

EMPIRICAL FORECAST MODELS FOR GUIDING DECISION-MAKING IN COMPLEX
LANDSCAPES WITH COMPETING WILDLIFE MANAGEMENT GOALS

by

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(Under the Direction of Robert J. Warren and Steven B. Castleberry)

ABSTRACT

Wildlife managers can improve their effectiveness by understanding the expected response of target and non-target species to management actions prior to implementation. Empirical forecast modeling that uses quantitatively-derived habitat relationships to describe the change in distribution for a species under potential future habitat conditions offers managers a robust tool for assessing management actions. The need for quantitative tools to assess management outcomes is compounded in landscapes with competing management objectives where a poorly informed decision could have profound impacts on a locally sensitive species. Currently, there is a distinct void of practical case studies that apply forecasting procedures to evaluate habitat management actions leaving a framework for structuring the modeling process largely undescribed for wildlife managers. In an attempt to help fill that void, I demonstrate the application and utility of results produced from single- and multi-species empirical forecast models in a politically tense management environment commonplace on military installations. I sought to balance the conflicting management goals of single-species conservation promoted by the Endangered Species Act, and multi-species management promoted by the Sikes Act on military bases. Using Fort Bragg, North Carolina as a case study, I used logistic regression and

hierarchical occupancy models to empirically describe habitat relationships for 5 species including the endangered red-cockaded woodpecker (*Picoides borealis*), northern bobwhite (*Colinus virginianus*), white-tailed deer (*Odocoileus virginianus*), eastern fox squirrel (*Sciurus niger niger*), and eastern wild turkey (*Meleagris gallopavo silvestris*). I tested how species distributions would change under proposed alterations to the current habitat management strategy. My results identified how habitat management actions should be prioritized both structurally (e.g., reduction in small-diameter pine density, and avoidance of reduction in large-diameter pine density), and spatially (targeting areas of largest net benefit) that would balance the needs for the endangered species with those of other sympatric species. In addition, my methods are data-driven (empirical), making decisions derived from them justifiable and defensible. In times when wildlife managers are increasingly asked to do more with less, empirical forecast models offer a means to streamline effort and cost while balancing the habitat needs of multiple species.

INDEX WORDS: Empirical forecast model, Endangered Species Act, forecasting, Fort Bragg, habitat, management, military, North Carolina, Sikes Act

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DEDICATION

This entire endeavor is dedicated to my loving family. You have taught me strength, humility, and honor, as well as the importance of all three.

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CHAPTER 1
INTRODUCTION AND LITERATURE REVIEW FOR EMPIRICAL FORECAST
MODELING ON FORT BRAGG, NORTH CAROLINA, USA

INTRODUCTION

Wildlife managers can improve their effectiveness by understanding the expected response of target and non-target species to habitat management actions prior to implementation. Quantitative models that describe the distribution of a species relative to habitat conditions are especially effective in predicting species responses to changes in habitat management (Lawler et al. 2011). Models of this nature are termed empirical forecast models (hereafter forecasting). Forecasting using empirical data was first reported during the 1940's in the field of macroeconomics, and is still used today to predict economic responses to policy changes (Bodkin et al. 1991). There is potential for transferring the principles of forecasting to wildlife habitat management, but further exploration is needed. Though calls to use empirical methods to inform wildlife management decisions have spanned more than 3 decades (e.g., Christensen 1980, Lawler et al. 2011), there are surprisingly few examples reported in the literature that demonstrate in practical terms how to implement forecasting for habitat management on discrete landscapes.

Managers need a robust tool for assessing management actions to justify and sometimes defend habitat management decisions (Starfield 1997). Forecasting could fill that need as it requires quantitative species-specific habitat relationships that could describe the likely change in distribution for a species under alternative future habitat conditions. The need for quantitative

tools to assess management outcomes is compounded in landscapes with competing management objectives where a poorly informed decision could have profound impacts on locally sensitive species. Currently, a void exists of practical case studies that apply forecasting procedures to evaluate proposed habitat management actions. A description of a workable framework for structuring the modeling process could benefit wildlife managers. Using Fort Bragg, North Carolina as a case study, my dissertation research demonstrated forecasting procedures for single- and multi- species habitat management, and showed how model results could inform management decisions by evaluating the effectiveness of alternative management scenarios at achieving management goals.

Management of natural resources is required for military installations under the “Measure of Merit” issued by the U.S. Department of Defense. However, there is inherent incongruence between the basic principles of the Sikes Act (1960) and the Endangered Species Act (1973) regarding wildlife habitat management on military land holdings. The Sikes Act mandates the structure of management by requiring integrated wildlife and natural resource management on all military installations in coordination with both federal and state agencies. Conversely, the Endangered Species Act encourages a single-species approach to habitat management. Specifically, the act places much emphasis on designating, maintaining, and improving critical habitat for recovery of threatened and endangered species, and threatens strong penalties for noncompliance (Perkins et al. 2008). Variance between habitat needs of sympatric species is inevitable (Gause 1934, Rescigno and Richardson 1965), and can create conflicts on how best to manage habitat for multiple species concurrently. Furthermore, resolutions for those habitat management conflicts are often unclear without a framework that can integrate the needs for each species into a structured decision process based on solid evidence. Establishing spatially

explicit, habitat use models for multiple species can allow prediction of responses for each species simultaneously to prescribed or unplanned alterations to current habitat conditions (Mazzotti et al. 2001). Maintaining compliance with both the Sikes and Endangered Species acts without forecasting may be difficult.

Fort Bragg represents a functional example of the conflict between the Sikes and Endangered Species Acts. The base is inhabited by red-cockaded woodpecker (*Pecoides borealis*; hereafter RCW), which has been federally protected under the Endangered Species Act since 1970. Currently, natural resource management decisions on Fort Bragg heavily favor habitat improvements for RCW (Britcher 2006) without a gauge of how other wildlife populations may be influenced. Besides RCW, Fort Bragg is home to several other terrestrial game and nongame species including, but not limited to, white-tailed deer (*Odocoileus virginianus*), northern bobwhite (*Colinus virginianus*), eastern wild turkey (*Meleagris gallopavo silvestris*), eastern cottontail (*Sylvilagus floridanus*), northern raccoon (*Procyon lotor*), southern fox squirrel (*Sciurus niger niger*), gray squirrel (*Sciurus carolinensis*), coyote (*Canis latrans*), bobcat (*Lynx rufus*), gray fox (*Urocyon cinereoargenteus*), and Virginia opossum (*Didelphis virginiana*). Based on more than four decades of harvest records, some game species appear in decline (Appendix A), which may be attributed to shifts in habitat management strategies. To properly manage these species and their habitat, landscape-level management decisions supported by empirical evidence are needed that effectively integrate the habitat needs of all species of concern, not just the endangered RCW.

Economic impacts could also stem from species-biased management decisions. The current management on Fort Bragg resembles an ‘umbrella species’ approach with RCW as its focal species (Simberloff 1998). Umbrella species management assumes that if the landscape is

successfully managed for RCWs, which prefer open mature longleaf pine (*Pinus palustris*), then the populations of all other desired species consistent with the longleaf pine ecosystem will be maintained. Habitat conditions on Fort Bragg are actively manipulated to maintain or create specific longleaf pine stand composition and structure while reducing hardwood encroachment based on requirements for RCWs (US Fish and Wildlife Service 2003). Current management practices include silvicultural actions to thin longleaf stands, remove hardwoods, and apply prescribed fire during growing seasons on a 3-year rotation. Without forecasting, it is unknown whether timber harvest and prescribed fire prescriptions are adequately addressing ecological needs of all species of concern. As such, wildlife populations are exposed to potential and perhaps sudden declines in abundance. Furthermore, operating under sub-optimal timber harvest could directly affect revenue generated from timber sales. Additional economic impacts could occur without forecasting by restricting managers to reactive management, which is always a step behind the problem (Williams et al. 2002). Costs associated with recovering a species and its habitat are often drastically higher than preventing potential problems before they materialize. A proactive approach using forecasting procedures could help identify potential problems before they occur.

BACKGROUND

Fort Bragg

In 1918, Camp Bragg was established in North Carolina to expand the U.S. Army's facilities for artillery training. At the time the site was described as 50,800 ha of desolate sand hills dominated by large longleaf pines, which was not too dissimilar to local historical accounts from the late 1700's where forests were described as open groves in the style of England, and the ground cover was minimal and not brushy (Schaw 1776). By 1922, the U.S. Congress made

Camp Bragg a permanent post and changed the name to Fort Bragg. Since that time the post has expanded to cover 64,280 ha, including the 1997 purchase of the Overhills property (~4,230 ha) located on the northeastern corner of the base.

Fort Bragg is located within the Sandhills physiographic region in North Carolina. The Sandhills are described as xeric, flat-topped, sandy ridges, and broad flat valleys composed of sand, clay, and gravel (Griffith 2002). Almost two thirds of Fort Bragg is forested (~40,000 ha), much of which is second and third growth longleaf pine (Cantrell et al. 1995). Other forested stands found on site include loblolly (*Pinus taeda*), slash (*P. elliottii*), pond (*P. serotina*), and shortleaf (*P. echinata*) pine, as well as mixed pine hardwood, and hardwood-dominated stands mostly along drains and waterways. There are three artillery impact areas on the base that are off limits except for military activities, and which often experience frequent and sudden disturbance. Also present are four major and two minor parachute drop zones (~250 ha and 100 ha each, respectively). The parachute drop zones offer early succession habitat maintained through frequent mechanical disturbance (mowing) and dormant-season burning. In addition, there are wildlife openings (n = 1,296) dispersed across the landscape primarily targeting white-tailed deer, eastern wild turkey, northern bobwhite, and mourning dove (*Zenaida macroura*). Fire breaks in the form of dirt roadways are positioned throughout most of the landscape running east-west and spaced about 0.3 km apart.

Current habitat management activities on Fort Bragg favor RCW (Britcher 2006), and include silviculture prescriptions and prescribed burning. Approximately 10% of the forested landscape (~4,000 ha) is thinned annually to create or maintain total pine basal area targets and remove encroaching hardwoods as required by RCW management goals (Department of Defense 2001). Timber harvesting occurs on a 120-year rotation for longleaf and a 100-year rotation for

other pines (Cantrell et al. 1995, Carter et al. 1995). Prior to 1989, dormant-season burns occurred on roughly a 3- to 5-year rotation (Cantrell et al. 1995). From 1989 to present, the prescribed burn frequency was changed to a growing-season burn on a 3-year rotation.

There is a long tradition of hunting on Fort Bragg with records of harvest and hunter effort going back over 4 decades (Appendix A). White-tailed deer, eastern wild turkey (after their reintroduction to Fort Bragg in 1989), and northern bobwhite are popular terrestrial game species, but fox squirrel, gray squirrel, northern raccoon and eastern cottontail are also taken. A Quail Unlimited chapter has been active on Fort Bragg since 1993, and in 2006, a Quality Deer Management Association chapter (QDMA) was started on a portion of the post (~4,000 ha).

Habitat Models

Predicting species distributions across heterogeneous landscapes is a common tool used by wildlife resource managers. The idea of using habitat characteristics to predict occurrence of specific species is not new (e.g., Merriam 1890, Adams 1908). In fact, while in pursuit of game, hunters throughout history have employed these concepts to better their probability of success. Ecological concepts such as niche partitioning, habitat selection, and limiting resources support the notion of species using different habitats in predictable patterns (Verner et al. 1986, Morrison et al. 1992). In the early 1900's, pioneers in the burgeoning wildlife management discipline began using science to formally link habitat and species occurrence relationships (e.g., Adams 1908, Stoddard 1931). Since then, species-habitat relationship models have become commonplace in the published literature (Short 1986). Researchers and wildlife managers develop habitat models for many reasons including but not limited to predicting presence or absence of a species in a specific area, mapping current or potential geographic distributions, and estimating population size (Morrison et al. 1992). Predicting the distribution of suitable but

currently unoccupied habitat is of special interest in reintroduction efforts or invasive species expansion (Fielding and Haworth 1995). Furthermore, predicting the impacts of proposed habitat treatments or management actions on wildlife species has tremendous value for managers, which often requires understanding of landscape level species-habitat relationships (Austin et al. 1996, Hunter et al. 2006).

Models of wildlife-habitat relationships can be based on either deductive or inductive reasoning. Most early efforts in developing habitat models were deductive, relying on expert opinion and literature reviews of physiological, habitat, and behavioral constraints (Short 1986, Guisan and Zimmermann 2000), and were frequently fraught with inadequacies (Cook and Irwin 1985, Clark and Lewis 1983, Van Horne and Wiens 1991, Williams 2003). More recent technological advances have greatly enhanced our ability to construct inductive habitat models that are spatially explicit using empirical data (Tobalske and Tobalske 1999, Heglund 2002). Inductive habitat models are commonly developed by comparing measurements of habitat variables near observed species locations with either random locations or locations where the species was determined absent (Rota et al. 2011). With care, predictive habitat use models offer potential for assessing habitat availability over large areas in ways that are less labor intensive and more cost effective than the large-scale survey efforts required to cover equivalent areas (Mack et al. 1997, Dettmers and Bart 1999). Moreover, once habitats are made spatially explicit within a Geographic Information System (GIS), land managers can perform ‘what if’ scenarios to evaluate the relative impacts of proposed habitat management on focal species (Dettmers and Bart 1999, Van Horne 2002, Lawler et al. 2011). Thus, integration of a validated habitat model within a GIS framework can provide a powerful decision-making tool.

Species-habitat relationship modeling typically proceeds with a number of assumptions. These models represent mathematical simplifications of complex relationships between a species and the assemblage of habitat conditions present (Reichert and Omlin 1997). Yet, the ultimate utility of a model is dependent on the existence of strong and predictable relationships between a species and those habitat variables (Cardillo et al. 1999). By modeling habitat use of a species, researchers assume that certain measurable habitat characteristics are capable of explaining the likelihood of occurrence of the species, which may or may not be the case. Additionally, our understanding of source-sink dynamics warns of using animal presence as an indicator of preferred habitat or habitat quality (Holt 1985, Pulliam 1988). See Beutel et al. (1999) for a good discussion of critical assumptions and predictability of habitat use models.

Few examples exist where forecasting is used to inform habitat management decisions for localized landscapes (Vogel and Hicks 2000, Lawler et al. 2011). Forecasting requires development of spatially explicit tools with the ability to evaluate potential changes to habitat conditions for single or multiple species across a landscape. Conroy and Moore (2002) state that habitat models are only useful if they make predictions about consequences of management actions that are better than what managers could do in the absence of the model. Furthermore, Van Horne (2002) affirms that integrated habitat models linked together through mathematical algorithms and displayed using GIS only offer utility if the critical model components are substantiated by evidence.

OBJECTIVES

My goal was to outline a framework of how to incorporate forecasting into the decision making process for habitat management on localized jurisdictions like Fort Bragg. I used two practical examples to illustrate the framework and show how it could balance the tension

between the competing management objectives of the Sikes and Endangered Species Acts on military installations. My first example demonstrated how a single-species forecast model could be structured to help identify management options that improve habitat conditions for one species (bobwhite) when potential actions are largely limited without strong evidence for support by other constraints. My second example demonstrated how to structure a multi-species forecast model to identify management alternatives that best balance the habitat needs for several species of variable management priority. For both examples the process was divided into 2 phases: the first phase (habitat model development) developed the relevant species-habitat relationship models, and the second phase (forecasting procedure) quantified the predicted change in useable space relative to alternative habitat management scenarios. In both cases, the expected results were designed to test the consequences of alternative management actions prior to implementation to help inform the decision-making process for managers.

DISSERTATION FORMAT

The dissertation research that follows uses Fort Bragg as a case study for how to balance the habitat management needs for multiple species using forecasting procedures amid competing management objectives. The chapters of this dissertation were written in manuscript format. The initial chapter following this review demonstrates the application of a single-species empirical forecast model and how it can help guide management efforts both structurally and spatially to guide better habitat management decision making for a locally important species. Next, I demonstrate the use of a multi-species empirical forecast model for balancing decision-making between several species in a complex landscape that has competing wildlife management objectives. Finally, I end by discussing implications of my dissertation research and the niche it fills in our current ideology within the wildlife management profession.

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CHAPTER 2

SINGLE-SPECIES EMPIRICAL FORECAST MODELS

FOR GUIDING DECISION-MAKING IN COMPLEX LANDSCAPES WITH

COMPETING WILDLIFE MANAGEMENT GOALS

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ABSTRACT

Forecasting magnitude of response by a species to alternative management scenarios can be an effective tool for making informed habitat management decisions, but a structured framework to implement such a forecasting procedure is needed. We used the complexities of habitat management for northern bobwhite (*Colinus virginianus*) inhabiting Fort Bragg, North Carolina that is dominated by management objectives for the imperiled red-cockaded woodpecker (*Picoides borealis*) as a case study to demonstrate the use of single-species empirical forecast models as a viable forecasting tool. We estimated bobwhite density using whistling males and Royle repeat-visit ($n = 3$) point count ($n = 454$) methods that account for detection probability during the 2009 breeding season, and modeled these density estimates against habitat characteristics. Using an information theoretic approach, we found strong support (model weight $[w_i] = 0.6075$) for describing bobwhite density using inverse relationships with 3 overstory density covariates: large pine (>35.6 cm dbh) basal area, small pine (7.6 – 35.6 cm dbh) trees/ha, and small hardwood (7.6 – 24.5 cm dbh) basal area. We projected a bobwhite density surface across Fort Bragg using the spatial distribution of overstory structure and model outputs, validated against independent data ($n = 85$). In our forecasting procedure, we altered overstory structure across Fort Bragg according to proposed shifts in habitat management and calculated corresponding expected change in bobwhite density. Our results estimate that targeted reductions in small pine trees/ha would account for 82% of the total potential increase in bobwhite density from mean baseline estimates (0.070 male bobwhite/ha \pm 0.017) across Fort Bragg compared to if all 3 covariates were reduced (0.115 male bobwhite/ha). However, reducing small pine density alone would only account for 27% of the total potential increase in area that would support higher bobwhite densities (≥ 3 bobwhite/ listening radius) compared to if

all 3 overstory covariates were reduced instead. Evidence suggests thinning could be prioritized spatially to target stands supporting high densities of small pines, but if the management goal is to establish large areas capable of supporting higher bobwhite densities then all 3 overstory structure covariates should be reduced. In addition, reducing small pine densities appears compatible with red-cockaded woodpecker habitat management recommendations. Using our empirical forecast modeling framework to guide habitat management decisions is data-driven and spatially explicit, thereby making decisions readily defensible amid the heavy scrutiny common for publicly owned lands, or in designated critical habitat zones for imperiled species. Furthermore, using empirical forecast models to guide habitat management decisions on military installations specifically can help keep the installation in compliance with both the single-species management required by the Endangered Species Act and the multi-species management promoted by the Sikes Act.

KEY WORDS: *Colinus virginianus*, density, empirical forecast model, Endangered Species Act, forecasting, Fort Bragg, habitat, management, North Carolina, northern bobwhite, Sikes Act.

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INTRODUCTION

Natural resource managers regularly make decisions that affect wildlife habitat quality and quantity. When managing economically important, locally sensitive, or imperiled species, poor habitat management strategies can have a profound and lasting impact, which emphasizes the importance of making better-informed decisions. The ability to evaluate the potential outcome of a habitat management decision improves with increased understanding of the

expected population response to changes in management actions being considered (Lawler et al. 2011). Forecasting species response to management changes prior to implementation can be a powerful evaluation tool when appropriate empirical methods are used (Christensen 1980, Li et al. 2000, Lawler et al. 2011). Use of empirical data to develop wildlife-habitat relationship models that are spatially explicit across a landscape can provide a reliable means of forecasting species responses to natural or prescribed habitat alterations (Christensen 1980, Austin et al. 1996, Lawler et al. 2011), and can help prioritize management actions. This style of modeling application, which is designed to evaluate impacts of alternative habitat management actions on one species, is termed Single-species Empirical Forecast Modeling. Despite the utility of empirical forecast models (hereafter forecasting), few examples exist where they were used as predictive tools to inform management decisions until recently (e.g., Spies et al. 2007, Nielsen et al. 2008). Need exists for a structured framework to guide managers in applying forecasting procedures on localized jurisdictions, and this need is compounded for landscapes with complex management environments.

Managers can perform ‘what-if’ scenarios to quantitatively forecast impacts of alternative habitat management actions on a local population when habitats are made spatially explicit in a Geographic Information System (GIS) (Dettmers and Bart 1999, van Horne 2002, Guisan and Thuiller 2005, Lawler et al. 2011). Technological advances and increased availability of remote-sensed data have greatly enhanced our ability to construct spatially explicit habitat models (Tobalske and Tobalske 1999, Heglund 2002, Huettmann and Gottschalk 2011). Species–habitat relationship models are most often developed by comparing measurements of habitat variables near observed species locations with either random locations or locations where the species was determined to be absent. The latter is more informative, but both approaches can offer predictive

and cost-effective utility in describing habitat associations for species over large spatial extents (Mack et al. 1997, Dettmers and Bart 1999, MacKenzie et al. 2002).

The idea of forecasting species response to potential habitat changes is not new, but the range of what constitutes a species response is wide. In an early example of forecasting, Geier and Best (1980) projected the expected direction of population change for multiple small mammal species in response to alternative riparian habitat management scenarios. Though helpful, these predicted responses offer no measure of magnitude of expected change, thereby making it difficult to prioritize management decisions. Pereira and Itami (1991) demonstrated how a spatially explicit probability surface of potential use by Graham Mountain red squirrel (*Tamiasciurus hudsonicus grahamensis*) would likely change under predicted future habitat conditions. Similarly, Twedt et al. (2007) reported how a probability surface of potential use for northern bobwhite (*Colinus virginianus*) would change under projected changes in land use. These studies certainly have merit for resource managers, but they do not account for probability of detection during observations, which require added and sometimes problematic assumptions about how to interpret their habitat use findings (Williams et al. 2001, MacKenzie et al. 2002, Conroy and Carroll 2009). Other more recent investigations account for detection probability during forecasting procedures by using hierarchical occupancy methods to estimate change in species distribution while assessing alternative management scenarios (Spies et al. 2007, Zipkin et al. 2010). These recent studies limit the expected species response to a binary occupied or unoccupied surface. Such results can address growth or shrinkage of useable space for a species, but cannot quantify the expected change in density for an already occupied area in response to various habitat changes. Repeat-count occupancy methods account for detection probability and can incorporate habitat covariates to estimate population density (Royle 2004). Forecasting

changes in population density rather than probability of occurrence provides a more descriptive evaluation for magnitude of response relative to habitat alterations.

Difficulty in improving habitat management for northern bobwhite (hereafter bobwhite) inhabiting longleaf pine (*Pinus palustris*) systems that are also intensively managed for federally endangered red-cockaded woodpecker (*Picoides borealis*; hereafter RCW) illustrate the importance of forecasting procedures to improve habitat management decision-making in complex management environments. The bobwhite is considered a recreationally, socially, and economically important game bird that is also experiencing prolonged population declines across its distribution (Burger et al. 1999). Though numerous factors influence bobwhite population trends, range-wide declines are often linked to habitat loss in both quality and quantity (Brennan 1991, Peterson et al. 2002). Many studies suggest intensive habitat management for RCW, which requires open pine-grassland landscapes commonly associated with longleaf pine-wiregrass (*Aristida stricta*) ecosystems, encourages localized positive population response by bobwhite (Brennan 1991, Fuller 1994, Engstrom and Baker 1995, Wilson et al. 1995, Chamberlain and Burger 2005). However, examples exist where bobwhite populations show a negative trend with the establishment of RCW management, and no signs of recovery despite multiple decades of active RCW habitat improvement (e.g., Fort Bragg, North Carolina; Appendix B). On military lands, the Sikes Act (1960) mandates the application of integrated natural resource management that promotes multi-species rather than single-species management, yet the Endangered Species Act (1973) can mandate single-species conservation on the same landscape. For natural resource managers on military installations, the political tensions created by attempts to integrate habitat improvement for a locally important species like bobwhite with recovery of an endangered species like RCW can be difficult to balance, thereby

creating a complex management environment (Boice 2000). Forecasting offers managers quantitatively derived predictions of species responses to potential shifts in habitat management prior to implementation. Decisions guided by forecasting procedures are more defensible under the often intense scrutiny common for public lands because they are data-driven, spatially explicit, and provide estimates of magnitude of impact (Peterson et al. 2002). Furthermore, it is possible to design and evaluate proposed changes in habitat management that fit site-specific restrictions like those created by the confines of the RCW recovery plan.

We aimed to establish a framework for applying a single-species empirical forecast model to a localized jurisdiction like Fort Bragg military installation. The forecasting procedure was set to test the consequences of alternative habitat management scenarios on the density distribution of bobwhite to help inform the decision-making process for managers. We showed how a single-species forecast model could be structured to help identify management options that would improve habitat conditions for one species (bobwhite) when potential actions are largely limited by other constraints. The process was divided into 2 phases: the first phase (habitat model development) developed the relevant species-habitat relationship models, and the second phase (forecasting procedure) quantified the predicted change in useable space relative to alternative habitat management scenarios.

STUDY AREA

Fort Bragg encompasses 62,577 ha in the Sandhills physiographic region of North Carolina (35.040° to 35.270° N, -78.900° to -79.380° W). The managed forested landscape represents 90% of the total area and is divided into 10 habitat management compartments (mean = 5,628 ha; Figure 2.1). Sandhills are described as xeric, flat-topped, sandy ridges, with broad flat valleys composed of sand, clay, and gravel (Griffith et al. 2002). Almost two thirds of Fort

Bragg is forested (~40,000 ha), much of which is second and third growth longleaf pine (Cantrell et al. 1995) and averaged 14.7 m²/ha of combined hardwood and pine basal area (83% pine) at the time of this study. Other forested stands include loblolly (*P. taeda*), slash (*P. elliotii*), pond (*P. serotina*), and shortleaf (*P. echinata*) pine, as well as mixed pine hardwood, and hardwood-dominated stands mostly along drains and wetlands. Current habitat management efforts are focused on habitat improvements for RCWs (Britcher 2006) with the majority of practices designed to maintain good quality RCW habitat or transition degraded habitat back to an open pine-wiregrass complex consistent with good quality RCW habitat (Department of Defense 2001). In 2005, the RCW Sandhills East Recovery Unit that includes Fort Bragg exceeded the 350-group minimum required for long-term recovery of the population (Britcher 2006), 5-years earlier than expected (Belfil and Farley 2008). Selective thinnings are used to reduce canopy closure, and frequent prescribed fires (3-year cycle) are used to arrest succession and control midstory pine and hardwood densities (US Fish and Wildlife Service 2003). The majority of burns are high-intensity, growing-season burns (May-June) that cover large continuous blocks. There are 3 artillery impact areas within the base interior totaling 8,048 ha that are off limits except for military activities, and experience frequent and sudden disturbance. Also present are six parachute drop zones ranging from 107 to 498 ha (mean = 316 ha) totaling 1,897 ha. The parachute drop zones offer early succession habitat maintained through mechanical disturbance and dormant-season burning. There are small wildlife openings (n = 1,221) dispersed across the landscape primarily targeting white-tailed deer (*Odocoileus virginianus*), eastern wild turkey (*Meleagris gallopavo silvestris*), bobwhite, and mourning dove (*Zenaida macroura*).

METHODS

Habitat Model Development

We conducted whistling male call-counts within management compartments from 26 May to 7 July 2009 to ensure high likelihood of encompassing the peak calling season (Rosene 1957). Surveys were conducted between 0600 and 1200 hours to coincide with peak daily calling times for males (Roseberry 1982, Hansen and Guthery 2001). Each point received a 1-min cool-down period where observers waited quietly and prepared for data collection followed by a 7-min sampling period where the total number of different males heard calling were recorded (Palmer et al. 2005). We varied repeat visits ($n = 3$) to each point across the allowable 6-hour time frame to minimize temporal bias. Locations for point counts were selected along vehicle-accessible firebreaks and secondary dirt roads using a random point generator in ArcMap 9.3 (Environmental Systems Research Institute 2009). During any given day of surveys the visited points were > 500 m apart, but no minimum distance limitations were enforced for subsequent points visited later in the season, which effectively allowed for overlap between listening radii from different days. For each point count, start time and total number of unique males heard were recorded along with azimuth and estimated distance to each bird to help ensure only unique individuals were counted. We did not survey if wind was > 15 km/hr or if there was any precipitation (Robel et al. 1969). The average maximum listening radius for points was assumed to be 400 m to stay consistent with other call count studies (e.g., Stoddard 1931, Chamberlain and Burger 2005, Masters et al. 2009), but this distance was not tested specifically at our study site or with our observers ($n = 3$). Fort Bragg wildlife biologists collected independent call count data concurrently for model validation procedures following identical protocols as described above.

Habitat covariates used in modeling bobwhite density on Fort Bragg were selected a priori from available habitat data, and fit into one of four major habitat structure categories that we hypothesized may influence the distribution of bobwhites across the landscape. To avoid problems associated with multicollinearity in our models, we used Pearson's correlations test in SAS 9.1 (SAS Institute Inc. Cary, NC, USA) with an $r^2 > 0.5$ limit to constrain which covariates from our a priori list to include in analyses (Table 2.1). We hypothesized overstory pine conditions measured in trees/ha and basal area would be predictive of bobwhite density based on findings from other studies (Cram et al. 2002, Miley and Lichtler 2009) and that the relationship may differ among tree size classes. We considered hardwood overstory separate from pines but used similar metrics (Table 2.1). Other studies identified potential links between understory conditions like percent grass cover (Twedt et al. 2007, Lohr et al. 2011) or degree of overhead exposure to predators (i.e., cone of vulnerability) and bobwhite density (Guthery 1997, Kopp et al. 1998). We also thought bobwhite may distribute relative to site-specific characteristics rather than vegetative parameters; therefore, we chose to include the time since last burn (Wilson et al. 1995) and total hectares of wildlife openings located within listening radii as possible explanatory variables.

Habitat covariates in overstory pine, overstory hardwood, understory cover, and site specific categories were obtained from available forest and understory inventory data collected December 2008–February 2009. The forest overstory data were projected at the forest stand level, and understory inventory data were averaged within each forest stand. All habitat layers were converted to raster (5-m cell size) format for analysis using ArcMap 9.3. Habitat covariate values were calculated as area-weighted means (HawthsTools 3.27) within a 400-m listening radius around each point-count location (Table 2.1).

Because our point-count listening radii were allowed to overlap we needed to evaluate the degree of spatial autocorrelation in our data prior to habitat relationship modeling procedures to determine if censorship was required (Legendre et al. 2002). We examined spatial structure in our response variable (maximum number of unique males heard across 3 sample occasions) to determine if a minimum distance between points should be enforced. We plotted a correlogram of mean Moran's I correlation coefficient across 50-m increments (max = 800 m) using program SAM 4.0 (Rangel et al. 2010). Moran's I values close to zero show little or no autocorrelation (Legendre and Legendre 1998), whereas values near 1 and -1 signify positive and negative autocorrelation, respectively. We identified the minimum allowable distance between point-count locations for subsequent analyses as the distance for which mean Moran's I values for our response variable consistently stayed between 0.2 and -0.2. Lacking adequate guidance in the literature, our ± 0.2 threshold was arbitrary, but set a priori to constrain what we perceived as a conservative restriction on allowable spatial autocorrelation levels in our dataset.

We examined bobwhite density relative to detection and habitat covariates using information theory (Akaike 1973). Competing models were constructed in program PRESENCE (Version 3.0; Hines 2006) under a specified poisson prior distribution using the single-season, repeat-count design and the number of unique male bobwhites heard calling at point-count locations (Royle 2004). The repeat-count design assumes closure within the listening radius of each point between sample periods and formulates an estimate of density (Royle 2004). To remain robust to this assumption, we sampled each point on three consecutive days unless weather exceeded our allowable range of conditions in which case sampling was continued on the next allowable day. We designed our suite of models to allow each habitat structure category (Table 2.1) to compete against each other singly and in combinations including the global model.

We used Akaike's Information Criterion (AIC) to distinguish between the competing models and identify the best approximating model given our data (Akaike 1973, Burnham and Anderson 2002). In addition, the null model ($p(\cdot) \lambda(\cdot)$) was included as a standard for comparison. Detection (p ; probability a male bobwhite was recorded given that it was present) was also examined to determine if it was influenced by changes in time of day when the survey occurred. To account for uncertainty, we used model-averaging procedures among all models that performed within 2 Δ AIC points of the top model (Burnham and Anderson 2002) to produce a composite model. All habitat covariates identified in the composite model were subjected to sensitivity analysis where covariate values were steadily increased from 0 to the maximum observed value on the study site while keeping all other covariates set equal to their corresponding observed mean value.

We used a quasi-validation procedure to provide a measure of credibility to the density estimates and habitat relationships produced from model outputs. A formal validation procedure for the Royle repeat-count model is currently unavailable, but would require estimating the expected probability of a given poisson distribution (or negative binomial, and zero-inflated negative binomial distribution) given the observation and the range of possible observations under a binomial distribution. Instead, our approach compared residuals from the independent dataset with those calculated from points used to create the composite model. We calculated expected bobwhite density (E_d) for each location point of the independent data and an equal number of randomly selected points from our original dataset based on composite model parameter estimates (Equation 1). The E_d estimate includes both the male bobwhite we would expect to hear plus the ones we would not hear even though they were present at the time of observation (Royle 2004). We then determined the observed density (O_d) for each listening

radius by recording the highest number of males heard among the 3 visits. However, the O_d only included males actually heard during observation, whereas the ones present but not heard were unaccounted for in our analysis. As such, if our model represents a reasonable approximation of bobwhite density relative to the habitat covariates, then mean O_d values must underestimate mean E_d values in both the independent and original datasets. However, the closer that the detection probability is to 100%, the smaller the difference should be between O_d and E_d (Royle 2004). Additionally, if our model is adequate, residuals ($O_d - E_d$) calculated from our independent and original data sets should not differ from each other. We conducted a two-tailed t-test to assess if residuals differed between validation and original datasets using SAS and an alpha 0.05 threshold, which was chosen a priori.

$$\text{Log}(\lambda_i) = \beta_0 + \sum_{j=1}^k x_{ij}\beta_j \quad \text{where...} \quad (\text{Equation 1})$$

λ_i = Estimated density of male bobwhite within the listening radius at point i .

β_0 = Estimated model intercept.

x_{ij} = Values for $j = 1, 2, \dots, k$ measurable covariates at site i .

β_j = Estimated coefficient for parameter $j = 1, 2, \dots, k$ covariates.

Forecasting Procedure

After completing model selection procedures, we used model outputs to project the distribution of bobwhite density across Fort Bragg at the resolution of 5-m raster cells. We began by calculating area-weighted means for each habitat covariate identified in our best-performing model for each 5-m grid cell across the manageable landscape using a 400-m radius as if it were a point-count location. The best-performing model refers to either a single model that clearly outperforms other considered models ($>2 \Delta\text{AIC}$ separation), or the composite model composed of all models within $2 \Delta\text{AIC}$ of the best-performing model along with the model-averaged parameter estimates. To make our density estimates spatially explicit, we calculated E_d

(Equation 1) for each 5-m raster cell based on its area-weighted mean habitat conditions and estimated covariate coefficients. Finally, we calculated the mean E_d across each management compartment separately and across Fort Bragg as a whole for use as baseline values for comparison to predicted bobwhite densities following shifts in habitat management strategies.

The next step was to define the shifts in habitat management strategies and how they would alter habitat covariates from our best-performing model. We explored two broad and opposing shifts in management strategy: forest stand reductions that aimed for less dense forests, and a moratorium on burning and thinning (progression of succession) that would increase forest stand density. In stand reduction scenarios, the value for overstory forest stand parameters would be reduced to half of the mean value observed across point-count locations (Table 2.1); however, if the value was already less than half the observed mean, then it was left unaltered. Understory cover parameters would increase by 1.5 times the current conditions with overstory stand reductions as a result of increased light penetration through the canopy (Engstrom and Palmer 2003). Furthermore, forest structure reductions were not allowed within 100 m of streams or wetlands due to restrictions on allowable timber harvest and the likely presence of the endangered St. Francis' satyr butterfly (*Neonympha mitchellii francisi*), which is an obligate user of wetland habitats. Also, no habitat alterations were allowed within restricted military areas like artillery zones, parachute drop zones, or other military-designated training fields where habitat conditions and management options are fixed. Under succession scenarios, habitat covariate values for overstory forest structure were doubled except in the above-described military-restricted zones, and understory cover covariate values were reduced by half due to less sunlight penetration (Engstrom and Palmer 2003).

Next we estimated magnitude of impact the potential management scenarios were predicted to have on the bobwhite population. We gauged the impacts by estimating the change in 3 bobwhite population and habitat availability metrics including density (male bobwhite/ha), amount of useable space (area with ≥ 1 male bobwhite predicted to occur within a 400-m listening radius), and amount of high density areas (≥ 3 male bobwhite predicted to occur within a 400-m listening radius) across Fort Bragg. After each management scenario was imposed across the landscape and habitat conditions were altered accordingly, new habitat covariate area-weighted means (400-m radius) were calculated for each cell. We considered scenarios where each habitat covariate identified in the best-performing model was altered separately and in combinations with the other covariates. For each case, a new predicted bobwhite density was calculated (Equation 1) for each cell as if the habitat alterations were already a part of the landscape. Finally, new mean predicted bobwhite densities were calculated across Fort Bragg and individual management compartments, and then compared to baseline estimates. All GIS operations were performed in ArcMap 9.3.

RESULTS

Habitat Model Development

We sampled 454 point-count locations, each revisited on 3 consecutive days during the 2009 bobwhite breeding season. The nearest-neighbor distance between point-count locations ranged from 11 – 1,648 m (mean = 417 m, SE = 12). Overall, we found little evidence of spatial autocorrelation for number of calling males heard among points (Moran's $I_{\text{avg}} = -0.005$). However, examination of the correlogram indicated limited spatial structure in our response variable at distances < 150 m, as indicated by mean Moran's I values exceeding the 0.2 and -0.2 thresholds (Figure 2.2). As such, we imposed a 150-m minimum allowable distance between

points, which eliminated 49 locations and left 405 available for model construction. The naïve estimate of occupancy (the proportion of sites where male bobwhites were detected at least once) was 0.484, leaving 209 sites without detections. Positive detections ranged from 1 to 5 unique males, totaling 482 individuals recorded across 1,215 sample days (mean = 0.40 males/sample day, SE = 0.02). Among the different management compartments (Figure 2.1), Compartment 1 had the highest mean detection rate (mean = 0.50 males/sample day, SE = 0.06), and Compartment 6 had the lowest (mean = 0.23 males/sample day, SE = 0.04).

Model selection indicated detection probability (p) was influenced by time of day the survey occurred and bobwhite density per site (λ) was influenced by the additive effects of pine and hardwood overstory conditions (Table 2.2). Detection probability showed an inverse relationship between time of day and the combined probability of a male calling, given that it was present and that the observer heard and recorded the observation (Table 2.3). The probability of detection declined (Equation 2) from 0.45 at 0600 hrs when surveys began to 0.11 at 1200 hrs when surveys concluded (Figure 2.3). The combined overstory model (pine and hardwood conditions) was more than 2 AIC points lower and 2.77 times more likely than the next-best model ($W_i = 0.6075$), therefore no model averaging procedures were attempted (Table 2.2). All 3 habitat covariates (LP_{ba} , SP_{tph} , and SH_{ba}) in the best-performing model indicated a clear inverse relationship with bobwhite density (Table 2.3) and sensitivity was similar among the 3 overstory covariates (Figure 2.4). The derived estimate of occupancy from the best-performing model was 0.9476 (SE = 0.0228), nearly double the naïve estimate. The mean detection probability (p) across sampled points was 0.1857 (SE = 0.0250), and the estimated mean λ was 2.95 (SE = 0.44) males/listening radius, which converts to 0.064 calling male bobwhite/ha. The next-best model ($W_i = 0.219$) added understory cover covariates to the

combined overstory model with imprecise parameter estimates for percent grass and hardwood regeneration that had wide confidence intervals that spanned zero (0.0078 ± 0.0110 , and 0.0022 ± 0.0263 , respectively), indicating uncertainty about whether the parameters have a positive or negative relationship with bobwhite density. The third-best model ($W_i = 0.127$) added site-specific covariates to the combined overstory model with much the same results as the second-best model. Parameter estimates for mean area burned and total area of planted wildlife openings were imprecise with wide confidence intervals that spanned zero (-0.0398 ± 0.2266 , and 0.2829 ± 0.6168 , respectively), indicating uncertainty about the parameter's relationship with bobwhite density.

$$\text{Logit}(p_{ij}) = \alpha_0 + \alpha_1 x_{ij} \quad \text{where...} \quad (\text{Equation 2})$$

p_{ij} = Probability of detecting a male bobwhite at site i during observation j .

α_0 = Estimated detection probability model intercept (Table 2.3).

α_1 = Estimated coefficient for detection probability parameter (Table 2.3).

x_{ij} = Value of detection probability parameter (time) during observation j at site i .

The quasi-validation procedures we used to evaluate the performance of our best-performing model showed little evidence for lack of fit. The mean O_d for the validation dataset ($n = 85$) was 1.62 (SE = 0.16) calling males/site, which was less than the mean E_d (mean = 1.98; SE = 0.20). For the random subset of the model building data ($n = 85$) a similar relationship was observed between O_d (mean = 0.85; SE = 0.11) and E_d (mean = 1.67; SE = 0.10). Furthermore, the means of residuals from both datasets did not differ ($P = 0.058$).

Forecasting Procedure

Mean bobwhite density estimated across the manageable area of Fort Bragg was 0.070 ± 0.017 calling males/ha, but varied among individual management compartments (range 0.032 – 0.122 calling males/ha in compartments 10 and 8, respectively). Of the 3 habitat covariates in

our best- performing model, bobwhite density consistently responded strongest to scenarios that altered SP_{tph} (Figure 2.5). On average across management compartments, our model predicted that reducing SP_{tph} by itself under our stand density reduction scenario guidelines would increase quail density 5.1 times more than if SH_{ba} was reduced by itself, and 9.7 times more than if LP_{ba} was reduced by itself, instead. Additionally, we predicted that if all 3 habitat covariates were altered across Fort Bragg under the best-case scenario, mean bobwhite breeding density would increase to 0.115 calling males/ha (64% increase), which is only 18% higher than that predicted if SP_{tph} alone was altered. Bobwhite density in Compartment 8 was least responsive to improvements to habitat structure (all 3 habitat covariates) with an 18% increase predicted from baseline mean density, and Compartment 5 was most responsive with a 211% predicted increase. On average, impacts from forest stand succession scenarios involving all 3 overstory habitat covariates was forecasted to yield a 66% decrease in bobwhite density across Fort Bragg down to 0.024 calling males/ha. In general, the compartments with the higher baseline density estimates showed less dramatic increases in density relative to habitat improvements compared to low bobwhite density compartments, and the inverse was true for habitat quality reductions (Figure 2.5).

The availability of useable space and areas that would support higher densities of bobwhite differed dramatically between the different shifts in habitat management strategies we considered in this investigation. Based on current conditions, 42,160 ha (75.3%) in Fort Bragg's 10 management compartments were estimated to be useable with ≥ 1 male bobwhite/listening radius predicted present, but only 10,111 ha (18.1%) of the area would support higher densities of bobwhite (≥ 3 male bobwhite/listening radius). If SP_{tph} alone were thinned across all management compartments an additional 8,402 ha (15.0%) of Fort Bragg would become useable

compared to increases of 5,713 ha (10.2%) and 5,602 ha (10.0%) under separate stand reductions for LP_{ba} and SH_{ba}, respectively (Figure 2.6). If all 3 overstory covariates were thinned useable space would increase to include an additional 11,819 ha (21.1%) of the landscape compared to baseline levels, which is 1.4 times more than if SP_{tph} were reduced alone. Interestingly, the amount of area predicted to host higher densities of bobwhite (≥ 3 male bobwhite/listening radius) did not follow the same pattern of increase among the different reduction scenarios as observed with change in overall useable space (Figure 2.7). For instance, if all 3 overstory covariates were thinned, the amount of the landscape supporting higher bobwhite densities would increase by 20,866 ha (207%) from a baseline of 10,111 ha (Figure 2.6). If SP_{tph} alone was reduced an additional 5,602 ha (10.0%) of the landscape would be predicted to support higher bobwhite densities, but reductions in LP_{ba} and SH_{ba} were only likely to yield an additional 3,081 ha (5.5%) and 1,064 ha (1.9%), respectively. If forest density was allowed to increase (all 3 overstory covariates) across Fort Bragg due to a moratorium on burning and timber harvest then the useable space for bobwhite would decrease from baseline levels to 19.1% (10,699 ha) of the landscape (Figure 2.6), and the area that could support bobwhite at higher densities reduced to 6.9% (3,865 ha) of the landscape consisting primarily of the parachute drop zones that are maintained as early succession habitat.

DISCUSSION

Our study illustrated a framework for single-species empirical forecast modeling that can help resource managers make better-informed habitat management decisions. We demonstrated how using empirical forecast models to inform habitat management decisions can help prioritize actions both structurally and spatially across a given landscape relative to magnitude of impact. For example, focusing on thinning small pines to 94 trees/ha across Fort Bragg would account

for 82% of potential population density increase compared to the scenario in which large and small pines, as well as small hardwoods were thinned. Also, focusing efforts in Compartment 5 offered the greatest gains in bobwhite density compared to predicted outcomes for the other compartments. For instance, if the management goal for Fort Bragg was to increase the total area that can support higher bobwhite density (≥ 3 bobwhite/ listening radius) then all 3 habitat covariates should be reduced yielding a 207% increase across the manageable area of the compartment. This type of detailed information provides requisite knowledge for prioritizing management actions with an understanding of expected magnitude of response (Guisan and Zimmerman 2000, Lawler et al. 2011).

Reductions in small pine density across Fort Bragg may be mutually beneficial for bobwhite and the endangered RCW. Our results indicate that small pine density is the primary habitat component currently keeping bobwhite densities low on Fort Bragg, along with large pine and small hardwood basal area to lesser degrees (Figure 2.5). Low standing timber volume on landscapes has consistently been linked with high bobwhite density (Stoddard 1931, Rosene 1969). Lee and Brennen (1994) showed a strong inverse relationship between indexed abundance and increasing canopy closure spanning 38 years in Mississippi. Miley and Lichtler (2009) observed that several types of closed canopy habitats were less often used by calling males in south-central Florida over 13 years of surveys. Little et al. (2009) recently reported evidence in support of recommendations by Rosene (1969), Brennan (1999), and Burger (2001) to maintain total tree basal area (majority pine) below $9.2 \text{ m}^2/\text{ha}$ ($40 \text{ ft}^2/\text{acre}$) if the management goal is to maintain high bobwhite density in a southeastern pine forest landscape. We observed a mean combined pine and hardwood total basal area (83% pine) of $14.7 \text{ m}^2/\text{ha}$ ($64 \text{ ft}^2/\text{acre}$) across our study area, far above recommended levels for bobwhite but within the RCW management

guidelines (11.5–18.4 m²/ha; 50–80 ft²/acre) reported by Fort Bragg (Department of Defense 2001). In addition, according to independently recommended RCW management guidelines for Fort Bragg, preferred conditions for maintaining high-quality RCW habitat is described as having < 49 small pines (15.3–30.5 cm dbh; 6”–12” dbh) per ha, and 16–40 large pines (>35.6 cm dbh; >14” dbh) per ha (Walters et al. 2000, James et al. 2001). Current mean small pine density observed across our study points was 188 trees/ha (range = 21 – 558; Table 2.1), far exceeding the independent recommendations for RCW management (Walters et al. 2000, James et al. 2001). The discrepancy in size classification for small pines between Walters et al. (2000) and our study warrants some caution in choosing an appropriate small pine density target to benefit bobwhite while also ensuring low chance of negative impacts on RCW population recovery. Since our small pine dbh size classification was nearly twice as wide, we used 94 trees/ha (half of the mean observed among our point locations) in our simulated bobwhite habitat improvements, which was nearly double the recommended level by Walters et al. (2000). Based on findings from James et al. (2001) we believe this reduction in trees/ha was conservative and likely would still allow adequate tree recruitment into longleaf stands to promote continued RCW population recovery. Additionally, the current mean large pine (>35.6 cm dbh) density on Fort Bragg was 38 trees/ha, which is at the high end of recommended levels (Walters et al. 2000, James et al. 2001), but ranged from 2.9 – 76.1 trees/ha.

Our bobwhite habitat model represents an improvement over previous bobwhite studies in that we rigorously estimated density (as opposed to just occupancy) and also accounted for imperfect detection. Habitat models for bobwhite are relatively common and have occurred throughout their geographical distribution (Lee and Brennan 1994, Cram et al. 2002, Miley and Lichtler 2009, Twedt et al. 2007). By incorporating detection probability into the habitat

relationship comparisons, we provided a more informative outcome that requires fewer assumptions about the results than other previously used methods reported for bobwhite (MacKenzie et al. 2002, Royle 2004). Traditional call-count indices that related bobwhite density to habitat characteristics were first reported in the 1930's (Stoddard 1931), and still occur in more contemporary investigations (e.g., Cram et al. 2002, Chamberlain and Burger 2005). Because detection probability was not accounted for in these studies, we must assume they had an equal probability of hearing each male present within the listening radius regardless of sample time or male breeding status. Our investigation suggests the assumption of equal calling probability across sample times was likely violated for studies using the call-count index, unless all samples occurred within a short diurnal time period (Figure 2.3). Additionally, there are at least 4 broad categories of bobwhite males present on the landscape at any given moment during the breeding season: males looking for mates, males with an incubating mate, incubating males, and males with a brood (Rosene 1969, Roseberry and Klimstra 1984, DeVos and Mueller 1993, Suchy and Munkel 1993, Burger et al. 1995). It is likely that these broad categories are not mutually exclusive and experience overlap resulting from a loose mating system and extra-pair copulations (Burger et al. 1995, Faircloth 2008). There is evidence to suggest the different categories of males do not call at the same rate and that their proportion in the population changes within a season (Speake and Haugen 1960, Rosene 1969, Hansen and Guthrey 2001, Terhune et al. 2009). Violating the equal probability of observation assumption could put undue weight on the importance of frivolous habitat parameters or remove warranted weight from other important ones.

Although support for overstory conditions was expected, we also expected understory cover conditions (percent grass cover and hardwood regeneration density) to receive more

support in our habitat relationship analysis. Several investigators have suggested that as timber volume changes from high to low, the changing overstory conditions causes changes in the understory characteristics that bobwhite find increasingly more suitable (Guthery 1997, Engstrom and Palmer 2003, Little et al. 2009). Also, detections of bobwhite were consistently higher in places where percent grassland made up a larger portion of the area surrounding breeding bird survey routes in the West Gulf Coastal Plain (Twedt et al. 2007). The upper limit in the range for mean percent grass cover that we observed on our study sites was relatively low (58.75%), which may not have reached a critical threshold that would alter bobwhite habitat selection (Table 2.1). Some studies that reported a relationship between percent grass cover and bobwhite habitat selection measured this variable at the microhabitat scale of radio-marked birds (e.g., Ransom et al. 2008). It is possible that the scale of our study (400-m radius, area-weighted mean) was too coarse to detect microhabitat scale influences of percent grass cover on bobwhite distribution (Wheatley and Johnson 2009). The cone of vulnerability hypothesis promoted by Kopp et al. (1998) suggests that increased density of hardwood regeneration (stems/ha) should promote increased density of bobwhite because of a reduced risk of predation from avian predators. We report uncertainty about whether the relationship between bobwhite density and hardwood regeneration was positive or negative. It is possible that bobwhite select for hardwood regeneration conditions on a microhabitat level when they search for escape cover that is smaller than the scale considered in our investigation.

We also expected to find a response in bobwhite density to changes in site-specific conditions. For instance, Miley and Lichtler (2009) reported a strong initial increase in relative abundance of male bobwhite in the first year after dormant-season burns with declines occurring during the next 2 years before the next fire; they reported a similar but weaker response for plots

with growing-season burns similar to Fort Bragg. It is possible that bobwhites select habitats relative to time since burn, but may do so on a smaller scale than applied during our investigation. It is also possible that we removed critical variability in the covariate by calculating the area-weighted mean years since burn within the 400-m listening radius, but this could not be avoided without precise location data for individual bobwhites. The total area of planted food plots (wildlife openings) within listening radii was expected to have a positive influence on bobwhite density (Burt 1976, Singh et al. 2010), but our observations indicated uncertainty with this relationship. It is probable that food availability is naturally high during the breeding season so planted wildlife openings at this time offer little benefit to bobwhite, but this relationship may differ during winter when food is scarcer.

We allowed listening radii for point-count locations to overlap in our study. Our mean listening radius was assumed to be 400 m, but the Moran's I correlogram identified 150 m as the distance when our response variable (number of male bobwhite heard) became statistically independent (Figure 2.2). We suggest that habitat composition within listening radii often changes considerably with only minor directional shifts between locations, alleviating dependence between density estimates for locations with overlapping listening radii. If we are correct, then it would explain why we found very little spatial autocorrelation when the distance between points exceeded 150 m. This finding is in contrast to traditional bobwhite call count methods that require a ≥ 800 -m distance between points to reduce the chance of hearing the same bobwhite from different locations. High spatial autocorrelation produces semi-pseudoreplication among sample data, which can inflate or deflate actual importance levels of habitat covariates (Segurado et al. 2006). If little spatial autocorrelation exists in number of male bobwhite heard at point counts, then the biases associated with semi-pseudoreplication should be lessened

(Segurado et al. 2006). Another possible explanation for little observed spatial autocorrelation between points that were >150 m apart could be that our actual mean listening radius was considerably less than the assumed 400-m distance. The 400-m listening radius was based on estimates from open range habitats, which may overestimate the actual listening radius in a forested landscape with rolling hill topography (Cram et al. 2002) typical of the Sandhills physiographic region in North Carolina (Griffith et al. 2002). A smaller listening radius would cause less overlap between radii and, therefore, produce less spatial autocorrelation. Also, less spatial autocorrelation would be expected for point counts that occur in low density populations where no more than a few birds (0 – 5) are heard per point because the chances of consistently detecting birds multiple times among adjacent points would be low.

We used male bobwhite density as the population metric for our empirical forecast modeling procedure, but this process is not restrictive. Any quantifiable population parameter could be used. For example, impacts of altered habitat connectivity on population recruitment or dispersal could be modeled. Also, recent work by Murphy (2011) suggests similar methods could be used to forecast impacts of habitat change on meta-population genetic diversity. In fact, countless possibilities exist for different ways to apply empirical forecast modeling and are only limited by the needs and imagination of practitioners.

MANAGEMENT IMPLICATIONS

Though our habitat model only has localized applicability, our framework for empirical forecast modeling of species responses to potential habitat changes has utility for resource managers everywhere. Establishing expected outcomes to habitat management decisions prior to implementation is essential, especially when imperiled or locally important species are involved. Empirical forecast modeling can balance management tensions between 2 competing and

important wildlife management directives on localized landscapes like multi-species management and single-species conservation mandated by the Sikes and Endangered Species acts on military installations, respectively. Managers can use our framework to explore proposed shifts in habitat management before they are implemented on the landscape, and use the results to guide and justify their management decisions. For example, we used our empirical forecast model to evaluate the magnitude of expected bobwhite density response to habitat structure alterations likely to occur under different shifts in timber harvest and prescribed fire strategies for Fort Bragg. Such knowledge in the hands of natural resource managers promotes implementation of spatially and structurally precise prescriptions (Zipkin et al. 2010, Lawler et al. 2011). Estimates of magnitude are much more informative to practitioners and defensible amid potentially heavy scrutiny that can sometimes occur over proper management activity on public lands like military installations, national parks and forests, or in designated critical habitat zones for imperiled species (Peterson et al. 2002).

Aspects of the current habitat management strategies on Fort Bragg appear to encourage consistently high recruitment of young pines into the small size class category considered in our procedure. Habitat management strategies are considered largely monotypic across Fort Bragg with a 10-year rotation for thinning pine stands and intensive growing season burns on a 3-year cycle (Department of Defense 2001). The average stand conditions for small pines on Fort Bragg currently exceed recommended guidelines for RCW management (Walters et al. 2000, James et al. 2001), and our results suggest these conditions are limiting bobwhite recovery as well. Management prescriptions that aim to reduce the small pines per hectare should be viewed as a win-win for both bobwhite and RCW. We recommend further investigation into causes of high recruitment into stands of small size class pines, and alteration of the habitat management

strategies to reduce the trees per hectare within the size class. In addition, even though the mean total basal area for Fort Bragg is within the reported guidelines (Department of Defense 2001), the mean large pine density for Fort Bragg is near the upper limit independently recommended for RCW management (Walters et al. 2000, James et al. 2001). A reduction in large pine density to a more moderate level along with reductions to the small pine density across Fort Bragg is not likely to affect RCW recovery status on Fort Bragg, but would benefit bobwhite by reducing the overall basal area closer to recommended levels creating a win-win situation uncommon in natural resource management.

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FIGURE LEGENDS

Figure 2.1: Layout of the 10 habitat management compartments (1-10), 6 parachute drop zones, 3 artillery impact zones and developed areas for Fort Bragg Military Installation, North Carolina, USA.

Figure 2.2: Correlogram of mean Moran's I depicting the relationship between spatial structure in number of calling male bobwhites and increasing distance between locations where the dotted lines represent acceptable levels ($0.2 - -0.2$) of spatial autocorrelations.

Figure 2.3: Relationship between time of day for the survey and probability of detecting calling male bobwhites during the 2009 breeding season on Fort Bragg military installation, North Carolina, USA. Dashed lines represent the upper and lower 95% confidence limits.

Figure 2.4: Sensitivity analysis for the 3 overstory covariates (small pine trees/hectare; large pine basal area; and small hardwood basal area) identified as important predictors of bobwhite density from data collected during the 2009 breeding season on Fort Bragg, North Carolina. Vertical arrows indicate mean covariate values observed across the landscape, and range of covariate values encompasses observed values on Fort Bragg.

Figure 2.5: Forecasted change in baseline (-) bobwhite density (males/ha) to potential shifts in habitat management strategy across management compartments of Fort Bragg, North Carolina, USA. Simulated habitat alterations included progression of forest succession (●), and overstory stand reductions (x) in all combinations of the 3 predictive overstory parameters (small pine trees/hectare [sp]; large pine basal area [lp]; and small hardwood basal area [sh]) identified in the best-performing habitat model.

Figure 2.6: Forecasted change in useable space and the proportion of space that would support higher densities (3 males/listening radius) of bobwhite to potential shifts in habitat management strategy across management compartments of Fort Bragg, North Carolina, USA. Simulated habitat alterations included overstory stand reductions (a), and progression of forest succession (b) in all combinations of the 3 predictive overstory parameters (small hardwood basal area [SH_{ba}]; large pine basal area [LP_{ba}]; and small pine trees/ha [SP_{tph}]) identified in the best-performing habitat model.

Figure 2.7: Predicted spatial configuration of useable space, high density areas, and areas absent of bobwhite under a) current baseline conditions, b) small pine density (SP_{tph}) reduction, c) complete forest structure (SP_{tph} LP_{ba} SH_{ba}) reduction, and d) complete forest structure (SP_{tph} LP_{ba} SH_{ba}) succession scenarios across Fort Bragg, North Carolina, USA.

Table 2.1: Description of habitat covariates used in a priori models to assess the influence of 4 potential hypotheses to describe bobwhite density during the 2009 breeding season on Fort Bragg, North Carolina, USA.

| Habitat Structure Category | Variable | Code | Definition | Mean | Range^a |
|-----------------------------------|-----------------------------|-------------------|--|-------------|--------------------------|
| Pine Overstory | Large Pine ba ^b | LP _{ba} | Mean ba/ha of large pines (dbh ^d > 35.6 cm) | 5.4 | 0.3 – 11.0 |
| | Small Pine tph ^c | SP _{tph} | Mean tph of small pines (dbh 7.6 - 35.6 cm) | 188 | 20 - 558 |
| Hardwood Overstory | Small Hardwood ba | SH _{ba} | Mean ba/ha of small hardwoods (dbh 7.6 - 25.4 cm) | 1.3 | 0.0 – 6.2 |
| Understory Cover | Percent Grass | Grass | Mean percent grass cover | 24.7 | 0.2 - 58.7 |
| | Hardwood Regeneration | H _{reg} | Mean hardwood stems/ha (dbh < 7.6 cm) | 19 | 0 - 75 |
| Site Conditions | Years Since Burned | Burn | Mean years since last burn | 1.1 | 0.0 - 2.0 |
| | Wildlife Plots | Plot | Total area (ha) of created wildlife openings | 0.1 | 0.0 - 0.8 |

^a Range of area weighted mean values within 400-m buffer areas.

^b Basal area (m²) at breast height.

^c Trees per hectare.

^d Diameter (cm) at breast height (1.4 m).

Table 2.2: Ranking and weight of evidence (w_i) of candidate Royle repeat-count models that assess the influence of temporal and spatial habitat covariates on bobwhite detection probability (p) and density (λ), respectively, during the 2009 breeding season on Fort Bragg, North Carolina, USA.

| Model | K | AIC | Δ AIC | w_i |
|---|----|---------|--------------|--------|
| $p(t^a) \lambda(\text{PineOver}^b \text{HardOver}^c)$ | 6 | 1856.79 | 0 | 0.6075 |
| $p(t) \lambda(\text{PineOver} \text{HardOver} \text{UnderCover}^d)$ | 8 | 1858.83 | 2.04 | 0.2191 |
| $p(t) \lambda(\text{PineOver} \text{HardOver} \text{Site}^e)$ | 8 | 1859.92 | 3.13 | 0.1270 |
| $p(t) \lambda(\text{PineOver} \text{HardOver} \text{UnderCover} \text{Site})$ | 10 | 1862.06 | 5.27 | 0.0436 |
| $p(t) \lambda(\text{PineOver} \text{UnderCover})$ | 7 | 1867.55 | 10.76 | 0.0028 |
| $p(t) \lambda(\text{PineOver})$ | 5 | 1875.43 | 18.64 | 0.0001 |
| $p(t) \lambda(\text{PineOver} \text{Site})$ | 7 | 1879.28 | 22.49 | 0 |
| $p(t) \lambda(\text{HardOver})$ | 4 | 1902.14 | 45.35 | 0 |
| $p(t) \lambda(\text{HardOver} \text{UnderCover})$ | 6 | 1903.65 | 46.86 | 0 |
| $p(t) \lambda(\text{HardOver} \text{Site})$ | 6 | 1905.15 | 48.36 | 0 |
| $p(t) \lambda(\text{HardOver} \text{UnderCover} \text{Site})$ | 8 | 1906.85 | 50.06 | 0 |
| $p(t) \lambda(\text{UnderCover})$ | 5 | 1926.96 | 70.17 | 0 |
| $p(t) \lambda(\text{Site} \text{UnderCover})$ | 7 | 1930.52 | 73.73 | 0 |
| $p(t) \lambda(.)$ | 3 | 1941.59 | 84.80 | 0 |
| $p(t) \lambda(\text{Site})$ | 5 | 1945.48 | 88.69 | 0 |
| $p(.) \lambda(.)$ | 2 | 1988.64 | 131.85 | 0 |

^a t = Time of day survey occurred.

^b PineOver = Pine overstory conditions (LP_{ba} , and SP_{tph}).

^c HardOver = Hardwood overstory conditions (SH_{ba}).

^d UnderCover = Understory cover conditions ($Grass H_{reg}$).

^e Site = Site-specific conditions (Burn Plot).

Table 2.3: Model-derived covariate estimates, standard errors (SE), and confidence intervals (lower and upper) for detection probability (p) and density (λ) of northern bobwhite (*Colinus virginianus*) during the 2009 breeding season on Fort Bragg, North Carolina, USA.

| Parameter | estimate | SE | 95% Confidence Interval | |
|----------------------------|----------|--------|-------------------------|---------|
| | | | Lower | Upper |
| p (intercept) | -1.0715 | 0.1665 | -1.3978 | -0.7452 |
| p (t^a) | -0.0058 | 0.0009 | -0.0076 | -0.0040 |
| λ (intercept) | 0.3400 | 0.1228 | 0.0993 | 0.5807 |
| λ (SP_{tph}^b) | -0.0098 | 0.0017 | -0.0131 | -0.0065 |
| λ (LP_{ba}^c) | -0.0300 | 0.0055 | -0.0408 | -0.0192 |
| λ (SH_{ba}^d) | -0.0721 | 0.0171 | -0.1056 | -0.0386 |

^a t = time of day when survey occurred.

^b SP_{tph} = mean small pine (7.6-35.6 cm dbh) trees per hectare.

^c LP_{ba} = mean large pine (>35.6 cm dbh) basal area per hectare.

^d SH_{ba} = mean small hardwood (7.6-25.4 cm dbh) basal area per hectare.

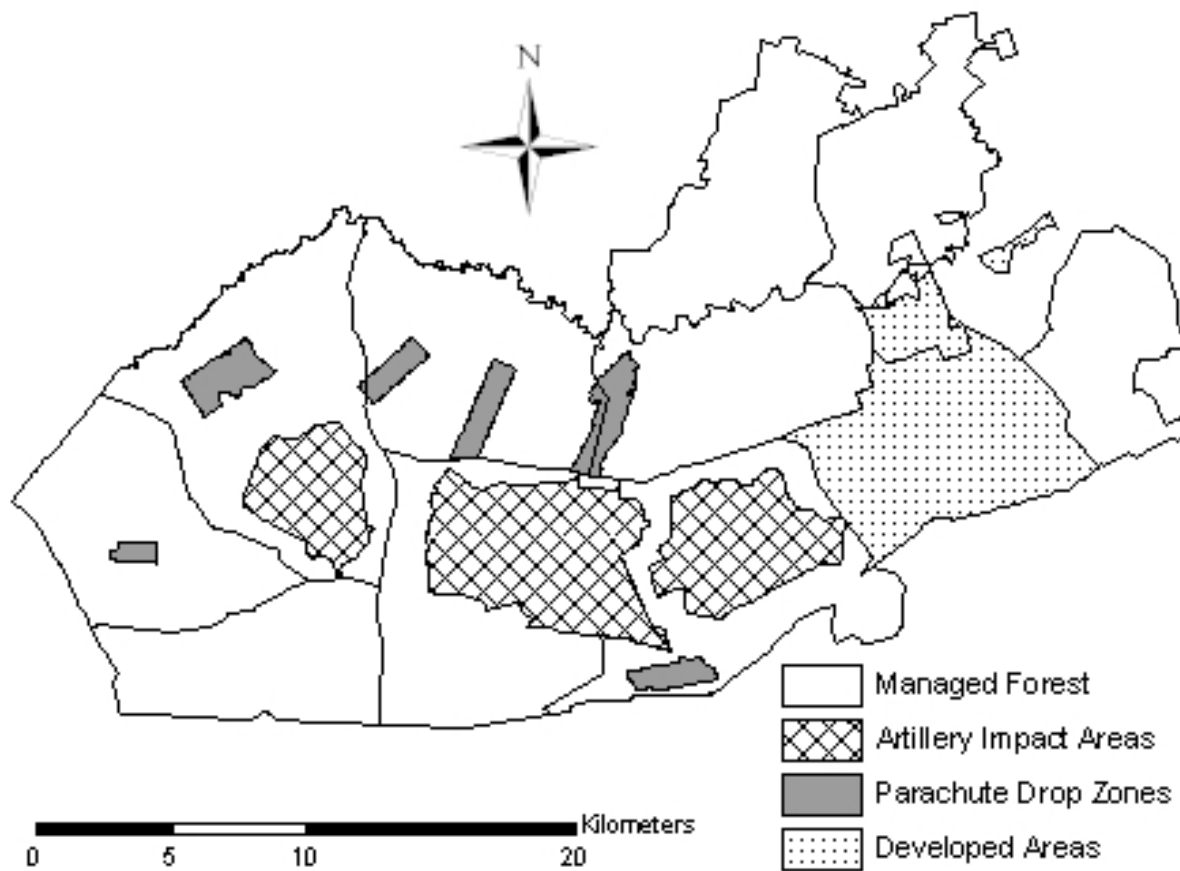


Figure 2.1.

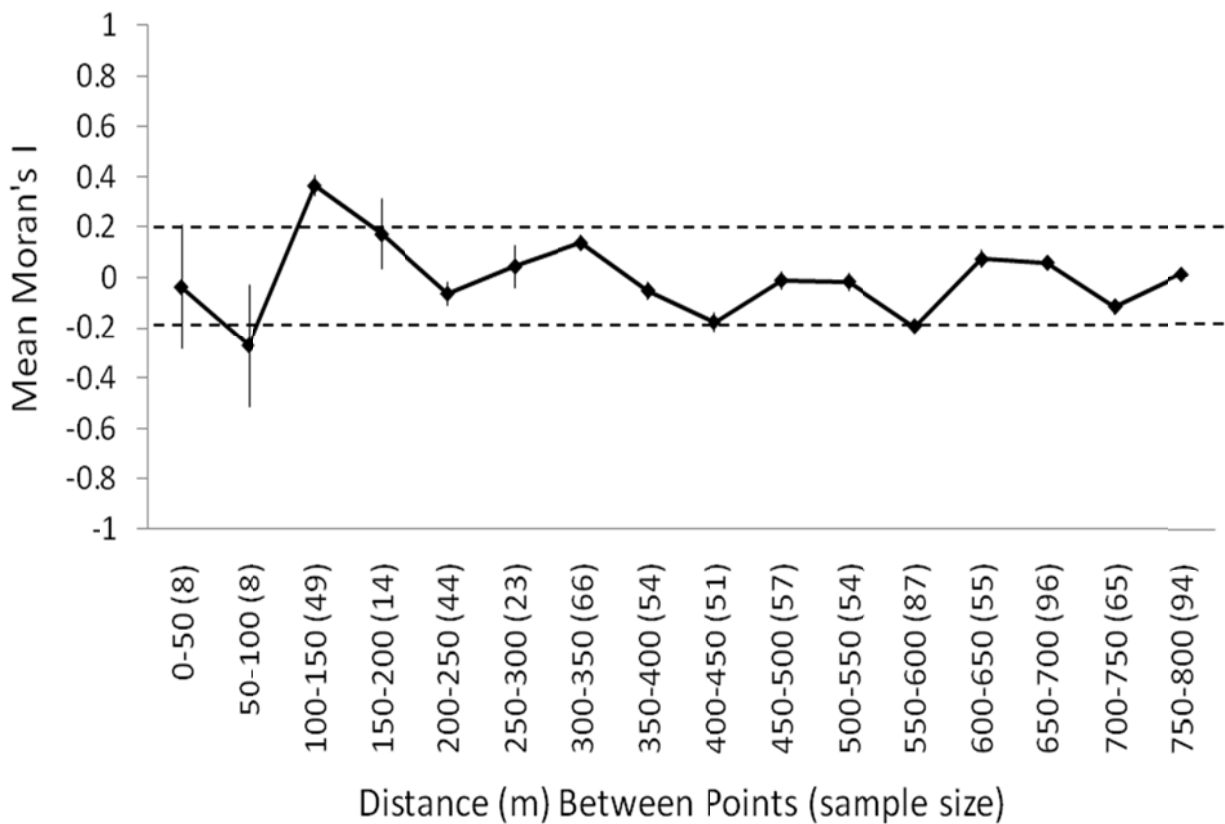


Figure 2.2.

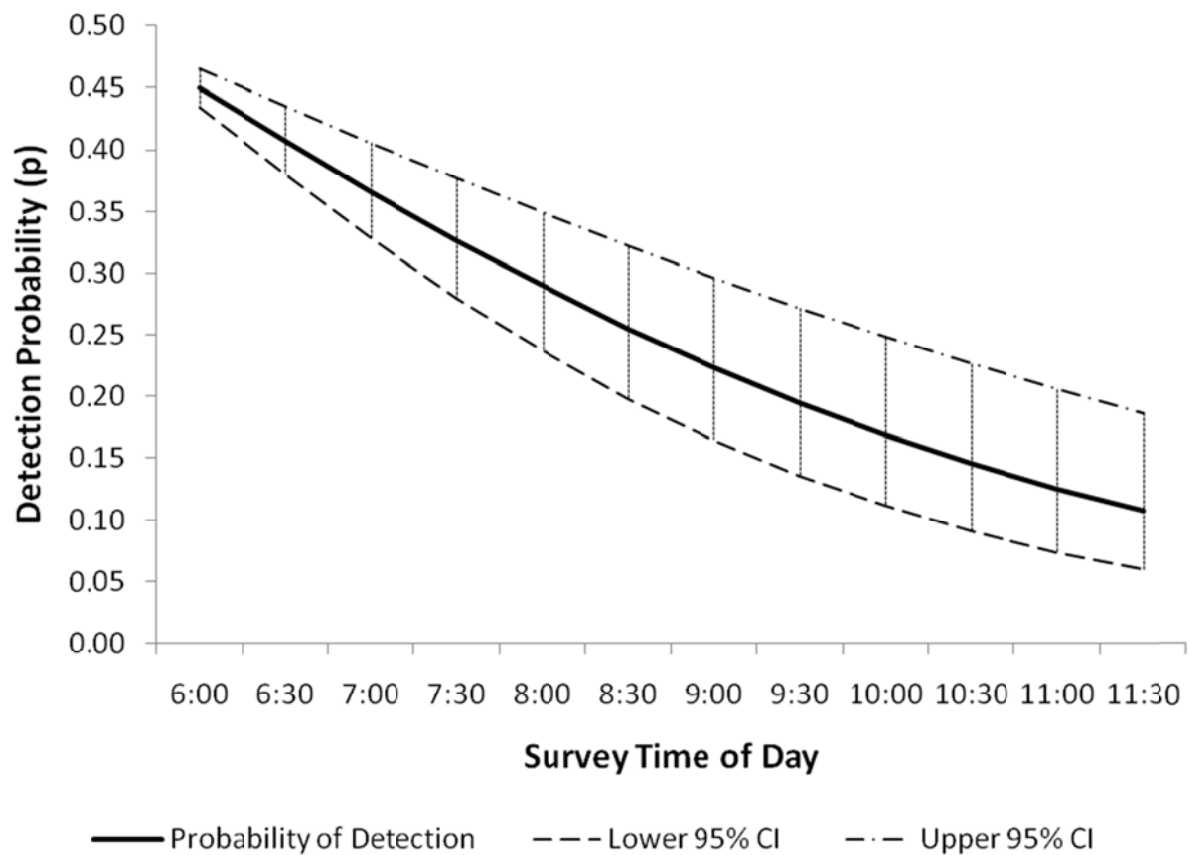


Figure 2.3.

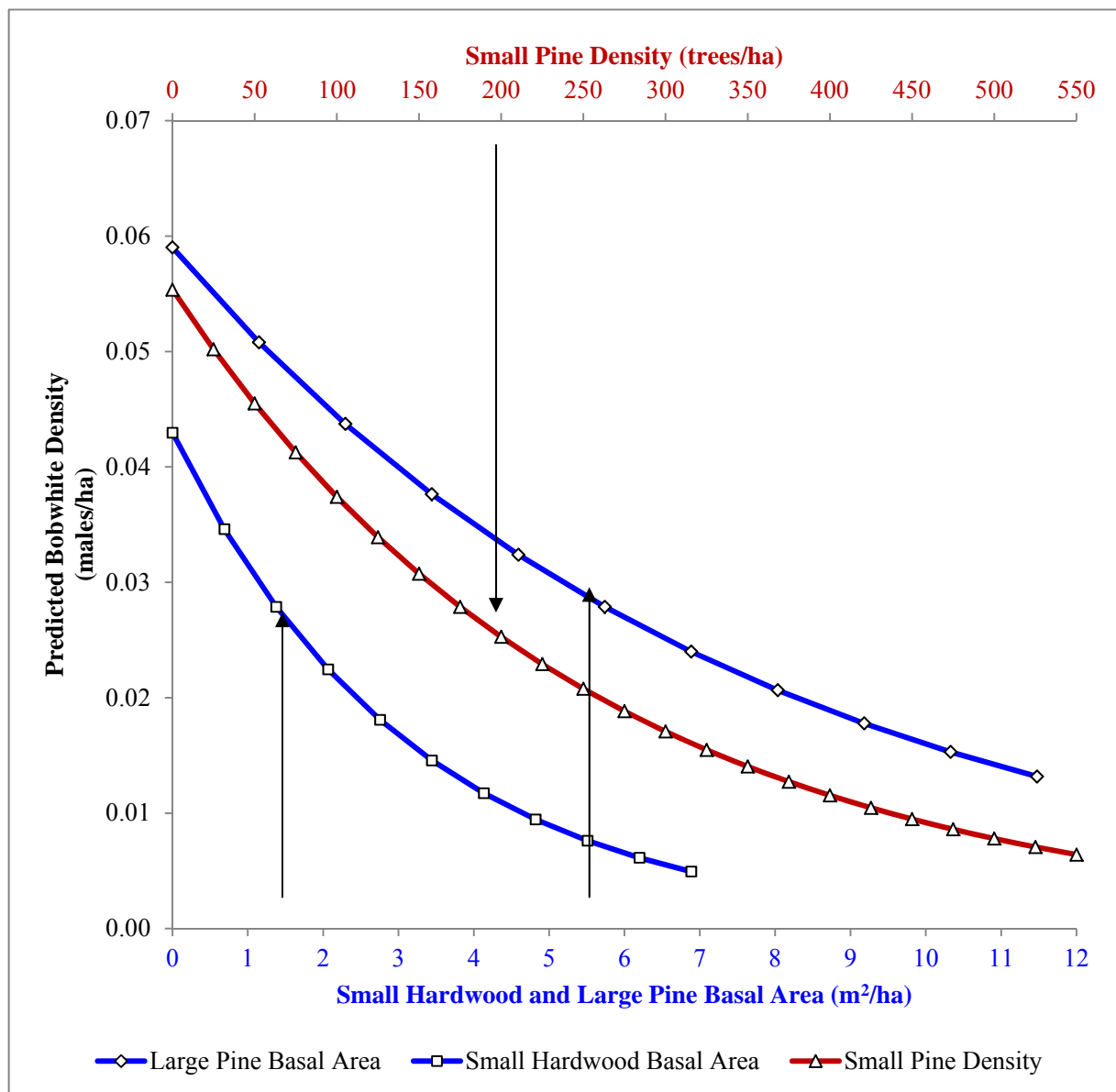


Figure 2.4.

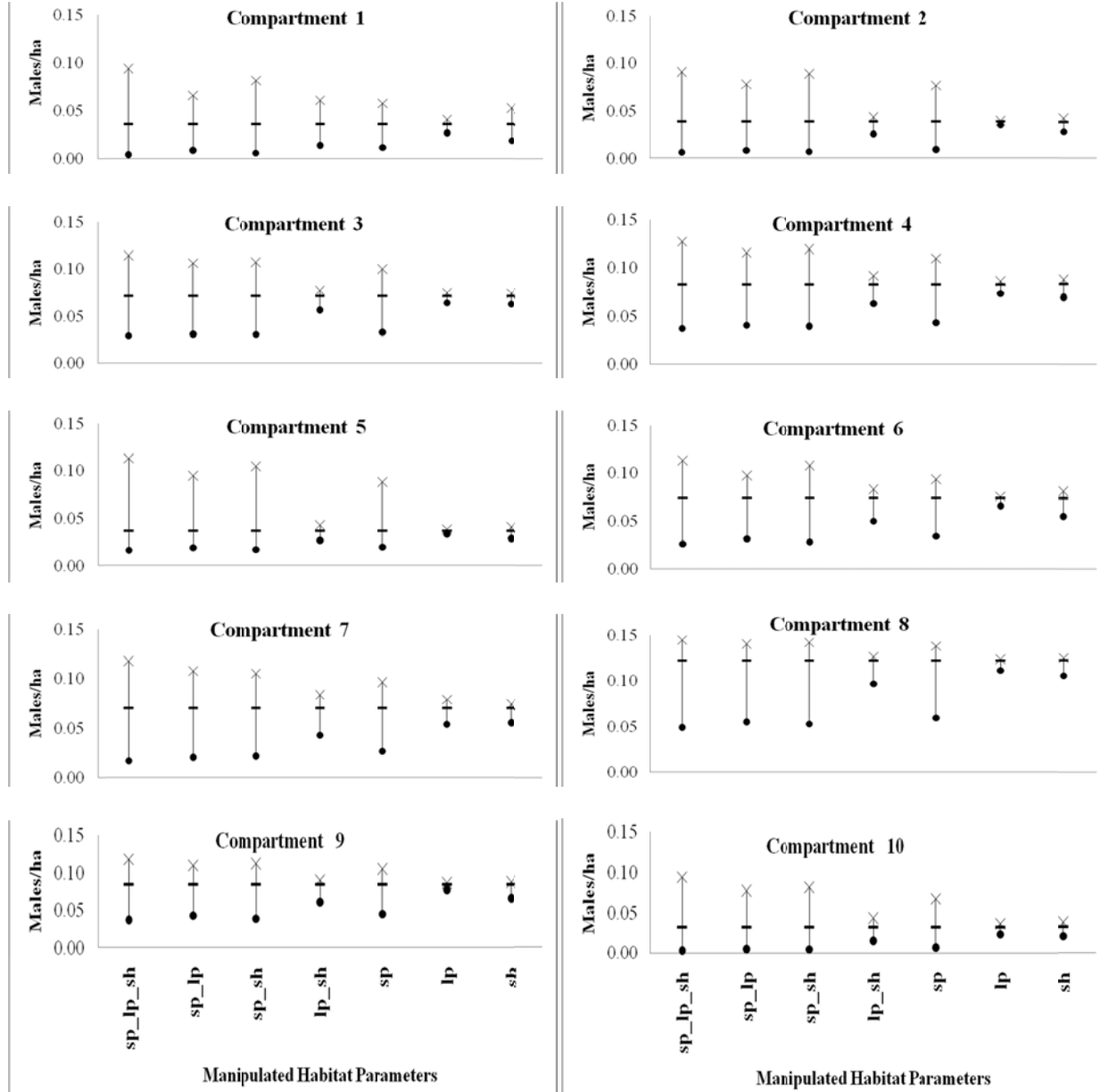


Figure 2.5.

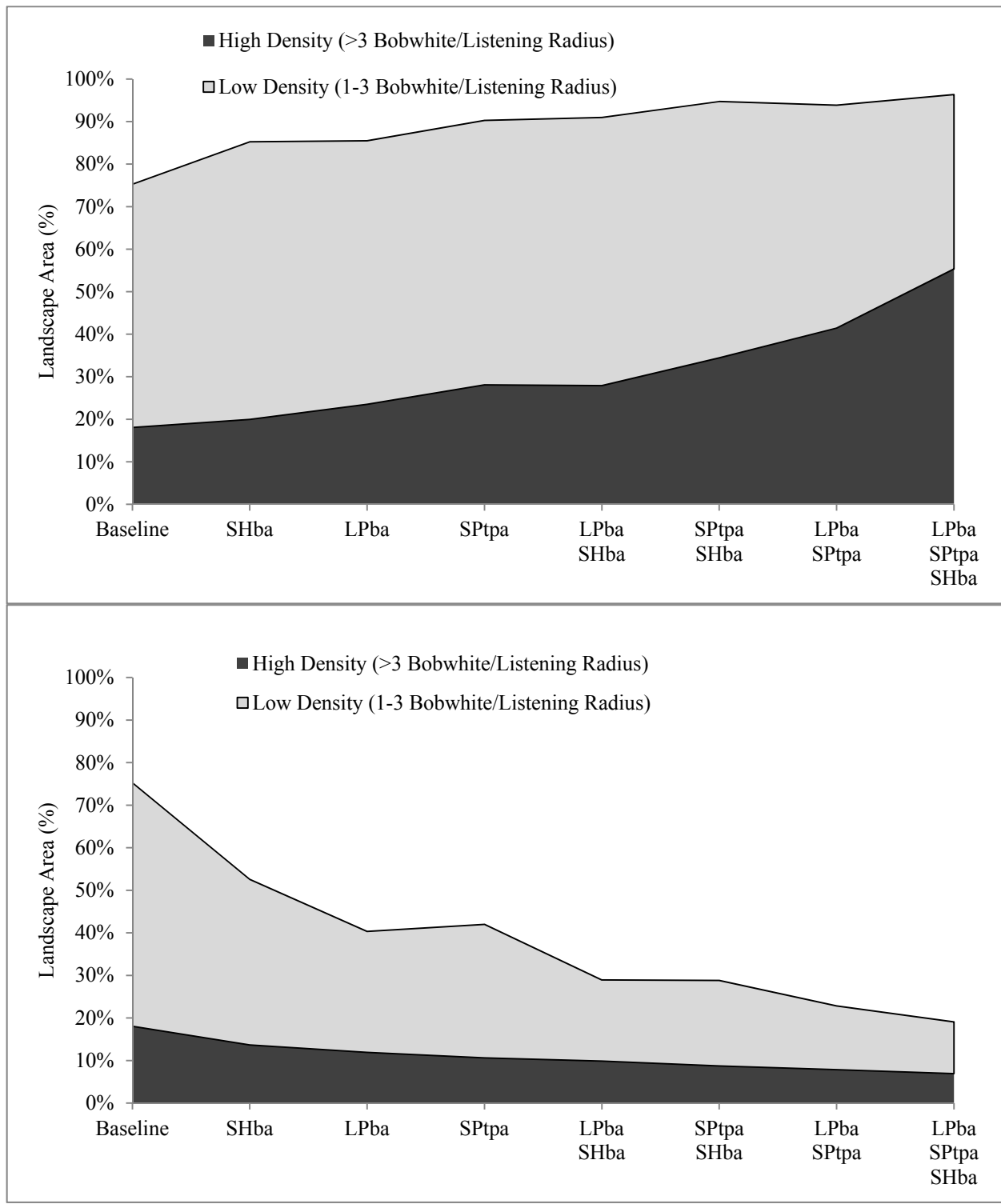


Figure 2.6:

Bobwhite Density Categories




-  Abscent (<1 Bobwhite/Listening Radius)
-  Low Density (1-3 Bobwhite/Listening Radius)
-  High Density (>3 Bobwhite/Listening Radius)

Figure 2.7.

CHAPTER 3

EMPIRICAL FORECAST MODELS FOR GUIDING DECISION-MAKING IN COMPLEX LANDSCAPES WITH COMPETING WILDLIFE MANAGEMENT GOALS

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ABSTRACT

Species distribution models are increasingly being used to help wildlife managers understand expected species responses to climate change, natural disasters, conservation plans, and management actions. For the latter, there is a distinct void of practical case studies that demonstrate how to structure the modeling process and incorporate results into informed decision-making. Furthermore, rarely are a practitioner's information needs for understanding the expected impacts from a management action as simple as a single species response. We demonstrate application of a multi-species empirical forecast model to habitat management scenarios proposed for Fort Bragg, North Carolina. We estimated species habitat relationships, devised from logistic regression or occupancy modeling procedures, for 5 species with differing management priorities including red-cockaded woodpecker (*Picoides borealis*), northern bobwhite (*Colinus virginianus*), white-tailed deer (*Odocoileus virginianus*), eastern fox squirrel (*Sciurus niger niger*), and eastern wild turkey (*Meleagris gallopavo silvestris*). We projected results for each species across the landscape and calculated baseline estimates of useable space for all of Fort Bragg and the 10 management compartments individually. Based on species habitat relationship results, we developed 4 habitat management scenarios that reduced total basal area in different ways and separately imposed them across the landscape. Predicted change in useable space (ha) for each species was calculated for each possible future habitat condition. Results were entered into a decision process designed to identify potential management options that would produce a net positive effect on the suite of species considered while factoring in relative management importance. We identified reductions in small diameter (7.6 – 35.6 cm dbh) pines as the parameter to focus total basal area reduction efforts that is best suited for balancing the habitat needs of all 5 species, producing a net increase in total useable space. Our

results also suggest the sensitivity of red-cockaded woodpecker to reductions of large diameter (> 35.6 cm dbh) pines is too great to include these trees in any management efforts to reduce total basal area. Additionally, model outputs indicate that where management effort was applied mattered with some management compartments producing disproportionately higher net increase in useable space among the species under the different management scenarios considered. We demonstrated that multi-species empirical forecast models have utility as a modeling framework practitioners can use to prioritize their management actions both structurally (e.g., inclusion of small diameter pine reductions and avoidance of large diameter pine reductions) and spatially in ways that are data-driven, making them justifiable and defensible. In times where wildlife practitioners are increasingly asked to do more with less, multi-species empirical forecast models offer a means to streamline management effort and cost.

KEY WORDS: Empirical forecast model, forecasting, Fort Bragg, habitat, management, military, multi-species, North Carolina.

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INTRODUCTION

Forecasting potential impacts of management actions on wildlife populations prior to implementation can be pivotal for making sound management decisions. Predictive models that describe the distribution of a species relative to habitat conditions are especially effective in evaluating species responses to changes in habitat management (Lawler et al. 2011). Models of this nature are termed empirical forecast models (hereafter forecasting). They were first reported in the field of macroeconomics, and are still used to predict economic responses to policy changes (Bodkin et al. 1991). There is potential for transferring the principles of forecast

modeling to wildlife management and needs further exploration. Though calls for forecasting in wildlife management have spanned more than 3 decades (e.g., Christensen 1980, Lawler et al. 2011), there are surprisingly few examples reported in the literature that demonstrate in practical terms how to implement a forecasting procedure.

There are many potential benefits to predicting habitat management outcomes, one of which includes identifying flawed management actions before implementation, avoiding subsequent damage to the resource. In addition, resource managers are often restricted by money, personnel, time, and available resources for implementing on-the-ground habitat improvements. Spatially explicit forecast models can help streamline management efforts targeting areas with the most potential to improve conditions for a species of interest, which would maximize their impacts while minimizing resource expenditures (Zipkin et al. 2010, Lawler et al. 2011). The potential benefits of forecasting to natural resource managers are clear, yet rarely are these predictions explicitly considered (Wiersma et al. 2011). In part, this shortfall may be due to a lack of clear examples of how a forecast model can be implemented on a discrete landscape.

Habitat management strategies designed to benefit one species are likely to have consequences for other sympatric species (Vinther et al. 2004). Nevertheless, because it is difficult to monitor and manage every aspect of a system, shortcuts have been developed to monitor and protect an individual species on a defined landscape in hopes the conservation and management of that species will also protect others occupying the same habitats (Block et al. 1995, Simberloff 1998). The crux of this concept is still in use today, but now terms like indicator, umbrella, keystone, or endangered species management are used as its moniker rather than single-species management. The hope of an overarching umbrella effect following a single-

species approach is considered more a matter of faith rather than of scientific research (Simberloff 1998). On the other hand, multi-species management is criticized for using too little species-specific information on which to base management decisions, thereby leaving uncertainty about actual benefits to the species (Block et al. 1995). With advances in geographic information systems (GIS), availability of detailed wildlife monitoring programs (i.e., Christmas Bird Count, Breeding Bird Survey, www.ebird.org), and ever-increasing computing power, the ability to link highly detailed information from multiple species into a cohesive multi-species management system becomes possible (Roberts et al. 2011).

Species distribution models can be used to predict species-specific responses to changes in localized habitat conditions (e.g., Pereira and Itami 1991, Spies et al. 2007, Zipkin et al. 2010). The Habitat Evaluation Procedure (HEP), which was developed so wildlife managers could provide qualitative impact assessments to predict species responses to future development proposals (Schamberger and Krohn 1982), represents one of the earliest attempts at a forecasting tool in wildlife management. Now, most models available as inputs for forecast modeling procedures are quantitative and constructed in increasingly innovative ways (e.g., Occupancy [MacKenzie et al. 2002], Repeat Count [Royle 2004], and MAXENT [Phillips et al. 2006]). Output produced from these models vary widely including binary classifications of sites as occupied or unoccupied, continuous ranges along a probability gradient (Sinclair et al. 2010), or continuous along a biological gradient (i.e., density). Depending on data quality, these procedures offer a measure of predictability for species occurrence relative to the spatial distribution of habitat parameters (Hooten 2011). Use of empirical data to develop wildlife habitat relationship models made spatially explicit across a landscape are also the backbone of effective forecasting (Christensen 1980, Austin et al. 1996, Lawler et al. 2011). Need exists for a

structured framework to guide managers in applying a multi-species forecasting procedure on localized landscapes, and this need is even greater on landscapes that manage for several species and multiple objectives.

The necessity for forecasting models is compounded when considering landscapes with complex management objectives. Military lands that harbor endangered species provide such a landscape, and can effectively demonstrate the application and potential benefits of a multi-species empirical forecast model. The Sikes Act (1960) mandates integrated natural resource management that promotes multi-species rather than single-species management on military land, yet the Endangered Species Act (1973) for the same landscape can mandate single-species conservation under the threat of reduced or eliminated training for troops from non-compliance. For natural resource managers on military installations, the political tensions created by attempts to integrate habitat improvement for locally important or sensitive species with habitat management directed towards recovering an endangered species can be difficult to balance (Boice 2000). This difficulty is exemplified on some installations in the southeastern United States where management for the endangered red-cockaded woodpecker (*Picoides borealis*; hereafter RCW) dominates the landscape, with little variation in management practices (Department of Defense 2001). Furthermore, it is assumed that RCW management acts as an umbrella that will benefit other species characteristic of the longleaf pine (*Pinus palustris*)-wiregrass (*Aristida stricta*) system (US Fish and Wildlife Service 2003), but tests of this assumption are lacking. Multi-species forecasting offers managers a quantitatively derived prediction of responses by several species to proposed habitat management prior to actual implementation and could be used to balance the conflicts between the Sikes and Endangered Species Acts.

Despite the potential utility of forecasting, few examples exist where they were used as predictive tools to inform management decisions (but see Spies et al. 2007, Nielsen et al. 2008). Herein we demonstrate the use of a multi-species empirical forecast model as a means to identify management approaches that balance habitat needs for a suite of mammalian and avian game species, and an endangered species. Specifically, we used a combination of basic logistic regression and hierarchical occupancy models to parameterize habitat relationship models for white-tailed deer (*Odocoileus virginianus*; hereafter deer), southern fox squirrel (*Sciurus niger niger*; hereafter fox squirrel), eastern wild turkey (*Meleagris gallopavo silvestris*; hereafter turkey), northern bobwhite (*Colinus virginianus*; hereafter bobwhite), and the federally endangered RCW. Of the mammals, deer are characterized as a big game generalist (Webb et al. 2007), and fox squirrel are considered a longleaf pine specialist (Perkins et al. 2008). Of the avian species, turkey are considered a habitat generalist (Badyaev et al. 1996), bobwhite are considered a declining grassland specialist (Stoddard 1931), and RCW are an old growth longleaf pine specialist (US Fish and Wildlife Service 2003). The combined species habitat relationship models were used to evaluate different potential habitat management scenarios for Fort Bragg, North Carolina. Our framework consisted of 2 primary steps: (1) habitat model development, (2) forecasting procedures.

STUDY AREA

Fort Bragg encompasses 62,577 ha in the Sandhills physiographic region of North Carolina (35.040° to 35.270° N, -78.900° to -79.380° W). The manageable landscape represents 90% of the total area and is divided into 10 habitat management compartments (mean = 5,628 ha). Sandhills are described as xeric, flat-topped, sandy ridges, with broad flat valleys composed of sand, clay, and gravel (Griffith et al. 2002). Most of Fort Bragg is forested (~40,000 ha),

much of which is second and third growth longleaf pine (Cantrell et al. 1995) and averaged 14.7 m²/ha (64.0 ft²/ac) of combined hardwood and pine basal area (83% pine) at the time of this study. Other forested stands include loblolly (*P. taeda*), slash (*P. elliottii*), pond (*P. serotina*), and shortleaf (*P. echinata*) pine, as well as mixed pine-hardwood, and hardwood-dominated stands mostly along drains and wetlands. Current habitat management efforts are focused heavily on habitat improvements for RCWs (Britcher 2006), with the majority of practices designed to meet RCW habitat requirements, or are intended to transition degraded habitat to an open pine-wiregrass complex representative of the historic condition (Department of Defense 2001). Forest management on site is based on a 10-year rotation using selective thinnings to reach or maintain forest structure targets (Department of Defense 2001). Frequent prescribed fires (3-year cycle) are used to further control midstory pine and hardwood densities and reset understory succession back to an early seral stage (U.S Fish and Wildlife Service 2003). The majority of burns are high-intensity, growing-season burns (May-June) that cover large continuous blocks. There are 3 artillery impact areas within the base interior totaling 8,048 ha that are off limits except for military activities, and experience frequent and sudden disturbance from ordnance detonation and increased fire frequency from ordnance-initiated fires. Also present are 6 parachute drop zones (mean = 316 ha; range 107 – 498 ha) totaling 1,897 ha that offer consistent early succession habitat maintained through mechanical disturbance and dormant-season burning. There are small food plot style wildlife openings (n = 1,221) dispersed across the landscape primarily targeting deer, turkey, bobwhite, and mourning dove (*Zenaida macroura*).

In 2005, the RCW Sandhills East Recovery Unit composed of Fort Bragg and adjacent properties exceeded the 350-group minimum of breeding clusters required for long-term

recovery of the population (Britcher 2006); this goal was reached 5 years earlier than expected (Belfil and Farley 2008). In contrast, spanning the period from when RCW was listed in 1970 to present, bobwhite populations have declined precipitously within Fort Bragg (Appendix B). Turkeys, which were extirpated from Fort Bragg, were reestablished within base boundaries in 1989. Since that time, the population has increased to a point where hunting was first allowed in 1994 with total harvest increasing from a few birds each year up to 25 birds harvested in 2006 (Appendix A). The deer harvest has fluctuated over time with a peak in 1990 (>1,200 animals reported), and fox squirrel has maintained a steady but low presence in the harvest record (Appendix A).

METHODS

Habitat Model Development

Location data.—Location data for species considered in this study were collected in a variety of ways that resulted in a range of data structures. Despite the variety, the output from each method was consistent, providing a probability of occurrence for each species. More importantly, each probability of occurrence was expressed as a function of habitat covariates, allowing for probability surfaces for each species to be projected across the landscape. The similarity in outputs (i.e., probability of occurrence) among species was considered important to allow direct and proportional comparisons between species-specific responses to changes in habitat conditions under different proposed habitat management scenarios.

We conducted whistling male call-counts for bobwhite on Fort Bragg from 26 May to 7 July 2009. Surveys were conducted between 0600 and 1200 hours and consisted of a 7-min sampling period where the number of different males heard calling was recorded. We visited each point over 3 consecutive days, varying repeat visits across the allowable 6-hour time frame

(MacKenzie et al. 2002). We selected locations for point counts along vehicle-accessible firebreaks and secondary dirt roads using a random point generator in ArcMap 9.3 (Environmental Systems Research Institute 2009). During any given day of surveys, the visited points were > 500 m apart, but between days a 150-m limit was imposed on the point distribution to minimize spatial autocorrelation (Chapter 2). For occupancy analyses, all bobwhite observations above 1 were reduced to 1 to signify the site was observed occupied during the survey; absences remained 0's. We did not survey if wind was > 15 km/hr or if there was any precipitation (Robel et al. 1969). The average maximum listening radius for points was assumed to be 400 m for consistency with other call count studies (e.g., Stoddard 1931, Chamberlain and Burger 2005, Masters et al. 2009).

We used 15 camera traps (Cuddeback® Capture 3.0 Megapixel Scouting Camera) with an infrared trigger sensor to document presence of deer, turkey and fox squirrel across the landscape. Locations for camera trap deployment were selected using a random point generator in ArcMap 9.3. Each location was pre-baited with whole-kernel corn 3-5 days prior to camera deployment. The bait pile was refreshed when the cameras were set for observation, and the deployment period lasted 7 days. Camera placements were restricted to tree mounts at approximately 1.4 m high located between 2 and 3 m from the bait pile with an unobstructed view. Cameras were set to take pictures throughout the day (0001-2400 hr) with a 5-min delay enforced between consecutive pictures. For deer, the data were used to populate an occupancy data structure with the continuous surveillance divided into discrete 24-hr sampling periods. A frequency distribution of when deer were captured by cameras identified 1500 hr as the low point in daily activity; therefore, we used that time as the cutoff between one sampling day and the next. Due to low encounter rates for turkey and fox squirrel, observation data were not

suitable for occupancy modeling. Instead, positive observations regardless of day of occurrence were used as inputs in a logistic regression analysis that included observations from other methods as well.

We set box traps to capture fox squirrels from September 2008 to October 2009 (Baumgartner 1940). Start positions for trap lines were selected randomly along fire-breaks and unpaved roadways using a random point generator in ArcMap 9.3. Trap lines consisted of 70 traps placed approximately 100 m apart along a randomly chosen path that followed firebreaks and unpaved roadways for efficient deployment and trap monitoring from a vehicle. Each trap was baited with whole-kernel corn, remained open for 3 days, and was checked daily for captures. Captured specimens were processed using a squirrel handling cone designed to allow quick, safe handling of squirrels without need for anesthesia (Koprowski 2002). Location coordinates, sex, weight, and standard measurements were recorded, and each squirrel was ear-tagged with individually number tags (Monel 1005-3, National Band and Tag Company, Newport, Kentucky, USA) before being release at the capture site.

We used track stations to document presence of turkey from October 2008 to October 2009. Locations for the track stations were selected using a random point generator in ArcMap 9.3. Track stations were positioned on the edge of unpaved roadways and firebreaks in sandy soils. For each station, we used a rake to disturb soil in a 2-m by 4-m area allowing for easy track recognition if the site was visited by a turkey. No bait or other attractants were used to increase detection probability. Stations were monitored for tracks for 5 consecutive days.

We used cluster boundaries delineated in 2008 by Fort Bragg biologists to document spatial occurrence of RCWs on Fort Bragg. Only clusters designated as active or breeding were retained for analysis. We excluded inactive clusters because it was not known whether those

clusters were not used because of poor habitat (hardwood encroachment, or too few birds to fill them). Furthermore, clusters located in areas not available for sampling (i.e., artillery zones) by other methods were excluded from analysis.

Species habitat relationships.—Habitat covariates associated with overstory, understory, or site specific (i.e., site index, time since burn, and food plot area) conditions were obtained from available forest and understory inventory data collected from December 2008–February 2009. Military contractors projected forest overstory data at the forest stand level, and other contractors averaged understory inventory data within each forest stand. Site specific data were available as all including site index values for each forest stand, stand age, the location and area of different wildlife opens, and time since last burn. Proximity data (i.e., distance to wetland) were calculated by measuring distances in meters to the nearest feature. All habitat layers were converted to raster (5 x 5 m cells) format for analysis using ArcMap 9.3.

Each species has a unique natural history that required different scales by which to link their respective location data to habitat conditions (Wiens 2002). Therefore, we assessed habitat conditions at no more than 4 biologically meaningful habitat scales relative to each species that ranged from a fine to landscape scale including: observation point location, 50% core home range size, 95% home range size, and twice the estimated 95% home range size (Table 3.1). Relevant scales for deer, turkey, and fox squirrel were selected from reported home range estimates in the literature (Table 3.1). Bobwhite habitat associations were limited to a 400-m radius due to listening radius constraints imposed by point count observations. Habitat assessments for RCW were restricted to the boundaries defined by the individual cluster area delineations (mean = 12.4 ± 0.8 ha). With the exception of RCW clusters, area assessments of habitat conditions were facilitated by placing a circular buffer around each location that was

equivalent in area to the above-described scales. Habitat covariate values were calculated as area-weighted means using HawthTools 3.27 in ArcMap 9.3 within each species-specific buffer size around each location.

We used logistic regression procedures to develop habitat relationship models for turkey, fox squirrel, and RCW. For turkey and fox squirrel, habitat conditions at occupied locations were compared to randomly selected locations, thereby, allowing inferences between actual habitat use and random habitat use (presence vs. random). For RCW, the intensity of monitoring protocols for the endangered species would suggest that areas where clusters were not found could robustly be classified as absent locations. As such, we randomly relocated new positions for each cluster while maintaining cluster shape and size and ensured boundaries of random clusters did not overlap with each other or with original cluster locations. Inferences from the RCW habitat associations allow comparisons of habitat selection versus habitat avoidance (presence vs. absence). For deer and bobwhite, data were sufficient to warrant fitting them with occupancy models (Rota et al. 2011) using Program PRESENCE (Hines 2006). Occupancy models are a derivative of the logistic model that operates in a hierarchical framework to account for the nuisance parameter of detection probability (MacKenzie et al. 2002). Occupancy model structured analysis allows inferences between habitat use and habitat avoidance (presence vs. absence).

To identify the scale at which deer, turkey, and fox squirrel habitat parameters performed best, we conducted a preliminary analysis using Akaike's Information Criterion (Akaike 1973; hereafter AIC) where the results of a series of univariate models of the different scales for each habitat parameter were developed and ranked against each other. The scale with the lowest AIC value was selected to continue in the habitat relationship modeling process. To avoid problems

associated with multicollinearity, we used Pearson's correlations test in SAS 9.1 (SAS Institute Inc. Cary, NC, USA) with an $r^2 > 0.5$ limit to determine which of the remaining covariates to include in analyses (Table 3.2).

For each species, we constructed a candidate set of competing habitat relationship models that we compared using a model selection inference strategy based on the bias-corrected AIC_c (Akaike 1973). For RCW, we chose 5 habitat parameters (Table 3.2) that described the pine and hardwood overstory and regeneration conditions (US Fish and Wildlife Service 2003), and arranged them into 25 competing models. For Bobwhite, we examined 8 habitat parameters that included 3 overstory, 2 understory, and 3 site-specific characteristics (Table 3.2). We constructed 25 models that could potentially describe the bobwhite distribution. For deer, we examined 7 habitat parameters including 2 overstory, 3 understory, and 2 site-specific characteristics (Table 3.2), and constructed 15 competing models. For fox squirrels, we chose 7 habitat parameters including 2 overstory, 2 understory, 1 site specific (Table 3.2), and 2 proximity (distance to wetland, and distance to nearest old growth pine) characteristics. We constructed 22 candidate models that could potentially describe the fox squirrel distribution. For turkey, we chose 10 habitat parameters including 3 overstory, 3 understory, 2 site specific (Table 3.2), and 2 proximity (distance to nearest hardwood habitat, and distance to nearest non-forested habitat) characteristics. We constructed 16 candidate models that could potentially describe the turkey distribution.

For logistic regression analyses, Goodness-of-fit (GOF) testing was performed on each species-specific fully parameterized (global) model using PROC LOGISTIC in SAS 9.1 (Hosmer and Lemeshow 1989). We used parametric bootstrapping procedures (10,000 iterations) to examine the fit of global models from each occupancy model candidate set (MacKenzie and

Bailey 2004). Specifically, we examined observed χ^2 test statistic divided by the bootstrapped χ^2 test statistic (\hat{c}) of the global models. Lack of fit was present if $\hat{c} > 1$, in which case variance estimates were corrected by multiplying \hat{c} by the estimated variances for all models in the respective candidate set (Burnham and Anderson 2002). To account for uncertainty, we used model-averaging procedures among all models for a species that performed within 2 Δ AIC points of the top model to create a composite model (Burnham and Anderson 2002).

Additionally, if the null model (intercept only) was identified as the top performing model for a species then that species would be eliminated from further analyses and forecasting procedures due to lack of predictability relative to changes in habitat conditions (Conroy and Moore 2002).

Forecasting Procedures

After completing model selection procedures, we used model outputs to project the probability of occurrence of each species across Fort Bragg at a 5-m raster cell resolution. We began by calculating area-weighted means for each habitat covariate identified in our best-performing species-specific models for each cell across the manageable landscape using a buffer representative of the scale used developing the model. For example, a 400-m radius would be used for any habitat variable used in the bobwhite model, but a 200-m radius would be used to calculate means from the RCW model (i.e., mean cluster size of 12.5 ha = approx. 200m radius circle). The best-performing model refers to either a single model that outperformed the other considered models ($>2 \Delta$ AIC separation), or the composite model composed of all models within 2 Δ AIC points of the best-performing model along with the model-averaged parameter estimates. To make our population parameter (i.e., probability of occurrence) spatially explicit for each species, we calculated expected probability of occurrence for each 5-m raster cell based on its area-weighted mean habitat conditions and corresponding estimated covariate coefficients using

Equation (1). Finally, we calculated the mean probability of occurrence across each management compartment separately and across Fort Bragg as a whole for use as baseline values for comparison to predicted species responses following the simulated shifts in habitat management strategy.

$$p_i = (1 + \exp(-1(\beta_0 + \beta_1 * x_{1i} + \dots + \beta_j * x_{ji})))^{-1} \quad \text{where...} \quad (1)$$

- p_i = Estimated probability of occurrence of the corresponding species at point i .
- β_0 = Estimated model intercept.
- x_{ji} = Values for $j = 1, 2, \dots, k$ measurable covariates at site i .
- β_j = Estimated coefficient for parameter $j = 1, 2, \dots, k$ covariates.

The next step was to define potential shifts in habitat management strategy and how they would alter habitat covariates from our best-performing models. The actual scenarios to be tested in this investigation were defined based on species-specific results of habitat relationships and thus, will be described in the results section. With that said, there are specific underpinnings that we used to define scenarios based on differing management priorities for the species. For Fort Bragg, the overarching objective was to ensure that the military mission of training troops was maintained. Contained under that, the natural resource management concerns were separated into primary and secondary goals. Primary goals include maintaining current RCW population levels above recovery goals and exploring ways to increase bobwhite densities (Fort Bragg wildlife management personnel; personal communication, July 2009). Secondary goals include improving habitat quality for other species (e.g., deer, turkey, and fox squirrel) or at least not causing irreparable degradation. The different ways to accomplish these objectives depend

on the relationships to specific habitat parameters identified in the species habitat relationship models that are described later.

Next we estimated the predicted impact of potential management scenarios on species distributions. We gauged these impacts by estimating the change in useable space (area with a probability of occurrence ≥ 0.5) for each species across Fort Bragg as a whole and within each of the 10 management compartments separately. Forest structure changes were restricted from areas within 100 m of streams or wetlands due to constraints from timber harvest protocols and possible presence of the endangered St. Francis' satyr butterfly (*Neonympha mitchellii francisi*), an obligate user of wetland habitats. Also, no habitat alterations were allowed within restricted military areas like artillery zones, parachute drop zones, or other military-designated training fields where habitat conditions and management options are fixed. After each management scenario was imposed across the landscape and habitat conditions were altered accordingly, new habitat covariate area-weighted means were calculated for each cell using the respective buffer as defined above. Then new probability surfaces were calculated (Equation 1) for each species as if the habitat alterations were already a part of the landscape (post management action). Finally, useable space was recalculated for each species across Fort Bragg and for individual management compartments, which were then compared to baseline estimates. All GIS operations were performed in ArcMap 9.3.

Finally, we developed an a priori decision structure to identify the best option among the scenarios considered and to recognize all other scenarios that offered positive alternatives. Our decision structure was based on weighted comparisons of altered useable space among the target species relative to management importance. For instance, we weighted alterations to the useable space (ha) for RWC by a factor of 3 relative to bobwhite (weight factor of 1) because any

backward trend in the recently recovered status of RCW should be weighed heavily just as any positive benefits to the RCW population should also be supported with a high weighting factor. Alterations to the secondary species were weighted by a factor of 0.5 as attributed to their lower relevance to management goals. We defined the additive combination of the change in useable space weighted by the corresponding priority factor for all species as the overall community index score. A positive community index score indicates a net positive increase in useable space for the species considered and negative values indicate a net decrease. For example, if bobwhite useable space (probability of occurrence ≥ 0.5) increased by 1,000, RCW useable space decreased by 300 ha, deer useable space increased by 500 ha, and fox squirrel useable space decreased by 200 ha, the resulting community index calculation would be as follows:

$$\begin{array}{rcccc} \text{Bobwhite} & \text{RCW} & \text{Deer} & \text{FoxSquirrel} & \text{Community Index} \\ 1,000(1) & - 300(3) & + 500(0.5) & - 200(0.5) & = 250 \end{array}$$

The community index score was calculated for Fort Bragg and for individual management compartment individually to identify which scenario performed best and which compartments offered the greatest community impact.

RESULTS

Habitat Model Development

Species location data.—We had 647 unique occurrences across all species and field observation techniques. In addition, we also included 358 active RCW cluster locations provided by Fort Bragg wildlife personnel, 263 of which were documented as breeding clusters (Fort Bragg; unpublished data). We set camera traps at 602 locations for 7 days, but in some cases cameras had to be pulled early resulting in a loss of 447 trap days for a total of 3,767 trap days. Deer were recorded on 464 camera days at 231 unique locations for a naïve occupancy

rate of 0.3837. Turkeys were recorded on 108 camera days at 41 locations for a naïve occupancy estimate of 0.0679. Fox squirrels were observed on 26 camera days at 17 locations for a naïve occupancy estimate of 0.0282. Track survey stations were set at 516 locations and monitored for 2,385 observation days; 195 observation days were lost to early termination of track station monitoring. We observed turkey tracks on 27 track days with no reoccurrences at the same location for a naïve occupancy estimate of 0.0523. We set 5,772 traps spanning 17,316 trap days. Fox squirrels were observed on 57 trap days with no reoccurrences at the same location for a naïve occupancy estimate of 0.0099. We caught 13 males, 36 females, and 8 of unknown sex due to pre-mature release from the capture bag, and ear-tagged 49 of the fox squirrels with 0 recaptures. We visited 454 point count locations 3 times each, but only used 405 locations after finding excessive spatial autocorrelation among points located < 150 m apart (Chapter 2). Of the 1,215 point count observation days, bobwhites were encountered 325 times at 196 different locations for a 0.4840 naïve occupancy rate.

Species habitat relationships.—The global bobwhite occupancy model indicated mild overdispersion ($\hat{c} = 1.665$) warranting an adjustment to model variances for a QAIC_c analysis. There were 3 competing models (< 2 Δ QAIC_c of the top model) identified from the a priori candidate set (Table 3.3). Our model selection approach indicated the best-approximating model (i.e., the one that garnered 25.0% of the model weight [w_i] among those considered) suggested that occupancy (Ψ_b) was influenced by the additive effects of total basal area (T_{ba}) and percent bare ground. This model was only 1.3 times more likely than the second-ranked model that added percent grass cover as a third explanatory variable, and 2.1 times more likely than a model that combined T_{ba} with the amount of area within 400 m of a location that was devoted to wildlife openings (Table 3.3). These 3 models (combined 56.7% w_i) were used to parameterize a

composite model with model-averaged parameter estimates and associated odds ratios (Table 3.4). The derived bobwhite occupancy estimate was 0.5453 (SE = 0.0084) with a detection probability of 0.5003 (SE = 0.0200).

The deer occupancy model showed excessive overdispersion ($\hat{c} = 12.464$) for its global model. Using QAIC_c, model selection indicated the best-performing model (42.0% w_i) for deer was where Ψ_d was influenced by the additive effects of stand age and site index (Table 3.5) where stand age was measured at the landscape level (1,000-m buffer; Table 3.1) and site index was measured at the home range level (350-m buffer; Table 3.1). This model was more than 2 QAIC_c points lower and 3.9 times more likely than the next-best model that added total hardwood trees/ha at the point of observation and pine trees/ha at the landscape level to the model. Thus, we did not perform model averaging (Table 3.4). The derived estimate of deer occupancy was 0.4633 (SE = 0.0114) with a detection probability of 0.2648 (SE = 0.0128).

The Hosmer Lemeshow GOF test for the fox squirrel logistic regression analyses showed adequate fit for the global model ($\chi^2 = 8.5426$, $p = 0.3823$). There were 2 logistic regression models identified in the confidence set ($< 2 \Delta\text{AIC}_c$ of the top model) as plausible explanations of what habitat conditions best predicted fox squirrel presence on Fort Bragg (Table 3.6). Our model selection approach indicated the best-approximating model (38.0% w_i) suggested that probability of presence was influenced by the additive effects of distance to the nearest wetland and distance to the nearest old growth pine. This model was only 1.6 times more likely than the second-ranked model that added the stand age as a third explanatory variable (Table 3.6). The 2 confidence set models (combined 61.8% w_i) were used to parameterize a composite model with model-averaged parameter estimates and associated odds ratios (Table 3.4).

The Hosmer Lemeshow GOF test for the turkey logistic regression analyses showed adequate fit for the global model ($\chi^2 = 4.8078$, $p = 0.7779$). The best-performing logistic regression model was the null model (intercept only) (Table 3.7). The null model (26.8% w_i) was 1.6 times more likely than the next-best model (Table 3.7), suggesting that turkeys had relatively uniform probability of presence across Fort Bragg. Despite 2 other models within 2 ΔAIC_c of the null model (top performing model), no parameter estimates were recorded and no model averaging occurred and turkeys were eliminated from forecast modeling efforts.

The Hosmer Lemeshow GOF test for RCW logistic regression analyses showed adequate fit for the global model ($\chi^2 = 6.9835$, $p = 0.5384$). Selection among the RCW logistic regression models indicated the best-performing model (64.0% w_i) suggested RCW presence was a function of the additive effects of total hardwood basal area, large diameter pine basal area, high hardwood regeneration (stems (taller than 2m high)/ha), and pine regeneration (stems/ha) (Table 3.8). This model was more than 2 AIC_c points lower and 2.8 times more likely than the next-best model that added number of small diameter pine trees/ha to the model (the global model). Thus, no model averaging of parameter estimates was necessary (Table 3.4).

Forecasting Procedures

Defined management scenarios.—We reviewed the positive and negative habitat associations described in the top or composite model of the different target species (Table 3.4) to identify 4 management scenarios for further evaluation. We aimed to exploit the polarized trends in habitat use associated with large diameter pine basal area (RCW) and total basal area (bobwhite) identified for our 2 species of primary concern (Table 3.4). Scenario 1 was designed to balance benefits for bobwhite with low to moderate losses in useable space for RCW by reducing both large and small diameter pine basal area (LP_{ba} and SP_{ba} , respectively).

Specifically, all areas within the manageable landscape (as defined above) where SP_{ba} was $> 3.4 \text{ m}^2/\text{ha}$ ($15 \text{ ft}^2/\text{ac}$) were reduced down to that level of basal area, and all areas identified with $> 4.6 \text{ m}^2/\text{ha}$ ($20 \text{ ft}^2/\text{ac}$) LP_{ba} were reduced down to that corresponding value. Our second scenario was a more conservative version of Scenario 1 for RCWs by limiting the LP_{ba} reduction to $8 \text{ m}^2/\text{ha}$ ($35 \text{ ft}^2/\text{ac}$). Scenarios 3 and 4 were designed as no-impact options for RCWs by leaving LP_{ba} unaltered while still altering SP_{ba} to $3.4 \text{ m}^2/\text{ha}$ and $4.6 \text{ m}^2/\text{ha}$ for scenarios 3 and 4, respectively. Though both species indicated an inverse relationship with hardwood basal area (Table 3.4), management to reduce hardwood basal area is already a stringent requirement for designated RCW habitats in the upland pines. Therefore, any additional hardwood reductions that could occur would have to be in bottomland hardwood forests where timber management is more restricted (Department of Defense 2001). For these reasons, we did not consider a hardwood reduction option among the scenarios. The species of lesser concern (deer, fox squirrel, and turkey) indicated little expectation of change in useable space as a result of most of the habitat alterations considered amongst our scenarios. For example, site index would not change if a stand is clearcut, and the distance to wetland areas would remain the same as well.

Scenario results.—In total, 42,511 ha were evaluated in our empirical forecast modeling process across Fort Bragg. For the habitat conditions present at the time of this study, bobwhite had the narrowest estimated distribution of useable space at 54.2% (Figure 3.1), and RCW had the widest spanning nearly 90% of the forested landscape (Figure 3.2). Deer also were predicted to occupy a large proportion of the landscape (Figure 3.3) compared to fox squirrels, which indicated that 65.9% was available for use (Figure 3.4). Although Scenario 1 provided the most pronounced increase in useable space ($> 11,000 \text{ ha}$) for bobwhite, there was more than expected loss (96.4%) in RCW useable space as a result of the scenario (Table 3.9). Scenario 2 had a

similar but slightly lessened impact (89.9% loss) on the potential RCW distribution (Table 3.9). Due to the severe impacts on RCW distribution imposed by scenario 1 and 2 those scenarios were not examined further. Scenario 3 and 4, which eliminated RCW-specific habitat covariates, found reducing SP_{ba} alone could raise the percent area occupied to >70% for each scenario (Table 3.9). For Scenario 3, distinct differences between compartments were observed. For instance, the community index value was largest for compartments 3 and 5, with both resulting in over 1,000 ha increase (1,443 ha and 1,337 ha, respectively) in useable space for bobwhite and no measurable impacts on the other species considered (Figure 3.5). Compartments 1 and 8 offered the least productive means of improving overall community habitat quality. Scenario 4 was not dissimilar from Scenario 3, with only slightly decreased impact levels recorded while raising the SP_{ba} target level for the landscape (Figure 3.5).

DISCUSSION

Our results suggest multi-species forecasting can identify potential solutions to complex habitat management problems for localized landscapes like Fort Bragg. We identify and discuss a few noteworthy outcomes from the results of our modeling process. For instance, we used the forecast model to describe a habitat management strategy that could balance habitat needs for multiple species of primary and secondary concern, which is a process that may be of importance to managers elsewhere who also operate under competing management goals. Also, we demonstrate how the modeling process could prioritize habitat management efforts both structurally and spatially allowing managers the chance to do more with less effort. In addition, we discuss how using RCW as an umbrella species without empirical evidence could be problematic for other species originally thought to be benefitting from the management. These potential benefits indicate that forecast modeling may provide wildlife managers with a tool

capable of finding practical solutions to complex habitat management conflicts for multiple species based on empirical evidence.

On many landscapes including Fort Bragg, management goals are often prioritized to favor one species over others. This tendency is especially pronounced if management of an endangered species is required (Block et al. 1995), and is considered reactive management designed to put out proverbial management “wild fires” when a “controlled burn” could be better suited for the task. One main crux to single-species reactive management on localized landscapes (i.e., RCW on Fort Bragg) is determining when management emphasis can be relaxed for a given species. For example, the RCW recovery unit that encompasses Fort Bragg reached its minimum recovery goal in 2005 (Britcher 2006, Belfil and Farley 2008) and empirical evidence (the contrasting trends in habitat use relative to increased large pine basal area for bobwhite and RCW) as well as long-term correlative evidence (Appendix B) indicates that bobwhite declines are likely tied to the same habitat management that brought about RCW recovery. There is inherent risk to adjusting management strategies that have been successful for RCW in the past; yet, we show that multi-species forecasting can reduce that risk by isolating habitat characteristics that do not influence RCW probability of occurrence (RCW neutral), but improve conditions for other species like bobwhite. Actions that manipulate RCW neutral habitat characteristics are low risk actions as long as the model inputs are sound (Conroy and Moore 2002).

Our approach laid a foundation for managers to structure decisions in habitat management that can weigh and balance potential benefits of an action for multiple species of variable management priority against each other. Our process lets managers ask whether changes in useable space for a federally endangered species like RCW should be considered on

an equal scale to changes for a non-imperiled species that is in decline, like bobwhite, or a species of lesser concern like deer. These differing views towards species importance can be built into the decision structure of the forecasting model. The need for a balanced habitat management plan is especially important for military bases where the Sikes Act (1960) mandates integrated natural resource management that promotes multi-species management, and the Endangered Species Act (1973) promotes single-species conservation on the same landscape. When the management goals of both Acts are applied to the same landscape they would seem to create inherent conflict. Consider that the Integrated Natural Resource Management Plan published for Fort Bragg in compliance with the Sikes Act recognized a habitat management conflict between bobwhite and RCW, but could not identify a strategy that benefitted both species citing a lack of empirical evidence for specific habitat needs of bobwhite as the reason (Department of Defense 2001). Without empirical evidence of specific bobwhite habitat needs on Fort Bragg, management was predominantly set to improve conditions for RCW. To the credit of the managers, suitable RCW habitat currently covers much of the base including nearly 90% of the area we evaluated (Figure 3.2); much less of the landscape is suitable to bobwhite (Figure 3.1). Our modeling process provided species habitat relationships for 5 species including bobwhite to fill that data deficiency for Fort Bragg, but more importantly we established a decision making tool that quantitatively identified management actions that were most likely to induce a net improvement among all species considered. The ability to rank alternative management approaches against each other is an important consideration for managers as they make habitat management decisions (Starfield 1997).

In economically stressed times, managers are forced to do more with less (Drew et al. 2011). We demonstrate that multi-species forecasting are a viable process wildlife managers can

use to streamline habitat management structurally and spatially across a landscape. For instance, managers on Fort Bragg could adjust forest management prescriptions to target an increased harvest of small diameter (7.6 – 35.6 cm dbh) pines to induce a positive response in bobwhite useable space without a detriment predicted for RCW, or the secondary species. Managers could also target specific management compartments (i.e., compartments 2, 3, 5) that would provide the largest total area increases in useable space for bobwhite (Figure 3.5). By focusing on a select few compartments for altering current habitat management procedures, an important feedback loop could be created to evaluate the efficacy of the change in management strategy at actually increasing bobwhite useable space while leaving RCW and the other species unaffected (Goodwin and Wright 1991, Starfield 1997). By targeting a small portion of the landscape (i.e., 3 compartments) managers would not be risking the entire RCW population, and not incur additional costs of implementation across the entire base.

Our results suggest that not all RCW habitat management is created equal relative to bobwhite, and that the claim “RCW are rightly termed an umbrella species” for the other traditional inhabitants of fire-adapted pine systems (U.S. Fish and Wildlife Service 2003; pg 105) may not be entirely accurate. Several sources claim that habitat management for RCW also benefits bobwhite (Brennan 1991, Fuller 1994, Engstrom and Baker 1995, Wilson et al. 1995, Chamberlain and Burger 2005), and when compared to the absence of any habitat management at all (i.e., late succession habitat), evidence supports this claim. The correlated decline of bobwhite hunter success rate with increased RCW habitat management (1967-2006) provides one example where RCW management may not have benefitted bobwhite (Appendix B). The range of acceptable habitat conditions documented in the recovery plan for RCW is wide, allowing some flexibility in management approaches (U.S. Fish and Wildlife Service 2003). Our

modeling process suggested that adjusting RCW habitat management protocols on Fort Bragg to improve habitat conditions for bobwhite was possible.

MANAGEMENT IMPLICATIONS

Resolutions to competing habitat management conflicts are often opaque without a framework that integrates the needs for each species into a structured decision process based on solid evidence (i.e., empirical data) (Starfield 1997). As such, maintaining compliance with both the Sikes and Endangered Species Acts without an empirically based forecast model would be difficult. Much forecast modeling occurs in regard to global climate change (Lawler et al. 2009), but managers also need tools to evaluate more immediate and practical management problems (Starfield 1997). Our process helps fill this void by demonstrating how to link spatially explicit habitat relationship models for multiple species of interest with alternative management scenarios, and how to build a decision structure to help understand trade-offs among the different management alternatives being considered. Using an empirical modeling process like ours would aid managers in making better-informed and more defensible decisions amid habitat management conflicts (Starfield 1997).

For Fort Bragg, the continued recovery status of RCW is a primary concern (Britcher 2006). According to the Integrated Natural Resource Management Plan for Fort Bragg, bobwhite represents “a population in crisis” (Department of Defense 2001: pg 179), thereby also making it a species of primary concern. Our use of forecasting has provided managers at Fort Bragg and elsewhere a potential means whereby they can balance the habitat needs for multiple species that are otherwise competing against each other for management effort and dollars. Forecasting provide a level of understanding as to precisely where across the landscape management actions will produce the greatest benefits, which affords managers with a vital

prioritization tool in times when they are increasingly asked to do more with less (Drew et al. 2011). Furthermore, for management entities that boast an integrated natural resource management plan, prioritizing management for one species, endangered or not, over others would benefit from a more inclusive evaluation tool that incorporates empirically derived impacts to other species that can be used to justify management decisions from a wildlife community perspective

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FIGURE LEGENDS

Figure 3.1: Predicted spatial configuration of useable space for bobwhite under A) current baseline conditions, B) Scenario 1 with small and large pines reduced heavily, C) Scenario 2 with small pines reduced heavily and large pines reduced moderately, D) Scenario 3 with small pines reduced heavily reduced, and E) Scenario 4 with small pines moderately reduced across Fort Bragg, North Carolina, USA from observations made Oct 2008 to Oct 2009.

Figure 3.2: Predicted spatial configuration of useable space for red-cockaded woodpecker under A) current baseline conditions, B) Scenario 1 with small and large pines reduced heavily, and C) Scenario 2 with small pines reduced heavily and large pines reduced moderately across Fort Bragg, North Carolina, USA from observations made Oct 2008 to Oct 2009.

Figure 3.3: Predicted spatial configuration of useable space for white-tailed deer under current baseline conditions across Fort Bragg, North Carolina, USA from observations made Oct 2008 to Oct 2009.

Figure 3.4: Predicted spatial configuration of useable space for eastern fox squirrel under current baseline conditions across Fort Bragg, North Carolina, USA from observations made Oct 2008 to Oct 2009.

Figure 3.5: Differential forecasted increases in useable space (ha) delineated by management compartment for northern bobwhite following the simulated implementation of the habitat management scenarios that reduce the small diameter pine forest structure by varying marks across Fort Bragg, North Carolina, USA.

Table 3.1: Description of scales (ha) at which habitat covariates were measured for input into habitat relationship models for northern bobwhite (BW), eastern fox squirrel (FS), eastern wild turkey (EWT), red-cockaded woodpecker (RCW), and white-tailed deer (WTD) across Fort Bragg, North Carolina, USA.

| Species | Point ^a | Core ^b | HR ^c | Landscape ^d | Source(s) |
|---------|--------------------|-------------------|-----------------|------------------------|-------------------------------|
| BW | - | - | - | 50 | Stoddard (1931) |
| WTD | yes | 34 | 150 | 300 | Webb et al. (2007) |
| FS | yes | - | 20 | 40 | Kanola and Humphrey (1990) |
| EWT | yes | 200 | 1000 | - | Badyaev et al. (1996) |
| RCW | - | - | - | 12 | Fort Bragg (unpublished data) |

^aThe habitat conditions found at the exact point of observation.

^bEstimated size (ha) of the 50% core area obtained from the source.

^cEstimated size (ha) of the 95% home range obtained from the source.

^dRepresents a doubling of the 95% home range area (ha) obtained from the source.

Table 3.2: Mean and maximum values of habitat covariates used in habitat relationship models for northern bobwhite (BW), eastern fox squirrel (FS), eastern wild turkey (EWT), red-cockaded woodpecker (RCW), and white-tailed deer (WTD) across Fort Bragg, North Carolina, USA. Minimums were all 0 except for Site Index which had a minimum of 21.

| Variable | Abrev. | Species | Description | Mean | Max |
|-----------------------------------|-------------------|----------------|--|-------------|------------|
| ^a Total ba | T _{ba} | BW, FS, EWT | Pine and Hardwood basal area/hectare | 66.5 | 188 |
| Total Hardwood ba | H _{ba} | RCW | Hardwood basal area/hectare | 50.5 | 139 |
| Total Pine tph | P _{tph} | EWT, WTD | Pine trees/hectare | 101.7 | 522 |
| Total Hardwood tph | H _{tph} | EWT, WTD | Hardwood trees/hectare | 37.7 | 563 |
| ^b Large Pine ba | LP _{ba} | BW, RCW | Large diameter pine basal area/hectare | 23.4 | 83 |
| Large Hardwood tph | LH _{tph} | FS | Large diameter hardwood basal area/ha | 5.0 | 31 |
| ^c Small Pine tph | SP _{tph} | BW, RCW | Small diameter pine trees/hectare | 29.8 | 514 |
| Small Hardwood ba | SH _{ba} | BW | Small diameter hardwood basal area/ha | 5.7 | 72 |
| Percent Grass | Grass | BW, WTD | Percent grass ground cover | 24.7 | 95 |
| Percent Bare Ground | Bare | BW, EWT | Percent exposed 'bare' ground | 10.5 | 98 |
| Percent Herbaceous | Herb | EWT, FS, WTD | Percent herbaceous plant ground cover | 5.0 | 55 |
| Tree ^d Regeneration | T _{reg} | WTD | Pine and hardwood regen. (stems/ha) | 13.4 | 783 |
| Pine Regeneration | P _{reg} | FS, RCW | Pine regeneration (stems/ha) | 9.2 | 779 |
| Hardwood Regen. | H _{reg} | EWT | Hardwood regeneration (stems/ha) | 7.6 | 102 |
| ^e High Hardwood Regen. | HH _{reg} | RCW | High Hardwood regen. (stems/ha) | 3.5 | 37 |
| Site Index | SI | BW, EWT, WTD | Longleaf site index value | 65.5 | 108 |
| Stand Age | Age | EWT, FS, WTD | Age (years) of dominant trees in stand | 49.0 | 144 |

^a'Total' includes trees > 7.6 cm dbh (> 3" dbh).

^b'Large' includes trees > 35.6 cm dbh (> 14" dbh).

^c'Small' includes trees between 7.6 and 35.6 cm dbh (3 - 14" dbh).

^d'Regeneration' includes understory trees < 7.6 cm dbh (< 3" dbh).

^e'High' includes all regeneration trees (< 7.6 cm dbh) that are also > 2 m in height.

Table 3.3: Ranking and model selection results corrected for overdispersion and small sample size(QAIC_c) of candidate occupancy models that examine influence of temporal and habitat covariates measured as area-weighted means (400 m buffer) on bobwhite occupancy (ψ) and detection probability (p), respectively, during 2009 breeding season on Fort Bragg, North Carolina, USA. The shaded area indicates the candidate model set used for model averaging.

| Model | K | QAIC _c | Δ QAIC _c | w_i |
|--|----|-------------------|----------------------------|-------|
| $\psi(\text{TOTba}^{\text{a}}, \text{Bare}^{\text{b}}) p(t^{\text{c}})$ | 6 | 1257.860 | 0.000 | 0.250 |
| $\psi(\text{TOTba}, \text{Bare}, \text{Grass}^{\text{d}}) p(t)$ | 7 | 1258.331 | 0.471 | 0.198 |
| $\psi(\text{TOTba}, \text{Plot}^{\text{e}}) p(t)$ | 6 | 1259.330 | 1.470 | 0.120 |
| $\psi(\text{Pine}^{\text{f}}, \text{Hardwood}^{\text{g}}, \text{Plot}) p(t)$ | 8 | 1260.082 | 2.222 | 0.082 |
| $\psi(\text{Pine}, \text{Hardwood}, \text{Bare}) p(t)$ | 8 | 1260.752 | 2.892 | 0.059 |
| $\psi(\text{TOTba}, \text{Grass}) p(t)$ | 6 | 1261.170 | 3.310 | 0.048 |
| $\psi(\text{TOTba}, \text{Burn}^{\text{h}}, \text{Plot}) p(t)$ | 7 | 1261.271 | 3.411 | 0.045 |
| $\psi(\text{TOTba}) p(t)$ | 5 | 1261.370 | 3.510 | 0.043 |
| $\psi(\text{Global}) p(t)$ | 13 | 1261.912 | 4.051 | 0.033 |
| $\psi(\text{Pine}, \text{Hardwood}, \text{Site}^{\text{i}}) p(t)$ | 8 | 1262.004 | 4.143 | 0.032 |
| $\psi(\text{Pine}, \text{Hardwood}) p(t)$ | 7 | 1262.151 | 4.291 | 0.029 |
| $\psi(\text{Pine}, \text{Hardwood}, \text{Grass}) p(t)$ | 8 | 1262.642 | 4.782 | 0.023 |
| $\psi(\text{TOTba}, \text{Burn}) p(t)$ | 6 | 1263.210 | 5.350 | 0.017 |
| $\psi(\text{Pine}, \text{Hardwood}, \text{Burn}) p(t)$ | 8 | 1263.982 | 6.122 | 0.012 |
| $\psi(\text{Pine}, \text{Hardwood}, \text{Understory}) p(t)$ | 9 | 1264.694 | 6.833 | 0.008 |
| $\psi(\text{Pine}, \text{Grass}) p(t)$ | 7 | 1269.351 | 11.491 | 0.001 |
| $\psi(\text{Pine}) p(t)$ | 6 | 1273.860 | 16.000 | 0.000 |
| $\psi(\text{Hardwood}) p(t)$ | 5 | 1279.810 | 21.950 | 0.000 |
| $\psi(\text{Grass}) p(t)$ | 5 | 1291.630 | 33.770 | 0.000 |
| $\psi(.) p(t)$ | 4 | 1297.160 | 39.300 | 0.000 |
| $\psi(\text{Plot}) p(t)$ | 5 | 1300.020 | 42.160 | 0.000 |
| $\psi(\text{Site}) p(t)$ | 5 | 1301.610 | 43.750 | 0.000 |
| $\psi(\text{Burn}) p(t)$ | 5 | 1301.630 | 43.770 | 0.000 |
| $\psi(\text{Bare}) p(t)$ | 5 | 1302.160 | 44.300 | 0.000 |
| $\psi(.) p(.)$ | 3 | 1326.650 | 68.790 | 0.000 |

^aTotal basal area for all trees > 7.6 cm dbh.

^bBare ground (%) exposed.

^cTime of day when observation occurred.

^dGrass cover (%).

^eTotal area of created wildlife food plot openings within the 400 m buffer around each point.

^fSmall pine (7.6 - 35.4 cm dbh) trees/ha, and large pine (> 35.4 cm dbh) basal area/ha.

^gSmall hardwood (7.6 - 35.4 cm dbh) basal area/ha.

^hTime sense last burn.

ⁱSite index value

Table 3.4: Model-averaged parameter estimates, standard error (SE), upper and lower 95% confidence intervals (UCI and LCI, respectively), and unit scaled odds ratios for habitat coefficients identified in the candidate suite of models that describe the probability of occurrence for northern bobwhite, eastern fox squirrel, white-tailed deer, and red-cockaded woodpecker on Fort Bragg, North Carolina, 2008-2009.

| Species | Parameter | Estimate | SE | LCI | UCI | Unit Scalar | Scaled Odds Ratio | Scaled LCI Odds Ratio | Scaled UCI Odds Ratio |
|---------------------------|---|----------|---------|---------|---------|---------------------|----------------------|--------------------------|--------------------------|
| Bobwhite ^a | Intercept | 0.2743 | 0.1328 | 0.0565 | 0.4921 | - | - | - | - |
| | Total ba ^c (>7.6cm dbh) | -0.0492 | 0.0102 | -0.0659 | -0.0325 | 1m ² /ha | 0.791 | 0.722 | 0.861 |
| | Bare ground (%) | -0.0418 | 0.0193 | -0.0734 | -0.0102 | 10% | 0.591 | 0.292 | 0.898 |
| | Grass cover (%) | 0.0161 | 0.0129 | -0.0050 | 0.0372 | 10% | 1.163 | 0.951 | 1.379 |
| | Plot area (ha) | 1.5116 | 0.7876 | 0.2199 | 2.8034 | 0.1 ha | 1.353 | 1.025 | 2.550 |
| Fox Squirrel ^b | Intercept | -0.3063 | 0.4593 | -1.2065 | 0.5938 | - | - | - | - |
| | Distance to Wetland | 0.0016 | 0.0006 | 0.0005 | 0.0027 | 100 m | 1.200 | 1.100 | 1.300 |
| | Distance to old growth pine | -0.0006 | 0.0003 | -0.0012 | 0.0000 | 100 m | 0.939 | 0.879 | 0.999 |
| | Stand age | 0.0088 | 0.0082 | -0.0073 | 0.0248 | 10 yrs | 1.090 | 0.930 | 1.250 |
| Deer ^c | Intercept | -1.0210 | 0.0660 | -1.1504 | -0.8917 | - | - | - | - |
| | Stand age | -0.0254 | 0.0093 | -0.0435 | -0.0073 | 10 yrs | 0.749 | 0.574 | 0.927 |
| | Site index | 0.0258 | 0.0104 | 0.0055 | 0.0462 | 10 | 1.262 | 1.055 | 1.473 |
| RCW ^d | Intercept | -1.0014 | 0.2363 | -1.4645 | -0.5383 | - | - | - | - |
| | Hardwood ba (>7.6 cm dbh) | -0.2885 | 0.0535 | -0.3934 | -0.1836 | 1m ² /ha | 0.749 | 0.675 | 0.832 |
| | Large pine ba (>35.4 cm dbh) | 0.308 | 0.039 | 0.23156 | 0.3844 | 1m ² /ha | 1.361 | 1.261 | 1.469 |
| | High Hardwood Regeneration ^f | -0.0319 | 0.0132 | -0.0578 | -0.0060 | 10 stem/ha | 0.692 | 0.462 | 0.939 |
| | Pine Regeneration (< 7.6 cm dbh) | 0.0135 | 0.00444 | 0.0048 | 0.0222 | 10 stem/ha | 1.138 | 1.049 | 1.231 |

^aAll habitat covariates measured at a 400 m buffered scale around each point of observation.

^bAll habitat covariates measured at the point scale.

^cStand age was measured at a 1,000 m buffered scale around each point of observation.

^dAll habitat covariates measured within the core use area delineated for each cluster (mean = 11.4 ± 2.5 ha).

^eBasal area measured as m²/hectare.

^fRegeneration measured as tree stems per hectare.

Table 3.5: Ranking and model selection results of candidate occupancy models that examine influence of habitat covariates measured at different biological scales on white-tailed deer occupancy (ψ) for Fort Bragg, North Carolina, USA (2008-2009). The shaded area indicates the best performing candidate model.

| Model | K | QAIC _c | Δ AIC _c | w_i |
|--|----|-------------------|---------------------------|-------|
| $\psi(\text{Age1000}^a \text{ SI350}^b) p(.)$ | 5 | 2575.411 | 0.000 | 0.420 |
| $\psi(\text{Age1000 SI350 Htpa0}^c \text{ Ptpa1000}^d) p(.)$ | 7 | 2578.109 | 2.698 | 0.109 |
| $\psi(.) p(.)$ | 4 | 2578.277 | 2.866 | 0.100 |
| $\psi(\text{Grass0}^e \text{ Herb0}^f \text{ Regen350}^g \text{ P_age1000 SI350}) p(.)$ | 8 | 2578.663 | 3.252 | 0.083 |
| $\psi(\text{Regen350}) p(.)$ | 4 | 2579.437 | 4.026 | 0.056 |
| $\psi(\text{Age1000}) p(.)$ | 4 | 2579.807 | 4.396 | 0.047 |
| $\psi(\text{Regen350 Grass0 Herb0}) p(.)$ | 6 | 2580.231 | 4.821 | 0.038 |
| $\psi(\text{Grass0}) p(.)$ | 4 | 2581.017 | 5.606 | 0.025 |
| $\psi(\text{SI350}) p(.)$ | 4 | 2581.207 | 5.796 | 0.023 |
| $\psi(\text{Ptpa1000}) p(.)$ | 4 | 2581.367 | 5.956 | 0.021 |
| $\psi(\text{Htpa0}) p(.)$ | 4 | 2581.647 | 6.236 | 0.019 |
| $\psi(\text{Herb0}) p(.)$ | 4 | 2581.707 | 6.296 | 0.018 |
| $\psi(\text{Global}) p(.)$ | 10 | 2582.052 | 6.642 | 0.015 |
| $\psi(\text{Ptpa1000 Htpa}) p(.)$ | 5 | 2582.151 | 6.740 | 0.014 |
| $\psi(\text{Grass0 Herb0 Regen350 Htpa0 Ptpa1000}) p(.)$ | 8 | 2582.653 | 7.242 | 0.011 |

^aArea-weighted mean stand age measured in a 1,000 m buffer around points.

^bArea-weighted mean site index measured in a 350 m buffer around points.

^cHardwood trees/ha in the stand of the observation point (no buffer).

^dArea-weighted mean pine trees/ha (trees > 7.6 cm dbh) measured in a 1,000 m buffer around points.

^eMean grass cover (%) in the stand of the observation point (no buffer).

^fMean herbaceous plant cover (%) in the stand of the observation point (no buffer).

^gArea-weighted mean total trees(< 7.6 cm dbh)/ha measured in a 350 m buffer around points.

Table 3.6: Ranking and model selection results of candidate logistic regression models by AIC_c and model weight (w_i) that examine influence of seven habitat covariates on the probability of occurrence for eastern fox squirrel across Fort Bragg, North Carolina, 2008-2009. The shaded area indicates the candidate model set used for model averaging.

| Model | K | AIC_c | ΔAIC_c | w_i |
|---|---|---------|----------------|-------|
| D_wet ^a D_OldGr ^b | 4 | 356.916 | 0 | 0.380 |
| D_wet D_OldGr Age ^c | 5 | 357.857 | 0.941 | 0.238 |
| D_wet D_OldGr Herb ^d Preg ^e | 6 | 359.617 | 2.701 | 0.099 |
| D_wet | 3 | 360.092 | 3.176 | 0.078 |
| D_wet D_OldGr Basal ^f LHtpa ^g | 6 | 360.628 | 3.712 | 0.059 |
| D_wet D_OldGr Age Herb Preg | 7 | 360.809 | 3.893 | 0.054 |
| D_wet D_OldGr Age Basal LHtpa | 7 | 361.192 | 4.275 | 0.045 |
| D_wet D_OldGr Basal LHtpa Herb Preg | 8 | 363.482 | 6.565 | 0.014 |
| D_OldGr | 3 | 364.028 | 7.112 | 0.011 |
| GlobalModel | 9 | 364.49 | 7.574 | 0.009 |
| Herb | 3 | 366.223 | 9.307 | 0.004 |
| Age Herb Preg | 5 | 367.027 | 10.110 | 0.002 |
| Herb Preg | 4 | 367.191 | 10.275 | 0.002 |
| Age | 3 | 368.249 | 11.333 | 0.001 |
| Age Basal LHtpa | 5 | 368.41 | 11.494 | 0.001 |
| Age Basal LHtpa Herb Preg | 7 | 369.842 | 12.926 | 0.001 |
| Intercept | 2 | 370.028 | 13.112 | 0.001 |
| Basal | 3 | 370.245 | 13.329 | 0.000 |
| LHtpa | 3 | 370.506 | 13.590 | 0.000 |
| Preg | 3 | 370.75 | 13.834 | 0.000 |
| Basal LHtpa Herb Preg | 6 | 370.849 | 13.933 | 0.000 |
| Basal LHtpa | 4 | 371.605 | 14.689 | 0.000 |

^aDistance to designated wetland habitat.

^bDistance to the nearest old growth pine tree.

^cAge of the dominant trees of the stand.

^dHerbaceous plant cover (%).

^ePine stems/ha (trees < 7.6 cm dbh).

^fCombined pine and hardwood total basal area (trees > 7.6 cm dbh).

^gLarge hardwood trees/ha (trees > 35.4 cm dbh).

Table 3.7: Ranking and model selection results of candidate logistic regression models by AIC_c and model weight (w_i) that examine the influence of four categories of habitat covariates on the probability of occurrence for eastern wild turkey across Fort Bragg, North Carolina, 2008-2009.

| Model Name | K | AIC_c | ΔAIC_c | w_i |
|---|----|---------|----------------|-------|
| Intercept | 2 | 231.427 | 0 | 0.268 |
| Understory ^a | 5 | 232.381 | 0.954 | 0.166 |
| Proximity ^b | 4 | 232.591 | 1.165 | 0.149 |
| Understory + Proximity | 7 | 233.463 | 2.036 | 0.097 |
| Understory + Site ^c | 7 | 233.824 | 2.397 | 0.081 |
| Site | 4 | 233.946 | 2.519 | 0.076 |
| Understory + Proximity + Site | 9 | 234.947 | 3.520 | 0.046 |
| Proximity + Site | 6 | 235.080 | 3.653 | 0.043 |
| Overstory ^d | 5 | 235.851 | 4.425 | 0.029 |
| Overstory + Proximity | 7 | 237.352 | 5.926 | 0.014 |
| Overstory + Site | 7 | 238.278 | 6.851 | 0.009 |
| Overstory + Understory | 8 | 238.555 | 7.128 | 0.008 |
| Overstory + Understory + Site | 10 | 239.436 | 8.010 | 0.005 |
| Overstory + Proximity + Site | 9 | 239.770 | 8.343 | 0.004 |
| Overstory + Understory + Proximity | 10 | 240.014 | 8.587 | 0.004 |
| Overstory + Understory + Proximity + Site | 12 | 240.766 | 9.339 | 0.003 |

^aIncludes bare ground (%), herbaceous plant cover (%), and hardwood stems/ha (trees < 7.6 cm dbh).

^bIncludes distance to hardwood habitat, and distance to early succession habitat.

^cIncludes stand age of the dominant trees, and site index.

^dIncludes combined basal area, and separate trees/ha for pine and hardwood for trees > 7.6 cm dbh.

Table 3.8: Ranking and model selection results of candidate logistic regression models by AIC_c and model weight (w_i) that examine influence of five habitat covariates on the probability of occurrence for red-cockaded woodpecker across Fort Bragg, North Carolina, 2009.

| Model Name | K | AIC _c | ΔAIC _c | w_i |
|--|---|------------------|-------------------|-------|
| Hba ^a LPba ₁₄ ^b HighHreg ^c Preg ^d | 6 | 795.727 | 0 | 0.640 |
| Global Model | 7 | 797.756 | 2.029 | 0.232 |
| Hba LPba ₁₄ Preg | 5 | 799.817 | 4.09 | 0.083 |
| Hba SPtpa3 ₁₄ LPba ₁₄ Preg | 6 | 801.693 | 5.966 | 0.032 |
| Hba LPba ₁₄ HighHreg | 5 | 804.548 | 8.821 | 0.008 |
| Hba SPtpa3 ₁₄ LPba ₁₄ HighHreg | 6 | 806.345 | 10.618 | 0.003 |
| Hba LPba ₁₄ | 4 | 808.267 | 12.54 | 0.001 |
| Hba SPtpa3 ₁₄ LPba ₁₄ | 5 | 809.714 | 13.987 | 0.001 |
| LPba ₁₄ HighHreg Preg | 5 | 827.465 | 31.738 | 0 |
| SPtpa3 ₁₄ LPba ₁₄ HighHreg Preg | 6 | 829.057 | 33.33 | 0 |
| LPba ₁₄ HighHreg | 4 | 847.159 | 51.432 | 0 |
| SPtpa3 ₁₄ LPba ₁₄ HighHreg | 5 | 849.139 | 53.413 | 0 |
| LPba ₁₄ Preg | 4 | 865.822 | 70.095 | 0 |
| Hba HighHreg Preg | 5 | 866.433 | 70.706 | 0 |
| SPtpa3 ₁₄ LPba ₁₄ Preg | 5 | 867.7 | 71.973 | 0 |
| Hba Preg | 4 | 872.823 | 77.096 | 0 |
| HighHreg Preg | 4 | 880.137 | 84.41 | 0 |
| LPba ₁₄ | 3 | 893.445 | 97.718 | 0 |
| SPtpa3 ₁₄ LPba ₁₄ | 4 | 895.433 | 99.706 | 0 |
| Hba HighHreg | 4 | 897.836 | 102.109 | 0 |
| Hba | 3 | 903.996 | 108.269 | 0 |
| Preg | 3 | 912.067 | 116.34 | 0 |
| HighHreg | 3 | 920.377 | 124.65 | 0 |
| SPtpa3 ₁₄ | 3 | 958.29 | 162.563 | 0 |
| Intercept | 2 | 961.042 | 165.315 | 0 |

^aTotal hardwood basal area for trees > 7.6 cm dbh.

^bLarge pine basal area for trees > 35.6 cm dbh.

^cHigh hardwood regeneration (stems/ha) for trees < 7.6 cm dbh and taller than 2 m in height.

^dPine regeneration (stems/ha) for trees < 7.6 cm dbh.

^eSmall pine trees/ha for trees between 7.6 and 35.6 cm dbh.

Table 3.9: Forecasted landscape level changes in useable space (ha) predicted for northern bobwhite (BW), eastern fox squirrel (FS), red-cockaded woodpecker (RCW), and white-tailed deer (WTD) under different potential management scenarios for Fort Bragg, North Carolina, USA.

| Mgt Action | Bobwhite | | | RCW | | | Deer | | | Fox Squirrel | | | Index ^b Score |
|---------------|-----------------------|-------------------------------------|--------|-----------------------|------------------------|--------|-----------------------|------------------------|--------|-----------------------|------------------------|--------|-----------------------------|
| | Occupied Area (ha) | Δ Space ^a (ha) | Factor | Occupied Area (ha) | Δ Space (ha) | Factor | Occupied Area (ha) | Δ Space (ha) | Factor | Occupied Area (ha) | Δ Space (ha) | Factor | |
| Original | 23,052 | 0 | 1 | 37,937 | 0 | 3 | 36,573 | 0 | 0.5 | 28,023 | 0 | 0.5 | 0 |
| Scen. 1 | 34,897 | 11,845 | 1 | 1,352 | -36,584 | 3 | 36,573 | 0 | 0.5 | 28,023 | 0 | 0.5 | -97,908 |
| Scen. 2 | 33,028 | 9,976 | 1 | 4,988 | -32,949 | 3 | 36,573 | 0 | 0.5 | 28,023 | 0 | 0.5 | -88,872 |
| Scen. 3 | 31,595 | 8,543 | 1 | 37,937 | 0 | 3 | 36,573 | 0 | 0.5 | 28,023 | 0 | 0.5 | 8,543 |
| Scen. 4 | 30,044 | 6,991 | 1 | 37,937 | 0 | 3 | 36,573 | 0 | 0.5 | 28,023 | 0 | 0.5 | 6,991 |

^aChange in useable space (hectares) predicted following implementation of the management action.

^bCommunity index score calculated from additive changes in useable area for each species weighted by respective decision factor.

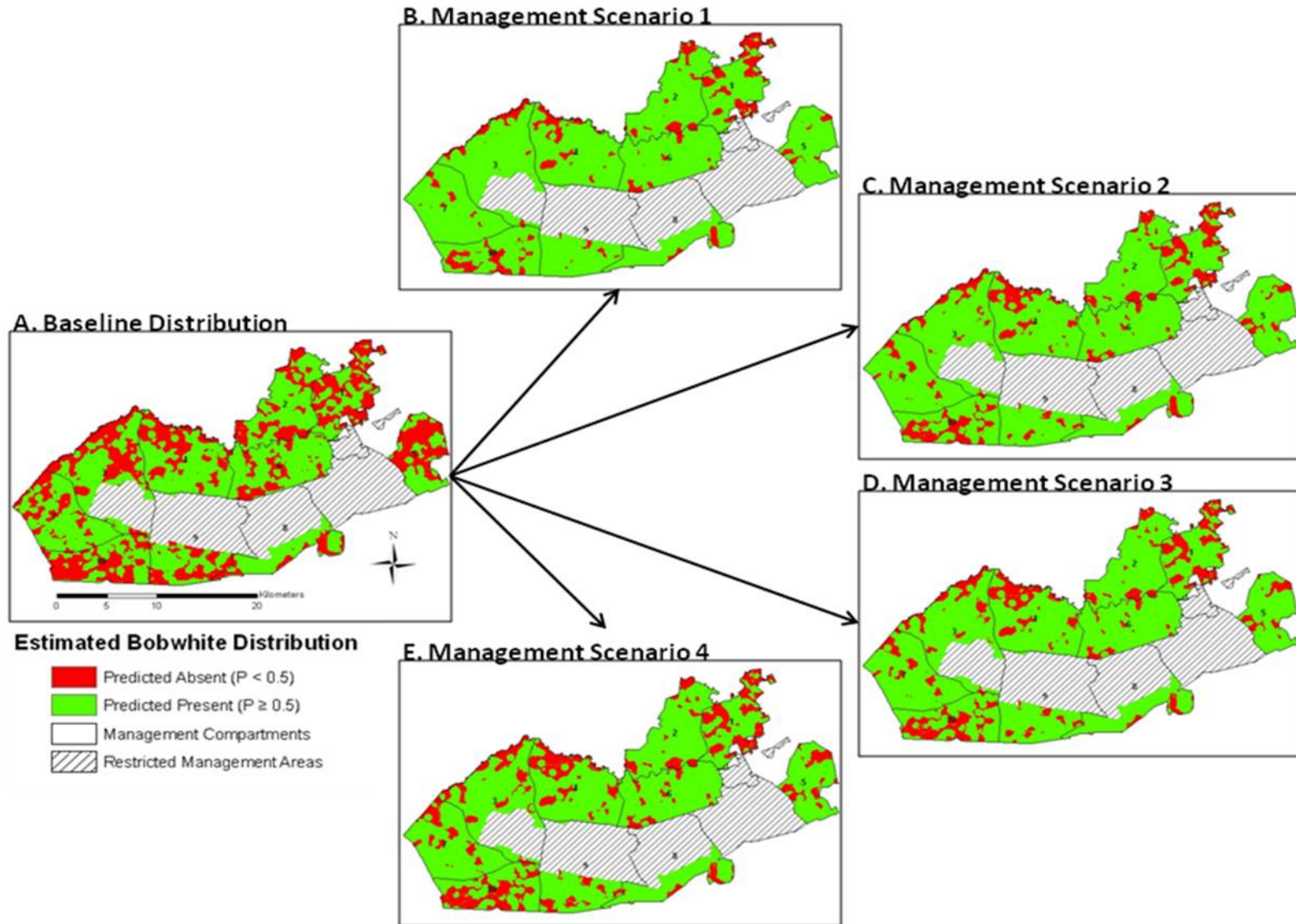


Figure 3.1:

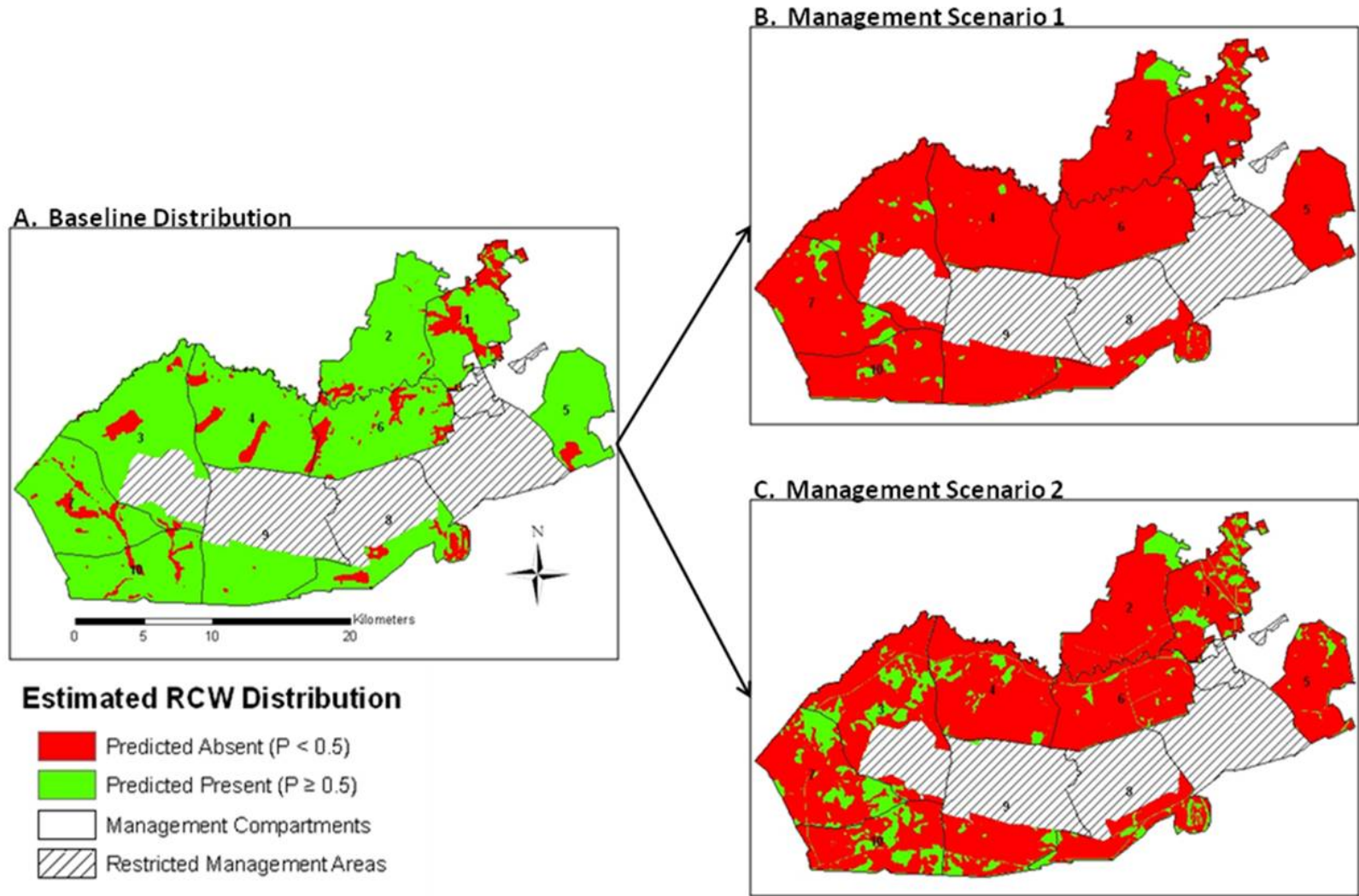


Figure 3.2:

Estimated White-tailed Deer Distribution

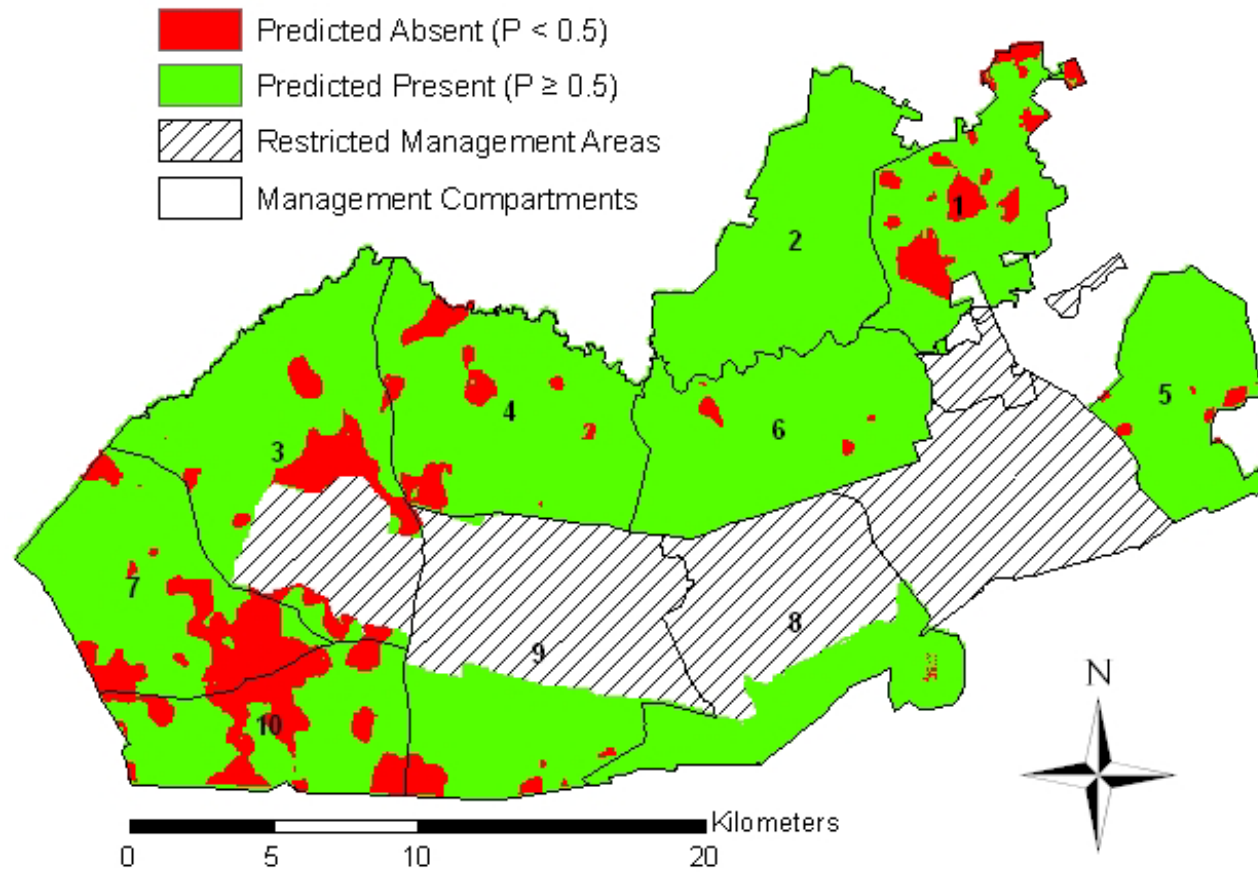


Figure 3.3:

Estimated Fox Squirrel Distribution

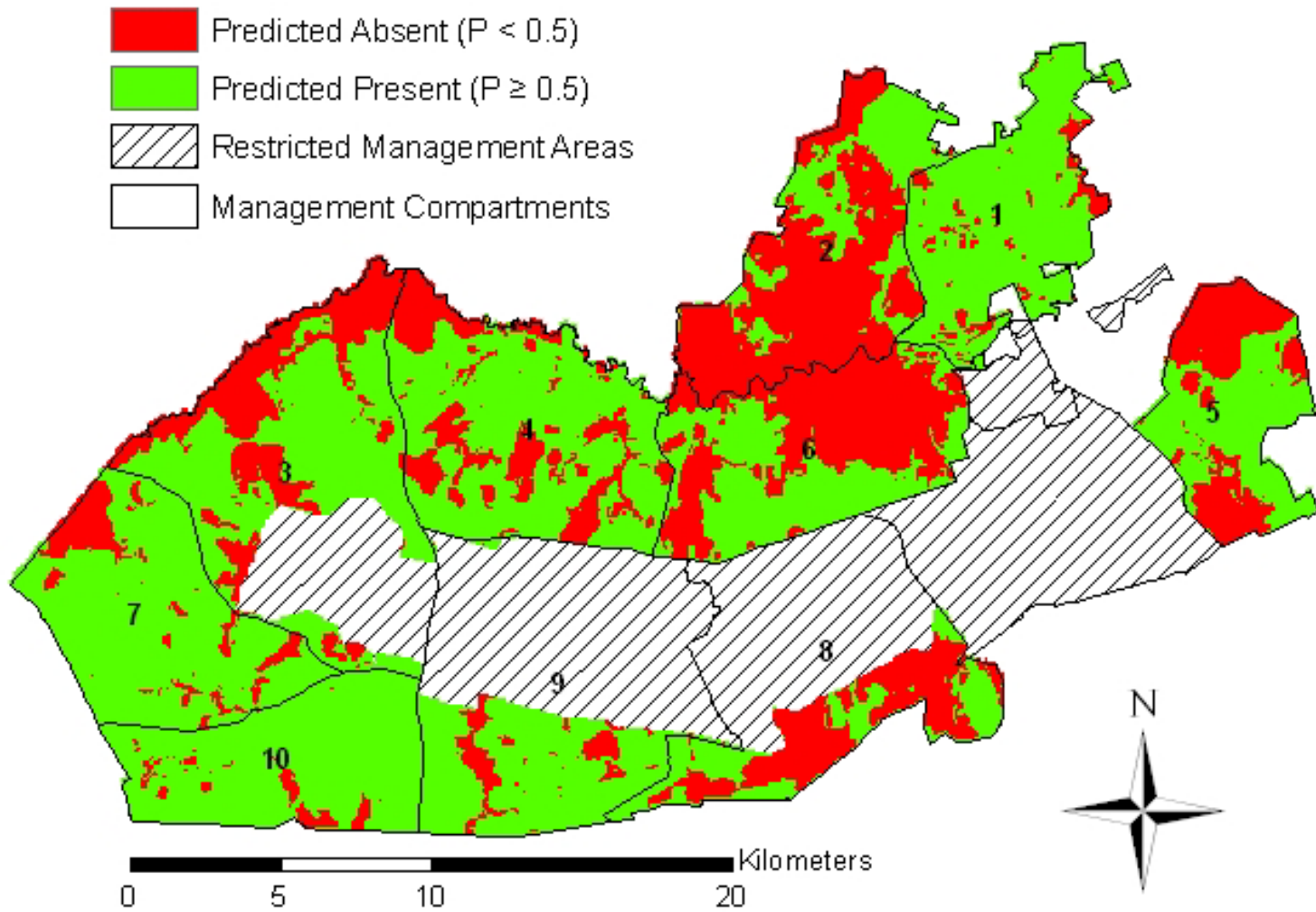


Figure 3.4:

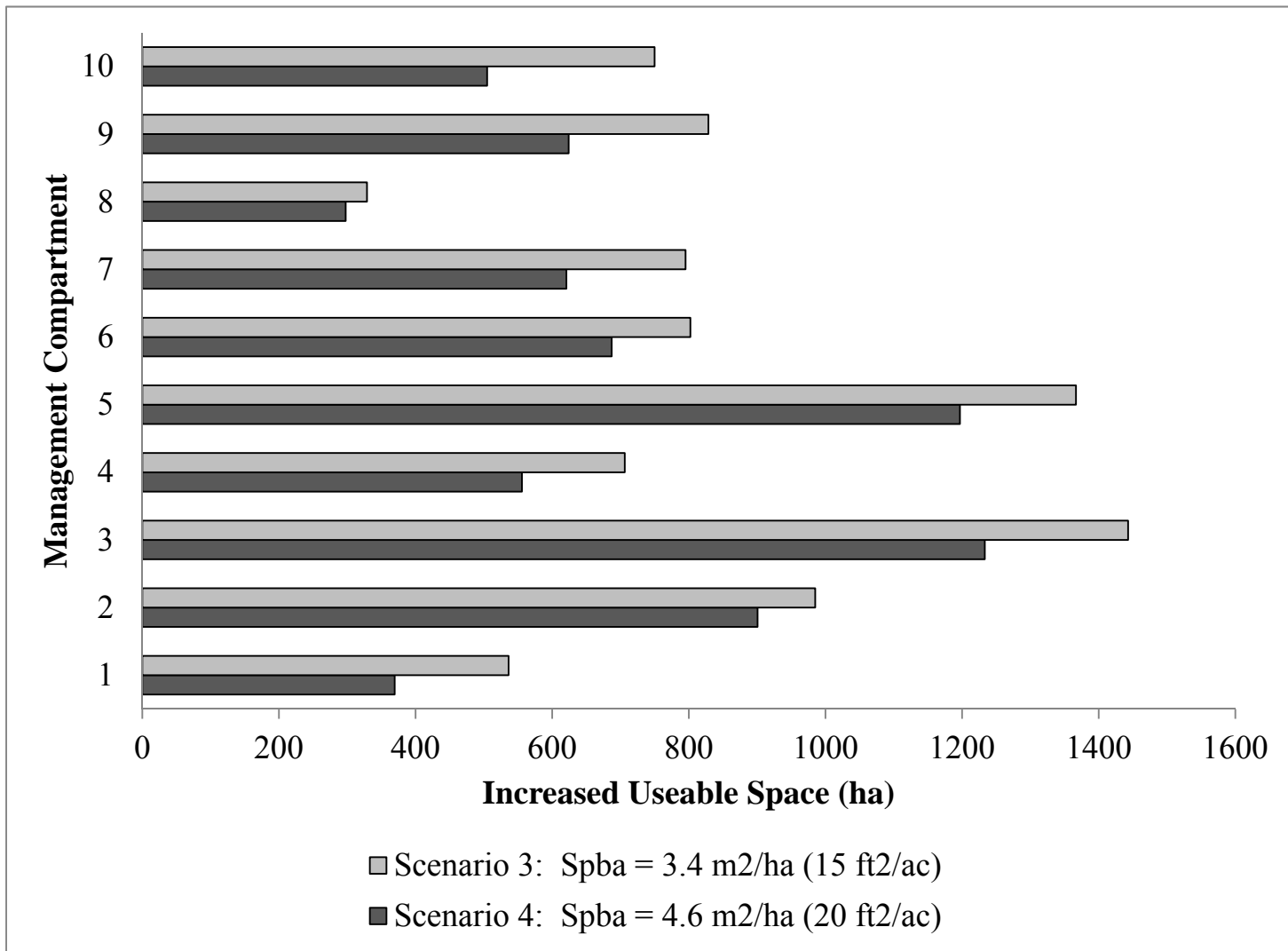


Figure 3.5:

CHAPTER 4
IMPLICATIONS FOR HABITAT MANAGEMENT DECISION MAKING
FROM EMPIRICAL FORECAST MODELING EFFORTS ON
FORT BRAGG, NORTH CAROLINA, USA

MANAGEMENT IMPLICATIONS

General Implications

In a society where wildlife managers are held accountable for the sustainability and diversity of the resource they oversee and where decision making is often held to intense public scrutiny, the question is not whether to model, but rather how to model (Starfield 1997). We demonstrate that empirical forecast models (hereafter forecasting) can be an effective problem-solving tool suitable for finding practical solutions in complex landscapes with competing wildlife management goals. Complex problems in natural resource management, involving multiple and sometimes competing objectives, have been challenging practitioners to find more creative and innovative methodological approaches for years (Mendoza and Martin 2006). Modeling is considered a robust approach to problem-solving in wildlife management, but a lack of practical examples, among other things, has limited their use amongst practitioners (Starfield 1997). Our investigation helped fill a void of practical demonstration for the application and benefits available through forecasting.

Focusing on habitat needs and habitat management when conducting wildlife management has been recognized as a priority for practitioners since the first wildlife management textbook was published in 1933 (Leopold 1933). At that time the recognized tools

of the trade for improving habitat conditions were listed as the axe, cow, plow, gun, and fire, and the “art” of wildlife management was knowing when and where to apply these different tools. Now, we use computers, satellites, and sophisticated statistical modeling to understand when, where, and now why to apply modern forms of these same tools. In addition, we can use statistical modeling to forecast the expected magnitude of response by the focal species of interest as well as other sympatric species that may also be impacted. The Habitat Evaluation Procedure (HEP) was one of the earliest forecasting tools available and helped wildlife managers predict species responses in qualitative terms to future development projects (Schamberger and Krohn 1982). The benefits for using empirical rather than qualitative approaches to forecasting has been documented for decades (Christiansen 1980), but by and large only a small portion of our profession has become knowledgeable enough with the increasingly sophisticated GIS software and statistical procedures to embrace a modeling atmosphere towards wildlife management problem-solving. Before forecasting can be used on a wider basis, more examples like the one we demonstrated are needed to illustrate how to implement this kind of modeling procedure in a variety of complex management systems. Furthermore, to instill a culture of modeling amongst practitioners, a more pervasive inclusion of additional examples in the literature, and an institutionalization of the concepts and application of models to address wildlife management problems are needed (Starfield 1997).

Empirical forecast modeling, whether for single or multiple species, offers managers quantitatively derived predictions of species responses to potential shifts in habitat management prior to implementation. Decisions guided by these types of models are more defensible because they are data-driven, spatially explicit, and provide estimates of magnitude of impact (Peterson et al. 2002). Structured decision making can help take the impassioned emotion out of

management decisions; management decisions should be rooted in scientific evidence to achieve a specified and well-defined outcome. The zealous adherence to management protocols that favor game, nongame, endangered species, or timber management in spite of scientifically derived, contradictory information is detrimental to comprehensive management of the resources. With an a priori establishment of model inputs into a decision structure as well as an agreed means of decision selection, it may be possible to reduce tensions between managers.

Several landscapes under different management jurisdictions are highly suitable for forecasting approaches. As demonstrated in this investigation, military installations are a prime candidate because of conflicting management directives caused by the inherent incongruence between the Sikes Act (1960) and Endangered Species Act (1973) regarding wildlife habitat management. The Sikes Act requires integrated wildlife and natural resource management (i.e., multi-species management) on all military installations in coordination with both federal and state agencies. Conversely, the Endangered Species Act encourages a single-species approach that places much emphasis on designating, maintaining, and improving critical habitat for recovery of threatened and endangered species, and threatens strong penalties for noncompliance (Perkins et al. 2008). Other lands under federal jurisdiction that would benefit from forecasting approaches to evaluating changes to habitat management strategies include, but are not limited to the National Park Service, Bureau of Land Management, and U.S. Forest Service. Each of these entities manages discrete units of land that often require assessment of sweeping changes to habitat management strategies. These entities also promote a comprehensive ecosystem sustainability approach to management which favors using multi-species forecasting approaches. The applicability of forecasting is not limited to federal entities as state agencies also designate management areas that frequently alter habitat to benefit various species or ecosystems.

Implications to Fort Bragg

Fort Bragg is at a juncture where consideration of changes in habitat management strategy should occur by its suite of natural resource practitioners. Historically, Fort Bragg has not appeared to embrace a multi-species approach to its habitat management strategy. Since listing, recovery of the red-cockaded woodpecker (*Picoides borealis*; hereafter RCW) population has been the priority of habitat management activities (Britcher 2006) to the detriment of the northern bobwhite (*Colinus virginianus*; hereafter bobwhite) population to the point it is considered “a population in crisis” (Appendix B; Department of Defense 2001: pg 179). Yet, under this RCW management monoculture, the woodpecker population has exceeded its minimum local recovery goal (Britcher 2006). With the minimum recovery goal achievement, more flexibility in habitat management could be explored to address habitat needs for bobwhite or other species. In past considerations, the lack of understanding about specific habitat needs for bobwhite in relevant forestry terms like trees per hectare or basal area compared to light penetration and canopy closure have limited the ability of practitioners to include specific measures to improve habitat conditions for this species (Department of Defense 2001). Our investigation directly and empirically addresses this information gap, while simultaneously assessing impacts on the useable space available for RCW and other secondary priority species.

The general habitat needs for bobwhite in southeastern pine forests are well documented with clear and numerous examples of relative density that is negatively correlated with total basal area (Stoddard 1931, Guthery 1997, Engstrom and Palmer 2003, Little et al. 2009). Our investigations confirm a similar relationship on Fort Bragg using empirical data that measured both likelihood of occurrence, and density while accounting for detection probability. Furthermore, we identified how to prioritize management efforts structurally and spatially to

maximize benefits to bobwhite while minimizing effort and resource expenditures (time, personnel hours, etc.). Specifically, small pines (7.6 – 35.4 cm dbh; 3 – 14” dbh) were identified as the primary overstory structure that is limiting bobwhite density and distribution across the landscape. Currently, these pines average 6.8 m²/ha (29.8 ft²/ac) across the landscape, which represents 56.0% of the total pine basal area and 46.4% of the overall basal area that includes pine and hardwoods. Though RCW showed strong negative associations with declines in large pines (> 35.4 cm dbh), they indicated no preferential selection (positive or negative) for changes in small pine density. Because of our empirical forecast modeling, Fort Bragg now can better understand what structural component of the habitat (small pines) on which to concentrate stand reduction efforts if they want to promote positive increases for bobwhite without worry of impacting the RCW recovery status for the base. Moreover, we also show empirically that this approach would also likely not impact the useable space of eastern wild turkey (*Meleagris gallopavo silvestris*), eastern fox squirrel (*Sciurus niger niger*), or white-tailed deer (*Odocoileus virginianus*).

The level to which the small pines should be reduced on Fort Bragg needs further consideration. We measured small pine density 2 different ways during our modeling assessments. First, by reducing the small pine trees per hectare down to 94 (only in manageable areas as defined in previous chapters) from the original average of 188 we predicted an average 46% increase in bobwhite density across the base to 0.094 males/ha. Second, by reducing small pine basal area down to 3.4 m²/ha (15 ft²/ac) we predicted an addition of more than 8,500 ha in useable space for bobwhite. The question that remains is at what level can small pine density be reduced and still promote adequate recruitment into the large pine size class. Walters et al. (2000) recommended 49 trees/ha for trees 15.3–30.5 cm dbh (6–12” dbh) for Fort Bragg

specifically. Unfortunately, our forest structure data does not coincide with this size range (7.6 – 35.4 cm dbh; 3 – 14” dbh).

Finally, our forecasting approach identified a means to spatially prioritize management efforts that would produce the most benefits for bobwhite, while still maintaining no net loss of useable space for other primary and secondary priority species. Focusing on a few discrete management compartments across Fort Bragg offers several benefits to both the resource and the base practitioners. First, there is always risk associated with changing habitat management strategies that have been successful in the past (at least for one species). Despite our modeling effort and the empirical support it offers towards adjusting habitat management strategies, there is still a chance that negative impacts to RCW are possible in ways we did not measure. By focusing on 3 of the 10 compartments for improving habitat for bobwhite, monitoring efforts can be used to validate the predictions of the model both for benefits to bobwhite and for no negative impacts on RCW without placing the remainder of the RCW population at risk. Second, by maintaining different habitat management strategies on different compartments, Fort Bragg would avoid perpetuating a monoculture habitat management approach. Monocultures by definition limit biodiversity, and with all the different species on Fort Bragg, those considered explicitly in this study and those not, the change in habitat management strategy is likely to benefit more than just bobwhite. Third, the designation of 3 compartments that are managed specifically to improve bobwhite has tremendous public relations benefits. If those 3 management compartments were called Quality Quail Management Units, the local Quail Unlimited group would likely be very supportive. There is already a precedent for such designations on Fort Bragg with Compartment 1 being described as the Quality Deer

Management unit for Fort Bragg, which garners support from the local Quality Deer Management citizens group.

CONCLUSION

In conclusion, managers of wildlife populations, whether game, nongame, or imperiled, need tools that are practical and precise that can help prioritize habitat management efforts both structurally and spatial across their jurisdiction, especially when differing management objectives compete for management resources. As we demonstrated on Fort Bragg, forecasting procedures are such a tool. We show that structurally, if Fort Bragg reduced the small pine (7.6 – 35.4 cm dbh; 3 – 14” dbh) density they could significantly improve bobwhite habitat conditions making more space suitable and increasing bobwhite density, while not degrading habitat conditions for the recovered RCW population. We show spatially, if Fort Bragg focused small pine density reduction in 3 compartments (any combination of compartments 2, 3, 5, 7 and 10) they would induce the strongest responses by the bobwhite population. We also conclude that focusing on a select few compartments offers potential for additional yet unmeasured benefits by eliminating the current RCW management monoculture and the creation of Quality Quail Management Zones.

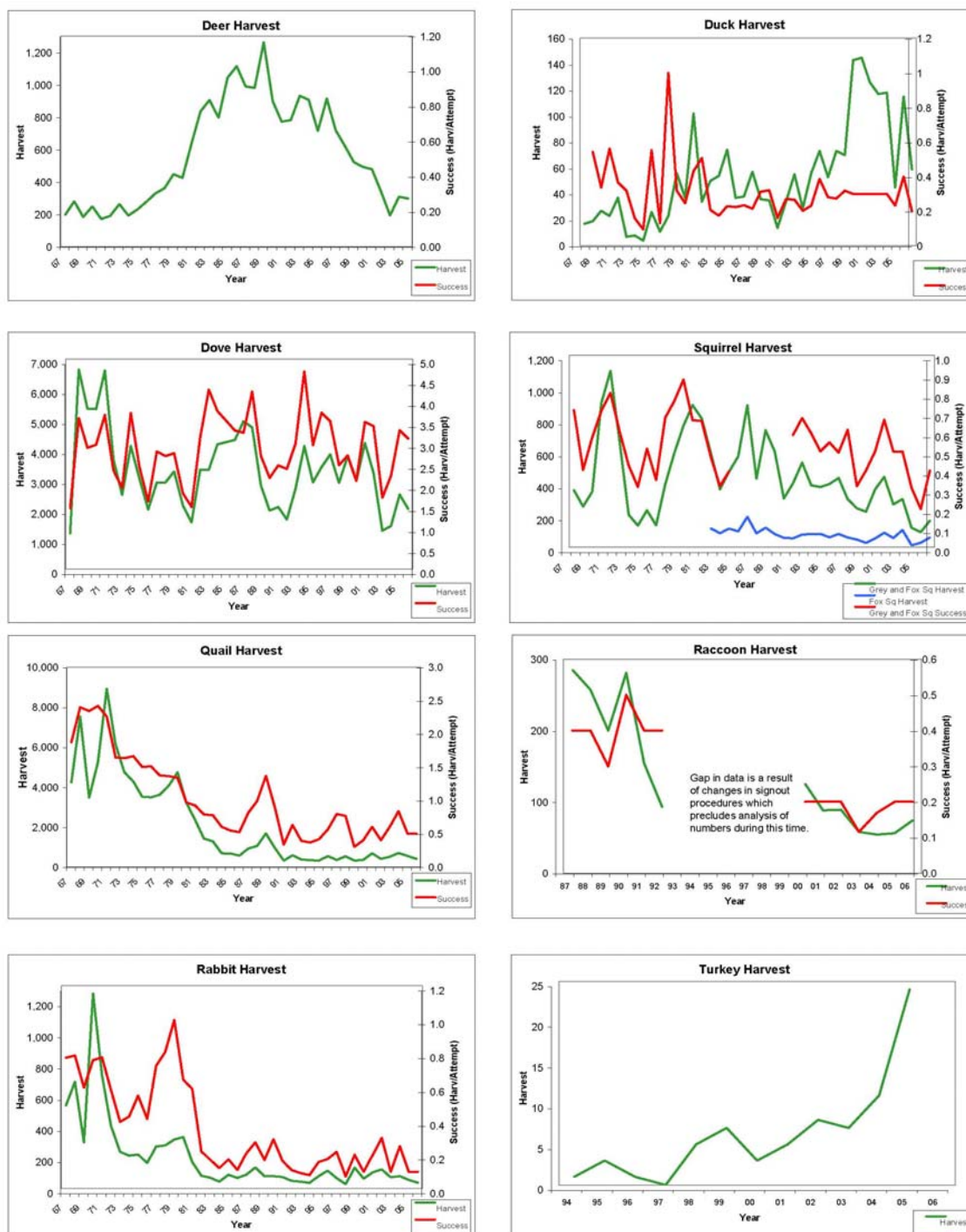
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Appendix A: Annual hunter harvest and success rates for game species reported at on-base mandatory check stations from 1967 – 2006 for Fort Bragg, North Carolina, USA.



Note: Similarity in yearly fluctuations of Harvest and Success suggest that changes are more likely a result of wildlife population changes, not just a result of more or less hunting effort.

Appendix B. Change in total harvest and hunter success (mean harvest /attempt) for bobwhites over 41 years (1967-2007) and how it coincides with key habitat management changes

(numbered boxes) on Fort Bragg, North Carolina, USA. Box 1 represents the beginning of habitat management changes to favor RCW (1976-1990) where the yearly average sawtimber and pulpwood volume harvested on Fort Bragg decreased by 68% and 80%, respectively compared to the yearly average harvest that occurred 1955-75 (US Department of Defense 2001). Box 2 indicates a shift to more intensive RCW habitat management that began in 1993 where volume of harvested Sawtimber dropped 93% compared to pre-RCW management levels (1955-75) (Department of Defense 2001).

