MAKING ENROLLMENT DECISIONS FOR PRIVATE LANDS CONSERVATION UNDER SPATIAL COMPLEXITY: A CASE STUDY ON THE NORTHERN BOBWHITE (COLINUS VIRGINIANUS)

by

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ABSTRACT

Addressing resource allocation problems in a decision making framework allows for resources to be optimally allocated in such a way that addresses all objectives relevant to the decision. Private land incentive programs pursue conservation objectives by allocating financial resources to landowners to promote specific management practices, but fixed program budgets usually require hard choices to be made among potential enrollments. Such incentive programs are used heavily to bolster grassland bird species such as the northern bobwhite (*Colinus virginianus)*, but often programs targeting this declining species are vague about their objectives and how they allocate resources on private lands for the species. I cast the problem of resource allocation into the PrOACT cycle and describe a proposed framework for making decisions about which landowners to enroll in conservation incentive programs. I then simulate the proposed model-based framework and compared it to a rank-and-scoring approach and a randomized approach of selecting applicants. I find that, depending on resource constraints, the model-based framework outperforms both the rank and scoring approach as well as the randomized approach. The model-based framework returns a greater number of species and is more cost effective. These results strengthen the argument for employing a decision analytic-based approach when distributing public resources for conservation.

INDEX WORDS: Northern Bobwhite, *Colinus virginianus*, Structured Decision Making, Optimization, Spatial Prioritization

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TABLE OF CONTENTS

Appendices

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

Decision analysis can be formalized to address many management problems. A common application of decision analysis is in resource allocation problems where a manager must identify how to best select a set of resources or actions within the constraint of a fixed budget. Examples include allocating funding to multiple endangered species (Gerber et al. 2018) and selecting patches of habitat to create a reserve network (van der Burg et al. 2018). Private land conservation incentive programs can be set up as a resource allocation problem where the fixed set of options (i.e., parcels of land) are compared based on how well they address the conservation objectives (e.g., how many species of interest each parcel contains) and then selection for enrollment is limited by an annual budget. Examples of private land conservation initiatives include programs such as Working Lands for Wildlife (WLFW) which have been explicitly created in the US to offer financial incentives for private landowners to apply conservation actions to their property to benefit targeted wildlife (Litvaitis et al. 2021).

The tenets of decision analysis offer a variety of approaches to address the challenges around resource allocation in conservation incentive programs. A variety of planning and decision support frameworks have been created to address resource management problems in complex socioecological systems (Schwartz et al. 2018). Program managers may set up a point-and-scoring approach where they identify a variety of elements that a program is targeting through indirect attributes; for example, if a program is focused on increasing the population of a target species, additional points may be attributed to parcels that has land cover similar to the habitat that the target species favors. If programs are set up under the lens of formal decision analysis, the program objectives would be used to determine which parcels to select by any of several approaches. One approach casts the selection as a multi-criteria decision problem where each potential enrollee was directly evaluated on how well they meet each of multiple objectives (e.g., amounts of habitat area, potential to apply conservation actions, etc.). When the problem can be formulated around a single objective, another approach uses mathematical programming, specifically optimization algorithms, to identify the optimal portfolio. Kleinmuntz (2007) describes a general resource allocation framework but other approaches such as linear programming or heuristic approaches can also be used (Conroy and Peterson 2013). Predictive models that underlie mathematical programming or heuristic optimization approaches can directly identify the impact of enrolling specific enrollees on the objective (e.g., abundance of a species).

For any conservation program to be most effective, programs must first specify their objectives (Hemming et al. 2022). Many programs do not have specific criteria to enroll private landowners despite the magnitude of public funds distributed through such programs. Other programs such as the Conservation Reserve Program (CRP) have identified 22 conservation objectives and created an environmental benefit index to select enrollees (Burger 2006; Stubbs 2014). Some programs target specific flagship species; for example, the northern bobwhite (*Colinus virginianus*) is targeted in Working Land For Wildlife's Savanna and Grasslands Project for Bobwhite. Other incentive programs have been created solely for the northern bobwhite, thus creating a single-species objective problem which simplifies some of the decision making because funds can be used to target the conservation practices that best benefit the species of interest and apply those practices on enrolled lands.

Despite the amount of capital designated for the northern bobwhite, no framework exists to determine how different patches are selected for conservation and/or restoration. Transparent decision making is needed to ensure that the optimal habitat for the northern bobwhite is selected for restoration and conservation and that the funding is used efficiently. The purpose of this research is to inform decision making in conservation incentive programs using the principles of decision analysis and Structured Decision Making (SDM). By doing so, I aim to address the resource allocation problem posed by incentive programs in a way that is transparent, repeatable, and meets the objectives of the program. Focusing on the northern bobwhite allows me to set up a program with practical objectives using realistic management and biological parameters.

This project fulfills the following objectives:

1) Critically examine the decision-making frameworks being used to inform northern bobwhite management as indicated in state management plans. (Chapter 2)
2) Build a model-based framework to simulate a private landowner incentive program based on the tenets of structured decision making with realistic parameters used for northern bobwhite management. (Chapter 3)
3) Compare the model-based enrollment framework to the status quo framework employed by state agencies. (Chapter 3)

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CHAPTER 2

An Overview of the State of Northern Bobwhite Management Programs through the Lens of Decision Making[1]

[1] Stanley, A.E., C.T. Moore, and J. A. Martin. To be submitted to *Conservation Biology*

Abstract

The northern bobwhite (*Colinus virginianus*) is a declining grassland bird species managed across 25 states in the United States. Intensive management and habitat restoration for northern bobwhite conservation is leveraged through conservation incentive programs such as US Department of Agriculture's Environmental Quality Incentives Program or Working Lands for Wildlife's Savanna and Grasslands Project for Bobwhite. Many of these programs are administered in collaboration among state and federal entities and often supported by non-governmental organizations. Given that these are public agencies and programs, we aim to evaluate state management of northern bobwhites and identify how decisions are made and what, if any, tenets of decision science are used in making these decisions. We find that some agencies are using objectives to guide their decision making but few accurately identify and link fundamental objectives to means objectives. We also find little information about the design and implementation of conservation incentive programs despite the fact that many states indicate that they use such federal programs for northern bobwhite conservation, and several have created their own incentive programs. As such, we lay out a framework for a model-based conservation incentive program that follows the steps of Structured Decision Making which uses a combination of problem decomposition and values-focused thinking. We aim to illustrate how decision making can be used to inform selection of private landowners for incentive programs, not only in the context of the northern bobwhite, but also in other species-specific incentive programs.

Key Words: Structured Decision Making; Conservation Planning; Prioritization; Northern Bobwhite; PrOACT

Introduction

Conservation incentive programs (incentive programs) have emerged as a response to the pressing issues of habitat destruction, biodiversity loss, and the degradation of ecosystem services (Scherr and McNeely 2008; Börner et al. 2017). Given that approximately 70% of land in the United States is privately owned, the involvement of private landowners is crucial in achieving conservation objectives (Heard 2000; Lubowski et al. 2006; Capano et al. 2019). Conservation incentive programs typically contractually engage private landowners in conservation by offering financial incentives to retire land from agricultural production and implement conservation practices (e.g., annual rental fee) or cover the costs associated with implementing the conservation practice (e.g., cost sharing or equipment loans).

Conservation incentive programs are created to address conservation aims but are not without a core set of challenges. To achieve one or more conservation aims, incentive programs distribute financial resources intended to implement practices on specific land parcels in a region. They share a similar concern of how to deliver finite resources most effectively through time and over space to achieve conservation goals. However, incentive programs differ in size (e.g., resources available, spatial footprint, eligible landowners), funding mechanisms, and other attributes that make comprehensive solutions infeasible. Furthermore, complex socioecological systems are characterized by the same uncertainties that challenge conservation incentive programs (Folke et al. 2005). Because incentive programs rely on voluntary participation from private landowners who make decisions based on various factors (Burger 2006; Rodriguez et al. 2012; Golden et al. 2013; Epanchin-Niell et al. 2022; Mitani and Lindhjem 2022), funding organizations have only partial control over how actions are implemented. Most programs lack formal mechanisms for selecting which lands to enroll despite receiving more applications for enrollment than financial resources can support (Stubbs 2014; Hellerstein 2017). Whether a formal selection process is followed or not, programs must repeat this decision with different funding levels each year and with contracts that are set for different lengths of time. Consequently, although all incentive programs share the same goal of efficiently allocating financial resources to benefit conservation, they operate in a dynamic context with two levels of decision makers—the program agents who select participating private landowners and the selected private landowners who choose their actions—but often without benefit of a formal decision-making structure.

Because incentive programs allocate public resources to select private citizens to provide public conservation benefits, the implementation challenges and effectiveness of these programs merit consideration. Comprehensive agriculture and conservation legislation, commonly referred to as the 'Farm Bill,' initially aimed to retire erodible farmland, but it has since expanded its focus to address broader environmental benefits, leading to the establishment of major incentive programs in the United States (Baylis et al. 2022). The Conservation Reserve Program (CRP) stands as the largest program in the United States, with a substantial allocation of 23.7 billion dollars in its annual budget in 2018 (FSA 2018). Such national programs apportion their budgets by state; for example, North Carolina was allocated $588,000 through CRP funding in 2012 for its Wildlife Habitat Incentives Program (WHIP) program. Recently, the amount of land enrolled in CRP has been declining due to a lower nationwide enrollment cap, raising concern about the efficient allocation of resources for maximizing conservation benefits (Baylis et al. 2022).

The cost effectiveness of Farm Bill dollars broadly related to environmental benefits has been explored (Claassen et al. 2013; Hellerstein 2017) but results of studies conducted to determine effectiveness are varied (Drum et al. 2015b). Evaluating the efficacy of incentive programs, at least on avian species, has predominantly focused on the biological responses of target species such as northern bobwhites (*Colinus virginianus*; NOBO or bobwhite), waterfowl, and ruffed grouse (*Bonasa umbellus*), yielding mixed results (Ryan et al. 1998; Adkins et al. 2021; Williams et al. 2021). In situations where the relationship between conservation actions and species outcomes remains uncertain, it becomes imperative to examine program-wide effectiveness. Merits of formal decision framing for allocation of public resources have been detailed for other programs of conservation, including developing species recovery strategies (Gerber et al. 2018).

Conservation incentive programs exist at both federal and state levels, and they adopt various funding and structural mechanisms. At the federal level, the main source of funding for conservation practices on working lands stems from the Farm Bill and its subsequent amendments. Programs created under the Farm Acts of 1996 and 2002 focus on implementing practices on working lands to benefit wildlife (WHIP, Working Lands for Wildlife Initiative [WLFW], Environmental Quality Incentives Program [EQIP]), and have incorporated wildlife protection goals (Burger 2006). At the state level, funding for incentive programs comes from state general appropriations, "dedicated funding" such as license plate sales or hunting license fees, or non-governmental organizations such as Quail Forever, Ducks Unlimited, and Ruffed Grouse Society (George 2002). Federal programs are often administered at the state level via the Natural Resources Conservation Service (NRCS) or Farm Services Administration (FSA) offices, so partnerships form between state and federal governments to allocate federal funds. George (2002) found that 79% of state incentive programs are administered by state departments of fish and game in partnership with other entities, and 62% of programs surveyed partnered with federal agencies. The scale of programs is typically linked to the funding source; programs can range from nationwide to a few select counties (Börner et al. 2017). Programs have been created with different conservation aims: Working Lands for Wildlife targets individual at-risk species while other programs such as the North American Wetlands Conservation Fund focus on habitat restoration intended to benefit multiple species or communities (Litvaitis et al. 2021; Krainyk et al. 2022).

Conservation planning and decision tools offer promising solutions to tackle several challenges encountered in conservation incentive programs (Schwartz et al. 2018). Both systematic conservation planning (Margules and Pressey 2000) and structured decision making (Runge 2011) share key attributes in establishing the problem context, stating clear and quantifiable objectives, identifying alternatives (such as planning units or actions), predicting consequences of actions, and acknowledging uncertainties to seek the best alternatives that achieve the stated objective(s). The application of formal decision-making tools in natural resource management aligns with the principles of values-focused thinking (Keeney 1996). Increasingly, federal agencies have recognized the importance of incorporating formal conservation planning and decision analysis into conservation management processes to enhance transparency, public buy-in, replicability, and defensibility of the decision-making process (Fuller et al. 2020). The utilization of these conservation planning and decision tools offers valuable avenues for overcoming challenges encountered in conservation programs, including incentive programs.

Systematic conservation planning (SCP), commonly applied to spatially explicit problems, provides a framework for identifying cost-effective resource allocation to achieve predefined targets, such as wildlife population goals (Margules and Pressey 2000; van der Burg et al. 2018). Imposing cost as a constraint, SCP identifies different portfolios of area within a geographic extent that satisfy multiple objectives (Sarkar et al. 2006). SCP problems are often solved with spatial prioritization tools, such as Marxan (Ball et al. 2009) or prioritizr (Hanson et al. 2017), which have been developed within this framework to aid in the planning process (Lessmann et al. 2014). However, when problems are temporally dynamic in addition to spatially explicit, include multiple uncertainties, and require models that link spatial configurations to objectives, SCP tools require proxy representations of objectives as well as problem simplifications which may not fully explore all possibilities resulting in potentially less optimal solutions (Sarkar et al. 2006; Lessmann et al. 2014).

Another valuable tool is structured decision making (SDM), often implemented through the PrOACT cycle, which aims to identify actions that best meet multiple, and at times conflicting, objectives. The PrOACT cycle comprises five core steps in the decision-making process (Hammond 1999; Hemming et al. 2022). First, problem framing involves identifying essential decision elements, including stakeholders and the legal and regulatory context. Second, setting objectives involves articulating the values and goals of the decision-maker and stakeholders that the process aims to achieve. Third, identifying alternatives is the specification of all possible actions that can be taken by the decision maker to address the decision problem. Fourth, evaluating consequences involves assessing the outcome of each alternative against the specified objectives. Finally, assessing trade-offs determines the action that best satisfies all the specified objectives. The framework often utilizes tools such as expert elicitation, multicriteria assessment, and adaptive optimization (Runge et al. 2011a; Runge et al. 2011b). It is important to emphasize the values-focused nature of decision making within the SDM framework in comparison to other decision-making approaches. The SDM approach centers on the identification of objectives and uses them as the driving force for subsequent evaluations. In decision analysis, values or preferences are elicited to articulate the objectives of the decision-maker(s), and the outcomes of alternative management actions are evaluated relative to one another based on their predicted ability to achieve these objectives.

We examined publicly available documentation to discern what decision frameworks drive the conservation planning processes of incentive programs in use. We aimed to highlight the potential of SDM in improving the design, implementation, and evaluation of conservation incentive programs. To do so, we illustrated how decision-making frameworks can be used in an idealized theoretical example. Then we contrasted this constructed framework against the tools and elements of decision making used by practitioners (i.e., natural resource agencies) charged with administering conservation incentive programs. We reviewed the planning documentation created by state programs for conservation of the northern bobwhite. We selected this species because it is a highly valued game species that is in range-wide decline, and it receives considerable funding from incentive programs (Evans 2012). We therefore believed it plausible that programs intended to benefit this species would be more likely than many other incentive programs to leverage elements from conservation planning and decision analysis to increase the efficacy of ecological and conservation outcomes. By focusing on a single species, we hoped to reduce some of the complexity in the conservation context and facilitate a comparison of programs across the species' range.

Elements of a Prototype Decision Framework for Conservation Incentive Programs

Using the PrOACT cycle, we illustrate attributes of a prototype framework for making decisions about which landowners to enroll in conservation incentive programs. We establish this decision structure under the assumption that spatial prioritization has been used to subset the geographic extent of our decision and then use the PrOACT cycle to break down the problem addressing which landowners should be enrolled in a fictional incentive program. This process enables the selection of participants based on objectives, transparency, and repeatability and integrates knowledge into the decision.

Spatial prioritization identifies a restricted geographic area for enrollment. For species-specific incentive programs, spatial prioritization can limit the geographic scope of a problem based on species' range area and further reduce the size of a problem by excluding areas that are too costly, have a low likelihood of private landowner engagement, or have poor habitat quality or low potential to be restored. Programs should format this spatial reduction as a decision problem because benefits resulting from reduced problem complexity (fewer enrollments to process and less personnel time invested) are traded off against risks of missing ideal species habitat or habitat which would otherwise be enrolled. As such, this can be seen as the first step of problem framing. Programs should be explicit in what factors into the geographic scope. If more than one species is being targeted by the program, this effort might not be as straightforward, but it is no less important. For species with smaller ranges, it may not be necessary to limit the geographic extent of the problem below the species range. Spatial prioritization tools are best applied to determine the problem scope (i.e., study or focal area) to limit the number of plausible alternatives (i.e., total number of candidate enrollees).

Problem statements are typically set up as a set of choices that lead to different outcomes, which in turn fulfill objectives to differing degrees (Conroy and Peterson 2013). For conservation incentive programs, the set of choices is the different combinations of landowners' specific parcels that potentially could be enrolled (Figure 2.1). The outcome of interest is the conservation benefit of enrolling those lands (and not enrolling others), and the benefit is measured by the objectives set by the program.

Objectives are used to measure decision success because they concisely state what matters to the decision maker in a way that can be measured (Figure 2.1). If there are multiple objectives or an objective is composed of subobjectives (i.e., broken down into component pieces), then objectives hierarchies are used to show relationships and dependencies (Runge 2011; Keeney 2007). Fundamental objectives are situated at the top of the hierarchy and represent the ultimate goals of the decision process. Means objectives show how to achieve the fundamental objectives through specific targets. For example, for a single-species incentive program, a possible fundamental objective could be, "to increase the population of the target species by 10% in the focal areas within 5 years". The means objective (i.e., how to accomplish this) could be a statement as specific as "increase habitat quality in the focal area by increasing the number of prescribed burns in private land." Multi-objective problems create multiple, sometimes competing objectives; multiple objectives would be expected to occur in incentive programs that target multiple resources such as multiple species with different habitat requirements. In addition to biological objectives, multiple types of objectives such as social (public safety), public acceptance (hunter satisfaction), and economic (cost or management) can be considered (Keeney 1996). Objectives are quantified by the creation of measurable attributes that serve to evaluate how different alternatives perform against values articulated in the objectives. Some objectives can be quantified to a natural scale, such as a cost objective assessed in dollars, but those that cannot can be represented through a proxy, such as public satisfaction on a rank scale from 1 to 10. (Keeney and Gregory 2005).

Program (or initiative) wide objectives, typically found in planning documents, should be directly tied to objectives governing decisions made in incentive programs. If the fundamental objective of a program is to increase the abundance of a species, and one strategy to do so is to implement an incentive program focused on habitat restoration on private land, then the incentive program is a means objective or a way to achieve the fundamental objective. To meet the fundamental objective, the incentive program should seek to select the combination of parcels that results in the greatest population increase. If an incentive program is also identified as a strategy to increase the number of landowners engaged or enhance ecosystem services in focal areas, then there are objectives other than population increase at play, and the best way to assign importance to the different objectives is to use an objectives hierarchy. An objectives hierarchy is a visualization of objectives where the fundamental objectives are supported by means objectives. By setting up an objectives hierarchy, we may see that we have several means objectives; for example, enhancing ecosystem services is an important means to the fundamental objective of increasing the population, as this action increases habitat quality which in turn affects the population. As described, enhancing ecosystem services serves as a means objective because its satisfaction leads to some other objective we identify as fundamental. However, we may identify enhancement of ecosystem services as a fundamental objective for its own sake, simply because we declare it important to do so. We can then identify how the other objectives should be represented in the incentive program and the relative importance (weights) that should be assigned to each one.

The alternatives in this problem are all possible combinations of landowners who have submitted applications to the incentive program (Figure 2.1). As the number of landowners increases, so does the number of alternatives and complexity of the problem. Depending on how the problem is formulated, this number could be limited by the geographic region of focal areas, where incentive program eligibility may be restricted to specified counties.

Consequences are linked to alternatives and work to explicitly evaluate the alternatives according to objectives. This usually takes the form of modeling, either using mathematical models or simple flow diagrams, that show the relationships between decisions, outcomes, and other factors (Conroy and Peterson 2013). Models allow us to take assumptions, state them explicitly, and apply them in the comparison of alternatives. For example, if biologists think that burning improves habitat quality more than other conservation practices and would thereby bring greatest increase to a focal species' population, then models would allow us to compare alternatives that employ this practice to others that do not. Within the context of this decision problem, there are multiple ways to implement models and compare alternative combinations of private landowners to enroll. Models with mathematical structures could allow us to directly choose different combinations of private landowners to enroll and make predictions of the outcome in terms of our stated objectives. If there is a single fundamental objective to increase the population, then one can model the expected population if landowners ABC as opposed to XYZ are selected for enrollment. A second approach is a rank-and-scoring system where elements that are thought to be important are included as different attributes in a transparent scoring structure. If different conservation practices are available and included as attributes, then practices that are thought to increase the population (e.g., burning) would receive more points, which are commonly subjectively assigned by the decision maker. Points are attributed to different options within an attribute based on relative importance; if location is more important than conservation practice, then the total number of points that can be allocated will be greater than when options are of relative importance. A third approach also uses a rank-and-scoring system, but one that has evolved without structure and is not transparent or linked to objectives. We often see this model in practice, and its appeal is that it expresses the decision problem in a set of proxy quantities assumed to operate independently and assumed to scale with the population response. Scientific thought and value preferences likely underlie the creation of these systems, but those details are not open to inspection, understanding, or debate.

There are a number of uncertainties in conservation incentive programs which can be acknowledged and incorporated in the model-based approach but are not present in either of the rank-and-scoring approaches. The degree of management control is often limited (partial controllability); whether private landowners apply the specific conservation actions they request to apply is uncertain (Thackston et al. 2009). Biological models used to identify the best outcome for target species can include degrees of demographic and environmental uncertainty that induce stochasticity in estimates of abundance or probability of extinction (Johnson et al. 2014). Considerations such as spatial connectivity of populations or habitats can be included in appropriate model structures. The spatial configuration of the landscape can have ramifications depending on the life history traits and habitat needs of target species.

For single-objective problems, optimization identifies the most preferred among a set of possible solutions, formally exploring trade-offs among candidate solutions (Figure 2.1). A search algorithm can be used to find the best portfolio or combination of landowners to enroll in a program. For this type of problem, heuristic optimization algorithms (e.g., genetic algorithms or simulated annealing) have been successfully used for similar problems (Drum et al. 2015a). In multi-objective decision frameworks, trade-off exploration is used to find best alternatives for different degrees of importance assigned to the objectives. Trade-off analysis can also be used to compare the performance of solutions against different timelines and for different levels of certainty (Runge et al. 2020). To resolve competing objectives, incentive programs can use weights to set importance among objectives, or they can pursue one of the objectives under a constraint to meet satisfaction thresholds for the other objectives. For example, multi-species targets or additional aspirational objectives may result in trade-offs among objectives, and trade-off analysis can inform which selection of parcels best fits the problem by including weights of relative importance to different objectives. In cases where incentive programs target multiple species with different habitat needs, potentially different sets of private landowners are selected for enrollment based on the specific assignment of objective weights (Yeiser et al. 2021).

Examination of Planning Documentation for State Bobwhite Conservation Programs

Bobwhite populations experienced a range-wide decline of 83% from 1966–2015 (Sauer et al. 2017) leading to intensive management and habitat restoration activity (Ciuzio et al. 2013). Much of this restoration is currently being leveraged in the form of incentive programs which create habitat intended to establish new populations or increase existing populations (Burger et al. 2006; Riffell et al. 2008; Blank 2013; Ciuzio et al. 2013). Most incentive program dollars for bobwhites are derived from the Farm Bill, but, for example, two states provide funding for their own incentive programs: Missouri's Conservation Sales Tax (Missouri Department of Conservation) funded from an excise tax on taxable items statewide and Georgia's Bobwhite Quail Initiative (BQI) funded through its specialty bobwhite license plate sales (Georgia Department of Natural Resources). In 2004, the creation of a new CRP conservation practice CP33 (Habitat Buffers for Upland Birds) made Farm Bill dollars explicitly available to the species (Burger et al. 2006). This allowed private landowners to receive Farm Bill dollars through the CRP to conduct habitat restoration for bobwhites, and it allowed states and partnerships to leverage the funding allocated for this practice. Additionally, in response to the species' decline, state and federal agencies, non-profit institutions and universities organized to create the Northern Bobwhite and Grassland Initiative (NBGI) which is the main organization responsible for interstate coordination on bobwhite efforts. The Biologist Ranking Index (BRI) was a range-wide conservation planning effort spearheaded by NBGI and led to the creation of spatially explicit bobwhite density goals and a prioritization of areas for bobwhite restoration (Riley et al. 2019). States associated with NBGI have used this framework as a starting point to identify their own priority areas for incentive programs.

To determine to what degree bobwhites are managed in a way consistent with the principles of conservation planning and structured decision making, we accessed bobwhite management plans from all states affiliated with NBGI. We contacted the northern bobwhite coordinator of each state to obtain the state's plan and had a 100% response rate. Of the 25 states affiliated with NBGI, 12 had a formal bobwhite management plan document, but we included 14 states in this study because other relevant planning documents were provided from state coordinators. Of these 14, only 3 states provided documentation on the decision process for selecting private landowners in incentive programs.

We identified and assessed the different objectives listed in state plans. We included all statements that governed decision making from a plan and assembled objectives hierarchies where possible. Linguistic differences across plans revealed terms that we categorized as different types of objectives, including "mission", "goal", "objectives", "strategies", and "task". For states with formal management plans, we also requested any documentation used to inform incentive programs operated within the state. Using these documents as case studies, we present attributes of systematic conservation planning and structured decision making found in state programs.

Nine states listed priority areas in their plans although the rationale behind the selection was mixed and scarcely noted. Arkansas attributed the inclusion of National Bobwhite Conservation Initiative (now NBGI) Biologist Ranking Index, the amount of public land located within these designated counties, and the approximate acreage of historical early successional vegetation in its designation of areas. Kentucky provided a scoring sheet which was used to identify their priority areas. While the score was not based on biological considerations and all questions focused heavily on human dimensions, the inclusion of the scoring sheet made the consideration transparent and repeatable.

We found that programs often silo their objectives based on programmatic focus such as monitoring, habitat, or education, but closer inspection uncovered more overlap and interaction among higher and lower-order objectives than suggested in the program plan. We found that programs typically use a collection of measurable, indirect means objectives as a proxy for a single (and sometimes unstated) fundamental objective such as increasing the abundance of bird populations. The approach presumes that satisfaction of the multiple means objectives leads to satisfying the fundamental objective, though the relationships between the two were rarely made explicit. For example, the Tennessee plan identifies goals for habitat, population, outreach, and research. We identified the population goal as the fundamental objective because it was evident that all other goals and objectives were in support of the population goal. However, in our attempt to construct part of the objectives hierarchy from the description in the state plan, we found it necessary to create additional, intermediate-level means objectives not included in the plan to provide logical linkages between the objectives stated in the plan and the fundamental objective (Figure 2.2). We argue that the stated habitat goal in the Tennessee plan serves to address a means objective: improve and augment early successional habitat. In turn, this objective is linked to a higher order means objective: increase vital rate parameters for NOBO such as survival. This objective ultimately leads to the fundamental objective of increasing the population. Essentially the state lists several goals and objectives all seemingly serving as fundamental objectives; however, they clearly are various means to the fundamental objective of population increase. Likewise, the Arkansas plan focuses its main goals/objectives on programmatic areas, but the plan does not include a population goal which would presumably be the fundamental objective.

Interactions among objectives from different program areas lead to possible misidentifications of objective types. We also saw that the isolated programmatic approach to goal setting resulted in missing interactions among objectives. A means objective can address more than one fundamental objective in objectives hierarchies, but if objectives are only considered in the context of a specific goal, then the application or interaction of that objective to different areas will not be considered. For example, the objective in Pennsylvania's state plan: "Conduct wildlife population and habitat monitoring within the LEAD BQFA" is set up under a top-level goal of research and monitoring, but it is also a means objective for the fundamental population objective. Furthermore, this narrow approach to objectives setting conflates not only fundamental and means objectives, but also obscures process objectives that may be of keen interest to the program. Florida and Georgia are the only states to explicitly include process objectives in their plans. Florida had the fundamental objective, "Ensure the Strategic Plan for Northern Bobwhite Restoration in Florida is implemented" and Georgia implicitly alluded to multi-year revisions, "We recommend the BQI plan be revised every 5 years guided by this adaptive feedback process." Many more states likely had revision timelines as part of the strategies that they included, but if process objectives are not explored, then there is a chance that they are swept up as part of an objective when they should stand on their own. For example, stakeholder engagement goals could be part of an effort to enroll habitat, or they could be important in and of their own right. Finally, objectives should be linked to quantitative attributes that are specific, measurable, achievable, relevant, and time-specific (SMART) (Maxwell et al. 2015) which, based on our review, was rarely demonstrated in any plan.

In most management programs, conservation incentive programs were not explicitly linked to fundamental objectives but were included in some means objectives. Stated (or unstated) fundamental objectives of most programs were related to increasing the abundance of bird populations but rarely linked to means objectives related to improving habitat or engaging private landowners. Examples of states with explicit fundamental objectives included Missouri (“Sustain and increase wild bobwhite populations within focused geographies”) and Kentucky (“Increase bobwhite populations in focus areas”). On the other hand, listed means objectives indicated that states sought to implement conservation and habitat improvement on private lands presumably by applying incentive programs, specifically in regions identified as priority areas. Incentive programs were implicitly referred to in such means objectives, and specific programs were not named. Examples of means objectives that aimed to leverage private landowners for habitat improvement included Texas (“Develop incentives to promote sound science-based management activities on privately owned lands with priority conservation concerns”) and West Virginia (“Restore, enhance or create quail habitat in conjunction with early successional habitat development on appropriate state and private lands where practicable”).

The 14 planning documents included in this analysis do not clearly state the decision-making process used to select landowners for enrollment in incentive programs, even when objectives refer directly to private landowner incentive programs or include strategic goals to increase the number of acres or individuals enrolled in programs. Information from ancillary documentation provided by the states of Kentucky, Missouri and Georgia indicates that ranking systems based on similar attributes such as location or conservation practices may be commonly used.

The Kentucky private lands program leverages the Wildlife and Southeastern Kentucky Early Successional Habitat (SEKESH) Initiatives Fund Account which is administered through USDA EQIP and is available "specifically for applicants with land located in the forested Southeastern portion of the State." The number of points attributed to each element of the landowner questionnaire is not listed in the documentation and therefore the weight or importance of attributes is unclear. Questions focused on habitat type and cover, location, and practice. Only one question was specifically attributed to bobwhite ("3l. Does this application include applying a practice in the Bobwhite Quail Focus Area?") although others pertained to practices that could benefit the species.

In a component of the Missouri WHIP (2010 Cooperative Conservation Partnership Initiative Mississippi River Basin Healthy Watersheds Initiative Lower Grand Focus Area), ranking points assigned to landowner applications are attributed across three tiers: national priorities (250 points), state priorities (25 points), and local priorities (21 points). Bobwhites are implicitly included in national priorities as a "wildlife species of concern", and explicitly in the state and local priorities where points are attributed to practices enhancing habitat for bobwhite and whether the planned practices are in designated Quail Focus Areas.

In Georgia, the funding for landowner cost share is split between EQIP and Georgia's BQI. The BQI began in 2001 as a state-run incentive program funded from license plate sales. While smaller compared to national incentive programs, the state received approximately 11,000 contract applications from 2017-2020 (personal communication; Dallas Ingram, Georgia Department of Natural Resources). Attributes used in the BQI rank scoring system are unrelated to objective statements listed in the planning documentation for the state program. When evaluating a specific planning unit, the allocation of points takes into account the following factors listed in order of importance: 1) the location within the landscape, particularly whether the land falls within a state-defined focal area or not, 2) the current land use on the property and conservation practices to be applied, and 3) the history of prescribed burning and whether a wildlife management plan has been created.

In summary, we found that state programs for northern bobwhite define objectives to different degrees of specificity, do not always connect objectives to measurable attributes, and rarely identify linkages among objectives. In turn, this challenges the decision-making process related to enrollment in incentive programs as guidance as to what distinguishes better from poorer enrollments is opaque or even contradictory. The three states that administer their own incentive programs use point-based attributes that typically consider location, habitat quality or type, and conservation practices. The precise scoring system and weighting of these attributes vary among programs but appear not to be linked directly to planning objectives. Our findings are consistent with other studies, for example, a review of State Wildlife Action Plans (SWAPs) found that at the planning level, states struggle to identify strategic aspects of plans such as setting objectives (Lerner et al. 2006). Failing to include objectives could stem from institutional limitations or reluctance from program leaders to explicitly state objectives to which programs would be held accountable.

Conclusion

By focusing on fundamental objectives and building out objectives hierarchies (with assistance from stakeholders and experts), states could benefit from objectives frameworks that provide coherency and clearer guidance for conservation decision making for northern bobwhite. Decision making would also benefit from increased transparency in the hypothesized consequences of actions. Quantitative models are useful for specifying relationships between habitat characteristics, their arrangement on the landscape, and northern bobwhite populations. Additionally, models capture uncertainties that obscure the linkage between actions and outcomes.

Of the bobwhite programs examined, there was no direct link between program objectives stated in planning documents, the selection of focal areas, and decisions made in conservation incentive programs. We found conservation planning frameworks used varying degrees of transparency. State planning documents implied that the identification of focal areas in states likely arose from application of NBGI criteria rather than from analytical efforts by the states themselves. We observed the identification of incentive programs as a means to increase bobwhite habitat and populations, but the linkage between such programs and the documentation for the state program was missing. For states documenting incentive programs that they leverage or administered, no model-based decision tool was evident in any program.

A focus by states on fundamental conservation objectives could lead to planning frameworks that are underpinned by transparent, testable, and data-informed scientific relationships. Such focus would result in upper-level administrators and state biologists articulating the assumptions underpinning the current program objectives, uncovering hidden objectives, and ensuring that objectives were consistent across all elements of the program. Specifically, articulating assumptions would allow for the exploration of biological uncertainties and whether these uncertainties could affect the selection of focal area or enrollments in incentive programs.

Additionally, while we have identified that states struggled with setting clear and hierarchical objectives, identifying focal areas, and making decisions around incentive program enrollment, other strategic aspects of plans such as prioritizing actions and setting up monitoring systems to track actions and habitat conditions were also missing. Monitoring and surveillance are particularly important because without monitoring or feedback, there is no way to measure success or to adapt decision making to gained knowledge. In the scientific literature, there are few examples of strategic planning or decision frameworks implemented on incentive programs (Drum et al. 2015a; Drum et al. 2015b; Krainyk et al. 2022).

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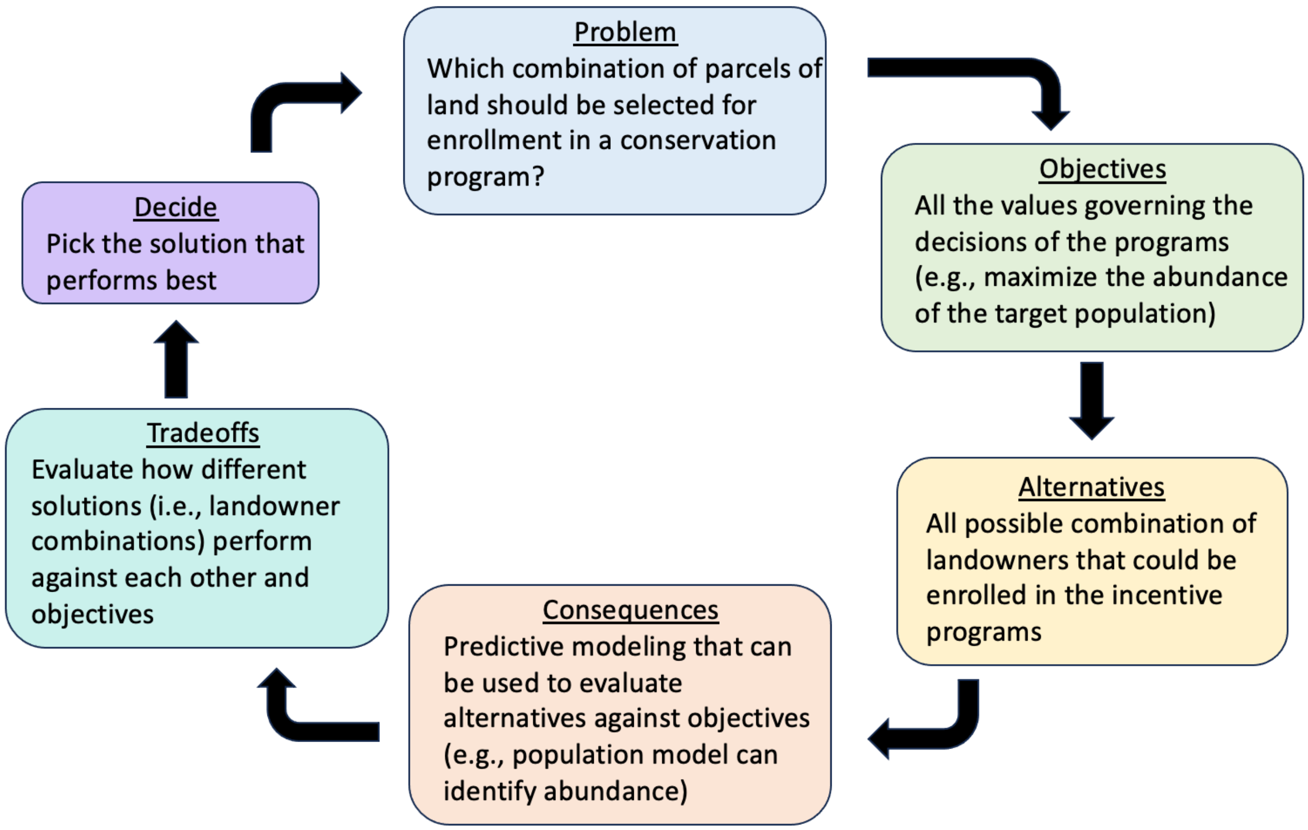

Figure 2.1. A proposed decomposition of the decision problem inherent in selecting enrollees in conservation incentive programs, as approached through the PrOACT (Problem, Objectives, Alternatives, Consequences, Trade-offs) cycle.

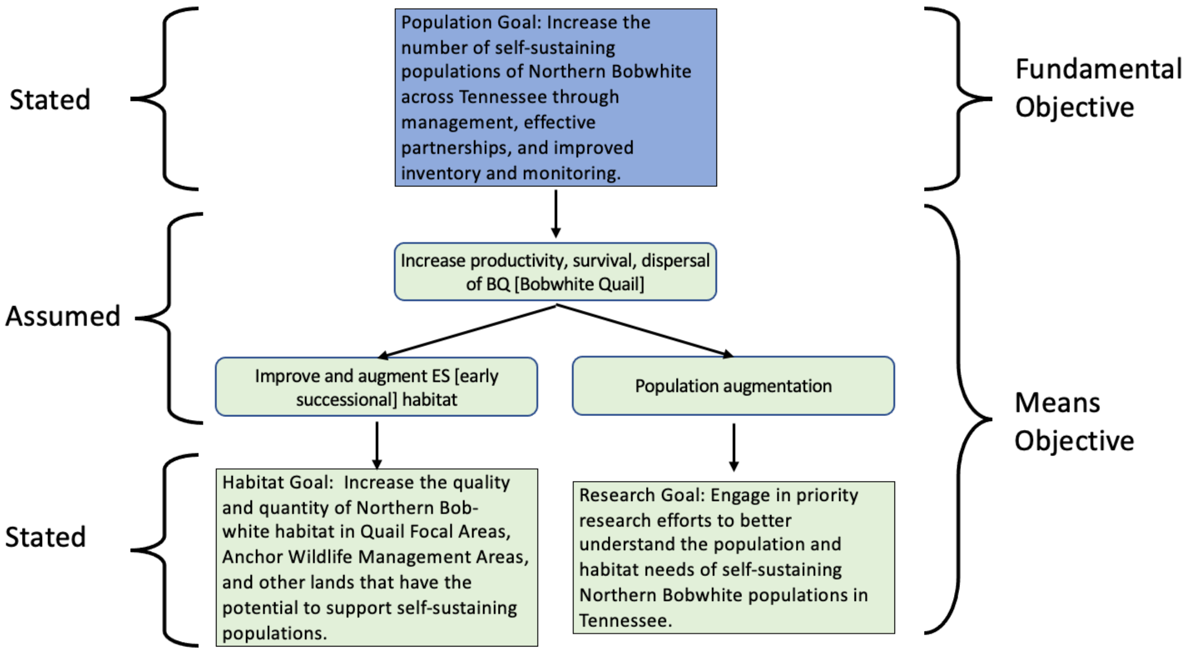

Figure 2.2. Implied Objectives Hierarchy for the Tennessee Bobwhite Management Plan. The state's declared objectives from the plan are found in square boxes while the assumed additional objectives are found in the boxes with curved edges. The fundamental objective is in the blue box while all means objectives are in green boxes.

CHAPTER 3

Model-based Spatial Prioritization Improves Expected Outcomes in Conservation Incentive Programs [1]

[1] Stanley, A.E., C.T. Moore, J. Hepinstall-Cymerman, E. Bellier, and J. M. Yeiser, and J. A. Martin. To be submitted to *Conservation Biology*

Abstract

Conservation incentive programs offer financial incentives to encourage private landowners to engage in conservation. In the U.S., certain incentive programs at the state and federal levels are used to increase the amount and quality of habitat available on managed landscape mosaics for declining animal species. For the northern bobwhite (*Colinus virginianus*), such programs include the Environmental Quality Incentive Program of the U.S. Department of Agriculture (USDA) or Conservation Practice 33 of the USDA Conservation Reserve Program. Despite the substantial amounts of money available via these programs, funding is not sufficient to entirely restore the species' former distribution across its range. Thus, sponsoring agencies with finite budgets must make discrete choices about which geographies are targeted to most efficiently allocate funds to achieve desired objectives. Because decision making in a context of spatial complexity and uncertainty is inherently difficult, the problem of selecting participating landowners is sometimes cast into simplified scoring rubrics that mask the assumed underlying relationships between actions and bird response. We developed a prototype decision framework for selecting enrollees and compared its performance to the status quo approach of scoring applicants or selecting applicants at random. Our framework is built on a spatially explicit and individual-based northern bobwhite population model that includes biological processes of survival, productivity, and dispersal. We simulated the frameworks on randomly sampled landscapes from existing focal regions identified for the northern bobwhite. We used a genetic algorithm to construct and evaluate portfolios of participant selection, where better portfolios were those that predicted more birds would be supported within imposed constraints of cost. We confirmed that portfolios provided by our model-based approach outperformed those provided by either the status quo scoring or the random selection frameworks. Future conservation incentive programs should consider using model-based approaches to target parcels of land that will return greater resource value while minimizing cost.

Keywords: bobwhite, grassland birds, structured decision making, optimization, conservation planning, landscape ecology

Introduction

Resource allocation plays a crucial role in conservation planning as limited resources always challenge decision makers' objectives to maximize conservation outcomes. Conservation practitioners, land managers and policymakers must make difficult decisions about resource demands and competing priorities. Resource allocation in conservation involves the irreversible distribution of finances, personnel time, and conservation actions (Salafsky et al. 2008). This process involves consideration of multiple factors such as biodiversity priorities, ecological threat, cost-effectiveness, stakeholder preferences, and socioeconomic constraints (Bottrill et al. 2008; Joseph et al. 2009; Bartkowski et al. 2020). When these preferences are articulated as clear objectives and constraints, analytical tools can be used to find optimal solutions. Quantification of resource problems allows for conflicting or competing objectives such as socio-economic and environmental values to be evaluated through trade-offs or imposed as constraints. Modeling tools are used to represent complex systems and to incorporate uncertainty, and the predictions from models can be used in optimization algorithms. One example of systematic resource allocation is the prioritization of endangered species recovery actions (Gerber et al. 2018). Particularly when government agencies are allocating public funds and resources, such tools can be used to increase transparency and accountability.

A conservation incentive program is inherently a decision problem where an actor (e.g., a public natural resource agency) irreversibly allocates resources to a subset of possible alternatives to achieve a public conservation objective. Conservation incentive programs (referred to here as incentive programs or programs; also referred to as agri-environmental schemes in European countries), are used by governments to pay private landowners to change farming or forestry practices in favor of conservation. Payments offset the economic burden of forgone profits or reimburse landowners for applying conservation management practices. At each cycle of decisions, privately-owned patches of the landscape selected for enrollment in a program are drawn from a large set of possible alternatives, and the conservation practices funded on those landscapes are an irreversible commitment to expending monies at that moment in time.

Programs set up explicitly for wildlife may have different forms of financial incentives (i.e., cost-share vs land rental), but all these programs were established with the same assumption: habitat protection or restoration benefits wildlife. Programs can also implement different payment structures: action-based ("input- , measure-based, or action-oriented schemes") programs where landowners are paid a set amount for implementing an assigned management practice within a pre-specified area, or results-based schemes ("performance-, outcome-, output-, success-based or -oriented payments/schemes") which offer conditional payments based on the result of conservation actions assessed on metrics such as the amount of biodiversity supported (Nguyen et al. 2022). The U.S. mainly implements action-based programs with little focus on the result of effectiveness of actions, with a few exceptions (George, 2002; Fales et al. 2016). In action-based programs, financial resources are optimally distributed when management practices implemented on enrolled, pre-specified areas of a private landowners' property are expected to have the greatest conservation result on the landscape. The result of interest is program-dependent and likely relates to the focus of the program; if the program is targeting a specific animal or plant species, then a population increase would be a reasonable expectation of success. Although the problem is colloquially described as "private landowner enrollment," enrollment decisions most commonly apply at the level of specific forest stands, fields, or other subdivisions of a single privately-owned property or set of properties.

Programs use different approaches to structure their decision on which lands to enroll. Programs set up for private landowner enrollment could be based on biological models, systematic rankings, or no selection basis at all (i.e., randomly selected or first-come, first-served). Each approach is underscored by a different way of thinking about the system of private landowner incentive programs. Model-based frameworks that can use estimates of population abundance to determine which parcels to select are likely the most resource efficient. Such frameworks can leverage evolutionary optimization algorithms to identify the optimal allocation of resources because they are simple to design, can be combined with simulation models, and can explore many potential solutions (Bartkowski et al. 2021). Simulation models such as individual-based population models can incorporate individual life-history and behavioral responses as well as larger population dynamics and landscape ecology. As such, individual-based models can provide insight on specific population objectives. Uncertainties regarding population parameters or processes can be included in the framework to actively consider and potentially reduce as part of the selection process. Few studies have conceptualized the optimal allocation of resources for conservation objectives (Bartkowski et al. 2021) or applied optimal allocation schemes to existing incentive programs (Reynolds et al. 2006; Yeiser et al. 2021b). Programs structured around the optimal allocation of resources tend to include population parameters in optimization algorithms (Yeiser et al. 2021b).

Systematic ranking schemes underlie some incentive programs. Generally, these are implemented as a point-based ranking system where certain attributes with assumed conservation value are assigned points or weighted such that parcels with those attributes are more likely to be selected. Point-based systems can be transparent and based on biological principles if the problem objectives are clarified and the preferences are transparent (Krainyk et al. 2022). Some attributes used in point-based incentive programs include spatial components through the specification of a focal area which limits the geographic scope of the problem and apportions more points to parcels located in the focal area (e.g., the Bobwhite Quail Initiative of the Georgia Department of Natural Resources). The Conservation Reserve Program (CRP), the largest incentive program in the U.S., uses a point-based ranking system, but the attributes are vague and not directed at landscape considerations such as neighborhood effects (Hellerstein 2017). Other programs do not make the point-scoring system explicit or publicly available. In such cases, it is hard to assess the attributes that programs deem important in distributing public funds or whether any systematic approach is used at all for parcel selection.

Models can be used to inform decisions. In many decision-making contexts, models can support decision making by synthesizing existing knowledge in a way that is transparent, systematic, and able to represent sources of uncertainty (Addison et al. 2013). Models can be quantitatively complex or a qualitative representation of the system (Addison et al. 2013). Systematic decision-making frameworks such as Structured Decision Making (SDM) can inform what models should be used for a decision problem. In the context of private landowner incentive programs, models can be used to link actions to biological outcomes and thus directly inform trade-offs involved in the selection of applicants (i.e., which field or forest stand belonging to a specific private landowner will generate higher conservation value if selected), or they may indirectly inform selection by outlining attributes that the decision maker cares about, thus creating a rule-based approach to selection. While models can represent socio-economic systems and provide information about the social feasibility of selecting specific landowners through agent-based models (Bartkowski et al. 2020) and SDM (Drum et al. 2015), individual actors as decision makers are not considered under the scope of this paper. Barriers to the implementation of models in incentive programs likely include spatial complexity and uncertainty which are inherently difficult to work with. Still, when used for decision making, a model-based framework can both quantify parametric uncertainty and apply monitoring outcomes to reduce that uncertainty (Addison et al. 2013). Specifically in action-based schemes there is not a measurement of result after a practice is implemented. Instead, the decision about who to enroll could occur under a modeling approach that directly questions how any targeted group of enrollees/applicants modifies the landscape in a way expected to affect the biological response of the target species.

Finally, some programs, particularly those that lack evidence of a systematic selection process in place, likely operate on a first-come, first-serve basis until the budget is depleted (Talberth et al. 2015). This approach is a random or haphazard selection system, where there is no formalization of the selection process, and attributes that impact the efficacy of a program such as spatial arrangement of selected areas relative to existing habitat and population viability are not considered.

Grassland birds have been a large focus of conservation efforts due to recent declines (Ciuzio et al. 2013). Such species are found in highly fragmented habitat and mostly on private lands (Brennan and Kuvlesky 2005). The intensification of farming has consequences for grassland species because the less agriculturally-productive areas of land such as field buffers are now being converted to cropland (Smith 2004). Thus, grassland bird habitat is highly vulnerable to loss and degradation on private working lands. Incentive programs have been cited as the best strategy to aid population recovery of grassland birds because they create habitat on private land (Riffell et al. 2008; Burger et al. 2019). New programs have evolved, and new practices have been created and funded in established programs to incentivize agricultural producers to adopt bird-friendly management practices (Burger 2006; Gudlin et al. 2019). Depending on land use and vegetation cover, practices include field buffer creation, brush management, prescribed burning, and forest stand improvement (thinning and burning). Practices are often applied according to the habitat needs of specific species. Here, we focus on the northern bobwhite (*Colinus virginianus*; NOBO or bobwhites) which serves as a flagship species for other fire-dependent grassland birds and early successional wildlife. As such, restoration practices for bobwhites include reestablishing early successional habitat in agricultural fields and pine forests (Arredondo et al. 2007). Incentive programs such as Georgia's Bobwhite Quail Initiative (BQI) have been created explicitly to increase the population of the species.

In this paper we sought to explore different decision frameworks used for resource allocation in conservation incentive programs. We simulated multiple decision frameworks for private landowner enrollment in conservation incentive programs over different landscape sizes and percentages of landscape enrollment. We used this information to address two questions: Given the different ways to allocate resources to conservation incentive programs, are there efficiencies gained by using one framework over another? Are differences between allocation frameworks dependent on the size of the landscape under consideration or the amounts of land enrolled in a program? We addressed these questions using the conservation context of the northern bobwhite and the parameters of a program that has been designed and implemented for the species within the state of Georgia.

Methods

Our simulation experiment proceeded in seven steps detailed in the subsections below: (1) creating a study area landscape with layers representing private property boundaries and habitat quality; (2) drawing samples of experimental landscapes from the study area landscape; (3) identifying forest stands on each landscape that qualify for enrollment in a conservation incentive program; (4) replicating the assignment of potential conservation practices across qualifying stands; (5) creating a layer of post-practice habitat quality for each replicate of potential conservation practices; (6) applying three schemes (decision frameworks) for selecting enrollees given each replicate of potential conservation practices on each sample landscape and under each of five enrollment constraints; and (7) comparing performance among frameworks on the abundance of birds produced as predicted under a spatially explicit individual-based bird population model.

The first decision framework uses an existing bird population model (unpublished data; James Martin, University of Georgia) within a heuristic optimization algorithm to identify which combination of land parcels produces the greatest expected number of bobwhites across the landscape when conservation practices are applied on those parcels. The second framework is based on the ranking scoring rubric created by the Bobwhite Quail Initiative of the Georgia Department of Natural Resources (GA DNR) in 2015 and represents the status quo approach for making enrollment decisions in conservation incentive programs in Georgia: each application is scored based on certain attributes such as land use and location, and the highest scoring parcels of land are selected for the program. The third framework randomly selects potential applicants.

Study Area Landscape

Our study area landscape was the geographic region defined by the focal landscapes of BQI (Figure 3.1; Figure 3.2). The main goal of the BQI is to increase and maintain populations of wild bobwhites by restoring and maintaining early successional and woodland savanna habitat (Thackston et al. 2009). These focal landscapes are areas identified with high restoration potential for bobwhites and where the state agency is explicitly trying to enroll private landowners using state and federal funds. While the focal landscapes are found in three distinct regions of the state (east, central, southwest) and classified into two priority tiers, we considered the combined 1,123,025-ha area as one continuous study area and made no geographic distinctions among regions for the purposes of our study.

We used the Landfire Existing Vegetation Cover (EVC) 2022 data to identify four vegetation classes: forest, shrub, herbaceous (grass) and row crops. All 6 crop classes distinguished by the National Agricultural Statistics Service (NASS) were combined to create the row crop class (Rollins 2009). To simplify the decision problem, we only considered upland forest stands greater than 0.4 ha as candidates for enrollment, as stands below this threshold size would not be realistically enrolled in programs like BQI. We used the Landfire Existing Vegetation Type (EVT) 2022 data to identify upland forest pixels (Rollins 2009; Supplementary Information).

For each county in the BQI focal landscape, we used property boundaries available from the county's tax assessor's office (Jimmy Nolan, Carl Vinson Institute of Government, University of Georgia; accessed version March 2020). These counties included Burke, Jenkins, Screven, and Bulloch in the east, Emanuel, Laurens, Bleckley, Dodge, Pulaski, Wilcox, and Dooly in the central part of the landscape, and Lee, Terrell, Calhoun, Dougherty, Baker, Mitchell, Grady, Thomas, Brooks, and Decatur in the southwestern landscape. Contiguous counties were appended together using ArcGIS Pro Version 3.x (ESRI) and clipped to a 5-km buffer of the BQI focal landscapes layer. We removed all water bodies included in the NHDplus Geodatabase (Buto and Anderson, 2020). We also removed any parcels not privately owned or classified as a protected area as these are not typically eligible for Farm Bill monies. We removed these parcels by identifying parcels designated as "federal", "state", "local", "designated" or "tribal" in the Protected Area database version 3.0 (USGS 2021). All GIS layers were projected to the NAD 1983 UTM Zone 17N coordinate system and rasterized to a resolution of 30m using the nearest neighbor resampling technique, registered to the Landfire EVC layer. To increase computational efficiency in later steps of the simulation, we aggregated all layers to a 90m resolution using aggregate with the modal function in the Terra package of R (Hijmans et al. 2022).

Sampling Experimental Landscapes

We used two sizes of fishnet to clip the study area landscape into 322 small (2,630 ha) and 169 large (5,261 ha) landscapes (Figure 3.3; Figure 3.4). The size of the landscape has implications for the comparison between approaches because as the size of the landscape increases, the number of potential enrollees (i.e., private landowners and candidate stands) increases, as does the computational cost of the running the simulation. From the population of landscapes, we randomly selected a sample of 20 experimental landscapes for each size category.

Defining Stands for Enrollment

We used the clumps function in the raster package (Hijmans, 2020) in program R (R Core Team 2021) with the Rook's rule (4-way neighborhood) as our adjacency metric to create forest patches from all raster cells that met the previously specified requirements of "forest" and "upland". Identified patches of forest were further divided by private landowner boundaries to create landowner-specific patches (stands). We excluded stands that did not meet our size requirement of 0.4 ha for enrollment. Private landowners could have more than one stand eligible for enrollment in the incentive program. For all private landowners with forest stands on their property, we accounted for some rejection where private landowners would not be interested in enrolling all their forested land in the conservation incentive program or may not be interested in enrolling in the program. As such we randomly selected 10% of stands (without respect to ownership) and removed them from consideration for enrollment.

Potential Conservation Practices

While there are a multitude of conservation practices that can be applied to working lands under conservation incentive programs, we selected three practices that would be applied to upland forest for bobwhites including prescribed burning ("controlled burn" or "prescribed fire"), brush management (the removal of woody understory plants), and forest stand improvement (forest thinning and prescribed fire combined) which cost $98.84/ha, $197.68/ha, and $296.52/ha, respectively (values based on BQI scoring Guidelines 2020).

For each sample landscape, we attached a potential conservation practice to each qualifying stand; the practice became realized in the experiment if the stand was selected in the decision framework. Conservation incentive programs will receive applications where the potential enrollee has already worked with a biologist from the relevant agency to identify conservation practices for their property. To mimic this, across all eligible private landowner stands we randomly assigned one of the practices according to the following probabilities: burning - 0.125, brush management - 0.125, and forest stand improvement - 0.75 (USDA 2022). To account for stochasticity that could result in a poor distribution of actions, we replicated the random distribution of potential conservation practices 10 times across each sample landscape. The 10 replications were fixed across decision frameworks; therefore, frameworks were compared on the same set of potential conservation practices.

Habitat Quality

The bird population model underlying our experiment used spatial input on habitat quality. Therefore, we used the Landfire Existing Vegetation Cover (EVC) to create a habitat quality layer on the logit scale as required by the population model. Of the 4 vegetation classes, only forest, shrub, and herbaceous classes were recorded with percent cover. For cells classified as row crops, we assigned the average logit value from a habitat quality model (unpublished data; Victoria Nolan, University of Georgia). For shrub and herbaceous classes, we used responses from an expert opinion habitat survey where experts were asked to define habitat quality for bobwhites across ranges of percent cover for certain types of vegetation (unpublished data; James Martin, University of Georgia; Supplementary Information). We fitted survey estimates using spline regressions, predicted all values for the full range of percent cover, and then transformed those predictions to the logit scale (Supplementary Information). Forest cover was not included in the expert elicitation survey, so we identified a simple linear relationship on the logit scale between percent forest cover and habitat quality (Supplementary Information). All other classes present in EVC (i.e., developed or water) were set to the lowest value of habitat quality.

For each potential conservation practice, we computed the expected change in habitat quality through simple piece-wise linear relationships on the logit scale. We assumed that change in habitat quality for both burning and brush management was conditional on amount of percent tree cover. When tree cover was less than 30 percent, we assumed that the highest value of habitat quality is returned. For tree cover greater than 30 percent, we assumed that habitat quality declines linearly with percent tree cover (Supplementary Information). Forest stand improvement combines two actions: thinning and burning. We assumed that all stands are thinned by 50% when the practice is applied, but to no less than 30% cover. We assumed that after stands have been thinned, the same linear relationship for burning is applied to return the habitat quality value (Supplementary Information).

Selection of Enrollees Under Alternative Decision Frameworks

Bird population model

We simulated the initial abundance and distribution, movement, and growth of bobwhite populations on sample landscapes using a spatially explicit and individual-based population model (unpublished data; Edwige Bellier, University of Georgia). The key input to the model is a spatial coverage of habitat quality for each 90-meter pixel. The model accounted for the annual life cycle of the bobwhite; individuals were given stochastic and realistic vital rates, different sex and mating behaviors, fecundity, and productivity rates, as well as mechanisms for spring and autumn dispersal (Yeiser et al. 2021a). The spatial scale at which bobwhites respond to changes on the landscape (Chandler and Hepinstall-Cymerman 2016) was included as a user-set parameter ("scale of effect") in the model (Yeiser et al. 2021b; Yeiser et al. 2018). The model places the initial northern bobwhite coveys (group or flock) on the landscape according to habitat quality and allows the population to move around the landscape in response to annual vital rates and to changes in habitat quality arising through conservation practices or other means. All parameters in the original version of the model were unchanged except the number of coveys initiated on the landscape and the scale of effect; we used values of 25 coveys and 8000 m, respectively, for 2,630-ha landscapes and 50 coveys and 8000 m, respectively, for 5,261-ha landscapes.

For all decision frameworks, we used the population model to predict absolute bird abundance over fixed time frames (10 and 30 years) brought about by applying conservation practices on specific stands in a landscape. We predicted abundance under conditions of imposed conservation practices, which we assumed were implemented instantaneously at the start of the time frame, and we assumed the created habitat conditions remained unchanged afterward.

Enrollment constraints for all frameworks

To reflect realistic budget constraints that affect all conservation incentive programs, we imposed area constraints on the percentage of the landscape that could be enrolled, thus limiting the number of stands that could be enrolled. We simulated decision making under five different caps on the percentage of the sample landscape that was eligible for enrollment: 5%, 10%, 15%, 20%, and 25%. Across the different sizes of landscape (2,630 ha and 5,261 ha), a cap on enrollment percentage induced different amounts of total area eligible. For example, at 5% of landscape enrollment, 132 ha and 263 ha could be enrolled on a 2,630-ha and a 5,261-ha landscape, respectively.

Optimized framework

Our first framework used a heuristic search that was set up explicitly to maximize bird abundance on the landscape. We used a binary genetic algorithm in program R using the package GA (Scrucca 2013) to perform optimal selection of forest stands for a single year (Holzkämper et al. 2006). For each landscape size (2,630 ha and 5,261 ha), we allowed all properties with forest stands that met our eligibility criteria to be considered for enrollment by the genetic algorithm. All qualifying stands in a sample landscape were represented as a chromosome in the algorithm, where enrollment or exclusion of a specific stand was coded as a binary gene. Thus, a candidate portfolio of enrolled stands was represented as a chromosome with certain genes activated and others deactivated. Genetic algorithms create a population of chromosomes, or multiple candidate portfolios of stand selections, which are subject to computational operations mimicking rules of evolutionary biology, including random pairing, crossover of genetic material, mutation, and survival to succeeding generations (Goldberg, 1989). Each chromosome coded for a specific portfolio of enrolled stands and was associated with a fitness value, namely, predicted bird abundance. Over many generations, the algorithm promotes those chromosomes (solutions) with greater fitness.

Because we replicated the random assignment of conservation practices 10 times across the same sample landscape, the fitness value for a landscape was the average bird abundance returned from all 10 replications of potential conservation practices. We imposed the percentage of landscape enrollment constraint by assigning a low fitness value to any candidate solution that identified a set of stands where total area exceeded the area implied by the enrollment cap.

We allowed the algorithm to run until it met a stopping criterion of no improvement in the best fitness value for 30 consecutive generations, or 80 total generations, whichever came first. The algorithm population size (number of candidate solutions per generation) was 40 individuals, and we provided the algorithm with an initial population of solutions. One individual seeded into the initial population was the final solution for the rank-scoring framework (see next section), and the other 39 individuals were generated by randomly selecting the same proportional number of stands as the percentage of landscape enrollment constraint (i.e., if 50 eligible stands occurred in a sample landscape and the constraint was limited to 10 percent of the landscape, then 5 stands were selected at random to construct one of the initial candidate solutions). We set the mutation rate to 0.1 and the probability of crossover to 0.8. We set elitism at 10% to ensure the best 10% of individuals (n = 4) survive each iteration (generation) of the model run; all other individuals (n = 36) survive to the next generation with probabilities proportional to their fitness.

Ranking framework

We used a modified version of the 2015 ranking form created by BQI for Environmental Quality Incentives Program (EQIP) funds (personal communication; Dallas Ingram, Georgia Department of Natural Resources). This framework is point based (i.e., the attributes of the applicant are scored) and composed of 5 questions about the candidate stand (‘planning unit’), with a maximum assignment of points possible:

(1) which, if any, BQI focal landscape does the planning unit occur within? (200 points);

(2) what land uses are currently in place within the planning unit? (75 points);

(3) are approved conservation practice standard scenarios to be implemented within the planning unit? (75 points);

(4) is there a plan written by a wildlife biologist or is there a forest stewardship plan with wildlife as primary objective? (25 points); and

(5) has the planning unit had a silvicultural (not associated with site preparation or agriculture) prescribed burn within the past 3 years? (25 points).

We removed questions 4 and 5 from our analysis because relevant information was not available in our spatial data; therefore, each individual landowner was eligible to receive a maximum of 350 points instead of the original 400. We used GIS layers to evaluate questions 1 to 3. Question 1 has two components of the focal landscape, each with different scores: GA DNR’s focal area and the National Bobwhite Conservation Initiative (NBCI) 2.0 Biologist Ranking Information (BRI). We used GA DNR GIS layers which denoted the focal landscape (Thackston et al. 2009) and NBCI’s BRI layer (Morgan et al. 2016; Figure 3.1). Question 2 identified 6 different classes of land use with points available based on the proportion of each class found on the property (Supplementary Information). We created this classification using the Landfire Existing

Vegetation Cover and Existing Vegetation Type (Supplementary Information), calculated the proportional amount for each property boundary, and then assigned the corresponding number of points for each potential stand. For question 3, we used the randomly assigned action (see "Potential Conservation Practices" section above). We set the points to each action according to the BQI ranking form as follows: burning – 15 points, forest stand improvement – 15 points, and brush management – 8 points.

To select stands for enrollment under the ranking framework, we calculated the total number of points per stand. We then ranked the stands and successively selected the highest-ranked stands until the collective area of the selected stands exceeded the given percentage of the landscape enrollment constraint (i.e., 5% cap). When multiple stands had the same point value, we randomly selected stands for inclusion. For the sample landscape we predicted bird abundance using the selected stands to inform the changes to habitat quality. We repeated this process for each of the 10 potential conservation practice replications, and the final score of each sample landscape was the averaged bird abundance.

<u>Random selection framework</u>

We included a random selection framework where stands were chosen sequentially at random for enrollment until the percentage of landscape enrollment constraint was reached. For the sample landscape containing the set of selected stands, we predicted bird abundance. We repeated these steps across the 10 potential conservation practice replications, and we averaged the abundance metrics. To ensure repeatability and to allow comparison to the ranking framework, selection was not re-randomized across percent enrollment scenarios; i.e., all stands selected under one enrollment cap would be in the selection set at higher enrollment caps.

Comparison of Frameworks

We compared average bird abundance and average cost of implementation among solutions provided by each decision framework. For any portfolio of stand selections, we estimated its cost of implementation by totaling the area in each of the three practices and multiplying each total by its per hectare cost. As we did for bird abundance, we averaged estimates of cost across the 10 potential conservation practice replications. We calculated the average and standard error of these statistics across the 20 sample landscapes and plotted the results by combinations of landscape size and enrollment percentage caps. We declared no difference in results if standard error whiskers overlapped.

We computed measures of efficiency by taking the cumulative number of birds produced over a 10-year period and dividing by the total amount spent. The resulting metric is the sum of birds produced across 10 years per thousand dollars spent.

All framework scenarios were run on the high performance computing cluster Sapelo2 at the University of Georgia and required up to 48 hours to complete a full set of 200 samples (20 sample landscapes x 10 potential action landscapes per sample landscape); the ranking and random frameworks were run in parallel and took less than 12 hours to finish while the model-based framework was run in serial and took approximately 12 hours to run for the 2,360-ha landscape and approximately 24 hours to run for the 5,261-ha landscape. All data manipulation and analyses were conducted in R version 4.1.2. Unless otherwise stated, the results describing the distributions are stated as the mean ± the standard error.

Results

The average sampled landscape had 42.8 (± 19.0) and 74.5 (± 30.4) landowners for the 2,630-ha 5,261-ha landscapes, respectively. The forested area on the 2,630-ha landscape averaged 855.5 ha (± 295.4 ha) which was subdivided into 104.7 (± 29.5) unique forest stands. The 5,261-ha landscapes averaged 1776.5 ha (± 578.1) of forest among 182.8 (± 49.1) unique forest stands. Once the 10% of unique forest stands were removed from enrollment consideration, the modified experimental landscapes contained 40.4 (± 17.4) landowners and 800.1 (± 290.9) ha of forest on the 2,630-ha landscape and 70.2 (± 28.8) landowners and 1625.5 (± 568.9) ha of forest on the 5,261-ha landscape (Table 3.1).

We simulated the individual based population model over 10 and 30-year time frames across each unique scenario combination of landscape size, percent of landscape enrolled, and enrollment framework using 200 experimental landscape–potential conservation practice replicates per scenario. To visualize the process, we present the spatial arrangement of covey locations and selected stands for a single array of potential conservation practices on a 2,630-ha sample landscape (Figure 3.5). As expected, the effect of the constraint on percent of landscape enrolled is evident with more stands selected for enrollment at higher percentage caps than lower (Figure 3.5). Additionally, the greedy nature of the ranking-based enrollment can be visualized in the figure because parcels selected at the lower percentage caps always appear in the selections under higher caps. Because we enforced order of parcel selection to be consistent across percent enrollment scenarios under the random selection framework, the visualization confirms that stands selected at lower enrollment caps also appear in selections under higher caps (Figure 3.5).

The model-based framework resulted in greater expected bird abundance compared to the random and ranking-based frameworks in every scenario except for the 20% and 25% landscape enrollment scenarios on the 2,630-ha landscape and the 25% landscape enrollment scenario on the 5,261-ha landscape (Figure 3.6, 3.7). For example, at 10 years, the model-based framework predicted 82 more birds than the random framework and 72 more birds than the ranking framework on the 2,630-ha landscape at 5% landscape enrollment (Figure 3.6). The difference between the average number of birds returned by the model-based framework and the other frameworks depended on landscape size; as the percentage of the landscape increases in the 5,261-ha landscape the difference is more pronounced compared to the 2,630-ha landscape. In nearly all cases, there was no difference between the random and ranking frameworks regardless of the percentage of the landscape enrolled or the size of the landscape. The results for predicted abundance were consistent when the frameworks were run on a 10-year or a 30-year population model (Figure 3.6, 3.7), suggesting that the populations stabilize under the model at or before 10 years.

The difference in cost of implementing the selected enrollment varied slightly across frameworks according to the percentage of the landscape enrolled (Figure 3.6, 3.7). When the percentage of enrollable landscape was smaller (5 – 15%), there was little to no difference between the cost of implementing frameworks. At larger percentages of the landscape (20 – 25%), there was a notable difference between frameworks where the cost of the model-based framework was 18 - 42% less than that of the random or ranking frameworks (Figures 3.6, 3.7; Table 3.2).

We define pareto optimality as the solution that maximizes the total abundance and minimizes the cost of implementing management actions. For all percent enrollment scenarios, the model-based frameworks for the 2,630-ha and 5,261-ha landscapes comprise the Pareto-optimal solutions – no other solution provides greater bird abundance and smaller cost (Figure 3.6, 3.7). Efficiency can also be compared across landscapes by directly comparing the amount of area enrolled (Figure 3.8). For example, the area contained by either 10% of the 2,630-ha landscape or 5% of the 5,261-ha landscape is 236 ha. The other direct comparison is at 526 ha, corresponding to 20% of the 2,630-ha landscape and 10% of the 5,261-ha landscape. In both comparisons, the ranking and random frameworks tend to be more efficient in the 2,630-ha landscape than in the larger landscape. In the model-based framework, we do not see a difference in efficiency between the 2,630-ha landscape at the 10% enrollment cap and the 5,261-ha landscape at 5%, but the framework is more efficient applied in the 2,630-ha landscape at the 20% cap than in the 5,261-ha landscape at 10%.

Discussion

We aimed to better understand how to best allocate resources in conservation incentive programs. Based on the results of our simulation, for conservation action-based programs, resources are more optimally allocated using a model-based framework than a rank-scoring approach or random approach. In every landscape scenario we tested, the point estimate of mean bird abundance under the model-based approach exceeded those by either the rank-scoring or random approaches. However, differences between frameworks diminished with increasing percentage of landscape enrollment, likely as the non model-based frameworks had successively greater chances of selecting more of the highest quality habitat already discovered by the model-based framework.

Differences in performance and efficiency between the model-based and other frameworks diminished as the constraint on allowable percentage of enrollable landscape was relaxed (made larger). This pattern was likely due to how the frameworks were created and the amount of available habitat. Both the ranking and random framework are set up to enroll private landowners until all land available for enrollment is consumed. They differ in that the ranking framework is a greedy approach, where the order of parcel acquisition is driven by a score accumulation. But because neither framework is based on a prospective assessment of how many birds could be produced, both are inefficient compared to the model-based approach. In contrast, the model-based approach is purely based on the resulting prediction of population abundance and does not enroll as much land to achieve the same benefit. When smaller percentages of the landscape are available for enrollment, the model-based framework vastly outperforms the other frameworks because the model-based framework can identify the best habitat for the species out of the limited amount available. Conversely, when larger percentages of the landscape are allowable for enrollment and more quality habitat is available from which to choose, the non model-based frameworks have better chances of identifying many of the same parcels found by the model-based framework.

Our findings are supported by landscape ecology literature and likely due to the parameterization of connectivity in the population model. Landscape connectivity has implications for population dynamics (Taylor et al. 2006); the use of the scale of effect parameter informed survival and productivity which has ramifications for the configuration of parcels or the spatial structure of the landscape (Miguet et al., 2016). King and With 2002 found that landscape structure impacts dispersal unless habitat was abundant as well as the creation of contiguous areas of good habitat as well as corridors to promote movement and colonization between habitat. The model-based approach was able to exploit these tenants because the population model was run on each selection of parcels and respond to the structure of a given landscape. This resulted in a more productive landscape in a smaller footprint than the other approaches were able to produce because they were not informed by the scale of effect in the population model.

In addition to providing greater efficiency, the model-based framework also provides broader generalizability and can address uncertainty. For example, we set up the model-based framework to select stands for enrollment under no knowledge about which practice would be applied. Alternatively, we could have set up a framework to optimize both selection of stands and assignment of conservation practice to those stands; though much more challenging to implement, it is feasible to design. The flexibility of the model-based approach also allows us to incorporate monitoring information that can be used to update parameters in the model and reduce uncertainty over time. Under the model-based framework, we can identify the best parcels to enroll given our current knowledge about dynamics of the system. After enrollment and conservation activities, monitoring data on the resulting population and the practices implemented (we assume that adherence to practices prescribed is not perfect) can revise our knowledge and lead to updates of the model to better inform decision making.

Private landowners interact with the agencies running incentive programs in different ways. Agencies can actively recruit private landowners for enrollment by seeking out those with the best habitat or previous engagement in conservation, or they can passively recruit private landowners by allowing landowners to come to them and request resources for conservation through financial incentives (Ciuzio et al. 2013). We are assuming that agencies have the forward knowledge of which individuals would not be interested in enrollment and therefore, which parcels are beyond the reach of the agency to influence habitat change. This assumption is more straightforward to include in our modeling framework, but it is highly possible that private landowners are not willing to engage after they have been selected by the framework. This form of partial controllability is not recognized in our model; therefore, in this circumstance, the model is vulnerable to providing misleading results because parcel selection recommendations may be based on false expectations about how habitats might be connected. Another form of partial controllability is noncompliance where enrolled participants do not apply the conservation practices after they are already enrolled in an incentive program (Thackston et al. 2009). While this was not included in our simulation, current research has already indicated that there is a high degree of noncompliance in existing incentive programs (Yeiser et al., 2020). Noncompliance would likely impact the model-based and ranking frameworks as selection is based on completing practices assigned to selected parcels and resulting changes to habitat quality (Thackston et al. 2009).

The limitations of this study are mainly due to simplifying assumptions and computational constraints. Due to data limitations, we made simplifying assumptions around the relationship between landcover and habitat quality. While we had originally created 8-km buffers around each landscape to account for the bobwhite's scale of effect, computational constraints (i.e., time of the model to run) prevented us from including them in the simulation. The population model includes stochastic variation in vital rates and other parameters, but we controlled the stochasticity in the model to ensure that the same parameters were being used across all frameworks resulting in an equal comparison. The degree to which changing the parameters in the population model will affect the outcome could be uncovered through a sensitivity analysis, which we did not undertake in this analysis due to computational constraints.

There are different costs associated with implementation across the frameworks. While all frameworks were run on a high-performance computing cluster for consistency, the landscape sizes presented here could have been run on a single machine with 10 gb of memory for approximately 24 hours. For a larger landscape, more computing power would be needed, or the problem would need to be set up in parallel. Incentive programs would benefit from having in-house staff with knowledge about optimization or the finances to outsource this part of the analysis. There would likely be a cost trade-off where the model-based approach would have a higher cost of implementation than the random and ranking approaches which require less in-house expertise (Iacona et al., 2018). Such cost trade-offs are important to consider as part of a broader consideration for how the model-based framework fits into the decision-making process for managers.

The scope of our work was limited to the enrollment of parcels where we assume that a list of eligible properties is available to a private lands biologist who locally administers a conservation incentive program. However, our approach fits within larger decision-making contexts for incentive programs; for example, decisions about recruitment of private landowners into incentive programs. Such decisions depend on the level of engagement a private lands biologist can generate and the objectives of individual landowners (Litvaitis et al., 2021; Morgan et al., 2019).

Compared to other optimization-type decisions for conservation, the model-based framework presented here is unique in that it relies on both spatial prioritization as well as structured decision making. The problem is set up such that focal areas or regions of potential private landowner enrollment have already been established which is a form of spatial prioritization. Structured decision making is then used to set up the optimization and explore possible solutions. While a portfolio problem is solved with pre-identified solutions and optimization is used to compare the performance of each portfolio (Runge et al, 2020), the model-based approach leverages the genetic algorithm workflow to create multiple portfolios, analyze them, and then generate new portfolios, and continues this process until a stopping rule is reached. Both spatial prioritization and SDM approaches seek to optimize selection (i.e., of parcels or protected areas), but spatial prioritization also makes the assumption that if something is selected, that there is no uncertainty in the resulting outcome (Schwartz et al., 2017). Structured decision making allows for the incorporation of uncertainty in optimization and as such, the model-based framework could be modified to formally include partial controllability and aleatory uncertainty.

Given the limited financial resources available for habitat restoration, funds should be allocated optimally to bolster populations. The bobwhite is currently experiencing an annual decline of 3-5% of the population per year (Hernández et al. 2013). Private landowner incentive programs are a policy solution designed to help the species. Given that the programs allocate public resources to private entities to enhance a public good, it is in the public interest to improve how these programs are implemented.

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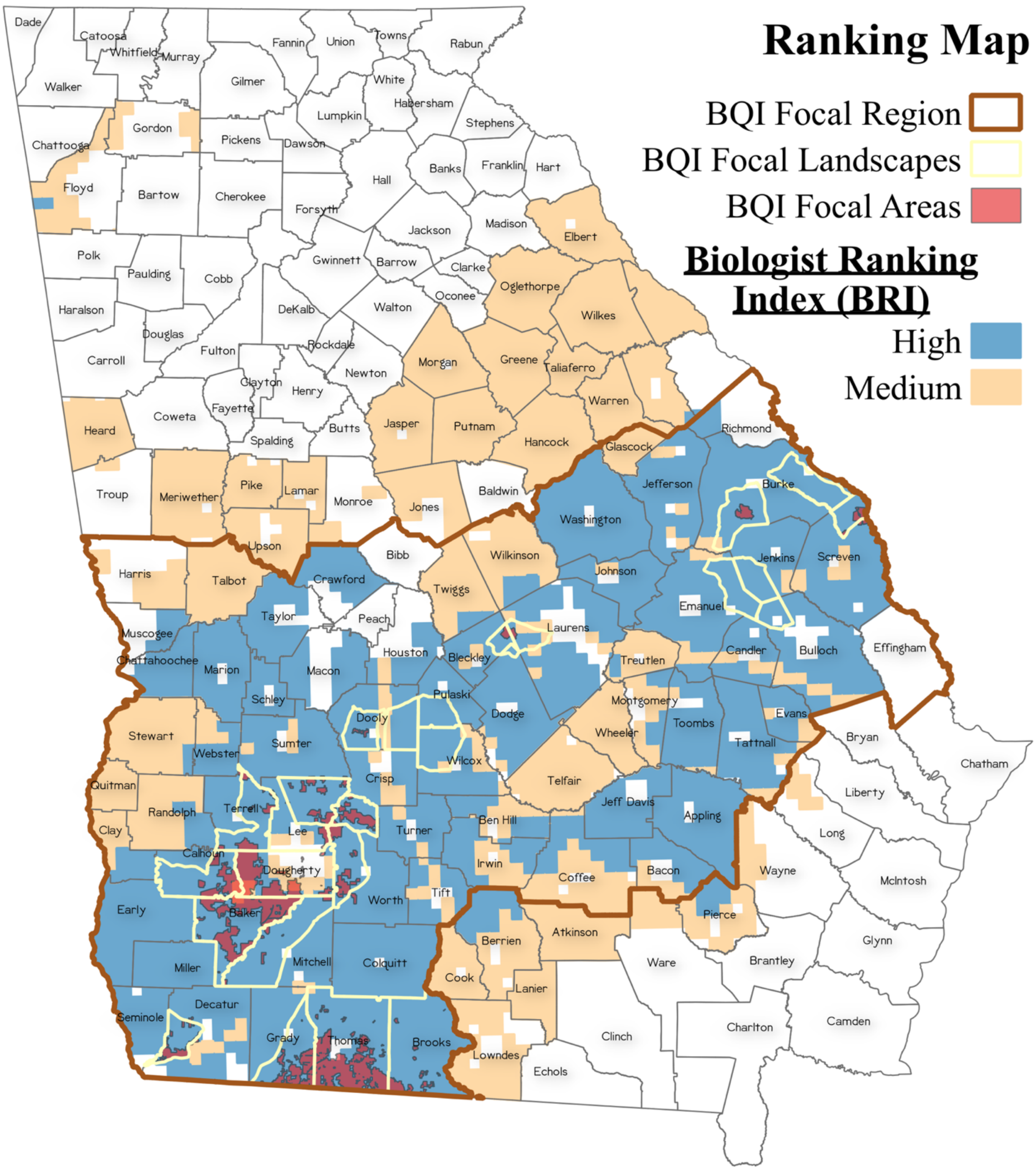


Figure 3.1 Georgia's Bobwhite Quail Initiative Map. Georgia's Bobwhite Quail Initiative recognizes three spatial levels of organization. The focal region (brown line) aligns with the upper coastal plain physiographic province. Focal landscapes (yellow outline) are formally delineated into an eastern, central and southwestern region. Focal areas are solid dark brown. Blue and light brown colors refer to tiers of the Biologist Ranking Index, a planning product of

the National Bobwhite Conservation Initiative. Source: Georgia Department of Natural Resources. Source: Georgia Department of Natural￼Resources

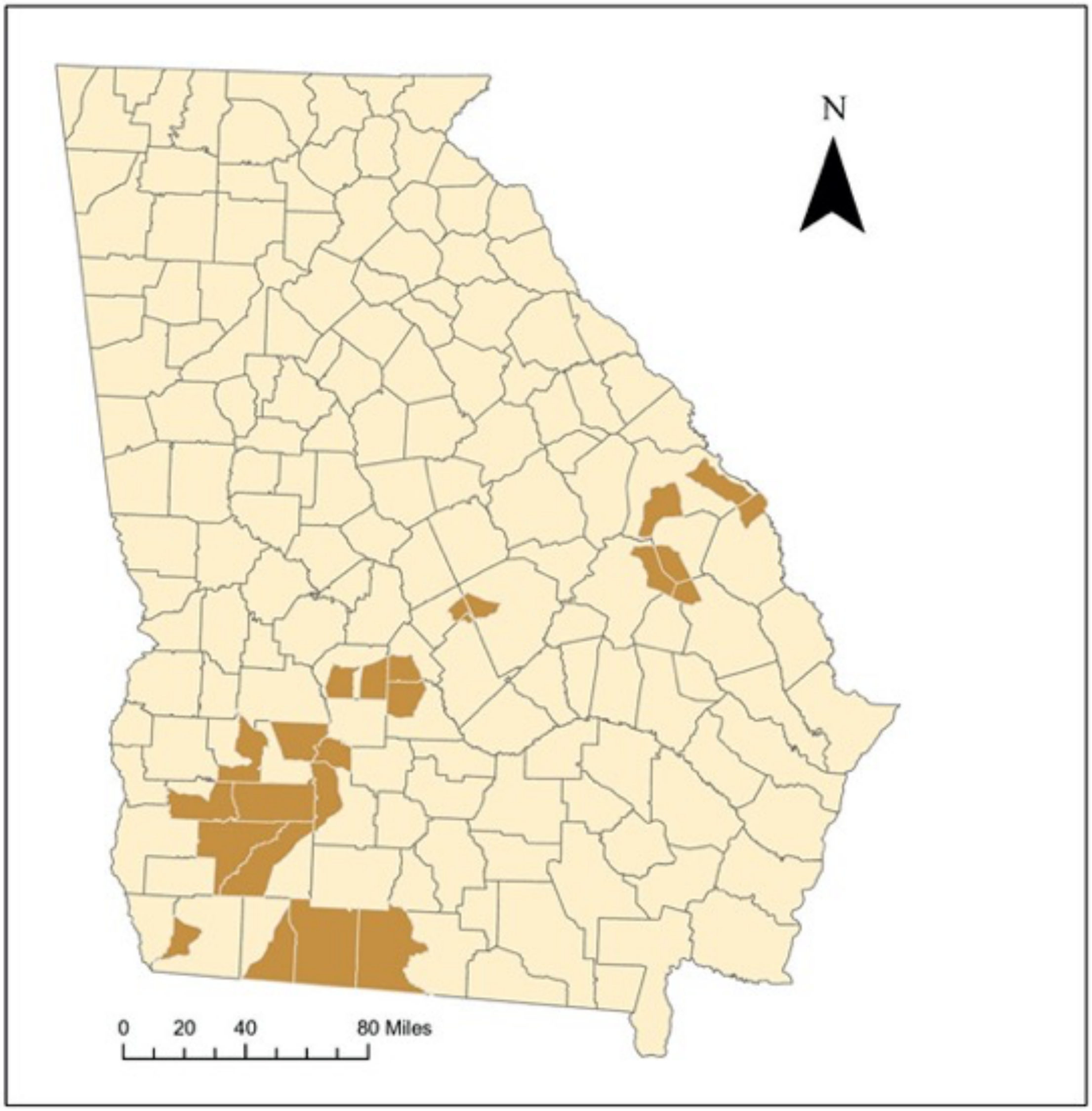


Figure 3.2 Focal areas from Georgia's Bobwhite Quail Initiative. The focal area is tan and counties are outlined in light beige.

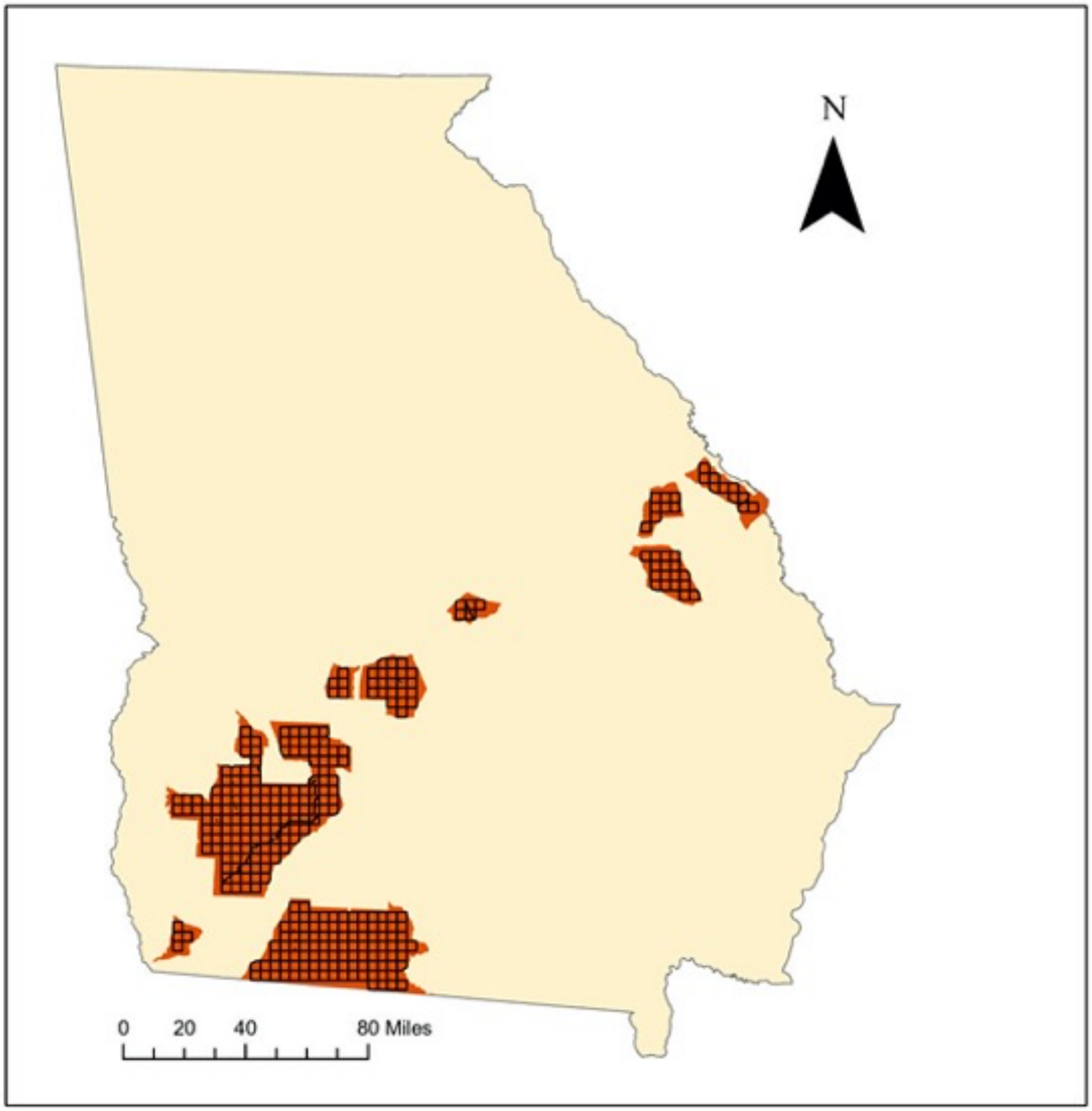


Figure 3.3 Map of landscape samples available for the smaller landscape (2,630 ha). The fishnet of 322 2,630-ha landscapes included in random sample of landscapes used in simulation

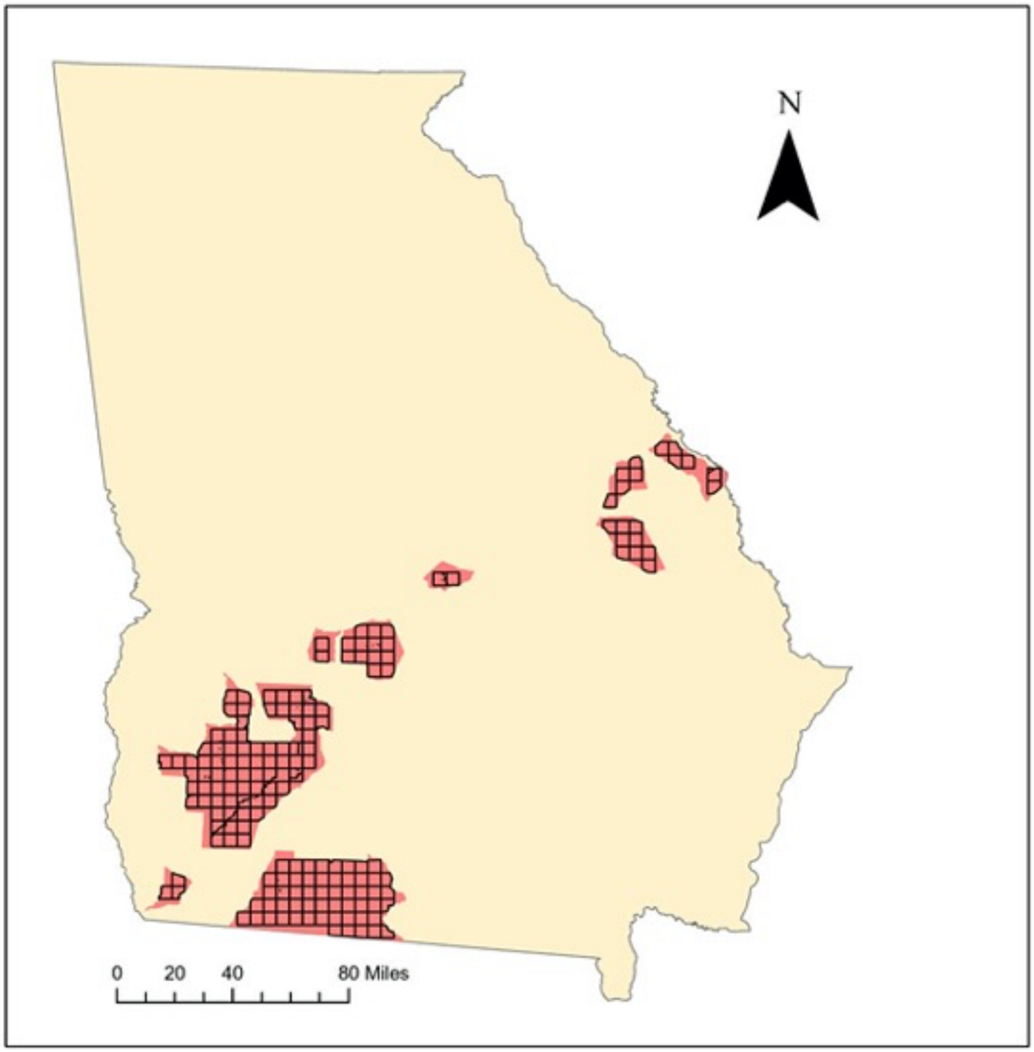


Figure 3.4 Map of landscape samples available for the larger landscape (5,261 ha). The fishnet of 169 5,261-ha landscapes included in random sample of landscapes used in simulation

Table 3.1. Summary statistics - Summary statistics (minimum value, first quantile, median, mean, third quartile, maximum value, and standard deviation) for amount of upland forest area, count of private landowners, and count of unique forest stands, by landscape size. We present summary statistics for landscapes prior to (original) and following (modified) removal of 10% of unique forest stands, and the difference (Δ) between the two sets of metrics.

Landscape	Variable	Min	q1	median	mean	q3	Max	Standard Deviation
2,630 ha	Original forest area (ha)	264.1	742.2	817.7	855.5	1009.9	1359.2	295.4
	Modified forest area (ha)	245.4	660.8	775.6	800.1	967.1	1343.0	290.9
	Δ forest area (ha)	13.8	27.1	48.6	55.4	67.6	183.1	41.5
	Original count of private landowners	14.0	30.5	35.5	42.8	57.3	89.0	19.0
	Modified count of private landowners	12.0	28.5	33.5	40.4	52.8	82.0	17.4
	Δ number of private landowners	0.0	0.8	2.0	2.5	3.3	9.0	2.5
	Original count of unique forest stands	53.0	76.5	109.5	104.7	132.0	157.0	29.5
	Modified count of unique forest stands	48.0	68.5	98.5	93.7	118.0	140.0	26.1
	Δ number of unique forest stand	5.0	8.0	11.0	11.0	14.0	17.0	3.4
5,261 ha	Original forest area (ha)	499.0	1520.8	1700.2	1776.5	2145.3	3120.1	578.1
	Modified forest area (ha)	478.7	1355.5	1574.6	1625.5	1946.0	3027.8	568.9
	Δ amount of forest area (ha)	20.3	91.7	120.7	150.9	209.4	315.9	77.9
	Original count of private landowners	18.0	53.8	71.0	74.5	96.5	138.0	30.4
	Modified count of private landowners	17.0	50.0	67.5	70.2	90.5	130.0	28.8
	Δ number of private landowners	1.0	2.8	4.0	4.3	6.3	8.0	2.3
	Original count of unique forest stands	109.0	134.8	184.0	182.8	208.8	287.0	49.1
	Modified count of unique forest stands	97.0	120.0	164.5	163.5	186.5	257.0	44.1
	Δ number of unique forest stands	12.0	14.8	19.5	19.3	22.3	30.0	5.0

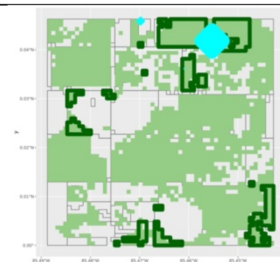
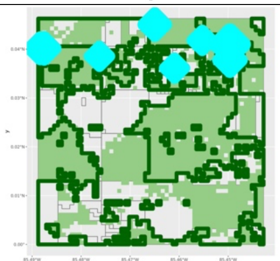
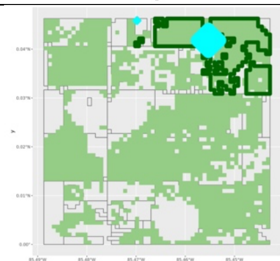
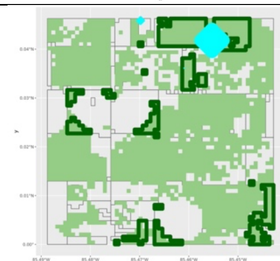
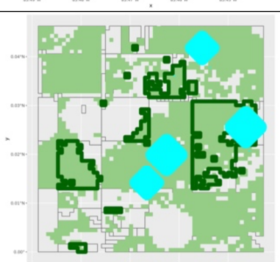
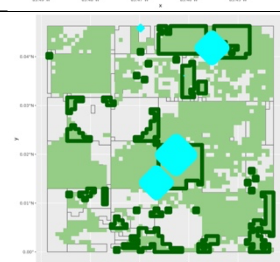
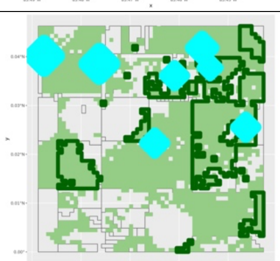
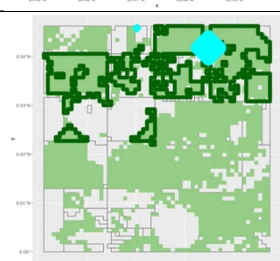
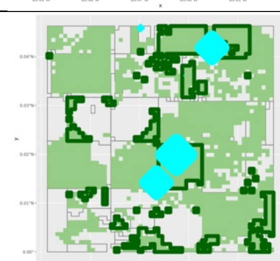
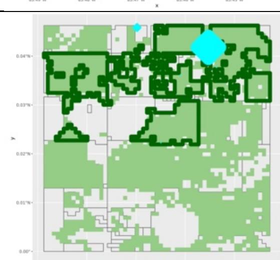
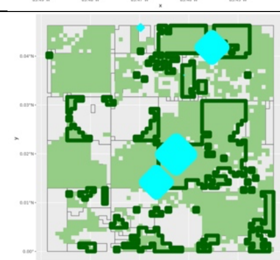
	Framework		
Percent	**Model based**	**Ranking**	**Random**
5			
10			
15			
20			
25			

Figure 3.5: Visualization of frameworks across different percentages of landscape enrollment on a single sample landscape. For a single sample of a 2,630-ha landscape and a single replication of management practices, we display the spatial arrangement of covey locations and selected stands. Forest stands eligible for selection are represented in light green; those that have been selected for enrollment are shown with a dark green border. Contiguous patches of forest may constitute multiple distinct stands, dissected by property boundaries (not shown). Covey size is correlated with the size of the blue diamond; multiple coveys found at the same location are aggregated and represented as a single point..

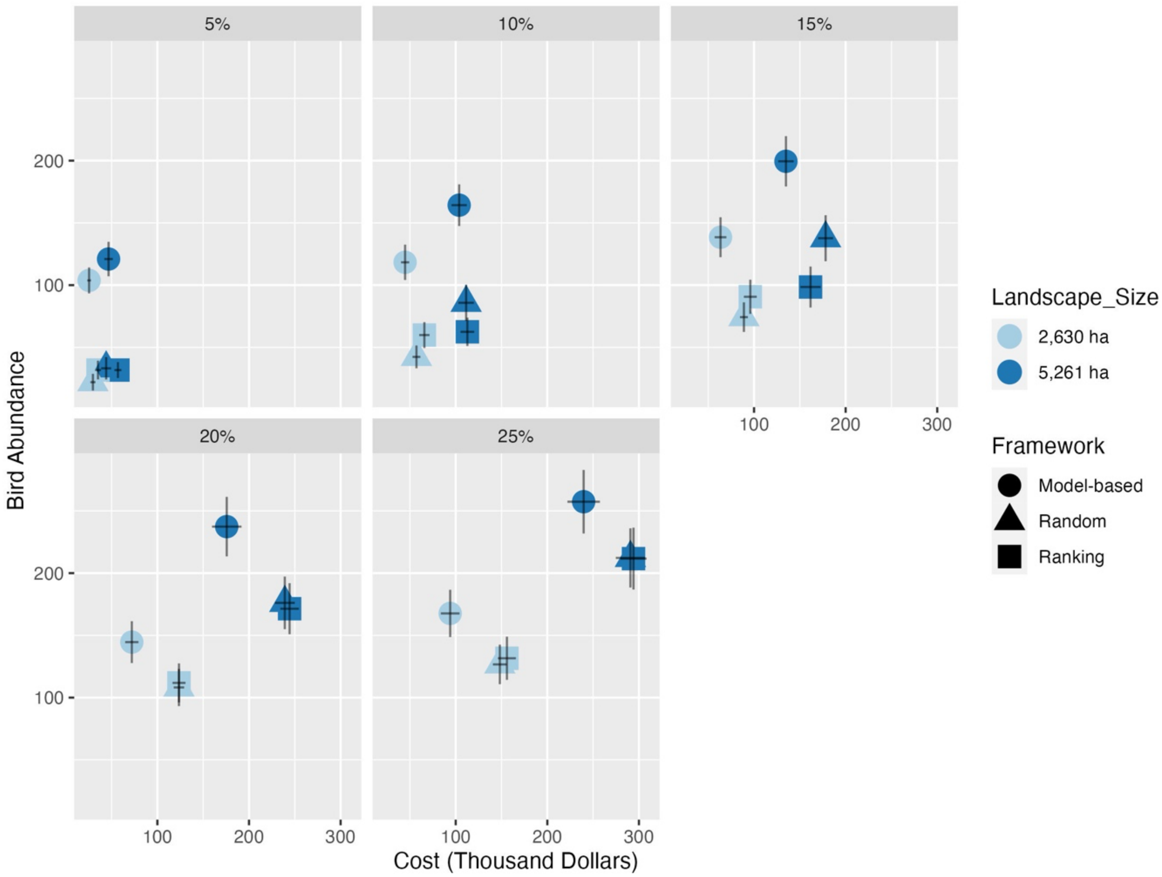


Figure 3.6 The Total Number of Birds Returned Over 10 years per Thousand Dollars Spent
Expected number of birds returned over 10 years against cost, under alternative decision frameworks (symbol shape), and by combinations of landscape size (symbol color) and percent of landscape enrolled (figure panels). Plot whiskers represent standard errors.

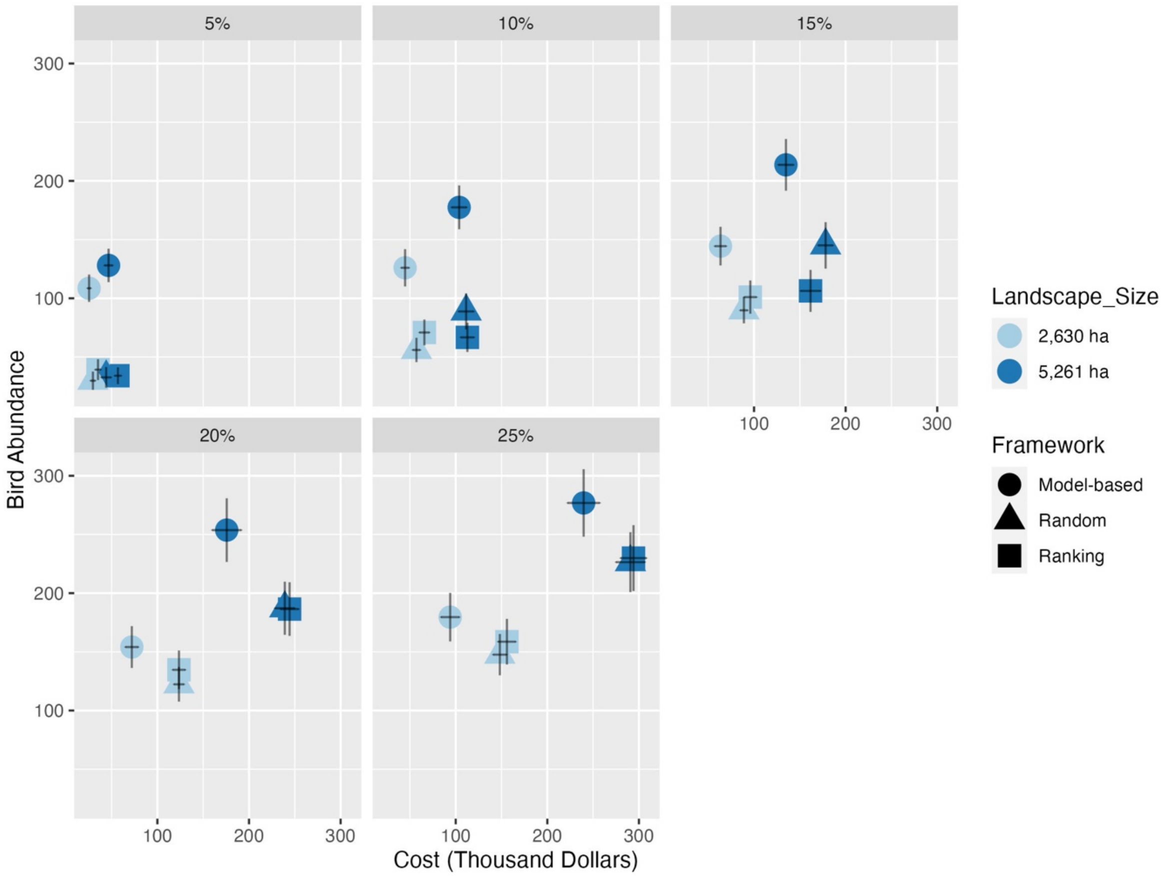


Figure 3.7. The Total Number of Birds Returned Over 30 years per Thousand Dollars Spent Expected number of birds returned over 30 years against cost, under alternative decision frameworks (symbol shape), and by combinations of landscape size (symbol color) and percent of landscape enrolled (figure panels). Plot whiskers represent standard errors.

Table 3.2. Predicted costs over 10 years of implementing conservation practices under alternative decision frameworks, by landscape size and percent of landscape enrolled.

Landscape Size	Percent of Landscape Enrolled	Framework	Mean Cost (Thousand Dollars)	Cost Standard Error	Cost Standard Deviation
2,630 (ha)	5%	Model based	25.44	46.55	8.84
		Ranking	35.16	33.50	14.32
		Random	29.60	29.93	12.34
	10%	Model based	44.75	63.38	19.79
		Ranking	65.79	46.55	25.12
		Random	57.13	40.88	19.16
	15%	Model based	63.41	71.56	28.57
		Ranking	95.93	61.29	31.48
		Random	88.95	53.05	19.07
	20%	Model based	72.06	75.12	32.23
		Ranking	123.55	69.84	31.59
		Random	123.53	66.80	25.37
	25%	Model based	93.95	84.91	45.47
		Ranking	155.90	77.50	43.62
		Random	148.16	70.95	33.85
5,261 (ha)	5%	Model based	46.68	61.87	20.63
		Ranking	56.91	28.38	17.01
		Random	44.06	40.11	24.50
	10%	Model based	103.78	74.70	37.31
		Ranking	112.73	50.89	33.38
		Random	111.37	64.90	37.97
	15%	Model based	134.84	90.34	37.88
		Ranking	161.69	73.57	49.41
		Random	178.13	82.67	36.60
	20%	Model based	175.69	106.84	71.92
		Ranking	244.28	91.69	45.24
		Random	239.07	94.47	48.42
	25%	Model based	239.66	114.02	79.27
		Ranking	294.09	111.11	63.61
		Random	290.70	106.29	71.23

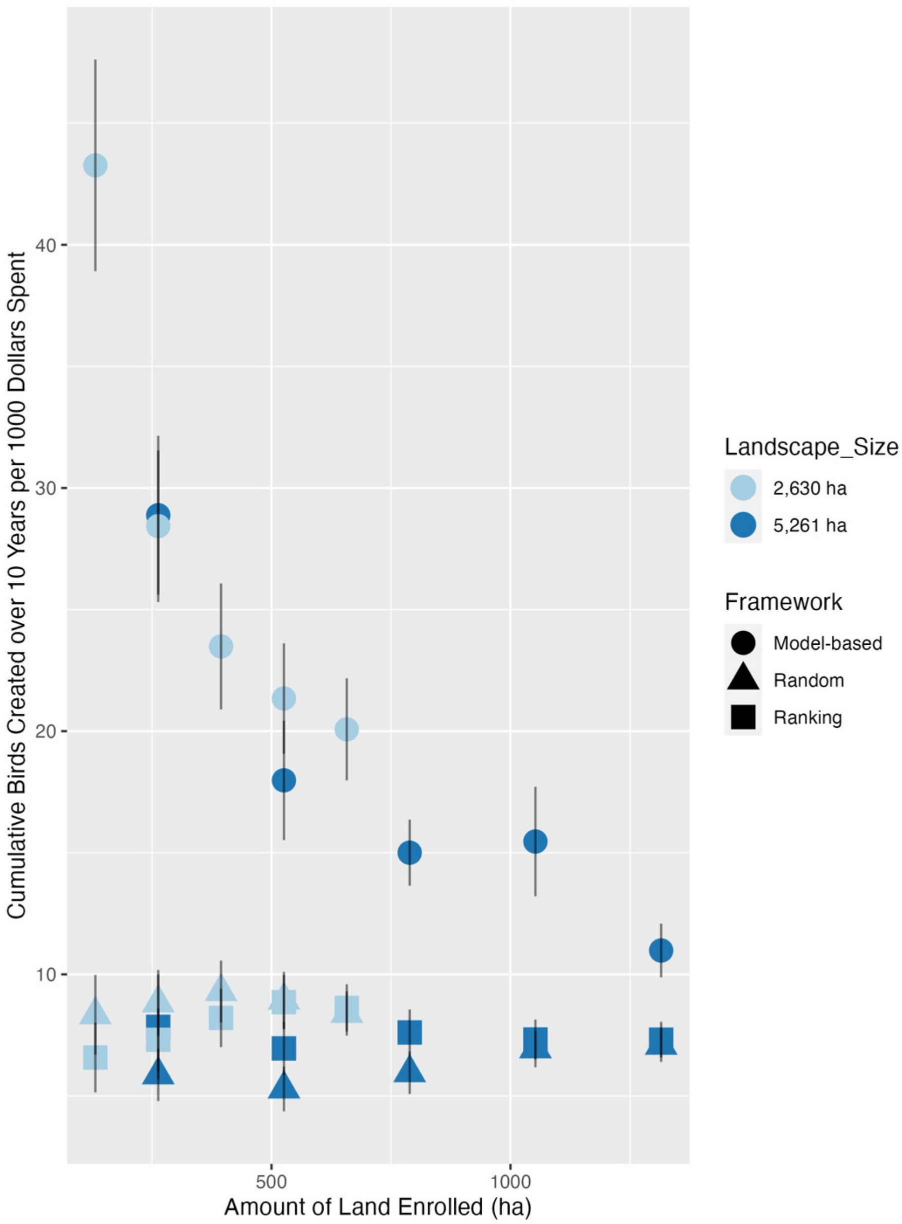


Figure 3.8 The Efficiency in the Number of Dollars Spent for the Number of Birds Returned Over 10 Years.

Efficiency in the number of birds returned over 10 years for the number of dollars (thousands) spent by decision framework (symbol shape) and landscape size (symbol color). Plot whiskers represent standard errors.

CHAPTER 4

Conclusions

In the spring of 2023, the U.S. Department of Agriculture (USDA) announced (USDA press release, 27 Jun 2023) that it would be spending 500 million dollars over the next five years on wildlife conservation and leveraging programs such as Conservation Reserve Program (CRP) and Working Lands for Wildlife (WLFW). The northern bobwhite became a 2.0 WLFW focal species in 2018 (QuailForever.org, 15 Jan 2021), with practices promoting its conservation set up in CRP. While it is unclear how much of this funding will be directed towards bobwhites, a proportion of this funding in addition to existing conservation efforts and incentive programs amounts to a massive investment in the species. These funds are being channeled through public programs and most of the effective conservation is occurring through conservation practices on private land.

To identify the current state of state-run programs for bobwhites, I completed a grey literature review of management plans from states engaged in the Northern Bobwhite and Grassland Initiative (NBGI). While most plans referred in various capacity to increasing bobwhite populations through engaging with private landowners, they were not explicit in how they did so or what sources of funding were being leveraged in these public-private partnerships. The objectives found in these plans were typically a collection of indirect means objectives that served as a proxy for a single fundamental objective. The fundamental objective of most programs – often implicit – was to increase the abundance of the bobwhite, but there was not a direct link between this fundamental objective and other related objectives listed in plans such as improving habitat or engaging with landowners. States that explicitly referred to private landowner incentive programs as a way to increase populations did not include details about how conservation incentive programs operated. Only three states had established linkages to conservation incentive programs in their state management plans. Even Georgia, which has an in-house incentive program funded by license plate sales, did not mention its incentive program by name in its state management plan or identify how that program was run in internal documents.

Incentive programs, regardless of which species they are targeting, can be set up using the structured decision-making framework and guided by the steps of the PrOACT cycle. After the scope and extent of the problem has been addressed in problem framing, the second step of the PrOACT cycle is to identify the objectives. I found that most state-run quail programs do not have tractable objectives hierarchies. While federal programs were not the primary focus of this thesis, funds are typically allocated from the national office to state offices and distributed in partnership with state biologists. As such, the objectives of both the state agency and federal program are important in determining how funds should be allocated according to the principles of decision science. Alternatives, the third step of PrOACT, are simply the different combinations of private landowners that can be enrolled. I identified three different schemes embedded in the consequences step of PrOACT: model-based, transparent ranking and scoring, and opaque ranking and scoring. For a model-based framework, optimization serves as the trade-off step of PrOACT. The purpose of my second chapter was to demonstrate the need to treat conservation incentive problems as a resource allocation problem, particularly for the bobwhite. But my broader purpose was to outline the fundamentals of conservation incentive programs within the structured decision-making framework to make the principles transferable to other species targeted by programs such as WLFW. The goal of my third chapter was to show how such a program could be set up using realistic management parameters in a simulation.

I established a simulation of a conservation incentive program using parameters specific to bobwhites and bound by realistic constraints of existing programs. Program attributes specific to the bobwhite included the individual-based model used to estimate abundance, the type of habitat that could be enrolled (upland forest), the conservation practices applied to favor the species (forest stand improvement, burning, and brush management), and the costs associated with each action. Each component could be changed within this framework to adapt the approach to a different target species. Program attributes common to all private landowner incentive programs included the identification of private landowner property boundaries, the removal of a fraction of landowners or pieces of property representing disinterest in the program, and cost constraints affecting how much of the landscape could be enrolled.

Using identical starting data layers, I compared different enrollment frameworks in the simulation for a conservation incentive program targeting the northern bobwhite and found that the model-based approach outperformed the ranking and scoring framework and the random selection framework regardless of landscape size or the percentage of the landscape enrolled in the program. Set up as a pareto frontier, the model-based framework produced a greater number of birds for a lower cost.

The efficiencies found in using the model-based framework strongly suggest that this approach should be used for bobwhite management, and it is likely promising for other programs with a single-species objective. The two limitations that could act as barriers to implementation are the assumptions made about landowners in the simulation and technical obstacles. For the simulation, we assumed that 90% of upland forest stands were available and that the owners of those stands were willing to participate in a conservation program. This approach assumes prior knowledge about all landowners in a specified area or, if set up such that private lands biologists would attempt to actively recruit landowners, it does not dynamically adjust for the rejection rate. In applications of the rank and scoring approach, programs select from a list of known willing participants. If that list was represented as a raster layer, then the same approach presented here could be used to select among willing participants. Technical obstacles include familiarity with and application of predictive population models, use of optimization procedures, and access to high performance computing systems; these obstacles may exist within agencies with limited staff and budgets. However, given the return on investment when a model-based approach is used, future research could address the cost of implementing a model-based approach and could identify whether including the cost of personnel training and computational resources results in efficiencies across the landscape. Given the differences between approaches in the analysis presented here, those efficiencies will likely still exist.

APPENDIX A

Supplementary Information

Model-based Spatial Prioritization Improves Expected Outcomes in Conservation Incentive Programs

Contents:

GIS Data Processing

Existing Vegetation Type (EVT) 2022:
Of all the vegetation identified as forest in EVC, we only include pixels that fell into the upland category from EVT. Upland classifications were based on the descriptions of LandFire designated Ecological Systems (NatureServe, 2018). The following classifications were included if they fell in a selected clipped landscape:

East Gulf Coastal Plain Northern Dry Upland Hardwood Forest
Southern Appalachian Northern Hardwood Forest
Southern Appalachian Oak Forest
Southern Piedmont Mesic Forest
Allegheny-Cumberland Dry Oak Forest and Woodland
Central and Southern Appalachian Montane Oak Forest
South-Central Interior Mesophytic Forest
East Gulf Coastal Plain Northern Mesic Hardwood Slope Forest
Southern Coastal Plain Limestone Forest
Southern Coastal Plain Dry Upland Hardwood Forest
Southern Atlantic Coastal Plain Dry and Dry-Mesic Oak Forest

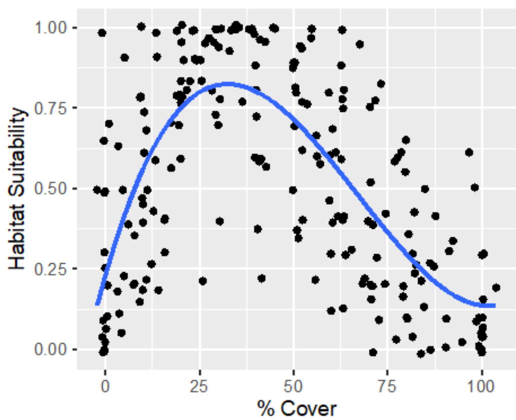
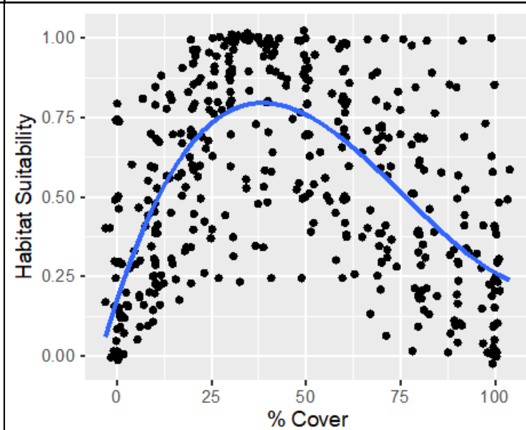
Piedmont Hardpan Woodland and Forest
Southern Atlantic Coastal Plain Mesic Hardwood Forest
Atlantic Coastal Plain Fall-line Sandhills Longleaf Pine Woodland
Atlantic Coastal Plain Upland Longleaf Pine Woodland
East Gulf Coastal Plain Interior Upland Longleaf Pine Woodland
Central and Southern Appalachian Spruce-Fir Forest
Southeastern Interior Longleaf Pine Woodland
Southern Appalachian Montane Pine Forest and Woodland
Southern Appalachian Low-Elevation Pine Forest
Florida Longleaf Pine Sandhill
Southern Coastal Plain Mesic Slope Forest
Southern Piedmont Dry Pine Forest
Southern Ridge and Valley / Cumberland Dry Calcareous Forest
Cumberland Sandstone Glade and Barrens
Southern Piedmont Dry Oak Forest
Southern Piedmont Dry Oak-(Pine) Forest
Central Florida Pine Flatwoods
East Gulf Coastal Plain Near-Coast Pine Flatwoods
East Gulf Coastal Plain Southern Loblolly Flatwoods
Florida Peninsula Inland Scrub Woodland
Southern Coastal Plain Blackland Prairie Woodland
North-Central Appalachian Acidic Cliff and Talus
Panhandle Florida Limestone Glade
Southern and Central Appalachian Mafic Glade and Barrens
Southern Appalachian Granitic Dome
Southern Atlantic Coastal Plain Florida Beach
Southern Piedmont Glade and Barrens
Southern Piedmont Granite Flatrock and Outcrop
Southern Ridge and Valley Calcareous Glade and Woodland
Northeastern North American Temperate Forest Plantation
Northern & Central Native Ruderal Forest
Southeastern Native Ruderal Forest
Southeastern North American Temperate Forest Plantation
Southeastern Ruderal Shrubland

NatureServe. 2018. International Ecological Classification Standard: Terrestrial Ecological Classifications. NatureServe Central Databases. Arlington, VA. U.S.A. Data current as of 28 August 2018.

Habitat Quality

Expert elicitation data for shrub and herbaceous categories

While the expert opinion habitat survey covered the entire habitat range of the northern bobwhite, we only used a subset of responses that came from the state of Georgia. This subset data included responses from 77 experts and 3 Bird Conservation Regions (Southeastern Coastal Plain, Peninsular Florida, and Piedmont). To get predictions for the Landfire Herbaceous class, we combined survey responses for percent cover of grasses and percent cover of forb. To get estimates for shrub and herbaceous Landfire categories, we fit a spline regression using the R package splines (Wang and Yan 2023). For both models, we set the degree of the polynomial to 3 (a cubic spline) and the location of the knots to the lower quartile, the median quartile, and the upper quartile of our data.

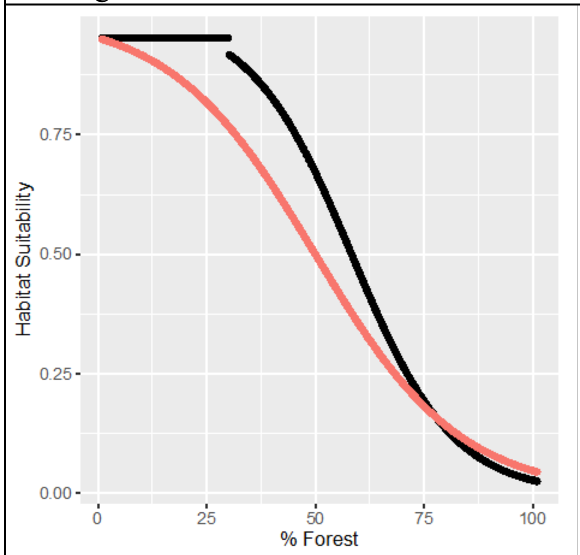
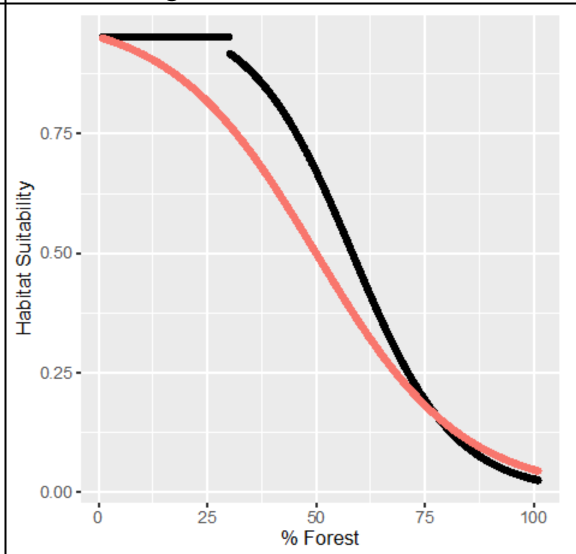
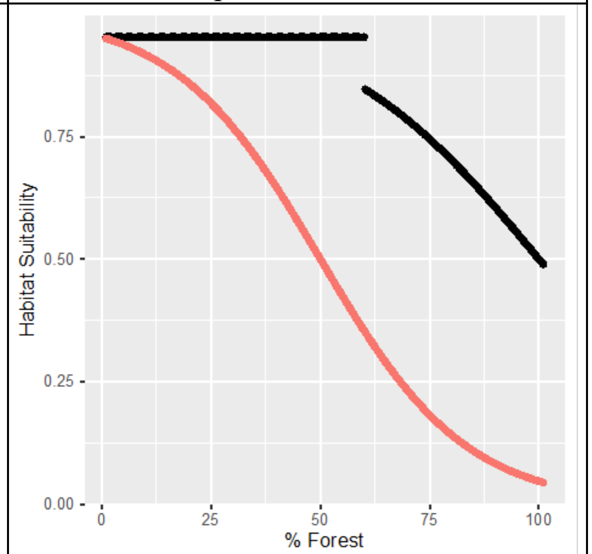
	Shrub	Herbaceous
RMSE	0.3796625	0.3663002
R2	0.01784575	0.01769371
Graphical Fit		

Linear relationship for forest cover

Habitat Suitability = -.06 * (% forest cover) +3

Habitat Quality Increase from Conservation Practices

The red curve is the simple relationship between percent forest cover and habitat suitability while the black line is the change that results from applying the specified action.

<table>
<tr><th>Burning</th><th>Brush Management</th><th>Forest Stand Improvement</th></tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$f(x) = \begin{cases} 3 & x \leq 30 \\ -0.085 * x + 4.29 & x > 30 \end{cases}$</td>
<td>$g(x) = \begin{cases} 3 & x \leq 30 \\ -0.085 * x + 4.29 & x > 30 \end{cases}$</td>
<td>$z = x * .5$
$h(z) = \begin{cases} 3 & z \leq 30 \\ -0.085 * z + 4.29 & z > 30 \end{cases}$</td>
</tr>
</table>

Wang W, Yan J. 2023. splines2: Regression Spline Functions and Classes. R package version 0.5.1. Retrieved from https://cran.r-project.org/web/packages/splines2/index.html.

Status Quo Ranking Information

Points assigned for priority landscape membership

Georgia BQI Priority Landscapes	Georgia BQI Landscape Ranking	
	Points	Weight
Within 1 mile of a Focal Area	50	25%
Priority 1 Focal Landscape	100	50%
Priority 2 Focal Landscape	75	38%
High BRI	50	25%
Medium BRI	25	13%
Low BRI	10	5%
None	0	0%

Caption: SI – Figure 1: Points associated with Georgia's BQI Priority Landscapes.

Points assigned to land uses

	Portion of Property			
Landuse	1-25%	26-50%	51-75%	76-100%
Bottomland hardwood	5	5	0	0
Exotic grass production	25	20	15	10
Open canopy pines with native groundcover	20	30	40	50
Pine stand with sparse native groundcover*	10	15	20	25
Row crop	25	25	20	10
Upland hardwood	25	20	15	10

**Includes pine stands that have predominately exotic ground cover*

https://landfire.gov/documents/LANDFIRE_Ecological_Systems_Descriptions_CONUS.pdf

EVT_Name	Ecological Systems name in the LANDFIRE EVT legend
EVT_Fuel	Ecological Systems code used for Fuel product development
EVT_Fuel_N	Ecological Systems class name used for Fuel product development
EVT_LF	Vegetation lifeform (e.g., Tree, Shrub, Herb, Sparse)
EVT_GP	Collapsed vegetation type code
EVT_GP_N	Collapsed vegetation type name (e.g., Grasslands and Steppes, Hammocks, Longleaf Pine)
EVT_PHYS	Vegetation physiognomy (e.g., Grassland, Riparian, Hardwood, Sparsely Vegetated)

To identify the above land use categories, we use a combination of information found in the Landfire Existing Vegetation Cover (EVC) and Existing Vegetation Type (EVT) 2022 datasets.

Exotic grass production was assigned to raster values when the EVT collapsed vegetation type name ("EVT_GP_N") contained the string "pasture"
Row Crop was assigned to raster values when the EVT collapsed vegetation type name ("EVT_GP_N") contained the string "crop"

Bottomland Hardwood was identified by first subsetting the EVT Vegetation physiognomy ("EVT_PHYS") that contained the string "Hardwood" or "Conifer-Hardwood" and then removing all Ecological System names ("EVT_Name") that contained the string "upland".

Upland Hardwood was identified the same way as Bottomland Hardwood by first subsetting the EVT Vegetation physiognomy ("EVT_PHYS") that contained the string "Hardwood" or "Conifer-Hardwood" but then only keeping Ecological System names ("EVT_Name") that contained the string "upland".

Pine was identified by subsetting all collapsed EVT vegetation type names ("EVT_GP_N") that contained the string "pine". To delineate between open and closed stands, we created two masks from the EVC dataset. For the tree cover category in EVC, we subset all pixels with tree cover less than 50% and used a mask to identify the open canopy pine. All other cells classified as pine were assigned to pine stand with sparse native groundcover.