.vector(DataIn[,18])
Sky[,3]<-as.vector(DataIn[,19])
#format year for p11 detection: 2010=0, 2011=1
YearDetect<-array(data=0,dim=c(272,3))
YearDetect[,1]<-as.vector(DataIn[,10])
YearDetect[,2]<-as.vector(DataIn[,10])
YearDetect[,3]<-as.vector(DataIn[,10])
#format year for p10 detection
Year1Detect<-array(data=0,dim=c(272,3))
Ones<-rep(1,111)
Zeros<-rep(0,161)
Year1Detect[,1]<-c(Ones,Zeros)
Year1Detect[,2]<-c(Ones,Zeros)
Year1Detect[,3]<-c(Ones,Zeros)
```

```
Year2Detect<-array(data=0,dim=c(272,3))
Year2Detect[,1]<-YearDetect[,1]
Year2Detect[,2]<-YearDetect[,1]
Year2Detect[,3]<-YearDetect[,1]

#BIRD DATA
#format y
y<-array(data=NA,dim=c(272,3))
yIn<-as.vector(DataIn[,8:10])
ymatrix1<-as.matrix(DataIn[,4],nrow=272,ncol=1)
ymatrix2<-as.matrix(DataIn[,5],nrow=272,ncol=1)
ymatrix3<-as.matrix(DataIn[,6],nrow=272,ncol=1)
ynumeric1<-as.numeric(ymatrix1)
ynumeric2<-as.numeric(ymatrix2)
ynumeric3<-as.numeric(ymatrix3)
y[,1]<-ynumeric1
y[,2]<-ynumeric2
y[,3]<-ynumeric3
#format method
method<-array(data=NA,dim=c(272,3))
methodIn<-as.vector(DataIn[,11:13])
methodmatrix1<-as.matrix(DataIn[,7],nrow=272,ncol=1)
methodmatrix2<-as.matrix(DataIn[,8],nrow=272,ncol=1)
methodmatrix3<-as.matrix(DataIn[,9],nrow=272,ncol=1)
methodnumeric1<-as.numeric(methodmatrix1)
methodnumeric2<-as.numeric(methodmatrix2)
methodnumeric3<-as.numeric(methodmatrix3)
method[,1]<-methodnumeric1
method[,2]<-methodnumeric2
method[,3]<-methodnumeric3

SiteDataIn<-read.csv("CategoricalSiteCovariates.csv", header=TRUE)
Decid50<-as.vector(SiteDataIn[,4])
Everg50<-as.vector(SiteDataIn[,5])
HighComplex<-as.vector(SiteDataIn[,6])
CWD<-as.vector(SiteDataIn[,7])
Insect<-as.vector(SiteDataIn[,8])
Invasive<-as.vector(SiteDataIn[,9])
Snag<-as.vector(SiteDataIn[,10])

#read in data relevant to model
data<-list(y=y, method=method, nsites=272, k=3, Year1Detect=Year1Detect,
Year2Detect=Year2Detect, Decid50=Decid50)

library(R2OpenBUGS)
#code for bugs
```

```
sink("Model_psi1_p11-1.txt")
cat("
model{
  psi_0~dunif(0,1)
  CD50~dunif(0,1)
  a1~dnorm(0,0.368)

  p11_yr1~dunif(0,1)
  p11_yr2~dunif(0,1)

  p10_yr1~dunif(0,0.5)
  p10_yr2~dunif(0,0.5)
  b~dunif(0,1)

  lpsi_0<-log(psi_0/(1-psi_0))

  #likelihood specification
  for(i in 1:nsites){
    Decid50[i]~dbern(CD50)

    logitpsi[i]<-lpsi_0 + a1*Decid50[i]
    logitpsitrun[i]<-min(999,max(-999,logitpsi[i]))
    psi[i]<-1/(1+exp(-logitpsitrun[i]))

    z[i]~dbern(psi[i])

    for(j in 1:k){
      cert[i,j]<-z[i]*b
      method[i,j]~dbern(cert[i,j])

      p11[i,j]<-p11_yr1*Year1Detect[i,j] + p11_yr2*Year2Detect[i,j]

      p10[i,j]<-p10_yr1*Year1Detect[i,j] + p10_yr2*Year2Detect[i,j]

      mu[i,j]<-(1-z[i])*(1-method[i,j])*p10[i,j] + (1-z[i])*method[i,j]*0 +
method[i,j]*z[i]*1 + z[i]*(1-method[i,j])*p11[i,j]
      y[i,j]~dbern(mu[i,j])
    }#survey
  }#site
}#model
",fill=TRUE)
sink()

inits<-function()list(psi_0=runif(1,0,1), CD50=runif(1,0,1), a1=rnorm(1),
p11_yr1=runif(1,0,1), p11_yr2=runif(1,0,1),
p10_yr1=runif(1,0,0.25), p10_yr2=runif(1,0,0.25), b=runif(1,0,0.25))
```

```
inits1<- inits()
inits2<- inits()
inits3<- inits()

inits<- list(inits1, inits2, inits3)
#parameters to be monitored
params<-
c("psi","z","psi_0","CD50","a1","p11_yr1","p11_yr2","p10_yr1","p10_yr2","b")
#MCMC settings (iterations, thinning, burnin, chains)
settings<-c(100000,5,50000,3)

out=bugs(data=data,inits,parameters=params,model.file="Model_psi1_p11-
1.txt",n.iter=settings[1],n.thin=settings[2],
n.burnin=settings[3],n.chains=settings[4],codaPkg=FALSE,debug=FALSE,
OpenBUGS.pgm="C:/OpenBUGS322/OpenBUGS.exe",working.directory=getwd())

Results<-out$summary
write.table(Results,file="Results-BHVI-Model_psi1_p11-1.csv",sep=",")
```

Model 1 affecting ψ and Model 1 affecting *p11* from the third set of candidate models: year-specific true positive detection probabilities and local-scale elevation and landscape-scale percent forest affecting the occupancy probabilities

```
DataIn<-read.csv("BHVI.csv", header=TRUE)
#DETECTION VARIABLES
#format Julian date
JulianScale<-array(data=0,dim=816)
JulianScale[1:272]<-DataIn[,14]
JulianScale[273:544]<-DataIn[,15]
JulianScale[545:816]<-DataIn[,16]
JulianScaleIn<-scale(JulianScale)
JulianDate<-array(data=0,dim=c(272,3))
JulianDate[,1]<-as.vector(JulianScaleIn[1:272])
JulianDate[,2]<-as.vector(JulianScaleIn[273:544])
JulianDate[,3]<-as.vector(JulianScaleIn[545:816])
#minutes after 5:59am
TimeScale<-array(data=0,dim=816)
TimeScale[1:272]<-DataIn[,11]
TimeScale[273:544]<-DataIn[,12]
TimeScale[545:816]<-DataIn[,13]
TimeScaleIn<-scale(TimeScale)
Time<-array(data=0,dim=c(272,3))
Time[,1]<-as.vector(TimeScaleIn[1:272])
Time[,2]<-as.vector(TimeScaleIn[273:544])
Time[,3]<-as.vector(TimeScaleIn[545:816])
#sky condition
Sky<-array(data=0,dim=c(272,3))
Sky[,1]<-as.vector(DataIn[,17])
Sky[,2]<-as.vector(DataIn[,18])
Sky[,3]<-as.vector(DataIn[,19])
#format year for p11 detection: 2010=0, 2011=1
YearDetect<-array(data=0,dim=c(272,3))
YearDetect[,1]<-as.vector(DataIn[,10])
YearDetect[,2]<-as.vector(DataIn[,10])
YearDetect[,3]<-as.vector(DataIn[,10])
#format year for p10 detection
Year1Detect<-array(data=0,dim=c(272,3))
Ones<-rep(1,111)
Zeros<-rep(0,161)
Year1Detect[,1]<-c(Ones,Zeros)
Year1Detect[,2]<-c(Ones,Zeros)
Year1Detect[,3]<-c(Ones,Zeros)
Year2Detect<-array(data=0,dim=c(272,3))
```

```
Year2Detect[,1]<-YearDetect[,1]
Year2Detect[,2]<-YearDetect[,1]
Year2Detect[,3]<-YearDetect[,1]

#BIRD DATA
#format y
y<-array(data=NA,dim=c(272,3))
yIn<-as.vector(DataIn[,8:10])
ymatrix1<-as.matrix(DataIn[,4],nrow=272,ncol=1)
ymatrix2<-as.matrix(DataIn[,5],nrow=272,ncol=1)
ymatrix3<-as.matrix(DataIn[,6],nrow=272,ncol=1)
ynumeric1<-as.numeric(ymatrix1)
ynumeric2<-as.numeric(ymatrix2)
ynumeric3<-as.numeric(ymatrix3)
y[,1]<-ynumeric1
y[,2]<-ynumeric2
y[,3]<-ynumeric3
#format method
method<-array(data=NA,dim=c(272,3))
methodIn<-as.vector(DataIn[,11:13])
methodmatrix1<-as.matrix(DataIn[,7],nrow=272,ncol=1)
methodmatrix2<-as.matrix(DataIn[,8],nrow=272,ncol=1)
methodmatrix3<-as.matrix(DataIn[,9],nrow=272,ncol=1)
methodnumeric1<-as.numeric(methodmatrix1)
methodnumeric2<-as.numeric(methodmatrix2)
methodnumeric3<-as.numeric(methodmatrix3)
method[,1]<-methodnumeric1
method[,2]<-methodnumeric2
method[,3]<-methodnumeric3

LandLocalDataIn<-read.csv("ContinuousLandscapeLocalCovariates.csv",
header=TRUE)
ElevIn<-as.vector(LandLocalDataIn[,13])
PForestAIn<-as.vector(LandLocalDataIn[,5])
PDevelAIn<-as.vector(LandLocalDataIn[,4])
PForestOIn<-as.vector(LandLocalDataIn[,12])
PHouseForestIn<-as.vector(LandLocalDataIn[,11])
PDevelOIn<-as.vector(LandLocalDataIn[,9])
PHouseLawnIn<-as.vector(LandLocalDataIn[,10])
PatchAreaForestIn<-as.vector(LandLocalDataIn[,6])
ShapeForestIn<-as.vector(LandLocalDataIn[,7])
ClumpyForestIn<-as.vector(LandLocalDataIn[,8])
ElevScale<-scale(ElevIn)
PForestAScale<-scale(PForestAIn)
PDevelAScale<-scale(PDevelAIn)
PForestOScale<-scale(PForestOIn)
```

```
PHouseForestScale<-scale(PHouseForestIn)
PDevelOScale<-scale(PDevelOIn)
PHouseLawnScale<-scale(PHouseLawnIn)
PatchAreaForestScale<-scale(PatchAreaForestIn)
ShapeForestScale<-scale(ShapeForestIn)
ClumpyForestScale<-scale(ClumpyForestIn)
Elev<-as.vector(ElevScale)
PForestA<-as.vector(PForestAScale)
PDevelA<-as.vector(PDevelAScale)
PForestO<-as.vector(PForestOScale)
PHouseForest<-as.vector(PHouseForestScale)
PDevelO<-as.vector(PDevelOScale)
PHouseLawn<-as.vector(PHouseLawnScale)
PatchAreaForest<-as.vector(PatchAreaForestScale)
ShapeForest<-as.vector(ShapeForestScale)
ClumpyForest<-as.vector(ClumpyForestScale)

#read in data relevant to model
data<-list(Elev=Elev, PForestA=PForestA, y=y, method=method, nsites=272, k=3,
Year1Detect=Year1Detect, Year2Detect=Year2Detect)

library(R2OpenBUGS)
#code for bugs
sink("Model_psi1_p11-1.txt")
cat("
model{
  psi_0~dunif(0,1)
  a1~dnorm(0,0.368)
  a2~dnorm(0,0.368)

  p11_yr1~dunif(0,1)
  p11_yr2~dunif(0,1)

  p10_yr1~dunif(0,0.5)
  p10_yr2~dunif(0,0.5)
  b~dunif(0,1)

  lpsi_0<-log(psi_0/(1-psi_0))

  #likelihood specification
  for(i in 1:nsites){
    logitpsi[i]<-lpsi_0 + a1*Elev[i] + a2*PForestA[i]
    logitpsitrun[i]<-min(999,max(-999,logitpsi[i]))
    psi[i]<-1/(1+exp(-logitpsitrun[i]))

    z[i]~dbern(psi[i])
```

```
    for(j in 1:k){
      cert[i,j]<-z[i]*b
      method[i,j]~dbern(cert[i,j])

      p11[i,j]<-p11_yr1*Year1Detect[i,j] + p11_yr2*Year2Detect[i,j]

      p10[i,j]<-p10_yr1*Year1Detect[i,j] + p10_yr2*Year2Detect[i,j]

      mu[i,j]<-(1-z[i])*(1-method[i,j])*p10[i,j] + (1-z[i])*method[i,j]*0 +
method[i,j]*z[i]*1 + z[i]*(1-method[i,j])*p11[i,j]
      y[i,j]~dbern(mu[i,j])
    }#survey
  }#site
}#model
",fill=TRUE)
sink()

inits<-function()list(psi_0=runif(1,0,1), a1=rnorm(1), a2=rnorm(1),
p11_yr1=runif(1,0,1), p11_yr2=runif(1,0,1),
p10_yr1=runif(1,0,0.25), p10_yr2=runif(1,0,0.25), b=runif(1,0,0.25))

inits1<- inits()
inits2<- inits()
inits3<- inits()

inits<- list(inits1, inits2, inits3)
#parameters to be monitored
params<-c("psi","z","psi_0","a1","a2","p11_yr1","p11_yr2","p10_yr1","p10_yr2","b")
#MCMC settings (iterations, thinning, burnin, chains)
settings<-c(100000,5,50000,3)

out=bugs(data=data,inits,parameters=params,model.file="Model_psi1_p11-
1.txt",n.iter=settings[1],n.thin=settings[2],
n.burnin=settings[3],n.chains=settings[4],codaPkg=FALSE,debug=FALSE,
OpenBUGS.pgm="C:/OpenBUGS322/OpenBUGS.exe",working.directory=getwd())

Results<-out$summary
write.table(Results,file="Results-BHVI-Model_psi1_p11-1.csv",sep=",")
```

Model 15 for local- and landscape-scale covariates affecting *ψ*, Model 2 for site-scale covariates affecting *ψ*, and Model 1 affecting *p11* from the fourth set of candidate models

```
DataIn<-read.csv("BHVI.csv", header=TRUE)
#DETECTION VARIABLES
#format Julian date
JulianScale<-array(data=0,dim=816)
JulianScale[1:272]<-DataIn[,14]
JulianScale[273:544]<-DataIn[,15]
JulianScale[545:816]<-DataIn[,16]
JulianScaleIn<-scale(JulianScale)
JulianDate<-array(data=0,dim=c(272,3))
JulianDate[,1]<-as.vector(JulianScaleIn[1:272])
JulianDate[,2]<-as.vector(JulianScaleIn[273:544])
JulianDate[,3]<-as.vector(JulianScaleIn[545:816])
#minutes after 5:59am
TimeScale<-array(data=0,dim=816)
TimeScale[1:272]<-DataIn[,11]
TimeScale[273:544]<-DataIn[,12]
TimeScale[545:816]<-DataIn[,13]
TimeScaleIn<-scale(TimeScale)
Time<-array(data=0,dim=c(272,3))
Time[,1]<-as.vector(TimeScaleIn[1:272])
Time[,2]<-as.vector(TimeScaleIn[273:544])
Time[,3]<-as.vector(TimeScaleIn[545:816])
#sky condition
Sky<-array(data=0,dim=c(272,3))
Sky[,1]<-as.vector(DataIn[,17])
Sky[,2]<-as.vector(DataIn[,18])
Sky[,3]<-as.vector(DataIn[,19])
#format year for p11 detection: 2010=0, 2011=1
YearDetect<-array(data=0,dim=c(272,3))
YearDetect[,1]<-as.vector(DataIn[,10])
YearDetect[,2]<-as.vector(DataIn[,10])
YearDetect[,3]<-as.vector(DataIn[,10])
#format year for p10 detection
Year1Detect<-array(data=0,dim=c(272,3))
Ones<-rep(1,111)
Zeros<-rep(0,161)
Year1Detect[,1]<-c(Ones,Zeros)
Year1Detect[,2]<-c(Ones,Zeros)
Year1Detect[,3]<-c(Ones,Zeros)
Year2Detect<-array(data=0,dim=c(272,3))
Year2Detect[,1]<-YearDetect[,1]
Year2Detect[,2]<-YearDetect[,1]
```

```
Year2Detect[,3]<-YearDetect[,1]

#BIRD DATA
#format y
y<-array(data=NA,dim=c(272,3))
yIn<-as.vector(DataIn[,8:10])
ymatrix1<-as.matrix(DataIn[,4],nrow=272,ncol=1)
ymatrix2<-as.matrix(DataIn[,5],nrow=272,ncol=1)
ymatrix3<-as.matrix(DataIn[,6],nrow=272,ncol=1)
ynumeric1<-as.numeric(ymatrix1)
ynumeric2<-as.numeric(ymatrix2)
ynumeric3<-as.numeric(ymatrix3)
y[,1]<-ynumeric1
y[,2]<-ynumeric2
y[,3]<-ynumeric3
#format method
method<-array(data=NA,dim=c(272,3))
methodIn<-as.vector(DataIn[,11:13])
methodmatrix1<-as.matrix(DataIn[,7],nrow=272,ncol=1)
methodmatrix2<-as.matrix(DataIn[,8],nrow=272,ncol=1)
methodmatrix3<-as.matrix(DataIn[,9],nrow=272,ncol=1)
methodnumeric1<-as.numeric(methodmatrix1)
methodnumeric2<-as.numeric(methodmatrix2)
methodnumeric3<-as.numeric(methodmatrix3)
method[,1]<-methodnumeric1
method[,2]<-methodnumeric2
method[,3]<-methodnumeric3

LandLocalDataIn<-read.csv("ContinuousLandscapeLocalCovariates.csv",
header=TRUE) ElevIn<-as.vector(LandLocalDataIn[,13])
PForestAIn<-as.vector(LandLocalDataIn[,5])
PDevelAIn<-as.vector(LandLocalDataIn[,4])
PForestOIn<-as.vector(LandLocalDataIn[,12])
PHouseForestIn<-as.vector(LandLocalDataIn[,11])
PDevelOIn<-as.vector(LandLocalDataIn[,9])
PHouseLawnIn<-as.vector(LandLocalDataIn[,10])
PatchAreaForestIn<-as.vector(LandLocalDataIn[,6])
ShapeForestIn<-as.vector(LandLocalDataIn[,7])
ClumpyForestIn<-as.vector(LandLocalDataIn[,8])
ElevScale<-scale(ElevIn)
PForestAScale<-scale(PForestAIn)
PDevelAScale<-scale(PDevelAIn)
PForestOScale<-scale(PForestOIn)
PHouseForestScale<-scale(PHouseForestIn)
PDevelOScale<-scale(PDevelOIn)
PHouseLawnScale<-scale(PHouseLawnIn)
```

```
PatchAreaForestScale<-scale(PatchAreaForestIn)
ShapeForestScale<-scale(ShapeForestIn)
ClumpyForestScale<-scale(ClumpyForestIn)
#finalized formatting
Elev<-as.vector(ElevScale)
PForestA<-as.vector(PForestAScale)
PDevelA<-as.vector(PDevelAScale)
PForestO<-as.vector(PForestOScale)
PHouseForest<-as.vector(PHouseForestScale)
PDevelO<-as.vector(PDevelOScale)
PHouseLawn<-as.vector(PHouseLawnScale)
PatchAreaForest<-as.vector(PatchAreaForestScale)
ShapeForest<-as.vector(ShapeForestScale)
ClumpyForest<-as.vector(ClumpyForestScale)

SiteDataIn<-read.csv("CategoricalSiteCovariates.csv", header=TRUE)
Decid50<-as.vector(SiteDataIn[,4])
Everg50<-as.vector(SiteDataIn[,5])
HighComplex<-as.vector(SiteDataIn[,6])
CWD<-as.vector(SiteDataIn[,7])
Insect<-as.vector(SiteDataIn[,8])
Invasive<-as.vector(SiteDataIn[,9])
Snag<-as.vector(SiteDataIn[,10])

#read in data relevant to model
data<-list(y=y, method=method, nsites=272, k=3, Year1Detect=Year1Detect,
Year2Detect=Year2Detect, JulianDate=JulianDate, Everg50=Everg50,
Elev=Elev, PDevelO=PDevelO)

library(R2OpenBUGS)
#code for bugs
sink("Model_15.txt")
cat("
model{
  psi_0~dunif(0,1)
  CE50~dunif(0,1)
  a1~dnorm(0,0.368)
  a2~dnorm(0,0.368)
  a3~dnorm(0,0.368)
  a4~dnorm(0,0.368)
  a5~dnorm(0,0.368)

  p11_0~dunif(0,1)
  c1~dnorm(0,0.368)
  c2~dnorm(0,0.368)
  c3~dnorm(0,0.368)
```

```
  p10_yr1~dunif(0,0.5)
  p10_yr2~dunif(0,0.5)
  b~dunif(0,1)

  lpsi_0<-log(psi_0/(1-psi_0))
  lp11_0<-log(p11_0/(1-p11_0))

  #likelihood specification
  for(i in 1:nsites){
    Everg50[i]~dbern(CE50)

    logitpsi[i]<-lpsi_0 + a1*Everg50[i] + a2*Elev[i] + a3*PDevelO[i] +
a4*Elev[i]*Everg50[i] + a5*PDevelO[i]*Everg50[i]
    logitpsitrun[i]<-min(999,max(-999,logitpsi[i]))
    psi[i]<-1/(1+exp(-logitpsitrun[i]))

    z[i]~dbern(psi[i])

    for(j in 1:k){
      cert[i,j]<-z[i]*b
      method[i,j]~dbern(cert[i,j])

      logitp11[i,j]<-lp11_0 + c1*Year2Detect[i,j] + c2*JulianDate[i,j] +
c3*JulianDate[i,j]*JulianDate[i,j]
      logitp11trun[i,j]<-min(999,max(-999,logitp11[i,j]))
      p11[i,j]<-1/(1+exp(-logitp11trun[i,j]))

      p10[i,j]<-p10_yr1*Year1Detect[i,j] + p10_yr2*Year2Detect[i,j]

      mu[i,j]<-(1-z[i])*(1-method[i,j])*p10[i,j] + (1-z[i])*method[i,j]*0 +
method[i,j]*z[i]*1 + z[i]*(1-method[i,j])*p11[i,j]
      y[i,j]~dbern(mu[i,j])
    }#survey
  }#site
}#model
",fill=TRUE)
sink()

inits<-function()list(psi_0=runif(1,0,1), CE50=runif(1,0,1), a1=rnorm(1), a2=rnorm(1),
a3=rnorm(1), a4=rnorm(1), a5=rnorm(1),
p11_0=runif(1,0,1), c1=rnorm(1), c2=rnorm(1), c3=rnorm(1),
p10_yr1=runif(1,0,0.25), p10_yr2=runif(1,0,0.25), b=runif(1,0,0.25))

inits1<- inits()
inits2<- inits()
inits3<- inits()
```

```
inits<- list(inits1, inits2, inits3)
#parameters to be monitored
params<-
c("psi","z","psi_0","CE50","a1","a2","a3","a4","a5","p11_0","c1","c2","c3","p10_yr1","
p10_yr2","b")
#MCMC settings (iterations, thinning, burnin, chains)
settings<-c(200000,5,150000,3)

out=bugs(data=data,inits,parameters=params,model.file="Model_15.txt",n.iter=settings[1
],n.thin=settings[2],
n.burnin=settings[3],n.chains=settings[4],codaPkg=FALSE,debug=FALSE,
OpenBUGS.pgm="C:/OpenBUGS322/OpenBUGS.exe",working.directory=getwd())

Results<-out$summary
write.table(Results,file="Results-BHVI-Model_15.csv",sep=",")
```

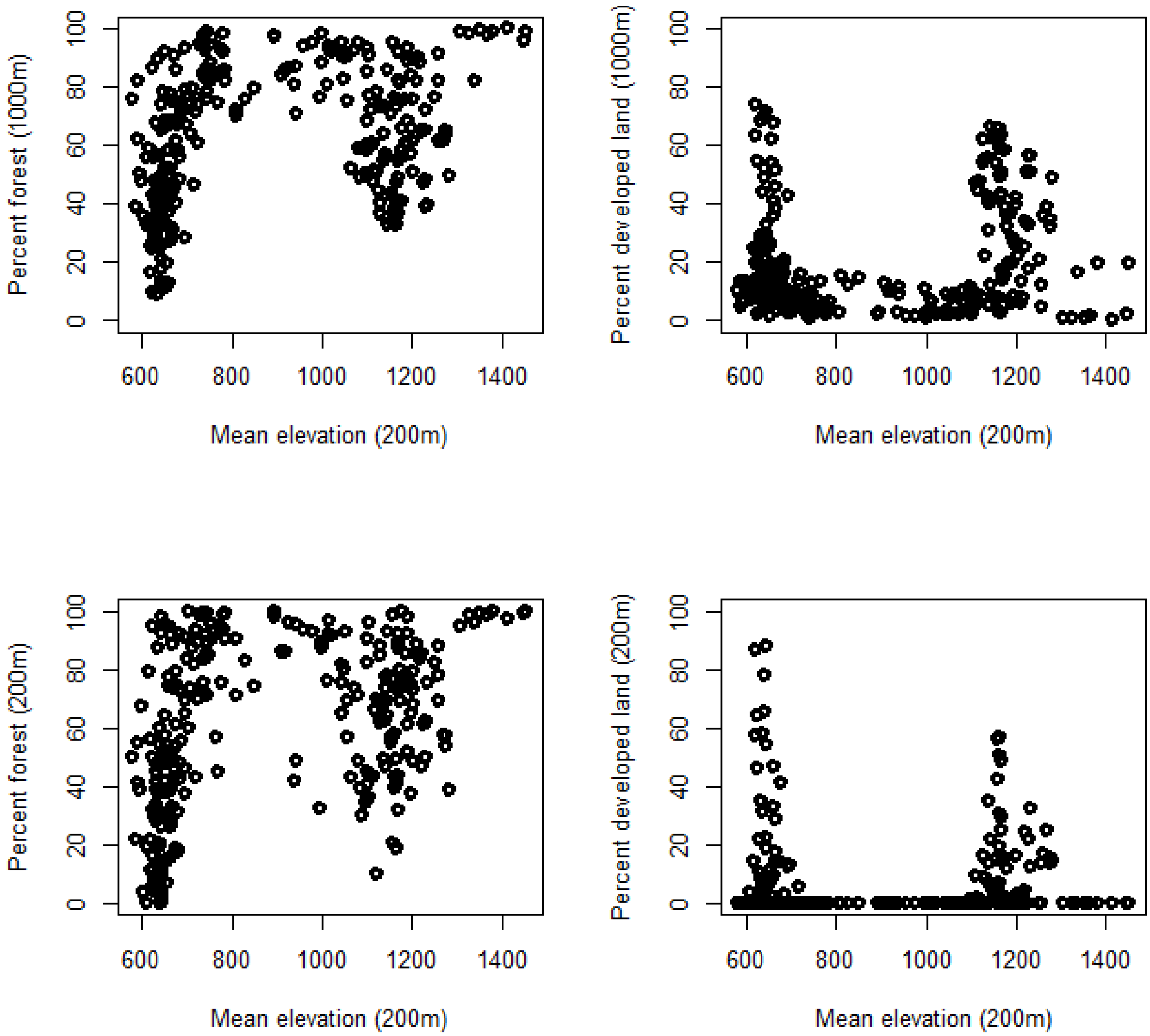
APPENDIX F

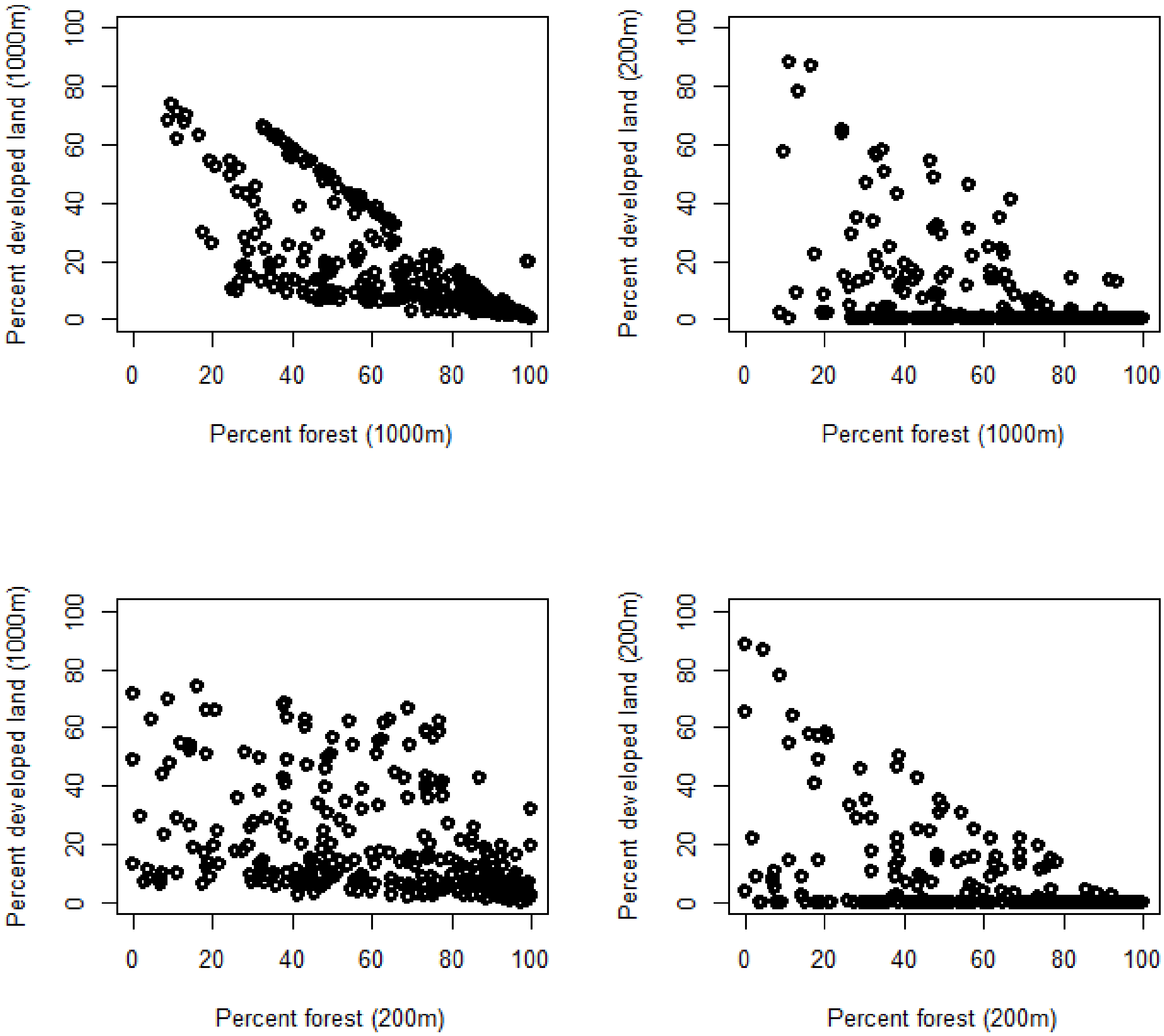
CORRELATION OF COVARIATES FOR CHAPTER 3

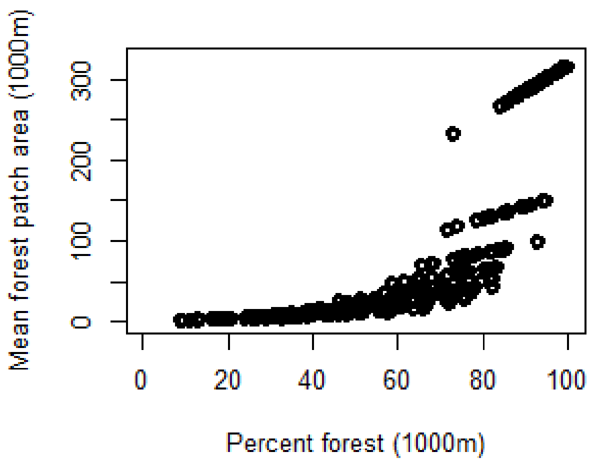
Table F.1: Pearson correlation coefficients for local- (within 200m of point count sites) and landscape-scale (within 1000m of point count sites) covariates at 272 sites in Macon County, NC.

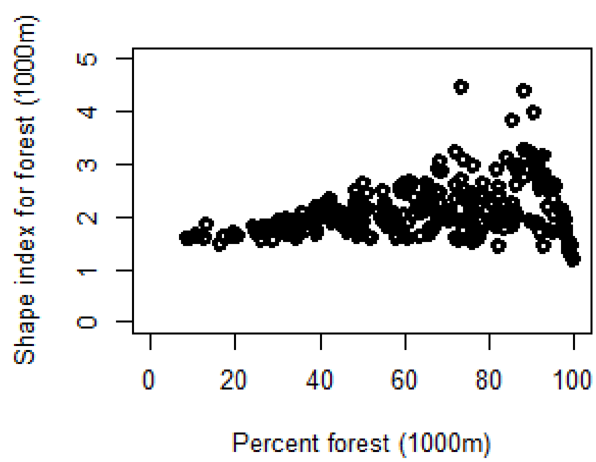
	Percent developed (1000m)	Percent forest (1000m)	Mean forest patch area (1000m)	Mean shape index forest patches (1000m)	Forest clumpiness index (1000m)
Percent developed (1000m)	1.00	-0.71	-0.52	-0.25	0.17
Percent forest (1000m)	-0.71	1.00	0.78	0.37	-0.37
Mean forest patch area (1000m)	-0.52	0.78	1.00	0.43	-0.59
Mean shape index forest patches (1000m)	-0.25	0.37	0.43	1.00	0.02
Forest clumpiness index (1000m)	0.17	-0.37	-0.59	0.02	1.00
Percent developed (200m)	0.58	-0.47	-0.28	-0.21	0.10
Percent house with lawn (200m)	0.04	-0.34	-0.25	-0.12	0.17
Percent house with forest (200m)	0.37	-0.19	-0.21	-0.03	0.09
Percent forest (200m)	-0.38	0.74	0.61	0.28	-0.36
Elevation (200m)	0.19	0.29	0.22	0.14	-0.18

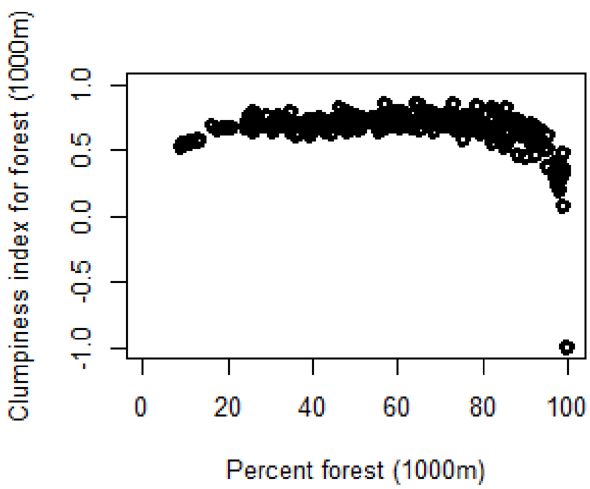
	Percent developed (200m)	Percent house with lawn (200m)	Percent house with forest (200m)	Percent forest (200m)	Elevation (200m)
Percent developed (1000m)	0.58	0.04	0.37	-0.38	0.19
Percent forest (1000m)	-0.47	-0.34	-0.19	0.74	0.29
Mean forest patch area (1000m)	-0.28	-0.25	-0.21	0.61	0.22
Mean shape index forest patches (1000m)	-0.21	-0.12	-0.03	0.28	0.14
Forest clumpiness index (1000m)	0.10	0.17	0.09	-0.36	-0.18
Percent developed (200m)	1.00	-0.14	0.03	-0.48	-0.05
Percent house with lawn (200m)	-0.14	1.00	-0.09	-0.42	-0.30
Percent house with forest (200m)	0.03	-0.09	1.00	-0.12	0.20
Percent forest (200m)	-0.48	-0.42	-0.12	1.00	0.34
Elevation (200m)	-0.05	-0.30	0.20	0.34	1.00


Percent forest (1000m)
Mean elevation (200m)
Percent developed land (1000m)
Mean elevation (200m)
Percent forest (200m)
Mean elevation (200m)
Percent developed land (200m)
Mean elevation (200m)
0
20
40
60
80
100
600
800
1000
1200
1400


Percent developed land (1000m)
Percent forest (1000m)
Percent developed land (200m)
Percent forest (1000m)
Percent developed land (1000m)
Percent forest (200m)
Percent developed land (200m)
Percent forest (200m)
0
20
40
60
80
100


Mean forest patch area (1000m)
0
100
200
300
0
20
40
60
80
100
Percent forest (1000m)


Shape index for forest (1000m)
0
1
2
3
4
5
0
20
40
60
80
100
Percent forest (1000m)


Clumpiness index for forest (1000m)
-1.0
-0.5
0.0
0.5
1.0
0
20
40
60
80
100
Percent forest (1000m)

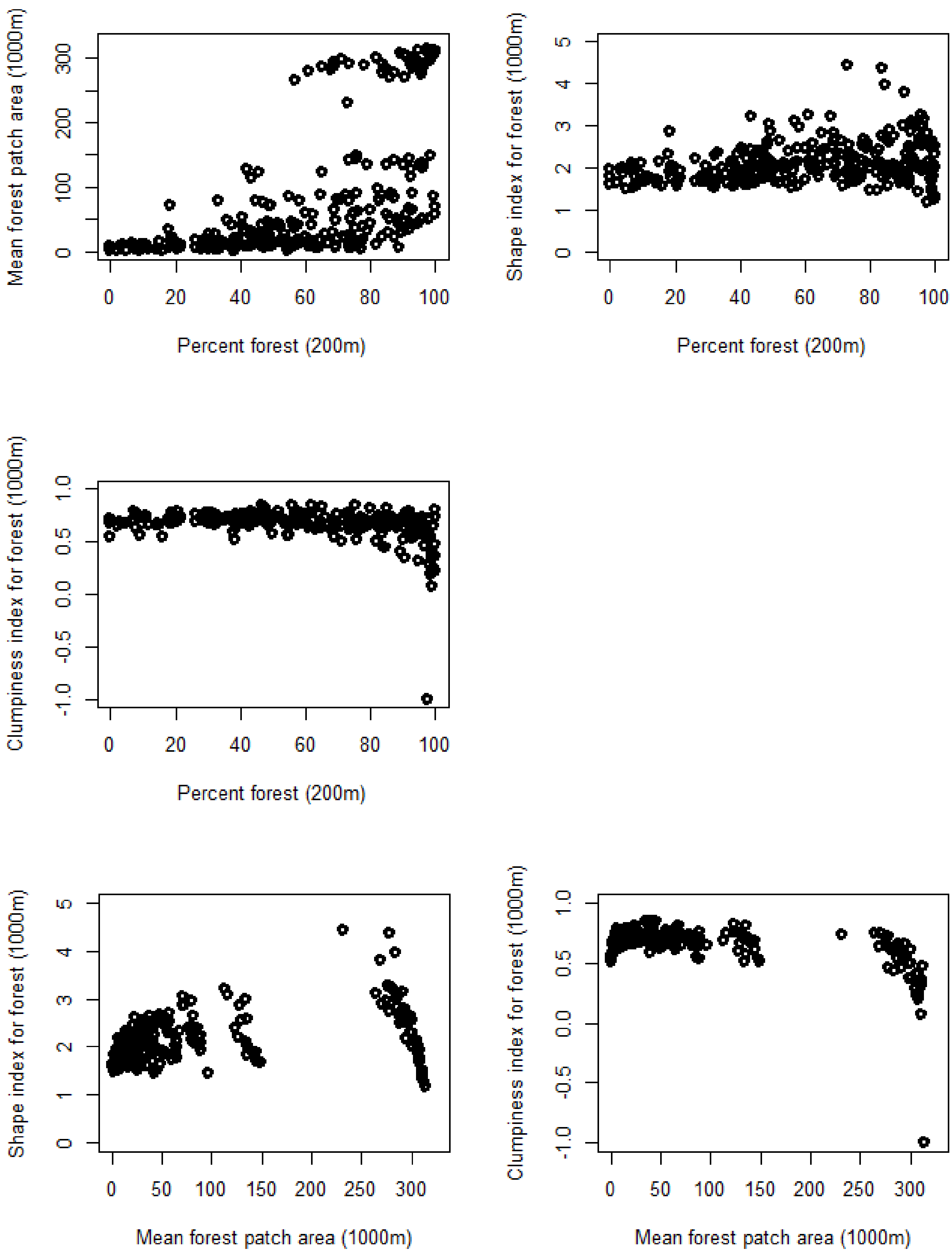


Figure F.1: Covariance of local- (within 200m of point count sites) and landscape-scale (within 1000m of point count sites) variables at 272 sites in Macon County, NC.

APPENDIX G

INTERVIEW SCRIPT FOR CHAPTER 4

Interview consent script

My name is Paige Barlow. I am a PhD student from the University of Georgia, and I am conducting research in Macon County with the Coweeta Long-Term Ecological Research program.

If from snowball sampling: I am a friend of (*Macon County friend's name*), and he/she thought you might be interested in participating in a study I am doing.

If from random stratified sampling: I got your name from the publically-available Macon County property records. You qualify for a study we are doing because you own at least 50 acres with at least 10 acres of forest.

During the last two summers, I have studied birds in Macon County. I visited people's property all around Macon County and identified what kinds of birds were there.

This summer, I am talking with Macon County landowners to understand how they take care of their land and what they think about birds in Macon County. I am studying what Macon County landowners think, and I am not advocating for any policies or regulations, and I respect private property rights.

I am doing phone interviews to try to understand how Macon County landowners take care of their land, what they want their land to be like, and what they think about birds. I am also trying to identify people who would like to participate in some discussion meetings over the summer.

I would like to invite you to participate in a 30 minute phone interview.

Your participation is voluntary and represents no risk or harm to you. You may refuse to participate or stop the interview at any time without giving any reason and without penalty or loss of benefits to which you are otherwise entitled. If you decide to participate in the interview, you might feel uncomfortable sharing your opinions during the interview, but you do not have to answer any question you are uncomfortable with. You can ask questions at any point during the interview and your responses will be confidential. Only my professor and I will have access to your responses. A code will be used to connect your name and contact information to your interview responses. The key to the code will be kept in a password protected computer file that only my professor and I will have access to. This key will be kept indefinitely.

This study will provide you the opportunity to share and ask questions about land maintenance and birds in Macon County. By participating in this study, you will contribute to a study that is interested in the economic, social, and environmental health of your property and community. This study is part of my dissertation research project.

Questions or concerns about your rights as a research participant should be directed to The Chairperson, University of Georgia Institutional Review Board at (706) 542-3199 or irb@uga.edu.

Would you like to participate in the interview about what you think about land and birds in Macon County?

If yes, proceed to Interview questionnaire

Interview questionnaire
I am interested in what you think about taking care of land and about birds in Macon County. There aren't "right" or "wrong" answers.

I. Land Ownership:

- How long have you owned property in Macon County?
    - (If recent property owner) Did you visit Macon County before purchasing property? How long did you visit?
    - Why did you choose to purchase this property?

II. Birds:

- Have you noticed any birds on your property?
- How do you feel about birds? Are there things you like or dislike about birds?

III. General Use of Land:

- Do you have different kinds of plants on your property, like around your house, fields, or wooded areas? What different things do you do in those areas to take care of them?
- What would your ideal property look like?
- What do you think would be harmful to your land?

IV. Development:

- What do you think Macon County will look like 20 years from now?
- In you could have things just the way you wanted, what would Macon County look like 20 years from now?

V. Demographics:

- Gender
- Age
- Occupation

VI. Focus Group:
I am looking for people who would like to meet 4 times in a group of 6 people to discuss taking care of land and birds in Macon County. In these meetings I would like to try to understand what Macon County landowners think about taking care of their land, what they want their land to be like, and what they think about birds. These will just be discussions, and no decision or regulation will result from the meetings. I respect private property rights and will not advocate for any policies or regulations. The people attending the meetings will have different opinions, but we would like these to be friendly meetings where everyone is able to express their thoughts.

Does this sound like something you would like to participate in?

Would you be available to meet 3 times this summer and 1 time next summer in Otto?

How flexible is your summer schedule? What day of the week and time of the day would you be available?

Do you have any questions?

Once we identify all the discussion group participants, I will get back in touch with you about whether you have been selected and when the first meeting will be.

APPENDIX H

MATERIALS USED DURING WORKSHOPS FOR CHAPTER 4

Prompts for exercise to consider decision statement and identify objectives

- What does “forest maintenance” mean to you? What are some examples?
- What does the “health of forest bird populations” mean to you? How could someone tell if bird populations are healthy or not?
- How far into the future should we think about the effects of forest maintenance choices?
- What do you value?
- What do you want to achieve?
- What are your goals?
- What would make you happy?
- What do you want to avoid?
- What do you want from your forest?
- How is your forest important to you and your community?
- Are forest birds important to you and your community? How?
- Are wild animals important to you and your community? How?
- Is nature important to you and your community? How?

Worksheet to elicit objective weights

Instructions:

- Rank scenarios from 1 = best to last = worst
- Give each scenario a grade between 100 and 0
- The grade reflects how satisfied you would be with that outcome, where 100 = completely satisfied
- Make sure your grades reflect your ranking
    - Scenario ranked 1 has highest grade,
    - Scenario ranked 2 has second highest grade, …

	Native species diversity	Exotic species abundance	Water quality	Rank	Grade
Worst	Large decrease in native species diversity	Large increase in exotic species abundance	Large decrease in water quality	4	0
Water scenario	Large decrease in native species diversity	Large increase in exotic species abundance	Large increase in water quality		
Native scenario	Large increase in native species diversity	Large increase in exotic species abundance	Large decrease in water quality		
Exotic scenario	Large decrease in native species diversity	Large decrease in exotic species abundance	Large decrease in water quality		

	Human safety	Property safety	Rank	Grade
Worst	Low safety	High level of damage	3	0
Property scenario	Low safety	No damage		
Human scenario	High saftey	High level of damage		

	Rural livelihood	Rural landscape	In the family	Development	Rank	Grade
Worst	33-0% of income from the property	Lose a lot	33-0% of property in the family	More than two divisions	5	0
Livelihood scenario	100-67% of income from the property	Lose a lot	33-0% of property in the family	More than two divisions		
Landscape scenario	33-0% of income from the property	Maintain	33-0% of property in the family	More than two divisions		
Family scenario	33-0% of income from the property	Lose a lot	100-67% of property in the family	More than two divisions		
Development scenario	33-0% of income from the property	Lose a lot	33-0% of property in the family	No divisions		

	Safety	Net income	Heritage	Aesthetics	Forest health	Rank	Grade
Worst	Low human safety & High level of property damage	Negative	Lose a lot of rural landscape, 33-0% of income from the property, 33-0% of property in the family, More than two divisions	Bad	Low native species diversity, High exotic species abundance, Low water quality	6	0
Safety scenario	High human safety & No property damage	Negative	Lose a lot of rural landscape, 33-0% of income from the property, 33-0% of property in the family, More than two divisions	Bad	Low native species diversity, High exotic species abundance, Low water quality		
Net income scenario	Low human safety & High level of property damage	Positive	Lose a lot of rural landscape, 33-0% of income from the property, 33-0% of property in the family, More than two divisions	Bad	Low native species diversity, High exotic species abundance, Low water quality		
Heritage scenario	Low human safety & High level of property damage	Negative	Maintain rural landscape, 100-67% of income from the property, 100-67% of property in the family, No divisions	Bad	Low native species diversity, High exotic species abundance, Low water quality		
Forest scenario	Low human safety & High level of property damage	Negative	Lose a lot of rural landscape, 33-0% of income from the property, 33-0% of property in the family, More than two divisions	Bad	High native species diversity, Low exotic species abundance, High water quality		

Aesthetics scenario	Low human safety & High level of property damage	Negative	Lose a lot of rural landscape, 33-0% of income from the property, 33-0% of property in the family, More than two divisions	Good	Low native species diversity, High exotic species abundance, Low water quality

Worksheet to elicit attribute scores

Instructions:

- Give each level a grade between 100 and 0
- The grade reflects how satisfied you would be with that outcome, where 100 = completely satisfied

Net income

Level	Grade
Positive	
Even	
Negative	

Property development

Level	Grade
No divisions	
Up to two divisions	
More than two divisions	

Property in the family

Level	Grade
100-67% of property in the family	
66-34% of property in the family	
33-0% of property in the family	

Income from property

Level	Grade
100-67% of income from property	
66-34% of income from property	
33-0% of income from property	

Rural landscape

Level	Grade
Maintain	
Lose a little	
Lose a lot	

Human safety

Level	Grade
High safety	
Moderate safety	
Low safety	

Property damage

Level	Grade
No damage	
Low damage	
High damage	

Diversity of native species

Level	Grade
Very high	
Moderately high	
Moderately low	
Very low	

Exotic species abundance

Level	Grade
High	
Medium	
Low	

Water quality

Level	Grade
High	
Medium	
Low	

Aesthetics

Level	Grade
Good	
Bad	

APPENDIX I

ANALYSIS DETAILS FOR CHAPTER 4

Details about decision options identified by landowner participants

Property enrolled in the Present-Use Value (PUV) program is taxed at the present-use value rather than at the full market value. In general, forestland can be enrolled in the PUV program if there is at least one tract that is at least 8 ha in area and forestland management complies with a written sound management plan for commercial timber production. Then the enrolled forestland is assessed at its current use of commercially growing trees. Because land is assessed at a lower value under the PUV program, property taxes on enrolled land are lower than they would be at full market value. We evaluated the decision options involving the PUV program assuming that the landowner would have a forest management plan developed and timber sales administered by Forest Stewards (FS) or a comparable organization. During crown thinning, the best trees are left about 12 m apart, which reduces competition among trees and facilitates growth. With group selection, all trees within 0.2-0.4 ha patches are cut, and in a shelterwood harvest with residual trees, trees are left 18-30.5 m apart to serve as seed trees. According to experts at FS who have worked in Macon County, an average large private forest in Macon County is about 60 years old, and a timber harvest could be conducted in 10-30 years. Therefore, we considered a 30 year timeframe for our decision analysis because one timber harvest could occur and landownership turnover is likely after 30 years, especially since over 25% of the Macon County population is over 65 years of age (U.S. Census Bureau 2013).

A conservation easement is a legal agreement in which a property owner restricts some of their ownership rights, for example, the right to subdivide or mine the land. Often, development rights are restricted in a conservation easement so that historic sites or ecological attributes will be protected. The landowner retains ownership of the property and can sell or bequeath the property, but the terms of the conservation easement continue with the property title for all future owners. Qualifying landowners may receive federal income and capital gains tax deductions, state income tax credits, lower property taxes, and/or lower estate taxes. We evaluated the decision options involving conservation easements assuming that the landowner would donate a permanent easement through the Land Trust for the Little Tennessee (LTLT) or a similar organization. For the past several years, funds have not been available to compensate landowners in Macon County for establishing permanent conservation easements.

Details about formatting to integrate experts' conditional probabilities and landowners' decision network and attribute scales

First, for the water quality, exotic species abundance, and native species diversity nodes, Series 1 identified three levels in the attribute scale while Series 2 identified two levels. Experts were asked to provide probabilities for three levels of the attribute, and we converted the probabilities to two levels by dividing the probability assigned to the second level in a three-level scale between the levels in a two-level scale. However, if the probability for the first or third level in a three-level scale was zero or one, we kept that probability and calculated the probability for the remaining level.

Second, we calculated conditional probabilities for the native species diversity node by assigning probabilities for attribute levels when the forest was of less, equal, or more conservation value compared to an untouched forest for birds and herpetofauna (Table L.2). It is challenging to describe the response of taxa because different species have different niches. Total abundance of birds or herpetofauna is not adequate because it does not convey whether there are many individuals of a few generalist species or individuals from many species. Species richness indicates the total number of species but does not indicate information about the size of populations. Species evenness is not appropriate because there is no expectation about how similar population sizes should be among species. Therefore, we quantified the response of wildlife taxa to forests in terms of conservation value. In general, a conservation value index is a weighted sum of species' abundance (Götmark et al. 1986, Nuttle et al. 2003, Twedt 2005). The weight scales the abundance according to the species' conservation priority. We did not ask experts to complete any calculations, but rather to conceptualize their probabilities in regards to the forest's conservation value for birds or herpetofauna. We also assigned probabilities for attribute levels when the forest had lower, equal, or greater abundance of shade-intolerant trees compared to an untouched forest. Then, the probabilities for birds, herpetofauna, and shade-intolerant trees were averaged corresponding to each outcome combination. We first calculated probabilities for the four-level attribute scale for Series 1 and converted the probabilities for the two-level attribute for Series 2 by summing the Series 1 probabilities for the very high and moderately high levels and summing the Series 1 probabilities for the moderately low and very low levels.

Third, at the time that landowners completed the conditional probability tables, we had not finalized the decision to include shelterwood harvest as a decision option. Landowners had said they were not interested in clearcutting, presumably because of aesthetics and a notion that clearcutting is bad for the environment, so we did not consider clearcutting and initially did not give much attention to shelterwood harvest. However, discussions with an expert at FS and the consideration of shade-intolerant tree abundance led us to include shelterwood harvests in the decision options. Consequently, probabilities had not been completed for the effects of shelterwood harvests on rural landscapes in the Series 1 decision network. Therefore, we filled in probabilities that were consistent with the other probabilities in this node and asked landowners for revisions at the fourth workshop, but landowners did not request changes. Similarly, selling 1 ha was not included in the decision options when we asked the expert to provide conditional probabilities related to shade-tree abundance. We generated probabilities by multiplying the probabilities of each attribute level given personal use by 0.95, calculated the mean probabilities for each attribute level by averaging across the decision options that had unique probabilities provided by the expert, multiplied each mean probability by 0.05, and added the weighted mean probability for each attribute level and the corresponding weighted personal use probability.

Fourth, an expert from the LTLT and an expert from FS provided conditional probabilities for levels of net income given decision options. However, the LTLT may not have direct experience with the finances of timber harvests and FS may not have specific information about conservation easement finances. Therefore, we talked to FS about the costs and revenue associated with crown thinning, group selection, and shelterwood harvests and to the LTLT about the costs of conservation easements with and without timber harvest. We also discussed how property taxes would be affected by various decision options with FS, the LTLT, and the Macon County tax assessor. For this analysis, we did not consider effects on income tax or estate tax because they are very landowner-specific, and this project focused on an evaluation of an average large, forested property in Macon County. After we compiled financial estimates from the experts (Appendix K), we generated conditional probabilities for levels of net income given decision options and weighted them equally with the two sets of conditional probabilities from the LTLT and FS. Based on the information provided by the LTLT and FS, we also determined that a landowner would not be able to earn more than 33% of their income from the forest, making the node describing the proportion of income derived from the property deterministic.

APPENDIX J

QUESTIONNAIRES USED IN WORKSHOPS FOR CHAPTER 4

Questionnaire distributed before the Bayesian decision network results were presented
Which decision option do you think will be best at meeting the objectives?

Do you think other decision options will be almost as good? Which decision options would be close alternatives?

Do you currently use one or more of the decision options we are studying? Which do you use?

If the results indicate that the best decision option is not one of the decision option that you expected, would you consider re-evaluating your preferences for the decision options?

No
Most likely no
Maybe
Most likely yes
Yes

Might the results of our analysis affect how you manage your forest?

No
Most likely no
Maybe
Most likely yes
Yes

Might the results of our analysis lead you to consider discontinuing what you are currently doing to manage your forest?

No
Most likely no
Maybe
Most likely yes
Yes

Might the results of our analysis lead you to consider doing something new to manage your forest?

No
Most likely no
Maybe
Most likely yes
Yes

Questionnaire distributed after the Bayesian decision network results were presented
Would you be interested in having the decision network personalized for your property and your objectives so that you can evaluate different methods to manage your forest?
(We are not able to personalize them, but we would like to gauge your interest so that, if there is a demand, perhaps someone would be interested in offering this service to landowners.)

No
Most likely no
Maybe
Most likely yes
Yes

Would you pay someone to personalize the decision network for your property and your objectives so that you can evaluate different methods to manage your forest?

No
Yes

If yes, what do you think would be a fair price?

After participating in this project, will you reconsider whether what you are currently doing to manage your forest is the best option for you?

No
Most likely no
Maybe
Most likely yes
Yes

After participating in this project, will you investigate forest management options other than the option you are currently using?

No
Most likely no
Maybe
Most likely yes
Yes

Which forest management options might you investigate?
What was your overall experience of the project?

Very good
Good
OK
Poor
Very poor

How well did you understand the material being presented?

Understood all of the material
Understood most of the material
Understood about half of the material
Did not understand most of the material
Did not understand any of the material

What was the most unclear, confusing, or difficult to understand?

What did you enjoy or benefit from the most?

What did you not enjoy or not benefit from?

Do you have any recommendations for us that would help us with future projects?

APPENDIX K

FINANCIAL DETAILS ABOUT THE DECISION OPTIONS FOR CHAPTER 4

These figures represent average expected amounts for a large, private forest in Macon County, North Carolina. This information was provided by Forest Stewards, the Land Trust for the Little Tennessee, and the Macon County tax assessor.

- Analysis based on an average hypothetical property
    - 30 ha property
    - 22 ha of forest

- At market value
    - Value of $819,537.60 ($27,317.92 per ha)
    - Property taxes = 2,286.51 dollars/year * 30 years = $68,595.33

- Timber harvest
    - Expenses
        - Create forest management plan = $1,087.26
        - Update forest management plan twice in 30 years = $1,087.26
        - Timber sale administration once = $4,756.77
        - Property tax = 30.17 dollars/year * 30 years = $904.99
    - Income
        - Crown-thinning = $9,513.55
        - Group selection = $12,231.71
        - Shelterwood = $17,668.02

- Conservation easement
    - Stewardship and legal defense fund
        - Timber harvest = $10,250
        - No timber harvest = $5,000
    - Survey = $6,000
    - Baseline documentation report = $2,500
    - Attorney and closing costs = $1,500
    - Property tax
        - Timber harvest = $904.99
        - No timber harvest = Depends on assessment but generally 50-80% reduction in property value, so work with 65% reduction = $24,008.37

- Sell 1 ha
  - Sell price = $27,317.92
  - Taxes on 29 ha = $66,308.82
  - Variable expenses involved in finding buyer and finalizing sale

APPENDIX L

COMPLETED CONDITIONAL PROBABILITY TABLES FOR CHAPTER 4

Table L.1: Scientific experts completed the conditional probability tables related to shade-intolerant tree abundance, exotic species abundance, the conservation value of the forest for herpetofauna, the conservation value of the forest for birds, water quality, erosion severity, fire severity, human safety, property damage, and net income. The landowners completed the conditional probability tables related to maintaining a rural landscape, keeping the property in the family, minimizing development, and aesthetics. Calculation of the conditional probabilities for the native species diversity node is discussed in the paper. If the conditional probability tables differ between the two series of discussion meetings, the series is indicated above the table.

Decision option	Expert	High severity of fire	Low severity of fire	No fire
No modification	1	0.01	0.04	0.95
No modification	2	0	0	1
Personal use	1	0.01	0.04	0.95
Personal use	2	0	0	1
Thinning	1	0.01	0.04	0.95
Thinning	2	0	0	1
Group selection	1	0.01	0.04	0.95
Group selection	2	0	0	1
Shelterwood	1	0.01	0.04	0.95
Shelterwood	2	0	0	1
Easement with no modification	1	0.01	0.04	0.95
Easement with no modification	2	0	0	1
Easement with personal use	1	0.01	0.04	0.95
Easement with personal use	2	0	0	1
Easement with thinning	1	0.01	0.04	0.95
Easement with thinning	2	0	0	1
Easement with group selection	1	0.01	0.04	0.95
Easement with group selection	2	0	0	1
Easement with shelterwood	1	0.01	0.04	0.95
Easement with shelterwood	2	0	0	1
Sell 5 acres, remainder personal use	1	0.01	0.04	0.95
Sell 5 acres, remainder personal use	2	0	0.2	0.8

Decision option	Expert	High severity of erosion	Medium severity of erosion	Low severity of erosion
No modification	1	0	0.3	0.7
No modification	2	0.05	0.35	0.6
Personal use	1	0	0.3	0.7
Personal use	2	0.1	0.4	0.5
Thinning	1	0	0.3	0.7
Thinning	2	0.15	0.45	0.4
Group selection	1	0.1	0.3	0.6
Group selection	2	0.2	0.45	0.35
Shelterwood	1	0.1	0.3	0.6
Shelterwood	2	0.22	0.43	0.35
Easement with no modification	1	0	0.3	0.7
Easement with no modification	2	0.05	0.35	0.6
Easement with personal use	1	0	0.3	0.7
Easement with personal use	2	0.1	0.4	0.5
Easement with thinning	1	0	0.3	0.7
Easement with thinning	2	0.15	0.45	0.4
Easement with group selection	1	0.1	0.3	0.6
Easement with group selection	2	0.2	0.45	0.35
Easement with shelterwood	1	0.1	0.3	0.6
Easement with shelterwood	2	0.22	0.43	0.35
Sell 5 acres, remainder personal use	1	0.5	0.3	0.2
Sell 5 acres, remainder personal use	2	0.22	0.43	0.35

Erosion severity	Fire severity	Expert	No property damage	Low property damage	High property damage
High severity	High severity	1	0	0.2	0.8
High severity	High severity	2	0.2	0.6	0.2
High severity	Low severity	1	0	0.3	0.7
High severity	Low severity	2	0.4	0.5	0.1
High severity	None	1	0	0.3	0.7
High severity	None	2	0.55	0.4	0.05
Medium severity	High severity	1	0	0.4	0.6
Medium severity	High severity	2	0.3	0.55	0.15
Medium severity	Low severity	1	0	0.5	0.5
Medium severity	Low severity	2	0.5	0.45	0.05
Medium severity	None	1	0	0.5	0.5
Medium severity	None	2	0.65	0.35	0
Low severity	High severity	1	0.15	0.5	0.35
Low severity	High severity	2	0.3	0.55	0.15
Low severity	Low severity	1	0.25	0.5	0.25
Low severity	Low severity	2	0.85	0.1	0.05
Low severity	None	1	0.25	0.5	0.25
Low severity	None	2	1	0	0

Erosion severity	Fire severity	Expert	High human safety	Moderate human safety	Low human safety
High severity	High severity	1	0	0.2	0.8
High severity	High severity	2	0.2	0.6	0.2
High severity	Low severity	1	0	0.3	0.7
High severity	Low severity	2	0.4	0.5	0.1
High severity	None	1	0	0.3	0.7
High severity	None	2	0.55	0.4	0.05
Medium severity	High severity	1	0	0.4	0.6
Medium severity	High severity	2	0.3	0.55	0.15
Medium severity	Low severity	1	0	0.5	0.5
Medium severity	Low severity	2	0.5	0.45	0.05
Medium severity	None	1	0	0.5	0.5
Medium severity	None	2	0.65	0.35	0
Low severity	High severity	1	0.15	0.5	0.35
Low severity	High severity	2	0.3	0.55	0.15
Low severity	Low severity	1	0.25	0.5	0.25
Low severity	Low severity	2	0.85	0.1	0.05
Low severity	None	1	0.25	0.5	0.25
Low severity	None	2	1	0	0

Decision	Expert	Negative net income	Even net income	Positive net income
No modification	1	1	0	0
No modification	2	1	0	0
No modification	3	1	0	0
Personal use	1	1	0	0
Personal use	2	1	0	0
Personal use	3	1	0	0
Thinning	1	0.33	0.33	0.34
Thinning	2	0.33	0.33	0.34
Thinning	3	0.33	0.33	0.34
Group selection	1	0.2	0.4	0.4
Group selection	2	0.2	0.4	0.4
Group selection	3	0.2	0.4	0.4
Shelterwood	1	0.1	0.3	0.6
Shelterwood	2	0.1	0.3	0.6
Shelterwood	3	0.1	0.3	0.6
Easement with no modification	1	1	0	0
Easement with no modification	2	1	0	0
Easement with no modification	3	1	0	0
Easement with personal use	1	1	0	0
Easement with personal use	2	1	0	0
Easement with personal use	3	1	0	0
Easement with thinning	1	0.4	0.4	0.2
Easement with thinning	2	0.2	0.2	0.6
Easement with thinning	3	0.9	0.1	0
Easement with group selection	1	0.2	0.3	0.5
Easement with group selection	2	0.15	0.15	0.7
Easement with group selection	3	0.75	0.2	0.05
Easement with shelterwood	1	0	0	1
Easement with shelterwood	2	0.1	0.1	0.8
Easement with shelterwood	3	0.6	0.3	0.1
Sell 5 acres, remainder personal use	1	0	0	1
Sell 5 acres, remainder personal use	2	0.05	0.1	0.85
Sell 5 acres, remainder personal use	3	0.33	0.34	0.33

Series 1

Net income	100-67% of property in the family	66-34% of property in the family	33-0% of property in the family
Positive	1	0	0
Even	0.8	0.1	0.1
Negative	0.1	0.4	0.5

Series 2

Net income	Aesthetics	100-51% of property in family	50-0% of property in family
Positive	Good	0.9	0.1
Positive	Bad	0.7	0.3
Even	Good	0.8	0.2
Even	Bad	0.4	0.6
Negative	Good	0.6	0.4
Negative	Bad	0.1	0.9

Series 1

Decision option	Maintain rural landscape	Lose a little rural landscape	Lose a lot of rural landscape
No modification	1	0	0
Personal use	0.9	0.1	0
Thinning	0.9	0.1	0
Group selection	0.8	0.2	0
Shelterwood	0.7	0.3	0
Easement with no modification	1	0	0
Easement with personal use	1	0	0
Easement with thinning	0.9	0.1	0
Easement with group selection	0.8	0.2	0
Easement with shelterwood	0.7	0.3	0
Sell 5 acres, remainder personal use	0.2	0.6	0.2

Series 2

Income from property	Future development	Maintain rural landscape	Lose rural landscape
100-51% of income	No division	0.8	0.2
100-51% of income	At least one division	0.6	0.4
50-0% of income	No division	0.7	0.3
50-0% of income	At least one division	0.25	0.75

Series 1

Net income	No division	Up to two division	More than two divisions
Positive	0.8	0.2	0
Even	0.4	0.4	0.2
Negative	0	0.5	0.5

Series 2

Net income	No division	At least one division
Positive	0.9	0.1
Even	0.75	0.25
Negative	0.1	0.9

Series 2

Rural landscape	Native diversity	Water quality	Good aesthetics	Bad aesthetics
Maintain	High	Low	0.3	0.7
Maintain	High	High	1	0
Maintain	Low	Low	0.1	0.9
Maintain	Low	High	0.7	0.3
Lose	High	Low	0.2	0.8
Lose	High	High	0.8	0.2
Lose	Low	Low	0	1
Lose	Low	High	0.2	0.8

Series 1

Decision option	Expert	Low water quality	Medium water quality	High water quality
No modification	1	0	0.3	0.7
No modification	2	0.05	0.35	0.6
No modification	3	0.03	0.07	0.9
Personal use	1	0	0.3	0.7
Personal use	2	0.1	0.4	0.5
Personal use	3	0.05	0.1	0.85
Thinning	1	0	0.3	0.7
Thinning	2	0.15	0.45	0.4
Thinning	3	0.1	0.15	0.75
Group selection	1	0.1	0.3	0.6
Group selection	2	0.2	0.45	0.35
Group selection	3	0.15	0.35	0.5
Shelterwood	1	0.1	0.3	0.6
Shelterwood	2	0.22	0.43	0.35
Shelterwood	3	0.25	0.35	0.4
Easement with no modification	1	0	0.3	0.7
Easement with no modification	2	0.05	0.35	0.6
Easement with no modification	3	0.03	0.07	0.9
Easement with personal use	1	0	0.3	0.7
Easement with personal use	2	0.1	0.4	0.5
Easement with personal use	3	0.05	0.1	0.85
Easement with thinning	1	0	0.3	0.7
Easement with thinning	2	0.15	0.45	0.4
Easement with thinning	3	0.1	0.15	0.75
Easement with group selection	1	0.1	0.3	0.6
Easement with group selection	2	0.2	0.45	0.35
Easement with group selection	3	0.15	0.35	0.5
Easement with shelterwood	1	0.1	0.3	0.6
Easement with shelterwood	2	0.22	0.43	0.35
Easement with shelterwood	3	0.25	0.35	0.4
Sell 5 acres, remainder personal use	1	0.5	0.3	0.2
Sell 5 acres, remainder personal use	2	0.22	0.43	0.35
Sell 5 acres, remainder personal use	3	0.08	0.12	0.8

Series 2

Decision option	Expert	Low water quality	High water quality
No modification	1	0	1
No modification	2	0.225	0.775
No modification	3	0.065	0.935
Personal use	1	0	1
Personal use	2	0.3	0.7
Personal use	3	0.1	0.9
Thinning	1	0	1
Thinning	2	0.375	0.625
Thinning	3	0.175	0.825
Group selection	1	0.25	0.75
Group selection	2	0.425	0.575
Group selection	3	0.325	0.675
Shelterwood	1	0.25	0.75
Shelterwood	2	0.435	0.565
Shelterwood	3	0.425	0.575
Easement with no modification	1	0	1
Easement with no modification	2	0.225	0.775
Easement with no modification	3	0.065	0.935
Easement with personal use	1	0	1
Easement with personal use	2	0.3	0.7
Easement with personal use	3	0.1	0.9
Easement with thinning	1	0	1
Easement with thinning	2	0.375	0.625
Easement with thinning	3	0.175	0.825
Easement with group selection	1	0.25	0.75
Easement with group selection	2	0.425	0.575
Easement with group selection	3	0.325	0.675
Easement with shelterwood	1	0.25	0.75
Easement with shelterwood	2	0.435	0.565
Easement with shelterwood	3	0.425	0.575
Sell 5 acres, remainder personal use	1	0.65	0.35
Sell 5 acres, remainder personal use	2	0.435	0.565
Sell 5 acres, remainder personal use	3	0.14	0.86

Series 1

Decision option	Expert	High abundance of exotic species	Medium abundance of exotic species	Low abundance of exotic species
No modification	1	0	0.3	0.7
No modification	2	0.2	0.3	0.5
Personal use	1	0	0.3	0.7
Personal use	2	0.25	0.35	0.4
Thinning	1	0	0.3	0.7
Thinning	2	0.3	0.4	0.3
Group selection	1	0.1	0.3	0.6
Group selection	2	0.35	0.4	0.25
Shelterwood	1	0.15	0.25	0.6
Shelterwood	2	0.37	0.38	0.25
Easement with no modification	1	0	0.3	0.7
Easement with no modification	2	0.2	0.3	0.5
Easement with personal use	1	0	0.3	0.7
Easement with personal use	2	0.25	0.35	0.4
Easement with thinning	1	0	0.3	0.7
Easement with thinning	2	0.3	0.4	0.3
Easement with group selection	1	0.1	0.3	0.6
Easement with group selection	2	0.35	0.4	0.25
Easement with shelterwood	1	0.15	0.25	0.6
Easement with shelterwood	2	0.37	0.38	0.25
Sell 5 acres, remainder personal use	1	0.5	0.3	0.2
Sell 5 acres, remainder personal use	2	0.37	0.38	0.25

Series 2

Decision option	Expert	High abundance of exotic species	Low abundance of exotic species
No modification	1	0	1
No modification	2	0.35	0.65
Personal use	1	0	1
Personal use	2	0.425	0.575
Thinning	1	0	1
Thinning	2	0.5	0.5
Group selection	1	0.25	0.75
Group selection	2	0.55	0.45
Shelterwood	1	0.275	0.725
Shelterwood	2	0.56	0.44
Easement with no modification	1	0	1
Easement with no modification	2	0.35	0.65
Easement with personal use	1	0	1
Easement with personal use	2	0.425	0.575
Easement with thinning	1	0	1
Easement with thinning	2	0.5	0.5
Easement with group selection	1	0.25	0.75
Easement with group selection	2	0.55	0.45
Easement with shelterwood	1	0.275	0.725
Easement with shelterwood	2	0.56	0.44
Sell 5 acres, remainder personal use	1	0.65	0.35
Sell 5 acres, remainder personal use	2	0.56	0.44

Decision	Expert	Less conservation value for birds	Equal conservation value for birds	More conservation value for birds
No modification	1	0	1	0
No modification	2	0	1	0
Personal use	1	0.15	0.75	0.1
Personal use	2	0.1	0.9	0
Thinning	1	0.25	0.5	0.25
Thinning	2	0.2	0.8	0
Group selection	1	0.65	0.2	0.15
Group selection	2	0.3	0.7	0
Shelterwood	1	0.8	0.15	0.05
Shelterwood	2	0.4	0.6	0
Easement with no modification	1	0	1	0
Easement with no modification	2	0	1	0
Easement with personal use	1	0.15	0.75	0.1
Easement with personal use	2	0.1	0.9	0
Easement with thinning	1	0.25	0.5	0.25
Easement with thinning	2	0.2	0.8	0
Easement with group selection	1	0.65	0.2	0.15
Easement with group selection	2	0.3	0.7	0
Easement with shelterwood	1	0.8	0.15	0.05
Easement with shelterwood	2	0.4	0.6	0
Sell 5 acres, remainder personal use	1	0.9	0.1	0
Sell 5 acres, remainder personal use	2	0.65	0.35	0

Decision	Expert	Less conservation value for herps	Equal conservation value for herps	More conservation value for herps
No modification	1	0	1	0
No modification	2	0	1	0
Personal use	1	0	1	0
Personal use	2	0.15	0.82	0.03
Thinning	1	0.1	0.8	0.1
Thinning	2	0.3	0.5	0.2
Group selection	1	0.5	0.45	0.05
Group selection	2	0.2	0.5	0.3
Shelterwood	1	0.9	0.1	0
Shelterwood	2	0.5	0.05	0.45
Easement with no modification	1	0	1	0
Easement with no modification	2	0	1	0
Easement with personal use	1	0	1	0
Easement with personal use	2	0.15	0.82	0.03
Easement with thinning	1	0.1	0.8	0.1
Easement with thinning	2	0.3	0.5	0.2
Easement with group selection	1	0.5	0.45	0.05
Easement with group selection	2	0.2	0.5	0.3
Easement with shelterwood	1	0.9	0.1	0
Easement with shelterwood	2	0.5	0.05	0.45
Sell 5 acres, remainder personal use	1	0.1	0.9	0
Sell 5 acres, remainder personal use	2	0.5	0.45	0.05

Decision option	Lower abundance of shade-intolerant trees	Equal abundance of shade-intolerant trees	Greater abundance of shade-intolerant trees
No modification	0	1	0
Personal use	0.33	0.34	0.33
Thinning	0.1	0.6	0.3
Group selection	0.1	0.1	0.8
Shelterwood	0.1	0.1	0.8
Easement with no modification	0	1	0
Easement with personal use	0.33	0.34	0.33
Easement with thinning	0.1	0.6	0.3
Easement with group selection	0.1	0.1	0.8
Easement with shelterwood	0.1	0.1	0.8
Sell 5 acres, remainder personal use	0.32	0.35	0.33

Series 1

Trees	Herpetofauna	Birds	Very high native diversity	Moderately high native diversity	Moderately low native diversity	Very low native diversity
Less shade-intolerant	Less conservation value	Less conservation value	0	0.33	0.34	0.33
Less shade-intolerant	Less conservation value	Equal conservation value	0.17	0.39	0.23	0.22
Less shade-intolerant	Less conservation value	More conservation value	0.25	0.30	0.23	0.22
Less shade-intolerant	Equal conservation value	Less conservation value	0.17	0.39	0.23	0.22
Less shade-intolerant	Equal conservation value	Equal conservation value	0.33	0.44	0.11	0.11
Less shade-intolerant	Equal conservation value	More conservation value	0.42	0.36	0.11	0.11
Less shade-intolerant	More conservation value	Less conservation value	0.25	0.30	0.23	0.22
Less shade-intolerant	More conservation value	Equal conservation value	0.42	0.36	0.11	0.11
Less shade-intolerant	More conservation value	More conservation value	0.50	0.28	0.11	0.11
Equal	Less conservation value	Less conservation value	0.17	0.39	0.23	0.22

Equal	Less conservation value	Equal conservation value	0.33	0.44	0.11	0.11
Equal	Less conservation value	More conservation value	0.42	0.36	0.11	0.11
Equal	Equal conservation value	Less conservation value	0.33	0.44	0.11	0.11
Equal	Equal conservation value	Equal conservation value	0.50	0.50	0	0
Equal	Equal conservation value	More conservation value	0.58	0.42	0	0
Equal	More conservation value	Less conservation value	0.42	0.36	0.11	0.11
Equal	More conservation value	Equal conservation value	0.58	0.42	0	0
Equal	More conservation value	More conservation value	0.67	0.33	0	0
More shade-intolerant	Less conservation value	Less conservation value	0.25	0.30	0.23	0.22
More shade-intolerant	Less conservation value	Equal conservation value	0.42	0.36	0.11	0.11
More shade-intolerant	Less conservation value	More conservation value	0.50	0.28	0.11	0.11
More shade-intolerant	Equal conservation value	Less conservation value	0.42	0.36	0.11	0.11

More shade-intolerant	Equal conservation value	Equal conservation value	0.58	0.42	0	0
More shade-intolerant	Equal conservation value	More conservation value	0.67	0.33	0	0
More shade-intolerant	More conservation value	Less conservation value	0.50	0.28	0.11	0.11
More shade-intolerant	More conservation value	Equal conservation value	0.67	0.33	0	0
More shade-intolerant	More conservation value	More conservation value	0.75	0.25	0	0

Series 2

Trees	Herpetofauna	Birds	High native diversity	Low native diversity
Less shade-intolerant	Less conservation value	Less conservation value	0.33	0.67
Less shade-intolerant	Less conservation value	Equal conservation value	0.55	0.45
Less shade-intolerant	Less conservation value	More conservation value	0.55	0.45
Less shade-intolerant	Equal conservation value	Less conservation value	0.55	0.45
Less shade-intolerant	Equal conservation value	Equal conservation value	0.78	0.22
Less shade-intolerant	Equal conservation value	More conservation value	0.78	0.22
Less shade-intolerant	More conservation value	Less conservation value	0.55	0.45
Less shade-intolerant	More conservation value	Equal conservation value	0.78	0.22
Less shade-intolerant	More conservation value	More conservation value	0.78	0.22
Equal	Less conservation value	Less conservation value	0.55	0.45
Equal	Less conservation value	Equal conservation value	0.78	0.22
Equal	Less conservation value	More conservation value	0.78	0.22
Equal	Equal conservation value	Less conservation value	0.78	0.22
Equal	Equal conservation value	Equal conservation value	1	0
Equal	Equal conservation value	More conservation value	1	0
Equal	More conservation value	Less conservation value	0.78	0.22
Equal	More conservation value	Equal conservation value	1	0
Equal	More conservation value	More conservation value	1	0
More shade-intolerant	Less conservation value	Less conservation value	0.55	0.45
More shade-intolerant	Less conservation value	Equal conservation value	0.78	0.22
More shade-intolerant	Less conservation value	More conservation value	0.78	0.22
More shade-intolerant	Equal conservation value	Less conservation value	0.78	0.22
More shade-intolerant	Equal conservation value	Equal conservation value	1	0
More shade-intolerant	Equal conservation value	More conservation value	1	0
More shade-intolerant	More conservation value	Less conservation value	0.78	0.22

More shade-intolerant	More conservation value	Equal conservation value	1	0
More shade-intolerant	More conservation value	More conservation value	1	0

Table L.2:
Probabilities for attribute levels when the forest was of less, equal, or more conservation value compared to an untouched forest for birds and herpetofauna or when the forest had lower, equal, or greater abundance of shade-intolerant trees compared to an untouched forest. The probabilities for birds, herpetofauna, and shade-intolerant trees were averaged corresponding to each outcome combination in the native species diversity node.

	Very high native species diversity	Moderately high native species diversity	Moderately low native species diversity	Very low native species diversity
Less conservation value, Lower shade-intolerant tree abundance	0	0.33	0.34	0.33
Equal conservation value, Equal shade-intolerant tree abundance	0.5	0.5	0	0
Greater conservation value, Greater shade-intolerant tree abundance	0.75	0.25	0	0